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"Pricing intermittent renewable energy"

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Abstract

The energy transition requires significant investment in intermittent renewable energy sources, such as solar and wind power. New generation capacities are generally procured through fixed price contracts, such as power purchase agreements and contracts for difference, or feed-in tariffs. With these designs, renewable technologies are selected based on their generation, regardless of their adequacy with demand and supply by other technologies. We show that fixed-price contracts implement the optimal portfolio of renewable technologies 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 the bonus-malus for solar and wind power in California, France, Germany, and Spain and decompose it to identify the key market factors driving the adjustment. We argue that the bonus-malus measures the cost of integrating intermittent generation into the energy mix. Therefore, it should be added to the levelized cost of energy (LCOE) to obtain the cost of generating an additional megawatt-hour with a specific renewable technology.

Keywords: Electricity market, levelized cost of energy, climate change, intermittent renewable energy, feed-in tariff, power purchase agreement, contract for difference.
JEL codes: D47, L23, Q41, Q48

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1 Introduction

Limiting climate change requires a rapid shift away from fossil fuels towards large-scale investments in zero-emission sources such as nuclear, hydropower, solar, and wind. Developing new generation capacity involves long-term investments with life cycles typically exceeding twenty years. However, the returns on such investments are highly uncertain because they depend on future electricity prices that are difficult to predict over such long time horizons. Moreover, electricity markets offer limited hedging opportunities, with forward contracts rarely extending beyond two to three years. Investors are therefore exposed to unexpected price shocks in energy markets due to the introduction of new technologies (e.g., shale gas and oil), weather-related disasters, or geopolitical events (e.g., the war in Ukraine). For these reasons, relying solely on market signals may not be sufficient to mobilize the scale of investment needed for the energy transition. Public authorities have developed other instruments to foster investment in new generation of renewable energy sources.

In the last twenty years, most of solar and wind power investment have been driven by long term contracts, such as Feed-in tariffs (FiT), Power Purchase Agreements (PPA) and Contracts for Differences (CfD). Historically, FiT have been implemented in many countries and states such as China, France, Japan, Germany, California, Ontario and the United Kingdom, to launch the energy transition. These tariffs guarantee a fixed price (premium) per megawatt-hour (MWh) fed to the grid. The price is set by public authorities. More recently, new investments have been procured through renewable energy auctions.[1] Investors bid a price per MWh at which they are willing to sell their production. The winning bid defines a price per MWh at which the selected producers are remunerated. Under a PPA, electricity is sold to retailers or electricity-intensive consumers at a price determined by an auction or negotiated bilaterally. Under a two-way CfD, investors receive a fixed, prearranged strike price for the electricity produced over the lifetime of the plant. The electricity produced is sold on the wholesale market. Producers pay the difference between the wholesale market price and the strike price to a third party (usually the government) if the former exceeds the latter. The third party pays the producer the difference in the reverse case, when the wholesale price is lower than the strike price. Recently, the European authorities explicitly recommended PPAs and CfDs in Regulation 2024/1747 as a key policy tool to support investment in intermittent renewable energy sources.[2]

[1]According to IRENA (2019), more than 100 countries have used renewable energy auctions, including Brazil, India, Germany, and the United Kingdom, for a global capacity of 100 gigawatt auctioned in 2028.

[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 source of en-

We develop a framework to analyze investment in intermittent renewable energy sources for the energy transition with fixed price contracts. In our framework, both electricity demand and supply from renewables have random components. 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 derive the optimal investment in renewable energy sources as a benchmark. In doing so, we obtain an optimality condition that links the expected social cost of an additional megawatt-hour (MWh) generated by all renewable energy technologies with the expected social cost of one MWh produced by the current energy mix. This condition allows us to compare the cost of providing one MWh in expectation with various renewable technologies in a given energy mix. In line with Joskow (2011), it extends the concept of levelized cost of energy (LCOE) to account for an intermittent electricity supply and variable demand. The LCOE is transformed into the economic cost of energy (ECOE) by adding a term that measures the covariance between electricity production and wholesale prices. The ECOE of one MWh of this technology is lower than the LCOE when the covariance is positive, and higher when it is negative. Therefore, a "bonus" should be associated with this technology if its generation correlates positively with the electricity price. Symmetrically, a "malus" should be applied if there is negative correlation. The ECOE can be used to compare investments in different renewable technologies and locations.

Next, we investigate a market-only solution to the energy transition when carbon emissions are priced at their social cost. We show that, in competitive markets, the wholesale price signal triggers optimal investment in new generation of renewable energy sources. The efficiency of the market outcome relies on the assumption that risk-neutral investors can perfectly forecast the future wholesale price during the lifespan of their power generation equipment. We believe that uncertainty and the lack of visibility with respect to future electricity prices justify the use of CfDs to encourage investment in new generation capacity.

We analyze the extent to which a fixed price contract can foster investment in the right renewable energy technologies. We consider two ways to implement fixed price contracts: FiTs and procurement of PPAs or CfDs. First, we characterize FiTs that would decentralize optimal investment. The tariff is equal to the expected future wholesale market price adjusted with the "bonus-malus", i.e., the covariance between generation and the wholesale market price divided by the average capacity factor. If the covariance is positive, a bonus should be applied to the expected price because the renewable technology is more valuable

ergy in (c) and (e) are not intermittent, our analysis mainly focuses on (a) and (b).

when it produces electricity that is scarce relative to demand. Conversely, in the case of negative covariance, the renewable technology is less valuable as it produces when electricity is abundant. Second, rather than setting prices with FiTs, the regulator can procure new generation capacity through CfDs. We propose an auction design that triggers investment in the most appropriate renewable technologies. The auction is technology-neutral, meaning all renewable technologies can participate by bidding a price per MWh of production. However, the price is technology-specific and endogenously determined by the procurement process. Investors are paid the winning bid, adjusted by the bonus-malus assigned to their technology, for each MWh produced. We show that a first-price auction with technology-specific bonus-malus adjustments implements the optimal portfolio of renewable energy equipment.

Using public data from four electricity markets in California, France, Germany, and Spain, we propose empirical estimates of the bonus-malus that correct the LCOE or the strike price in CfDs. Specifically, we demonstrate how the bonus-malus depends on market-specific fundamentals and varies based on technological factors. Overall, we find that renewable energy sources should generally be penalized due to negative covariance between renewable energy availability (capacity factor) and wholesale market prices. However, there is significant heterogeneity in terms of location, time dimension, and technology. To further highlight the importance of location and technology factors (e.g., solar panel orientation) within each market, we use simulated output from solar and wind plants in Germany.

Finally, to understand the importance of the elements that influence the adjustment term, we decompose the bonus-malus using a second-order Taylor approximation. Instead of relying on market electricity price to assess the adequacy of the renewable technology with the energy mix, we derive a bonus-malus based on technological parameters such as capacity factors, installed capacities, the curvature of the marginal social cost of electricity supply, and electricity consumption. We then calculate the total bonus-malus based on the individual elements, using market data combined with hourly bidding data from the wholesale electricity markets in Spain and California. Our findings show that both approaches lead to comparable estimates of the bonus-malus and explain the observed differences.

Three factors determine the bonus-malus associated with a given renewable technology: the cannibalization effect of investments in the same technology, its compatibility with other technologies in the energy mix, and its compatibility with electricity consumption. The cannibalization effect assigns a malus to the LCOE (i.e., ECOE>LCOE), increasing with the installed generation capacity of the same technology and the variance of power generation with this technology (i.e., the variance of the renewable technology's capacity factor). The second term in the bonus-malus decomposition quantifies the adequacy with other renewables. This term depends on the covariance between the availability of power generated by the renewable technology and the cumulative generation of other renewable technologies. It is associated with a bonus because the covariance between solar power and wind power generation is negative in our data. Therefore, the LCOE of solar should be reduced by this bonus, which accounts for the complementary nature of solar and wind power in ensuring a reliable electricity supply (i.e., ECOE<LCOE). Finally, the term in the decomposition that captures adequacy with electricity use depends on the covariance between the power supply of the renewable technology and electricity consumption. The covariance is positive, meaning that power generated by the renewable technology tends to occur when consumption is high, in all markets except France for solar. In case of positive covariance, the third term of the decomposition is negative. Hence a bonus should be assigned to wind or solar power based on its adequacy with consumption in all countries except in France for solar.

Related literature. Many studies have investigated how intermittency in electricity generation impacts the design of public policies and markets that foster investment in renewable energy sources (Abrell et al. 2019, Ambec and Crampes 2019, Reguant 2019, Holland et al. 2022, among others). However, to the best of our knowledge, none of these studies consider long term contracts such as PPAs and CfDs as an instrument to foster investment in intermittent renewables. Some of them have analyzed FiTs. Ambec and Crampes (2019) and Reguant (2019) conclude that FiTs do not trigger optimal investment in intermittent renewables in the absence of a carbon price. Abrell et al. (2019) show that the payment for renewable generation should vary with the wholesale market price, and, therefore, cannot be a FiT. We contribute to this literature by showing that technological-specific FiTs can induce optimal investment in intermittent renewables when carbon emissions are priced at their social cost. Furthermore, we derive the optimal FiT formula. It is equal to the expected electricity price adjusted by the technology-specific bonus-malus. Finally, we estimate the optimal FiT using data from four electricity markets.

Some studies have also examined the efficiency of CfDs for both investment in new generation and dispatch (Kröger et al. 2022, Schlecht et al. 2024, Ambec et al. 2025). Schlecht et al. (2024) argue that CfDs should be purely financial contracts, decoupling payment from actual generation to induce optimal dispatch. Kröger et al. (2022) examine the efficiency and risk-sharing properties of CfDs. However, none of these studies propose a specific design to encourage optimal investment in renewables, as we do.

Other studies have investigated the design of auction mechanisms for the procurement of renewable energy (e.g., Fabra and Llobet 2023, Lamp et al. 2024). The closest paper to ours is Fabra and Montero (2022). In their paper, the authors analyze the trade-offs in the choice between a technology-neutral uniform price auction and separate technology-specific auctions. They show that the regulator faces a trade-off between rent and efficiency and that the optimal mechanism depends on the extent to which information asymmetry can be overcome. Unlike their analysis, we demonstrate that a single auction with differentiated prices dominates both designs. Furthermore, we highlight how the bonus-malus system can quantify the total cost of adding intermittent renewable energy capacity.[3]

Finally, several papers have empirically estimated the social value of an additional MW of new wind or solar capacity in a given energy mix (e.g., Gowrisankaran et al. 2016, Callaway et al. 2018, Kaffine et al. 2020, Petersen et al. 2024). We contribute to this literature by providing a simple formula to assess the cost of integrating wind or solar power into a given energy mix, which should be added to the LCOE to obtain the ECOE. We estimate this integration cost for California, France, Germany, and Spain. The estimated values allow to select the more suitable renewable energy source for a marginal increase of power generation.

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. On the supply side, electricity is produced from existing (mostly thermal) production capacity and new generation of intermittent renewable energy such as wind and solar power. The private cost of producing Q megawatt-hours (MWh) of electricity with the current energy mix is denoted $C(Q)$. It is increasing with Q ($C'(Q) > 0$), and convex ($C''(Q) > 0$). The production capacity of the existing energy mix is denoted $\overline{Q}$. The greenhouse gas emitted by the Q MWh produced are $e(Q)$ tons of CO_2 equivalent, increasing with Q. Each ton being valued with an

[3]Lamp et al. 2024 empirically study the implications of pricing rules (uniform versus pay-as-bid) on market outcomes and subsidy payments in German solar auctions.

environmental cost δ, the social cost of Q MWh generated with the current energy mix is

$$SC(Q) = C(Q) + e(Q)\delta. \tag{1}$$

New generation from renewable energy sources can be of different types. Each type is denoted i with $i = 1, ..., n$. Renewable source i is described by the cost of installing new capacity r_i per megawatt (MW), a technical parameter k_i representing the maximal power that can be delivered by i at cost r_i, and a capacity factor ω_i. The capacity cost r_i varies in the range $[\underline{r}_i, +\infty)$ according to the density function g_i and the cumulative function G_i. We denote by $\tilde{r}_i \geq \underline{r}_i$ the marginal capacity cost of the most costly generator (e.g., wind turbine or solar panel) of technology i. The total installed capacity of renewable i is therefore $K_i = k_i G(\tilde{r}_i)$ with a cost of $k_i \int_{\underline{r}_i}^{\tilde{r}_i} r_i dG(r_i)$.

Renewable production being intermittent, the capacity factor ω_i varies with location and weather conditions such as sunshine or wind speed. It is a random variable with support $[\underline{\omega_i}, 1]$, where $\underline{\omega_i} \geq 0$. Installing K_i yields $\omega_i K_i$ MWh of renewable electricity. The expected capacity factor of renewable i is denoted $E[\omega_i]$ for $i = 1, ..., n$. 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 to be served, with $D \in [\underline{D}, \overline{D}]$. Let $f(D, \boldsymbol{\omega})$ denote the joint density function of random variables D and $\boldsymbol{\omega} = (\omega_1, ..., \omega_n)$, $F(D, \boldsymbol{\omega})$ the cumulative, $f_D(D|\boldsymbol{\omega})$ and $f_{\boldsymbol{\omega}}(\boldsymbol{\omega}|D)$ the conditional joint densities, $F_D(D|\boldsymbol{\omega})$ and $F_{\boldsymbol{\omega}}(\boldsymbol{\omega}|D)$ the conditional joint cumulatives. We assume $\overline{D} \leq \overline{Q}$, which means that peak demand can be supplied with the current energy mix, so that we do not need to worry about curtailment or blackouts.

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 then 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 outcome

Given the installed thermal capacity, the optimal energy mix is defined as the investment in renewable energy sources $\boldsymbol{K}^* = (K_1^*, ..., K_n^*)$ that minimizes the expected cost of electricity generation, anticipating that capacities will be optimally dispatched. The optimal dispatch is such that, given renewable generation $\sum_{i=1}^{n} \omega_i K_i$, for any realization of demand D, renewables are entering first in the merit order complemented with thermal power up to quantity demanded. Hence, given D and $\boldsymbol{K}$, the supply of thermal production is

$$Q = \max\left\{D - \sum_i \omega_i K_i, 0\right\}. \tag{2}$$

Since $K_i = k_i G_i(\tilde{r}_i)$ and k_i is fixed, finding K_i is equivalent to finding $\tilde{r}_i$ for $i = 1, ..., n$. The optimal renewable capacities K_i^* for $i = 1, ..., n$ can be found by minimizing the expected cost of supplying electricity with respect to $\tilde{r}_i$,

$$E[SC(Q)] + \sum_i k_i \int_{\underline{r}_i}^{\tilde{r}_i} r_i dG_i(r_i),$$

subject to (2). Differentiating with respect to $\tilde{r}_i$ for $i = 1, ..., n$ yields the following first-order conditions:[4]

$$-E[SC'(Q)\omega_i k_i g(\tilde{r}_i))] + k_i \tilde{r}_i g(\tilde{r}_i) = 0$$

for $i = 1, ..., n$. After simplifying by k_i and $g(\tilde{r}_i)$ that are not random, we obtain the optimal cut-off cost $\tilde{r}_i^*$ as a function of the optimal thermal power production Q^* for every renewable unit i:

$$\tilde{r}_i^* = E\left[\omega_i SC'(Q^*)\right], \tag{3}$$

for $i = 1, ..., n$. After using the definition of the covariance[5], we obtain

$$\frac{\tilde{r}_i^*}{E[\omega_i]} - \frac{cov(\omega_i, SC'(Q^*))}{E[\omega_i]} = E\left[SC'(Q^*)\right], \tag{4}$$

for $i = 1, ..., n$. 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 $\tilde{r}_i^*$ divided by the expected capacity factor $E[\omega_i]$. The second term reduces the LCOE by the covariance between the varying capacity factor ω_i and the marginal cost of thermal generation divided by the expected capacity factor. The right-hand side displays

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

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

the expected marginal social cost of thermal power production, including climate costs. The optimal cut-off costs $\tilde{r}_i^*$ for $i = 1, ..., n$ can be found by combining the first-order conditions (4) for $i = 1, ..., n$ with the binding constraint (2) that defines the optimal thermal power supply Q^* with optimal capacity investment $K_i^* = k_i G_i(\tilde{r}_i^*)$ for $i = 1, ..., n^*$.

The efficiency condition (4) implies that, for any pair of renewables i and j, we have

$$\frac{\tilde{r}_i^* - cov(\omega_i, SC'(Q^*))}{E[\omega_i]} = \frac{\tilde{r}_j^* - cov(\omega_j, SC'(Q^*))}{E[\omega_j]}. \tag{5}$$

The LCOE, net of the covariance between renewable availability and thermal power marginal cost divided by the average capacity factor, should be the same among renewable energy sources. 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 the energy mix is at least as important. Technologies with a positive correlation should receive a bonus, giving an economic cost of energy (ECOE) 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 investigate 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 new generation capacity $\boldsymbol{K}$, dispatch is optimal. For realizations of D and $\boldsymbol{\omega}$ such that $D \leq \sum_i \omega_i K_i$, demand can be fully served by renewables at zero marginal cost, and thus the wholesale electricity price is $p = 0$. In contrast, if $D > \sum_i \omega_i K_i$, the demand net of renewable generation is $Q = D - \sum_i \omega_i K_i > 0$. It is supplied by thermal power plants. The market price is equal to the marginal cost of the last MWh supplied, which includes the cost of carbon emissions, that is:

$$p = SC'(Q). \tag{6}$$

The expected profit of the renewable investment k_i at cost r_i is:

$$E[\pi_i(r_i)] = (E[\omega_i p] - r_i)\, k_i.$$

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

$$\tilde{r}_i^e = E[\omega_i p], \tag{7}$$

for $i = 1, ..., n$. All new generation plants with cost $r_i < \tilde{r}_i^e$ are built so that the total production capacity is $K_i^e = k_i G_i(\tilde{r}_i^e)$. If carbon is priced at its social cost[6], replacing p defined in (6) with $\tau = \delta$ and using (1) yields the optimality conditions (4) for $i = 1, ..., n$. Hence $\tilde{r}_i^e = \tilde{r}_i^*$ and, therefore, $K_i^e = K_i^*$ for $i = 1, ..., n$: investment in new generation is socially optimal. We thus 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. In practice, however, investors are unable to accurately predict future wholesale prices over long periods. Typically, future markets in electricity span 2-5 years, which is well below the lifetime of new generation equipment. Therefore, the assumption of rational expectation does not hold. This market failure justifies the design of public policies to encourage investment in renewables. We now investigate the effectiveness of the most common policies: fixing Feed in Tariffs for renewable electricity produced by new generation capacity, or procuring new generation capacity by means of PPAs or CfDs.

[6]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

Let us denote p_i^s the fixed price assigned to renewable technology i for $i = 1, ..., n$. The expected profit of a generation plant of type i with capacity k_i and with a fixed price p_i^s is:

$$E[\pi] = (E[\omega_i]p_i^s - r_i)k_i. \tag{8}$$

First, we show that fixing the FiT at the expected wholesale market price leads to inefficient investment in new renewable generation unless the renewable capacity factor is uncorrelated with the price. Substituting $p_i^s = E[p]$ into (8) and equalizing the expected profit to zero yields a cut-off capacity cost $\tilde{r}_i^s = E[\omega_i]E[p]$. Compared to the efficient cut-off implemented with competitive wholesale markets $\tilde{r}_i^* = \tilde{r}_i^e$ defined in (7), we have:

$$\tilde{r}_i^* - \tilde{r}_i^s = E[\omega_i p] - p_i^s E[\omega_i] = E[\omega_i]E[p] - E[\omega_i]p_i^s + cov(\omega_i, p), \tag{9}$$

where the last equality is due to the aforementioned definition of covariance. With a strike price equal to the average spot price $p_i^s = E[p]$, we obtain $\tilde{r}_i^* - \tilde{r}_i^s = cov(\omega_i, p)$. Hence this strike price will trigger under-investment in renewable of type i whenever $cov(\omega_i, p) > 0$ (positive correlation between demand and renewable production) and over-investment if $cov(\omega_i, p) < 0$ (negative correlation).

Second, we derive the optimal FiT. Equalizing (9) to zero shows that $\tilde{r}_i^* = \tilde{r}_i^s$ if

$$p_i^s = E[p] + \frac{cov(\omega_i, p)}{E[\omega_i]}. \tag{10}$$

The optimal FiT is equal to the average future price $E[p]$ adjusted by a *bonus-malus* featuring the covariance between renewable generation ω_i and market price p. 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 average price.

Proposition 2 *Pricing renewable technology i at $p_i^s = E[p] + \frac{cov(\omega_i, p)}{E[\omega_i]}$ per MWh for $i = 1, ...n$ attracts the optimal investment in new renewable generation. It rewards energy sources that are positively correlated with market prices and penalizes those that are negatively correlated. A FiT equal to the average market price leads to underinvestment (resp. overinvest-*

ment) in renewable energy if the market price p and the capacity factor ω_i are positively (resp. negatively) correlated.

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 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. Reversely, 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 $\boldsymbol{K}^* = (K_1^*, ..., K_n^*)$ with $K_i^* = k_i G_i(\tilde{r}_i^*)$ for $i = 1, ..., n$, where $\tilde{r}_i^*$ 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. The winning bid is the highest bid among all the selected investments. The price should be equal to the highest bid adjusted by the bonus-malus associated with the renewable technology. The proof is provided in Appendix A.[7]

Proposition 3 *A single auction on new generation capacity implements the optimal portfolio of renewable technologies with differentiated prices* $p_i^s = \widehat{b} + \dfrac{cov(\omega_i, p)}{E[\omega_i]}$ *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. 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 $b_i(r_i) = \frac{r_i}{E[\omega_i]}$ in equilibrium. Investments

[7]Notice that one can show that the procurement auction described in Proposition 3 implements the optimal renewable technology portfolio $\boldsymbol{K = (K_1^*, ..., K_n^*)}$ not only at the first best total capacity $\mathcal{K}^* = \sum_i K_i^*$ but also for any total capacity lower than first-best: $\sum_i K_i \leq \sum_i K_i^*$.

are selected on the basis of LCOE alone, missing an important characteristic of renewables: their adequacy to the energy mix. New generation technologies should be selected on the basis of their ECOE, that is, not only their 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 an investor with cost r_i is $b_i^e(r_i) = \frac{r_i - cov(\omega_i, p)}{E[\omega_i]}$. Investments are selected based on the ECOE (=LCOE net of the bonus-malus). The LCOE is reduced if the generation occurs when electricity is expensive (positive covariance). The bonus makes this investment more useful for a same value of LCOE. Conversely, the LCOE is 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 Empirical analysis

How should the fixed price p_i^s be set to foster optimal investment in renewable capacity? Equation (10) 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 panel orientation and 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).[8] 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

[8] 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`.

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, and production from all generation sources, including solar and wind.[9] 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. For the case of California, we collect similar data from CAISO for the period June 2018 to December 2023, aggregating production and prices at average system-wide hourly values.[10] Figures A.1 and A.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 (2019-2020 in the case of CAISO) for the main calculations.[11] Finally, figure A.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.

To get a better sense of the evolution of the key variables that determine the bonus-malus, Figure 1 plots the average capacity factor and the correlation between DAM prices and renewable capacity factors calculated at an annual frequency.

The figure shows that the average capacity factors $E[w_i]$ of renewables have been largely stable over the time period 2015 to 2023, with the exception of wind in California. On the other hand, focusing on the annual correlation of DAM prices and the capacity factors in panels (c) and (d) of figure 1, we find a stable correlation only for wind, but not for solar. In the case of solar, we generally find a positive correlation for individual years and countries at the beginning of our sample, but this correlation turns more negative over time in all countries.

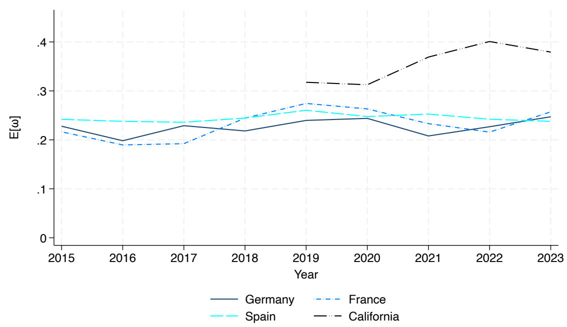
This evolution highlights the so-called "cannibalization effect", which is particularly pronounced in the case of solar. Solar production from existing plants is typically highly cor-

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

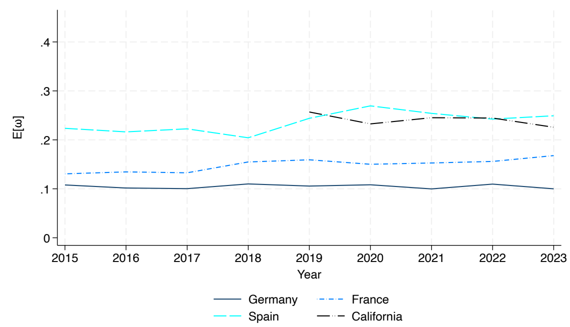
[10]We obtain data on production from 'Today's Outlook' and data on DAM prices from 'OASIS'. We aggregate the prices from the three main bidding zones (NP15, ZP26, and SP15) into a single price and convert all prices into €/MWh for comparability, taking into account the average of the annual exchange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

[11]As highlighted in Dertwinkel-Kalt and Wey (2025) end consumers typically did not face extreme energy prices during this period due to price breaks and related policies.

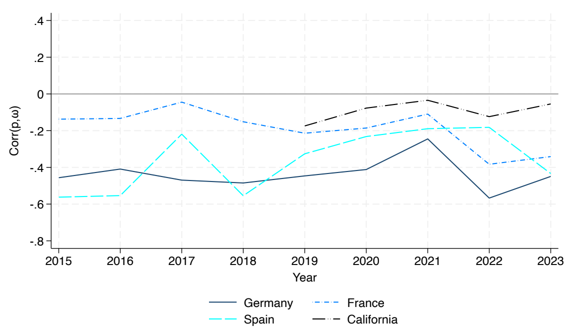
Figure 1: Expected capacity factors and correlation of market price and capacity factor over time



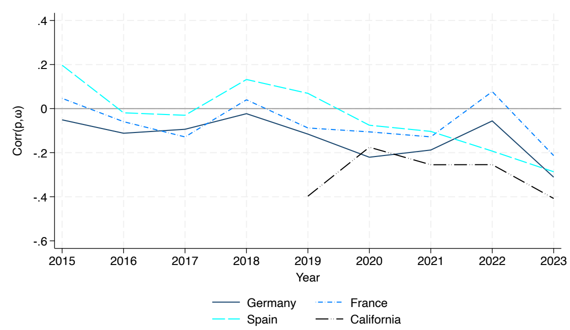
(a) $E[\omega_w]$, wind



(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. Panel (a) for solar and panel (b) for wind.

related within a given market, and new solar installations tend to mirror the production patterns of existing capacity, making new investment less valuable.

4.2 Estimating the bonus-malus

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. We rely on the period 2015 to 2020, when market conditions and prices were largely stable, to obtain estimates of the optimal correction term. Table 1 shows the bonus-malus that should be applied when considering different sample periods, starting in the range 2015 to 2020. Each row advances the starting year by one, so that the last row corresponds to 2020 only. The calculations are based on hourly data.

Table 1: Bonus-malus when considering optimal strike price

	Wind				**Solar**			
Period	DE	FR	ES	CA	DE	FR	ES	CA
2015-2020	-5.17	-1.9	-3.08		-2.4	-1.22	0.05	
2016-2020	-5.29	-2.06	-2.87		-2.68	-1.62	-0.46	
2017-2020	-5.8	-2.22	-2.42		-2.87	-1.63	-0.61	
2018-2020	-5.68	-2.32	-2.61		-3.03	-0.93	-0.57	
2019-2020	-5.07	-2.02	-1.65	-1.99	-4.37	-1.9	-0.48	-8.4
2020-2020	-5.21	-2.05	-1.58	-1.77	-5.87	-2.35	-1.06	-7.25
Average DAM price	34.6	40.33	46.85	30.1	34.6	40.33	46.85	30.1

Notes: The table displays the bonus-malus for wind and solar technology defined as $\frac{cov(\omega_i,p)}{E[\omega_i]}$ for different markets and time periods as well as the average day-ahead market (DAM) price for 2015-2020 in €/MWh. California (CA) data based on 2019-2020. Prices in US-$ have been converted to €using the average annual exchange rates.

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 the case of Germany, where the average wholesale price should be reduced by 5.17 €/MWh considering the sample period 2015-2020.[12] This corresponds

[12]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).

to about 15% of the average wholesale price of 34.6 €/MWh in this period. Limiting the sample to more recent years does not significantly affect this penalty. 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 years after years. In fact, the evolution towards larger penalties in solar can be explained by the aforementioned cannibalization effect. A particularly interesting case is Spain, where we find a positive value (bonus) when considering 2015-2020. Yet, over time the covariance between the capacity factor and prices turns negative and we find a malus of 1 €/MWh in 2020. In line with this observation, California, a market largely dominated by solar technology, shows the largest penalties for solar of about 7.2-8.4 €/MWh (about 25% of the average DAM price in 2019-2020).

Instead of setting a single strike price, the policymaker could also explore seasonal differences in energy demand and renewable energy availability to account for heterogeneity in the value of renewable production over the year. We thus calculate the bonus-malus for the sample period 2015-2020 at the monthly frequency. The results are shown in Appendix table A.1 and highlight the fact that there is more seasonal heterogeneity for solar than there is for wind. Interestingly, we find that renewable production from solar should receive a bonus in the winter months, but less so in the spring and summer. Also, when the monthly values take on positive and negative values (as is the case for France and Spain), the monthly values do not directly translate into the overall bonus-malus as reported in Table 1.

4.3 Differentiating the bonus-malus by location and technology

We proceed by analyzing the bonus-malus for different locations and technologies within a given country. To do so, we differentiate the existing wind technology into onshore and offshore wind and consider different onshore wind locations in the same country. We also show how solar panel orientation and location choices can affect the optimal correction factor using simulated renewable output. To implement this analysis, we focus on the case of Germany as it has both types of wind technologies installed during the sample period 2015-2020 and also has non-negligible differences in terms of average production profiles for both solar and wind over space.

First, focusing on realized production from offshore and onshore wind, we calculate both the correction factor for the sample period 2015-2020, and the seasonal differences by focusing on monthly data aggregates. The results are presented in Appendix table A.2. We find larger penalties for onshore wind, which is however mostly driven by differences in the capacity factors (0.52 in case of offshore wind versus 0.21 in the case of onshore wind). While all monthly correction terms are negative, we find large differences by month-of-year, with the highest penalties in winter months.

Next, we simulate the output of both solar plants and wind farms at two different locations in Southern and Northern Germany, relying on data from *Renewables Ninja*.[13]

To maximize the potential differences in resource availability, for solar investment we consider two locations in Bavaria (Munich) and Brandenburg (Berlin) with a solar plant facing either south, west, north, or east. We consider also the case of a solar tracker. For the case of wind investment, we obtain simulated output for the same type of wind turbine in Lower Saxony (northwest Germany) and Bavaria (southeast Germany).

Figure A.5 in Appendix C.3 plots the average hourly DAM prices together with the simulated capacity factors for both solar (panel a) and wind (panel b). Panel (a) shows only installations in southern Germany and highlights that while the total output is maximized with south-facing panels, these type of installations generally have a negative correlation with DAM prices. East and west facing panels, on the other hand, have lower total production, but a different correlation with wholesale market prices. While east-facing panels produce closer to the first daily peak, west-facing panels at this location will produce mostly when electricity is least valuable in terms of DAM prices. We also simulate the performance of a two-axis tracker solar system, which maximizes overall yield. Focusing on wind in panel (b), we highlight the level difference in terms of expected capacity factor of the two locations (average of 0.33 in the north versus 0.14 in the south).

Using the simulated output we calculate the implied bonus-malus when considering different technologies and locations and present it in Table 2. The table shows that there are important differences in the optimal strike price for the same technology in different locations within the same market. For example, when looking at different technologies within the same location (solar panel orientation), we show that the malus is smallest for the tracking system, followed by east-facing panels, in line with the implied capacity factor and correlations shown in Figure A.5. Interestingly, for wind we find a very comparable penalty of about 4.8 €/MWh. However, this is the result of both the differences in the capacity factor (which is significantly lower in the south) and the differences in the covariance term.

[13] *Renewables Ninja* simulates hourly production data for specific locations based on observed weather data (see Pfenninger et al. 2016 and Staffell et al. 2016) ; source: `https://www.renewables.ninja`.

Table 2: Bonus-malus with optimal strike price: different solar and wind locations and technology

	Solar		Onshore Wind
Location	**Panel orientation**	**Bonus-malus**	**Bonus-malus**
South	South	-1.41	-4.76
	West	-2.15	
	North	-1.78	
	East	-0.86	
	Flat	-1.85	
	Tracker	-0.62	
North	South	-1.87	-4.79
	West	-2.51	
	North	-1.73	
	East	-1.12	
	Flat	-2.14	
	Tracker	-1.07	

Notes: Bonus-malus in €/MWh, defined as $\frac{cov(\omega_i,p)}{E[\omega_i]}$ for different simulated renewable output employing data from *Renewables Ninja*. Hourly data is simulated based on observed weather data for the years 2015-2020.

5 Decomposition of the bonus-malus

5.1 Theory

To better quantify the ECOE, which measures the cost of an additional MWh of renewable energy production, we decompose the bonus-malus term that corrects the LCOE in the marginal value of new renewable generation derived in (4). In Appendix B, we use a Taylor quadratic approximation of $SC(Q)$ around the average electricity production denoted $Q_0^* := E[Q^*]$ to obtain

$$\frac{\tilde{r}_i^*}{E[\omega_i]} + \underbrace{SC''(Q_0^*)}_{(a)} \left\{ \underbrace{\frac{V[\omega_i]K_i}{E[\omega_i]}}_{(b)} + \underbrace{\frac{\sum_{j\neq i} cov(\omega_i,\omega_j)K_j}{E[\omega_i]}}_{(c)} - \underbrace{\frac{cov(\omega_i,D)}{E[\omega_i]}}_{(d)} \right\} \approx E\left[SC'(Q^*)\right], \quad (11)$$

where $V[\omega_i]$ is the variance of ω_i. Condition (11) is an optimality condition for the investment in renewable technology i. Both sides of the equality quantify the expected marginal cost of one additional MWh: if it comes from the actual 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 (11) 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 first term that multiplies the curly bracket is the curvature of the supply curve function (the merit order). It quantifies how costly the intermittency of renewable i's generation is to the energy mix. The convexity of the supply function measures the flexibility of the energy mix to respond to variations in renewable supply and/or demand. The steeper the slope of the supply curve, the more costly it is to ramp up or ramp down production to accommodate variations in renewable supply or variations in demand.[14]

(b) The numerator of the first term inside the curly brackets $V[\omega_i]K_i$ 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_i.

(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_j. 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.[15]

(d) The numerator of the last term is the covariance between renewable generation and electricity demand $cov(\omega_i, D)$.[16] 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 second correction term is negative. The renewable

[14] In a different setting, Liski and Vehviläinen (forthcoming) 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.

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

[16] If we denote θ as the fraction of maximum demand $\overline{D}$, we have $D = \theta\overline{D}$ so that $cov(\omega_i, D) = \overline{D}cov(\omega_i, \theta)$ 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.

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 (nominators of terms (b) to (d) in equation (11)) focusing separately on wind (w) and solar (s) technology in the four different markets. These estimates are based on market data on installed renewable capacity, hourly capacity factor for wind and solar, and total hourly demand (load). We present the results in Table 3, where we express the covariance between load and the renewable capacity factor in terms of the maximum load share, θ.

Table 3: Individual elements of decomposition

		Wind			**Solar**			
	$\overline{D}$	$cov(\omega_w, \theta)$	$V[\omega_w]$	K_w	$cov(\omega_s, \theta)$	$V[\omega_s]$	K_s	$cov(\omega_w, \omega_s)$
DE	79939	0.00249	0.02878	51837	0.00605	0.02595	42193	-0.00534
FR	94492	0.00433	0.02803	13068	-0.00052	0.03937	7573	-0.00532
ES	41015	0.00073	0.02076	23096	0.01158	0.0754	6950	-0.00698
CA	46933	0.00062	0.04315	5979	0.00485	0.08902	13899	-0.00964

Notes: Decomposition following equation (11). We express $cov(\omega_i, D) = \overline{D}cov(\omega_i, \theta)$ with $i \in \{s; w\}$ and $\theta \in [0, 1]$. The table shows the maximum load over the sample period and the average installed capacity for wind and solar (K_w and K_s, respectively). Main sample: 2015-2020 (CA: 2019-2020), based on hourly data.

Focusing on maximum load, $\overline{D}$, we find that France distinguishes itself from the other countries with a peak electricity demand particularly high in winter due to the widespread use of electric heating. This seasonal effect also influences the covariance terms, which are 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 A.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 4 calculates the terms (b) through (d) of Equation (11).

Table 4: Main elements of decomposition

	Wind			**Solar**		
Term in (11)	$\frac{V[\omega_w]K_w}{E[\omega_w]}$ (b)	$\frac{cov(\omega_s,\omega_w)K_s}{E[\omega_w]}$ (c)	$-\frac{cov(\omega_w,\theta)\overline{D}}{E[\omega_w]}$ (d)	$\frac{V[\omega_s]K_s}{E[\omega_s]}$ (b)	$\frac{cov(\omega_s,\omega_w)K_w}{E[\omega_s]}$ (c)	$-\frac{cov(\omega_s,\theta)\overline{D}}{E[\omega_s]}$ (d)
DE	6598.5	-996.55	-880.39	10368.66	-2621.36	-4579.94
FR	1592.2	-175.12	-1778.48	2074.89	-483.82	341.95
ES	1959.55	-198.26	-122.37	2278.37	-700.91	-2064.99
CA	818.92	-425.3	-92.36	5056.09	-235.53	-930.17

Notes: The table presents estimates for the main elements (b) to (d) in equation (11). Positive values increase the ECOE, while negative values decrease it. Main sample: 2015-2020 (CA: 2019-2020), 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 4) that helps to smooth aggregate supply, and the positive covariance with demand (term (d), right-hand column for wind or solar in Table 4). Note that in line with Equation (11) we express this last term as benefit by pre-multiplying it with -1.

Focusing on term (c) the covariance between renewable technologies, 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 demand turns out to be negative for solar (a cost). It is a benefit for all other countries for both solar and wind investment. We find strong heterogeneity in this last parameter depending on daily load as well as seasonal differences in electricity demand, such as the use of electricity heating in France in winter.

When all components are summed up, we generally observe a negative net adjustment (a malus) for renewable investment, with the exception of wind in France and solar in Spain. The positive value for solar in Spain is consistent with the aggregate results presented in Table 1. However, the positive adjustment for wind in France is more surprising. This is due to differences in the covariance between wind capacity factors and load compared to their covariance with DAM prices. While French DAM prices follow a similar pattern to those in Germany (see Figure A.3 in Appendix), electricity load in France shows greater variability − especially in the late evening hours − resulting in a stronger positive correlation between wind generation and electricity demand than between wind generation and DAM prices.

Finally, to put the estimates in context and to calculate the total implied bonus-malus from the decomposition, we require an estimate of the derivative of the curvature of the supply curve for each market at the expected load. To do so, we rely on hourly bid data from the wholesale electricity markets in Spain and California, where individual demand and supply bids are publicly available.[17]

Appendix section C.4 describes the detailed data as well as the data cleaning procedure that we use to obtain hourly supply and demand bids in these markets. In the case of Spain, we have a total of 93 million individual bids available for the years 2015-2020, and in the case of California 23 million bids. 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 in Table 5.

Table 5: Total bonus-malus with Taylor approximation

		Wind	**Solar**
	$S''(Q_0^*)$	Bonus-malus	Bonus-malus
ES	0.0033	-5.41	1.61
CA	0.0019	-0.57	-7.39

Notes: The table presents estimates for the decomposition term (a) in equation (11) and calculates the total implied bonus-malus, expressed in €/MWh. Main sample: 2015-2020 (CA: 2019-2020), based on hourly bids from day-ahead wholesale markets in Spain and California (see Appendix section C.4 for details).

We find an average malus for wind of 5.4 €/MWh and a bonus for solar of 1.6 €/MWh in the case of Spain. For California, we find a malus of about 0.6 €/MWh for wind and of 7.4 €/MWh for solar. These estimates should be compared with those obtained in table 1, which are based on DAM prices rather than demand, cost, and production capacities. In the case of Spain, the decomposition yields a slightly larger bonus-malus in absolute terms. However, the estimates have the same sign, and are comparable in magnitude. For California, we again

[17]As an alternative, we could estimate the slope of the supply function by reconstructing the marginal cost curve of electricity supply in each country. However, since detailed fuel prices and plant-specific efficiency estimates are generally unavailable, this method would likely produce a flat, step-wise supply curve, which could bias the local curvature estimates.

find that the sign and magnitude are the same for the two approaches, but the estimates are slightly smaller in absolute terms. Overall, finding similar estimates with the two approaches lends credibility to our estimates, as they are based on different underlying assumptions.

The 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. Finally, the decomposition is based on a second-order Taylor approximation and is therefore close to, but not equal to the exact value by definition.

6 Conclusion

Decarbonizing the economy requires substantial investment in clean power generation technologies, which have the disadvantage of being highly dependent on weather conditions. The choice of these technologies and their location should be in line with the needs to be met, in particular to reach their production peaks at times of high demand. It is therefore inefficient to pay for the MWh produced by intermittent technologies regardless of the statistical characteristics of their availability. Investments in technologies and/or locations whose intermittent production is negatively correlated with demand should not be encouraged. Our article shows that all remuneration systems, in particular Feed-in tariffs, Power Purchasing Agreements and Contracts for Difference, should modulate the remuneration through a bonus-malus system designed to encourage investment in renewable energy in the technology and/or locations where they are most socially useful. The correction term should be added to remuneration per MWh. It can be computed with market data. It involves the correlation between the renewable source availability and wholesale market price. Alternatively, the correction term can be computed with demand, costs and generation data. It involves the correlation between demand and generation of the renewable energy source, the correlation among generation from different renewable sources as well as the variance of generation.

Using data from California, France, Germany, and Spain, we have shown that the price to pay for solar and wind technologies is generally lower than the expected wholesale prices, meaning that if the actual strike price is set equal to the expected wholesale price, it should be complemented with a malus.

This purchasing policy may appear discriminatory and could therefore be challenged by competition authorities. In fact, it is not, since the sum of “wholesale price expectation + bonus-malus” is the relevant indicator of the scarcity of the contingent MWh, which we name

Economic Cost of Energy (ECOE). In this paper we provide different ways to calculate the bonus-malus based on past market data. Yet, the paper also highlights that the accurate calculation of the bonus-malus depends on many factors such as the technology and location of each investment. It is therefore not easy to implement and the policy maker likely needs to set approximate values for each technology (e.g., onshore wind vs. offshore wind, adjustable solar panels vs. fixed panels facing south or west, etc.) and by location (north vs. south).

In general, our estimates are based on ex-post market data and thus on the idea that policy makers can perfectly forecast future prices. We also assume risk-neutral investors and that technological factors are fixed. Some key questions include how the policy maker should adjust the bonus-malus to changing market and technology conditions, such as the introduction of energy storage[18] or electric vehicles.[19] In the same vein, we do not consider the limitation and costs imposed by the electricity grid.[20] We leave this as a promising avenue for future research.

[18]Ambec and Crampes (2019) and Andrés-Cerezo and Fabra (2023) have modeled energy storage in similar frameworks of energy provision with intermittent renewables.

[19]Electricity vehicles can make consumers more responsive to retail market prices (Bailey et al., 2024). Furthermore, Electric vehicle charging impacts the marginal value of renewables and the optimal energy mix (Heid et al. 2024).

[20]See Joskow and Tirole (2000), Yang (2022), Ambec and Yang (2024), and Gonzales et al. (2023) for theoretical and empirical analysis of investment on both new generation and interconnection capacity. Similarly, our work does not consider interconnected markets as discussed in Ito and Reguant (2016) or Buchsbaum et al. (2024).

A Proof of Proposition 3

Let us denote $b(r_i)$ the bidding strategy of investors in technology i with cost r_i. Consider the following bidding strategy for a technology i with cost r_i per MW installed:

$$b_i^e(r_i) = \frac{r_i - cov(\omega_i, p)}{E[\omega_i]} \tag{12}$$

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 is denoted $\tilde{r}_i$. It satisfies the following condition: $b_i^e(\tilde{r}_i) = \widehat{b}$ for $i = 1, ..., n$. Combined with (12), it yields:

$$\frac{\tilde{r}_i - cov(\omega_i, p)}{E[\omega_i]} = \frac{\tilde{r}_j - cov(\omega_j, p)}{E[\omega_j]} = \hat{b},$$

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

$$\widehat{b} = \frac{\tilde{r}_i^* - cov(\omega_i, p)}{E[\omega_i]} \tag{13}$$

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

Next we show that $b_i^e(r_i)$ defined in (12) are equilibrium strategies because no investor has incentive to deviate from it in equilibrium. Given the strike price $p_i^s = \widehat{b} + \dfrac{cov(\omega_i, p)}{E[\omega_i]}$ defined in Proposition 3, the expected profit with a given strategy $b_i(r_i)$ for the investor with technology i and cost r_i is

$$E[\pi_i(r_i)] = \begin{cases} \left[\left(\widehat{b} + \dfrac{cov(\omega_i), p}{E[\omega_i]}\right) E[\omega_i] - r_i\right] k_i & \text{if} \quad b_i(r_i) \leq \widehat{b}, \\ 0 & \text{if} \quad b_i(r_i) > \widehat{b}. \end{cases} \tag{14}$$

Plugging the winning bid defined by (13) in (14) yields

$$E[\pi_i(r_i)] = \begin{cases} (\tilde{r}_i^* - r_i)\, k_i & \text{if} \quad b_i(r_i) \leq \widehat{b}, \\ 0 & \text{if} \quad b_i(r_i) > \widehat{b}. \end{cases} \tag{15}$$

Consider an investor in technology i with cost r_i. First, suppose that $b_i^e(r_i) \leq \widehat{b}$ so that the investment is implemented if the investor bids $b_i^e(r_i)$ defined in (12). If the investor deviates by bidding lower $b_i(r_i) < b_i^e(r_i)$, the investor's payoff changes only if the investor is pivotal, that is if $b_i^e(r_i) = \widehat{b}$. By lowering the bid, the investor lowers the winning bid $\widehat{b}$. The price assigned to the equipment plan p_i^s defined in Proposition 3 is then strictly lower and so is also the investor's expected profit. The investor is thus worse-off by bidding $b_i(r_i) < b_i^e(r_i)$ if its bid modifies the winning bid $\widehat{b}$, while its payoff is unchanged otherwise. Suppose now that the investor deviates by bidding higher $b_i(r_i) > b_i^e(r_i)$. The investor's payoff changes only when $b_i(r_i) > \widehat{b}$, in which case the investor is not selected and, thus, his or her payoff is nil. The investor is not better-off.

Second, suppose now that $b_i^e(r_i) > \widehat{b}$ so that the investment is not implemented. If the investor deviates by bidding lower $b_i(r_i) < b_i^e(r_i)$, his payoff changes only if $b_i(r_i) \leq \widehat{b}$, in which case, the investor is selected. However, using the definition of $b_i^e(r_i)$ in (12), $b_i^e(r_i) > \widehat{b}$ implies $E[\omega_i]\widehat{b} + cov(p, \omega_i) - r_i < 0$ and, therefore, the investor's expected profit defined in (14) is negative. Hence the investor is worse-off when bidding lower. If the investor deviates by bidding higher $b_i(r_i) > b_i^e(r_i)$, he or she is not selected and thus the investor's payoff is unchanged, equal to 0.

B Decomposition of the bonus-malus in the energy mix

A Taylor approximation of the social cost of electricity generation yields $SC(Q) \approx SC(Q_0^*) + SC'(Q_0^*)(Q - Q_0^*) + \frac{1}{2}SC''(Q_0^*)(Q - Q_0^*)^2$. Differentiating this approximation with respect to Q yields $SC'(Q) \approx SC'(Q_0^*) + SC''(Q_0^*)(Q - Q_0^*)$. Therefore $cov(\omega_i, SC'(Q))$ is approximated by

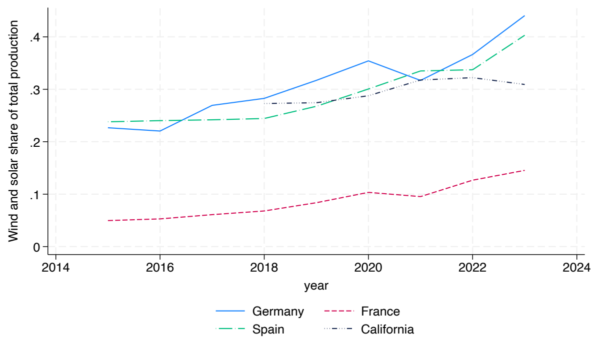
$$\begin{aligned}
cov(\omega_i, SC'(Q)) &\approx cov(\omega_i, SC''(Q_0^*)Q) \\
&= SC''(Q_0^*)cov(\omega_i, Q) \\
&= SC''(Q_0^*)cov(\omega_i, D - \textstyle\sum_j \omega_j K_j) \\
&= SC''(Q_0^*)\left\{cov(\omega_i, D) - \textstyle\sum_{j \neq i} cov(\omega_i, \omega_j)K_j - V[\omega_i]K_i\right\}
\end{aligned}$$

where the equality in the second line is due to the fact that $SC''(Q_0^*)$ 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 $cov(\omega_i, SC'(Q))$ in (4) by the above approximation yields (11).

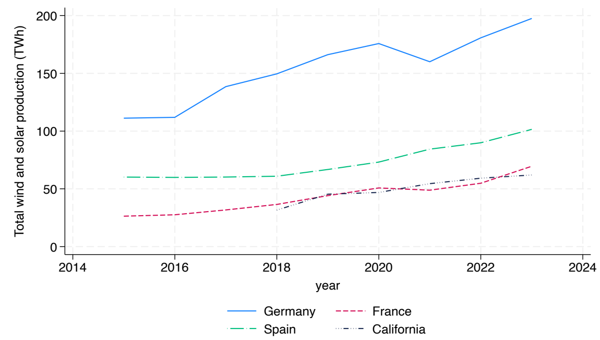
C Data Appendix

C.1 Background on energy markets under consideration

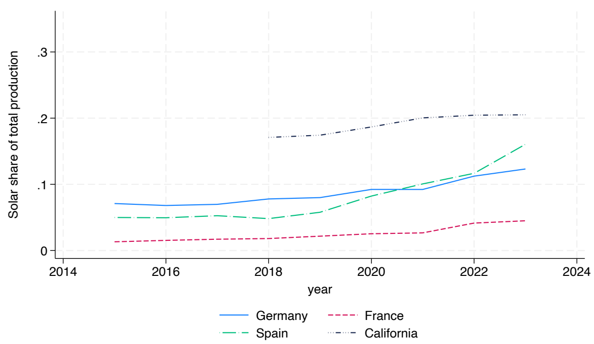
Figure A.1: Evolution of renewables (RES) in total energy production



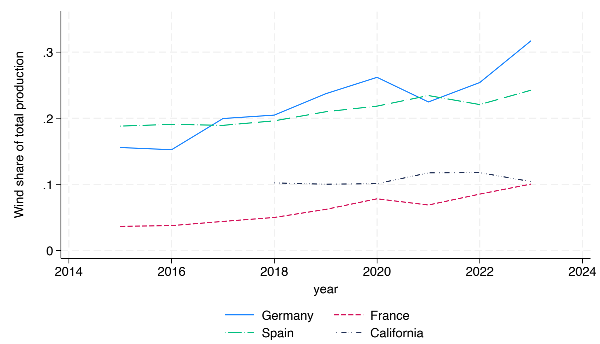
(a) Share of RES (wind and solar) in total production



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



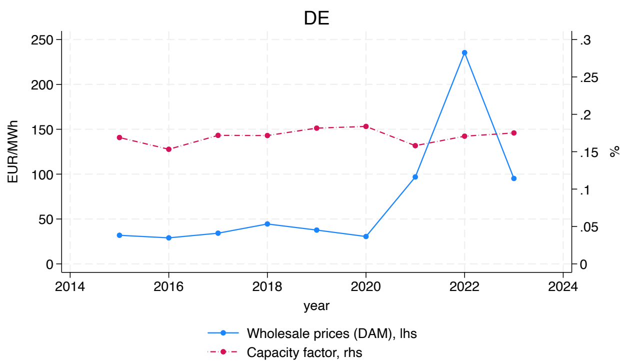
(c) Share of solar in total production



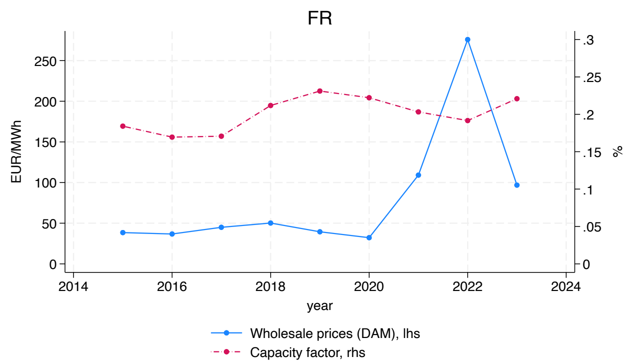
(d) Share of wind in total production

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

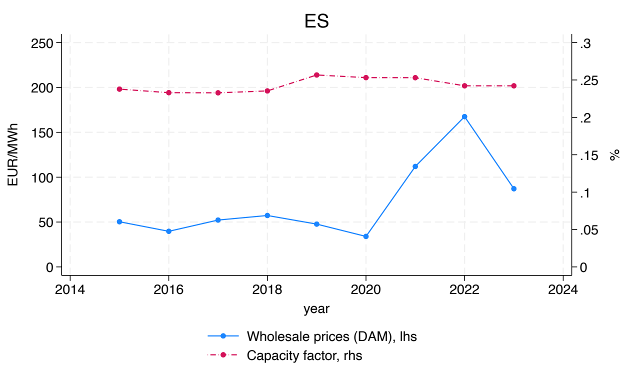
Figure A.2: Average capacity factor for solar and wind energies and day-ahead market prices



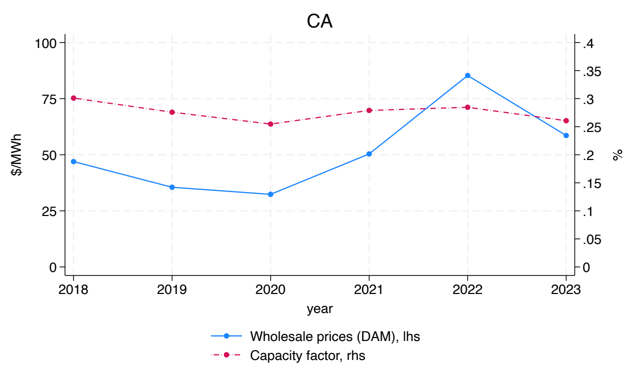
(a) Germany



(b) France



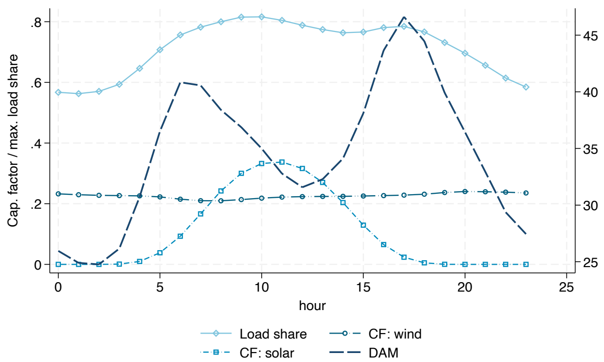
(c) Spain



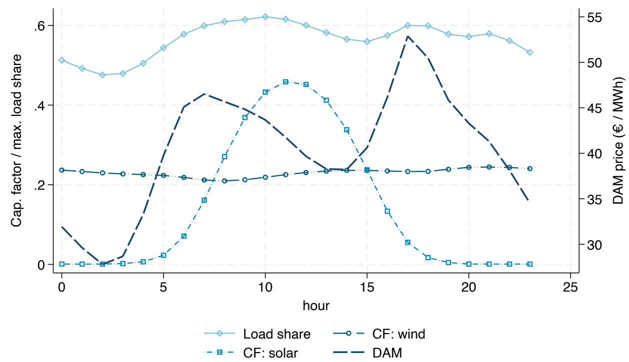
(d) California

Note: Annual average day-ahead market 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.

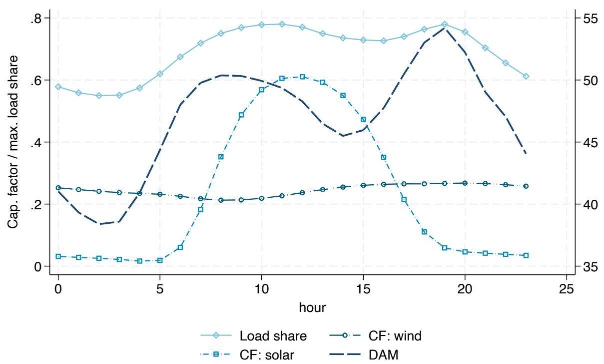
Figure A.3: Average hourly load, capacity factors, and DAM prices



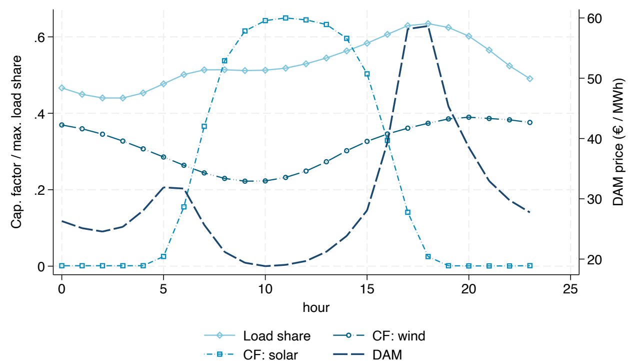
(a) Germany



(b) France



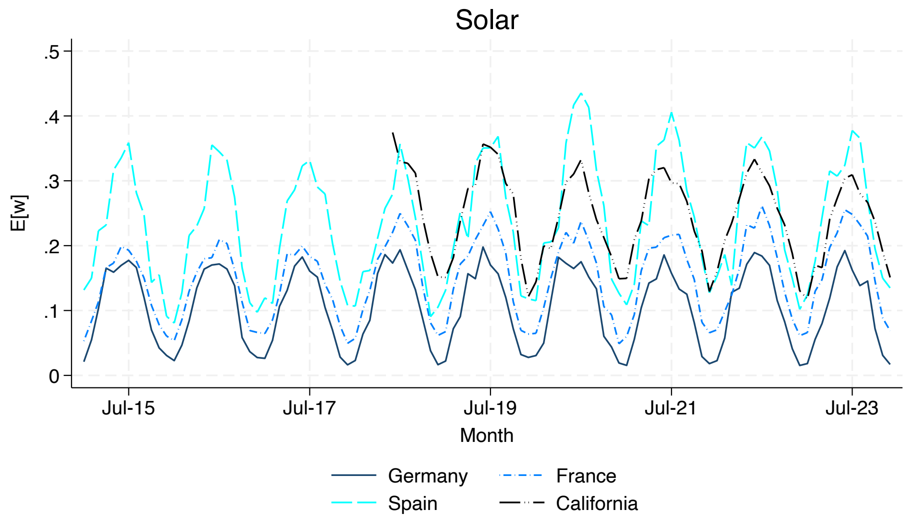
(c) Spain



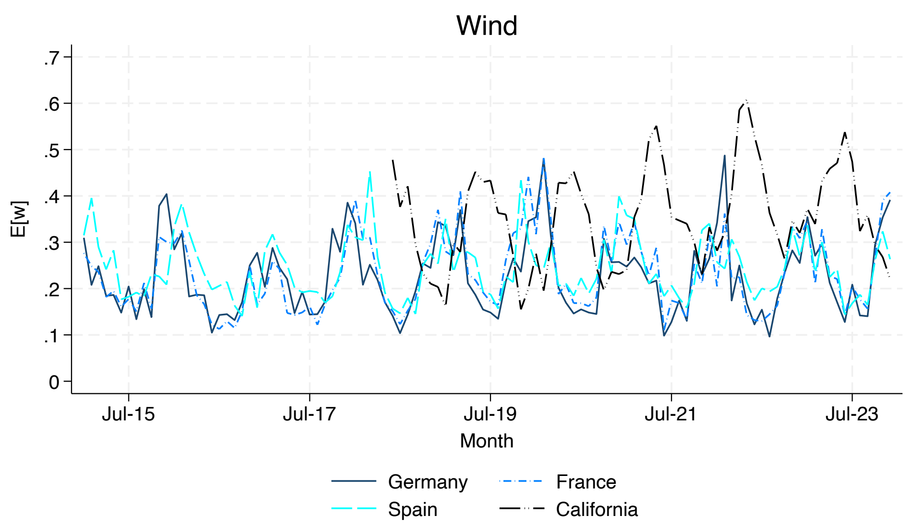
(d) California

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 A.4: Evolution of capacity factor



(a) Solar



(b) Wind

Notes: Evolution of the expected capacity factor (average capacity factor by month of sample. Panel (a) for solar and panel (b) for wind.

C.2 Monthly definition of the capture price

Table A.1: Bonus-malus in euros/MWh with optimal strike price - monthly aggregation

	Wind				**Solar**			
Month	DE	FR	ES	CA	DE	FR	ES	CA
1	-7.316	-5.286	-2.667	-1.266	4.933	5.664	3.993	-7.474
2	-6.256	-3.801	-3.812	2.172	1.776	1.887	1.209	-13.581
3	-4.631	-2.316	-2.429	-0.831	-1.94	-0.995	0.745	-11.408
4	-3.167	-1.503	-1.98	-0.384	-4.295	-0.85	0.403	-8.909
5	-3.357	-1.172	-2.558	0.6	-2.161	-0.597	-0.104	-6.889
6	-4.009	-1.728	-2.087	0.368	-0.742	1.424	-0.472	-4.532
7	-5.124	-2.095	-1.865	0.595	-0.673	1.852	0.994	-2.815
8	-3.475	-1.221	-1.495	-0.087	-1.209	1.381	0.247	-7.193
9	-4.528	-2.164	-3.651	-0.683	-1.318	2.406	0.177	-5.735
10	-5.864	-3.373	-3.287	-2.666	0.608	2.063	-0.374	-7.945
11	-6.269	-4.218	-3.537	-1.254	2.154	2.252	1.066	-9.106
12	-7.784	-5.445	-4.043	-1.104	3.293	4.539	2.209	-8.262
Average DAM price	34.602	40.336	46.848	30.1	34.602	40.336	46.848	30.1

Notes: The table displays the bonus-malus for wind and solar technology defined as $\frac{cov(\omega_i,p)}{E[\omega_i]}$ for different markets and time periods using monthly time aggregation. The average day-ahead market (DAM) price for 2015-2020 in €/MWh is reported for comparison. California data based on 2019-2020. Prices in US-$ have been converted to € using the average annual exchange rates.

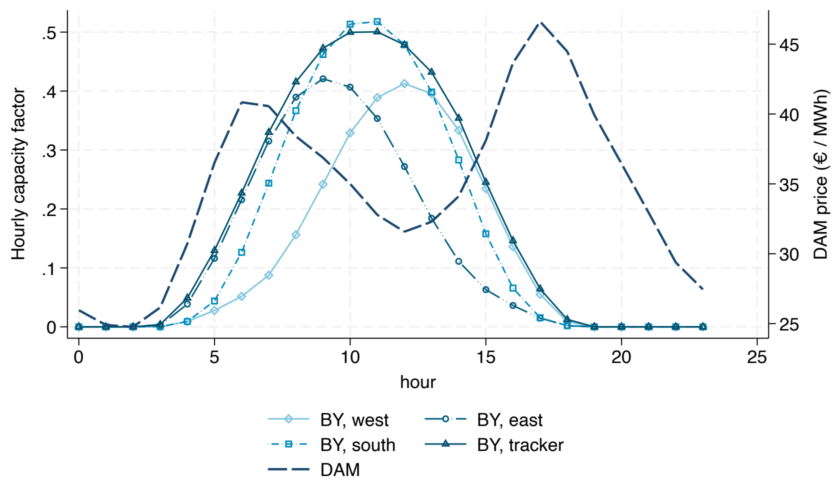
Table A.2: Bonus-malus with optimal strike price, offshore and onshore wind in Germany in euros/MWh

Month	**Offshore**	**Onshore**
1	-4.069	-7.89
2	-2.432	-6.918
3	-2.531	-4.939
4	-1.939	-3.363
5	-2.138	-3.701
6	-3.031	-4.199
7	-4.429	-5.311
8	-4.128	-3.504
9	-3.671	-5.09
10	-2.391	-6.569
11	-5.834	-6.731
12	-5.902	-8.525
2015-2020	-3.109	-5.685

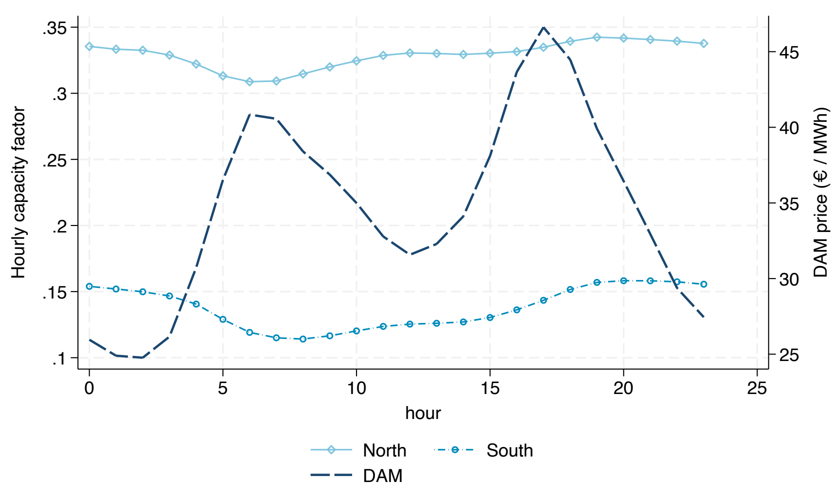
Notes: Bonus-malus for offshore and onshore wind in Germany. Monthly aggregation and overall for the sample period 2015-2020.

C.3 Differentiating the bonus-malus by location and technology

Figure A.5: Simulated renewable output and wholesale market prices



(a) Solar in South Germany, different panel orientation



(b) Wind in South and North Germany

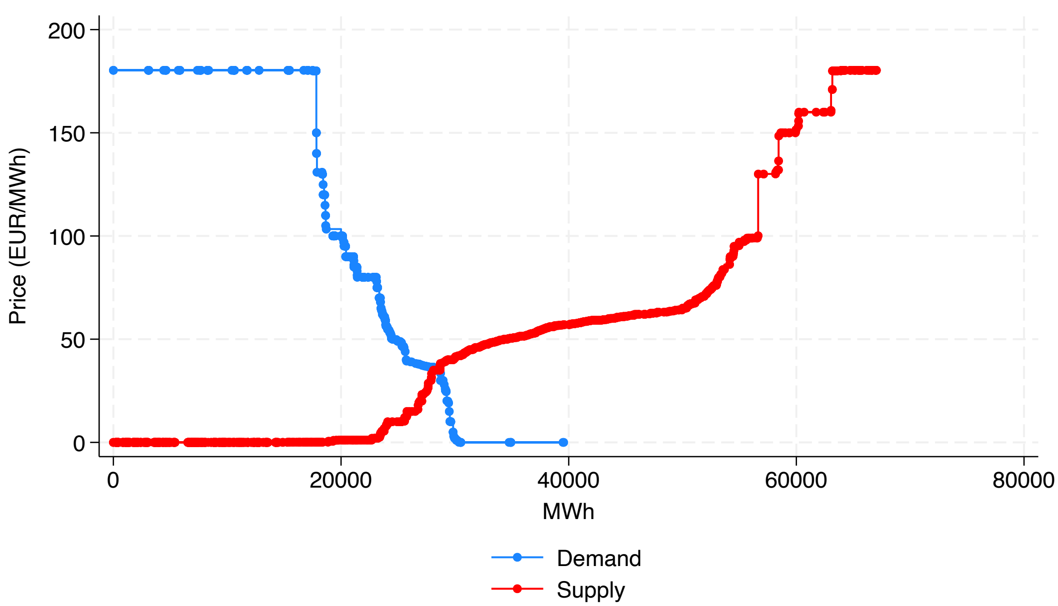
Notes: Panel (a) shows the average simulated hourly capacity factors for a 1 MW solar plant in Bavaria (Germany) with different panel orientation (west, east, south-facing, and tracker) together with average DAM prices over the sample period 2015-2020. Panel (b) considers the simulated capacity factor for a 1 MW wind turbine in Southeast and Northwest Germany. Time expressed in Coordinated Universal Time (one hour difference to Central European time).

C.4 Bidding data from Spain and California

In order to decompose the bonus-malus in section 5, we need an estimate of $SC''(Q_0^*)$, which represents the slope of the supply curve function 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.[21] 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 process), we calculate the market clearing prices based on the raw bids by equating cumulative supply and demand for each hour in the sample. Figure A.6 shows an example for a given hour in the sample.

Figure A.6: OMIE bidding data (Spain)



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

Since there are a few hours in which the Portuguese and Spanish markets are separated,

[21] 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. Main data files: curva_pbc_XXXX.

for our calculation we focus only on hours in which the market was integrated. Note that 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 the years 2019 to 2020 to match the main estimation sample period. Data for the last 5 years can be obtained from OASIS.[22] 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 (forthcoming) to pre-process the data.[23] Figure A.7 shows as 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.

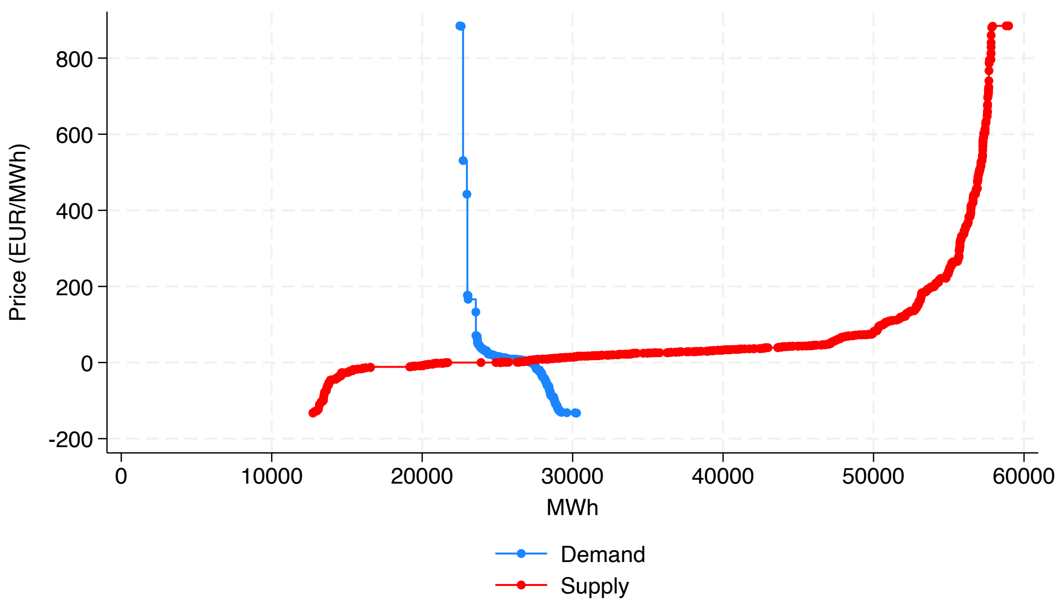
Estimation. In a first step, for each hour of the sample we construct the market clearing price based on the demand and supply bids so that all demand is covered. Note that we do not consider electricity flows to neighboring markets (imports/exports). Second, we calculate the average load for each hour of the day in the sample period.[24] 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 table 5 in the text and use this single value to determine the value of the bonus-malus with the decomposition.

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

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

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

Figure A.7: CAISO bidding data (California)



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

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