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Feed-in Tariffs, Intermittency, and Inefficient Investment

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Abstract

Feed-in tariffs (FiTs) have been instrumental in expanding renewable electricity generation but can distort investment by insulating producers from market price volatility. This paper develops a two-stage model of electricity markets with stochastic demand and supply shocks, showing that a higher share of intermittent renewable generation increases electricity price volatility and lowers the market value of intermittent output. FiTs create a volatility externality, because investors are insulated from the negative covariance between intermittent generation and market prices. The resulting misallocation of investment, both across intermittent technologies and in total intermittent capacity, leads to an inefficient electricity mix causing excessively volatile electricity prices and welfare losses.

The model's predictions are tested using hourly and quarter-hourly data from the German electricity market (Jan.~2015--Dec.~2025). ARX and ARIMAX--GARCH estimates indicate that a one–percentage-point increase in renewable market share raises short-run realized price volatility by about 2% for wind and 6% for solar, while significantly lowering unit revenues. A proxy for the volatility externality suggests marginal investment costs roughly 10--25\% above the socially optimal level under the German FiT.

Keywords: Feed-in tariffs, intermittent renewables, investment, externalities, energy policy, electricity markets.

JEL classification: Q42, Q48, C32, H23.

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Sammendrag

Strømprisene har de siste årene blitt et omdiskutert tema. For husholdninger har høye og ustabile priser påvirket levekostnader og økonomisk trygghet, mens de for industrien har blitt et potensielt konkurranseproblem. Samtidig har energipolitikken vært preget av en omfattende omstilling, der fossil energi skal erstattes av fornybare kilder som sol- og vindkraft. Denne artikkelen analyserer sammenhengen mellom økende prisvolatilitet og rask utbygging av fornybar energi.

Overgangen til fornybar energi er viktig for å redusere klimagassutslippene. Samtidig skiller sol- og vindkraft seg fra tradisjonelle energikilder ved at produksjonen varierer med værforholdene. Når solen skinner eller vinden blåser, produseres det mye kraft; ellers lite. Denne væravhengigheten påvirker direkte hvordan strømpriser dannes i markedet og hvor stabile de er over tid.

Et sentralt virkemiddel i europeisk fornybarpolitikk har vært prisgarantier, ofte omtalt som feed-in-tariffer. Slike ordninger gir produsenter en fast pris per kilowattime, uavhengig av markedsprisen, for å redusere investeringsrisiko og fremme rask kapasitetsutbygging. I Norge brukes tosidige differansekontrakter for å stimulere investeringer i havvind. Også disse innebærer i praksis en fast produsentpris over tid.

Artikkelen undersøker hva som skjer med verdien av fornybar kraft, strømprisene og investeringsinsentivene når en økende andel av produksjonen er væravhengig. Med utgangspunkt i det tyske kraftsystemet dokumenteres at høyere andel sol- og vindkraft er forbundet med mer volatile strømpriser og lavere markedsverdi for disse teknologiene. ARX- og ARIMAX–GARCH-estimater indikerer at en økning i fornybar markedsandel på ett prosentpoeng øker den kortsiktige realiserte prisvolatiliteten med om lag 2 prosent for vind og 6 prosent for sol, samtidig som inntektene per MWh reduseres signifikant.

Artikkelen utvikler også en teoretisk modell for elektrisitetsmarkeder med stokastiske etterspørsels- og tilbudssjokk. Modellen viser at en høyere andel variabel fornybar kraftproduksjon øker prisvolatiliteten i kraftmarkedet og reduserer markedsverdien av slik produksjon. Feed-in tariffer og tosidige differansekontrakter skaper en eksternalitet relatert til volatilitet fordi investorer skjermes fra den negative kovariansen mellom variabel fornybar produksjon og markedspriser. Den påfølgende feilallokeringen av investeringer, både mellom ulike fornybarteknologier og i samlet fornybar kapasitet, gir en ineffektiv kraftmiks med for høy prisvolatilitet og tilhørende velferdstap. Et mål på volatilitetseksternaliteten antyder at marginale investeringskostnader under det tyske FiT-regimet ligger om lag 10–25 prosent over det samfunnsøkonomisk optimale nivået.

1 Introduction

Government support for renewable energy and the decarbonization of electricity markets has become widespread across advanced economies. A central feature of this transition has been price guarantees and revenue-stabilization schemes such as feed-in tariffs (FiTs) and Contracts for Difference (CfDs), which stabilize producer revenues by insulating investors from wholesale price risk (Morawiecka and Scott, 2024; REN21, 2017). While such measures have successfully incentivized investment in wind and solar power, the interaction between revenue-stabilization schemes and renewable intermittency, and its implications for price volatility and investment efficiency, remains poorly understood. This issue has become increasingly relevant as renewable penetration continues to rise in many electricity markets (IEA, 2024c).

Electricity markets play a central role in economic welfare because electricity is a key intermediate input in production and household consumption. Disruptions or sustained price volatility therefore have well-documented economic and distributional consequences (Ozturk, 2010; Stern, 2011; World Bank, 2020). Europe's recent energy crisis underscores this point: the sharp rise in wholesale prices following reduced Russian gas supply and Germany's nuclear phase-out exposed structural vulnerabilities and triggered substantial fiscal interventions.[1]

The theoretical model developed in this paper shows that insulating producers from output price risk through a FiT generates a volatility externality: as the share of intermittent renewable generation increases, electricity price volatility rises and the profitability of intermittent producers declines. Moreover, such schemes distort investment incentives by insulating renewable producers from market price signals, thereby preventing them from internalizing the negative covariance between intermittent output and electricity prices. The resulting misallocation of investment, both across intermittent technologies and in the aggregate level of intermittent capacity, produces an inefficient energy mix that amplifies volatility and heightens systemic risk in electricity markets.[2] In contrast to revenue-stabilization schemes such as FiTs, investment subsidies can expand renewable capacity without removing price risk from producers and therefore avoid misallocation of investment across intermittent technologies.

Previewing the main empirical findings, the analysis uncovers economically large effects: greater renewable penetration markedly increases electricity price

[1]For example, several countries in the European Union and the United Kingdom have temporarily resorted to coal to increase security of electricity supply, and Spain and Portugal were granted a temporary exemption by the European Commission allowing them to cap the price of gas and coal used for electricity generation (IEA, 2023).

[2]See Gautam et al. (2009), IEA (2023), Kroposki et al. (2017), and MarketWatch (2024) on grid stability and intermittent renewable energy.

volatility, lowers the value of electricity generated by intermittent sources, and leads to excess investment under FiTs relative to the welfare-optimal benchmark. Beyond their effect on investment incentives, FiTs also function as a distortionary tax and as a transfer to the owners of FiT-eligible generation.

The theoretical predictions are tested using data for Germany, one of the earliest and most extensive adopters of FiTs. Introduced through the Renewable Energy Act (WWEA, 2024) in 2000, Germany's FiT guarantees long-term, fixed prices for renewable electricity generation. The FiT regime successfully expanded renewable capacity and contributed to one of the highest renewable shares among industrialized countries. Wind and solar power accounted for 53% of Germany's electricity generation in 2025.

The empirical analysis estimates autoregressive models with exogenous regressors (ARX) to assess how the shares of wind and solar generation affect electricity price volatility, and autoregressive moving-average models with exogenous regressors and generalized autoregressive conditional heteroskedasticity errors (ARIMAX–GARCH) to evaluate how renewable shares influence the value of electricity generated by intermittent sources. The models control for exogenous factors such as fossil fuel prices and weather conditions. The results are consistent with the theoretical predictions: higher shares of intermittent renewables significantly increase electricity price volatility and reduce the profitability of wind and solar power. A one-percentage-point increase in renewable market share raises short-run realized electricity price volatility by roughly 2 percent for wind and about 6 percent for solar. Because realized volatility is persistent, the implied long-run responses are mechanically larger, though the interpretation of these long-run elasticities warrants caution.

The estimated decline in the value of electricity generated by intermittent sources following a one-percentage-point increase in renewable market share ranges from 1% to 7%, depending on the technology. The paper also constructs an empirical measure of the investment distortion induced by FiTs, suggesting that in 2025 marginal investment costs exceeded socially optimal levels by approximately 25% for solar, 20% for onshore wind, and 10% for offshore wind.[3]

Germany provides an ideal case study owing to its high renewable penetration and long-standing FiT system. Figure 1 illustrates the evolution of wholesale electricity prices, their volatility (see Section 3.2), the share of intermittent energy sources, and the price of natural gas—one of the key determinants of electricity

[3] Expected revenues per unit of intermittent generation are below the expected spot price. If firms receive a FiT equal to this expected price, the value of installed capital (and thus marginal investment costs) exceeds expected revenues by about 10–25%, depending on the energy source. The gap widens when FiTs are set above expected prices, a policy often justified by externalities and learning-by-doing (see Arrow, 1962; Golombek and Hoel, 2005; Kverndokk and Rosendahl, 2007).

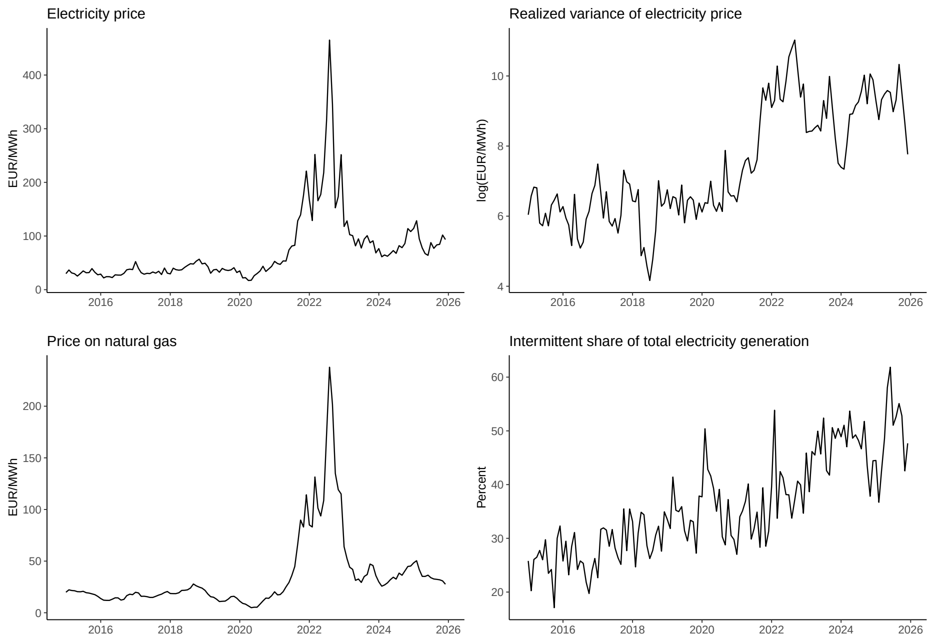

Figure 1: Selected price variables and the intermittent share of total electricity generation. Monthly data from Jan. 2015 to Dec. 2025 for Germany.

prices in Germany. The rise in volatility is particularly pronounced after 2021, coinciding with both high renewable shares and external shocks such as the European energy crisis.[4]

In this paper, the analysis focuses on FiTs as a canonical revenue-stabilization scheme, while the underlying mechanism applies more broadly to other policies, including CfDs and minimum purchase prices for green certificates. For instance, the United Kingdom operates a CfD mechanism that provides long-term revenue stabilization for low-carbon electricity generators through a guaranteed strike price.[5] CfD-based support mechanisms have subsequently been adopted or announced in several European countries, particularly for capital-intensive offshore wind projects. For example, France has implemented large-scale two-sided CfD schemes awarded through competitive tenders, covering multiple offshore wind parks and extending over multi-decade contract horizons (Enerdata, 2025). Similar CfD or CfD-like auction designs are also used in countries such as Norway, Den-

[4] Russia's invasion of Ukraine in February 2022 disrupted European gas supplies and triggered a sharp increase in electricity prices.

[5] When the reference wholesale price falls below the strike price, the government compensates the generator for the difference; when the market price exceeds the strike price, the generator repays the excess. See DESNZ (2024) and Newbery (2016) for more on the CfD, and IEA (2024b) on green certificates in Belgium.

mark, and Belgium, reflecting a broader European shift toward market-compatible revenue stabilization instruments for renewable energy deployment (see Morawiecka & Scott, 2024; OWB, 2023; Regjeringen.no, 2025).

Beyond electricity markets, the same economic mechanism arises in settings where policy instruments or market arrangements insulate producers from output price risk. Examples include fixed-price contracts in agriculture, supply-managed sectors such as dairy, and long-term contracts in natural gas markets. In each case, insulating producers from market signals may induce overinvestment in risk-intensive technologies and amplify output volatility.

This paper relates to four strands of the literature on electricity markets and energy policy. First, it contributes to research on renewable energy subsidies and investment (e.g., Fell and Linn, 2013; Kitzing, 2014). Abrell et al. (2019) show that differentiated subsidies for wind and solar are optimal but yield only small welfare gains, while Lamont (2008) demonstrates that the marginal value of intermittent generation declines with penetration. This study extends that literature by showing how FiTs distort investment incentives: by insulating producers from market price volatility, FiTs prevent investors from fully accounting for intermittency risks, leading to an inefficient energy mix and greater market volatility.

Second, the paper builds on studies of electricity market design and price volatility (e.g., Nicolosi, 2010; Sensfuß et al., 2008; Woo et al., 2021). Ketterer (2014) employs a GARCH model to analyze the effect of wind power on German electricity prices. This paper extends that work by including both wind and solar generation, controlling for fossil fuel prices, and using recent data covering the post-2022 energy crisis.

Third, it contributes to the literature on the cannibalization effect—the decline in unit revenues associated with increasing renewable penetration (e.g., Clò and D'Adamo, 2015; Lamont, 2008; López Prol et al., 2020; Peña et al., 2022; Zipp, 2017).[6] Stiewe et al. (2025) show that the value of domestic renewables is depressed not only by domestic expansion but also by capacity growth in neighboring markets. While Stiewe et al. (2025) examines how monthly market value (i.e., revenue normalized by the electricity price) is affected by intermittent output, the present paper focuses on monthly revenue. Whereas the use of market value facilitates the analysis of a stationary variable that captures the relative performance of intermittent energy, the analysis of monthly revenue entails studying a unit-root process that additionally reflects the aggregate impact of intermittent supply on electricity prices (see also Figures 3 and 6).

Finally, the paper contributes to research on externalities and price distortions in regulated markets (e.g., Kitzing, 2014; Pigou, 1920). Joskow (2011) shows

[6] Profitability may decline for all generation technologies as capacity expands, but the effect is stronger for intermittent renewables due to concentrated output and limited flexibility.

that levelized cost comparisons tend to overvalue intermittent technologies relative to dispatchable ones. The present study identifies a volatility-related investment externality arising from policy design, demonstrating that feed-in tariffs (FiTs), by shielding investors from price risk, encourage overinvestment in technologies that exacerbate price volatility and can reduce social welfare. Empirically, the paper quantifies a partial-equilibrium investment distortion arising from risk-insulating price guarantees, rather than estimating comprehensive welfare losses.

The remainder of the paper is organized as follows. Section 2 presents the theoretical model linking FiTs, intermittency, price volatility, and investment distortions. Section 3 describes the empirical strategy and provides the main results, and Section 4 concludes with implications for energy transition policy design.

2 Theoretical Framework

The theoretical model is structured in two stages. In Stage 1 (Investment), power plants (or firms) invest in energy source–specific production technologies and capacities. In Stage 2 (Market Equilibrium), the representative consumer chooses electricity consumption, and firms determine electricity production levels.[7] The model is solved backwards to identify the subgame perfect Nash equilibrium.

Consider an economy with a price-taking representative consumer who maximizes utility from electricity consumption. The representative consumer may represent both households and firms that use electricity as a factor of production. The concave utility function is given by:

$$u(x_d) = (u_1 + \eta)\, x_d - \frac{u_2}{2} x_d^2, \tag{1}$$

where x_d denotes electricity consumption, u_1 and u_2 are strictly positive constants, and $\eta \sim \left(0, \sigma_\eta^2\right)$ is a stochastic variable with expected value equal to 0 and variance σ_η^2. For example, η could reflect fluctuations in temperature, a key determinant of household electricity demand, or variation in demand for the output of power-intensive industries. I assume that the stochastic variable is bounded such that $u_1 + \eta > 0$ (e.g., $\eta \sim \text{Uniform}(-\xi, \xi)$ with $u_1 > \xi$, or follows a truncated normal distribution with mean zero).

The representative consumer solves $\max_{x_d} (u(x_d) - p x_d)$, where p denotes the price of electricity.[8] Under the assumption of an interior solution with strictly

[7] Stage 2 is static with a random price realization; volatility is therefore interpreted as the variance of price uncertainty across states, rather than temporal variation.

[8] An alternative model formulation in which the consumer maximizes utility subject to a budget constraint does not yield a tractable analytical solution for the full model, including investment in period 1.

positive consumption levels, it follows that:

$$x_d = \frac{u_1 + \eta - p}{u_2}. \tag{2}$$

Equation (2) implies that electricity demand increases with the size of the stochastic shock η and decreases with the price p.

The theoretical framework incorporates three stylized types of electricity production:

1. Low-emission electricity from *intermittent energy sources* is characterized by stochastic production and exogenous supply for a given capacity. The supply of electricity from firm $i \in I^s = 1, 2, \ldots, n_s$ using intermittent source $s \in S = 1, 2, \ldots, \overline{s}$ is given by $(1 + \theta_{si})\,\alpha_{si}$, where α_{si} is plant capacity and $\theta_{si} \sim \left(0, \sigma^2_{\theta_{I^s}}\right)$ is a stochastic variable determined by, for example, weather conditions. Expected production per unit of capacity (α_{si}) is normalized to 1. I assume that the distribution of θ_{si} is bounded below by -1, so that $1 + \theta_{si} \geq 0$ for all $i \in I^s$ and $s \in S$. Examples of intermittent energy sources include solar power, wind power, and wave power.

2. *Non-intermittent low emission (NLE)* energy sources such as nuclear power plants, hydroelectric plants, and biomass. I model this energy source category with a single representative plant whose maximum output is given by the capacity parameter β.

3. Electricity from *fossil-fueled power plants*. Output from this energy source, denoted by y, is endogenous and depends on the electricity price as well as the representative power plant's supply cost.

For convenience, I will henceforth refer to the above technology types as 'intermittent,' 'NLE,' and 'fossil.'

Suppose the regulator imposes a Pigouvian emission tax, χ, per unit of emissions from fossil. The resulting cost of emissions per unit of output is then given by $k_1\chi$, where $k_1 > 0$ denotes the emissions intensity. The variable cost function for electricity from the representative fossil-fueled power plant is given by:

$$c(y) = (c_1 + \varepsilon)\,y + \frac{c_2}{2}y^2, \tag{3}$$

where $c_1 = k_1\chi + k_2$, the positive k_2 and c_2 are cost measures, and $\varepsilon \sim (0, \sigma^2_\varepsilon)$ is a stochastic variable determined by the prices on fossil fuels and other input factors in fossil-fueled electricity production. Increasing marginal costs reflect that the cheapest fossil plants are used first, followed by progressively more expensive ones (merit order).

I abstract from capacity constraints in fossil fuels, and operational costs and emissions associated with both intermittent and NLE energy sources. This simplifying assumption is justified by the fact that these components generally represent only a small share of total costs for such producers, in contrast to fossil fuel plants, where fuel expenditures (for example, coal and natural gas) constitute a substantial portion of total supply costs.[9]

The above trichotomy is stylized. Random elements affect all sources of electricity production, and the NLE category is very broad. For instance, modern nuclear plants and hydro with reservoirs are considerably more flexible than run-of-river hydro or older nuclear facilities.

The power plants can choose the technology parameters α_{si}, β, k_1, k_2 and c_2 in the first stage of the game (depending on plant type). The energy source specific investment cost functions $\kappa^s(\alpha_{si})$ and $\kappa(\beta)$ are both convex and increasing in the relevant capacity parameters α_{si} and β. Last, $\kappa(k_1, k_2, c_2)$ is convex and decreasing in k_1, k_2 and c_2, and satisfies $\kappa(\cdot) \to \infty$ as $k_1 k_2 c_2 \to 0$. I assume $c_1 + \varepsilon \geq 0$.[10]

The realizations of the stochastic variables η, ε, and θ_{si} occur between Stages 1 and 2. Firms therefore invest under uncertainty in Stage 1 but know their costs and the equilibrium prices when making production decisions in Stage 2. The representative consumer acts only in Stage 2, choosing electricity consumption under full information. This implies that firms within each intermittent energy category $s \in S$ are identical in Stage 1, as they face the same uncertainty and technology choices, but become heterogeneous in Stage 2. Consequently, for each intermittent energy source $s \in S$, all firms invest in the same technology, i.e., $\alpha_{si} = \alpha_s$ for all $i \in I^s$ (cf., Section 2.4). I henceforth omit the firm-specific subscript i in the intermittent-technology parameter α_{si} in Sections 2.1–2.2.

I assume the shocks to demand, intermittent supply, and fossil costs are stochastically independent; that is, $\mathrm{E}(\eta\theta_{si}) = \mathrm{E}(\eta\varepsilon) = \mathrm{E}(\varepsilon\theta_{si}) = 0$ for all $i \in I^s$ and $s \in S$. These assumptions are crucial for deriving interpretable analytical results. Furthermore, I assume that the shocks to intermittent energy supply are symmetrically correlated within each energy source category, i.e., the correlation coefficients are given by $\rho_s = \mathrm{E}(\theta_{si}\theta_{sj})/\sigma^2_{\theta_{I^s}}$ for each $s \in S$ and all $i, j \in I^s$ with $i \neq j$. This implies that the variance of the aggregate intermittent energy source–specific shock $\theta_s = \sum_{i \in I^s} \theta_{si}$ is $\sigma^2_{\theta_s} = n_s (1 + (n_s - 1)\rho_s)\, \sigma^2_{\theta_{I^s}}$ for all $s \in S$. It can be shown that symmetric correlation requires $\rho_s \in [-1/(n_s - 1), 1]$, which is a necessary condition for the variance-covariance matrix of the variables θ_{si} to be valid (i.e., positive semidefinite). Therefore, we have $\sigma^2_{\theta_s} \in \left[0, n_s^2 \sigma^2_{\theta_{I^s}}\right]$, with the variance strictly increasing in the correlation coefficient ρ_s. Finally, the correlation

[9]Issues specific to nuclear power, such as radioactive radiation and waste management, are not addressed in this paper. Likewise, costs associated with intermittent energy, such as the extensive land use required for wind power, are omitted.

[10]This setup builds upon the theoretical frameworks in Krysiak (2008) and Storrøsten (2024).

between two firms using different energy sources is given by $\rho = \mathrm{E}\left(\theta_{si}\theta_{zj}\right)/\sigma_{\theta_{si}}\sigma_{\theta_{zj}}$ for all $s, z \in S$ ($s \neq z$), $i \in I^s$, and $j \in I^z$. Symmetric correlations imply that $\rho \in [-1/(\overline{s}-1), 1]$.

Supply of intermittent energy is given by:

$$\sum_{s \in S} \sum_{i \in I^s} \left(1 + \theta_{si}\right) \alpha_s = \alpha + \Theta, \tag{4}$$

where $\alpha = \sum_{s \in S} n_s \alpha_s$ and $\Theta = \sum_{s \in S} \sum_{i \in I^s} \alpha_s \theta_{si}$ refer to the deterministic and stochastic components, respectively. We have $\mathrm{E}(\Theta) = 0$, and the variance of Θ is given by (see Appendix C):[11]

$$\sigma_{\Theta}^2 = \sum_{s \in S} \left(\alpha_s^2 n_s \left(1 + \left(n_s - 1\right) \rho_s\right) \sigma_{\theta_{I^s}}^2 + 2\rho \sum_{z < s} \alpha_s n_s \sigma_{\theta_{I^s}} \alpha_z n_z \sigma_{\theta_{I^z}} \right). \tag{5}$$

Supply of electricity from NLE plants equals capacity β when the electricity price p is strictly positive, and zero otherwise.[12]

Supply of electricity from fossil energy solves $\max_y (py - c(y))$, with $c(y)$ given by Equation (3) and solution $y = \left(p - c_1 - \varepsilon\right)/c_2$.

Total supply of electricity from the three energy sources is given by:

$$x_s = \alpha + \Theta + \beta + \frac{p - c_1 - \varepsilon}{c_2}, \tag{6}$$

and the electricity market equilibrium satisfies $x_s = x_d \equiv x$. In this paper, I focus on the case with a strictly positive electricity price, $p > 0$.[13]

The market-clearing price then follows from Equations (2) and (6):

$$p = \frac{c_1 u_2 + c_2 u_1 - c_2 u_2 \left(\alpha + \beta\right)}{c_2 + u_2} + \frac{c_2 \eta + u_2 \varepsilon - c_2 u_2 \Theta}{c_2 + u_2} \equiv \mathrm{E}(p) + \Psi_p, \tag{7}$$

where $\mathrm{E}(p)$ and Ψ_p refer to the expected value and the stochastic component of p, respectively. The equilibrium price in the interior solution with $y > 0$ is determined by the marginal supply cost of electricity from fossil plants and consumer demand. The shock to intermittent supply Θ affects the residual demand faced by the fossil

[11] Note that σ_{Θ}^2, $\sigma_{\theta_s}^2$, and $\sigma_{\theta_{I^s}}^2$ denote the variance of total intermittent supply Θ, energy source–specific intermittent supply per unit of capacity θ_s, and intermittent firm–specific supply θ_{si}, respectively.

[12] Hydroelectric power plants with reservoirs maximize the present value of water and produce only when the electricity price is relatively high, given that water is scarce. This behavior is not captured here. Hydro with storage accounted for 2.9% of German electricity generation in 2024.

[13] There exists a solution where intermittent supply is larger than demand. In this case the price is 0 with free disposal, and negative otherwise (negative electricity prices occurs in Germany). The model abstracts from issues related to grid stability; see, e.g., IEA (2023).

plants and thus influences the price through the convex fossil supply costs. The realized market-clearing electricity price may be low if intermittent energy has a large market share and the shock to intermittent supply Θ is large and positive. Conversely, the price may be very high if Θ is large and negative.

2.1 Electricity price volatility and intermittent renewable energy

The variance of the electricity price is given by (cf. Equation (7)):

$$\sigma_p^2 = \frac{c_2^2\sigma_\eta^2 + u_2^2\sigma_\varepsilon^2 + c_2^2u_2^2\sigma_\Theta^2}{(c_2+u_2)^2}. \tag{8}$$

It follows that:

$$\frac{\partial\sigma_p^2}{\partial\alpha_s} = \frac{c_2^2u_2^2}{(c_2+u_2)^2}\frac{\partial\sigma_\Theta^2}{\partial\alpha_s}, \tag{9}$$

where σ_Θ^2 is given by Equation (5). It can be shown that $\partial\sigma_\Theta^2/\partial\alpha_s$ in Equation (9) is more likely to be positive if the energy source–specific correlation coefficients, ρ_s, are positive (see Appendix C). This is a reasonable assumption since, for example, output from solar power plants supplying the same electricity market tends to be positively correlated, as does power from wind farms. However, the cross-source correlation coefficient ρ may be smaller or even negative. Data on German intermittent renewable energy sources indicate that $\partial\sigma_p^2/\partial\alpha_s$ in Equation (9) is positive (see Section 3.2). Equation (9) shows that the variance of the electricity price is highly likely to increase with intermittent capacity (α_s), while it is unaffected by capacity in NLE (β) and by the fossil cost-slope parameter (c_1) (cf. Equation (8)). Finally, the variance in the electricity price increases (decreases) in the cost parameter determining the curvature of the fossil supply cost function, c_2, if the variance in fossil supply cost (σ_ε^2) is small (large) compared to the variances in intermittent supply (σ_Θ^2) and consumer demand (σ_η^2). That is, while a more flexible fossil supply structure mitigates volatility arising from intermittent generation and stochastic electricity demand, it can also amplify overall price volatility, as fossil producers adjust electricity output in response to fluctuations in fuel prices—such as those of natural gas or coal.[14] We state the following proposition on intermittent supply and the electricity market:

Proposition 1. *The variance of the electricity price increases with the capacity of intermittent energy, except in cases where the correlation coefficients ρ and ρ_s approach their respective lower bounds. A sufficient condition for $\frac{\partial\sigma_p^2}{\partial\alpha_s} > 0$ is that $\rho \geq 0$.*

[14] We have $\partial\sigma_p^2/\partial c_2 = \left(2u_2\left(c_2\left(\sigma_\eta^2 + \sigma_\Theta^2u_2^2\right) - \sigma_\varepsilon^2u_2\right)\right)/(c_2+u_2)^3$ from Eq. (8).

Proof. See Appendix C. □

Proposition 1 and Equation (7) highlight the importance of stochastic relationships among different energy sources. This is a key consideration for policymakers seeking to maintain price stability while increasing the share of intermittent energy sources such as solar and wind power in the electricity mix. For instance, if existing intermittent capacity is dominated by solar power, directing new investments toward wind power may help reduce future price volatility.[15] This issue is particularly relevant to the discussion of FiTs and excess price volatility in Section 2.3. Proposition 1 is empirically tested in Section 3.2.

2.2 Profitability and welfare across low emission energy technologies

Let $\pi(\alpha_s)$ and $\pi(\beta)$ denote profits from intermittent and NLE energy sources, respectively. Then expected profits are given by (see Appendix C):

$$\begin{aligned} \mathrm{E}\left(\pi\left(\alpha_s\right)\right) &= \left(\mathrm{E}(p) + \operatorname{cov}\left(p, \theta_{si}\right)\right)\alpha_s,\ \forall s \in S,\ \forall i \in I^s, \\ \mathrm{E}\left(\pi\left(\beta\right)\right) &= \mathrm{E}(p)\beta, \end{aligned} \tag{10}$$

where $\operatorname{cov}(p, \theta_{si})$ is the covariance between the equilibrium electricity price and the supply of intermittent firm $i \in I^s$. It is given by (see Appendix C):

$$\operatorname{cov}\left(p, \theta_{zi}\right) = \frac{-c_2 u_2}{c_2 + u_2}\left(\alpha_z\left(1 + \left(n_z - 1\right)\rho_z\right)\sigma_{I^z}^2 + \rho\sigma_{I^z}\sum_{s \neq z} n_s \alpha_s \sigma_{I^s}\right),\ \forall s, z \in S. \tag{11}$$

Equation (10) implies that expected profits per unit of installed capacity are higher for NLE energy sources such as nuclear or biomass than for intermittent energy sources, given that the covariance in Equation (11) is negative. Because expected output per unit of capacity is, by construction, equal for both types of sources, the difference does not stem from the fact that intermittent capacity tends to experience more downtime than NLE. For instance, wind turbines do not generate electricity when there is no wind. Rather, the difference arises because the equilibrium electricity price tends to be low when the supply of intermittent energy is high, and vice versa (cf. Equation (7)).

Expected welfare in Stage 2 is given by (see Appendix C for the derivations of expected welfare and fossil profits):

$$\mathrm{E}\left(W\right) = \mathrm{E}\left(u\left(\mathrm{E}\left(x\right)\right)\right) - \mathrm{E}\left(c\left(\mathrm{E}\left(y\right)\right)\right) + \frac{\sigma_\eta^2 + \sigma_\varepsilon^2 - c_2 u_2 \sigma_\Theta^2}{2\left(c_2 + u_2\right)}, \tag{12}$$

[15] Although beyond the scope of this paper, similar reasoning supports investments in grid infrastructure and greater integration of electricity markets across regions.

where the double expectation operators arise because the utility and cost functions are evaluated at $\eta = \varepsilon = 0$ in Equations (1) and (3). We observe that welfare increases with both σ_ε^2 and σ_Θ^2. Although the consumer values smooth consumption, welfare may nevertheless rise due to the ability to adjust to realized shocks; for example by increasing the output of fossil electricity when it becomes inexpensive. Note that the consumer utility function (1) is deliberately simple and omits features such as adjustment costs. The same applies to the specification of electricity supply costs.

We have the following result on relative advantages of the two low emission technologies NLE and intermittent:

Proposition 2. *Let* $\operatorname{cov}(p, \theta_{si}) < 0$ *in Equation (11). Then the expected revenue, profit and welfare per unit of generated electricity are higher for NLE than for intermittent energy.*

Proof. See Appendix C. □

This result does not stem from differences in expected electricity prices or consumption, as capacity is scaled such that the expected output from one unit of intermittent capacity α_s is equal to that of NLE capacity β. Rather, the result arises due to the volatility in intermittent supply. Note that investment costs are not included in the welfare calculation.

The German data indicate that $\operatorname{cov}(p, \theta_{si}) < 0$ for all intermittent renewable energy sources with a non-negligible market share.[16] Figure 3 in Section 3.3 plots monthly unit revenues by energy source for Germany from January 2015 to December 2025.

2.3 Feed-in tariffs

Feed-in tariffs (FiTs) guarantee a fixed wholesale electricity price for electricity from renewable energy for a specific time period (e.g., 20 years). The fixed price is set above the expected electricity price to promote the production of renewable energy. In this paper, I use the German FiT implemented under the German Renewable Energy Act (EEG) as an example. The EEG also involves priority access to the power grid for green electricity. The German FiT is financed by the

[16] Let ϱ denote Pearson's product–moment correlation coefficient between electricity output from intermittent sources and the electricity price. One-sided tests for correlation between paired samples (`cor.test`), using hourly and quarter-hourly data presented in Sect. 3.1, reject the null hypothesis $\varrho \geq 0$ with p–values well below one percent for onshore wind, offshore wind, and solar power. These results should be interpreted with some caution, however, since the electricity price series exhibits a unit root, whereas output is trend-stationary (cf. Table 8 in App. D).

EEG surcharge on all electricity consumers and differentiated by energy source, the size of the plant, and the year the installation was put into operation.[17]

I will henceforth assume that a subset of intermittent firms $\varsigma \subset S$ is eligible for a FiT, denoted $\tau_{s\in\varsigma} \geq \mathrm{E}(p)$, and refer to them as green sources producing green electricity. Supply of green electricity is defined analogously to intermittent energy in Equation (4), i.e., we have: $\sum_{s\in\varsigma}\sum_{i\in I^{\varsigma}}(1+\theta_{si})\,\alpha_s \equiv \alpha_{\varsigma}+\Theta_{\varsigma}$. Key beneficiaries of the FiT in Germany are wind power, solar power, and biomass.

We have the following result:

Proposition 3. *A feed-in tariff (FiT) increases the consumer price of electricity, lowers the equilibrium producer price for non-FiT generators, and reduces electricity consumption in the short run. The expected value of the transfer to FiT-eligible producers is given by* $\sum_{s\in\varsigma}\alpha_s\,(\tau_s - \mathrm{E}(p) - \mathrm{cov}(p,\theta_{si}))$.

Proof. See Appendix C. □

Proposition 3 states that the effects of the FiT are similar to those of any distortionary tax, including an associated efficiency (deadweight) loss. In the short run, the increased profits of FiT-eligible producers are more than offset by the losses incurred by electricity consumers and producers that do not receive the FiT. The realized value of the transfer from the consumer to some green electricity source $s \in \varsigma$ caused by the FiT simply equals $(\alpha_s+\theta_s)\,(\tau_s - p)$, but the expected value of the transfer in Proposition 3 includes the covariance $\mathrm{cov}\,(p,\theta_{si})$ because of the correlation between intermittent electricity supply and the electricity price. Thus, the *expected* value of the feed-in subsidy per unit of green electricity generated is larger than the difference between the tariff rate and the expected price (given that $\mathrm{cov}\,(p,\theta_{si}) < 0$).

2.4 Endogenous capacity and investment

In Stage 1, intermittent firm $i \in I^s$ maximizes expected profits with respect to capacity:

$$\max_{\alpha_{si}}\left(\mathrm{E}\left(\pi\left(\alpha_{si}\right)\right) - \kappa\left(\alpha_{si}\right)\right), \tag{13}$$

with the investment cost function satisfying $\partial\kappa/\partial\alpha_{si} > 0$. Expected profits are given by Equation (10) in the case of an intermittent firm receiving the market-clearing price p, and $\alpha_{si}\tau_s$ if the firm is eligible to a FiT. The solution is given

[17] See App. B for details on the EEG. The EEG subsidy amounted to about 23 billion euros in 2024 (source: CEW). Haan and Simmler (2018) examine how windfall revenues are divided between plant and land owners in Germany, finding that wind turbine subsidies accounted for 4 percent of overall agricultural income in 2007. See also Winter and Schlesewsky (2019).

by:

$$\begin{aligned} \kappa_{\alpha_{si}}\left(\alpha_{si}\right) &= \mathrm{E}(p) + \mathrm{cov}\left(p, \theta_{si}\right), \\ \kappa_{\alpha_{si}}\left(\alpha_{si}\right) &= \tau_s, \end{aligned} \tag{14}$$

where the upper and lower lines of the equations refer to the cases without and with a FiT (τ_s), respectively. Further, the expected price $\mathrm{E}(p)$ is given by Equation (7), and $\mathrm{cov}\left(p, \theta_{si}\right)$ is given by Equation (11). Note that Equation (14) follows directly from the Envelope Theorem and Equations (10) and (13).

Let us first examine the case with no FiT. Equation (14) then states that the marginal investment cost equals the increase in expected profits following a marginal increase in capacity α_{si}. Importantly, the firm thereby internalizes the fact that intermittent firms tend to have an average revenue per unit of electricity sold that is below the expected electricity price, as captured by $\mathrm{cov}\left(p, \theta_{si}\right)$. Equation (14) states that, everything else equal, the firms will invest more in intermittent energy sources whose output has low correlation with existing intermittent capacity. This does not only maximize the intermittent firms' expected profit, but also the expected utility and welfare from use of electricity (cf., Equation (12)). The reason is that this yields a more stable supply of electricity, which also benefits the consumer. Under a FiT, the marginal investment cost simply equals the FiT.

How do the investment levels in Equation (14) compare to the socially optimal investment levels? To address this question, suppose a benevolent social planner maximizes expected welfare with respect to intermittent capacity in Stage 1. Let $a = \{\, \alpha_{si} : s = 1, \ldots, \overline{s},\ i = 1, \ldots, n^s \,\}$ denote the set of all intermittent-technology parameters α_{si} across technologies s and firms i. I show in Appendix C that the social planner solves:

$$\max_{a,\beta,k_1,k_2,c_2} \mathrm{E}\left(u\left(x\right) - c\left(y\right) - \sum_{s\in S}\sum_{i\in I^s} \kappa^s\left(\alpha_{si}\right) - \kappa\left(\beta\right) - \kappa\left(c_2, k_1, k_2\right) \right), \tag{15}$$

with solution for all α_{si}:

$$\kappa_{\alpha_{si}}\left(\alpha_{si}\right) = \mathrm{E}\left(p\right) + \mathrm{cov}\left(p, \theta_{si}\right). \tag{16}$$

Equation (16) states that the socially optimal marginal investment cost equals the change in expected welfare following a marginal increase in capacity α_{si} (see Equation (11), and Equations (29) and (30) in Appendix C). We further observe that the firm chooses the socially optimal investment level when operating in a competitive market without a FiT (cf., Equations (14) and (16)). We state the following result:

Proposition 4. *Investment in green electricity production capacity is socially suboptimal under a FiT if* $\operatorname{cov}(p, \theta_{si}) \neq 0$*, both in terms of overall investment levels and the energy source mix. Investment levels are optimal in the absence of a FiT.*

Proof. The proposition follows from Equations (14) and (16). □

Proposition 4 states that the firms' investment levels in green electricity capacity maximize welfare if and only if there is no FiT. There are three sources of suboptimal investment under the FiT:

1. Investment levels are socially suboptimal because the marginal cost of investment is larger than the associated marginal increase in welfare (given $\tau_s \geq \mathrm{E}(p)$ and $\operatorname{cov}(p, \theta_{si}) < 0$). Note that the model framework does not feature positive externalities related to green energy investment such as technology spillovers or learning by doing.

2. The FiT does not promote an energy mix in which the marginal cost of supplying electricity is equalized across green energy sources, unless the tariff is uniform (i.e., $\tau_s = \tau$ for all $s \in \varsigma$). Although equalizing marginal investment costs across intermittent sources is socially suboptimal, a non-uniform FiT can further amplify this inefficiency unless it is explicitly designed to account for $\operatorname{cov}(p, \theta_{si})$ (cf. Equations (14) and (16)).[18]

3. The green firms do not internalize the uncertainty related to intermittent energy supply under the FiT, because they receive a fixed price τ_s. The result is that firms invest in an energy source mix that induces suboptimally large fluctuations in electricity prices and electricity use under the FiT. For example, in the case of the German Energiewende, the firms do not internalize that electricity prices in Germany tend to be relatively low when conditions for wind power are good. This causes over-investment in wind power, which in turn increases the volatility in the German electricity price paid by consumers.

Points 1 and 2 may reflect intentional policy objectives aimed at promoting investment in specific green energy technologies beyond the competitive equilibrium level. Point 3, by contrast, is unlikely to constitute a deliberate outcome of the FiT. We further note from Equation (16) that the socially optimal marginal investment cost of intermittent energy sources declines as the share of intermittent

[18]The German FiT varies across energy sources and sites. For example, the FiT for wind energy onshore is calculated from the average highest bids in the tendering procedure two years earlier, whereas it varies for solar. See EU EEG for details.

generation increases, reflecting that the covariance between intermittent output and the electricity price becomes increasingly negative as the number of intermittent firms rises (cf. Equation (11)). It follows that the difference between the socially optimal investment given by Equation (16), and the socially suboptimal investment under a FiT given by Equation (14), increases with the share of intermittent energy. Point 3 above is examined empirically in Section 3.4.

Suppose the FiT is replaced with an investment subsidy $\nu_\varsigma > 0$, such that intermittent firm $i \in I^s$ solves $\max_{\alpha_{si}} \left(\mathrm{E}\left(\pi\left(\alpha_{si}\right)\right) + \nu_s \alpha_i - \kappa\left(\alpha_{si}\right)\right)$. Then Equation (14) is replaced with:

$$\kappa_{\alpha_{si}}\left(\alpha_s\right) = \mathrm{E}(p) + \mathrm{cov}\left(p, \theta_{si}\right) + \nu_s,\ \forall s \in \varsigma, \tag{17}$$

with $\nu_s > 0$ for all $s \in \varsigma$. Equation (17) implies that, under a standard investment subsidy $\nu_s > 0$, green firms internalize the covariance between output and the electricity price. At the same time, they invest more than in the pure competitive equilibrium (i.e., in the absence of both a FiT and an investment subsidy). Hence, we have the following result:

Proposition 5. *An investment subsidy may encourage greater investment in green energy sources without causing the excess price volatility associated with the FiT.*

Proof. The proposition follows from Equations (14), (16) and (17). □

Proposition 5 provides theoretical support for replacing FiTs with standard investment subsidies. In particular, expected welfare, as defined in Equation (12), is higher under an appropriately specified investment-subsidy regime that satisfies $\nu_s \leq \tau_s - \mathrm{E}(p) - \mathrm{cov}(p, \theta_{si})$ for all $s \in \varsigma$ than under a FiT. This improvement arises because the investment subsidy induces a less volatile supply of electricity from intermittent energy sources, reflected in a lower variance of aggregate supply shocks (i.e., a reduction in σ_Θ^2).

While the solutions to the investment problems of the NLE and fossil energy sources are delegated to Appendix C, several key points are worth noting. First, firms' investments in NLE and fossil technologies are socially optimal if the emission price χ equals the Pigouvian tax, consistent with the First Fundamental Theorem of Welfare Economics.

Second, marginal investment costs in NLE capacity, such as nuclear or biomass, are higher than those for intermittent energy sources (given $\mathrm{cov}\left(p, \theta_{si}\right) < 0$ and no subsidies). The reason is that the expected revenue per unit of electricity generated is higher for NLE technologies than for intermittent power (cf., Equation (10)).

Third, the optimal fossil technology choice with respect to the flexibility parameter c_2 changes when the energy mix contains a larger share of intermittent power, such as wind or solar. The value of flexibility rises as electricity prices become more volatile. For example, a gas-fired power plant can adjust output more quickly to volatile prices than a mine-mouth coal-fired power plant, making investment in gas-fired technologies relatively more profitable as the share of intermittent energy increases. Consequently, a higher share of intermittent energy renders part of the existing real capital in fossil-fueled power plants suboptimal. This is a cost that should be taken into account when implementing policies that promote renewable electricity. Moreover, it may be beneficial to combine subsidy schemes such as FiTs with measures aimed at replacing, for instance, large base-load lignite coal plants with more flexible gas-fired power plants.

Finally, the deadweight loss induced by the FiT leads to lower producer prices for electricity producers that are not eligible for the FiT (cf. Proposition 3), implying reduced investment in energy sources that are not FiT-eligible. This is noteworthy, as positive externalities may arise not only for FiT-supported technologies, but also for technologies that do not receive FiT support.

2.5 Contracts for Difference

While the theoretical discussion is framed around FiTs, the underlying mechanism extends to two-sided Contracts for Difference (CfDs). Like FiTs, CfDs stabilise investors' revenues by linking remuneration to a fixed strike price. However, they do so through financial settlement against a wholesale price benchmark and are typically allocated via competitive auctions.

Specifically, under a stylised two-sided CfD with strike price $K_s = \tau_s$ and no state-contingent provisions, expected revenues per MWh coincide with those under a FiT, implying an equivalent first-order investment condition (see Equation (14)). In practice, CfD schemes may include design features such as the suspension of support during negative price periods and requirements that supported generators remain responsive to balancing and other market signals (e.g., Baringa Partners LLP, 2015; European Commission, 2025). CfDs therefore do not generally fully replicate the incentive properties of a pure FiT.

Intermittency-induced price volatility and the decline in the market value of weather-dependent output due to a negative price–quantity covariance arise from the equilibrium interaction of stochastic demand, residual fossil supply, and intermittent generation. This mechanism is expected to remain relevant under CfD-based support. As a result, the volatility externality identified under FiTs continues to operate under CfDs, although its quantitative magnitude depends on contract design. What differs across FiT and CfD instruments is primarily the incidence of the cannibalisation cost and the extent to which investors internalise the price–quantity covariance in capacity investment decisions. Further, whereas a FiT acts as a distortionary wedge between wholesale prices and private revenues (cf. Proposition 3), a two-sided CfD instead operates largely as a state-contingent transfer that preserves participation in wholesale markets.

3 The German energy transition

Figure 2 shows German electricity output by energy source over the last two decades. The transformation of Germany's electricity market is driven by the *Energiewende* policy, which emphasizes the phase-out of nuclear and fossil fuels in favor of renewable energy sources. The transition to renewables has been primarily facilitated by the Renewable Energy Act (EEG), initially implemented in 2000, which introduced FiTs and guaranteed priority grid access for renewable energy producers.

This section empirically examines how the increasing share of intermittent energy in the German electricity mix has affected the volatility of German electricity prices (Section 3.2) and the market value of electricity produced by intermittent generators (Section 3.3). Finally, Section 3.4 presents a measure that quantifies the negative externality caused by FiTs on investment in renewables (cf. Propositions 3 and 4).[19] Details on the econometric modelling are provided in Appendix D.

3.1 Data and econometric framework

Table 1 summarizes the main variables used in the empirical analysis. All series are aggregated to the monthly frequency in the econometric regressions in Sections 3.2 and 3.3. The dataset spans January 2015 to December 2025 and combines ENTSO-E data on electricity prices and generation, ICE Dutch TTF natural gas futures, and spatially weighted weather observations from Open-Meteo.[20] A range of additional variables, including financial indices, GDP, EU ETS allowance prices, and lagged exogenous variables, were considered but excluded because they did not improve model fit.

Unit root tests were conducted, including the Augmented Dickey–Fuller, Phillips–Perron, and Zivot–Andrews tests. Detailed results are reported in Appendix D. The electricity price volatility measure ($log(RV_t)$; see Equation (18)) behaves as a trend-stationary variable, consistent with its construction from monthly averages of high-frequency squared returns. Weather variables are stationary, and the wind and solar shares are best characterized as trend-stationary. By contrast, electricity

[19] See Böhringer et al. (2017) for an empirical study of how the EEG triggered a massive increase in German renewable electricity production (i.e., investment levels—not the distortion caused by externalizing price volatility). Findings in Böhringer et al. (2017) cast doubt on the additional positive innovation effects attributed to the FiT.

[20] I use spot price data and generation by source to calculate revenues. Although this reflects the market value of electricity, it does not equal the revenue of intermittent firms receiving FiTs (cf. Eq. (14)).

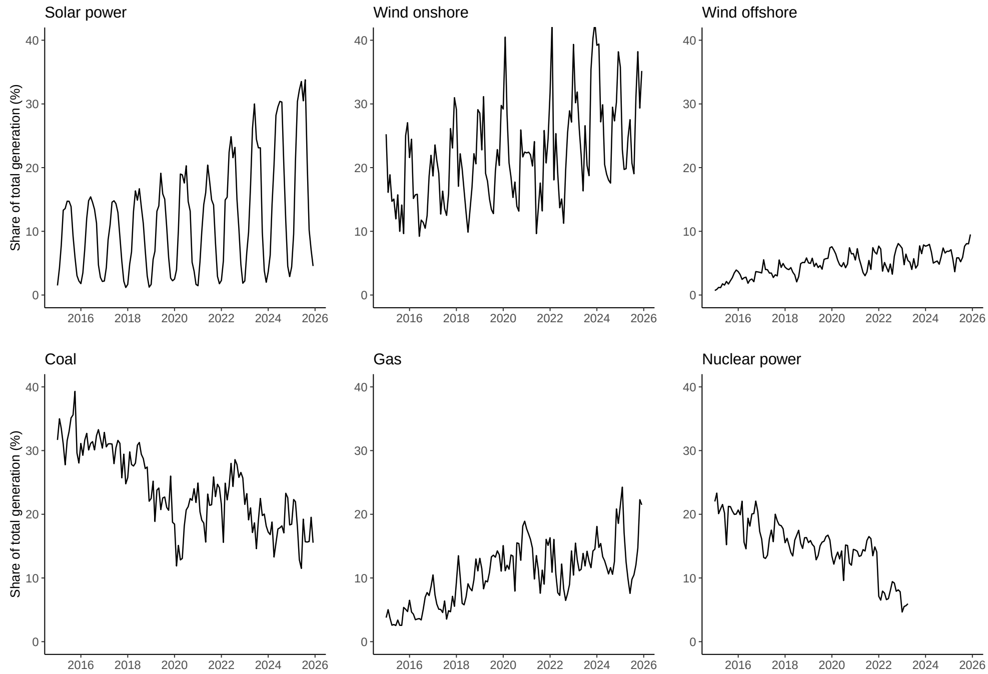

Figure 2: German electricity generation. Selected energy sources. Percent of total generation. Monthly aggregates from Jan. 2015 to Dec. 2025.

Table 1: Overview of key time series[1]

Variable	**Underlying variable**	**Frequency**	**Source**
Price	Day-ahead EPEX-spot price (BZN|DE-LU)	Hourly/15min[2]	ENTSO-E
Generation	Actual electricity generation by source (BZN|DE-LU)	Hourly/15min[2]	ENTSO-E
Gas price	ICE Dutch TTF Natural Gas Futures (TFMBMc1)	Daily[3]	Investing
Weather[4]	Air temperature, wind speed, solar radiation	Hourly	Open-Meteo

[1]Data from Jan. 2015 to Dec. 2025.
[2]Hourly data for the years 2015–2018, and data at 15-minute intervals thereafter.
[3]Data are only available on business days.
[4]Weighted spatial averages for each of the three weather variables, see Appendix D.

and natural gas prices, as well as the revenue variables, behave as integrated processes and are therefore included in stationary first differences. Results from more detailed testing procedures, including seasonal and structural-break diagnostics, are reported in Appendix D.

The empirical analysis exploits variation in the equilibrium share of intermittent generation. Accordingly, the estimated coefficients describe how price volatility and revenues respond when the electricity system operates with higher intermittent penetration, holding other observed determinants constant, irrespective of the underlying policy or market forces generating that penetration.

3.2 Intermittent renewables and electricity price volatility

Proposition 1 states that a higher share of intermittent renewable energy increases electricity price volatility. This section presents four econometric models that empirically test this hypothesis.

Realized variance (RV) is widely used as a volatility measure in empirical studies of high-frequency financial time-series data (Andersen & Bollerslev, 1997; Andersen et al., 2001, 2003).

Let r_{tkh} denote the intraday change in the electricity spot price from hour $h-1$ to hour h on day k in month t. Daily realized variance is defined as:

$$RV_{tk}^{D} = \sum_{h=1}^{N_{tk}} r_{tkh}^2, \tag{18}$$

where N_{tk} is the number of intraday observations on day k in month t. In the electricity market context, intraday price changes are measured in levels rather than logarithms to accommodate the occurrence of zero and negative prices. Monthly realized variance is then computed as the average of daily realized variances,

$$RV_t = \frac{1}{D_t} \sum_{k \in m(t)} RV_{tk}^{D}, \tag{19}$$

where t indexes the month, D_t denotes the number of observed days in month t, and $m(t)$ is the set of days belonging to month t. The dependent variable in the empirical analysis is the natural logarithm of monthly realized variance, $y_t = \log(RV_t)$; see the upper-right panel of Figure 1.

In the following, the empirical results are first presented together with a brief description of the econometric specification and their economic interpretation. Model selection, diagnostic testing, and robustness checks are then addressed in subsequent sections.

3.2.1 Econometric results and interpretation

Consider the following ARX(p) specification of monthly realized variance, where the conditional mean depends on its own first p lags and a vector of contemporaneous exogenous regressors:

$$y_t = \mu_0 + \sum_{i=1}^{p} \phi_i y_{t-i} + \boldsymbol{x}_t^\top \boldsymbol{\beta} + \varepsilon_t, \qquad \varepsilon_t \sim \mathcal{N}(0, \sigma^2). \tag{20}$$

Here, y_t denotes the electricity price volatility measure $\log(RV_t)$, $\sum_{i=1}^{p} \phi_i y_{t-i}$ captures the autoregressive component, $\boldsymbol{x}_t$ is a vector of stationary exogenous variables, including intermittent energy shares and indicator variables (see Table 2 for the specification of $\boldsymbol{x}_t$ across models), and $\boldsymbol{\beta}$ is the companion coefficient vector. More general specifications were explored, including ARIMAX$(1,1,1)$ models and extensions with GARCH dynamics for ε_t. However, the parsimonious ARX(1) specification defined in Equation (20), with $p = 1$, was found to be adequate given the data (see Section 3.2.3).

Table 2 reports estimates from the preferred ARX(1) specifications for electricity price volatility, corresponding to variants of Equation (20). In all models, the estimated coefficients on wind and solar shares are positive and statistically significant. This empirical evidence aligns with Proposition 1, which predicts that greater intermittent penetration induces more frequent and more pronounced price excursions, increasing volatility.

The results further indicate that positive shocks to natural gas prices significantly increase electricity price volatility. This finding is consistent with the theoretical framework, as higher gas prices raise the marginal cost of adjusting electricity generation from gas-fired power plants. Finally, higher temperatures dampen electricity price volatility.

Wind power output is approximately proportional to the product of installed wind capacity and wind speed. Accordingly, the wind share is closely related to the capacity share of wind power in the electricity mix.[21] By analogous reasoning, the solar share is similarly linked to the capacity share of solar power. At the same time, the shares of wind and solar generation also depend on the availability of electricity from other sources, such as fossil fuels and nuclear power. Consequently,

[21] Wind speed and solar irradiance are statistically significant in model specifications where the trend-stationary shares of wind and solar power enter in levels, but not in first differences as in Table 2. While these specifications continue to suggest sizeable cannibalization effects for intermittent technologies, their overall model performance is inferior to the formulations in first differences. The relationship between wind speed and electricity generation is nonlinear (Lehneis et al., 2021). Data on capacity by source are only available at an annual frequency from ENTSO-E.

Table 2: Determinants of electricity price realized variance

	Model 1	**Model 2**	**Model 3**	**Model 4**
Intercept (μ)	7.392***	6.459***	5.827***	5.752***
	(0.627)	(0.204)	(0.335)	(0.404)
AR(1) (ϕ_1)	0.926***	0.669***	0.690***	0.745***
	(0.030)	(0.086)	(0.083)	(0.081)
Wind share (Δ)	2.105***	2.063***	2.080***	1.871***
	(0.619)	(0.689)	(0.667)	(0.666)
Solar share (Δ)	5.893**	5.516**	5.698**	6.914***
	(2.306)	(2.495)	(2.424)	(2.584)
Log(gas price) (Δ)	0.819***	0.863***	0.862***	0.851***
	(0.298)	(0.326)	(0.316)	(0.309)
Celsius (Δ)	−0.046***	−0.045**	−0.046***	−0.026
	(0.016)	(0.018)	(0.017)	(0.019)
Time trend			0.015**	0.016**
			(0.007)	(0.007)
Post–Aug 2021		2.409***	1.505***	1.309**
		(0.360)	(0.563)	(0.606)
Seasonal dummy Sept.				0.570**
				(0.284)
Seasonal dummy Oct.				0.567**
				(0.278)
Number of observations	131	131	131	131
Ljung–Box p-val. (lag 12)	0.377	0.737	0.746	0.162
ARCH LM p-val. (lag 12)	0.041**	0.602	0.180	0.289
Shapiro–Wilk p-val.	0.600	0.148	0.783	0.656
PP test (residuals)	−154.3***	−144.0***	−145.6***	−151.4***
ADF test (residuals)	−5.596***	−5.329***	−4.882***	−5.286***
Log Likelihood	−114.6	−111.2	−108.3	−99.1
AIC	243.2	238.4	234.6	238.1
BIC	263.3	261.4	260.4	295.6

Notes: $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$. Standard errors in parentheses. Insignificant seasonal dummies are not reported in Model 4. All variables accompanied by "(Δ)" are first differences. Post–Aug 2021 equals 1 from August 2021 onward and 0 otherwise. Share variables are measured in percentage points of total electricity generation. The null hypotheses are no autocorrelation (Ljung–Box), no conditional heteroskedasticity (ARCH LM), normality (Shapiro–Wilk), and a unit root (Phillips–Perron; augmented Dickey–Fuller). Estimation is conducted using `R` and the `TSA` package.

these share variables should not be interpreted as proxies for intermittent capacity or output alone, but rather as equilibrium outcomes reflecting a broader set of regulatory and market conditions that determine the composition of electricity generation. For the purposes of this analysis, the precise source of variation in renewable shares, whether capacity additions, the nuclear phase-out, or changes in fossil fuel and ETS prices, is secondary. The objective is to characterize how electricity markets behave when operating with a high share of intermittent generation, regardless of the underlying source of that share.

Short-run elasticities derived from Table 2 are reported in Table 3. The renewable variables are measured in percentage points of total electricity generation. As a result, even moderate coefficients translate into comparatively large percentage changes in realized volatility.[22]

Table 3: Short-run electricity price volatility elasticities

	Model 1	**Model 2**	**Model 3**	**Model 4**
Wind share (pp)	2.1	2.1	2.1	1.9
Solar share (pp)	6.1	5.7	5.9	7.2

Note: Elasticities are calculated using the estimates reported in Table 2 and evaluated at the sample mean. Generation shares are measured in percentage points of total electricity generation.

3.2.2 Model specification and diagnostic evaluation

Beginning with Model 1 in Table 2, the estimated autoregressive coefficient is very large and highly significant. Residual diagnostics indicate conditional heteroskedasticity, but no serial correlation or departures from normality.

The upper right panel of Figure 1 provides visual evidence suggestive of a structural break in the volatility time series (measured as realized variance). In particular, the series appears to transition from a regime of relatively low volatility early in the sample to a regime of higher volatility from mid–2021 onward. This observation motivates formal tests for structural instability in the conditional mean under Model 1. The supF test of Andrews (1993) rejects the null hypothesis of coefficient stability at the 1% level, providing evidence of at least one structural break in the conditional mean relationship.[23] Breakpoint estimation following Bai

[22]The implied long-run elasticities depend mechanically on the magnitude of the estimated autoregressive coefficient. Because the persistence parameter enters the long-run multiplier as $(1-\hat{\phi}_1)^{-1}$, small differences in $\hat{\phi}_1$ can produce large differences in the implied long-run response (Hamilton, 1994; Kilian, 2009).

[23]Unlike the Chow test, which evaluates parameter stability at a prespecified date, the supF statistic computes Chow-type tests over all admissible breakpoints and rejects stability when the

and Perron (1998, 2003) identifies a statistically significant break in August 2021.[24]

Model 2 augments Model 1 by including a step dummy for the structural break suggested by the supF test, equal to zero prior to August 2021 and one thereafter. Allowing for a single post–2021 level shift substantially improves model fit and residual diagnostics. Extensions permitting slope breaks through interactions between the structural-break dummy and renewable and gas-price variables do not yield significant estimates of the coefficients, nor do specifications with multiple break dummies. Taken together, this evidence suggests that the structural break reflects a discrete increase in the level of electricity price volatility rather than a change in the marginal effects of the explanatory variables.

Model 3 extends Model 2 by incorporating a linear time trend. Allowing for a deterministic trend alongside the August 2021 structural break improves model fit and attenuates the estimated magnitude of the break dummy, suggesting that the volatility series reflects both a discrete regime shift and a gradual adjustment process.

Model 4 augments Model 3 by including monthly seasonal dummy variables. While the inclusion of seasonal effects renders the temperature variable insignificant, only two of the eleven monthly dummies are individually statistically significant, suggesting that seasonality is largely captured by temperature (with gas prices and intermittent renewable shares potentially also absorbing seasonal variation). Moreover, the higher AIC and BIC indicate that the inclusion of seasonal dummies does not improve overall in-sample fit relative to Model 3. Accordingly, Model 3 is taken as the preferred specification, while Model 2 provides a parsimonious benchmark and Model 4 is reported as a robustness check.

The sample contains 132 monthly observations, which imposes a natural limit on the number of exogenous variables that can be included. Gas prices summarize the marginal costs of price-setting plants in Germany's merit order, while coal prices are highly correlated with gas prices. We therefore adopt a parsimonious specification in which the gas price serves as the primary proxy for fossil marginal costs. Measures of wind speed and solar irradiance are not statistically significant in alternative model specifications. In addition, temperature captures the dominant drivers of electricity demand, while structural-break dummies absorb large shifts in market conditions. Together, these controls account for the main

supremum statistic is sufficiently large. These tests detect changes in the conditional relationship between variables rather than shifts in a single series.

[24] August 2021 is also identified as a structural break when a time trend is included, as in Models 3 and 4. Breakpoint estimation further suggests the presence of two breaks (May 2019 and August 2021 without a trend; July 2020 and October 2022 with a trend), although the associated BIC values are close to those of the single-break specification. Models formulated with these two breakpoints do not yield statistically significant break dummies, however. See App. D for supF test output.

determinants of price volatility, while preserving degrees of freedom and avoiding overfitting.

3.2.3 Robustness and alternative specifications

A series of robustness checks reported in Appendix D confirm the stability of the baseline results. Removing autoregressive dynamics (Model 5) produces substantial serial correlation and ARCH effects, underscoring the need to model persistence in realized volatility. Using the first difference of $\log(RV_t)$ (Model 6) or including nuclear generation (Model 7) leaves the qualitative results for wind and solar largely unchanged, though with lower precision.

To assess potential endogeneity in renewable penetration, Models 8–9 estimate IV–ARX(1) variants of Model 3. Wind and solar shares are instrumented with monthly wind speed and solar irradiance, respectively, yielding very strong first-stage relationships. Durbin–Wu–Hausman tests fail to reject exogeneity of renewable shares. The IV estimates are close to the baseline non-IV estimates in Models 2–3 in Table 2.

Finally, restricting the sample to the pre-crisis period ending in December 2020 (Model 10) produces estimates similar to those obtained for the full sample, confirming that the main findings are not driven by the exceptional market conditions of 2021–2022.

3.3 Intermittent power and revenue cannibalization

Proposition 2 states that increasing the share of intermittent energy sources, like solar and wind, lowers the market price of electricity during periods of high generation, thereby reducing the unit revenues and profitability of these sources themselves. This phenomenon, often referred to as cannibalization in renewable energy, is examined empirically in this section.

Figure 3 presents the normalized average market value per unit of electricity sold for selected energy sources in Germany. For each source, the market values are calculated by multiplying output by the electricity price at 15-minute or hourly intervals (see Table 1). These values are aggregated to monthly totals and normalized by the product of the average monthly price and total monthly production. Hereafter, we refer to these market values as revenues.[25] A value of 1 occurs, for example, if the energy source maintains a constant and positive output throughout the month. A value above 1 indicates that the source tends to produce more when

[25]The revenues of German intermittent energy sources eligible for feed-in tariffs (FiTs) are decoupled from the market value of electricity as calculated using the spot price in this section. In this instance, the cost of cannibalization is borne either by electricity consumers or by the state budget. See App. B for further details.

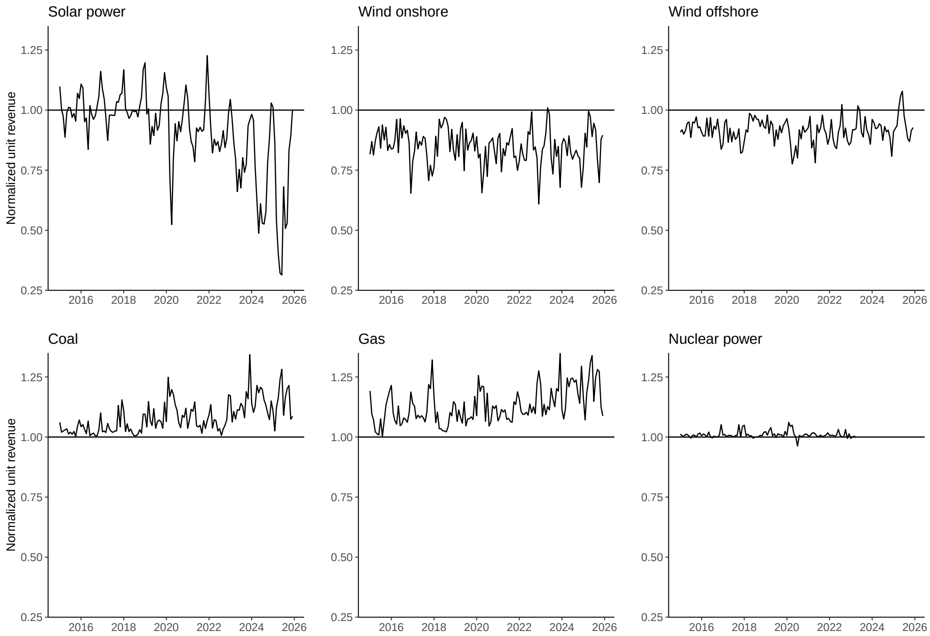

Figure 3: Average revenue per unit of output by source. Monthly means from Jan. 2015 to Dec. 2025, normalized by the electricity price.

prices are high, whereas a value below 1 suggests higher output during low-price periods. Note that Figure 3 reports revenue per unit of electricity *generated*, which differs from revenue per unit of installed *capacity*. For instance, wind power does not generate electricity during periods without wind.

The dependent variable is monthly unit revenue, which corresponds to the graphs in Figure 3, except that it is not normalized by the electricity price.[26] Unit revenues are modelled in first differences because unit root tests indicate that the level series behave as integrated processes (see Appendix D).

In the following, the main cannibalization estimates are presented and interpreted economically across technologies. The econometric specification, model selection, and diagnostic assessment are discussed subsequently.

3.3.1 Econometric results and interpretation

Consider the following ARIMA–GARCH model with exogenous regressors:

[26]The non-normalized time series are presented in Fig. 6 in App. D. These series track the electricity price shown in Fig. 1 and are less informative than the normalized variables in Fig. 3.

$$\begin{aligned}\Delta y_t = \mu + \sum_{i=1}^{p}\phi_i \Delta y_{t-i} + \sum_{i=1}^{q}\theta_i \varepsilon_{t-i} + \boldsymbol{x}_t^\top \boldsymbol{\beta} + \varepsilon_t, \quad \varepsilon_t = \sigma_t z_t \\ \sigma_t^2 = \omega + \alpha_1 \varepsilon_{t-1}^2 + \varsigma_1 \sigma_{t-1}^2, \quad z_t \sim t_\nu(0,1).\end{aligned} \tag{21}$$

Here Δy_t denotes the stationary first-difference of intermittent unit revenue, $\sum_{i=1}^{p}\phi_i \Delta y_{t-i}$ is the autoregressive component, $\sum_{i=1}^{q}\theta_i \varepsilon_{t-i}$ is the moving average component, $\boldsymbol{x}_t$ is a vector of stationary exogenous variables (see Table 4), and $\boldsymbol{\beta}$ is the accompanion coefficient vector. The innovation z_t follows a standardized Student-t distribution with ν degrees of freedom, allowing for heavy-tailed shocks.

Table 4 reports estimates from the preferred AR(1)/MA(1)–iGARCH(1,1) specifications for wind and solar power revenues, corresponding to variants of Equation (21). The results show a strong and statistically significant cannibalization effect for all three technologies, in line with the theoretical prediction stated in Proposition 2. Moreover, increases in the market share of either wind or solar power reduce unit revenues for the other technologies. This cross-technology cannibalization likely reflects reduced dispatch of gas-fired generators during periods of high intermittent output.

The theory further suggests that cannibalization may arise from correlated intermittent production profiles. Using 15-minute observations from January 2019 onward, we obtain moderate and statistically significant negative correlation between wind and solar generation ($r = -0.23$, $p < 0.001$), consistent with diurnal and meteorological patterns in Northern Europe. Despite this negative correlation, both technologies depress market prices when abundant, producing the observed cross-effects in revenues. That is, even with negatively correlated outputs, each technology reduces prices when abundant, so both exert downward pressure on the other's revenues. As expected, higher natural gas prices raise unit revenues for all technologies, reflecting the direct influence of gas-fired generators on marginal pricing.

Both the linear and quadratic terms for solar share are negative, indicating a concave and monotonically decreasing response of Δy_t to positive shocks in solar power market penetration (the quadratic term is not statistically significant for wind). Consequently, the marginal effect of solar power becomes increasingly negative as the magnitude of the shock increases. For example, a one (ten) percentage point increase in the share of solar power is associated with a short-run reduction in unit revenue of approximately EUR 4.4 (EUR 50.8) per MWh. This nonlinear relationship is consistent with the visual evidence for solar power reported in Figure 3.

The estimated dynamic structures differ across technologies. For solar power, the preferred AR(1) specification implies mean-reverting dynamics in changes in unit revenues, indicating that revenue shocks adjust gradually and do not per-

Table 4: Determinants of unit revenues of electricity from intermittent energy sources

	Solar power (Δ)	**Wind onshore (Δ)**	**Wind offshore (Δ)**
Wind share (Δ)	-0.871^{***}	-0.899^{***}	-0.766^{***}
	(0.169)	(0.127)	(0.096)
Solar share (Δ)	-4.289^{***}	-0.723^{***}	-0.885^{***}
	(0.472)	(0.158)	(0.122)
Solar share^2 *(Δ)*	-0.079^{**}	—	—
	(0.036)	—	—
Gas price (Δ)	1.370^{***}	1.263^{***}	1.345^{***}
	(0.485)	(0.133)	(0.083)
Solar radiation (Δ)	0.189^{***}	—	—
	(0.031)	—	—
Mean intercept, μ	1.089^{**}	0.339^{**}	0.368^{*}
	(0.528)	(0.145)	(0.203)
AR(1), ϕ_1	-0.325^{***}	—	—
	(0.123)	—	—
MA(1), θ_1	—	-0.704^{***}	-0.646^{***}
	—	(0.184)	(0.122)
Variance intercept, ω	15.335	6.463^{**}	9.548^{**}
	(16.989)	(2.870)	(4.184)
ARCH(1), α_1	0.433^{**}	0.559^{***}	0.788^{***}
	(0.181)	(0.139)	(0.213)
GARCH(1), ς_1	0.567	0.441	0.212
Student-t (ν*)*	2.716^{**}	5.498^{**}	6.250^{*}
	(1.069)	(2.455)	(3.349)
Number of obs.	131	131	131
Log-likelihood	−457.6	−436.5	−425.3
Weigh. Ljung–Box (p-val.)	0.932	0.953	0.864
ARCH–LM (p-val.)	0.880	0.907	0.601
Nyblom joint stat	1.930	1.703	1.533
Sign bias test	0.988	0.871	0.453

Note: $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$. Robust QML standard errors are reported in parentheses. Variables denoted by "(Δ)" are first-differenced. For iGARCH specifications, the restriction $\alpha_1 + \varsigma_1 = 1$ is imposed; ς_1 is therefore not separately estimated, and its standard errors are equal and not reported. All models assume Student-t innovations. The sample period is January 2015–December 2025. Estimation is conducted using `R` and the `rugarch` package (Galanos, 2025).

sist over time. By contrast, the preferred MA(1) specifications for both onshore and offshore wind suggest that revenue dynamics are dominated by short-lived innovations, with shocks largely reversed in the subsequent period. This pattern is consistent with technology-specific adjustment mechanisms, whereby solar revenues exhibit smoother and more persistent adjustment, while wind revenues are primarily affected by transitory disturbances associated with short-term supply variability (see also Figure 2).

Table 5: Short-run electricity unit revenue semi-elasticities

	Solar power	**Wind onshore**	**Wind offshore**
Wind share (pp)	−1.4	−1.5	−1.1
Solar share (pp)	−7.1	−1.2	−1.3

Notes: Semi-elasticities are computed using the estimates in Table 4 and evaluated at the sample mean, reflecting the level response of unit revenue to a one-percentage-point permanent increase in generation shares.

Table 5 reports key semi-elasticities (percent response to pp change) derived from Table 4. The estimated short-run semi-elasticities indicate substantial cannibalization effects across renewable technologies. For solar power, a one–percentage-point increase in the solar share reduces unit revenues by approximately 7 percent within the same month, indicating strong intra-technology price pressure. Wind power also exhibits own-technology cannibalization, albeit of smaller magnitude. Cross-technology effects are likewise economically meaningful: increases in the wind share reduce solar revenues by slightly more than 1 percent, and vice versa. Offshore wind appears somewhat less exposed to own-technology effects, but remains sensitive to changes in both solar and onshore wind penetration.

3.3.2 Model specification and diagnostic evaluation

The findings in Section 3.2, particularly the presence of a time trend and increasing volatility at higher shares of intermittent generation, suggest that the conditional variance of the first-differenced unit revenue series exhibits conditional heteroskedasticity. The initial specifications therefore model volatility using a standard GARCH(1,1) process. However, because the estimated persistence is close to unity for all three sources, indicating highly persistent volatility dynamics, the final model specifications impose the integrated GARCH(1,1) (iGARCH) restriction $\alpha_1 + \varsigma_1 = 1$. While a unit root in the level implies that the variance of the process grows without bound over time, an iGARCH specification implies non-stationarity in the conditional variance, even when the level of the series remains stationary.[27]

[27] The standard GARCH estimates are very similar to the iGARCH results, with slightly higher conditional variances and marginally weaker performance in the Nyblom stability tests;

An additional consideration is the presence of a structural break in electricity price volatility around August 2021, documented in Section 3.2. Since unit revenues are defined as the product of prices and quantities, a regime shift in price volatility mechanically propagates into the variance of revenue innovations. Such breaks are known to induce near-unit persistence in GARCH-type models when not explicitly modeled, suggesting that the high estimated persistence may partly reflect structural change rather than genuine long-memory behavior. This provides further support for the use of an iGARCH specification, which offers a parsimonious representation of highly persistent volatility without imposing fractional integration.

Several ARIMA(p,1,q) specifications were evaluated for the conditional mean, each combined with either a standard or an integrated GARCH(1,1) process for the conditional variance. Model selection drew on the Akaike and Bayesian information criteria, log-likelihood values, and a comprehensive set of diagnostic checks (see Appendix D). The preferred specifications differ across technologies, with an ARIMA(1,1,0) model selected for solar power, while an ARIMA(0,1,1) specification performs best for both onshore and offshore wind. The Student-t specification fits better than the normal distribution, indicating fat-tailed revenue changes driven by occasional extreme price or output events.

The supF procedure identifies a structural break in July 2022 in unit revenues for all three intermittent energy sources (see Appendix D). This breakpoint coincides with the abrupt shift in German electricity price formation during the European gas-supply crisis, when reductions in Russian gas flows triggered extreme wholesale price volatility. The break is detected in the static specification but becomes insignificant once dynamics are introduced, suggesting that the instability result is not robust to explicitly modeling persistence.

Diagnostic tests confirm the adequacy of the preferred models (see Appendix D). Weighted Ljung–Box tests show no remaining serial correlation in standardized residuals, and ARCH–LM tests reveal no evidence of unmodeled conditional heteroskedasticity. Nyblom tests support parameter constancy for all coefficients, and sign-bias tests reveal no asymmetric volatility effects. The cannibalization coefficients are stable across the ARIMA(p,1,q) and GARCH variance specifications considered during model selection; although alternative lag structures or restricted volatility models generally deteriorate model fit, they do not materially change the sign or economic magnitude of the estimated effects.

see Appendix D. A fractionally integrated specification, fiGARCH(1,1), likewise confirms highly persistent volatility dynamics but adds complexity without clear improvements in fit or diagnostics. See Engle and Bollerslev (1986) and Tayefi and Ramanathan (2012) for details on iGARCH and fiGARCH models.

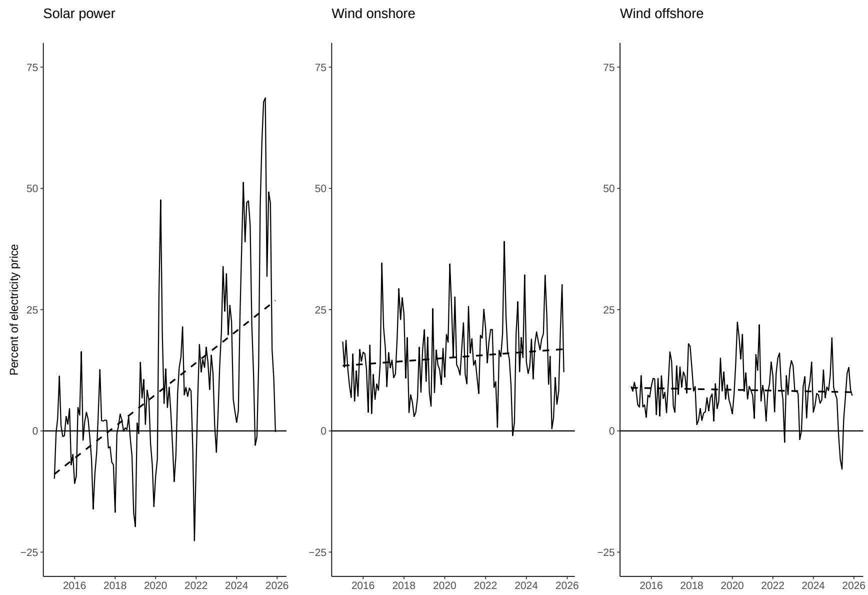

Figure 4: Disturbance to marginal investment cost caused by a FiT satisfying $\tau_s = \mathrm{E}(p)$, measured using realized revenue (Z_t^2). Disturbance reported per capacity unit that produces a single MWh over its full lifetime (no discounting). Monthly means and dotted linear trend line.

3.4 Feed-in tariffs and investment distortions in green energy

Proposition 4 states that investment in green energy is socially suboptimal under FiTs, as FiTs insulate intermittent producers from market price signals. This section introduces an empirical measure of this volatility externality and evaluates its magnitude for Germany's major intermittent technologies.

The empirical measure constructed in this section is not a direct estimate of welfare losses, but a quantitative proxy for the marginal investment distortion created by insulating intermittent producers from electricity price risk through a feed-in tariff. The measure compares expected unit revenues at market prices with expected revenues under a fixed tariff, abstracting from other rationales for public intervention such as learning-by-doing, network externalities, or carbon-pricing imperfections. Within the theoretical framework of Section 2, this gap corresponds to the wedge between privately optimal investment under a risk-insulating price guarantee and the socially optimal benchmark in which investors internalize the covariance between output and prices.

Suppose that expected revenues per unit of electricity generated from intermittent sources are systematically lower than the expected spot price (cf. Equation (10) and Figure 3). Further, suppose that the FiT equals the expected electricity price for all eligible energy sources, i.e., $\tau_s = \mathrm{E}(p)$ for all $s \in \varsigma$, and that the expected price equals the time-averaged mean. Then, Equations (14) and (16) imply that the shadow value of capital under a FiT exceeds its socially optimal level, given $\mathrm{cov}(p, \theta_s) < 0$. This mechanism gives rise to a volatility externality, since FiT-eligible producers do not internalize that electricity prices are typically low when intermittent supply is high.

This section investigates the significance and magnitude of this externality across intermittent energy sources in Germany. Specifically, it examines whether feed-in tariffs generate marginal investment distortions for intermittent technologies that are significantly positive in the data. Note that the investment distortion becomes more pronounced if the FiT exceeds the expected spot price. FiTs above expected prices are often justified by policymakers as accounting for externalities and learning-by-doing (see Arrow, 1962; Golombek and Hoel, 2005; Kverndokk and Rosendahl, 2007).

Let $\tau_s = \mathrm{E}(p)$. Then, the disturbance to marginal investment costs caused by the FiT in period t, denoted Z_t^1, equals the gap between realized unit revenue and the mean electricity price over the period t (cf. Equations (10), (14), and (16)):

$$Z_t^1 = \overline{p}_t - \left(\frac{\sum_{h \in t} p_h q_h}{\overline{q}_t} \right), \qquad Z_t^2 = 100 \frac{Z_t^1}{\overline{p}_t}, \tag{22}$$

where p_h and q_h denote the price and output at time $h \in t$, $\overline{x}_t$ is the mean of $x_t \in \{p_t, q_t\}$ in period t (e.g., h may index hours within month t), and $\mathrm{E}(p) = \overline{p}$.[28] Note that Z_t^2 expresses Z_t^1 as a percentage of the monthly electricity price. While Z_t^1 is non-stationary (exhibiting a unit root), the measure Z_t^2 is stationary in standard unit-root tests. Clearly, Z_t^2 is a coarse metric and should therefore be interpreted with caution, as the analysis abstracts from other potential externalities and the German FiT is not uniform across energy sources.

Figure 4 graphs the measure Z_t^2 for German intermittent renewables. Disturbances are reported as percentages of the monthly electricity price: for example, a value of 15% indicates that the average monthly spot price exceeds realized unit revenue by 15%. If a producer bases investment decisions on a FiT fixed at the monthly average price, marginal investment costs under such a FiT would be approximately 15% above the socially optimal level implied by the model (cf. Equations (14)–(16)). Because investment decisions reflect expected conditions over longer horizons, the linear trend may provide a more meaningful indication of medium-run distortions than month-to-month fluctuations.

[28] All prices and quantities used in the calculation of the Z_t's are observed data (Table 1). Their expression follows from the analytical model, but all components are computed directly from observed prices and quantities.

We observe that the magnitude of Z_t^2 has increased markedly for solar power. This pattern aligns with the substantial expansion of solar capacity (see Figure 2) and is consistent with the theoretical prediction that the distortion increases with the market share of the intermittent source. In particular, the rise in solar Z_t^2 reflects both the rapid growth in its market share and the increasingly negative covariance between electricity prices and solar output over the sample period.

In 2025, the trend values imply marginal investment costs around 20% above the socially optimal level for onshore wind and around 10% for offshore wind, while the corresponding distortion for solar reaches roughly 25%.

Table 6: Test for significance of the externality measure Z_t^2 by energy source

	Solar		**Wind Onshore**		**Wind Offshore**	
	M_trend	*M_int*	*M_trend*	*M_int*	*M_trend*	*M_int*
Intercept	-9.621^{***}	9.058^{**}	13.412^{***}	15.147^{***}	8.892^{***}	8.448^{***}
	(3.493)	(3.649)	(1.284)	(0.720)	(1.040)	(0.584)
Trend	0.283^{***}	–	0.026	–	-0.007	–
	(0.055)	–	(0.016)	–	(0.013)	–
No. of Obs	132	132	132	132	132	132

Note: $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$. Newey–West robust standard errors (12 lags).

Table 6 examines whether Z_t^2 is statistically different from zero. Intercept-only models yield significantly positive mean distortions for all technologies, while the trend enters significantly positive only for solar power. Figure 4, however, suggests that a simple linear trend fits the solar data poorly.

Figure 5 complements this analysis by reporting Newey–West confidence intervals for Z_t^2 in each month. Unlike Figure 4, which highlights medium-run trends, Figure 5 evaluates whether Z_t^2 is significantly different from zero within each month. For wind power, the measure is significantly positive for most of the sample. For solar, positive significance arises primarily in the latter years, mirroring its rising market share.

Overall, the evidence is consistent with the theoretical prediction that the FiT-induced volatility externality creates upward distortions in marginal investment incentives, contributing to overinvestment in FiT-eligible intermittent renewables in Germany.

The estimates should be interpreted as partial-equilibrium magnitudes rather than comprehensive welfare losses. They quantify the efficiency cost of risk insulation in a regulated market and provide an order-of-magnitude assessment of how price-based subsidy schemes distort investment incentives through the price-risk channel alone.

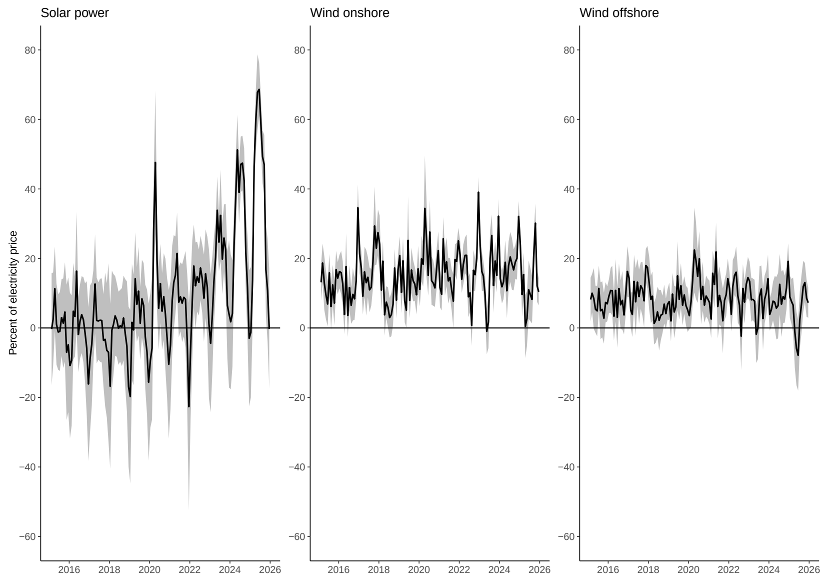

Figure 5: Disturbance to marginal investment cost caused by a FiT satisfying $\tau_s = \mathrm{E}(p)$, measured using realized revenue (Z_t^2). Disturbance reported per capacity unit that produces a single MWh over its full lifetime (no discounting). Monthly means with Newey-West 95% confidence intervals.

4 Conclusion

This paper examines how revenue-stabilization schemes such as FiTs and CfDs interact with the intermittency of renewable electricity generation to generate inefficiencies in electricity markets. The theoretical model shows that intermittent renewables increase price volatility and that, under a FiT regime, producers do not internalize these price fluctuations. Because revenues are decoupled from market prices, FiTs distort both the composition and the overall level of investment in intermittent generation, leading to overinvestment in technologies that amplify volatility and ultimately to welfare losses. This volatility externality arises not from a traditional Pigouvian mechanism, but from insulating producers from the covariance between their output and market prices. The same mechanism operates under Contracts for Difference (CfDs), although its impact on investors' revenues is attenuated relative to a pure FiT.

Unlike revenue-stabilization schemes, investment subsidies can support the expansion of renewable capacity while preserving exposure to market prices and therefore avoid distortions in the allocation across intermittent technologies. This distinction has important implications for policy design: support schemes that maintain price exposure can promote renewable deployment without inducing the misallocation inherent in revenue-stabilization schemes. More broadly, the results suggest that policies which insure producers against price risk may distort investment incentives by weakening the informational role of market prices. Examples include FiTs, CfDs, long-term gas contracts, and fixed-price agricultural contracts.

Using German data, the empirical analysis shows that higher shares of wind and solar power significantly increase electricity price volatility and reduce unit revenues for intermittent producers. A one–percentage point increase in renewable market share raises short-run volatility by about 2% for wind and 6% for solar, and lowers unit revenues by 1–7%. The market impact of intermittent renewables depends not only on correlations among renewable sources, but also on the composition and flexibility of non-intermittent generation. Hence, caution is warranted when extrapolating these results to other electricity markets. Finally, the model-based estimates imply that, under the German FiT, marginal investment costs for intermittent capacity may exceed socially optimal levels by 10–25%, pointing to potentially meaningful welfare losses.

From a welfare perspective, it is important to account for the broader system costs associated with generation mixes in which the composition and scale of intermittent capacity give rise to excess electricity price volatility. Volatile output from intermittent renewables typically necessitates large-scale storage investment (IEA, 2024a) or additional backup generation to maintain system balance (Edenhofer et al., 2011; Hirth et al., 2015; Joskow, 2011), often relying on fossil-fueled plants. This reliance undermines part of the climate benefits of renewables and increases system costs through underutilized infrastructure (Hirth, 2013; Milligan et al., 2010). Extensive transmission expansion and grid modernization are likewise required to accommodate fluctuating output (Brown et al., 2018).[29] Large shares of intermittent capacity may also reduce system inertia, complicating frequency stabilization and increasing blackout risk (Gautam et al., 2009; Kroposki et al., 2017).

This article focuses on electricity price volatility and the value of generated electricity. A comprehensive welfare assessment would also require explicit consideration of supply-side costs. Appendix A therefore reviews the literature on supply costs to place the results in context.

The analysis abstracts from grid constraints, transmission bottlenecks, and positive externalities such as learning-by-doing. Future work could extend the framework to multi-country settings or incorporate energy storage, demand response, and cross-border electricity trade. Another promising direction is to relax the assumption of independent shocks, either across intermittent energy sources

[29]In the context of the German *Energiewende*, the electricity grid is currently unable to fully utilize all renewable electricity generated. To address this constraint, Germany is projected to invest approximately 650 billion euros in grid expansion by 2045. Annual investments must more than double by the target year for climate neutrality, from around 15 billion euros in 2023 to approximately 34 billion euros annually. Sources: IMK and CEW.

or between intermittent supply and demand, to better understand how renewable support policies interact with volatility, integration costs, and cross-border market dynamics.

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A Appendix: Electricity supply costs

The Levelized Cost of Electricity (LCOE) is a widely used metric for comparing the unit costs of different energy technologies. It represents the average cost per megawatt-hour of building and operating a generating plant over its lifetime.[30] LCOE estimates vary significantly due to differences in assumptions about capital costs, capacity factors, fuel prices, financing conditions, regulatory environments, and technology assumptions. Table 7 summarizes a selection of LCOE estimates from the literature. Interested readers are encouraged to consult the original sources listed in Table 7 for further details.

Table 7: LCOE estimates for selected electricity generation technologies (USD/MWh)

Source	Nuclear	Offshore Wind	Onshore Wind	Coal	Gas	Solar PV
IEA/NEA (2020) – Europe	69	88	50	88	71	56
EIA (2023) – U.S. average	71	100	31	89	43	23
Lazard (2023)	141–221	72–140	24–75	68–166	39–101	24–96
IRENA (2023)	n.a.	75	33	n.a.	n.a.	44
Idel (2022) – Germany*	90/105	243/484		69/78	31/35	749/1380

*Estimates of full system LCOE (LFSCOE), including, e.g., backup capacity and transmission costs. LFSCOE estimates are shown for 95% and 100% market shares (i.e., 95%/100%). Wind LFSCOE values combine onshore and offshore.

Because the LCOE captures the full cost of generating power from different energy sources, comparison with the normalized revenue per unit of electricity shown in Figure 3 is useful for assessing the profitability of investments across technologies. On average, from Jan. 2015 to Apr. 2025, the revenue per unit of electricity generated from German nuclear power plants exceeded that from offshore wind, solar power, and onshore wind by 9%, 11%, and 19%, respectively (based on the sample shown in Figure 3). However, this may change as the share of intermittent energy increases (cf., the results in Section 3.3).

From a welfare economics perspective, it is important to recognize that the LCOE metric does not account for system-level costs. For example, as noted in Section 4, energy systems with high shares of intermittent renewables require additional backup capacity to maintain system balance (Edenhofer et al., 2011; Hirth et al., 2015; Joskow, 2011) and reduce system inertia (Gautam et al., 2009; Kroposki et al., 2017). Results from Idel (2022) (see Table 7) and Ueckerdt et al. (2013) suggest that the system costs of intermittent energy sources can be several times higher than their LCOE and tend to increase with market penetration.

[30] See Ueckerdt et al. (2013), Timilsina (2020), and Idel (2022) for discussions on LCOE.

B Appendix: Feed-in tariffs in Germany

Under the *Erneuerbare-Energien-Gesetz* (EEG), German producers of wind, solar, and other renewable electricity technologies have been entitled to a *feed-in tariff* (FiT), a technology-specific fixed payment per unit of electricity fed into the grid. The FiT guarantees a predetermined price, typically for a 20-year period, insulating producers from short-term wholesale price risk. For large renewable projects, the FiTs are determined through an auction system, in which capacity is put to tender and contracts are awarded to the lowest bids. The EEG was historically financed by adding a renewables levy to electricity bills (with reduced rates for power-intensive and trade-exposed industries), but this levy was abolished in mid-2022 to shield consumers from high electricity prices. Since then, the EEG has been funded through proceeds from the EU Emissions Trading System (ETS) and the federal state budget (Bundesministerium der Finanzen (BMF), 2023). Consequently, German electricity consumers now face a single retail electricity price that reflects wholesale market conditions (largely driven by fossil fuel prices), regulated network charges, supplier margins, and taxes. The cost of supporting renewable energy is now borne by the state rather than directly through electricity bills.[31]

Following successive EEG reforms (notably EEG 2012 and EEG 2017), an increasing share of renewable producers have shifted from fixed FiTs to a market premium scheme. Under this arrangement, producers sell their electricity directly on the wholesale market and receive a variable premium equal to the difference between a technology-specific reference value and the realized market price. Both schemes ensure that the producer's total remuneration per kWh approximates the guaranteed FiT level while maintaining the merit-order integration of renewable electricity into the market (see Agora Energiewende, 2021; Bundesministerium für Wirtschaft und Klimaschutz (BMWK), 2023).

The financial flows associated with FiTs are managed through dedicated EEG accounts administered by the four German transmission system operators (TSOs). Each TSO records (i) revenues from the sale of renewable electricity on the wholesale market, and (ii) expenditures in the form of FiT or market-premium payments to renewable producers. The EEG funding gap is defined as the difference between total FiT payments and the corresponding market revenues: $G_t = P_t^{\text{FiT}} - R_t^{\text{market}}$, where G_t denotes the aggregate funding gap in year t, P_t^{FiT} the total payments to renewable producers, and R_t^{market} the revenues from selling renewable electricity on the spot market.

To recover this gap, the TSOs projected expected payments, market revenues, and national electricity consumption for the upcoming year. The *EEG surcharge* (*EEG-Umlage*) was then determined as $u_t = \frac{E(G_t)}{E(Q_t)}$, where u_t denotes the surcharge rate (in €/kWh) and $E(Q_t)$ the expected total electricity consumption. This surcharge was uniformly added to all consumer electricity bills, ensuring that aggregate surcharge revenues approximately equaled total subsidy payments to renewable producers. Any surplus or deficit on the EEG accounts was carried forward and adjusted in the following year's rate (Bundesnetzagentur & Bundeskartellamt, 2021).

[31] See BWE and Futurepolicy for more on the EEG.

C Appendix: proofs and derivations

Derivation of Equation (5): We first note that:

$$\sigma_\Theta^2 = \mathrm{E}\left(\Theta^2\right) - \left(\mathrm{E}\left(\Theta\right)\right)^2 = \mathrm{E}\left(\Theta^2\right) = \mathrm{E}\left(\left(\sum_{s\in S}\sum_{i\in I^s}\alpha_s\theta_{si}\right)^2\right).$$

We further have

$$\begin{aligned}
&\mathrm{E}\left(\left(\sum_{s\in S}\sum_{i\in I^s}\alpha_s\theta_{si}\right)^2\right)\\
&= \mathrm{E}\left(\left(\alpha_1\sum_{i\in I^1}\theta_{1i} + \alpha_2\sum_{i\in I^2}\theta_{2i} + \alpha_3\sum_{i\in I^3}\theta_{3i} + ... + \alpha_{n_s}\sum_{i\in I^{n_s}}\theta_{n_s i}\right)^2\right)\\
&= \mathrm{E}\left(\left(\alpha_1\sum_{i\in I^1}\theta_{1i}\right)\alpha_1\sum_{i\in I^1}\theta_{1i}\right)\\
&+ \mathrm{E}\left(\left(2\alpha_1\sum_{i\in I^1}\theta_{1i} + \alpha_2\sum_{i\in I^2}\theta_{2i}\right)\alpha_2\sum_{i\in I^2}\theta_{2i}\right)\\
&+ \mathrm{E}\left(\left(2\alpha_1\sum_{i\in I^1}\theta_{1i} + 2\alpha_2\sum_{i\in I^2}\theta_{2i} + \alpha_3\sum_{i\in I^3}\theta_{3i}\right)\alpha_3\sum_{i\in I^3}\theta_{3i}\right) + ...\\
&+ \mathrm{E}\left(\left(2\alpha_1\sum_{i\in I^1}\theta_{1i} + 2\alpha_2\sum_{i\in I^2}\theta_{2i} + ... + \alpha_{n_s}\sum_{i\in I^{n_s}}\theta_{n_s i}^2\right)\alpha_{n_s}\sum_{i\in I^{n_s}}\theta_{n_s i}^2\right),
\end{aligned}$$

where I used the general formula: $\left(\sum_s a_s\right)^2 = \sum_s a_s^2 + \sum_{s<z} a_s a_z = (a_1)\,a_1 + (2a_1 + a_2)\,a_2 + (2a_1 + 2a_2 + a_3)\,a_3 + ...$ Note that we have:

$$\begin{aligned}
\left(\alpha_s\sum_{i\in I^s}\theta_{1s}\right)\alpha_s\sum_{i\in I^z}\theta_{si} &= \alpha_s^2\left(n_s + (n_s-1)\rho_s\right)\sigma_{\theta_{I^s}}^2,\\
\left(\alpha_s\sum_{i\in I^s}\theta_{1s}\right)\alpha_z\sum_{i\in I^z}\theta_{zi} &= \alpha_s\alpha_z n_s n_z \rho\sigma_{\theta_{I^s}}\sigma_{\theta_{I^z}}.
\end{aligned}$$

Inserting we get:

$$\mathrm{E}\left(\left(\alpha_1\sum_{i\in I^1}\theta_{1i}\right)\alpha_1\sum_{i\in I^1}\theta_{1i}\right) = \alpha_1^2 n_1\left(1 + (n_1-1)\rho_1\right)\sigma_{\theta_{I^1}}^2,$$

$$\mathrm{E}\left(\left(2\alpha_1\sum_{i\in I^1}\theta_{1i}+\alpha_2\sum_{i\in I^2}\theta_{2i}\right)\alpha_2\sum_{i\in I^2}\theta_{2i}\right)$$
$$=2\alpha_1\alpha_2n_1n_2\rho\sigma_{\theta_{I^1}}\sigma_{\theta_{I^2}}+\alpha_2^2n_2\left(1+(n_2-1)\rho_2\right)\sigma^2_{\theta_{I^2}},$$

$$\mathrm{E}\left(\left(2\alpha_1\sum_{i\in I^1}\theta_{1i}+2\alpha_2\sum_{i\in I^2}\theta_{2i}+\alpha_3\sum_{i\in I^3}\theta_{3i}\right)\alpha_3\sum_{i\in I^3}\theta_{3i}\right)$$
$$=2\alpha_1\alpha_3n_1n_3\rho\sigma_{\theta_{I^1}}\sigma_{\theta_{I^3}}+2\alpha_2\alpha_3n_2n_3\rho\sigma_{\theta_{I^2}}\sigma_{\theta_{I^3}}+\alpha_3^2n_3\left(1+(n_3-1)\rho_3\right)\sigma^2_{\theta_{I^3}},$$

$$\mathrm{E}\left(\left(2\alpha_1\sum_{i\in I^1}\theta_{1i}+2\alpha_2\sum_{i\in I^2}\theta_{2i}+2\alpha_3\sum_{i\in I^3}\theta_{3i}+\alpha_4\sum_{i\in I^4}\theta_{4i}\right)\alpha_4\sum_{i\in I^4}\theta_{4i}\right)$$
$$=2\alpha_1\alpha_4n_1n_4\rho\sigma_{\theta_{I^1}}\sigma_{\theta_{I^4}}+2\alpha_2\alpha_4n_2n_4\rho\sigma_{\theta_{I^2}}\sigma_{\theta_{I^4}}+2\alpha_3\alpha_4n_3n_4\rho\sigma_{\theta_{I^3}}\sigma_{\theta_{I^4}}+\alpha_4^2n_4\left(1+(n_4-1)\rho_4\right)\sigma^2_{\theta_{I^4}},$$

$$\mathrm{E}\left(\left(2\alpha_1\sum_{i\in I^1}\theta_{1i}+2\alpha_2\sum_{i\in I^2}\theta_{2i}+...+\alpha_{n_s}\sum_{i\in I^{n_s}}\theta^2_{n_si}\right)\alpha_{n_s}\sum_{i\in I^{n_s}}\theta^2_{n_si}\right)$$
$$=2\alpha_1\alpha_{n_s}n_1n_{n_s}\rho\sigma_{\theta_{I^1}}\sigma_{\theta_{I^{n_s}}}+2\alpha_2\alpha_{n_s}n_2n_{n_s}\rho\sigma_{\theta_{I^2}}\sigma_{\theta_{I^{n_s}}}+...+\alpha^2_{n_s}n_{n_s}\left(1+(n_{n_s}-1)\rho_{n_s}\right)\sigma^2_{\theta_{I^{n_s}}}.$$

Hence, the full expression can be written $\sum_{s\in S}\left(\alpha_s^2n_s\left(1+(n_s-1)\rho_s\right)\sigma^2_{\theta_{I^s}}+2\rho\sum_{s<z}\alpha_s\alpha_zn_sn_z\sigma_{\theta_{I^s}}\sigma_{\theta_{I^z}}\right)$. Equation (5) follows.

Derivation of supply from fossil fuels:

Equation (7) and the fossil producer's first-order condition imply that electricity supply from fossil plants is given by:

$$y=\frac{u_1-c_1-u_2\left(\alpha+\beta\right)}{c_2+u_2}+\frac{\eta-\varepsilon-u_2\Theta}{c_2+u_2}\equiv\mathrm{E}(y)+\Psi_y. \tag{23}$$

Equilibrium electricity supply is then equal to $\alpha+\Theta+\beta+y$, where $\alpha+\Theta$ and y are given by Equations (4) and (23), respectively.

Proof of Proposition 1: Equation (8) implies the following relationship between the variance of the electricity price and the technology parameters α_s, β, c_1, and c_2 of the energy sources:

$$\begin{pmatrix}\frac{\partial\sigma_p^2}{\partial\alpha_s} & \frac{\partial\sigma_p^2}{\partial c_1}\\ \frac{\partial\sigma_p^2}{\partial\beta} & \frac{\partial\sigma_p^2}{\partial c_2}\end{pmatrix}=\begin{pmatrix}\frac{c_2^2u_2^2}{(c_2+u_2)^2}\frac{\partial\sigma^2_\Theta}{\partial\alpha_s} & 0\\ 0 & \frac{2u_2\left(c_2\sigma^2_\eta-u_2\sigma^2_\varepsilon+c_2u_2^2\sigma^2_\Theta\right)}{(c_2+u_2)^3}\end{pmatrix}, \tag{24}$$

with:
$$\frac{\partial \sigma_\Theta^2}{\partial \alpha_s} = 2\alpha_s n_s \left(1 + \left(n_s - 1\right)\rho_s\right)\sigma_{\theta_{I^s}}^2 + 2\rho\sigma_{I^s} n_s \sum_{z\neq s} \alpha_z n_z \sigma_{I^z}, \tag{25}$$

for all $s, z \in S$. Inserting Equation (25) into the first diagonal term of Equation (24) yields the effect of an overall marginal increase in α_s, i.e., the change in variance when all firms $i \in I^s$ increase their production capacities simultaneously. The effect of a marginal increase in α_{si} for a single firm $i \in I^s$ is given by this expression divided by n_s. Proposition 1 follows directly from Equations (24) and (25).

Derivation of Equation (10): Expected profits for intermittent firms using source $s \in S$ is given by

$$\begin{aligned} \mathrm{E}\left(\pi\left(\alpha_s\right)\right) &= \mathrm{E}\left(p\left(1+\theta\right)\alpha_s\right) = \left(\mathrm{E}\left(p\right) + \Psi_p\right)\left(1+\theta_{si}\right)\alpha_s \\ &= \mathrm{E}\left(p\right)\alpha_s + \Psi_p\theta_{si}\alpha_s, = \left(\mathrm{E}\left(p\right) + \mathrm{cov}\left(\Psi_p, \theta_{si}\right)\right)\alpha_s, \end{aligned}$$

where I used Equation (7), and $\mathrm{cov}(\Psi_p, \theta_{si}) = \mathrm{E}(\Psi_p\theta_{si}) - \mathrm{E}(\Psi_p)\,\mathrm{E}(\theta_{si}) = \mathrm{E}(\Psi_p\theta_{si})$. Equation (10) follows. Regarding profits from nuclear, we simply have $\mathrm{E}\left(\pi\left(\beta\right)\right) = \beta\,\mathrm{E}\left(p\right)$, because output is non-stochastic and equal to capacity β.

Derivation of Equation (11): A similar calculation as used in the derivation of Equation (5) above yields:

$$\mathrm{E}\left(\Theta\theta_{si}\right) = \alpha_1\left(1 + \left(n_1 - 1\right)\rho_1\right)\sigma_{\theta_{I^1}}^2 + \rho\sigma_{\theta_{I^1}} \sum_{s\neq z} n_s\alpha_s\sigma_{\theta_{I^s}}$$

which yields Equation (11), because $\mathrm{cov}(\Psi_p, \theta_{si}) = \mathrm{E}(\Psi_p\theta_{si})$ (see the derivation of Equation (10)).

Derivation of expected profits for fossil energy sources: The profits of the fossil firm is given by $py - c(y)$, where $p = \mathrm{E}\left(p\right) + \Psi_p$, $y = \mathrm{E}\left(y\right) + \Psi_y$, and $c(y) = \left(c_1 + \varepsilon\right)y + c_2 y^2/2$ (cf. Equations (3), (7) and (23)). Hence, profits from fossil can be written:

$$\left(\mathrm{E}\left(p\right) + \Psi_p\right)\left(\mathrm{E}\left(y\right) + \Psi_y\right) - \left(c_1 + \varepsilon\right)\left(\mathrm{E}\left(y\right) + \Psi_y\right) - \frac{c_2}{2}\left(\mathrm{E}\left(y\right) + \Psi_y\right)^2$$

where the revenue is given by $\left(\mathrm{E}\left(p\right) + \Psi_p\right)\left(\mathrm{E}\left(y\right) + \Psi_y\right)$, with expected value:

$$\mathrm{E}\left(py\right) = \mathrm{E}\left(p\right)\mathrm{E}\left(y\right) + \mathrm{E}\left(\Psi_p\Psi_y\right) = \mathrm{E}\left(p\right)\mathrm{E}\left(y\right) + \frac{c_2\sigma_\eta^2 - u_2\sigma_\varepsilon^2 + c_2u_2^2\sigma_\Theta^2}{\left(c_2 + u_2\right)^2}.$$

The cost of fossil electricity is given by:

$$\left(c_1 + \varepsilon\right)\left(\mathrm{E}\left(y\right) + \Psi_y\right) + \frac{c_2}{2}\left(\mathrm{E}\left(y\right) + \Psi_y\right)^2 = c_1\,\mathrm{E}(y) + \frac{c_2}{2}\left(\mathrm{E}(y)\right)^2 + \varepsilon\Psi_y + \frac{c_2}{2}\Psi_y^2,$$

with expectation:

$$\mathrm{E}\left(c(y)\right) = c_1 \, \mathrm{E}(y) + \frac{c_2}{2} \left(\mathrm{E}(y)\right)^2 + \frac{c_2 \sigma_\eta^2 - \left(c_2 + 2u_2\right) \sigma_\varepsilon^2 + c_2 u_2^2 \sigma_\Theta^2}{2 \left(c_2 + u_2\right)^2}.$$

Expected profits is then given by: $\mathrm{E}\left(py\right) - \mathrm{E}\left(c\left(y\right)\right)$, which yields:

$$\mathrm{E}\left(\pi\left(c_1, c_2\right)\right) = \frac{c_2 \left(u_1 - c_1 - u_2 \left(\alpha + \beta\right)\right)^2}{2 \left(c_2 + u_2\right)^2} + \frac{c_2 \left(\sigma_\eta^2 + \sigma_\varepsilon^2 + u_2^2 \sigma_\Theta^2\right)}{2 \left(c_2 + u_2\right)^2}. \tag{26}$$

The relative profitability of fossil plants compared to intermittent and NLE depends on fossil production costs, which in turn depend on factors such as fuel prices.

Derivation of expected utility: We have $\mathrm{E}(u) = \mathrm{E}\left(\left(u_1 + \eta\right) x - \frac{u_2}{2} x^2\right)$, where $x = \alpha + \Theta + \beta + \mathrm{E}(y) + \Psi_y = \mathrm{E}(x) + \Psi_x$, with $\mathrm{E}(x) = \alpha + \beta + \mathrm{E}(y)$ and $\Psi_x = \Theta + \Psi_y$. Hence:

$$\begin{aligned}
\mathrm{E}\left(u\right) &= \mathrm{E}\left(\left(u_1 + \eta\right) \left(\mathrm{E}\left(x\right) + \Psi_x\right) - u_2 \left(\mathrm{E}\left(x\right) + \Psi_x\right)^2\right) \\
&= \mathrm{E}\left(x\right) \eta + \mathrm{E}\left(x\right) u_1 + \mathrm{E}\left(\eta \Psi_x\right) + \mathrm{E}\left(\Psi_x\right) u_1 - \mathrm{E}\left(x\right)^2 u_2 - \mathrm{E}\left(\Psi_x^2\right) u_2 - 2 \, \mathrm{E}\left(x\right) \mathrm{E}\left(\Psi\right)_x u_2 \\
&= \mathrm{E}\left(X u_1 - X^2 u_2 + \eta \Psi_x - \Psi_x^2 u_2\right).
\end{aligned}$$

Here, we have

$$\begin{aligned}
\mathrm{E}\left(\eta \Psi_x\right) &= \mathrm{E}\left(\eta \frac{\eta - \varepsilon - 2u_2 \Theta}{c_2 + u_2}\right) = \frac{\sigma_\eta^2}{c_2 + u_2}, \\
\mathrm{E}(\Psi_x^2) &= \mathrm{E}\left(\left(\Theta + \Psi_y\right)^2\right) = \mathrm{E}\left(\Theta^2 + 2\Theta \Psi_y + \Psi_y^2\right),
\end{aligned}$$

with

$$\begin{aligned}
\sigma_\Theta^2 &= \mathrm{E}(\Theta^2), \\
\mathrm{E}\left(\Theta \Psi_y\right) = \mathrm{E}\left(\frac{\eta - \varepsilon - u_2 \Theta}{c_2 + u_2} \Theta\right) &= -\frac{u_2}{c_2 + u_2} \sigma_\Theta^2, \\
\mathrm{E}\left(\Psi_y^2\right) = \mathrm{E}\left(\frac{\eta - \varepsilon - u_2 \Theta}{c_2 + u_2}\right)^2 &= \frac{u_2^2 \sigma_\Theta^2 + \sigma_\varepsilon^2 + \sigma_\eta^2}{\left(c_2 + u_2\right)^2}.
\end{aligned}$$

Inserting we get:

$$\mathrm{E}\left(u\right) = u_1 \, \mathrm{E}\left(x\right) - \frac{u_2}{2} \left(\mathrm{E}\left(x\right)\right)^2 + \mathrm{E}\left(\eta \Psi_x\right) - \mathrm{E}\left(\Psi_x^2\right) u_2 \tag{27}$$

$$= u_1 \, \mathrm{E}\left(x\right) - \frac{u_2}{2} \left(\mathrm{E}\left(x\right)\right)^2 + \frac{\sigma_\eta^2 \left(2c_2 + u_2\right) - u_2 \sigma_\varepsilon^2 - u_2 c_2^2 \sigma_\Theta^2}{2 \left(c_2 + u_2\right)^2}. \tag{28}$$

Derivation of expected welfare: Expected welfare is given by $\mathrm{E}\left(W\right) = \mathrm{E}(u(x)) - \mathrm{E}(c(y))$, with utility and cost functions given by Equations (1) and (3), respectively.

Expected utility is given by cf, Equation (28) and expected cost was calculated in the Derivation of Equation (26) above. Hence, expected welfare $\mathrm{E}(W)$ is:

$$u_1 \mathrm{E}(x) - \frac{u_2}{2}(\mathrm{E}(x))^2 + \frac{\sigma_\eta^2(2c_2+u_2) - u_2\sigma_\varepsilon^2 - u_2 c_2^2\sigma_\Theta^2}{2(c_2+u_2)^2}$$
$$-\left(c_1 \mathrm{E}(y) + \frac{c_2}{2}(\mathrm{E}(y))^2 + \frac{c_2\sigma_\eta^2 - (c_2+2u_2)\sigma_\varepsilon^2 + c_2 u_2^2\sigma_\Theta^2}{2(c_2+u_2)^2}\right),$$

with solution:

$$\begin{aligned}\mathrm{E}(W) &= \frac{2(c_1u_2+c_2u_1)(\alpha+\beta)+(u_1-c_1)^2-c_2u_2(\alpha+\beta)^2}{2(c_2+u_2)} + \frac{\sigma_\eta^2+\sigma_\varepsilon^2-c_2u_2\sigma_\Theta^2}{2(c_2+u_2)} \\ &= \mathrm{E}(u(\overline{x})) - \mathrm{E}(c(\overline{y})) + \frac{\sigma_\eta^2+\sigma_\varepsilon^2-c_2u_2\sigma_\Theta^2}{2(c_2+u_2)}\end{aligned} \tag{29}$$

Proof of Proposition (2): Differentiation of Equation (29) with respect to the technology parameters yields the following:

$$\begin{pmatrix} \frac{\partial \mathrm{E}(W)}{\partial \alpha_z} & \frac{\partial \mathrm{E}(W)}{\partial c_1} \\ \frac{\partial \mathrm{E}(W)}{\partial \beta} & \frac{\partial \mathrm{E}(W)}{\partial c_2} \end{pmatrix} = \begin{pmatrix} \mathrm{E}(p) - \frac{c_2u_2}{c_2+u_2}\frac{\partial \sigma_\Theta^2}{\partial \alpha_s} & -\mathrm{E}(y) \\ \mathrm{E}(p) & -\frac{1}{2}\mathrm{E}(y^2) \end{pmatrix}, \tag{30}$$

with $\partial\sigma_\Theta^2/\partial\alpha_s$ given by Equation (25).[32] Proposition 2 then follows from Equations (10), (11), (12), (25) and (30).

Proof of Proposition (3): Let ζ denote the EEG surcharge. Then the representative consumer solves $(u_1+\eta)x_d - \frac{u_2}{2}x_d^2 - (p+\zeta)x_d = (\overline{u}_1+\eta)x_d - \frac{u_2}{2}x_d^2$, with $\overline{u}_1 = u_1+\zeta > u_1$. Lower x_d and p then follows from Equations (2) and (7), respectively. The expected FiT value follows directly from Equation (10).

Investment in NLE and fossil energy sources: The representative NLE firm solves $\max_\beta(\mathrm{E}(\pi(\beta)) - \kappa(\beta))$ in Stage 1, with expected profits given by Equation (10). The solution is given by (see Appendix C):

$$\kappa_\beta(\beta) = \mathrm{E}(p), \tag{31}$$

where the expected price is given by Equation (7). We observe, by comparison with Equation (14), that marginal investment costs in NLE capacity are higher than for intermittent energy sources (given $\mathrm{cov}(p, \theta_{si}) < 0$ and no subsidies).

[32] Remember that $c_1 = \chi k_1 + k_2$, implying that $\frac{\partial \mathrm{E}(W)}{\partial k_1} = \frac{\partial \mathrm{E}(W)}{\partial c_1}\frac{\partial c_1}{\partial k_1} = -\chi \mathrm{E}(y)$ and $\frac{\partial \mathrm{E}(W)}{\partial k_2} = -\mathrm{E}(y)$.

The representative fossil firm solves $\max_{c_1,c_2}\left(\mathrm{E}\left(\pi\left(c_1,c_2\right)\right)-\kappa\left(k_1,k_2,c_2\right)\right)$ in Stage 1, with expected profits given by Equation (26). The solution is given by:

$$\begin{aligned} &-\kappa_{k_1}\left(\cdot\right)=\chi\,\mathrm{E}\left(y\right), \quad -\kappa_{k_2}\left(\cdot\right)=\mathrm{E}\left(y\right), \\ &-\kappa_{c_2}\left(\cdot\right)=\frac{1}{2}\,\mathrm{E}\left(y^2\right)=\frac{1}{2}\left(\left(\mathrm{E}\left(y\right)\right)^2+\frac{\sigma_\eta^2+\sigma_\varepsilon^2+u_2^2\sigma_\Theta^2}{\left(c_2+u_2\right)^2}\right). \end{aligned} \tag{32}$$

We observe that the emission intensity k_1 decreases as the emission price χ increases. Furthermore, the firm selects a more flexible technology (that is, a lower value of c_2) when output fluctuations intensify.

It is straightforward to show that firms' investments in NLE and fossil technologies are socially optimal if the emission price χ equals the Pigouvian tax. Specifically, Equations (30), (31), and (32) show that firms' investments in NLE capacity (β) and fossil technology parameters (k_1, k_2, c_2) equate marginal investment costs with the associated changes in expected welfare.[33]

Finally, the deadweight loss induced by the FiT entails lower producer prices for electricity producers that are not eligible for the FiT (cf. Proposition 3). Equations (14), (31), and (32) then imply lower investment in these energy sources.

[33] Optimal investment does not necessarily imply an optimal real capital stock if the firms' environment changes unexpectedly after the investment has been made—for instance, due to an increase in the share of renewables.

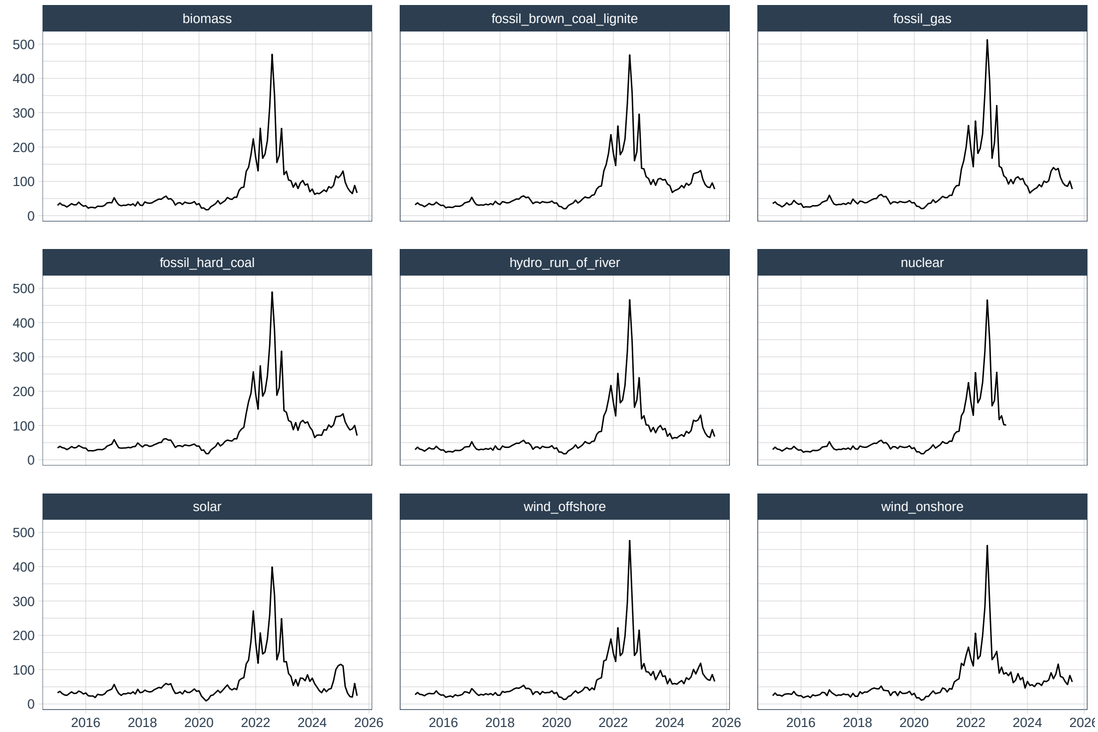

Figure 6: Average revenue per unit produced by energy source. Euro per MWh. Monthly aggregates. Germany.

D Appendix: Econometrics and figures

Detailed output from the econometric software R for Sections 3.2 and 3.3 is supplied in a separate txt. file.

D.1 Figures

D.2 Tests for stationarity

Table 8: Unit root test results and inferred orders of integration for key variables.

Variable	**ADF**	**PP**	**ADF-B**	**CADF**	**HEGY**	**ZA**	**I(·)**
Price	-2.907^{**}	-2.981^{**}	-2.074	-2.948^{**}	0.091^{*}	-4.2423	$I(1)$
log(RV)	-3.260^{*}	-3.729^{**}	-3.308^{*}	-3.855^{**}	0.743	-4.677^{*}	$I(0)$ TS
Gasprice	-2.703^{*}	-2.318	-2.703^{*}	-2.703^{*}	0.067^{*}	-3.809	$I(1)$
Rev.onsh.	-2.324	-2.254	-1.577	-2.400	0.201	-3.758	$I(1)$
Rev.offs.	-2.512	-2.549	-1.588	-2.691^{*}	0.142	-4.167	$I(1)$
Rev. solar	-4.147^{***}	-3.184^{*}	-2.148	-2.691^{*}	0.228	-4.861^{**}	$I(1)$
Wind sh.	-4.881^{***}	-5.454^{***}	-4.965^{***}	-4.881^{***}	0.1033	-5.043^{**}	$I(0)$ TS
Solar sh.	-6.897^{***}	-1.474	-2.868	-6.897^{***}	0.988	-7.921^{***}	$I(0)$ TS
Solar rad.	-7.773^{***}	-1.882	-3.258^{**}	-7.773^{***}	0.118	-7.956^{***}	$I(0)$
Wind spd.	-5.158^{***}	-6.013^{***}	-5.284^{***}	-6.700^{***}	0.001^{***}	-5.372^{***}	$I(0)$
Temp.	-6.885^{***}	-2.055	-3.564^{**}	-6.885^{***}	0.067^{*}	-6.984^{***}	$I(0)$

Note: $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$. Revenues are measured per unit of electricity generated. All tests are conducted under the null hypothesis of a unit root. log(RV) is the volatility measure for the electricity price.

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Table 8 reports the results of unit root tests for the regression variables. The tests include the Augmented Dickey–Fuller (ADF), Phillips–Perron (PP), ADF with bootstrapped standard errors (ADF-B), ADF with seasonal dummy variables (CADF), the HEGY (Hylleberg, Engle, Granger, and Yoo) seasonal unit root test (t_1) with bootstrapped standard errors, and the Zivot–Andrews (ZA) test allowing for a single structural break. All tests are conducted on monthly aggregates, corresponding to the data frequency used in the regressions, and include an integer and/or trend term when the etsimates are statistically significant. Lag selection follows the BIC criterion, which is appropriate given the limited sample size. Detailed test specifications are provided in the R output section of Appendix D (separate txt file). The table reports bootstrapped p-values for the HEGY test. In addition to the results presented in Table 8, the HEGY test ($F_{1:12}$) rejects the presence of seasonal unit roots for all variables at the 1% significance level, whereas the KPSS test does not reject the null hypothesis of stationarity for any variable at the 5% level.

While the PP, ADF-B, and HEGY tests are robust to heteroscedasticity and autocorrelation, the ADF, CADF, and ZA tests rely on the assumption of homoscedastic innovations (i.e., error terms). Accordingly, the PP, ADF-B, and HEGY tests may be more reliable for the price, volatility, and revenue variables, which exhibit ARCH effects (see Sections 3.2 and 3.3). By contrast, the standard ADF test typically has greater power than its more robust alternatives when innovations are homoscedastic and correctly specified, as is the case for the wind and solar shares (*pct*) and the weather variables.[34] Finally, only the ZA test allows for a structural break, which is relevant for the price, volatility, and revenue variables (see Sections 3.2 and 3.3).

Seasonal dummies in the CADF and HEGY tests can mitigate potential seasonal bias that might otherwise distort standard unit root tests for monthly data. However, including monthly dummies changes the distribution of the test statistics and reduces the tests' power. In this regard, it is noteworthy that the ADF and CADF tests—which are identical except for the inclusion of seasonal dummies in the CADF—yield similar results in Table 8, except for the strongly seasonal share of solar power.

Table 8 also reports the inferred order of integration applied in the subsequent analysis. Based on the test results, electricity and natural gas prices are treated as non-stationary. The tests further indicate that the revenue variables follow unit root processes.

For realized volatility (log(RV)), the ADF, PP, and CADF tests suggest stationarity, whereas the remaining tests indicate a unit root. The results suggest that the share of wind in the energy mix (wind share, onshore plus offshore) is trend stationary (TS). For the share of solar, however, the linear time trend does not enter significantly in the PP and HEGY regressions. By contrast, the ADF and ZA tests indicate that the solar share follows a trend-stationary process with highly significant time trends (p-values < 0.001). It is also noteworthy that the PP and HEGY tests fail to reject a unit root in solar radiation—a variable that is *a priori* stationary and closely related to the solar share. Moreover, an auxiliary PP test on seasonally adjusted data including monthly dummy variables rejects the unit root in the solar share at the 5% significance level. Overall, the share of solar power—like the share of wind—is best characterized as a trend-stationary process.

D.3 Instrumental-variable estimation

This section examines whether the estimated effects of intermittent renewable penetration on electricity price volatility are affected by endogeneity concerns. In particular, changes in wind and solar shares could be correlated with unobserved market conditions that also influence volatility.

To address this possibility, we estimate a set of instrumental-variables (IV) specifications in which changes in wind share are instrumented by contemporaneous onshore wind speed, and changes in solar share are instrumented by solar radiation. These instruments are based on exogenous meteorological conditions that directly affect renewable generation but are plausibly orthogonal to shocks in electricity price volatility.

Table 9 reports second-stage IV estimates for three specifications: a wind-only IV model, a solar-only IV model, and a model in which both renewable shares are treated as endogenous. First-stage diagnostics indicate that the instruments are highly relevant, with F-statistics well above conventional weak-instrument thresholds.

[34] See Davidson and MacKinnon (2006), Engle and Bollerslev (1986), and Schwert (1989) on tests for unit roots and bootstrapping, and Ghysels and Perron (1993) on seasonal adjustment and unit roots.

Across all IV specifications, the estimated coefficients on wind and solar penetration remain positive, statistically significant, and close in magnitude to those obtained under the baseline maximum-likelihood ARX specification. Formal Wu–Hausman tests fail to reject the null hypothesis of exogeneity of renewable shares. These findings suggest that endogeneity of intermittent renewable penetration is not empirically important in our setting.

Table 9: Instrumental-variable estimates of electricity price realized volatility

	Wind-IV	**Solar-IV**	**Both-IV**
intercept (μ)	1.979***	2.008***	2.016***
	(0.432)	(0.411)	(0.411)
ar1 (ϕ_1)	0.677***	0.672***	0.671***
	(0.073)	(0.069)	(0.069)
wind_share (Δ)	2.250***	2.415***	1.974***
	(0.673)	(0.656)	(0.658)
solar_share (Δ)	8.072***	7.479***	6.783***
	(2.051)	(1.988)	(2.058)
log(gasprice) (Δ)	1.386***	1.387***	1.339***
	(0.250)	(0.251)	(0.252)
celsius (Δ)	−0.055***	−0.051***	−0.048***
	(0.019)	(0.017)	(0.018)
time trend	0.001	0.001	0.001
	(0.002)	(0.002)	(0.002)
Post–Aug. 2021	0.839***	0.850***	0.855***
	(0.208)	(0.206)	(0.205)
Newey–West lag length	6	6	6
Weak instrument F (wind)	677.49		512.81
Weak instrument F (solar)		248.49	201.96
Wu–Hausman p-value	0.245	0.448	0.328
Number of observations	131	131	131
Adjusted R^2	0.894	0.894	0.894
Residual std. error (df = 123)	0.523	0.523	0.524

Note: $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$. The table reports second-stage IV estimates with Newey–West HAC standard errors. Standard errors in parentheses. In Wind-IV, Δwind_share is instrumented by Δwind_speed_onshore. In Solar-IV, Δsolar_share is instrumented by Δsolar_rad. In Intermittent-IV, both Δwind_share and Δsolar_share are instrumented by Δwind_speed_onshore and Δsolar_rad. All variables labeled "(Δ)" are first differences.