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Corresponding Author:	Jonas Grafström Luleå tekniska universitet Luleå, SWEDEN
First Author:	Jonas Grafström
Order of Authors:	Jonas Grafström
	Daniel Halvarsson
	Theo Herold
	Nadja Vinberg
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Electricity market structure and consequences for wind and solar power: Theory and evidence from the EU-27

JONAS GRAFSTRÖM[1], DANIEL HALVARSSON[2], THEO HEROLD[3] AND NADJA VINBERG[4]

Abstract

Did dominant firms on the national electricity market hold back the growth of wind and solar power? A theoretical model suggests they might, by limiting profitability for new renewable producers through strategic behavior and price effects. To test this question, panel data from all EU-27 member states between 2000 and 2022 is examined. The analysis uses econometric methods that address persistent trends, country differences, and endogeneity in the relationship between market concentration and renewable capacity growth. Results are consistent across a range of specifications: the market share of the largest producer shows no significant influence on the share of wind and solar capacity. Instead, the analysis points to the importance of earlier investments, regulatory design, and grid access. These findings suggest that policies aiming to reshape electricity markets should, going forward, focus less on structural concentration and more on the long-term features of support systems and infrastructure planning.

Keywords: Renewable energy, market competition, electricity markets, policy barriers, European energy transition, solar and wind power.
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[1] Luleå University of Technology and The Ratio Institute. E-mail: jonas.grafstrom@ltu.se
[2] The Ratio Institute. E-mail: Daniel.halvarsson@ratio.se
[3] Hanken School of Economics, Helsinki Graduate School of Economics and The Ratio Institute. E-mail: theo.herold@hanken.fi
[4] The Ratio Institute

1. Introduction

Despite a unified climate ambition expressed through EU targets and supportive frameworks like the Renewable Energy Directive (Directive 2023/2413), the actual rollout of wind and solar capacity varies between countries (Bórawski et al., 2023; Eurostat, 2024a; Eurostat, 2024b). The unevenness raises a fundamental question: why do some nations transition, while others fall behind? Many national electricity systems remain concentrated and dominated by vertically integrated incumbents. In such markets, limited competition can restrict grid access, delay the adoption of low-cost technologies, and reduce investment in decentralized renewables (Ritz, 2008; Twomey and Neuhoff, 2010; Newbery and Greve, 2017; Lundin and Tangerås, 2020, Semmler et al., 2022). These structural barriers, rather than purely economic or technological factors, may explain why deployment varies widely across countries (Jamasb and Pollitt, 2005; Pepermans, 2019; Nicolli and Vona, 2019; Ciucci, 2023).

In short, for the adoption of renewables, it matters who controls the wires and turbines as much as how sunny or windy it is. Reaching the EU's climate targets requires a rapid scale-up of variable renewables (Victoria et al., 2022), making it important to understand how market structure and market power affect deployment (Painuly, 2001; Jenner et al., 2012; Przychodzen and Przychodzen, 2020). The literature has largely focused on support schemes or declining technology costs (see e.g. del Río and Mir-Artigues, 2014; Busch et al., 2023; Grafström and Poudineh, 2023), and relatively few studies examine the role of market concentration in shaping renewable outcomes (Bourcet, 2020). This paper contributes to the market concentration literature by examining whether concentrated electricity markets deter the deployment of wind and solar across EU member states.[5]

A theoretical model of Cournot competition illustrates how market dominance can suppress renewable entry through pricing and strategic behavior. Guided by this mechanism, the empirical analysis tests whether the market share of dominant electricity producers is associated with lower solar and wind deployment across the EU-27 from 2000 to 2022. Using a dynamic panel approach with fixed effects and instrumental variables to account for persistence unobserved heterogeneity and endogeneity, the results show no consistent evidence of such a relationship. This finding is robust to several different specifications. Using the bias-correction

[5] If not stated differently, renewable will be used synonymous with solar and wind, while renewable energy sources, as defined by the Directive (EU) 2018/2001 also covers geothermal energy, ambient energy, tide, wave and other ocean energy, hydropower, biomass, landfill gas, sewage treatment plant gas, and biogas. In this paper we limit the source to wind and solar.

method of Chernozhukov and Fernández-Val (2019) applied to the model reaffirms the absence of an effect. The analysis suggests that other factors, such as past investment levels, regulatory frameworks, and support policies, may play a more decisive role in shaping renewable energy deployment than market structure alone.

The rest of the paper is organized as follows. Section 2 reviews EU electricity market liberalization and relevant literature. Section 3 presents a theoretical Cournot model and hypotheses on market concentration's impact on renewables. Section 4 outlines the empirical strategy, including the dynamic panel model. Section 5 describes data and statistics. Section 6 reports results, heterogeneity, and robustness checks. Section 7 discusses findings and policy implications. Section 8 concludes with insights and future research directions.

2. Background and literature review

2.1 Liberalization and Structural Change in EU Electricity Markets

Until the 1990s, electricity supply in Europe was dominated by vertically integrated and predominantly state-owned firms, responsible for generation, transmission, and distribution within national or regional monopolies (Tulloch et al., 2018; Halkos, 2019). The vertically integrated structure, justified by perceived economies of scale, initially supported electrification. Over time the structure led to inefficiencies, low investment levels, and opportunities for strategic withholding in markets with inelastic demand (Lundin and Tangerås, 2020; Akcura and Mutambatsere, 2024).

The 1996 and 2003 Electricity Directives introduced third-party network access and promoted unbundling of transmission and generation (Tulloch et al., 2018). These reforms stopped short of full ownership separation, allowing incumbents to retain market dominance. A second wave, culminating in the 2009 Third Energy Package, strengthened requirements by promoting ownership unbundling of transmission system operators, aiming to reduce vertical integration and stimulate competition (Ciucci, 2023).

However, fragmentation persisted due to incomplete cross-border transmission infrastructure, differences in market rules, and varying degrees of liberalization (Gajdzik et al., 2023; Zachmann et al., 2024; Eurostat, 2024b). Between 2019 and 2021, a third wave of reforms emphasized grid flexibility, renewable integration, and consumer rights. Following the 2022 geopolitical crisis, further policies targeted the reduction of dependency on Russian fossil fuels and accelerated the push toward a more resilient internal energy market (Ciucci, 2023).

Today, targeted policies remain a central pillar for the EU to reduce barriers and support renewable investment across the union. Support schemes have driven early deployment of particularly wind and solar, though their effectiveness has varied by design and implementation (del Río and Mir-Artigues, 2014; Busch et al., 2023). While feed-in tariff (FIT) schemes appears to have had substantial positive effects on investment levels and profitability, they have also contributed to market distortions by weakening cost pressure and encouraging overcapacity (Lin and Xie, 2024). In response, and in line with the 2014–2020 EU State Aid Guidelines, many member states transitioned from FIT to feed-in premium (FIP) schemes (Alolo et al., 2020).

While the effects of targeted policies are relatively well understood across EU member states, the broader role of market competition and competition law in shaping renewable energy deployment remains less understood (Gajdzik et al., 2023; Akcura and Mutambatsere, 2024). Empirical evidence suggests that more competitive retail and wholesale electricity markets are positively associated with higher levels of renewable penetration, as they facilitate entry, encourage innovation, and improve price signals (Beck and Martinot, 2004; Heiman and Solomon, 2004).

In contrast, policy instruments such as renewable portfolio standards (RPS) have shown limited capacity to reduce structural barriers to entry (Jenner et al., 2013; Acemoglu et al., 2017). These mechanisms often operate within existing market power dynamics and may not be sufficient to overcome incumbent resistance or infrastructure bottlenecks. As seen in recent policy debates, competition law itself may constrain the scope for strategic cooperation among firms pursuing large-scale decarbonization investments. For instance, the OECD Competition Committee (2023) notes that strict enforcement of antitrust rules could unintentionally hinder collaborative efforts that are essential for green transitions.

The timing and depth of electricity market liberalization also play a role. Early liberalizing countries tend to exhibit more competitive market structures than late adopters (Pepermans, 2019). Other structural and policy-related factors also serve to explain differences in the rate of renewable deployment: Carbon pricing, energy levies, social development, and public R&D expenditures are positively correlated with renewable deployment (Papież et al., 2018; Mac Domhnaill and Ryan, 2020; Grafström and Poudineh, 2023), while high per capita emissions and administrative hurdles tend to slow the transition (Przychodzen and Przychodzen, 2020; Gajdzik et al., 2023).

Despite progress, structural barriers persist. Grid congestion, infrastructure deficits, and uneven cross-border coordination continue to impede the integration of renewables across European markets (Gajdzik et al., 2023; Eurostat, 2024b; Gorman et al., 2025).

2.2 Market competition and renewable energy deployment

In concentrated markets, incumbents may act strategically to deter new entry: Incumbents can leverage their market power to withhold thermal capacity, resist grid integration, or price renewable at thermal prices to preserve margins (Twomey and Neuhoff, 2010; Lundin and Tangerås, 2020). This is further amplified by vertical concentration: Although EU-law mandates the legal unbundling of generation, transmission, distribution, and supply, implementation has often fallen short of achieving full structural separation. As a result, incumbents can continue to restrict infrastructure access to the detriment of new entrants, and in some cases preserve both horizontal and vertical dominance through regulatory lobbying (Ritz, 2008).

Renewable producers are poorly positioned to counter such behavior. The intermittent nature of wind and solar prevents them from exploiting price manipulation strategies available to thermal producers (Twomey & Neuhoff, 2010). Combined with their high upfront capital requirements and investment horizons, this asymmetry entrenches the market power of incumbents (Acemoglu et al., 2017; Hogan, 2022). Nonetheless, market liberalization measures have enabled wind and solar power to penetrate oligopolistic markets and dilute market concentration (Beck and Martinot, 2004; Heiman and Solomon, 2004).

Unlike thermal plants, wind and solar operate at near-zero marginal costs and typically benefit from priority dispatch (Hogan, 2022; Simshauser and Newbery, 2024). The resulting dynamic is known as the merit order effect: as low-cost renewable capacity enters the market, it displaces higher-cost thermal generation and drives down wholesale electricity prices (Acemoglu et al., 2017). While the merit order effect can stimulate the energy mix towards increased use of renewables, thermal producers on markets with high vertical integration may do so inefficiently, by charging renewable energy at thermal prices which can reduce welfare (Acemoglu et al., 2017). This phenomenon was recognized by the President of the European Commission, Ursula von der Leyen, in her 2022 State of the European Union speech: *"The current electricity market design – based on merit order – is not doing justice to consumers anymore. They should reap the benefits of low-cost renewables. So, we have to decouple the dominant influence of gas on* *the price of electricity. This is why we will do a deep and comprehensive reform of the electricity market"* (von der Leyen, 2022).

3. Theoretical framework and hypotheses

3.1. Stylized model

Acemoglu et al. (2017) presents a theoretical framework to capture the merit order effect, where the share of renewable electricity can only increase exogenously. Producers choose their thermal output level, and any (exogenous) entry dilutes the per-firm ownership shares of the renewable stock, thus reducing the overall renewable share. The underlying implication of the model is that with enough vertical integration, producers exploit the merit-order effect to charge renewable energy at thermal prices. Thermal firms face no competitive pressure from producers that invest in new renewable capacity. We modify the model to allow for mixed competition and long-term endogenous entry of renewable producers. We argue that this better captures today's electricity markets, with incumbents owning mixed energy portfolios and new entrants often focusing exclusively on renewables (Kim, 2013; Kattirtzi et al., 2021).

There is a continuum of competing producers of two types, with $n, m \in \mathbb{R}_+ (n, m \geq 1)$ denoting the short-term mass of thermal (n) and renewable (m) producers, respectively. In the long run, $n \geq 1$ and $m \geq 0$. All types are known (i.e., there are no uncertainty considerations). For simplicity, we abstract away from an exogenously defined stock of vertically integrated renewable plants as in Acemoglu et al (2017), with incumbent producers instead focusing solely on either thermal or renewables in their production.[6] Producers compete in a one-stage, static Cournot-oligopoly game.

Each thermal firm chooses $t_i \geq 0$ units of thermal capacity to dispatch, incurring a cost. Costs for thermal production are assumed to be linear and given by $C(t_i) = ct_i$ with marginal cost $c > 0$. Each renewable firm j supplies a fixed amount of renewable capacity $\bar{r} > 0$ at the prevailing market price, and any associated cost is viewed as sunk.[7]

[6] It is possible to include this exogenous renewable stock in the framework presented in this paper, without loss of generality. Let R_0 be the (initial) exogenously defined renewable capacity that is dispatched at zero marginal cost, and $\delta \in [0,1]$ denote the fraction of R_0 owned by the incumbent thermal producers. Thermal producer *i* thus owns a share $\frac{\delta}{n}$ of the initial renewable stock R_0, with $1 - \delta$ of the stock being owned exogenously. Renewable producers own no share in R_0.

[7] $\bar{r}$ can be thought of as fixed due to the capacity constraint of wind parks and solar farms. I.e., the capacity of these facilities is variable up to a maximum capacity and fixed afterwards at $\bar{r}$.

Total supply consists of all energy produced using thermal and renewable, $Q(t,\bar{r}) = nt_i + m\bar{r}$. Inverse demand is assumed to be strictly decreasing in $Q(t,\bar{r})$ and given by $P\big(Q(t,\bar{r})\big) = a - bQ(t,\bar{r})$, where $a\ c$ and $a, b > 0$.

Thermal producers maximize profits according to

$$\pi_i = t_i P\big(Q(t,\bar{r})\big) - C(t_i) \tag{1}$$

3.2 Model equilibrium

The model yields both short-run and long-run equilibria. In the short run, the number of renewable producers is fixed at m with each dispatching their fixed renewable capacity $\bar{r}$ at equilibrium price $P^*(m)$. Renewable producers can thus profit from the lack of renewable competition and earn positive profits. Short-run equilibrium details are provided in Appendix B.

In the long run, the number of renewable producers is endogenously affected by the market structure. Thermal producers influence the long-term price when choosing output level, which decreases the potential for market-driven renewable entry. Renewable producers pay a fixed cost $F_0 > 0$ to enter the market and incur a small-but-positive unit cost $k > 0$. The dominant producer, either thermal or renewable, can leverage its long run market power, given by the parameter $\rho \in [1, \infty)$, to affect this cost function $F(\rho) = \rho(F_0 + k)$.[8] There is no tangible dominance effect at $\rho = 0$, while the bite of market dominance intensifies as $\rho \to \infty$.

Renewable producers enter until equilibrium profits bind at zero, i.e.,

$$\pi_j^* = 0 \to \ P^*(m^*) = \frac{F(\rho)}{\bar{r}}, \tag{2}$$

which pins down the number of long-run renewable producers m^*. The free entry condition implies that only thermal producers earn positive long run profits while renewable producers earn zero profits. Long-run equilibrium is characterized by the following set of equations

$$Q^*(m^*) = \frac{a\bar{r} - F(\rho)}{b\bar{r}} \tag{3}$$

[8] The fixed cost F_0 can be viewed as an upfront capital investment into new solar or wind plants and k is the unit cost associated with operating the plant. The dominant producer's market power intensifies regulatory frictions, which can be thought of as restricted grid access, structural separation considerations, or lobbying.

$$nt^*(m^*) = \frac{n}{b}\left(\frac{F(\rho)}{\bar{r}} - c\right) \quad (4)$$

$$m^* = max\left(0, \frac{a + cn - (n+1)\frac{F(\rho)}{\bar{r}}}{b\bar{r}}\right) \quad (5)$$

$$S_{Renew}^*(m^*) = \frac{\bar{r}(a + nc) - (n+1)F(\rho)}{a\bar{r} - F(\rho)} \quad (6)$$

For a well-behaved interior equilibrium, we first assume $\frac{F(\rho)}{\bar{r}} > c$, which states that the average entry cost per renewable capacity is larger than the marginal cost for thermal producers and ensures positive thermal equilibrium production $t^*(m^*) > 0$. Second, assume $\frac{F(\rho)}{\bar{r}} < \frac{a+cn}{n+1}$ to ensure that at least one renewable producer $m^* > 0$ enters in the long run. Third, $a\bar{r} > F(\rho)$ is true by extension, thus ensuring a positive total quantity $Q^*(m^*) > 0$.

In the long run, renewable entry m^* is decreasing in thermal competition *n* and increasing in thermal marginal costs *c*. As *n* increases, the share of thermal output in the energy mix rises which constrains renewable entry m^*. And opposite, as *c* increases, the unit cost of t^* rises and overall supply contracts, leaving room for m^* to expand. The ability for m^* to adjust implies that equilibrium quantity $Q^*(m^*)$ and price $P^*(m^*)$ remain stable in the long run; this is in contrast to the short run, where m is exogenous and thus $Q^*(m)$ and $P^*(m)$ change with parameters *n* and *c*.

The initial capital cost F_0, unit cost k and the market dominance of the largest producer ρ all reduce the profitability of renewable entry, and importantly, this affects $Q^*(m^*)$ and $P^*(m^*)$. As costs increase, the competitive pressure of renewable entry decreases and m^* adjusts downward, which in turn causes $Q^*(m^*)$ to fall and $P^*(m^*)$ to rise. The implication is that the dominant producer's market power can affect not only the competitive pressure they face by new entrants in the long run, but also prices and quantities. In the short run, when renewable output $\bar{r}$ is fixed and costs are sunk, no such dynamics exist.

Empirically, the analysis aims to examine how market concentration, measured as the dominant producer's market power, affects the aggregate renewable adoption in Europe over multiple years. We thus turn attention to the renewable share $S_{Renew}^*(m^*)$ and pose the following proposition:

Proposition: *The renewable share $S^*_{Renew}(m^*)$ is decreasing in market power of the dominant producer ρ and increased thermal competition n.*

Proof: *Follows from direct differentiation of the closed-form expression for $S^*_{Renew}(m^*)$ with respect to ρ and n.*

In the model, ρ affects m^* through the cost channel $F(\rho)$, which in turn affects $S^*_{Renew}(m^*)$. The model predicts that for higher ρ, we should expect lower $S^*_{Renew}(m^*)$ (due to lower m^*). Empirically, we map this to observables by proxying dominance with the largest electricity producer's market share $\tilde{\rho}$ and renewable deployment with the capacity share $\tilde{S}_{Renew}$. Under stable capacity-factor conditions, $\tilde{S}_{Renew}$ is a monotone proxy for S_{Renew}, which implies an empirical hypothesis of a negative relationship going from $\tilde{\rho}$ to $\tilde{S}_{Renew}$. Robustness is implemented by employing multiple different proxies for both variables.

There are two caveats to highlight. First, the theoretical model treats all thermal units, as well as all renewable units, as technologically homogeneous. Real-world power systems feature substantial heterogeneity, e.g., both coal and gas are formally "thermal energy", while both wind and solar are "renewable energy", even when there exist considerable differences in cost structures, profitability and potential externalities. Empirically, our baseline outcome is the within-country wind and solar capacity share, and for robustness we employ a range of alternative definitions.

Second, for tractability the model assumes specialization, where neither incumbent thermal producers or renewable entrants carry mixed energy portfolios. One could introduce an exogenously defined stock of initial renewable capacity owned by a fraction of thermal firms – as in Acemoglu et al. (2017) – without loss of generality. In the present study, however, we study *within-country* renewable capacity share of total capacity and do not model *within-firm* portfolio dynamics. Nevertheless, many firms operate mixed portfolios in practice, and future studies should aim to link firm-level portfolio composition to market dominance and renewable adoption.

4. Empirical strategy

4.1 Empirical model

The estimation strategy builds on Przychodzen and Przychodzen (2020), extending their analysis to the EU context. They examined renewable electricity development in 27 transition countries (1990–2014), measured as the share of total electricity generation. They found that declining market competitiveness limited renewable deployment.

The empirical model, in this paper, is structured as follows:

$$rs_{it} = \alpha rs_{it-t} + \gamma y_{it-1} + x'_{it-1}\beta + \delta_t + c_i + \varepsilon_{it} \tag{7}$$

The dependent variable rs_{it} is the percentage share of the installed renewable (solar and wind) electricity capacity (MW) as a share of the total installed electrical capacity in country i during time t. The model includes a lagged dependent variable rs_{it-t} to capture persistency (α) in the development of renewable electricity. A measure of market structure y_{it-1} is the main variable of interest in the model, given by the one-period lagged market share of the largest electricity producer in the country. For both the renewable share and the concentration measure, the empirical analysis includes a series of robustness tests with alternatives to both.

The model also includes a vector of controls x_{it-t} at the country-year level to capture heterogeneity associated with market structure. Control variables the model with a lag and includes: a dummy variable for post EU-membership; log GDP per capita; GDP growth; the share of imported electricity; total electricity consumption per capita, and natural resource rent. Additional variables used in heterogeneity and robustness analysis include regulatory reform indicators, grid unbundling, the environmental stringency index, market entry timing, FITs, and fossil-fuel subsidies.

Electricity markets differ across EU member states in structural ways that are not easily captured through observed variables—for example, legacy infrastructure, political support for renewables, or regulatory culture. To account for such time-invariant country-specific heterogeneity, the model includes a full set of country fixed effects c_i. These absorb all unchanging characteristics that may influence both market structure and renewable deployment.

Similarly, year fixed effects δ_t are included to capture common shocks and trends affecting all countries, such as global energy prices, EU-wide policy reforms, or economic disruptions like the COVID-19 pandemic. The lag structure helps isolate within-country variation over time. Lastly, ε_{it} is an error term that captures other omitted factors for which $E(\varepsilon_{it}) = 0$ for all i and t.

4.2. Identification strategy

A central concern is the potential for endogeneity, arising from both reverse causality and simultaneity bias between market concentration and renewable share. Policies that promote renewable investments such as FITs or grid access guarantees can increase the share of renewables in a country's electricity mix, which may, in turn, reduce the market share of incumbent producers. If unaccounted for, such feedback mechanisms can bias estimates of the causal effect of market structure.

To mitigate this, the market share variable is lagged by one year, reducing the likelihood that changes in the renewable share contemporaneously affect the measure of concentration. In addition, the use of dynamic panel estimators allows for deeper lags of the dependent and endogenous variables to be used as (internal) instruments mitigate bias in the one-year lagged explanatory and endogenous variable y_{it-1} and rs_{it-t}.

To strengthen identification, several different estimators are examined. The empirical model in (7) is first estimated using pooled OLS. For the estimator to yield unbiased estimates, all observable variables must be uncorrelated with the country fixed effect, i.e., $cov(x_{it}, c_i) = 0$, which is very unlikely to hold in this setting. To address this concern, results are also presented from a fixed effect (FE) regression, which only relies on variation within countries and over time. However, FE estimation can remain biased in dynamic panels due to the inclusion of the lagged dependent variable.

The presence of a lagged dependent variable introduces the so-called *Nickell bias*, a form of dynamic panel bias arising from correlation between the lagged outcome and the fixed effects. The bias only disappears as $T \rightarrow \infty$. With the period spanning from 2000 to 2022, T = 22 years, the bias is likely moderate. Still, given that renewable deployment likely depends on past capacity through multi-year investment cycles, the lagged dependent variable is retained to reflect the true dynamics.

To address the dynamic bias the Arellano-Bond (1991) estimator (AB for short) is employed that applies Generalized Method of Moments (GMM) to the first-differenced equation and uses lagged levels of the dependent variable as instruments. For example, rs_{it-2} can be used as an instrument for Δrs_{it-1}, under the exclusion restriction that rs_{it-2} is not correlated with the first differenced error term $\Delta\varepsilon_{it}$. This holds if ε_{it} in levels is not first order serially correlated. In practice, the condition is typically assessed by testing for the absence of second-order serial correlation in the first-difference error term.

The AB model does not restrict the instrument matrix to only include lagged dependent variables, provided that $E\left(y_{it-2,}\Delta\varepsilon_{it}\right) = 0$. Lagged versions of the endogenous market structure variable may also be included as potentially valid instruments, again under the assumption of no serial correlation in the error term. We leverage this to further address potential reversed causality.

A limitation of dynamic GMM estimators, such as the AB estimator, is the sensitivity to multiple instruments relative to sample size (N = 22, T = 21). Excess instruments can overfit endogenous variables and weaken test validity. To address instrument proliferation, the model applies restricted instrument sets and reports estimates using bias-corrected fixed effects and GMM approaches based on Chernozhukov and Fernández-Val (2019). Using bias-correction provide more robust inference with improved small-sample properties from using bootstrapped standard error.

5. Data

5.1 Sources and data sample

The present study employs a panel dataset collected mainly from Eurostat, covering characteristics related to electricity markets such as renewable electricity output and information on the market share of the largest producers. Complementary information about policies such as FITs and fossil fuel subsidies comes from OECD. The analysis also draws on information provided by the Global Power Market Structures Database from the World Bank Group that details the operating market structure on the global power market since the late 80's, which contains information about the specific market structure, transmission unbundling, regulatory information, and liberalization in the form the establishment of independent power producers at the country level.

The data sample used in the empirical analysis covers all 27 EU member states over the period 2000 to 2022. The time frame captures three major waves of EU electricity market reform, as well as significant expansion in wind and solar capacity. The empirical analysis focuses on within-country variation over time, with a structure suited for dynamic panel estimation. An overview of the variables is presented in Table 1.

Table 1: Descriptions of variables used in analysis

Variable	Description	Source	Comment
Dependent variables			
Renewable share	Cumulative share of solar and wind capacity in a given country-year (%)	European Commission	100*(Cumulative Solar and Wind Capacity [MW])/(Installed Electricity Capacity [MW])

Share solar	Cumulative share of solar capacity in a given country-year (%)	European Commission	100*(Solar Total Installed Capacity [MW])/(Installed Electricity Capacity [MW])
Share wind	Cumulative share of wind capacity in a given country-year (%)	European Commission	100*(Wind Total Installed Capacity [MW])/(Installed Electricity Capacity [MW])
Renewable capacity	Cumulative (MWh) of solar and wind capacity in a given country-year (log)	European Commission	log(Cumulative Solar and Wind Capacity [MW])
Explanatory variables			
Market share	Market share of the single largest electricity producer measured in generation and a given country-year	European Commission	Market Share Largest Producer [%]
Main producers	More than five main producers (dummy)	European Commission	Dummy(Main Producers, >5% Total [No.])
Total producers	Number of total producers (log)	European Commission	Log(Producers, Representing 95% Total [No.])
Share of main producers	Main producers as a share of total producers	European Commission	100*(Producers, Representing 95% Total [No.])/(Main Producers, >5% Total [No.])
Type of electrical market structure	(i) Vertically integrate utility (VIU), (ii) Single buyer model (SBM), (iii) Wholesale competition	World Bank (GPMSD)	Market structure coding: VIU 1a, 1b; SBM 2a, 2b; Wholesale competition 3a, 3b, 3c, 3d.
Main retailers	More than five main retailers (dummy)	European Commission	Dummy(Main Retailers, Sales >5% Total [No.])
Retail competition	Retail competition (dummy)	World Bank (GPMSD)	Market structure coding: 4b
Control variables			
GDP	GDP (€Mrd 2015) per capita (constant USD, PPP) (log)	European Commission	
Net imported electricity	Net electricity imports per country and year, (in Mtoe)	European Commission	Net Imports/Electricity
Electricity consumption	(per capita)	European Commission	Final Electricity per Capita [KWh/capita]
Natural resources rents	Total natural resources rents, sum of oil, natural gas, coal (hard and soft), mineral, and forest rents per country as share of GDP	World Bank	Data for 2022 not available
Post EU Accession (Dummy)	=1 for year ≥ each country's EU accession year; 0 otherwise		Author's coding (EC accession dates)
Regulation	Electrical market regulation (dummy)	World Bank (GPMSD)	
Unbundling	Transmission unbundling of ownership (dummy)	World Bank (GPMSD)	Unbundling with regards to the ownership of the network
ESI (Environmental Policy Stringency Index)	Stringency is defined as the degree to which environmental policies put an explicit or implicit price on polluting or environmentally harmful behavior. Ranging from 1-6.	OECD	2000-2020, 20/27 EU countries (excl. Latvia, Lithuania, Malta, Cyprus, Romania, Bulgaria, Croatia)
Privatization	Entry of independent private producer (dummy)	World Bank (GPMSD)	
Feed-in-Tariff for solar PV	Mean feed-in tariff for Solar PV by country and year. In current USD/kWh.	OECD	2000-2019
Feed-in-Tariff for wind	Mean feed-in tariff for Wind by country and year. In current USD/kWh.	OECD	2000-2019

Fossil Fuel Subsidies	Fossil Fuel Support as percentage of GDP	OECD	2010-2022. 23 EU counties. Massive spike in 2022 due to the large fiscal packages rolled out under the EU-wide energy-price crisis.

The outcome of interest and thus the key dependent variable in the empirical analysis is the renewable share, defined as the cumulative installed capacity of wind and solar power expressed as a percentage of total national installed electricity capacity. The share is calculated annually for each country using official data from the European Commission, combining solar photovoltaic and wind generation technologies.

Although the variable captures the relative presence of renewables, it does not reflect the scale of absolute capacity additions. As a result, smaller countries with limited capacity may still experience large movements in the renewable share from modest installations. To address the shortcoming, results are also presented using the log level of installed capacity as the dependent variable in the robustness analysis. The robustness analysis also shows results when looking at solar and wind separately in the renewable share.

The main explanatory variable capturing market power, and thus the degree of competition, is the one-period lagged market share of the largest electricity producer, measured as the percentage of national electricity generation accounted for by the leading firm in terms of electricity production in each year. It coincides with the concentration ratio for the largest firm and serves as a proxy for competition in the electrical market. The data is sourced from Eurostat (2024b).

Besides the concentration variable, several control variables are included to account for common sources of variation in the renewable share and the concentration measure. In the main model, the controls include: the first log GDP per capita and GDP growth, to capture economic conditions; the first lag of net electricity imports to capture exposure to international energy markets and interconnectedness; EU accession timing, as an institutional shift that may affect both regulation and investment, and the first lag of natural resource rent.

In addition to the main model, the empirical analysis contains further heterogeneity analyses, which helps distinguish the structural effect of market concentration from overlapping policy influences. In this analysis additional policy relevant variables are introduced, including indicators of electrical market liberalization, the environmental stringency index (ESI), FIT-levels, and fossil fuel subsidies.

ESI is a measure that comes from OECD and is available for 20 out of the 27 EU-countries up to 2020. It ranks the degree to which (1-6) that environmental policies put an explicit or implicit price on polluting or environmentally harmful behavior. The mean FITs for solar and wind generation come from the OECD dataset on renewable energy feed-in tariffs. FITs offer a guaranteed price per kWh fed into the grid, positively impacting investment decisions in renewable energy.

The analysis employs the market structure coding of all EU-27 members as developed by the World Bank Group to control the implementation of liberalization policies. In the robustness analysis, results are presented for several alternative measures, namely a dummy if the country has more than five main producers of electricity,[9] the log number of total electricity producers,[10] and the share of main producers in relation to the total number of producers. Note that for the main producer dummy and the log number of producers, the expected sign gets reversed compared to the concentration ratio as both variables reflect a larger electricity market in general and potentially lower market concentration. As for the share of main producers to the number of total producers, higher values are again interpreted as higher concentration and thus more market power.

Lastly, the robustness analysis also uses the Global Power Market Structure Database (GPMSD) from the World Bank information about the type of market structure from the World Bank data, which differentiates between markets that have a vertically integrated utility (VIU), single buyer model (SBM), or outright wholesale competition.[11] The analysis is further complemented by examining corresponding measures for electricity retailers.

5.2 Descriptive statistics

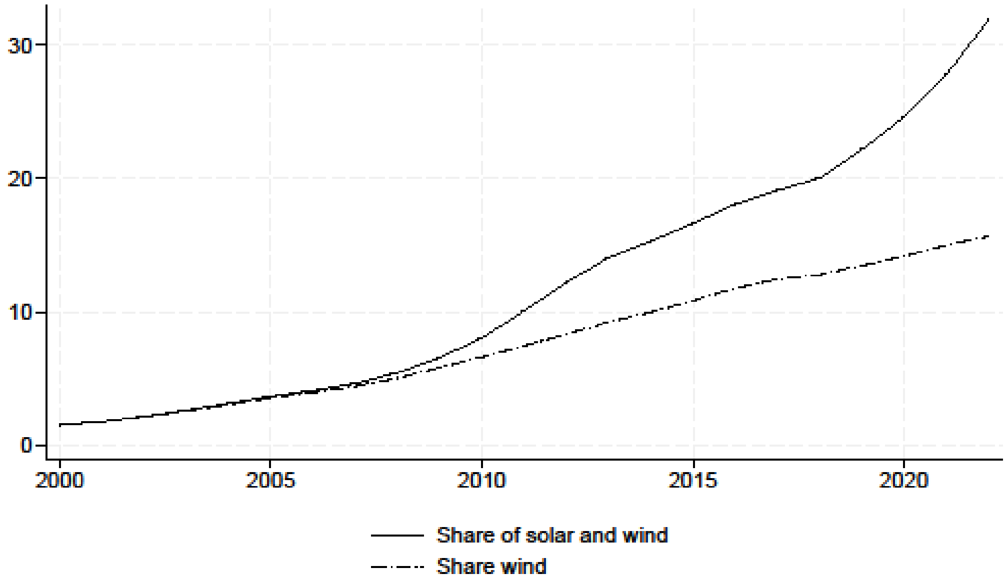
Looking at the period there are two emerging trends that is directly relevant to our analysis: on the one hand, the average renewable share, and particularly the share of solar electricity, has increased; on the other hand, average market concentration has decreased.

From the summary statistics presented in Table 2, the average renewable share is 12.11 percent across countries and over time, with a standard deviation of the same magnitude. Over the

[9] Main producer here refers to a producer of electricity that supplies no less than 5 percent of total electricity production.
[10] Data from EUROSTAT over total electricity production corresponds to the number of producers that together supply 95 percent of all electricity. We do not have full coverage, i.e., information on the last 5 percent of electricity producers.
[11] In VIU markets, customers can not choose supplier as one company has a monopoly on production, transmission and supply. In SBE markets there is a single buyer of electricity, and with wholesale competition in the electrical market, there is bilateral trading with a bid-based or cost-based power exchange.

period, however, the renewable share experienced a large increase and went from 1.5 percent to 32 percent between 2000–2022, which is detailed in Figure 1.

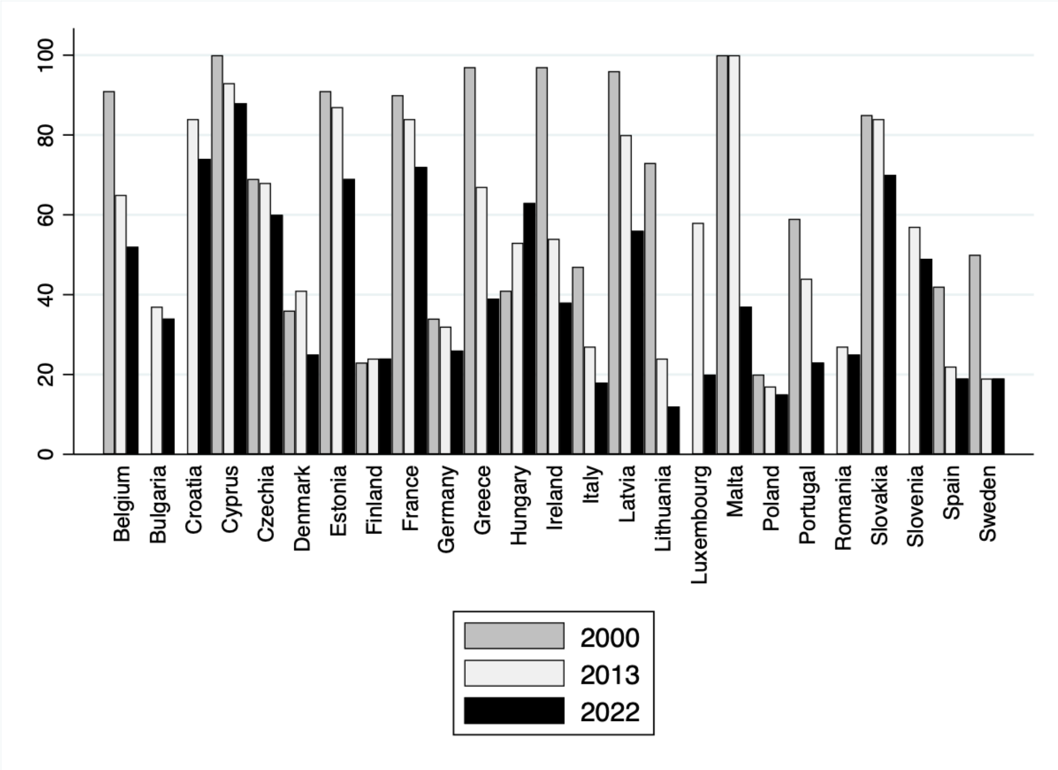
Wind power accounted for virtually the entire initial 1.5 percent. Compared to the total installed capacity, wind increased gradually over the period, amounting to 15.7 percent in 2022. In contrast, solar started to expand rapidly around 2010. By 2022, solar had overtaken wind in installed capacity and amounted to 51.1 percent of the renewable share.



Notes: The figure shows the average share (percent) of solar, and wind installed capacity over total installed capacity (percent) averaged across EU-27 countries. Own calculations based on EUROSTATA data.

Figure 1. The average renewable electricity shares across EU-27 over the period 2000-2022.

Figure 2 plots the largest company's market share in EU-27 countries in 2000, 2010 and 2022. The overall trend across EU countries has been toward reduced electricity market concentration, but substantial cross-country variation remains. While the average market share of the largest producer is 55.1, as seen in Figure 2, the largest producer in Cyprus controlled 87.5 percent of generation, compared to just 23.7 percent in Finland.



Source: European Commission (2024).

Figure 2. Largest company's share of domestic electricity production (percent).

The correlation coefficient between the renewable share (Figure 1) and the largest company share (Figure 2) is negative and amounts to -0.43. Year-by-year, data shows no sign of a clear trend, although it does display a weak negative development over the period. Rather than trending, over the measurement period the correlation oscillates in the range between -0.30 and -0.40. The largest negative correlation is in 2022 at -0.45, the least negative correlation is in 2017 at -0.26. Such correlations say nothing about causality between the two variables, and there are numerous other factors that can affect both variables.

The purpose of the empirical analysis is therefore to impose more restrictions on this relationship to answer the question we posed of whether a high market concentration may have hampered the development of renewable electricity resources in the EU.

Table 2. Summary statistics of variables

				Models		
Variable	Obs	Mean	Std. dev.	Main	Heterogeneity	Robustness
Outcome						
share renewable (solar and wind)	615	12.11	12.57	*		
share wind	615	7.95	9.10			*
share solar	615	4.16	6.45			*
log renewable capacity (solar and wind)	575	6.55	2.58			*
Explanatory						
market share largest producer	546	55.10	26.90	*		

five main producers	621	0.18	0.38			*
log number of total producers	544	3.16	1.91			*
share main producers	542	0.29	0.33			*
Electrical market structure						
vertically integrated utility (VIU)	621	0.10	0.30			*
single buyer model (SBM)	621	0.079	0.27			*
wholesale competition	621	0.82	0.38			*
Control						
log GDP per capita	621	-3.85	0.69	*		
net electricity import	621	0.01	1.39	*		
final electricity consumption per capita	621	6,413.06	3,109.45	*		
natural resource rent	594	0.55	0.71	*		
post EU accession	621	0.37	0.48	*		
market regulation	621	0.88	0.32		*	
Environmental stringency index (ESI)	420	2.77	0.77		*	
unbundled transmission ownership	621	0.35	0.48		*	
independent power producer	621	0.50	0.50		*	
feed-in tariffs	506	2.04	2.42		*	
fossil fuel subsidy	286	7.16	2.78		*	

Notes: Summary statistics represents the variables in the base sample spanning the period 2000 to 2022 for EU countries Austria, Belgium, Bulgaria, Cyprus, Czechia, Germany, Denmark, Estonia, Greece, Spain, Finland, France, Croatia, Hungary, Ireland, Italy, Lithuania, Luxembourg, Latvia, Malta, Netherlands, Poland, Romania, Sweden, Slovenia, Slovakia and reflects the number of missing observations. The table also accounts for the model in which the variables are used. These include one main model, and several heterogeneity and robustness models.

Particular attention should be given to both the feed-in tariffs and fossil-fuel support in Table 2, which amount to 2 percent and 7 percent, respectively on average. Due to data limitations, the coverage for these two variables is limited. For fossil fuel subsidies only 286 observations in the sample are available while the data for FITs omits some of the EU-27 countries.[12] Because of these limitations, we do not include fossil fuel subsidies and FITs in the main analysis and instead focus on them in the subsequent heterogeneity analysis.

6. Results

This section presents the empirical findings on the relationship between electricity market concentration and the deployment of wind and solar power across EU member states. Building on the theoretical framework and econometric strategy outlined in previous sections, the analysis estimates a dynamic panel model using OLS, fixed effects and Arellano-Bond GMM to account for unobserved heterogeneity, endogeneity, and the persistence of wind and solar power deployment.

[12] The main reason so few observations of fossil-fuel subsidies is because data collection by the European Commission only started in 2013. Data for feed-in-tariffs comes from OECD, which by construction excludes some EU-countries.

6.1. Main results

The empirical results from estimating the main model are presented in Tables 3. The main variable of interest is the *lagged* market share of the largest electricity producer (Market share$_{t-1}$), which serves as a proxy for market concentration. Results are reported across multiple specifications, including two samples in the form of a base sample and a reduced balanced sample. For the balanced sample, the table also includes the debiased estimates for market-share effect along with bootstrapped standard errors following the split-sample approach in Chernozhukov and Fernández-Val (2019). The table also presents two sets of results for both annual data and data at 5-year intervals.

This model examines the effect of market power on *new* renewable electricity. Why it is *new* renewable electricity comes from the inclusion of a lagged dependent variable in the model that captures the effect from current wind parks and already installed solar panels. The estimated coefficient for the lagged dependent variable is close to 1 and highly significant, showing strong signs of persistence, which is to be expected given that most of the installed electrical capacity from one year to the next is not decommissioned.

Table 3. Results for the market share of the largest producer on renewable electricity share

	Base sample						Balanced sample	
	Annual data				5y data		Annual data	
	OLS	FE OLS	AB GMM	FE OLS	FE OLS	AB GMM	FE OLS	AB GMM
Dependent variable: Renewable share$_t$	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Renewable share$_{t-1}$	1.016***	1.003***	0.747***		0.589***	0.441	0.996***	0.823***
	(0.010)	(0.021)	(0.087)		(0.116)	(0.316)	(0.023)	(0.087)
Market share $_{t-1}$	-0.003	0.006	-0.006	-0.063***	-0.057	-0.049	0.007	-0.010
	(0.003)	(0.007)	(0.025)	(0.019)	(0.054)	(0.068)	(0.013)	(0.025)
log GDP per capita	-3.760*	-4.176*	-4.293	11.898*	-3.001	-4.932	-4.432	-5.365
	(2.160)	(2.505)	(4.860)	(6.867)	(5.585)	(6.272)	(2.930)	(4.953)
log GDP per capita $_{t-1}$	4.119*	5.409*	4.245	-18.804***	-5.871	-7.257	6.331*	7.565
	(2.154)	(2.761)	(6.930)	(7.074)	(5.371)	(11.954)	(3.255)	(7.262)
Net imported electricity $_{t-1}$	0.054	0.242**	-0.551	-1.914***	-0.785	-3.976	0.981	-0.684
	(0.037)	(0.114)	(0.651)	(0.329)	(3.934)	(8.050)	(1.005)	(3.161)
Electricity consumption $_{t-1}$	-0.000	-0.000**	-0.000	-0.001**	3.512	0.459	1.263***	-5.323
	(0.000)	(0.000)	(0.000)	(0.000)	(2.111)	(6.382)	(0.480)	(7.925)
Natural resource rent $_{t-1}$	0.085	0.126	0.030	-0.932**	0.360***	0.896***	0.025*	0.009
	(0.094)	(0.139)	(0.718)	(0.400)	(0.132)	(0.293)	(0.014)	(0.022)
EU accession	0.002	0.075	-0.742	-3.538***				
	(0.196)	(0.239)	(0.868)	(0.840)				
Observations	515	515	485	516	89	65	399	378
Countries			26			24		21
Instruments			147			19		125
AR(1) p-value			0.047			0.299		0.058
AR(2) p-value			0.152			0.135		0.115
Hansen p-value			1.000			0.685		1.000
Bias correction							0.003	0.049

Bootstrapped s.e.	[0.033]	[0.058]

Notes: The dependent variable Renewable share$_t$ is the percentage share of the installed renewable (solar and wind) electricity capacity (MW) as a share of the total installed electrical capacity in country i in period t. In column 1, results come from pooled OLS cross-sectional regression. Country fixed-effects regressions are shown in columns 2, 4, 5, and 7. In column 3, 6 and 8, the model is estimated using the GMM following Arrelano and Bond (1991) "difference GMM", which uses instrumental variables to address the endogeneity of the lagged dependent variable and the Market share $_{t-1}$. We use 2nd to 4th lagged values of the dependent variable and market share as instruments. All models include a full set of year dummies. Robust standard errors are shown in parenthesis. The models are estimated on two samples. The base sample includes 27 European countries spanning the years 2000 to 2022. For the base sample, in addition to estimating the models using annual data, column 5 and 6 use five-year data. Thehe models are also estimated on a reduced balanced sample of 21 countries for the years 2003 to 2022 (from which Austria, Bulgaria, Serbia, Malta, Luxembourg, Romania, Netherlands are excluded due to missing observations). For the balanced sample, the table also shows the biased corrected estimate of Markets share $_{t-1}$ using the split sample algorithm in Chen, Chernozhukov, and Fernándes-Val (2019), with bootstrapped standard errors shown in brackets. For the Arellano-Bond estimates, we report the number of internal instruments, p-values for the Hansen overidentification test, along with the AR(2) test for no serial correlation. Significance level corresponds to * p<0.10 ** p<0.05 *** p<0.01. For more detailed information about the variables see Table 2.

The first column shows the OLS pooled estimates from a cross-sectional regression that shows a weak negative association of -0.003 (0.003) between Renewable share$_t$ and Market share$_{t-1}$. It is the expected sign according to the narrative that a larger incumbent electricity producer could inhibit the development of new renewable energy, in this case either solar or wind installed capacity.

Once country fixed effects are accounted for in column (2), however, the negative estimate turns positive, but still insignificant. The point estimate of 0.006 (0.007) for Market share$_{t-1}$ is still small in magnitude. As for the dynamic lag, it's estimated to be 1.003 (0.021) and thus remains close to unity. By including country fixed effects, all fixed cross-sectional heterogeneity is removed, reducing the identifying variation to changes within countries that occur over time. Comparing pooled and fixed-effect OLS does not yield strikingly different estimates for the control variables, expect for perhaps net imported electricity, which for the fixed effect model in column (2) with 0.242 (0.114) is both positive and significant.

Neither the pooled OLS nor the fixed effect OLS estimators can be relied upon to give a causal interpretation of the relationship between Market share$_{t-1}$ and Renewable share$_t$. To address potential endogeneity, column (3) reports results obtained using the Arellano and Bond (1991) GMM estimator. By using deeper lags of the dependent variable and the market share variable, it provides a way to address endogeneity.

Beginning with observation that the AB results are largely comparable to those from the pooled OLS and fixed-effect estimator: The point estimation for Market share$_{t-1}$ of -0.006 (0.025) is negative and insignificant. However, for the AB estimator to give reliable results there are several conditions that must be met: A rejected AR(1) test of no first order serial correlation in the first-differenced equation coupled with an inability to reject the AR(2) test of no second order serial correlation in the level equation. Looking at the Table 3 statistics, both conditions are met in column (3).

However, the Hansen J test registers a p-value of 1, which suggests that, although the estimator is likely robust, it suffers from too many instruments. It is a well-known problem when the number of time periods in the panel becomes even remotely large. According to Chen, Chernozhukov, and Fernándes-Val (2019), having too many time periods leads to invalid inference along with biased estimates in AB-models.

To address this concern, three approaches are outlined. The instrument count can be reduced by using only the second lag of the dependent variable and Market share$_{t-1}$, following the Anderson and Hsiao (1982) approach while retaining the GMM framework. Second, instead of using time dummies in the model that also goes into the instrumental matrix, a fourth-degree polynomial is used. While both methods do reduce the number of instruments, and the Hansen p-value when using the polynomial, they do not appear to have a sizable effect on the estimates. Despite showing similar results qualitatively, neither modification can satisfactory deal with the bias that stems from having a long panel. As a third option presents, the problem is addressed head on by debiasing the estimator using the split-sample strategy in Chen, Chernozhukov, and Fernándes-Val (2019).

The debiased estimates of Market share$_{t-1}$ along with bootstrapped standard error, shown in brackets, are presented for the fixed effect OLS and AB estimator using the balanced sample in column 7 and 8. As for the main estimates of Market share$_{t-1}$ from the balanced sample, it remains insignificant for fixed effect OLS 0.007 (0.013) and the AB-estimator -0.010 (0.025). Turning to their debiased version, they are still insignificant for both fixed effect OLS 0.003 [0.033] and AB -0.049 [0.058]. While the point-estimates remain largely the same, the standard errors resulting from bootstrapping are two-to-three times as large as the robust standard errors, which further adds weight to the result of no causal link going from Market share$_{t-1}$ to Renewable share$_t$.

Lastly, the remaining models present results excluding the lagged dependent variable (4) and including only data points at five-year intervals (5 and 6). In the absence of a dynamic lag, the AB estimator cannot be applied, and results are only reported using fixed effects OLS. This is the only model that records results with a negative and significant result for market share, which confirms that the concurrent trends accounted for in the previous section are also present within countries over the period. However, leaving out the dynamic lag from the model would result in biased estimates, making market shares in t-$_1$ correlated with the renewable share the same period, and for this reason cannot reliably be counted on to reflect a causal relationship.

As for the results from using 5-year data, it allows for an effect to play over longer periods. In this case, the estimates for market share is negative but also insignificant. From the low observation count, these estimates should be considered more uncertain. Although, the lower instrument count for the AB-model in column (6), reflected in the Hansen P-value smaller than 1, indicates a reduced risk of instrument proliferation compared to the main specification.

6.2. Heterogeneity results

While the results from the main specification in Table 43 showed little sign of a direct causal link between competition and the installed renewable electricity capacity, further results are reported from specifications where additional aspects of the electrical market are considered. First off, results are presented using several variables that capture policies relevant to electricity markets, which may influence how competition affects renewable electricity. These policy variables are two sets of dummy variables, one for when the electrical market became regulated and another for when the ownership of transmission was unbounded, and the environmental-stringency index (ESI). Second, results are presented for a specification that includes a privatization variable, defined as a dummy indicating the first entry of an independent power producer. Third, a variable for solar and wind FITs is added. Lastly, the results are presented from a model that incorporates a variable capturing fossil fuel subsidies.

In total, four additional models are estimated using both fixed effects OLS and Arellano-Bond GMM on the balanced sample, resulting in eight regressions. The corresponding results are presented in Table 4.

In short, adding these variables to the model does not appear to alter the insignificant results found in the main model for Market share$_{t-1}$. With regards to the estimated coefficients of the additional variables, neither the estimates for the policy related variables nor the privatization dummy were found to significantly affect the renewable share. In models 5 and 6, which include information on FITs, a positive and statistically significant association is observed for both the fixed effects and Arellano-Bond models, suggesting that higher tariffs are linked to a larger renewable share.

The final two models in columns 7 and 8 that include information about fossil fuel subsidies turn out insignificant. These models have considerably less observations because of the short panel available for the subsidies, which results in less statistical power. It can be seen in the estimates for FITs, which remain positive of the same magnitude, significant in the FE model but–due to higher standard errors–insignificant in the AB-model.

Table 4. Heterogeneity results for the market share of the largest producer on wind and solar PV electricity capacity as a share of total electrical capacity.

	Balanced sample							
	Electrical market policy		Privatization		Feed-in tariffs		Fossil-fuel support	
	Pooled OLS	Fixed effect OLS	Fixed effect OLS	Arellano-Bond GMM	Fixed effect OLS	Arellano-Bond GMM	Fixed effect OLS	Arellano-Bond GMM
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Renewable share $_{t-1}$	0.961***	0.807***	0.960***	0.806***	0.946***	0.807***	0.899***	0.827***
	(0.029)	(0.067)	(0.029)	(0.069)	(0.029)	(0.067)	(0.055)	(0.085)
Market share $_{t-1}$	0.004	-0.005	0.004	-0.004	0.004	0.002	0.021	-0.007
	(0.012)	(0.020)	(0.012)	(0.019)	(0.012)	(0.020)	(0.021)	(0.033)
Regulation_t	-0.621	-0.991	-0.616	-0.933	-0.169	-0.201	-0.228	1.569
	(0.466)	(1.686)	(0.467)	(1.775)	(0.416)	(1.577)	(0.770)	(1.961)
Unbundling_t	-0.314	-0.169	-0.321	-0.200	-0.012	0.218	0.197	0.009
	(0.292)	(0.636)	(0.300)	(0.665)	(0.288)	(0.501)	(0.502)	(0.591)
ESI								
Privatization			0.059	0.415	0.198	0.578	-0.582	-1.503
			(0.347)	(1.078)	(0.357)	(0.977)	(0.608)	(2.372)
Feed-in Tariffs					0.177***	0.172**	0.165**	0.183
					(0.046)	(0.085)	(0.072)	(0.127)
Fossil-fuel Subsidy							-0.022	-0.100
							(0.123)	(0.170)
Observations	289	272	289	272	289	272	187	170
Number of groups		17		17		17		17
Number of IV		116		117		117		82
AR(1) p-value		0.036		0.033		0.033		0.017
AR(2) p-value		0.034		0.152		0.135		0.115
Hansen p-value		1.000		1.000		0.685		1.000
Bias correction	-0.019	-0.014	-0.019	-0.018	-0.015	-0.003	0.076	-0.034
Bootstrap s.e.	[0.021]	[0.044]	[0.022]	[0.043]	[0.021]	[0.043]	[0.069]	[0.069]

Notes: The dependent variable Renewable share$_t$ is the percentage share of the installed renewable (solar and wind) electricity capacity (MW) as a share of the total installed electrical capacity in country i in period t. The table shows heterogeneity results when including additional control variables. Country fixed-effects regressions are shown in columns 1, 3, 5, and 7. In columns 2, 4, 6 and 8, the model is estimated using difference GMM following Arrelano and Bond (1991), which use instrumental variables to address the endogeneity of the lagged dependent variable and the Market share $_{t-1}$. For instruments, we use 2nd to 4th lagged values of the dependent variable and market share. All models include a full set of year dummies. Robust standard errors are shown in parenthesis. The models are estimated on the reduced balanced sample of 21 countries for the years 2003 to 2022 (which excludes Austria, Bulgaria, Serbia, Malta, Luxembourg, Romania, Netherlands from EU-27). Following the split sample algorithm in Chen, Chernozhukov, and Fernándes-Val (2019) biased corrected estimate of Markets share $_{t-1}$ are given for all models, with bootstrapped standard errors shown in brackets. For the Arellano-Bond estimates, we report the number of internal instruments, p-values for the Hansen overidentification test, along with the AR(2) test for no serial correlation. Significance level corresponds to * p<0.10 ** p<0.05 *** p<0.01.

6.3. Robustness

To assess whether the main results are driven by specific design choices, several robustness tests are conducted. Specifically, the analysis considers (i) an alternative outcome variable, (ii) alternative measures of electricity market concentration and competition, and (iii) competition in the retail electricity market rather than in electricity production. These results are presented in the Appendix in Tables A1–A3. The robustness analysis is conducted on the balanced sample. Models (1) to (4) examine wind and solar separately, expressed as a share of total installed electrical capacity, whereas columns (5) and (6) report results using the log level of combined installed wind and solar capacity (i.e. not expressed as a share).[13]

For the solar share, the FE model in column (1) shows a positive and significant result at the 10 percent level for market share, which is not reflected in the model for wind only. It suggests that solar and wind can be affected differently by the level of concentration. However, once the more reliable Arellano-Bond model—using instruments to address endogeneity—is applied, no significant result remains. Looking at the debiased estimates with bootstrapped standard errors, they also show no significant findings for market share. This is also the case when the renewable outcomes are measured in log-levels. The absence of an effect when looking at alternative outcomes thus strengthens the same results found in the main analysis in Table 3.

Next, turning to the market share variable, Table A2 presents the results from using several alternative measures, namely: a dummy for whether there are more than five producers of electricity; the log of total number of electricity producers; the share of main producers as a share of the total number of producers; and the type of market structure present in a country at a given year.

Again, no convincing evidence is found that absence of results presented in the main results table depends on the specific choice of how the concentration variables are specified. The common result in all these models is the highly significant lag of the dependent variable, which captures the stock of all previously installed electrical capacity. Considering this stock, however, any change in market concentration has no discernable impact on additions to the capacity of renewable electricity–be it additional wind parks or solar panels. Lastly, the robustness analysis considers market concentration on the retail side of the electricity market, with results using a dummy variable for countries with more than 5 electricity retailers

[13] For brevity, robustness results do not include estimates for control variables, even though the same set of baseline controls that were included in the main analysis are included in these models.

in column (1) and (2) and a dummy that encodes full retail competition on the electricity market as coded by the World Bank. Neither of these results give any indication that there would be a significant link between competition on the retail side of the electricity market and the development of renewable energy.

7. Discussion

These results indicate that renewable deployment is path dependent, shaped primarily by historical investment rather than short-term changes in market structure. Over the study period, policy frameworks have shifted more substantially than market concentration. Market concentration seems to explain little of the variation in renewable deployment for EU-27 countries during the first two decades since 2000. A finding that holds even after employing bias-corrected estimators, which substantially widens the confidence intervals and reinforces the absence of a causal relationship. Overall, variation in wind and solar deployment appears driven more by regulatory stability and infrastructure than by market structure. The results are unexpected.

The theoretical model developed for this paper posits that how electricity market concentration, through its effect on prices and entry conditions, could inhibit the long-run deployment of wind and solar power. The mechanism, adapted from Acemoglu et al. (2017), links incumbent market power to suppressed entry incentives for renewables. Empirically, the current paper found little consistent support for this channel. While the mechanism may operate in specific markets, it does not appear to hold systematically across EU-countries. Other structural or institutional drivers likely dominate at the EU level. Diagnostics support the reliability of the estimates. Attention can therefore turn to why the theoretical link fails to materialize empirically.

The effect of market concentration may also be muted by strong public policies supporting renewable deployment. Policies such as FITs, priority dispatch, and national targets can offset barriers associated with concentrated market structures. Previous research has shown that such interventions play a decisive role in shaping investment patterns, often overpowering underlying market signals (Beck and Martinot, 2004; del Río and Mir-Artigues, 2014). Many large energy firms are publicly owned and may not act as strict profit maximizers. Political mandates—such as maintaining low prices or meeting renewable targets—may shape the behavior of public utilities.

The findings also raise questions about timing, lag selection, and measurement precision. The one-year lag used for market share may be too short to capture longer investment cycles associated with wind and solar projects. Furthermore, market share is an imperfect proxy for competitive behavior; it does not account for entry barriers, informal market influence, or the complexity of grid access dynamics (Ritz, 2008; Twomey and Neuhoff, 2010). Although the analysis finds no strong causal link, it would be premature to conclude that market structure had no effect. Market power may interact with regulatory frameworks, ownership, and infrastructure in ways not reflected by simple concentration metrics. Structural reforms, including EU accession and liberalization packages, may have reduced the influence of market concentration over time. Market concentration may have had stronger effects early in the period, before regulatory reforms took hold. These are all important questions we leave for future research.

8. Conclusions and future research

This study investigated whether market concentration among electricity producers influences the deployment of wind and solar capacity across EU member states. A stylized Cournot model predicts that dominant firms, facing cost asymmetries and strategic incentives, may inhibit renewable entry to preserve price levels. Yet across all empirical specifications, no consistent relationship is found between market share and renewable deployment. The results suggest that, in the current institutional context, structural concentration alone is not a binding constraint.

Path dependence, driven by historical investment levels and stable policy frameworks, appears to shape deployment outcomes more than market concentration. This finding aligns with a broader literature emphasizing regulatory certainty, grid access, and support schemes as critical to renewable investment. Although liberalization and unbundling remain important institutional reforms, they are not sufficient to explain variation in solar and wind adoption without accounting for policy design and infrastructural readiness.

The absence of a significant relationship between market concentration and renewable deployment challenges the predictive power of canonical oligopoly theory when applied to mixed-technology electricity markets. In the stylized Cournot setting, market power distorts investment signals through strategic output withholding and price manipulation. Yet such dynamics presume a clear separation between incumbent and entrant, a condition that may not hold in EU electricity systems where incumbents increasingly hold heterogeneous portfolios spanning thermal and renewable assets (Steffen et al., 2022). When firms internalize both sides of the merit order effect, the incentive to suppress entry is diluted.

Moreover, the regulatory environment introduces non-market constraints on firm behavior, including mandated priority dispatch, carbon pricing, and binding renewable targets. These mechanisms alter the payoff structure underpinning exclusionary strategies, effectively shifting the equilibrium from one of strategic deterrence to one of constrained optimization under multi-objective regulation. In this setting, market share alone becomes a weak proxy for strategic conduct, and classical comparative statics may fail to capture the institutional mediation of firm behavior.

From a policy perspective, these findings offer two key implications. First, structural market concentration alone does not appear to be a binding constraint on renewable deployment – in the European context. Efforts to liberalize and unbundle electricity markets, while important, may not be sufficient to accelerate clean energy transitions unless they are paired with targeted support policies and investment in enabling infrastructure. Second, the results underscore, based on much previous literature on energy policy, the importance of long-term regulatory certainty, stable support schemes, and access to the grid, which may matter more than formal market structure in influencing renewable investment decisions.

Future research should investigate heterogeneous effects across technologies, ownership structures, and institutional settings. Firm-level data on generation portfolios and contractual arrangements could help unpack how incumbents integrate renewables and whether strategic behavior persists in more subtle forms. As the EU continues to reform its electricity markets and pursue decarbonization, understanding the structural and strategic barriers to renewable deployment remains a critical policy challenge.

Declaration of generative AI and AI-assisted technologies in the manuscript preparation process

During the preparation of this work the author(s) used ChatGPT in order to improve the language. After using this tool/service, the author(s) reviewed and edited the content as needed and take(s) full responsibility for the content of the published article.

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Appendix A: Robustness

Table A1. Robustness results for market share of the largest producer on alternative outcomes

	Balanced sample					
	Solar share		Wind share		log installed capacity solar and wind	
	FE OLS	AB GMM	FE OLS	AB GMM	FE OLS	AB GMM
	(1)	(2)	(3)	(4)	(5)	(6)
Share solar $_{t-1}$	1.038***	0.866***				
	(0.024)	(0.083)				
Share wind $_{t-1}$			1.003***	0.852***		
			(0.026)	(0.066)		
log Initial capacity $_{t-1}$ (log)					0.780***	0.743***
					(0.050)	(0.042)
largest producer market share $_{t-1}$	0.011*	0.023	0.000	-0.006	0.005	0.006
	(0.007)	(0.030)	(0.007)	(0.023)	(0.003)	(0.005)
Observations	399	378	399	378	390	369
Number of groups		21		21		21
Number of IV		126		126		126
AR(1) p-value		0.087		0.032		0.021
AR(2) p-value		0.966		0.041		0.122
Hansen p-value		1.000		1.000		1.000
Bias correction	0.007	0.041	0.004	-0.018	0.003	0.011
Bootstrap s.e.	[0.023]	[0.059]	[0.018]	[0.045]	[0.004]	[0.011]

Notes: The table shows results for alternative outcomes. Country fixed-effects regressions are shown in columns 1, 3 and 5. In column 2, 4 and 6 the model is estimated using difference GMM following Arrelano and Bond (1991), which use instrumental variables to address the endogeneity of the lagged dependent variable and the Market share $_{t-1}$. For instruments, we use 2nd to 4th lagged values of the dependent variable and market share. All models include a full set of year dummies and the basic controls included in the main model (not shown in the table).Robust standard errors are shown in parenthesis. The models are estimated on the reduced balanced sample of 21 countries for the years 2003 to 2022 (which excludes Austria, Bulgaria, Serbia, Malta, Luxembourg, Romania, Netherlands from EU-27). Following the split sample algorithm in Chen, Chernozhukov, and Fernándes-Val (2019) biased corrected estimate of Markets share $_{t-1}$ are given for all models, with bootstrapped standard errors shown in brackets. For the Arellano-Bond estimates, we report the number of internal instruments, p-values for the Hansen overidentification test, along with the AR(2) test for no serial correlation. Significance level corresponds to * p<0.10 ** p<0.05 *** p<0.01.

Table A2. Robustness results for alternative measures of concentration on wind and solar PV electricity capacity as a share of total electrical capacity.

	Balanced sample							
	Main producers > 5		Number of producers		Share of main producers		Type of electrical market	
	FE OLS	AB GMM	FE OLS	AB GMM	FE OLS	AB GMM	FE OLS	AB GMM
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Renewable share $_{t-1}$	0.993***	0.799***	1.005***	0.823***	1.004***	0.814***	0.997***	0.764***
	(0.025)	(0.058)	(0.028)	(0.068)	(0.026)	(0.058)	(0.026)	(0.075)
More than five main produxers $_{t-1}$	-0.365	-0.206						
	(0.259)	(0.415)						
Log number of Producers			0.072	0.122				
			(0.138)	(0.375)				
Share of main Producers					-0.668	-0.033		
					(0.429)	(0.569)		
Single buyer model							0.257	-0.324
							(0.407)	(0.402)

Wholesale Competition							-0.257 (0.535)	-0.303 (0.337)
Observations	399	378	378	356	378	356	399	378
Number of groups		21		21		21		21
Number of IV		123		126		126		116
AR(1) p-value		0.060		0.050		0.047		0.114
AR(2) p-value		0.367		0.536		0.736		0.568
Hansen p-value		1.000		1.000		1.000		1.000
Bias correction	-0.670	-0.539	-0.136	0.054	-0.509	0.361		
Bootstrap s.e.	[0.495]	[1.014]	[0.416]	[1.167]	[1.141]	[2.166]		

Notes: The table shows results for alternative measure of electrical market concentration. Country fixed-effects regressions are shown in columns 1, 3, 5 and 7. In column 2, 4, 6 and 8 the model is estimated using difference GMM following Arrelano and Bond (1991), which use instrumental variables to address the endogeneity of the lagged dependent variable and the Market share $_{t-1}$. For instruments, we use 2nd to 4th lagged values of the dependent variable and market share. All models include a full set of year dummies. Robust standard errors are shown in parenthesis. The models are estimated on the reduced balanced sample of 21 countries for the years 2003 to 2022 (which excludes Austria, Bulgaria, Serbia, Malta, Luxembourg, Romania, Netherlands from EU-27). Following the split sample algorithm in Chen, Chernozhukov, and Fernándes-Val (2019) biased corrected estimate of Markets share $_{t-1}$ are given for models 1 to 6, with bootstrapped standard errors shown in brackets. For the Arellano-Bond estimates, we report the number of internal instruments, p-values for the Hansen overidentification test, along with the AR(2) test for no serial correlation. Significance level corresponds to * p<0.10 ** p<0.05 *** p<0.01.

Table A3. Heterogeneity results for the retail concentration on wind and solar PV electricity capacity as a share of total electrical capacity.

	Balanced sample			
	Main retailers >5		Retail competition	
	FE OLS	AB GMM	FE OLS	AB GMM
	(1)	(2)	(3)	(4)
Renewable share $_{t-1}$	0.994*** (0.025)	0.807*** (0.072)	0.993*** (0.025)	0.794*** (0.074)
Market share $_{t-1}$	-0.259 (0.291)	-0.427 (0.539)		
Regulation_t			0.349 (0.331)	-0.393 (0.446)
Observations	399	378	399	378
Number of groups		21		21
Number of IV		122		109
AR(1) p-value		0.026		0.083
AR(2) p-value		0.255		0.515
Hansen p-value		1.000		1.000
Bias correction	0.219	-0.572	0.197	-0.913
Bootstrap s.e.	[0.485]	[0.948]	[0.582]	[1.487]

Notes: The table shows results for alternative measure of electrical market concentration on the retail side. Country fixed-effects regressions are shown in columns 1 and 3. In column 2 and 4 the model is estimated using difference GMM following Arrelano and Bond (1991), which use instrumental variables to address the endogeneity of the lagged dependent variable and the Market share $_{t-1}$. For instruments, we use 2nd to 4th lagged values of the dependent variable and market share. All models include a full set of year dummies. Robust standard errors are shown in parenthesis. The models are estimated on the reduced balanced sample of 21 countries for the years 2003 to 2022 (which excludes Austria, Bulgaria, Serbia, Malta, Luxembourg, Romania, Netherlands from EU-27). Following the split sample algorithm in Chen, Chernozhukov, and Fernándes-Val (2019) biased corrected estimate of Markets share $_{t-1}$ are given for all models, with bootstrapped standard errors shown in brackets. For the Arellano-Bond estimates, we report the number of internal instruments, p-values for the Hansen overidentification test, along with the AR(2) test for no serial correlation. Significance level corresponds to * p<0.10 ** p<0.05 *** p<0.01.

Appendix B – short run equilibrium

In the short run, the number of renewable producers is fixed at *m* and renewable producers simply dispatch their fixed renewable capacity $\bar{r}$ at equilibrium price $P^*(m)$. Renewable producers can thus profit from the lack of renewable competition and earn positive profits under certain circumstances, contrary to the long run where renewable producers always earn zero profits due to the equilibrium condition $P^*(m) = \frac{F}{\bar{r}}$.

Short run equilibrium is characterized by the following set of equations

$$P^*(m) = \frac{1}{n+1}(a + cn - bm\bar{r}) \quad (8)$$

$$Q^*(m) = \frac{1}{b(n+1)}(n(a-c) + bm\bar{r}) \quad (9)$$

$$nt^*(m) = \frac{n}{b(n+1)}(a - c - bm\bar{r}) \quad (10)$$

$$S^*_{Renew}(m) = \frac{m\bar{r}}{Q^*(m)} \quad (11)$$

Under the model assumptions, an increase in the number of exogenously given renewable producers m (each contributing a fixed $\bar{r}$) in the short run crowds out the per-firm thermal production $t^*(m)$, increases total supply $Q^*(m)$ and decreases market prices $P^*(m)$. It also increases the renewable share $S^*_{Renew}(m)$, which is driven both by the immediate increase in the number of entrants $m\bar{r}$ and by crowding out $t^*(m)$. This is similar to long run equilibrium, where $t^*(m^*)$, $Q*(m^*)$ and $P^*(m^*)$ are affected indirectly through m^*.

Contrary to the long run, the number of thermal competitors *n* and the marginal cost of thermal *c* affect $Q^*(m)$ and $P^*(m)$ directly. Increases in *n* expand thermal output $t^*(m)$, thus increasing $Q*(m)$ and decreasing $P^*(m)$ and $S^*_{Renew}(m)$. On the other hand, increases in *c* contracts thermal output $t^*(m)$, thus decreasing $Q^*(m)$ and increasing $P^*(m)$ and $S^*_{Renew}(m)$. In either case, the exogenous nature of m makes it unable to offset the effect caused by *n* and *c* that causes $t^*(m)$ to react – as it did in the long run. Short run equilibrium quantity and prices shift and the renewable share only changes due to changes in thermal output, not due to changes in thermal output *and* an opposite change in renewable entry.

Declaration of interests

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

☒The authors declare the following financial interests/personal relationships which may be considered as potential competing interests:

Jonas Grafstrom reports financial support was provided by Swedish Competition Authority. If there are other authors, they declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.