

Locational Investment Decisions under Zonal Pricing: Evidence from the European Union

(Working Paper - Please do not share)

^aEmmanuel Berrebi-Toledano*, ^aDiego Cebreros, ^bDavid Jambois,
^aYannick Perez

^aLGI CentraleSupélec, Université Paris-Saclay, 3 rue Joliot Curie, 91192 Gif-sur-Yvette, France

^bTotalEnergies OneTech,7-9 Boulevard Thomas Gobert, 91120 Palaiseau, France

April 3, 2026

Abstract

What drives locational generation investment decisions in zonal electricity markets? This study examines renewable energy investors' location choices across 21 EU countries (2014-2019) for investments exceeding 1 MW, using a logit model with country fixed effects. The analysis operationalizes multiple locational signals—resource availability, land costs, network capacity, administrative constraints, and social acceptance. Key findings first confirm natural resource availability as the strongest investment determinant in the absence of designed locational mechanisms. Then it counterintuitively shows that land and node with available capacity negatively impact investment location meaning that investors tend to select already crowded nodes potentially increasing the likelihood of congestion. Technology-specific analysis reveals land costs matter more for solar, while network and social acceptance constraints weigh more on wind. Despite country-level variation, the ranking of determinants remains consistent. The study reveals investor behavior complexity in zonal markets and suggests new empirical evidence with potential implications for designing compensation mechanisms and site allocation procedures.

Keywords: Locational signals; Network coordination; Zonal markets; European Union; Locational subsidies; Renewable investment.

1 Introduction

Although electricity systems investments in networks and generation assets need to be coordinated to connect production with consumption sites, investment decisions in these assets are made independently by different actors in liberalized markets: network expansion is typically undertaken by

*Corresponding author email: emmanuel.berrebi@centralesupelec.fr

a single regulated entity, while generation investments are carried out by multiple private actors. This separation makes coordination between generation siting decisions and network expansion a key determinant of system efficiency. Bad coordination could result in additional network investments in infrastructure or increased congestion, which have been shown to decrease operational efficiency and increase investment needs (Chao & Wilson, 2020; Jenabi et al., 2013; Kemfert et al., 2016; Rious, 2007; Rious et al., 2011; Tohidi et al., 2017).

Theory in this matter suggests that the first-best solution to provide optimal locational signals is to have granular energy prices that reflect the congestion costs, also known as Locational Marginal Pricing (LMP), which incentivize investors to locate generation where prices are high (Hogan, 1992; Scheppe et al., 1988). However, in regions such as the European Union (EU), energy prices are zonal; i.e., prices are uniform within a region and do not reflect congestion costs. In this case, LMP has been considered a suboptimal solution for political and economic reasons (European Commission, 2023; Joskow, 2021; Pollitt, 2023). Under this setup, the alternative solution is to improve coordination in particular by locational network charges and subsidies, which are deemed to act as locational signals to attract generation investments into specific locations (Eicke et al., 2020; Hadush et al., 2011). Notably, Thomassen and Fuhrmanek (2025) have estimated, through simulation, that in the EU, locational signals could reduce system costs by up to 29 billion euros annually through 2040, solely by lowering network congestion and reducing the need for grid expansion.

However, to the best of our knowledge, there is no comprehensive empirical study examining the location of power plants from an investor’s perspective in zonal markets. Existing contributions fall into two main strands. They either adopt an investor perspective while relying on simulation-based approaches, which necessarily entail simplifying assumptions about investors’ decision-making processes (Chao & Wilson, 2020; Grimm et al., 2021; Kemfert et al., 2016; Tohidi et al., 2017). Or, if they are empirical studies, they tend to focus on specific aspects of locational decisions without explicitly incorporating the investor’s decision-making perspective (Rediske et al., 2021; Rediske et al., 2018).

This gap may have important implications for the design of future coordination mechanisms. In particular, if interactions exist between deliberately designed locational signals and other relevant factors that are not fully accounted for in investors’ decision-making, policy interventions may fail to achieve their intended outcomes. Notably, in the EU, in a 2024 mission letter to the Commission for Energy and Housing, the European Commission President Ursula von der Leyen asks the Energy Commissioner, Dan Jorgensen, to implement measures to “improve locational price signals” in Europe to incentivize private generation investments (von der Leyen, 2024). Within this context, such a gap in our knowledge might be problematic, as even in the theoretically efficient market design of LMP, empirical evidence suggests that investors do not always respond to the main locational signals. Indeed, D. P. Brown et al. (2020) shows that investment does not concentrate

in areas with higher LMP. Against this background, improving the efficiency of electricity systems through better coordination of locational investment requires addressing the following research question: *What determines the location of generation assets in zonal electricity markets?*

To address this research question, we first propose a model of the investment decision process that explicitly integrates power plant site selection as a core step. This framework clarifies the role of location selection within the broader investment process. Specifically, we conceptualize the investor’s project evaluation as a two-stage problem: the location analysis is treated as a discrete-choice problem, in which investors screen and select potential locations to which the investment analysis is subsequently applied until a location satisfies the investment criteria. To model the process of location selection, we draw on the concept of locational signals, as introduced by Hadush et al. (2011) and further expanded by Eicke et al. (2020), to identify the set of potential determinants that might influence investors’ spatial choices. Among the determinants that we analyze are: the availability of natural resources, permitting and construction costs, land costs, network availability, and social acceptance, among others. We assess the average marginal effect that each of these locational signals have on locational siting decisions across the EU; through a logit model that we regress on a unique dataset that we constructed on observed renewable investment decisions higher than 1 MW across 21 EU countries over the period 2014–2019.

Our results, suggests that the availability of renewable resources is the most powerful locational signal to attract renewable investment. Paradoxically, a greater availability of nodes or lands for new power plant have a negative effect on investment decisions, since these lands are considered as too isolated from the grid or other generation assets and their remoteness can trigger substantial additional infrastructure costs. It means that investors are naturally driven to location where other investors are, which could increase the likelihood of congestion. Intuitions are confirmed when we deep in technology specific results. Indeed, land cost is a stronger determinant for solar than wind as it accounts for a more important part in the relative smaller solar CAPEX. Nevertheless, network and administrative constraints and social acceptance proxy have a stronger impact for wind, as a wind project in term of size and capacity may impact more a territory. Finally, while cross-country comparisons show that geographic and policy contexts create wide variation in results, the key determinants of investment remain identical and follow the same ranking.

This paper provide three main contributions. This study advances the literature on locational signals’ efficiency in two ways. First, we extend the analysis of locational signals made in Eicke et al. (2020) identifying multiple determinants in addition to resource availability such as grid node capacity, population density, or land costs that simultaneously influence investor siting decisions in zonal markets, revealing that locational signals are influenced by non-policy determinants. Second, we move beyond measuring signal strength alone by quantifying the actual behavioral impact of each determinant through Average Marginal Effects, enabling direct comparison of how different signals influence investment location choice. Third, the study demonstrates that interactions be-

tween undesigned and designed signals must be accounted for when network operators implement new locational mechanisms to prevent policy ineffectiveness. These findings could have direct implications for regulators and system operators seeking to design efficient compensation mechanisms and site allocation procedures.

The paper is structured as follows. Section 2 provides a literature review on locational signals for investment. Section 3 details the main challenges for the EU electricity systems. Section 4 presents our dataset. Section 5 develops the analytical framework to assess the performance of locational signals. In Section 6, we present the regression results. In Section 7, we discuss our contributions, and finally the Section 8 concludes the study.

2 Locational signals

Locational signals are indicators that inform investors about the economic advantages of investing in a specific location in order to connect generation assets to the electricity network. These signals can either attract investment by indicating locations in the electricity network where new generation capacity is likely to outperform investments made elsewhere, or they can signal potential risks, discouraging investment in locations where network constraints or other factors may reduce the profitability of generation assets (Eicke et al., 2020; Hadush et al., 2011).

Based on this definition, we classify locational signals into two broad categories: those that are deliberately designed by regulators or network operators to provide incentives to investors, and those that may influence investment decisions unintentionally, i.e., not as the result of a deliberate policy or design choice.

2.1 Purposely designed signals

Market-price granularity. Prices can be zonal, meaning that all energy transactions within a given geographic zone face the same price for a given market clearing, or nodal (also known as Locational Marginal Pricing, LMP), where prices differ across nodes. Nodal pricing creates stronger locational incentives for generation investors, as producers located in congested areas may receive higher prices for their electricity. By contrast, when prices are determined at the zonal level, this determinant provides weaker locational incentives.

Locational support schemes. Locational support schemes are subsidy mechanisms designed to encourage investments in specific locations. Several countries have implemented such policies to influence the spatial distribution of renewable generation. For example, Germany introduced locational differentiation in renewable support schemes (Haas et al., 2011). Mexico implemented locational auction mechanisms that apply premiums or penalties depending on plant location in order to reduce network imbalances and improve the geographic distribution of renewable gener-

ation (del Río, 2017). At smaller scales, regional support policies have also played an important role in the deployment of photovoltaic systems in Japan (Zhang et al., 2011).

Locational network charges. Network charges that vary by location can also act as locational signals. They have been proposed as a mechanism to direct generation investments toward less congested areas of the grid (Gammons et al., 2011; Hadush et al., 2011; Olmos & Pérez-Arriaga, 2009). Network costs may arise from connection charges, transmission usage charges, or transmission losses. Connection charges can follow either a shallow or deep cost approach. Under shallow charging, new generators pay only for their direct connection to the network. Under deep charging, generators must also cover the costs of broader network reinforcements required to accommodate their connection. The shallow approach facilitates market entry, while the deep approach better reflects network constraints and system stability considerations (Brunekreeft et al., 2005). Network costs may also depend on the distance that electricity must travel through the transmission network to reach demand centers or contractual buyers. The tariff design differs between countries, 27 tariffs zone in Great Britain through the Transmission Network Use of System charges, or simply two zones in Denmark since 2023. In addition, in some systems such as in Sweden and Norway, generators are charged for transmission losses, which increase with the distance between generation and demand centers (Hadush et al., 2011). These losses reduce the effective revenue from electricity sales. Some electricity systems incorporate this effect through Transmission Loss Adjustment Factors (TLAF), such as in Ireland (EirGrid & System Operator for Northern Ireland (SONI), 2012).

We now need to define other key elements beyond policy or regulatory design that that serve as key signals for investment decisions.

2.2 Non-designed signals

Access to natural resources. The importance of natural resources as a locational signal depends on the generation technology. For renewable technologies such as wind and solar, resource availability (e.g., wind speed or solar irradiation) strongly influences the productivity and profitability of projects, since electricity generation depends directly on these resources. For other technologies, different resources may be required; for example, nuclear power plants depend on access to large volumes of water for cooling.

Geography, land and building costs. Local geographic conditions can significantly influence the land and the construction costs. Factors such as distance to roads or cities, terrain slope, land orientation, and soil roughness can affect the feasibility and cost of building energy infrastructure (Amir & Nazari, 2021; Ghasempour et al., 2019; Rediske et al., 2021; Saraswat et al., 2021).

Social acceptance. Social acceptance refers to the likelihood that a project will be supported by local communities. Resistance to infrastructure projects, often referred to as the “Not In My Backyard” (NIMBY) effect, can significantly affect the feasibility of energy investments. Local public support therefore constitutes a positive locational signal, as it indicates that the likelihood of successful project development is higher in a given location (Carley et al., 2020; Jarvis, 2025).

Permitting process. The permitting process influences both the administrative costs and the time required to develop a project. Permitting costs and delays may depend on spatial planning policies (Lehmann & Tafarte, 2024; Reutter et al., 2024), as well as on the complexity and length of the permitting process (Meier & Lehmann, 2022). More complex administrative procedures can therefore weaken locational signals by increasing development risks and costs.

Network congestion. If congestion management rules are poorly designed, they may create opportunities for strategic behavior. In particular, generators may locate in areas where they can profit from congestion rents by exploiting redispatch mechanisms or other market imperfections (Martin et al., 2022; Pozzi et al., 2025).

In addition to these determinants explicitly discussed in the literature, other factors may also influence locational decisions but have received less explicit attention or may not be relevant for renewables. These include access to key infrastructure, which is particular for fossil-fuel generation technologies relying on transportation and storage infrastructure (pipelines, ports, railways...), and investors geographic diversification, whereby investors’ location choices depend on the of their existing generation assets. In this case, the effective locational signal perceived by an investor may depend on how a new project complements its existing investment portfolio.

2.3 The role of locational signals in investment decisions

Most of the literature on investment in utilities focuses primarily on non-locational factors, such as expected energy prices, technology choices, financing conditions, and regulatory risks. These dimensions are typically analyzed using discounted cash flow comparisons across alternative investment options, with decisions driven by the relative monetary value of each alternative (Johnson, 1994; Nabradi & Szöllösi, 2007). In this context of lumpy and irreversible investment, this financial analysis can be completed and integrated into a broader methodological approach called real options analysis (ROA) (Lee, 2011; Myers, 1977). The ROA explores managerial flexibility, through different option strategies such as deferring, abandoning or switching investments (Kim et al., 2017; Lee, 2011). Yet, very few studies integrate explicitly the locational choice for investment, and to the best of our knowledge it is absent in the field of energy economics. When location is discussed in ROA, it often emphasizes a limited set of locational signals such as exchange rate while ignoring other locational factors. It’s the case for two studies in the manufacturing sector (Huchzermeier

& Cohen, 1996; Kogut & Kulatilaka, 1994). In addition, the locational aspect is made at country level and does not study the granular aspect of site selection.

A second approach relies on analyzing the investment decision using non-quantitative measures, primarily through a multi-dimensional decision framework. Such an approach is in line with the seminal work of Hadush et al. (2011), which has suggested that locational signals can be conveyed through market and non-market mechanisms, and has been frequently used to explain the locational decisions. From this perspective, it assumes locational decisions depend on several complex factors, and that only using expected monetary values may be impractical (Shao et al., 2020). Under this approach, investors consider multiple locational signals simultaneously and must prioritize them according to their relative importance. However, the literature shows that these applications primarily focus on geographic and construction-related factors, such as terrain characteristics or proximity to infrastructure (Rediske et al., 2021; Rediske et al., 2018).

2.4 Prior empirical work on locational signals

Only one paper has studied how localized signals influence the siting decisions of renewable energy investments. In their paper, D. P. Brown et al. (2020) investigate whether price signals from Texas’s wholesale electricity market are strong and reliable enough to steer investment. Their study shows that for renewable technologies (Wind and solar), there is no significant relationship between expected LMPs and location. They also show that factors other than LMP intervene in investment location decisions, undermining their theoretical first-best role as a locational driver.

A strand of literature, which has had close relationships on locational signals have been those who have examined bidding zone configurations through the lens of market splitting — the division of large zones into smaller ones to better reflect physical constraints or topology control. However, this strand explores the regulator or TSO response to a congestion situation and presents these tools as remedy actions. This body of work ignores zonal locational decisions which are fundamental to understand how to avoid that investment decisions within a zone create the need for market-splitting or the use of topology control in the first place. Therefore, there is an important gap in our knowledge on how locational signals influence locational decisions in zonal-markets; among them, those in the EU.

3 Electricity systems in the EU

3.1 Design and challenges

A main feature of EU electricity systems; is that in contrast to the case of Texas, as shown by D. P. Brown et al. (2020), where electricity prices change by node; EU wholesale markets are zonal; which assumes that within a zone there are no congestions; and that a single price is set. Furthermore,

these markets are connected by HVDC (high-voltage direct current) links and managed through five different synchronous area - continental Europe, Nordic, Great Britain, Ireland, and the Baltic states. All the zones are operating at the same 50 Hz AC frequency internally.

A main challenge of the zonal design has been to accommodate the growth on generation capacity; which grew from 790 GW in 2010 to 1.110 GW in 2023, driven mainly by the rapid expansion of renewables: wind capacity nearly tripled from 79 GW to 219 GW, while solar surged from 30 GW to 247 GW. Over the same period, combustible fuel capacity declined from 415 GW to 381 GW (Eurostat, 2025). Among the countries that perhaps is the most relevant example, of facing those challenges is Germany; where current locational signals have created important network congestions because of the concentration of wind production units in the North Sea and points of demand in the south. Indeed, in 2023, Germany spent €2.35 billion redispatching 24.6 TWh of electricity, nearly ten times its 2020 expenditure, and alone accounted for approximately 55% of total EU congestion costs that year (ACER, 2024).

3.2 Policy Instruments to Mitigate Coordination Failures via Locational Signals

To improve the generation of better sitting, through locational signals they are two main types of instruments that have been used at the EU level: subsidy/malus schemes and network charges.

3.2.1 Locational network charges

According to ENTSO-E Economic Framework Working Group (2025), three European Member States have adopted a locational network charge system to deal with their spatially constraint territory: Sweden, Denmark and Ireland.

Loss factors Since 1996, the Swedish locational network mechanism is based on the latitude of the connection point of the generator in the grid. The more, the injection of energy in the network is done in the north of the country, characterized by a weak demand, the more a locational cost would be applied to the power plant.

Transmission charges For the Irish Island, the two States have adopted a nodal network charge mechanism for generation based on capacity. For each node location, a locational cost is added accounting for up to 30% of transmission investments recovery. The more an investment is far from the core network, the more the cost is growing (EirGrid & SONI, 2025). More recently, in 2023, Denmark has adopted a two-zone system with a different cost per MW per year depending on the power plant location between the production surplus areas and the areas dominated by consumption (Energinet, 2023).

3.2.2 Implemented locational subsidy mechanism

Presented by Eicke et al. (2020), Germany has adopted a locational mechanism to support wind onshore development. Based on the local forecast performance of the wind turbine compared to a reference case (Gütefaktor), a correction factor is applied to (Korrekturfaktor). A poor site (low Gütefaktor, below 100%) receives a higher strike price to remain economically viable; an excellent site (above 100%) receives a lower strike price because the resource is more abundant. As the correction factor is determined according to the location of the wind turbine, this mechanism can be seen as a locational signal. It is completed by two other policies: the first is a financial penalty applied to renewable projects connected to distribution grids where local renewable feed-in already exceeds local demand; the second is a quantity cap on wind energy auctions in the most grid-constrained regions of Germany.

Against this background, one can observe that in the EU the use of policy instruments to provide locational signals is at its early stages of implementation. However, their ambition has been suggested as important; for example, Thomassen and Fuhrmanek (2025) have estimated, through simulation, that in the EU, locational signals could reduce system costs by up to 29 billion euros annually through 2040. However, there is no comprehensive empirical study examining locational signals within bidding zones. Therefore, if interactions exist between the policy-designed locational signals and other relevant factors that are not fully accounted for in investors' decision-making, policy interventions may fail to achieve their intended outcomes. Therefore, in what follows, we provide an empirical investigation of the impact of locational signals on investors' decisions in the EU.

4 Data

The main dataset is derived from the inputs used by the PYPSA-EUR model (T. Brown et al., 2018), an optimization model of the European electricity system that has been extensively applied in academic research. In particular, we rely on two inputs. First, we use the power plant matching meta-database, which is regularly updated and integrates data from multiple sources, including the Global Energy Observatory, the ENTSO-E Transparency Platform, Open Power System Data, and the Global Power Plant Database. To have consistency with the empirical work conducted by D. P. Brown et al. (2020) we filter within this dataset all the generation units with nameplate capacities below 1 MW. Second, we also use the network-database of the PYPSA-EUR model, which compiles topological information from sources such as GridKit and OpenStreetMap, and that allows us to identify the location of each bus and its technical characteristics.

In addition, we use the CORINE Land Cover database (European Environment Agency (EEA), 2018) to characterize land use and land cover, which are essential for assessing the geographical distribution and availability of land. This is a harmonized land cover dataset covering the EU

member states at a spatial resolution of 100 meters (hectare-level mapping units). The dataset provides information on the shares of land cover types within each area, including artificial surfaces, agricultural land, forests, shrublands, bare land, wetlands, and water bodies (expressed as percentages of total land area).

Furthermore, we use the EU NUTS database (Eurostat, 2021), which provides harmonized shape-files of administrative units (e.g., municipalities, provinces, and regions) across the EU. These spatial units are defined in terms of geographic boundaries (km^2), allowing us to assign nodes and generation assets to administrative areas and compute land-use indicators.

Additionally, we use the ERA5 reanalysis dataset (Copernicus Climate Change Service (C3S), 2017), which combines historical observations with physical weather models to provide a consistent reconstruction of past weather conditions. From this dataset, we extract key meteorological variables—such as wind speeds at 100 meters (m/s), surface solar irradiance (W/m^2 , aggregated to $\text{kWh/m}^2/\text{year}$), and temperature ($^\circ\text{C}$)—which are used to estimate renewable generation potential and demand patterns.

Finally, we use Eurostat data on agricultural land prices and rents (Eurostat, 2022), which serve as a proxy for land costs. These data are reported in euros per hectare (EUR/ha) and, where available, euros per hectare per year (EUR/ha/year) for rental values, at the regional (NUTS 2) level across the European Union.

The database covers the period from 2013 to 2019 for countries within the European Union. This time frame is particularly suitable for our analysis for two main reasons. First, data availability improves significantly after 2015, when EU member states were required to centralize electricity system data on a common platform. Second, restricting the analysis to this period limits the influence of extraordinary events that could bias investment decisions, such as the COVID-19 pandemic, the large-scale financial recovery mechanisms implemented in Europe, and the beginning of the war in Ukraine in 2022, which led to substantial increases in oil and gas prices.

In total the database covers 1 041 GW of installed capacity from electricity generation assets across 21 of 27 EU countries ¹, of which 88.35 GW ($\approx 8.5\%$) were installed during our period of analysis. Furthermore, it comprises of 5 497 nodes, from which 2 911 ($\approx 53\%$) have at least a generation unit connected to it.

5 Empirical strategy

We divide our strategy into two subsections. First, we present the investment framework in which locational decisions are explicitly integrated, thereby motivating the choice of our econometric model and indicators. We then introduce the econometric specification and the selected indicators

¹Cyprus (CY) and Malta (MT) did not have available data. In addition countries with no observed variation in investment activity over the sample period—specifically Latvia (LV), and Slovenia (SI)—are excluded from the estimation.

to test the determinants of the location of generation assets.

5.1 Investment framework

We adopt a simplified four-step investment framework for studying locational investment decision within zonal markets from an investor perspective, as presented in Figure 1. In the first step, investors identify an investment opportunity based on a given technology and a specific zonal energy market. Technology and country choices are either for large investment companies, part of a broader portfolio strategy or for small or specialized company, out of their scope of investment field. In the second step, a set of alternatives within the zone related to this opportunity is evaluated. Each alternative may be assessed by calculating its discounted cash flow to estimate its investment value; several alternatives are considered until a set of minimum profitability and risk requirements is satisfied. In the third step, the project’s financial appraisal is conducted alongside a detailed engineering design. Finally, in the fourth step, the project is constructed and operated until the end of its life-cycle and its decommissioning.

Within this investment framework, the locational analysis—through which investors select where to site their generation investments within a zone—is a discrete decision process in which a set of alternatives is defined and evaluated based on their economic viability. This process contrasts with the common theoretical assumption in LMP-based frameworks, where investors observe nodal energy prices as a single locational signal that allows them to compare the economic attractiveness of different nodes in monetary terms. We suggest that, in practice, this process relies on comparing locations across dimensions that reflect positive locational signals for investors and can enhance project performance in economic evaluations.

Our framework can be compared to other investment processes detailed in the literature where the process does not explicitly consider the iterative action between site selection and economic viability of the project. For instance, in Singh et al. (2022), the authors details a schematic process of project assessment where the site selection comes after the estimation of energy generation. In Raptis and Aretoulis (2024), meteorological data are collected to assess to quality of the selected site for a solar project, assuming the importance of the locational signals in the process.

In the following subsection, we propose a model to assess which indicators investors consider as positive locational signals. Specifically, we evaluate how an improvement in the normalized value of these indicators by zone increases the likelihood that a project is built in a given node.

5.2 Model specification

Let Y_{jht} equal to 1 if node j attracts a new generation plant using technology h in year t , and 0 otherwise. While, our dataset includes entries from diverse generation technologies, including natural gas, solar, wind, biomass, storage, hydro, and coal. Our analysis focus on the entry of solar

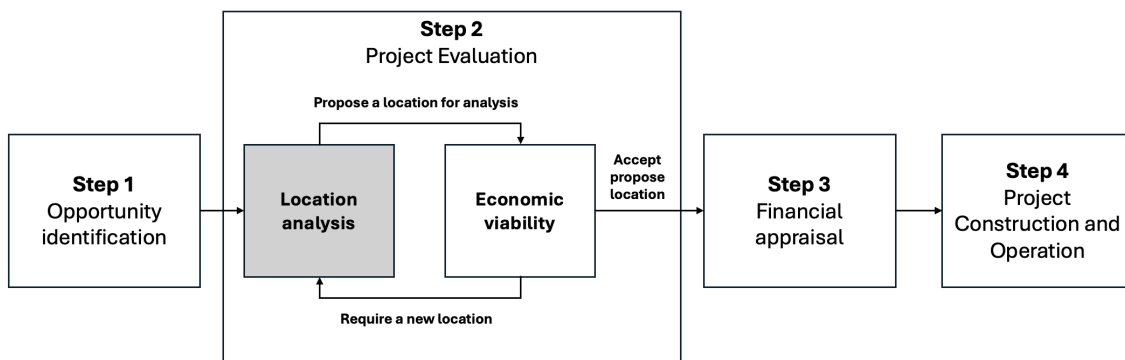


Figure 1: Investment framework with a 2-stage project evaluation.

and onshore-wind generation facilities technologies where the locational signals are ambiguous as they are not infrastructure constrained and the selection choice is more contentious. Indeed, nuclear plants require of specific infrastructure and wind offshore is mainly regulated as they are important economies of scale on aggregating the capacity to export the electricity to main land.

Following the specification model use by D. P. Brown et al. (2020), the probability that an investor invests a technology h at node j in year t investor can be model using using a binary choice with the following logistic specification:

$$P(Y_{jht} = 1) = \frac{\exp(U_{jht})}{1 + \exp(U_{jht})}. \quad (1)$$

We specify the investor utility U_{jht} as a function of a set of locational signals and fixed effects:

$$U_{jht} = \theta_{0h} + X'_{jt}\beta_h + \gamma_{th} + \omega_{ch} + \varepsilon_{jht}, \quad (2)$$

where X_{jt} is a vector of locational indicators at the node level. These variables include both time-varying and time-invariant characteristics of each location. Which we normalized using country-year standardization (z-scores), which has the advantage of allowing comparability across dimensions and that coefficients can be interpreted as the effect of a one-standard-deviation increase relative to the country-year distribution; which reflects the fact that the utility derived from a locational advantage depends on the relative position of a node to respect to others in the same zone .

The vector X_{jt} includes the following groups of determinants:

Natural resources. We proxy the quality of local renewable resources using technology-specific measures of average annual production potential at the node level. For wind, this corresponds to average wind speeds (m/s at 100 meters), while for solar it reflects surface solar irradiation (kWh/m²/year), both computed over the sample reference period using ERA data. These variables are time-invariant and capture the intrinsic physical suitability of a location for renewable generation.

Generation complementarity. To capture system-level diversification incentives, we construct an indicator of generation complementarity based on the correlation of local renewable production with the national generation mix. Specifically, we use one minus the correlation coefficient, so that higher values indicate greater diversification potential. This variable reflects investors' incentives to select locations in which they might be able to generate electricity where other assets from the same technology are not able to produce, potentially benefiting of higher electricity prices in the wholesale market.

Land costs. We proxy land-related opportunity costs using land price data (EUR/ha). Higher land costs increase the economic burden of project development and may reflect competing land uses or regulatory constraints. This variable varies over time and across locations.

Population density. In our effort to model the social acceptance and administrative burden associated with potential investments, we have constructed an indicator of human land-use intensity using the share of artificial land cover in the vicinity of each node, computed at the municipality level using CORINE Land Cover data. Artificial land cover includes urban and built-up areas such as residential zones, industrial and commercial sites, transport infrastructure, and other sealed surfaces. Higher values indicate greater human presence and competition for land, which may increase social acceptance constraints and limit the availability of suitable sites for renewable development.

Land availability. We measure land availability as the share of unused land in the vicinity of each node, computed at the municipality level using CORINE Land Cover data. Specifically, this indicator aggregates the shares of shrubland and bare land. Shrubland refers to areas dominated by low, woody vegetation (e.g., bushes and transitional woodland-shrub), while bare land includes sparsely vegetated or non-vegetated surfaces such as rocks, sand, and natural open spaces. Higher values indicate greater availability of suitable sites for renewable development, reflecting lower competition for land and fewer constraints on project siting.

Terrain complexity. We construct a composite indicator capturing physical constraints to construction, based on land cover characteristics (e.g., forests, wetlands, bare land) within a node-specific radius around each node. Such specific radius is determined by estimating the median distance between the farthest distance of a plant towards the node. To quantify landscape heterogeneity, we compute a Shannon entropy index over land cover classes within this geographic scope:

$$H_j = - \sum_i p_{ij} \log(p_{ij}), \quad (3)$$

where p_{ij} denotes the share of land cover type i within the sampled area around node j . Higher values of H_j indicate more heterogeneous landscapes, which are associated with greater construction complexity and higher development costs.

Land-use complexity. We construct an indicator of land-use complexity capturing administrative and spatial fragmentation across multiple governance levels. This measure combines entropy-based indices computed at the municipality, province, and regional levels, each reflecting the heterogeneity of land-use patterns within the corresponding administrative boundary. Specifically, the indicator is defined as the product of these three entropy measures. Higher values indicate greater fragmentation in land-use patterns and administrative jurisdictions, which may complicate permitting processes, increase coordination costs, and lead to delays in project development.

Node available capacity (lag). We proxy the available connection capacity at each node using an indicator that combines physical network capacity and existing utilization. Specifically, we construct this variable as the difference between the logarithm of the node’s connected line capacity (in MW-equivalent units)² and the logarithm of total installed generation capacity at the node. The measure is lagged by one period to reflect the information available at the time of investment decisions. Higher values indicate nodes with relatively greater available network capacity and lower congestion.

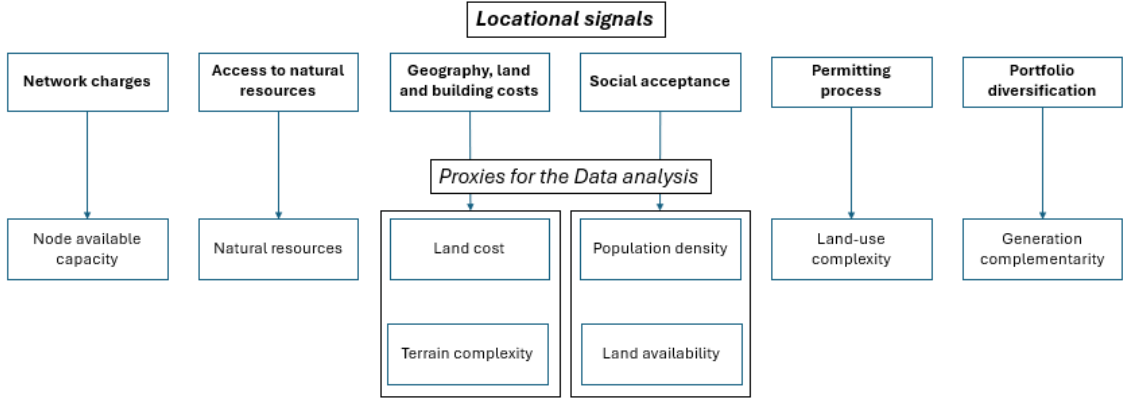


Figure 2: From Locational Signals Theory to the data analysis proxies

The terms γ_{th} and ω_{ch} denote year and country fixed effects, respectively, capturing common temporal shocks (e.g., macroeconomic factors such as increases in fossil fuel prices) and time-invariant cross-country heterogeneity such as and differences in electricity prices in the wholesale market.

The error term ε_{jht} captures unobserved determinants of investment at the node level.

Standard errors are clustered at the province level to account for spatial correlation in unobserved factors affecting investment decisions. Such level of geographical scope can capture, anticipated network expansions, regional development trends, or policy expectations on locational support mechanisms that we were not able to identify in our dataset that might induce correlation in the error term ε_{jht} . Failing to account for such intra-provincial correlation would lead to

²Line capacities are reported in apparent power (MVA). We convert these to active power (MW) using a constant power factor of 0.9, which reflects typical operating conditions in high-voltage transmission networks.

underestimated standard errors and overstated statistical significance.

To facilitate interpretation, we report in our main results, the average marginal effects (AMEs), for a given variable x_k , the marginal effect in the logit model is given by:

$$\frac{\partial P(Y_{jht} = 1)}{\partial x_{k,jt}} = \Lambda(U_{jht}) (1 - \Lambda(U_{jht})) \beta_{kh}, \quad (4)$$

where $\Lambda(U_{jht}) = \frac{\exp(U_{jht})}{1 + \exp(U_{jht})}$ is the logistic function. The average marginal effect is computed as:

$$AME_k = \frac{1}{N} \sum_{jht} \Lambda(U_{jht}) (1 - \Lambda(U_{jht})) \beta_{kh}, \quad (5)$$

which represents the average change in the probability of investment associated with a one-unit increase in x_k , evaluated over all observations in the sample. In the next section, we estimate a sequence of specifications in which variables are progressively added to X_{jt} in order to assess the marginal contribution of each group of locational drivers.

6 Results

6.1 Observed entry and determinants

In this subsection, we first, explore the general results, namely the observed new investment entry in a sample of European member states as well as general values of tested locational signals. Figure 3 shows an index of the geographical concentration of additional capacity during our study period, by country and technologies. The dotted lines represent the weighted average of technology capacity at the European level. Two groups of technologies can be easily distinguished. On the one hand, onshore wind and solar power plants are more geographically diffuse with on average less concentrated assets; on the other, gas plants, off-shore wind and other technologies that have significantly higher concentration across the EU. This might suggest that the first group relies on a broader range of determinants when selecting a location. Consequently, how the locational signals interact, might likely be more complex than in other technologies, where maybe only one main-criteria is used to determine the locational decisions. Thus, this figure suggests the importance of focusing on studying onshore wind and solar capacity entries and their interactions to locational signals.

Regarding the table 1, presenting the diversity of country network organization, we observe a great variability of network size and capacity additions among European countries. France, Germany, Spain or Italy concentrate the majority of the existing network and of new capacity of renewables. During our scope of study, the database does not show new investment entry for some countries, that are then excluded from our study, namely Bulgaria, Latvia, Slovakia, Slovenia. Concerning renewable resources among countries, northern European countries unsurprisingly have

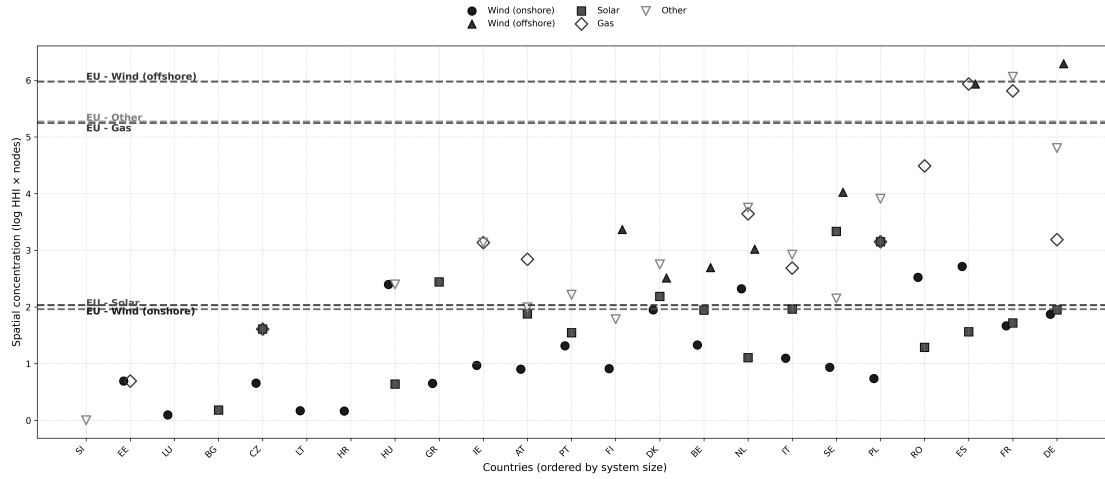


Figure 3: Distribution of additional capacity.

more wind than southern one, and vice versa for the solar resources. Countries with a great geographic diversity such as France (FR) meet a high standard deviation for their resources values.

Table 2 presents a typology of general results per technology and per locational signals. The results are based on more than 30000 observations made on 5000 nodes across 6 years of study. Solar and onshore wind power plants concentrate 78% of new entries during the studied period (resp. 45% and 37%). The high standard deviations relative to means across all technologies reflect high skewness — most additions are small, but a few very large projects pull the average up. Few offshore wind projects were installed in Europe but they represent a great amount of capacity. Solar and wind resources show relatively low variability (Std. Dev. modest relative to mean), suggesting a reasonably homogeneous resource base within most zones. Node available capacity has a great range (0.3 to 24,126 MW), reflecting the highly heterogeneous current grid state across Europe. Land cost also varies dramatically (€1,598 to €131,347/ha). Population density around nodes is low on average (0.199 share). A specific indicator is introduced for Germany to capture the locational subsidy mechanism described in section 3.3.2. The locational bonus/malus variable displays a strong disparity between its mean value and its standard deviation, suggesting that this mechanism generates spatial variability in investment incentives.

Table 1: Country-level summary of capacity additions (in MW) and average solar (kWh/m²/year) and wind (m/s) resources between 2014 and 2019

Country	Nodes	Nodes add.	Solar	Wind on.	Wind off.	Gas	Other	Solar res	Wind res
AT	111	20	5	729	0	47	26	140.7 (5.4)	3.79 (1.56)
BE	70	37	418	616	827	0	0	122.7 (3.3)	6.58 (0.55)
CZ	66	4	9	47	0	0	0	131.6 (3.0)	5.14 (0.31)
DE	787	489	4642	14524	589	1810	3193	123.0 (7.6)	5.79 (0.77)
DK	46	20	244	723	336	0	67	119.7 (3.9)	7.73 (0.59)
EE	17	1	0	18	0	0	0	118.8 (3.8)	8.19 (0.64)
ES	1032	370	15686	1629	20	23	0	187.8 (18.5)	4.39 (0.85)
FI	105	26	0	1726	42	0	823	110.1 (1.1)	7.98 (0.40)
FR	1211	419	4606	10949	0	667	3	143.7 (17.6)	5.49 (1.28)
GR	33	21	8	1528	0	0	0	193.5 (3.5)	7.22 (0.26)
HR	24	6	0	455	0	0	0	160.2 (8.0)	4.02 (0.39)
HU	54	10	291	20	0	0	40	152.0 (3.2)	5.30 (0.26)
IE	53	23	0	2188	0	313	68	110.9 (4.7)	6.89 (0.39)
IT	581	38	80	1261	0	201	89	164.1 (15.1)	3.20 (1.17)
LT	24	5	0	349	0	0	0	129.8 (2.4)	8.64 (0.67)
LU	16	4	0	78	0	0	0	124.9 (1.1)	5.91 (0.10)
NL	60	42	939	2914	1279	145	1609	122.2 (5.1)	7.44 (0.88)
PL	221	50	19	2346	0	1265	1163	124.3 (3.2)	6.06 (0.38)
PT	150	24	281	485	0	0	531	190.5 (9.4)	4.74 (0.92)
RO	156	17	332	413	0	46	0	156.3 (1.6)	4.25 (0.81)
SE	207	46	4	3904	0	0	536	105.6 (6.3)	6.11 (0.77)

Notes: Capacity values correspond to total installed capacity (MW). Standard deviations are reported below means for resource variables.

Table 2: Summary Statistics

	Mean	Std. Dev.	Min	Max	N
<i>Capacity Additions (MW)</i>					
Gas	2.875	27.886	0.000	630.000	1571
Other	13.228	107.500	0.000	1604.170	616
Solar	4.736	24.591	0.000	687.500	5820
Wind Offshore	58.362	126.983	0.000	584.000	53
Wind Onshore	9.650	28.908	0.000	607.608	4860
Solar resource (kWh/m ² /year)	149.509	29.856	97.408	213.316	30117
Wind resource at 100 m (m/s)	5.148	1.491	1.408	9.792	30117
Solar complementarity (index)	0.031	0.017	0.000	0.093	30117
Wind complementarity (index)	0.286	0.174	0.001	0.851	30117
Node available capacity (MW)	3072.999	3120.879	0.318	24126.032	30117
Land-use complexity (index)	7.576	3.805	0.147	22.264	30117
Terrain complexity (index)	27.720	11.858	-0.000	103.291	30101
Land cost (eur/ha)	15643.579	16159.273	1598.000	131347.000	23531
Population density (share)	0.199	0.227	0.000	1.000	30117
Locational bonus/malus (eur/MWh)	0.270	1.781	-6.945	17.810	10010
Observations			30117		
Total Nodes			5024		
Nodes with additions			1672		
Countries			21		
Period			2014–2019		

Notes: Resource availability is derived from ERA-based data. Solar resource corresponds to surface solar radiation (kWh/m²/year), and wind resource corresponds to wind speed at 100 meters (m/s), both averaged over the sample period. Wind values aggregate onshore and offshore resources at the node-year level. Generation complementarity is defined as one minus the correlation of node-level generation profiles with the country average. Land-use complexity is computed as the product of entropy measures at the municipality, province, and regional levels. Terrain complexity reflects land-use heterogeneity in the surrounding area, scaled by the radius determined by the distance to the farthest connected generation unit. Capacity additions statistics are computed conditional on nodes that experienced at least one addition for each technology during the sample period. Locational bonus+malus are reported conditional on nodes that experienced at least one capacity addition. Countries included: AT, BE, CZ, DE, DK, EE, ES, FI, FR, GR, HR, HU, IE, IT, LT, LU, NL, PL, PT, RO, SE.

6.2 Discrete entry analysis

6.2.1 Influence of locational signals per technology

Table 3 presents the results of the discrete entry regression for all technologies applying a country, year fix effect and clustering the standard error to the province level of spatial granularity. The results are presented in the form of Average Marginal Effect (AME), which represents the average change in the probability of investment associated with a one-unit increase of the locational signal, evaluated over all observations in the sample. This method enables interpretability and comparison across heterogeneous units of observed signals, technologies and countries.

We found many determinants that are statistically significant to be locational-signals for solar and onshore wind investments. The availability of natural resource is the main driver for investment location selection for both technologies but onshore wind are more driven by this determinant than solar plant. A node that has a standard-deviation higher than average on the Natural resource determinant, increases its probability of receiving an investment on 64,9% for onshore wind and 11,1% for solar. The availability of node and lands weakly impact location selection and surprisingly impact location choice negatively (-0,4% for onshore wind and solar). It suggests that investors prefers to locate to non remote areas in order to profit from existing infrastructures and pay less connection costs and transmission charges. In addition, it spotlights that investors prefer to select sites where other projects are operating, increasing the risk of crowding on the best sites, and potentially the appearance of congestions. Both technologies seem not to be influenced by the generation complementarity effect. Both technologies are negatively affected in the same way by the land-use complexity. The more there is different land use surrounding a possible plant location, the more it can create conflict and administrative issues discouraging renewable investments. Comparing solar and onshore wind technologies, we observe that Population density and terrain complexity are bigger repellents for wind than solar : we observe for wind, a diminution of respectively 1.9% and 1.3% of probability for a node of receiving an investment compared to a diminution of 1.1% and 0.6% for solar. The population density can be seen as a proxy for the NIMBY effect, and wind power plant can exert more visual nuisance for surrounding societies than a grounding solar power plant. The terrain complexity is also a bigger driver for wind as the building engineering is more complex for this technology than solar, and presence of slopes or irregularities can be detrimental for a wind project. On the other side, solar plants are statistically negatively impacted by the cost of lands (-0.8%) as it accounts for a relative more importance in the project CAPEX compared to wind (-0.2% with poor statistical significance).

A potential, issue arising from using country-dummies, is the differences among system size; might be driving the results; thus, to address this issue we perform a roll-out sample. In the figure 4, we analyze how each country affects the regression results for two of the main studied locational signals, namely the Natural resources and Node available capacity (lag). Each point corresponds

Table 3: Average marginal effect (one standard deviation change) of investment probability by technology

	Wind (On)	Wind (Off)	Solar	Gas	Other
Natural resources	0.649*** (0.136)	0.036 (nan)	0.111*** (0.011)		
Node available capacity (lag)	-0.004** (0.002)	-0.000 (0.016)	-0.004*** (0.002)	-0.000 (0.001)	-0.001 (0.000)
Terrain complexity	-0.013*** (0.003)		-0.006*** (0.002)	-0.003*** (0.001)	-0.000 (0.001)
Generation complementarity	-0.002 (0.002)	-0.000 (0.001)	0.012 (0.018)		
Land-use complexity	-0.007** (0.003)		-0.007** (0.003)	-0.000 (0.001)	0.001 (0.001)
Population density	-0.019*** (0.003)		-0.011*** (0.003)	-0.000 (0.001)	0.001** (0.000)
Land availability	-0.008** (0.004)		-0.007** (0.003)	0.001 (0.002)	-0.000 (0.001)
Land cost	-0.002 (0.003)		-0.008*** (0.002)	0.002 (0.003)	0.001 (0.001)
Observations (build=1)	1370	13	1324	376	114
Total observations	30117	30117	30117	30117	30117
Pseudo R^2	0.188	0.460	0.216	0.322	0.195
Year FE	Yes	Yes	Yes	Yes	Yes
Country Dummies	Yes	Yes	Yes	Yes	Yes
Clustered SE	Province	Province	Province	Province	Province

Notes: Data is expressed in z-values. Reported coefficients are average marginal effects. The number of investment events and total observations are reported to highlight differences in statistical power across technologies. Pseudo R^2 corresponds to McFadden's measure.

to the estimated AME after excluding a single country, while the horizontal lines represent 95% confidence intervals. The vertical solid line indicates the full-sample estimate, and the dashed line marks zero.

Concerning the available of solar resource, values remain robust after computing the roll-out sample estimate for the full counties. Concerning our endogenous variable, however, the node availability capacity signal for both technologies, removing France out of the sample suggests that our results are less robust; and that France has a significant weight pulling towards a negative impact of node capacity on increasing the likelihood of new investments; such results can be also considered as suggesting some "crowding effect" of investors trying to populate the best-performing nodes.

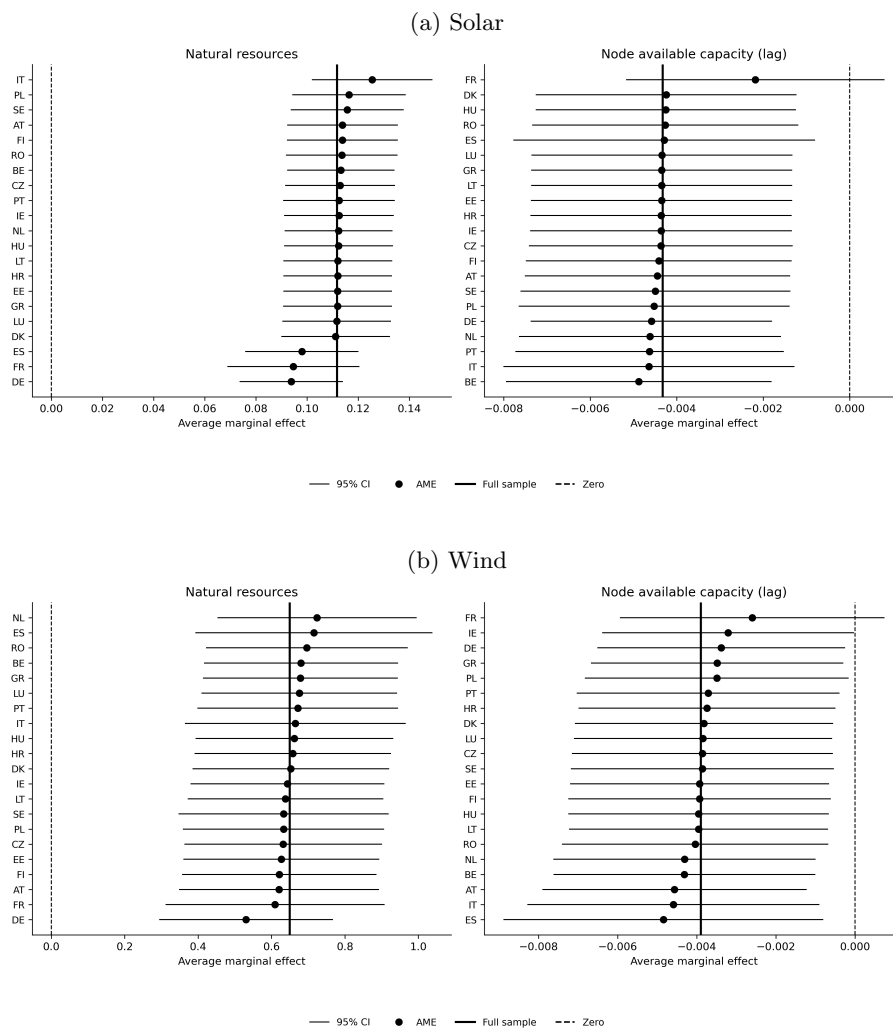


Figure 4: Country impact on locational signal strength per technology

6.3 Country-specific analysis

To compare the EU average effect, to the country-only effect; we regress independently the four EU countries that have shown to have the largest system size; and compare them to the sample of the rest of countries.

Concerning solar energy, the table 4 confirms the results of the figure 4, where we see that natural resource is the main driver for location selection and has a statistically significant value for France, Germany and Spain compared to the average European results. Italy confirms that the natural resource signal is not strong nor statistically significant to drive investment in the country. Terrain complexity is important in Germany as well as density of population, whereas land availability and land cost the second most powerful signals for France. It may show that France constraints more the sitting of renewables. The administrative sites dedicated to solar are more rare creating more pressure to grab it increasing the general cost of lands. Furthermore, France is the only country to have implemented in 2021 (but integrated in political agenda in 2018) a Zero net land take (*Zéro artificialisation nette*, ZAN) limiting the transformation of natural or agricultural lands into artificial ones. Grounded solar projects now need additional specific derogation to be installed. It may have sent the signal for investors and developers of land rush, consequently increasing prices specifically for this technology of high footprint. The ZAN does not apply to wind energy due to their small footprint explaining maybe why land cost and availability are less important for wind energy.

Concerning wind energy, the table 5 a preponderant impact of natural resources for the largest countries (except Italy)³. The social acceptance proxy, Population density, is stronger in Germany, revealing a stronger NIMBY in this country. The German locational subsidy mechanism is statistically significant in Germany and provides locational incentives for investments in the light of the figure 4, we can argue that the mechanisms are not enough significant to counterbalance the strong effect of natural resources.

Finally, robustness tests were conducted to test different specifications of the econometric model; different effects of country-dummies and year-fixed effects to test the robustness of the baseline logit model; and for collinearity by testing sequentially the additions of explicative variables to the regression.

³The natural resources value for Germany is oddly superior to 1, this need to be shortly analyzed

Table 4: Solar investment

	EU	FR	ES	DE	IT	Small
Natural resources	0.111*** (0.011)	0.190*** (0.025)	0.135*** (0.040)	0.133*** (0.049)	0.011 (0.008)	-0.008 (0.022)
Node available capacity (lag)	-0.004*** (0.002)	-0.015*** (0.005)	-0.005* (0.003)	-0.008 (0.006)	-0.006* (0.003)	-0.000 (0.001)
Terrain complexity	-0.006*** (0.002)	-0.008 (0.005)	-0.007** (0.003)	-0.024** (0.010)	-0.001 (0.001)	0.000 (0.002)
Complementarity	0.012 (0.018)	0.114 (0.103)	-0.166 (0.131)	0.080 (0.050)	-0.010 (0.028)	0.002 (0.008)
Land-use complexity	-0.007** (0.003)	-0.016* (0.009)	-0.011** (0.005)	-0.004 (0.014)	0.002 (0.002)	-0.002 (0.002)
Population density	-0.011*** (0.003)	-0.006 (0.005)	-0.010* (0.005)	-0.038*** (0.013)	-0.005** (0.003)	-0.002 (0.002)
Land availability	-0.007** (0.003)	-0.023*** (0.007)	0.002 (0.003)	0.196* (0.106)	0.001 (0.001)	-0.003 (0.003)
Land cost	-0.008*** (0.002)	-0.018*** (0.006)	-0.003 (0.005)		-0.003* (0.002)	-0.000 (0.002)
Locational subsidy				0.022*** (0.006)		
Build obs.	1324	413	359	417	9	126
Total obs.	30117	7266	6192	4707	3486	8466
Pseudo R^2	0.216	0.142	0.577	0.107	0.381	0.292
Countries	21	1	1	1	1	17
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Country FE	Yes	No	No	No	No	Yes
Clustered SE	Province	Province	Province	Province	Province	Province

Table 5: Wind investment

	EU	FR	ES	DE	IT	Small
Natural resources	0.649*** (0.136)	0.832*** (0.321)	0.403*** (0.082)	1.771*** (0.574)	0.244* (0.137)	0.449* (0.241)
Node available capacity (lag)	-0.004** (0.002)	-0.008* (0.004)	0.000 (0.001)	-0.004 (0.006)	0.001 (0.001)	-0.007** (0.003)
Terrain complexity	-0.013*** (0.003)	-0.027*** (0.006)	0.000 (0.001)	-0.029*** (0.011)	-0.004 (0.003)	0.002 (0.004)
Complementarity	-0.002 (0.002)	0.003 (0.008)	0.003 (0.002)	0.005 (0.008)	-0.003 (0.007)	0.002 (0.002)
Land-use complexity	-0.007** (0.003)	-0.021* (0.012)	-0.003** (0.001)	0.022* (0.013)	0.001 (0.003)	-0.019*** (0.004)
Population density	-0.019*** (0.003)	-0.025*** (0.006)	-0.005** (0.002)	-0.065*** (0.012)	-0.031** (0.014)	-0.007* (0.004)
Land availability	-0.008** (0.004)	-0.015* (0.008)	0.001 (0.001)	-0.117 (0.132)	-0.009 (0.008)	-0.002 (0.004)
Land cost	-0.002 (0.003)	-0.007 (0.004)	-0.000 (0.001)		-0.007 (0.004)	0.005 (0.003)
Locational subsidy				0.073*** (0.006)		
Build obs.	1370	349	32	576	35	378
Total obs.	30117	7266	6192	4707	3486	8466
Pseudo R^2	0.188	0.215	0.343	0.172	0.272	0.133
Countries	21	1	1	1	1	17
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Country FE	Yes	No	No	No	No	Yes
Clustered SE	Province	Province	Province	Province	Province	Province

7 Discussion

To efficiently coordinate network development with generation capacity investments in the European Union, purposefully designed locational signals have been proposed. However, despite their strong theoretical appeal, a key gap in our understanding concerns their effectiveness in shaping investors' behavior. This gap stems, first, from the limited empirical evidence available for zonal markets on locational investment decisions, and second, from findings in LMP-based systems suggesting that theoretical predictions do not fully translate into observed locational incentives.

Against this problem, our research provides two main contributions to the literature studying the efficiency of locational signals. A first contribution is that we extend the analysis made in Eicke et al. (2020): We prove the existence of many determinants influencing the locational decision and they might interact with locational policy tools. Confirming results of D. P. Brown et al. (2020), renewables are mainly influenced by natural resources. But the zonal configuration of European markets lead us to consider to strength of other statistically significant proxies of locational determinants such as Terrain complexity, Node available capacity, Population density or Land availability and costs. The study confirms that a variety of determinants in addition to renewable resources are taken into consideration by investors in zonal systems. This consideration exists by nature without proper mechanisms to send artificial signals to investors.

A second contribution, is that we are able to measure the impact of such determinants on investors decision-making process; which is an improvement to Eicke et al. (2020) weighted measures that compare locational mechanisms only assessing the impact on price differentiation without exploring the actual impact on investment decisions. Indeed, by quantifying the marginal effect of each signal using the AME methods, we are able to compare each signal with others on how they influence investments. Indeed, an increase by one standard deviation of a determinant gives how much does the probability of investment at this node increases. As a complement, we provide proxies of how one would need to design EU incentives across Europe to compensate for other signals.

Finally, our paper show potential interactions that might exist between non designed and designed signals affecting investment's location. This rises the risk that policy mechanisms targeting investment allocation to precise locations face significant effectiveness challenges when undesigned signals contradict their objectives. This concern is illustrated in D. P. Brown et al. (2020) by the case of locational marginal pricing (LMP) in the Texas electricity market, where price signals failed to steer renewable energy investment toward congestion-relieved zones as intended, while continuing to attract gas-fired capacity to traditionally profitable locations. These observations underscore a broader phenomenon: poorly coordinated signal regimes create perverse incentives that hamper policy interventions. Such complex dynamic opens an important avenue for future research is therefore how to efficiently allocate high-quality sites among competing investors with-

out exacerbating congestion as well as how to design compensation mechanisms that address the associated welfare losses.

8 Conclusions

The goal of the paper is to understand what determines the location of generation assets in zonal electricity markets, with a special focus on EU countries and renewable energies. We developed an investment framework to distinguish the location selection steps from financial and technical dimension of the investments and we linked the location selection stage to the theoretical background of locational signals. Then based on large dataset of realized investments and through a set of binary logit regressions, we confirmed the importance of locational signals in the location selection process, dominated by the signal of availability of natural resources. If the tested identified signals are all statistically significant, their importance is weak in the absence of designed mechanisms. The anti-correlation of node with available capacity shows that in the absence of designed mechanisms, the investors tend to develop project in already crowded nodes potentially increasing the likelihood of congestion. These findings could provide critical implications for designing effective compensation mechanisms and site allocation procedures.

Funding and Data Availability

Emmanuel Berrebi and Diego Cebreros have received funding from TotalEnergies. This funding had no influence on the study design, analysis, interpretation of results, or the conclusions presented in this paper.

All datasets and code used in this study are available upon reasonable request to the authors.

References

- ACER. (2024). *Monitoring report on cross-zonal electricity trade capacities* (Monitoring Report). Agency for the Cooperation of Energy Regulators. https://www.acer.europa.eu/monitoring/MMR/crosszonal_electricity_trade_capacities_2024
- Amir, K., & Nazari, M. (2021). A review on the applications of multi-criteria decision-making approaches for power plant site selection. *Journal of Thermal Analysis and Calorimetry*, *147*. <https://doi.org/10.1007/s10973-021-10877-1>
- Brown, D. P., Zarnikau, J., & Woo, C.-K. (2020). Does locational marginal pricing impact generation investment location decisions? an analysis of texas's wholesale electricity market. *Journal of Regulatory Economics*, *58*(2), 99–140. <https://doi.org/10.1007/s11149-020-09413-0>

- Brown, T., Hörsch, J., & Schlachtberger, D. (2018). PyPSA: Python for Power System Analysis. *Journal of Open Research Software*, 6(4). <https://doi.org/10.5334/jors.188>
- Brunekreeft, G., Neuhoﬀ, K., & Newbery, D. (2005). Electricity transmission: An overview of the current debate [Electricity Transmission]. *Utilities Policy*, 13(2), 73–93. <https://doi.org/https://doi.org/10.1016/j.jup.2004.12.002>
- Carley, S., Konisky, D. M., Atiq, Z., & Land, N. (2020). Energy infrastructure, nimbyism, and public opinion: A systematic literature review of three decades of empirical survey literature. *Environmental Research Letters*, 15(9), 093007. <https://doi.org/10.1088/1748-9326/ab875d>
- Chao, H.-p., & Wilson, R. (2020). Coordination of electricity transmission and generation investments. *Energy Economics*, 86, 104623. <https://doi.org/https://doi.org/10.1016/j.eneco.2019.104623>
- Copernicus Climate Change Service (C3S). (2017). Era5 reanalysis [European Centre for Medium-Range Weather Forecasts (ECMWF)].
- del Río, P. (2017). Designing auctions for renewable electricity support. best practices from around the world. *Energy for Sustainable Development*, 41, 1–13. <https://doi.org/https://doi.org/10.1016/j.esd.2017.05.006>
- Eicke, A., Khanna, T., & Hirth, L. (2020). Locational investment signals: How to steer the siting of new generation capacity in power systems? *The Energy Journal*, 41(6), 281–304. <https://doi.org/10.5547/01956574.41.6.aeic>
- EirGrid & SONI. (2025, September). *Approved 2025/2026 generator use of system charges (GTUoS): Accompanying note* (tech. rep.) (Published 8 September 2025). EirGrid and System Operator for Northern Ireland (SONI). https://cms.eirgrid.ie/sites/default/files/publications/2526.Approved_GTUoS_Tariffs_IE_v1.0.pdf
- EirGrid & System Operator for Northern Ireland (SONI). (2012). *Explanatory paper for transmission loss adjustment factor (tlaf) calculation methodology* (Technical Report) (Version 1.0. Published on 27/09/2012. Describes the methodology for calculating Transmission Loss Adjustment Factors (TLAFs) in the Single Electricity Market (SEM) of Ireland and Northern Ireland.). EirGrid and SONI. <https://www.eirgrid.com/>
- Energinet. (2023). *Development of energinet’s tariff design* (tech. rep.). Energinet. Retrieved March 26, 2026, from <https://energinet.dk/media/0mkn13bp/development-of-energinets-tariff-design.pdf>
- ENTSO-E Economic Framework Working Group. (2025, June). *Overview of transmission tariffs in europe: Synthesis 2023* (tech. rep.) (Published June 2025). European Network of Transmission System Operators for Electricity (ENTSO-E). Brussels, Belgium. <https://www.entsoe.eu>

- European Commission. (2023). *Commission staff working document: Impact assessment report accompanying the document proposal for a directive of the european parliament and of the council on the internal markets for electricity and gas and promoting renewables and on consumer protection* (Staff Working Document No. SWD(2023) 58 final). European Commission. Retrieved March 24, 2026, from <https://eur-lex.europa.eu/legal-content/EN/TXT/?uri=celex:52023SC0058>
- European Environment Agency (EEA). (2018). Corine land cover (clc) 2018, version 2020_20u1 [Copernicus Land Monitoring Service, accessed: 2026-03-18].
- Eurostat. (2021). Nuts — nomenclature of territorial units for statistics — 2021 shapefiles [GISCO, European Commission, accessed: 2026-03-18].
- Eurostat. (2022). Agricultural land prices and rents [Dataset: *apri_lprc*, accessed: 2026 – 03 – 18].
- Eurostat. (2025). Electricity and heat statistics [Data extracted in September 2025. Planned article update: October 2026. ISSN 2443-8219]. https://ec.europa.eu/eurostat/statistics-explained/index.php?title=Electricity_and_heat_statistics
- Gammons, S., Druce, R., Brejnholt, R., Strbac, G., Konstantinidis, C., Pudjianto, D., & Moreno, R. (2011, March 31). *Project transmit: Impact of uniform generation tnuos* (tech. rep.). NERA Economic Consulting. London, UK. <https://www.ofgem.gov.uk/publications/review-project-transmit-impact-uniform-generation-transmission-network-use-system-tnuos-prepared-rwe-npower>
- Ghasempour, R., Nazari, M. A., Ebrahimi, M., Ahmadi, M. H., & Hadiyanto, H. (2019). Multi-criteria decision making (mcdm) approach for selecting solar plants site and technology: A review. *International Journal of Renewable Energy Development*, 8(1), 15–25. <https://doi.org/10.14710/ijred.8.1.15-25>
- Grimm, V., Rückel, B., Sölch, C., & Zöttl, G. (2021). The impact of market design on transmission and generation investment in electricity markets. *Energy Economics*, 93, 104934. <https://doi.org/10.1016/j.eneco.2020.104934>
- Haas, R., Panzer, C., Resch, G., Ragwitz, M., Reece, G., & Held, A. (2011). A historical review of promotion strategies for electricity from renewable energy sources in eu countries. *Renewable and Sustainable Energy Reviews*, 15(2), 1003–1034. <https://doi.org/https://doi.org/10.1016/j.rser.2010.11.015>
- Hadush, S., Buijs, P., & Belmans, R. (2011). Locational signals in electricity market design: Do they really matter? *2011 8th International Conference on the European Energy Market, EEM 11*. <https://doi.org/10.1109/EEM.2011.5953086>
- Hogan, W. W. (1992). Contract networks for electric power transmission. *Journal of regulatory economics*, 4(3), 211–242.

- Huchzermeier, A., & Cohen, M. A. (1996). Valuing operational flexibility under exchange rate risk. *Operations Research*, 44(1), 100–113. Retrieved February 25, 2026, from <http://www.jstor.org/stable/171908>
- Jarvis, S. (2025). The economic costs of nimbyism: Evidence from renewable energy projects. *Journal of the Association of Environmental and Resource Economists*, 12(4), 983–1022. <https://doi.org/10.1086/732801>
- Jenabi, M., Fatemi Ghomi, S. M. T., & Smeers, Y. (2013). Bi-level game approaches for coordination of generation and transmission expansion planning within a market environment. *IEEE Transactions on Power Systems*, 28(3), 2639–2650. <https://doi.org/10.1109/TPWRS.2012.2236110>
- Johnson, B. E. (1994). Modeling energy technology choices: Which investment analysis tools are appropriate? [Markets for energy efficiency]. *Energy Policy*, 22(10), 877–883. [https://doi.org/https://doi.org/10.1016/0301-4215\(94\)90147-3](https://doi.org/https://doi.org/10.1016/0301-4215(94)90147-3)
- Joskow, P. L. (2021). Facilitating transmission expansion to support efficient decarbonization of the electricity sector. *Economics of Energy Environmental Policy*, 10(2), pp. 57–92. Retrieved March 24, 2026, from <https://www.jstor.org/stable/27166538>
- Kemfert, C., Kunz, F., & Rosellón, J. (2016). A welfare analysis of electricity transmission planning in germany. *Energy Policy*, 94, 446–452. <https://doi.org/https://doi.org/10.1016/j.enpol.2016.04.011>
- Kim, K., Park, H., & Kim, H. (2017). Real options analysis for renewable energy investment decisions in developing countries. *Renewable and Sustainable Energy Reviews*, 75, 918–926. <https://doi.org/https://doi.org/10.1016/j.rser.2016.11.073>
- Kogut, B., & Kulatilaka, N. (1994). Operating flexibility, global manufacturing, and the option value of a multinational network. *Management Science*, 40, 123–139. <https://doi.org/10.1287/mnsc.40.1.123>
- Lee, S.-C. (2011). Using real option analysis for highly uncertain technology investments: The case of wind energy technology. *Renewable and Sustainable Energy Reviews*, 15(9), 4443–4450. <https://doi.org/https://doi.org/10.1016/j.rser.2011.07.107>
- Lehmann, P., & Tafarte, P. (2024). Exclusion zones for renewable energy deployment: One man’s blessing, another man’s curse. *Resource and Energy Economics*, 76, 101419. <https://doi.org/https://doi.org/10.1016/j.reseneeco.2023.101419>
- Martin, P., Christine, B., Gert, B., & Marius, B. (2022). Strategic behavior in market-based redispatch: International experience. *The Electricity Journal*, 35(3), 107095. <https://doi.org/https://doi.org/10.1016/j.tej.2022.107095>
- Meier, J.-N., & Lehmann, P. (2022). Optimal federal co-regulation of renewable energy deployment. *Resource and Energy Economics*, 70, 101318. <https://doi.org/https://doi.org/10.1016/j.reseneeco.2022.101318>

- Myers, S. C. (1977). Determinants of corporate borrowing. *Journal of Financial Economics*, 5(2), 147–175. [https://doi.org/https://doi.org/10.1016/0304-405X\(77\)90015-0](https://doi.org/https://doi.org/10.1016/0304-405X(77)90015-0)
- Nabradi, A., & Szöllösi, L. (2007). Key aspects of investment analysis. *Applied Studies in Agribusiness and Commerce*, 1, 53–56. <https://doi.org/10.19041/Apstract/2007/1/7>
- Olmos, L., & Pérez-Arriaga, I. J. (2009). A comprehensive approach for computation and implementation of efficient electricity transmission network charges. *Energy Policy*, 37(12), 5285–5295. <https://doi.org/https://doi.org/10.1016/j.enpol.2009.07.051>
- Pollitt, M. G. (2023). *Locational marginal prices (lmps) for electricity in europe? the untold story* (tech. rep.). Energy Policy Research Group, University of Cambridge. Apollo - University of Cambridge Repository. <https://doi.org/10.17863/CAM.105488>
- Pozzi, L., Papadaskalopoulos, D., & Strbac, G. (2025). Analysing strategic behaviour in european energy and redispatch markets with high wind energy penetration. *2025 21st International Conference on the European Energy Market (EEM)*, 1–7. <https://doi.org/10.1109/EEM64765.2025.11050136>
- Raptis, P., & Aretoulis, G. (2024). Supporting strategy for investment evaluation of photovoltaic power generation engineering projects using multi-criteria decision analysis methods. *Solar Compass*, 12, 100092. <https://doi.org/https://doi.org/10.1016/j.solcom.2024.100092>
- Rediske, G., Burin, H., Rigo, P., Rosa, C., Michels, L., & Siluk, J. (2021). Wind power plant site selection: A systematic review. *Renewable and Sustainable Energy Reviews*, 148, 111293. <https://doi.org/https://doi.org/10.1016/j.rser.2021.111293>
- Rediske, G., Siluk, J., Gastaldo, N., Rigo, P., & Rosa, C. (2018). Determinant factors in site selection for photovoltaic projects: A systematic review. *International Journal of Energy Research*, 43. <https://doi.org/10.1002/er.4321>
- Reutter, F., Drechsler, M., Gawel, E., et al. (2024). Social costs of setback distances for onshore wind turbines: A model analysis applied to the german state of saxony. *Environmental and Resource Economics*, 87, 437–463. <https://doi.org/10.1007/s10640-023-00777-3>
- Rious, V. (2007, October). *Le développement du réseau de transport dans un système électrique libéralisé, un problème de coordination avec la production* [Theses]. Université Paris Sud - Paris XI. <https://theses.hal.science/tel-00218150>
- Rious, V., Perez, Y., & Glachant, J.-M. (2011). *Review of Network Economics*, 10(4). <https://doi.org/doi:10.2202/1446-9022.1284>
- Saraswat, S., Digalwar, A. K., Yadav, S., & Kumar, G. (2021). Mcdm and gis based modelling technique for assessment of solar and wind farm locations in india. *Renewable Energy*, 169, 865–884. <https://doi.org/https://doi.org/10.1016/j.renene.2021.01.056>
- Schweppe, F. C., Caramanis, M., Tabors, R., & Bohn, R. (1988). *Spot pricing of electricity*. Boston Mass. Dordrecht London : Kluwer academic publishers , cop. 1988.

- Shao, M., Han, Z., Sun, J., Xiao, C., Zhang, S., & Zhao, Y. (2020). A review of multi-criteria decision making applications for renewable energy site selection. *Renewable Energy*, 157, 377–403. <https://doi.org/https://doi.org/10.1016/j.renene.2020.04.137>
- Singh, N., Goswami, A., & Sadhu, P. (2022). Energy economics and environmental assessment of hybrid hydel-floating solar photovoltaic systems for cost-effective low-carbon clean energy generation. *Clean Technologies and Environmental Policy*, 25. <https://doi.org/10.1007/s10098-022-02448-1>
- Thomassen, G., & Fuhrmanek, A. (2025). *Locational price signals in europe* (KJ-01-25-525-EN-N). JRC. Luxembourg (Luxembourg), Publications Office of the European Union. <https://publications.jrc.ec.europa.eu/repository/handle/JRC142047>
- Tohidi, Y., Olmos, L., Rivier, M., & Hesamzadeh, M. R. (2017). Coordination of generation and transmission development through generation transmission charges—a game theoretical approach. *IEEE Transactions on Power Systems*, 32(2), 1103–1114. <https://doi.org/10.1109/TPWRS.2016.2581218>
- von der Leyen, U. (2024). Mission letter to dan jørgensen [Mission letter outlining the priorities and responsibilities assigned to Dan Jørgensen as Commissioner]. <https://commission.europa.eu/document/download/1c203799-0137-482e-bd18-4f6813535986.en?filename=Mission%20letter%20-%20JORGENSEN.pdf>
- Zhang, Y., Song, J., & Hamori, S. (2011). Impact of subsidy policies on diffusion of photovoltaic power generation. *Energy Policy*, 39(4), 1958–1964. <https://doi.org/https://doi.org/10.1016/j.enpol.2011.01.021>

A Supplementary figures and tables

Table 6: Power plant additions by technology and commissioning period. Entries report number of plants, with average capacity (MW) in parentheses.

Technology	Before 2014	2014–2020	After 2020	Total N	Total MW
Solar	4090 (8.9)	2369 (12.0)	3571 (15.1)	10030	118777
Wind Onshore	5065 (24.2)	2581 (20.0)	1228 (36.1)	8874	218639
Wind Offshore	28 (168.1)	23 (281.3)	27 (320.2)	78	19822
Natural Gas	1379 (135.6)	420 (10.8)	261 (49.3)	2060	204406
Other	3631 (129.0)	124 (66.3)	53 (46.2)	3808	478995

Table 7: Power plant additions by country and technology group. Entries report number of plants, with average capacity (MW) in parentheses.

Country	Technology	Before 2014	2014–2020	After 2020	Total N	Total MW
AT	Solar	0	0	61 (6.4)	61	388

Continued on next page

Country	Technology	Before 2014	2014–2020	After 2020	Total N	Total MW
AT	Wind Onshore	56 (40.7)	29 (25.8)	8 (27.1)	93	3244
AT	Natural Gas	17 (286.5)	1 (42.0)	0	18	4912
AT	Other	179 (88.2)	2 (12.0)	1 (170.0)	182	15978
BE	Solar	1 (38.4)	73 (5.7)	2 (13.5)	76	484
BE	Wind Onshore	29 (23.6)	34 (19.5)	15 (16.9)	78	1600
BE	Wind Offshore	5 (211.9)	3 (275.5)	3 (235.3)	11	2592
BE	Natural Gas	25 (206.6)	0	0	25	5165
BE	Other	42 (270.4)	0	0	42	11357
BG	Solar	208 (8.1)	0	7 (102.3)	215	2405
BG	Wind Onshore	17 (35.8)	0	0	17	608
BG	Natural Gas	6 (165.0)	0	0	6	990
BG	Other	44 (265.8)	0	0	44	11696
DE	Solar	2856 (7.1)	717 (6.5)	1436 (8.2)	5009	36716
DE	Wind Onshore	3015 (16.8)	1538 (12.9)	604 (14.7)	5157	79404
DE	Wind Offshore	1 (690.0)	13 (337.2)	0	14	5074
DE	Natural Gas	877 (40.9)	407 (4.5)	235 (17.1)	1519	41720
DE	Other	1691 (58.8)	96 (33.6)	39 (11.1)	1826	103047
DK	Solar	11 (37.6)	21 (26.1)	41 (31.6)	73	2257
DK	Wind Onshore	57 (27.7)	33 (20.4)	7 (33.3)	97	2484
DK	Wind Offshore	12 (186.0)	0	3 (318.3)	15	3187
DK	Natural Gas	13 (139.5)	0	0	13	1813
DK	Other	18 (377.0)	2 (33.5)	0	20	6854
EE	Solar	0	0	71 (6.3)	71	446
EE	Wind Onshore	10 (27.8)	1 (18.0)	4 (104.2)	15	713
EE	Natural Gas	2 (194.5)	0	0	2	389
EE	Other	1 (1369.0)	0	0	1	1369
ES	Solar	198 (24.0)	935 (17.1)	155 (105.0)	1288	36998
ES	Wind Onshore	686 (39.3)	41 (39.7)	65 (59.9)	792	32472
ES	Wind Offshore	0	1 (20.0)	0	1	20
ES	Natural Gas	87 (326.1)	1 (23.0)	0	88	28394
ES	Other	412 (120.7)	0	4 (50.0)	416	49944
FI	Solar	0	0	13 (12.5)	13	162
FI	Wind Onshore	13 (53.8)	42 (41.1)	88 (81.1)	143	9562
FI	Wind Offshore	0	1 (42.0)	0	1	42
FI	Natural Gas	31 (94.2)	0	0	31	2919
FI	Other	84 (156.8)	5 (164.6)	1 (70.0)	90	14061
FR	Solar	256 (9.3)	515 (8.9)	496 (8.5)	1267	11183
FR	Wind Onshore	445 (20.9)	468 (23.7)	131 (24.1)	1044	23580

Continued on next page

Country	Technology	Before 2014	2014–2020	After 2020	Total N	Total MW
FR	Wind Offshore	0	0	10 (302.4)	10	3024
FR	Natural Gas	38 (214.0)	2 (332.5)	2 (248.0)	42	9292
FR	Other	206 (480.3)	0	1 (97.0)	207	99042
GR	Solar	1 (5.2)	1 (8.0)	313 (13.3)	315	4166
GR	Wind Onshore	72 (24.4)	60 (26.6)	60 (30.1)	192	5155
GR	Natural Gas	16 (490.3)	0	2 (858.5)	18	9562
GR	Other	30 (250.6)	0	1 (660.0)	31	8179
HR	Solar	0	0	26 (3.7)	26	96
HR	Wind Onshore	10 (23.6)	12 (37.9)	5 (89.8)	27	1140
HR	Natural Gas	6 (156.8)	0	1 (500.0)	7	1441
HR	Other	22 (110.8)	0	0	22	2439
HU	Solar	0	10 (29.1)	309 (7.4)	319	2583
HU	Wind Onshore	10 (31.9)	0	0	10	319
HU	Natural Gas	16 (174.7)	0	1 (64.0)	17	2859
HU	Other	14 (269.1)	1 (40.0)	0	15	3807
IE	Solar	0	0	33 (37.2)	33	1226
IE	Wind Onshore	49 (34.5)	54 (40.8)	19 (45.4)	122	4755
IE	Wind Offshore	1 (25.0)	0	0	1	25
IE	Natural Gas	10 (441.6)	1 (313.0)	6 (148.2)	17	5618
IE	Other	12 (226.9)	1 (68.0)	0	13	2791
IT	Solar	228 (21.0)	8 (9.6)	13 (50.0)	249	5521
IT	Wind Onshore	220 (37.0)	41 (32.3)	18 (30.6)	279	10020
IT	Wind Offshore	0	0	1 (30.0)	1	30
IT	Natural Gas	116 (429.0)	2 (100.5)	3 (285.0)	121	50820
IT	Other	329 (103.0)	2 (44.5)	0	331	33987
LT	Solar	0	0	32 (9.4)	32	300
LT	Wind Onshore	9 (29.8)	7 (49.9)	7 (82.6)	23	1195
LT	Natural Gas	4 (377.0)	0	0	4	1508
LT	Other	3 (1200.3)	0	1 (70.0)	4	3671
LU	Wind Onshore	2 (12.5)	7 (17.6)	0	9	148
LU	Other	1 (1294.0)	0	0	1	1294
LV	Wind Onshore	2 (20.5)	0	1 (59.0)	3	100
LV	Natural Gas	3 (362.3)	0	0	3	1087
LV	Other	3 (512.0)	0	0	3	1536
NL	Solar	1 (85.0)	56 (19.1)	164 (22.5)	221	4840
NL	Wind Onshore	45 (43.2)	50 (33.5)	35 (53.0)	130	5475
NL	Wind Offshore	4 (123.0)	5 (239.4)	9 (433.9)	18	5594
NL	Natural Gas	53 (299.5)	1 (144.0)	1 (107.0)	55	16127

Continued on next page

Country	Technology	Before 2014	2014–2020	After 2020	Total N	Total MW
NL	Other	21 (420.3)	1 (1604.2)	0	22	10431
PL	Solar	3 (32.5)	2 (6.0)	286 (9.1)	291	2712
PL	Wind Onshore	78 (39.5)	71 (35.3)	73 (47.7)	222	9072
PL	Natural Gas	10 (124.1)	4 (316.3)	8 (501.2)	22	6516
PL	Other	82 (407.7)	2 (581.5)	1 (120.0)	85	34717
PT	Solar	10 (14.2)	16 (17.2)	66 (46.9)	92	3510
PT	Wind Onshore	108 (43.4)	12 (40.4)	4 (40.5)	124	5338
PT	Wind Offshore	0	0	1 (25.0)	1	25
PT	Natural Gas	17 (274.6)	0	0	17	4668
PT	Other	44 (211.6)	4 (132.8)	3 (166.0)	51	10339
RO	Solar	212 (5.8)	13 (26.3)	6 (77.3)	231	2027
RO	Wind Onshore	38 (131.2)	8 (51.6)	2 (54.0)	48	5506
RO	Natural Gas	13 (362.0)	1 (45.5)	1 (80.0)	15	4832
RO	Other	139 (112.8)	0	0	139	15683
SE	Solar	0	2 (4.6)	34 (7.9)	36	277
SE	Wind Onshore	94 (28.0)	73 (54.1)	82 (124.0)	249	16750
SE	Wind Offshore	5 (41.8)	0	0	5	209
SE	Natural Gas	11 (197.1)	0	0	11	2168
SE	Other	184 (150.1)	7 (76.6)	1 (130.0)	192	28291
SI	Solar	0	0	7 (4.3)	7	30
SI	Natural Gas	2 (245.0)	0	1 (110.0)	3	600
SI	Other	33 (96.0)	1 (47.4)	0	34	3215
SK	Solar	105 (4.3)	0	0	105	449
SK	Natural Gas	6 (167.5)	0	0	6	1005
SK	Other	37 (142.4)	0	0	37	5267

The geographical representation of new entry in the figure 6 confirms the heterogeneity of countries in terms of renewable energy investment. The majority of new market entries are concentrated in Europe’s so-called ”city belt,” stretching from Northern Italy to the Benelux region. Meanwhile, countries like Spain display a striking divergence between solar and wind new entries, reflecting deliberate political strategies to prioritize solar energy development given the country’s exceptional solar resource potential

Figure 5: Location of capacity additions per technology.

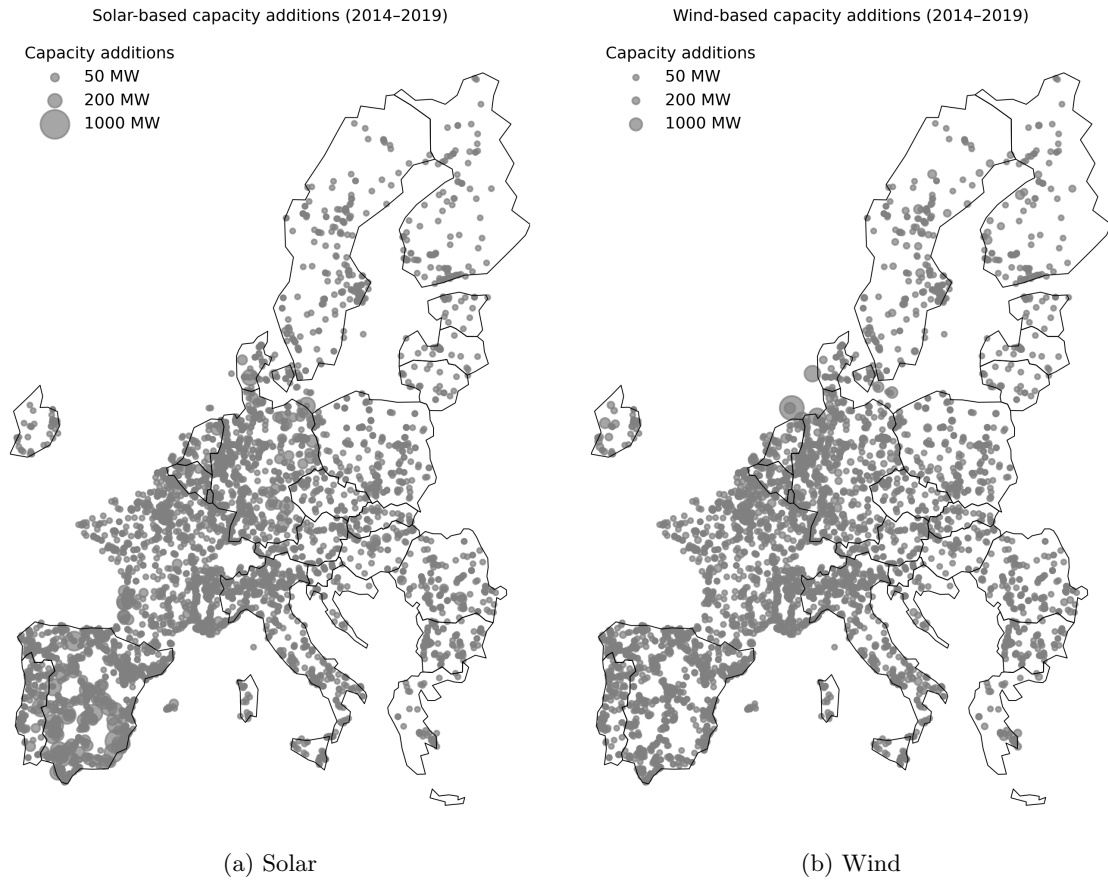


Figure 6: Location of capacity additions per technology.

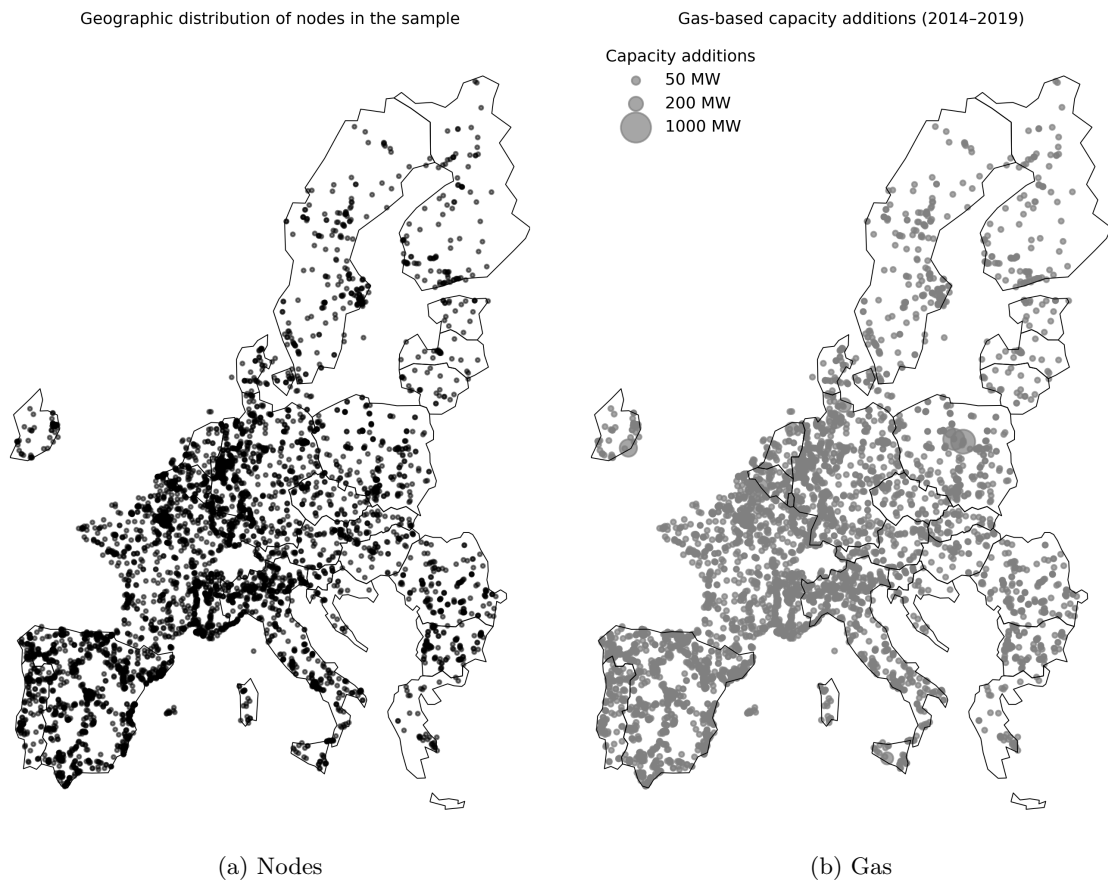


Table 8: Country averages (Appendix)

Country	Resource	Available capacity (MW)	Land-use complexity	Terrain complexity	Land cost (eur/ha)	Complementarity	Resource diversity	Population density	Land availability	Locational subsidy (eur/MWh)
AT	3.79 (1.56)	3587.68 (3383.39)	6.59 (2.05)	24.74 (3.67)	nan (nan)	0.03 (0.01)	0.03 (0.01)	0.12 (0.14)	0.05 (0.12)	0.07 (1.06)
BE	6.58 (0.55)	4016.74 (3614.84)	7.95 (2.49)	18.73 (5.05)	33905.09 (12885.88)	0.02 (0.01)	0.02 (0.01)	0.22 (0.14)	0.00 (0.01)	0.00 (0.00)
CZ	5.14 (0.31)	4236.41 (3700.01)	5.17 (1.84)	35.99 (5.42)	6235.46 (1882.08)	0.02 (0.01)	0.02 (0.01)	0.08 (0.09)	0.00 (0.00)	0.02 (0.34)
DE	5.79 (0.77)	4213.03 (3596.27)	5.04 (2.18)	29.38 (5.26)	nan (nan)	0.04 (0.02)	0.04 (0.02)	0.26 (0.20)	0.00 (0.00)	0.59 (2.60)
DK	7.73 (0.59)	3828.11 (2848.17)	5.27 (2.51)	45.98 (12.62)	17466.18 (3273.99)	0.02 (0.01)	0.02 (0.01)	0.12 (0.10)	0.00 (0.00)	0.00 (0.00)
EE	8.19 (0.64)	2425.58 (1176.84)	10.40 (0.86)	65.97 (4.69)	2875.50 (355.08)	0.01 (0.01)	0.01 (0.01)	0.06 (0.08)	0.00 (0.00)	0.00 (0.00)
ES	4.39 (0.85)	2656.33 (2866.16)	10.95 (2.82)	21.38 (4.31)	14379.20 (6971.69)	0.03 (0.02)	0.03 (0.02)	0.10 (0.10)	0.01 (0.03)	0.00 (0.00)
FI	7.98 (0.40)	4146.00 (2761.68)	5.35 (1.24)	44.70 (7.36)	7848.62 (2287.69)	0.00 (0.00)	0.00 (0.00)	0.06 (0.08)	0.00 (0.00)	0.00 (0.00)
FR	5.49 (1.28)	2398.19 (3003.41)	7.02 (4.48)	22.12 (4.94)	7098.46 (2621.68)	0.04 (0.01)	0.04 (0.01)	0.27 (0.28)	0.01 (0.06)	0.00 (0.00)
GR	7.22 (0.26)	7358.35 (4193.47)	10.33 (3.12)	87.10 (11.76)	30559.68 (31109.77)	0.00 (0.00)	0.00 (0.00)	0.15 (0.18)	0.03 (0.06)	0.00 (0.00)
HR	4.02 (0.39)	2064.32 (1773.26)	8.75 (1.94)	36.76 (3.10)	4666.93 (573.31)	0.02 (0.01)	0.02 (0.01)	0.11 (0.12)	0.01 (0.02)	0.00 (0.00)
HU	5.30 (0.26)	3839.91 (2895.75)	5.54 (1.60)	39.79 (7.52)	3847.37 (819.82)	0.01 (0.01)	0.01 (0.01)	0.15 (0.14)	0.00 (0.01)	0.00 (0.00)
IE	6.89 (0.39)	1317.30 (800.05)	3.85 (1.56)	37.22 (7.74)	25274.45 (3509.19)	0.03 (0.01)	0.03 (0.01)	0.13 (0.21)	0.00 (0.00)	0.00 (0.00)
IT	3.20 (1.17)	2763.88 (2540.81)	7.98 (2.99)	20.15 (4.73)	40061.80 (15768.54)	0.03 (0.01)	0.03 (0.01)	0.22 (0.24)	0.04 (0.10)	0.00 (0.00)
LT	8.64 (0.67)	3085.16 (1381.86)	8.54 (1.63)	38.38 (4.44)	3658.92 (531.91)	0.01 (0.01)	0.01 (0.01)	0.07 (0.11)	0.00 (0.00)	0.00 (0.00)
LU	5.91 (0.10)	1572.35 (859.88)	8.63 (1.58)	29.95 (1.47)	31534.33 (4569.31)	0.00 (0.00)	0.00 (0.00)	0.07 (0.04)	0.00 (0.00)	0.00 (0.00)
NL	7.44 (0.88)	4609.84 (3875.48)	6.39 (3.09)	26.46 (10.00)	64701.21 (13373.88)	0.02 (0.01)	0.02 (0.01)	0.34 (0.25)	0.00 (0.01)	0.04 (0.49)
PL	6.06 (0.38)	3209.75 (3134.00)	6.64 (2.02)	51.76 (6.51)	8568.12 (2166.78)	0.03 (0.01)	0.03 (0.01)	0.30 (0.22)	0.00 (0.00)	0.00 (0.00)
PT	4.74 (0.92)	3496.49 (2990.22)	12.01 (2.92)	26.45 (2.63)	73157.73 (22081.36)	0.01 (0.00)	0.01 (0.00)	0.19 (0.30)	0.01 (0.01)	0.00 (0.00)
RO	4.25 (0.81)	2896.41 (2587.12)	6.12 (2.02)	31.11 (5.60)	3194.31 (1655.89)	0.01 (0.01)	0.01 (0.01)	0.17 (0.20)	0.01 (0.04)	0.00 (0.00)
SE	6.11 (0.77)	3056.22 (2707.36)	4.96 (1.83)	48.82 (9.65)	5381.72 (3692.68)	0.04 (0.02)	0.04 (0.02)	0.10 (0.20)	0.01 (0.03)	0.00 (0.00)

B Logit regression robustness

Table 9: Determinants of Renewable Investment

	Wind			Solar		
	Pool	FE	FE+Cl	Pool	FE	FE+Cl
Natural resources	0.573***	0.651***	0.651***	0.111***	0.112***	0.112***
Node available capacity (lag)	-0.004***	-0.004***	-0.004**	-0.005***	-0.004***	-0.004***
Terrain complexity	-0.012***	-0.013***	-0.013***	-0.007***	-0.006***	-0.006***
Generation complementarity	-0.005***	-0.001	-0.001	0.020***	0.009	0.009
Land-use complexity	-0.008***	-0.006***	-0.006*	-0.004**	-0.007***	-0.007**
Population density	-0.024***	-0.020***	-0.020***	-0.013***	-0.011***	-0.011***
Land availability	-0.004**	-0.008***	-0.008**	-0.006***	-0.007***	-0.007**
Land cost	0.002	-0.002	-0.002	-0.005***	-0.008***	-0.008***
Observations	30117	30117	30117	30117	30117	30117
Pseudo R^2	0.070	0.182	0.182	0.053	0.213	0.213
Countries	21	21	21	21	21	21
Year FE	No	Yes	Yes	No	Yes	Yes
Country FE	No	Yes	Yes	No	Yes	Yes
Clustered SE	No	No	Yes	No	No	Yes

Table 10: Determinants of Solar Investment: Sequential Specifications

	S1	S2	S3	S4	S5	S6
Natural resources	0.090***	0.105***	0.105***	0.121***	0.112***	0.112***
Node available capacity (lag)						-0.004***
Terrain complexity		-0.013***	-0.012***	-0.007***	-0.006***	-0.006***
Generation complementarity			0.032*	0.020	0.012	0.009
Land-use complexity				-0.010***	-0.007**	-0.007**
Population density					-0.011***	-0.011***
Land availability					-0.007**	-0.007**
Land cost	-0.010***	-0.009***	-0.009***	-0.008***	-0.008***	-0.008***
Observations	30117	30117	30117	30117	30117	30117
Pseudo R^2	0.190	0.201	0.202	0.206	0.212	0.213
Countries	21	21	21	21	21	21
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes	Yes	Yes
Clustered SE	Province	Province	Province	Province	Province	Province

Table 11: Robustness: Alternative Estimation Methods (Solar)

	Baseline	Conditional	Probit	LPM
Natural resources	0.103*** (0.011)	0.104*** (0.007)	0.098*** (0.007)	0.098*** (0.006)
Node available capacity (lag)	-0.006*** (0.002)	-0.007*** (0.002)	-0.006*** (0.001)	-0.006*** (0.001)
Terrain complexity	-0.003* (0.002)	-0.005*** (0.002)	-0.004*** (0.002)	-0.004*** (0.001)
Generation complementarity	0.006 (0.026)	-0.018 (0.015)	-0.034*** (0.010)	-0.031*** (0.007)
Land-use complexity	-0.007** (0.003)	-0.003* (0.002)	-0.002 (0.002)	-0.003 (0.002)
Population density	-0.006** (0.003)	-0.008*** (0.002)	-0.008*** (0.002)	-0.006*** (0.001)
Land availability	-0.007** (0.003)	-0.005*** (0.002)	-0.005*** (0.002)	-0.005*** (0.001)
Land cost	-0.008*** (0.002)	-0.006*** (0.001)	-0.006*** (0.001)	-0.003** (0.001)
Observations	23515	22085	23515	23515
Countries	19	12	19	19
Pseudo R^2	0.302	0.059	0.062	
Controls	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	No	No
Country FE	Yes	Within	No	No
Clustered SE	Province	No	No	Yes

Notes: Baseline is logit with country and year fixed effects and clustered SE.
Conditional logit is estimated using within-country variation (fixed effects removed).
Standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 12: Determinants of Wind onshore Investment: Sequential Specifications

	S1	S2	S3	S4	S5	S6
Natural resources	0.968***	0.543***	0.587***	0.525***	0.644***	0.651***
Node available capacity (lag)						-0.004**
Terrain complexity		-0.022***	-0.022***	-0.015***	-0.013***	-0.013***
Generation complementarity			0.001	0.002	-0.001	-0.001
Land-use complexity				-0.014***	-0.006*	-0.006*
Population density					-0.019***	-0.020***
Land availability					-0.008**	-0.008**
Land cost	-0.006	-0.005*	-0.006*	-0.006*	-0.002	-0.002
Observations	30117	30117	30117	30117	30117	30117
Pseudo R^2	0.130	0.162	0.162	0.169	0.181	0.182
Countries	21	21	21	21	21	21
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes	Yes	Yes
Clustered SE	Province	Province	Province	Province	Province	Province

Table 13: Robustness: Alternative Estimation Methods (Wind onshore)

	Baseline	Conditional	Probit	LPM
Natural resources	0.592*** (0.125)	0.593*** (0.078)	0.584*** (0.079)	0.491*** (0.066)
Node available capacity (lag)	-0.005*** (0.002)	-0.005*** (0.001)	-0.005*** (0.001)	-0.005*** (0.001)
Terrain complexity	-0.010*** (0.003)	-0.009*** (0.001)	-0.010*** (0.001)	-0.014*** (0.002)
Generation complementarity	0.000 (0.002)	-0.002 (0.001)	-0.004*** (0.001)	-0.003** (0.002)
Land-use complexity	-0.011*** (0.003)	-0.009*** (0.002)	-0.008*** (0.002)	-0.007*** (0.001)
Population density	-0.014*** (0.003)	-0.015*** (0.002)	-0.014*** (0.002)	-0.011*** (0.001)
Land availability	-0.004 (0.003)	-0.004** (0.002)	-0.003* (0.002)	-0.003*** (0.001)
Land cost	-0.001 (0.002)	0.001 (0.001)	0.000 (0.001)	-0.000 (0.001)
Observations	23515	23515	23515	23515
Countries	19	19	19	19
Pseudo R^2	0.195	0.086	0.089	
Controls	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	No	No
Country FE	Yes	Within	No	No
Clustered SE	Province	No	No	Yes

Notes: Baseline is logit with country and year fixed effects and clustered SE.
Conditional logit is estimated using within-country variation (fixed effects removed).
Standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.