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Abstract

This paper examines the employment effects of utility-scale renewable energy deployment in Spain, combining administrative data on wind and solar installations with quarterly microdata from the Spanish Labour Force Survey at the provincial level. Using a local projection framework à la Jordà (2005), it estimates dynamic responses to installed capacity shocks, disaggregated by technology, phase, plant size, and education. Results show that solar and wind investments generate substantial provincial employment gains at their peaks: around 10.15 jobs per megawatt for solar and 12.4 for wind. Of the latter, about 2.4 jobs correspond to renewable skill-intensive occupations, whereas solar-related employment is more concentrated in other occupational categories. Additional spillover effects are identified: 2.8 jobs per MW from solar in economically linked provinces (at least one in occupations requiring intensive renewable skills), and around 0.5 renewable-skilled jobs per MW from wind, out of a total of 1.5 extraprovincial jobs. The employment effects vary sharply across phases and plant size. Job multipliers in the first investment wave (2005–2014) were 13 times higher for solar and almost 3 times higher for wind than in later years, partly due to falling costs and the shift towards larger plants. Small and medium-scale projects create more jobs per MW, either locally or via spillovers. Worker gains differ by education: solar plants primarily employ lower-educated workers locally, and vocational or university-trained workers extraprovincially. Wind plants create earlier and more consistent gains for highly educated workers, especially outside the host province. Under Spain's 2023–2030 energy plan, the estimated employment peak impact is 889,340 additional jobs from 2025 to 2030, while the observed impact from 2005 to 2024 is estimated at around 580,000 jobs.

Keywords: renewable energy; employment; spillovers; green skills; spatial heterogeneity.
JEL codes: L94; O25; R23; C33.

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1 Introduction

The global transition towards renewable energy is often portrayed as a dual engine for decarbonization and local economic revitalization. At the heart of this vision lies the promise of jobs for communities that host renewable infrastructure. However, as stated by Fabra et al. (2024), the local employment effects of utility-scale renewable energy projects remain uncertain. In many cases, residents in potential host areas express "Not In My Back Yard" concerns, fearing disruption without meaningful economic benefits. As renewable investments accelerate, understanding their employment impacts, both in magnitude and distribution, is essential for designing effective climate policy and securing public support for the energy transition.

This question is particularly relevant for Spain. Over the past two decades, the country has experienced rapid growth in solar photovoltaic and onshore wind capacity, driven by ambitious climate goals and supportive policies against a background of favorable resources' endowment for wind and solar energy deployment. Much of this capacity has been installed in rural provinces, which are often characterized by higher unemployment rates and population decline. Policymakers have promoted renewable energy as a catalyst for regional development in these areas (e.g. MITECO, 2024). Yet whether this expansion translates into actual job creation for local residents remains an open empirical question. Do renewable installations generate meaningful employment opportunities for nearby workers, or do the benefits primarily accrue to external firms and specialized labor?

Recent evidence from Fabra et al. (2024) offers a first look into these dynamics. Using aggregate data from more than 3,900 Spanish municipalities, the authors find that solar installations are associated with increases in local employment and declines in unemployment, while wind projects show smaller or statistically insignificant effects. These differences are attributed to the variation in labor intensity and skill requirements between technologies:

solar plants typically involve generic construction tasks that can be performed by local contractors, whereas wind projects demand specialized technical skills and heavy equipment, often provided by non-local firms.

In this paper, we build on this emerging literature by providing a micro-level analysis of the labor market effects of renewable energy investments in Spain. We construct a novel panel dataset that links detailed administrative records on the timing and location of renewable installations with individual-level data from the Spanish Labour Force Survey (Encuesta de Población Activa, EPA). This approach enables us to investigate not only overall employment trends but also who benefits: which occupations are favored, which types of workers gain jobs, and how effects vary by period, plant size and education level.

Our empirical strategy relies on local projections à la Jordà (2005) to estimate the dynamic impact of renewable capacity additions, disaggregated by technology, on provincial employment. We exploit exogenous variation in the timing and intensity of new capacity additions, investigating heterogeneous effects by phase, plant size, and education.

Our contributions are fourfold. First, by using microdata and examining spillovers to neighboring or economically linked provinces, we distinguish between jobs gained by local residents and those filled by commuters or residents in other provinces. Second, we identify "green occupations" or "renewable occupations" -terms we use interchangeably throughout this paper- based on the ESCO (European Skills, Competences, Qualifications and Occupations) taxonomy, as adapted to Spanish data in Barrutiabengoa et al. (2025a), and we assess whether renewable energy investments promote employment in occupations requiring green or renewable skills or not. Third, we examine temporal and size dynamics by separating the employment effects across different phases and plant dimensions, an important distinction given the technological evolution and changing scale of renewable plants in Spain. Finally, we analyze heterogeneity across education levels. In summary, this paper provides novel provincial-level evidence on the labor market impacts of renewable energy deployment.

By identifying the channels and limitations of green job creation, we contribute to a more realistic understanding of how clean energy transitions affect local economies.

The remainder of the paper is organized as follows. Section 2 reviews the relevant literature and contextualizes the Spanish case. Section 3 describes the data sources and presents the construction of the key variables, including our measures of renewable capacity deployment and green-skilled employment. Section 4 offers a descriptive overview of renewable roll-out across provinces and time. Section 5 outlines the empirical strategy, detailing the local projection framework and our identification approach. Section 6 presents the main results, including average employment effects, spillovers, and heterogeneity by phase, plant size, and education level. Section 7 uses these estimates to quantify the total employment impact of renewable expansion in Spain, both retrospectively (2005–2024) and under the 2023–2030 national energy plan. Finally, Section 8 concludes.

2 Literature review and background

The potential of renewable energy investments to stimulate local labor markets has become a focal point in policy and academic debates surrounding the green transition. While renewable deployment is often justified by its environmental and long-term macroeconomic benefits, there is increasing scrutiny on its distributional consequences, particularly whether these projects create meaningful employment opportunities for the communities that host them. This issue is especially salient in the context of utility-scale renewable projects, which often face local resistance under the "Not In My Backyard" dynamic (Germeshausen et al., 2023; Jarvis, 2025; Rand and Hoen, 2017). Concerns over land use, visual and environmental disruption, or limited local economic benefits frequently underlie opposition to new solar and wind facilities. Yet, as many countries frame green energy as a pillar of growth and industrial strategy (WorldBank, 2021; Sachs et al., 2020), robust empirical evidence is needed to assess whether renewable investments deliver on their promise of "green jobs."

Theoretical channels through which renewables may affect employment are well documented. Construction and installation phases are typically labor-intensive and may generate short-term jobs in civil engineering, electrical work, and ancillary services (Fabra et al., 2024). The extent of local hiring in this phase depends on the labor intensity of the technology, the skill composition required, and the availability of suitable workers. For instance, solar PV projects are generally more modular and less technically demanding than wind farms, enabling greater use of local labor. In contrast, wind energy often relies on specialized mobile teams and imported equipment, reducing its anchoring in local labor markets (International Renewable Energy Agency, 2017, 2022). Maintenance and operations require fewer workers and are often centralized or automated. Additional employment effects may arise indirectly via increased local demand for goods and services, though these general equilibrium effects are often modest and hard to isolate empirically (Moretti, 2010; Krekel et al., 2021; Sunak and Madlener, 2016).

Empirical studies have yielded mixed evidence on these mechanisms. In the United States, Brown et al. (2012) estimate modest job creation effects of wind energy at the county level, while Brunner and Schwegman (2022) find little impact on total employment but detect gains in local GDP and per capita income. Hartley et al. (2015) similarly find no significant job creation in counties with new wind farms. In contrast, studies on green stimulus programs such as the ARRA show more robust effects: Popp et al. (2022) estimate that each million dollars of green funding created approximately ten long-run jobs; Vona et al. (2018) find large local spillovers from green job creation into non-tradable sectors. In fossil fuel contexts, Feyrer et al. (2017) show that fracking activity generated 0.85 jobs per million dollars of output, while Komarek (2016) and Weber (2012) document substantial local gains from natural gas booms.

Cross-country evidence for Europe also presents mixed results. Azretbergenova et al.

(2021) apply panel data techniques to EU countries and find a statistically significant but economically modest effect of renewable energy production on employment, with strong heterogeneity across regions. Similarly, Fragkos and Paroussos (2018) use a general equilibrium model and estimate that renewables could support 1.3% of total EU employment by 2050, especially in sectors such as construction and bioenergy. However, the net effects depend crucially on the speed of deployment and the ability to retrain workers displaced from fossil fuel sectors.

At a more disaggregated level, Osei et al. (2022) compare employment effects in European and Asian countries, finding that institutional quality and supply chain depth are key mediators of job creation from renewables. This reinforces the notion that local absorptive capacity plays a decisive role in translating green investment into labor market gains.

Evidence from the Iberian Peninsula is particularly insightful. Costa and Veiga (2021) find that wind investments reduced unemployment in Portugal during the first wave of renewable expansion (1997–2017), but effects depended heavily on plant size and region. In Spain, Fabra et al. (2024) conduct one of the most comprehensive analyses to date, using panel data from over 3,900 municipalities between 2017 and 2021. They estimate dynamic employment and unemployment responses to solar and wind installations using local projections with two-way fixed effects. Their findings reveal that solar projects generate significant employment gains during the construction phase, about 0.55 job-years per MW, while wind projects have weaker and more transient effects. Most of the solar-induced job creation dissipates after the project becomes operational, and much of the employment associated with wind projects is filled by non-local workers. Importantly, Fabra et al. (2024) also examine fiscal spillovers, showing that renewable investments increase municipal revenues and per capita income, though the latter gains are largely attributable to capital income (e.g., land leases) in the case of wind. Serra-Sala (2023) complements this picture by finding that wind farms increase local fiscal revenues but have limited and uneven employment effects. Supporting this evidence, Blanco et al. (2021) use input-output modeling to assess Spain's 2011–2020 Renewable Energy Plan and find that regional multipliers vary widely, with rural areas benefiting less from job creation than urban centers with industrial capacity.

Recent macroeconometric studies further highlight the asymmetric nature of labor market responses. Naqvi et al. (2022) show that the effect of renewables on unemployment in Europe is nonlinear: positive shocks to renewable energy reduce unemployment more in periods of economic slack than during booms. This points to the countercyclical potential of green investments but also underscores their limitations as a universal employment tool.

Several studies also suggest that a significant portion of job creation in renewable energy is concentrated in mid-skill occupations and heavily gendered sectors. For instance, Mauritzen (2020) notes that wind energy contributes modestly to rural incomes in the U.S., but not through employment. These patterns raise concerns about the inclusiveness of renewable-driven job growth. Recent work by Barrutiabengoa et al. (2025a) in the Spanish context proposes a taxonomy of green occupations based on the ESCO classification, allowing for a more granular identification of jobs that require green/renewable skills. Incorporating such a framework is essential to distinguish between short-term construction jobs and long-term green employment that can support sustained transitions.

The Spanish case is particularly relevant given its two distinct waves of renewable investment. The first wave (2006–2014), triggered by generous feed-in tariffs, involved smaller, dispersed projects. The second wave (from 2018 onward), driven by auction schemes and falling costs, has produced larger plants concentrated in rural provinces with fragile labor markets and demographic decline (Fabra et al., 2024; IRENA, 2024). According to Red Eléctrica de España (2025), renewables now supply over half of Spain's electricity, with 34.9 GW of solar and 32.5 GW of wind installed by June 2025. This dramatic transformation creates both opportunities and risks for local labor markets. Gutiérrez et al. (2023) document spatial mismatches in Spain between economic activity and population, which may exacerbate inequalities in who benefits from the green transition.

Altogether, this literature suggests that while renewable energy investments have the potential to stimulate local labor markets, their actual impact is mediated by technology, timing, skill needs, and local absorptive capacity. For policymakers, this underscores the importance of complementary interventions, such as training programs or community benefit agreements to ensure that renewable energy transitions also yield inclusive and geographically balanced employment outcomes.

3 Data

Following Fabra et al. (2024), our baseline specification builds upon two key variables: installed renewable capacity, which serves as the exogenous shock, and employment, which constitutes the outcome variable of interest. This framework enables the estimation of impulse-response functions using local projections to assess the dynamic effects of renewable deployment on employment.

3.1 Installed renewable capacity

Data on renewable (wind and solar[1]) capacity installations were obtained from the PRETOR database,[2] Spain's official administrative registry of energy generation.[3] This registry contains detailed plant-level records, including information on location (municipality), installed capacity (in kilowatts), and several relevant administrative milestones.

In this study, we use the date of definitive registration as the benchmark for timing the shock. This date marks the formal inclusion of the plant in the remuneration scheme and is

[1] Rooftop solar panels installed for residential self-consumption are not included in the analysis.

[2] PRETOR - Sede Electrónica.

[3] Eligible technologies include renewable energy sources, cogeneration, and installations based on waste treatment.

granted only after the successful completion of all required technical inspections, as regulated by Royal Decree 413/2014 of 6 June.[4] However, due to delays in administrative processing, definitive registration may occur several months after the actual completion of construction. Therefore, in line with Fabra et al. (2024), we allow the employment effects to materialize ahead of the registration date, particularly during the construction phase.

In our baseline specification, we allocate installed capacity to the quarter in which definitive registration occurs ($t = 0$), while tracing its effects from eight quarters prior through four quarters after this date. We further distinguish between two renewable technologies: solar photovoltaic and onshore wind. This disaggregation allows us to explore potential heterogeneity in employment responses, given the differing labor intensities and installation processes associated with each technology. The data are grouped by province and quarters, and are presented in megawatts (MW).[5]

3.2 Employment data

Quarterly employment data are drawn from Spain's Labour Force Survey (Encuesta de Población Activa, EPA), produced by the Spanish Statistical Office (INE). We use province-level microdata from the first quarter of 2005 through the fourth quarter of 2024, which provides representative coverage over time and across Spanish provinces. To ensure comparability and smooth fluctuations due to seasonality, the employment series is seasonally adjusted using the Demetra+ software package.

Our primary outcome variable is the logarithmic quarterly difference in total employment at the provincial level. We focus on the aggregated outcome, although disaggregated results by period, plant size or education level are explored in subsequent analyses. To better capture employment effects in sectors more exposed to the green transition, we also

[4] Published in Spain's Official State Gazette (BOE-A-2014-6123).
[5] Kilowatts divided by 1,000, to enhance clarity

complement our analysis with a classification of ”green or renewable occupations” constructed by integrating EPA microdata with the ESCO (European Skills, Competences, Qualifications and Occupations) framework, following the methodology developed in Barrutiabengoa et al. (2025a). Specifically, renewable employment is defined as employment classified under CNOs 24, 31, 32, 71, 72, and 75. These six occupations correspond to the categories with the highest intensity of green skills identified in Barrutiabengoa et al. (2025a), and together they capture both the technical and manual dimensions of the renewable energy transition.[6] While the broader framework developed by Barrutiabengoa et al. (2025a) also identifies other green skill categories, such as those related to biodiversity or recycling, these are not considered in the analysis.

3.3 Indirect employment effects via interregional trade

To capture indirect or spillover employment effects across provinces, we compute a measure of employment growth in provinces economically connected to each focal province. This is achieved by multiplying the provincial employment growth vector in each period by an inter-provincial economic-flows matrix.

The interdependence matrix is sourced from the C-Intereg project, [7] and corresponds to the year 2019.[8] It contains bilateral trade linkages across all Spanish provinces. To isolate inter-provincial effects, we set the diagonal elements (representing self-dependence) to zero.

[6] CNOs 24, 31, and 32 include Science, Engineering, and Mathematics Professionals, Science and Engineering Associate Professionals, and Physical and Engineering Science Technicians, respectively, occupations that typically require advanced technical training and exhibit a high concentration of green competences. Meanwhile, CNOs 71, 72, and 75 encompass Construction Trades Workers, Metal, Machinery and Related Trades Workers, and Labourers in Mining, Construction, Manufacturing and Transport, categories more directly tied to on-site construction and installation activities. This extended definition allows us to better account for the full range of occupational profiles involved in the deployment and operation of renewable energy infrastructure.

[7] Annual Trade Dashboard – C-INTEREG.

[8] One could argue that using a fixed matrix of interprovincial linkages has certain drawbacks, as economic relationships between provinces may evolve over time. However, as shown in Barrutiabengoa et al. (2025b), replacing the matrix with time-varying alternatives does not materially affect the results, since the structure of interprovincial linkages does not change significantly in a statistical sense over the sample period.

The resulting matrix, denoted $\mathbf{W}$, captures the extent to which employment growth in one province may influence or reflect conditions in other economically linked provinces.

Let $\Delta \log(\mathbf{E}_t)$ be the vector of log differences in employment across provinces at time t. Then, the measure of extraprovincial employment growth affecting province i is given by:

$$\tilde{E}_{i,t}^{\text{spillover}} = \sum_{j \neq i} W_{ij} \Delta \log(E_{j,t}) \tag{1}$$

This transformation yields a corrected measure of employment growth in connected or economically proximate provinces -growth that may depend on the additions in megawatts in the focal province. In other words, it isolates the component of employment growth in other provinces that is potentially responsive to changes in installed capacity within the province under study. This spatially-weighted employment metric is later used to estimate extraprovincial impulse-response functions and assess the extent to which renewable investments in one region generate indirect employment in others.

3.4 Data integration and final sample

The final dataset consists of a panel of Spanish provinces observed quarterly from 2005Q1 to 2024Q4. Each observation includes the total (and renewable) employment levels, newly installed capacity by technology (solar or wind), and population controls. Installed capacity is normalized by lagged provincial population to account for size heterogeneity and avoid scale-induced endogeneity. Put another way, the shock is scaled to avoid imposing a relationship between province size and impact. The aim is to prevent larger provinces from mechanically exhibiting a greater effect from the same shock, which would be counterintuitive. Such a setup would implicitly suggest that installing the same amount of MW requires more workers in larger provinces -i.e., that they are less efficient.

This setup allows us to estimate dynamic local multipliers of renewable deployment on employment, while controlling for time -and province-fixed effects.

4 Renewable roll-out in Spain: an overview

The evolution of renewable energy deployment in Spain reveals two clearly differentiated phases, as depicted in Figure 1. The first phase, spanning from 2005 to 2014, was marked by a rapid expansion in installed capacity, fueled by generous public support mechanisms. This period culminated two years after the enactment of Royal Decree-Law 1/2012, which suspended economic incentives for new renewable, cogeneration, and waste-based electricity generation projects.[9] The scope of the moratorium was limited to installations that had not yet been formally registered in the remuneration scheme. As such, the aggregate capacity continued to grow temporarily, reflecting the completion and registration of projects that had secured preliminary approvals before the decree's entry into force.[10]

The second phase commenced with the gradual reactivation of support mechanisms. In 2015, public auctions were reinstated for wind projects and, two years later, extended to solar installations.[11] This marked the beginning of a new cycle of deployment, with a marked acceleration from 2018 onward.

Figure 1 also identifies two peaks in definitive registrations linked to regulatory discontinuities. The first, in Q3 2008, was driven by developers rushing to benefit from the favorable feed-in tariffs under Royal Decree 661/2007 before the introduction of RD 1578/2008, which lowered remuneration levels and imposed capacity quotas.[12] The second

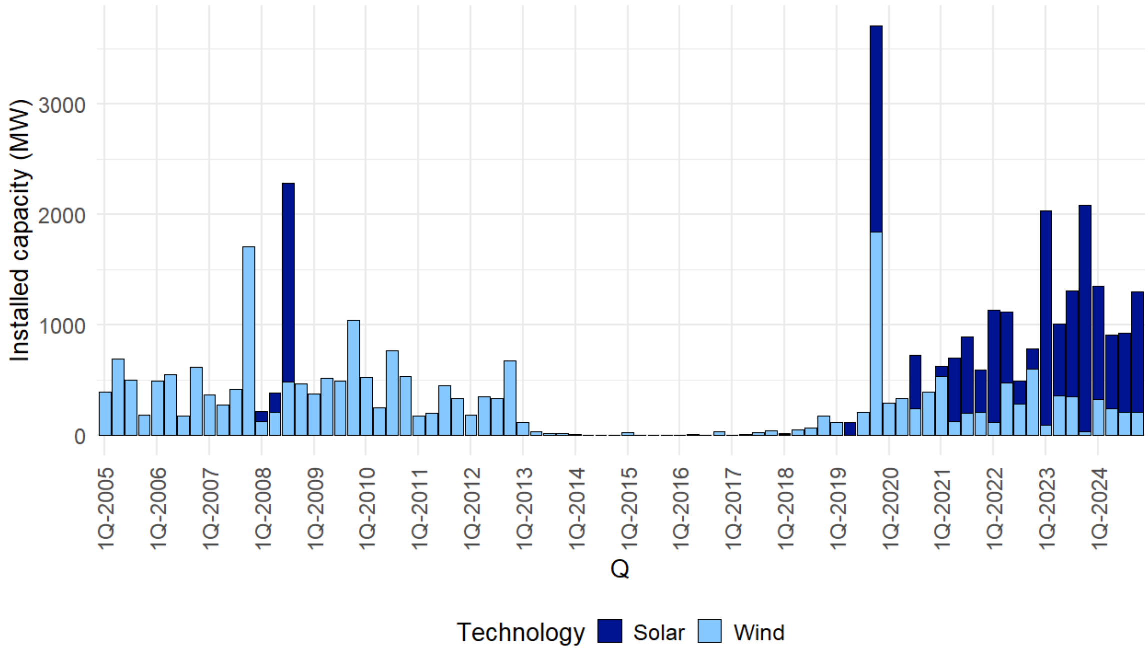
[9]Royal Decree-Law 1/2012 entered into force on January 28, 2012.

[10]Projects that had already been granted access permits or preliminary registration before the Royal Decree entered into force were still eligible to complete the process under the previous support scheme. For this reason, the first phase is extended up to two years beyond the enactment of the aforementioned Royal Decree, following the approach taken in the literature -for example, in Fabra et al. (2024).

[11]Orders IET/2212/2015 and ETU/315/2017 established the regulatory and remuneration conditions for these auctions.

[12]Royal Decree 1578/2008 replaced the previous system with a capped auction-based scheme, significantly reducing tariffs for new solar projects.

Figure 1: *Evolution of installed capacity in Spain*

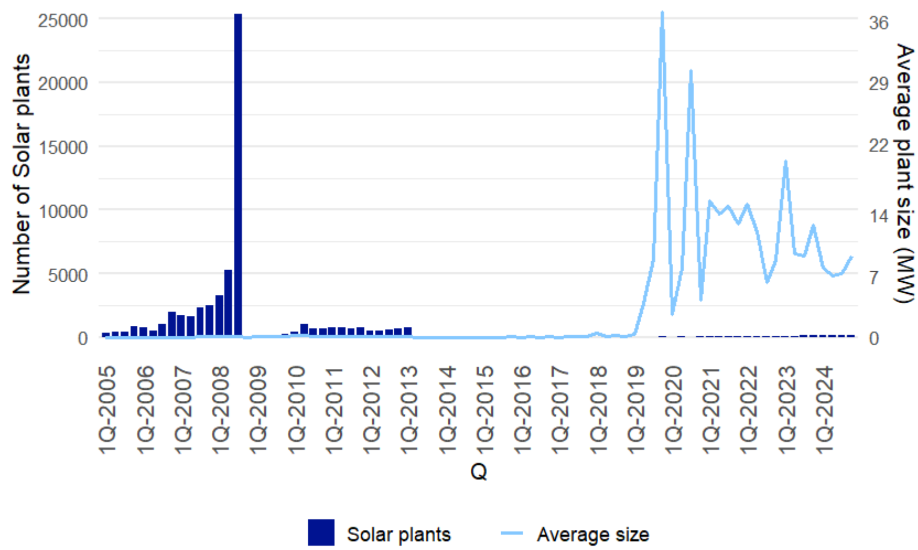


peak, in Q4 2019, reflected a similar regulatory anticipation effect, as developers sought to complete project formalities before the administrative milestones and deadlines introduced by RD-Law 23/2020 took effect.[13] Technological composition also shifted markedly across phases. Whereas the initial expansion was largely wind-driven, the second phase witnessed the dominance of solar capacity, which overtook wind as the leading source of cumulative installed renewable power by 2024.

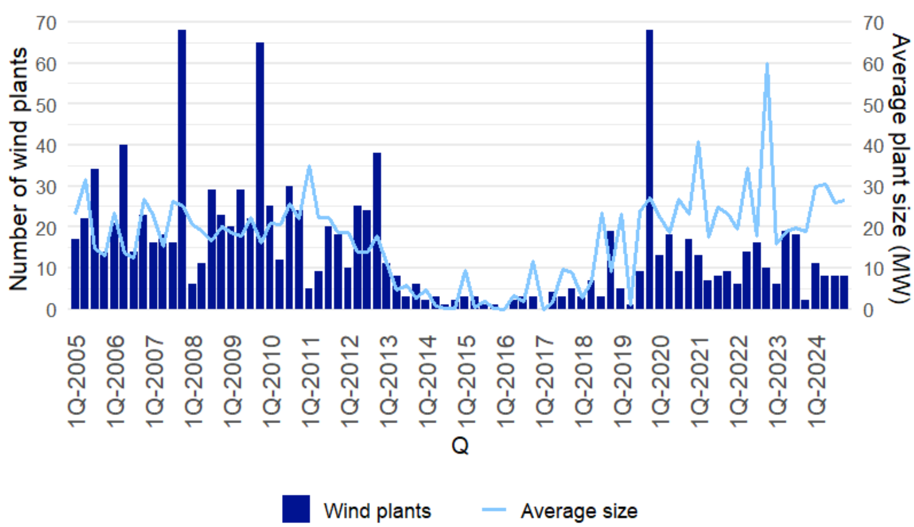
Beyond regulatory factors, the two phases also differ in terms of technological efficiency and deployment scale. According to IRENA (2024), the levelized cost of electricity (LCOE) for wind declined by 65% and for solar by 85% between 2010 and 2023. These cost reductions were accompanied by a profound transformation in the size and nature of new projects. For solar, the number of plants installed quarterly decreased from 1,457 to 71, while the average

[13] RD-Law 23/2020, effective from June 25, 2020, imposed binding conditions on the preservation of grid access rights.

Figure 2: *Number of plants and average size per year*



(a) Solar

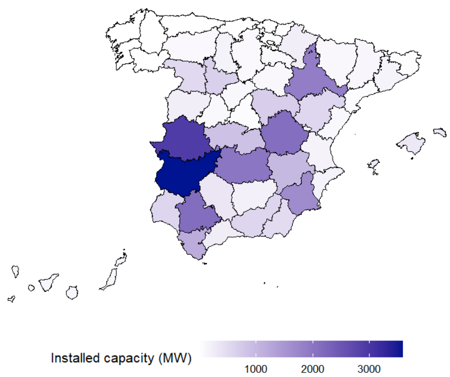


(b) Wind

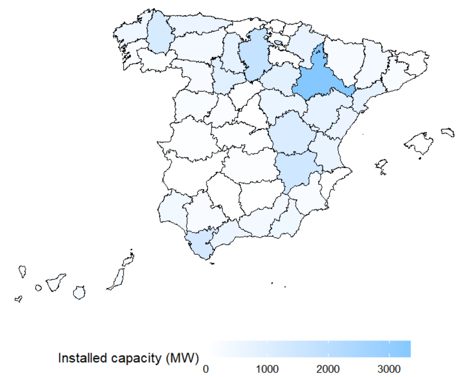
plant size rose from 0.07 MW to nearly 10 MW. In wind, the number of new plants declined from 20 to 12 per quarter, while the average capacity increased from 17.04 MW to 22.6 MW. These trends are illustrated in Figure 2. These structural shifts suggest that the employment effects of renewable deployment are not constant over time. Rather, they exhibit a degree of temporal heterogeneity that will be explored in subsequent sections.

Spatial heterogeneity is equally salient. Figures 3a and 3b show the geographic distribution of installed capacity by technology. Wind projects are concentrated in Galicia, the northeast, and the province of Cádiz, while solar installations are most prevalent in the southern regions. Figures 3c and 3d extend this analysis by depicting commercial proximity to renewable deployment, a metric that captures inter-provincial economic exposure to installed capacity based on trade linkages. Regions such as Madrid, Barcelona, Valencia, and Seville emerge as commercial hubs in both technologies, suggesting that they may experience indirect employment spillovers even in the absence of significant local deployment. This insight underpins the relevance of considering both direct and indirect channels when evaluating the labor market effects of renewable energy investments.

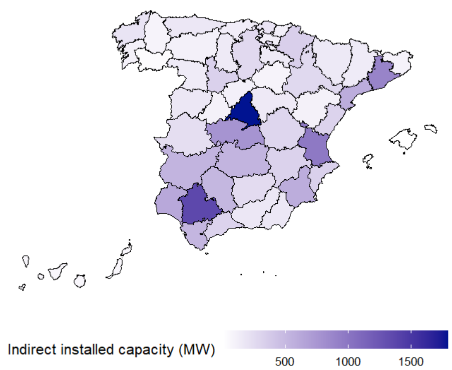
Figure 3: *Map of installed capacity by technology*



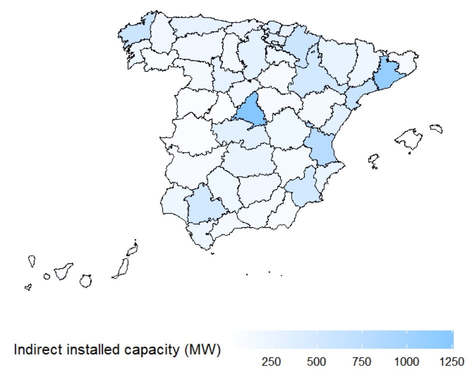
(a) Solar installed capacity



(b) Wind installed capacity



(c) Economically interconnected solar capacity



(d) Economically interconnected wind capacity

5 Baseline specification

5.1 Motivation and estimation framework

To estimate the dynamic employment effects of renewable capacity installations, we rely on the local projection (LP) method developed by Jordà (2005). LPs offer a flexible, transparent, and robust framework for studying impulse-response dynamics in panel settings with staggered treatment adoption, varying treatment intensities, and unit-specific heterogeneity. Unlike models that rely on strong structural assumptions or specific timing constraints, LPs allow researchers to estimate dynamic effects directly and non-parametrically, through a series of horizon-specific regressions.

Their growing popularity in applied work stems from this simplicity and robustness. As noted by Montiel et al. (2024), LPs allow for valid and conservative inference even in small samples and under complex data-generating processes, albeit at the cost of some statistical efficiency. This makes them particularly attractive in empirical settings, such as ours, where shocks are heterogeneous across space and time, and where inference robustness is paramount. Recent studies in macroeconomics and regional economics, such as Ramey and Zubairy (2018), Alloza and Sanz (2021), and Fabra et al. (2024), confirm the relevance of LPs for dynamic policy analysis in high-dimensional settings.

5.2 Regression specification

For each forecast horizon $h \in \{-H, \ldots, -1, 0, 1, \ldots, L\}$, we estimate the following regression:

$$y_{i,t+h} = \alpha_i + \gamma_t + \sum_{p=1}^{P} \beta_p y_{i,t-p} + \sum_{q=0}^{Q} \theta_q X_{i,t-q} + \sum_{p=0}^{P} \delta_p C_{i,t-p} + \varepsilon_{i,t+h} \tag{2}$$

where:

- $y_{i,t+h}$ is the outcome variable, defined as $\Delta \ln(E_{i,t})$, i.e., the quarterly employment growth rate. We estimate this equation using two different outcomes: (i) total provincial employment and (ii) extraprovincial (spatially-weighted) employment, as defined in Section 3.3, to separately identify intraand interprovincial effects.

- $X_{i,t}$ denotes the additional installed renewable capacity in megawatts, normalized by the provincial lagged population to avoid scale-induced endogeneity.[14]

[14]Beyond the direct effects on employment resulting from the construction and maintenance of renewable energy plants, such investments may also generate indirect, general equilibrium effects. Increased economic activity can lead to additional job creation in related sectors, but may also crowd out employment elsewhere in the local economy. Since we estimate reduced-form local projections, our approach captures both direct and indirect channels -without the need to explicitly model all underlying transmission mechanisms.

- $C_{i,t}$ is a vector of control variables that includes labor force in the final specification. Alternative controls, such as population density, have also been tested, each lagged P times. The results remain robust to the inclusion of these alternative specifications.

- α_i and γ_t are province and time (quarter) fixed effects, respectively.

- $\varepsilon_{i,t+h}$ is the error term.

We set $P = 9$ and $Q = 8$, allowing the model to trace dynamic effects over a horizon ranging from eight quarters before to four quarters after the installation event, i.e., $h \in [-8, 4]$, with $H = 8$ and $L = 4$. This window captures both the construction and initial operational phases of renewable energy projects, where most employment effects are expected to concentrate.

We include $P = 9$ lags of the dependent variable. This corresponds to $t-(q+1)$ under our baseline specification with $Q = 8$. Since the event window begins at $h = -8$ and construction is assumed to start around that time, this is the first horizon where a non-zero effect may plausibly occur. Consequently, the estimated coefficients for horizons earlier than $h = -8$ (if examined) would reflect pre-treatment dynamics and thus serve as a diagnostic as stated by Fabra et al. (2024).[15]

5.3 Impulse Response Functions and interpretation in levels

5.3.1 Cumulative responses

We construct accumulated impulse-response functions (IRFs) by summing estimated coefficients over the horizons using the following formula:

[15] One potential concern in panel settings with lagged dependent variables is the presence of dynamic panel bias (Nickell bias). However, in our context, this issue is mitigated by several factors: (i) our estimation strategy relies on local projections, which do not estimate dynamic parameters directly; (ii) our sample has relatively long time dimension; and (iii) our coefficients of interest are associated with exogenous variation in $X_{i,t}$, not with lagged outcomes. For these reasons, the bias is not a central concern in our framework.

$$\text{IRF}(h) = \exp\left(\sum_{s=0}^{h} \hat{\theta}_s\right) - 1 \tag{3}$$

This yields the cumulative percentage change in employment associated with an increase of one MW per capita.

5.3.2 Conversion to number of employed persons

To translate these IRFs into a more intuitive metric, the number of additional employed persons per MW, we rescale the responses using the following identity:

$$\text{IRF}_{\text{persons}}(h) = \text{IRF}(h) \cdot \left(\frac{E_{i,t-1}}{\text{Pop}_{i,t-1}}\right) \tag{4}$$

where $E_{i,t-1}$ is total employment and $\text{Pop}_{i,t-1}$ is the population in province i at time $t-1$. This transformation allows us to interpret the effect of a one-MW increase in installed capacity as the number of additional jobs it creates in absolute terms. When the dependent variable is extraprovincial employment, the same transformation is applied, but based on trade-weighted employment and population figures -that is, the product of the respective vectors and the interprovincial trade matrix.

When the dependent variable is restricted to renewable-intensive ("green") occupations, we adjust this further by multiplying by the share of renewable jobs in total employment:

$$\text{IRF}_{\text{green}}(h) = \text{IRF}(h) \cdot \left(\frac{E_{i,t-1}}{\text{Pop}_{i,t-1}}\right) \cdot \pi_{\text{green}} \tag{5}$$

where π_{green} denotes the proportion of renewable-intensive occupations (as defined by CNO codes 24, 31, 32, 71, 72, and 75) in total provincial employment. When analyzing the impact across other relevant groups, such as educational cohorts, we apply the same methodology, replacing π_{green} with the appropriate indicator, such as $\pi_{\text{edu cat}}$, each representing the share of the corresponding category in total employment.

5.4 Bootstrap inference

To construct confidence intervals for the estimated IRFs, we implement a two-step bootstrap procedure with 3,000 iterations. We begin by presenting results based on a standard resampling scheme by province, and then extend the analysis using a more demanding two-dimensional block-bootstrap design in Appendix 1. All impulse response functions report confidence intervals at the 68% and 84% levels, with the former depicted using a darker shading and the latter with a lighter one.

- **Step 1: Resampling by province (baseline approach).** At each iteration, we draw provinces with replacement and re-estimate the full set of local projection regressions using the complete time series for each selected unit. This procedure accounts for cross-sectional dependence and is widely used in panel-data applications of LPs.

- **Step 2: Block bootstrap over province-time panels.** To address potential serial correlation or time-varying uncertainty, we implement a two-dimensional block bootstrap. We sample rectangular blocks of province-time cells, preserving the temporal and cross-sectional structure of the panel. To ensure that all lag structures (of length P, and Q) are consistently defined in each resampled block, we trim the initial and final periods of the sample -typically discarding up to Q quarters at the beginning and L at the end. Furthermore, we restrict the resampling window to 8 years or 32 periods. This ensures that each bootstrap sample retains adequate temporal structure and comparable variability across iterations, thereby enhancing our ability to capture time-varying uncertainty and potential heteroskedasticity in the estimated responses. However, it introduces additional issues, as discussed in Appendix 1.

6 Results

This section presents the main empirical findings of the paper. We estimate the dynamic employment effects of renewable capacity deployment using local projections, as described in Section 5. All effects are expressed as the number of additional employed persons generated per megawatt of newly installed renewable capacity, and unless otherwise specified, are measured at the peak of their respective impulse response functions. The impulse-response functions are shown for a horizon ranging from eight quarters before the approval date ($t = 0$) to four quarters after, capturing both the construction and early operational phases of renewable projects.[16]

We begin by documenting the average responses across the full sample period (2005–2024), and then analyze heterogeneity across two clearly distinct phases of the energy transition in Spain: the first wave (2005–2014) and the second wave (2018–2024). These phases, illustrated in Figure 1, are characterized by sharp differences in project size, technological mix, and investment volume. We also examine the effects on neighboring provinces, renewable-related occupations (as defined by CNO codes), heterogeneity by plant size, and differences by education level.

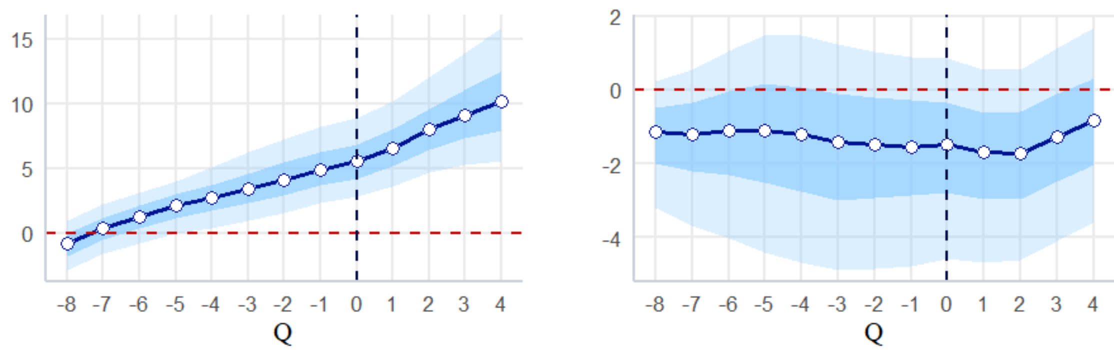
6.1 Baseline employment effects

Figure 4a plots the response for total employment. The installation of one additional MW of renewable capacity leads to a statistically significant increase in provincial employment, with effects starting approximately two years prior to the installation date and peaking around $t = 4$. Although we do not display the IRF beyond that point, the effect stabilizes from period 4 onwards. At their maximum, these effects reach nearly 10.15 new jobs per MW.

[16]The impulse response functions have been smoothed using a procedure functionally equivalent to penalized local projections (Barnichon and Brownlees, 2019), which impose a second-difference penalty directly during estimation. The original, unsmoothed IRFs are available in Appendix 2.

Approximately half of the employment effects are already visible during the construction phase and the initial stages of the plant. Since $t = 0$ corresponds to the day where electricity production is permitted, it is entirely expected that a relevant share of job creation occurs by that point. Nonetheless, it is interesting to observe that some additional employment emerges afterward. The median response averaged across horizons is approximately 4.4 jobs per megawatt installed.

Figure 4: *IRFs to an additional MW of solar installed capacity*

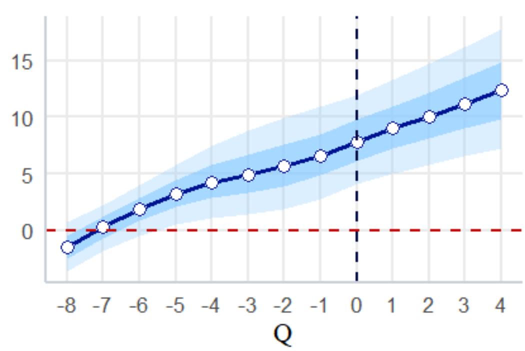


(a) Employment (b) Renewable employment

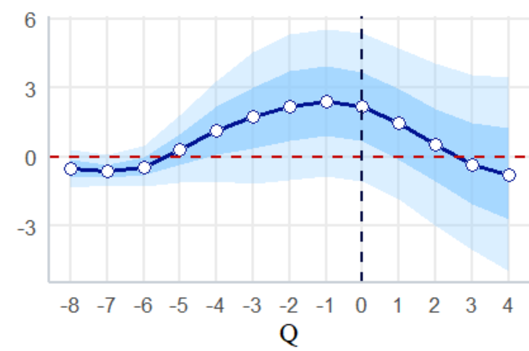
Figure 4b, which depicts the response of renewable employment to the installation of one additional megawatt of solar energy, does not reveal a statistically significant effect. This finding is consistent with prior literature -for instance, Fabra et al. (2024) emphasized that solar power deployment generally requires less specialized labor. Our results suggest that the provincial jobs that are created during solar installation may not align with the occupational profiles classified as ”green” under the ESCO framework, at least not according to the skill dimensions emphasized in its taxonomy. This may be related to employment being generated in occupational categories outside the core green CNOs identified by the ESCO framework, categories with lower green skill intensity but nonetheless essential for the construction and assembly of energy facilities.

Figure 5a shows the estimated dynamic impact of total employment in response to one additional MW of wind capacity. The employment response begins to rise steadily approximately two years prior to installation, consistent with the timing of pre-operational activities such as permitting, groundwork, and turbine assembly. The effect continues to grow throughout the construction window and into the operational phase, reaching a peak of nearly 12.4 new jobs per MW at $t = 4$. The employment response associated with wind projects exhibits a profile similar to that of solar installations, although with somewhat greater impact observed in the quarters leading up to $t = 0$. This could reflect the greater logistical and technical complexity of wind infrastructure, as well as the longer lead times required for project development and installation. However, the increase in employment also tends to level off approximately one year after the plant begins to operate, creating long-term jobs, as argued by Popp et al. (2022). The median response averaged across horizons is approximately 5.8 jobs per megawatt installed.

Figure 5: *IRFs to an additional MW of wind installed capacity*



(a) Employment



(b) Renewable employment

In contrast, Figure 5b illustrates the response of green skill-intensive employment to wind deployment. While the IRF displays a positive effect starting in the quarters leading up to installation, the estimated response is more modest in magnitude and not persistent over time. The peak reaches just above 2.4 renewable jobs per MW, after which the effect gradually dissipates and becomes more uncertain. This result is particularly noteworthy:

unlike in the case of solar, wind installations generate a statistically significant increase in renewable employment. This distinction suggests that wind energy projects may have a stronger alignment with occupations that require green skills.

The dynamic pattern and magnitude of the effects for solar are broadly consistent with the findings in Fabra et al. (2024), who estimate an impact of approximately five jobs per MW at the county level. While this figure is lower than our estimate, it remains closely aligned in both scale and interpretation. This is reasonable given that counties, as defined by Fabra et al. (2024), correspond to a smaller geographical unit than provinces -321 counties versus 50 provinces in Spain- suggesting that aggregating to the provincial level naturally amplifies the observed effect, as broader geographic units are better able to capture the effects, likely because the relevant labor supply is concentrated in larger urban centers, as well as in the provincial headquarters of major firms. In contrast, our estimates for wind diverge more substantially from those in Fabra et al. (2024), who find no statistically significant employment effect for wind deployment. Our results, by contrast, identify a clear and persistent positive impact. This discrepancy may indicate that wind-related employment effects are even more spatially concentrated and may therefore require a broader geographic scope to be fully captured. That is, employment gains from wind investments may cluster in specific areas -likely urban or industrial hubs within a province- making provincial-level analysis more suitable.

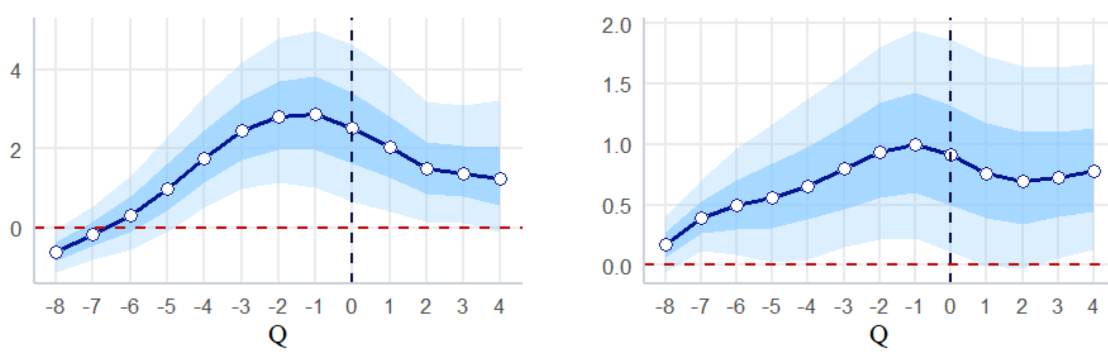
The disparity between renewable and total job responses also echoes evidence from the literature. Both Vona et al. (2018) and Popp et al. (2022) show that green investments under the American Recovery and Reinvestment Act led to the creation of direct and indirect jobs, with the latter often comprising the majority. Similarly, Mauritzen (2020) finds that the local presence of wind farms in the United States yields modest employment gains, primarily through indirect channels such as construction services or land lease payments, rather than via employment in core green occupations.

6.2 Spillover effects in economically connected provinces

We next examine whether renewable energy installations generate employment spillovers beyond the boundaries of the province in which the investment occurs. Figures 6 and 7 present IRFs based on spatially-weighted employment in economically connected provinces, using the interregional trade matrix described in Section 3.3.

Focusing on Figure 6a, we find statistically significant extraprovincial effects, with up to nearly three jobs (2.8) created in other provinces per megawatt of solar capacity installed. This is a non-negligible figure: given that approximately ten jobs are created within the province itself, it implies that around one-quarter of the total employment effect occurs outside the host province. Averaging the median response across all horizons yields an estimated 1.46 jobs per megawatt installed. This result highlights the broader economic footprint of renewable investments and underscores the importance of accounting for interregional linkages in impact evaluations. These workers may be temporarily assigned to the plants to perform construction, supervision, or management tasks, or may carry out such functions remotely.

Figure 6: *IRFs to an additional MW of solar installed capacity*



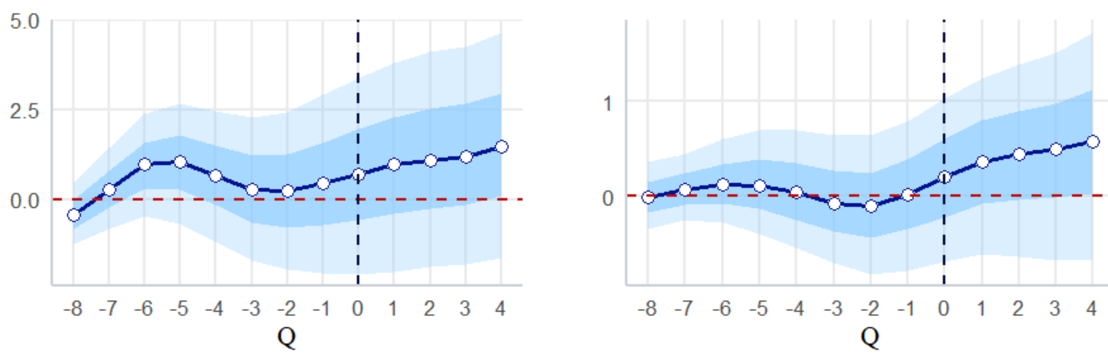
(a) Extraprovincial Employment

(b) Extraprovincial Renewable employment

Interestingly, we also find that a substantial share of these spillover jobs, slightly more than one-third, are in occupations classified as green skill-intensive under the ESCO-based taxonomy. This is in contrast to the within-province results, where green employment effects were non-significant. One plausible explanation is that more specialized, green-skill-intensive tasks may be performed by workers based in certain provinces, particularly in larger urban centers where technical expertise and service providers are concentrated. Blanco et al. (2021) already noted that rural areas generally benefit less from renewable-related job creation. However, this is likely explained not only by the concentration of skilled labor in large urban centers, but also by the fact that the headquarters of major firms are typically located in specific provinces, leading to a higher share of employment contracts being formalized there.

In both cases, the spillover effects are most pronounced around the installation phase or shortly before the plant becomes operational. This timing suggests that the extraprovincial impact may be driven by the temporary geographic mobility of workers and firms engaged in construction, installation, and commissioning activities, rather than by long-run operational needs.

Figure 7: *IRFs to an additional MW of wind installed capacity*



(a) Extraprovincial Employment

(b) Extraprovincial Renewable employment

Turning to wind, Figure 7a shows the extraprovincial effects associated with the installation of one additional MW of wind capacity. We again find positive spillovers in economically connected provinces, although the estimated effect is somewhat smaller and more uncertain than for solar. The peak reaches approximately 1.5 jobs created in other provinces per MW installed, around half of the magnitude observed for solar, and the confidence intervals are wider, reflecting greater statistical uncertainty. The median response, averaged over the entire horizon, amounts to roughly 0.7 jobs per megawatt. This more modest and less precise estimate may stem from the greater capital intensity and logistical complexity of wind projects, which could make their indirect labor footprint more variable across regions. In summary, extraprovincial employment spillovers represent about 10% of the total employment effect associated with wind installations.

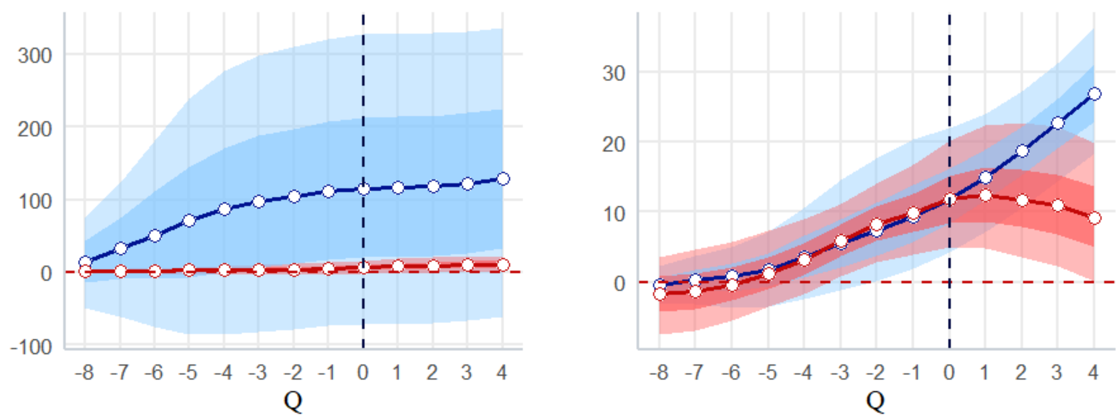
Nonetheless, an interesting feature of the wind results is the composition of the spillover employment. As shown in Figure 7b, approximately 40% of the extraprovincial jobs created correspond to occupations classified as green. This proportion is slightly higher than that observed for solar spillovers. These findings reinforce the idea that wind investments, while generating fewer total indirect jobs, are more strongly associated with specialized, green-skill-intensive labor. It is also noteworthy that these effects tend to emerge later, once the plant is already operational. As with solar, non-green spillover effects are most pronounced around the installation period or just before commissioning. This further supports the view that the extraprovincial effects are non-negligible, as argued by Krekel et al. (2021), Vona et al. (2018), Moretti (2010), and Moretti (2010) and primarily driven by non-specialized, mobile workforces and service providers engaged in the construction and commissioning of wind energy infrastructure prior to operation, but are later replaced by more stable, long-term jobs requiring green skills.

6.3 Heterogeneity by investment phase

To assess whether the employment effects of renewable investments have evolved over time, we split the sample into two distinct phases, following the temporal pattern highlighted in Figure 1 and initially identified by Fabra et al. (2024): (i) a first wave (2005–2014), characterized by smaller, more spatially dispersed projects with a predominance of wind technology, and (ii) a second wave (2018–2024), marked by the deployment of large-scale solar photovoltaic plants.

Figure 8 displays the impulse response functions for solar and wind, respectively, across both phases, with the first phase shown in blue and the second phase in red. Substantial differences are observed, particularly for solar technology. As shown in Figure 8a, the peak employment impact of solar in the first phase is close to 128 jobs per MW, compared to approximately 10.15 jobs per MW in the second phase, a difference of nearly a factor of 13. In addition, confidence intervals are substantially wider in the earlier period, rendering the response statistically non-significant at the 84% confidence level. This likely reflects greater heterogeneity in project characteristics and implementation contexts.

Figure 8: *IRFs to an additional MW of installed capacity by phases*



(a) Solar (b) Wind

This stark contrast can be partly attributed to differences in project scale and frequency, as discussed in Section 4.[17] In the first phase, the average number of solar plants commissioned per quarter was around 1,457, with a mean plant size of just 0.07 MW. By contrast, in the second phase, the number of installations per quarter dropped by 95% to 71, while the average plant size surged to 9.97 MW, a 14,143% increase. These scale shifts may influence

[17]It may also reflect differences in the financing mechanisms across phases -specifically, the shift from feed-in tariffs to competitive auctions- which, while less immediately observable, likely play a role in shaping labor market impacts. This channel warrants further investigation in future research.

employment outcomes through at least two main channels: (1) economies of scale, which reduce the amount of labor required per MW; and (2) technological improvements that lower installation and operational costs over time. The latter mechanism is supported by evidence in Fabra et al. (2024), who cite IRENA (2024) cost estimates: the average cost of solar installations fell approximately from \$4,728/kW to \$778/kW between the early and late phases, while wind costs declined from \$2,172/kW to \$1,159/kW.

Turning to wind, the differences across phases are less dramatic but still notable. The employment impact in the first phase peaks at around 27 jobs per MW, compared to roughly 12 jobs per MW in the second phase, more than a twofold difference. Adjusting for changes in technology costs (a 6x drop in cost for solar, 1.9x for wind), the employment intensity per dollar invested declines by a factor of approximately 2.1 for solar and 1.4 for wind.[18] This suggests that once we account for cost trends, the reduction in employment per MW between phases becomes more consistent across technologies.

These patterns likely reflect a confluence of factors that enhance productivity, including technological innovation, digitalization, standardization, and increasing returns to scale. Importantly, our findings are consistent with the phase-based heterogeneity documented in Fabra et al. (2024), and align with broader evidence on the evolving labor intensity of infrastructure and clean energy investments (e.g., Alloza and Sanz, 2021; Bartik et al., 2019). In the following subsection, we examine this hypothesis more directly by analyzing heterogeneity in employment effects by plant size.

[18]This interpretation implicitly assumes a relative increase in the cost of labor compared to capital, which could help explain part of the decline in employment per megawatt installed. However, other factors -such as gains in installation productivity driven by standardization, improved logistics, or greater reliance on specialized contractors- may also contribute to this pattern.

6.4 Heterogeneity by plant size

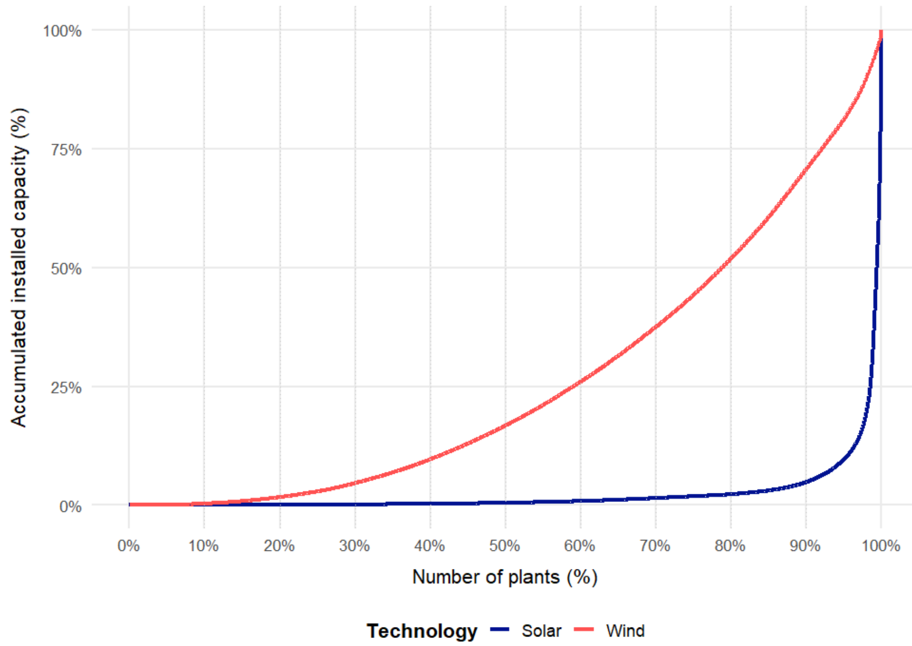
As discussed in the previous section, one of the most striking differences between the two investment phases lies in the scale of the projects implemented. In order to isolate the effect of plant size on employment outcomes, independent of time period, we now turn to an analysis of heterogeneity by plant size directly.

Figure 9 offers a clear visual representation of the distribution of installed capacity across projects, separately for wind and solar technologies. The contrast is stark. In the case of wind, cumulative installed capacity increases relatively linearly as we move through the ranked list of plants, suggesting a fairly uniform distribution of project sizes. Although some degree of convexity is present, reflecting the presence of moderately large projects, the growth is quite smooth. By contrast, solar investments exhibit a much more skewed distribution. Most solar plants are small in scale and contribute minimally to overall capacity, while a small number of very large plants account for the vast majority of installed capacity. The curve is markedly convex, exponential in shape, indicating the presence of extreme right-tail dominance in project sizes.

This extreme concentration of installed capacity among a handful of very large projects raises a natural question: to what extent do employment effects vary with plant size? In the next lines, we investigate whether smaller solar plants are associated with more labor-intensive deployment, and whether economies of scale reduce employment per MW in larger installations. As noted earlier, differences in scale may account for part of the residual gap in labor intensity -on the order of 1.4 to 2.1 times- observed between early and recent investments.

Given the highly unequal size distribution of solar projects, we adopt a classification method based on cumulative installed capacity rather than plant count. Specifically, we rank all solar plants from smallest to largest and group them into three categories according to

Figure 9: *Accumulated installed capacity by number of plants*



their contribution to total capacity:

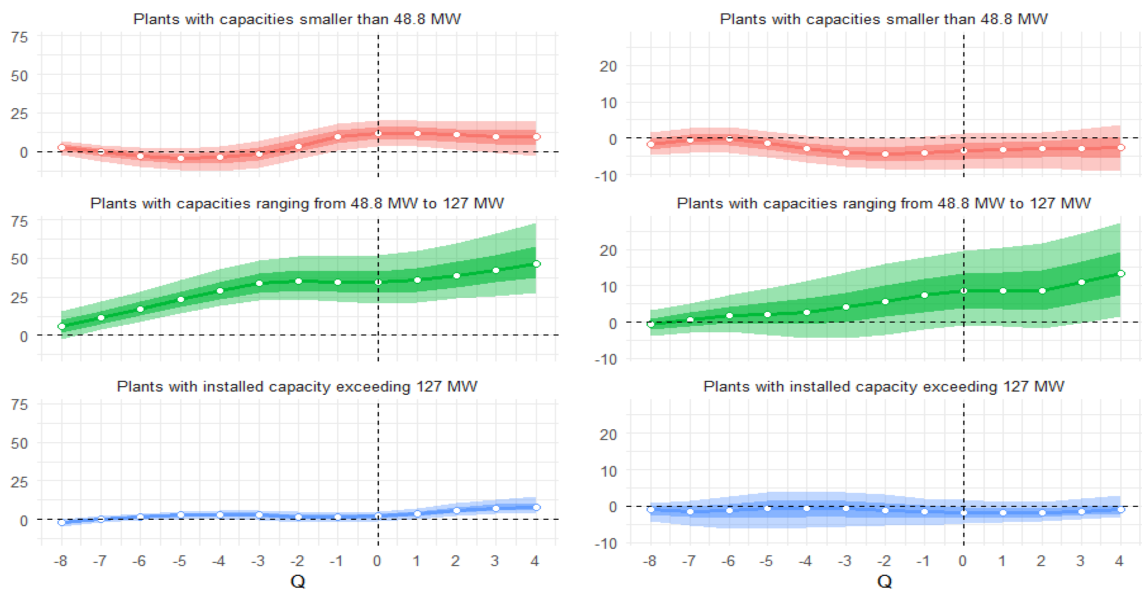
- **Small plants**: installations accounting for the bottom 50% of cumulative capacity. These do not exceed 49 MW and correspond to the regulatory threshold used in Fabra et al. (2024).

- **Medium plants**: installations contributing from the 50th to the 75th percentile of capacity, with sizes ranging from 49 to 127 MW.

- **Large plants**: installations making up the top 25% of cumulative capacity, comprising only 35 plants above 127 MW.

This approach yields highly asymmetric groups: while the small-plant segment contains 21,269 projects, the medium and large segments include only 100 and 35 plants, respectively. We adopt this capacity-based stratification precisely because the vast majority of plants, about 90%, represent only a small fraction (approximately 9%) of total capacity. A grouping based on equalplant windows would fail to capture the economic weight of the largest projects and would obscure key dynamics.

Figure 10: *IRFs to an additional MW of solar installed capacity*



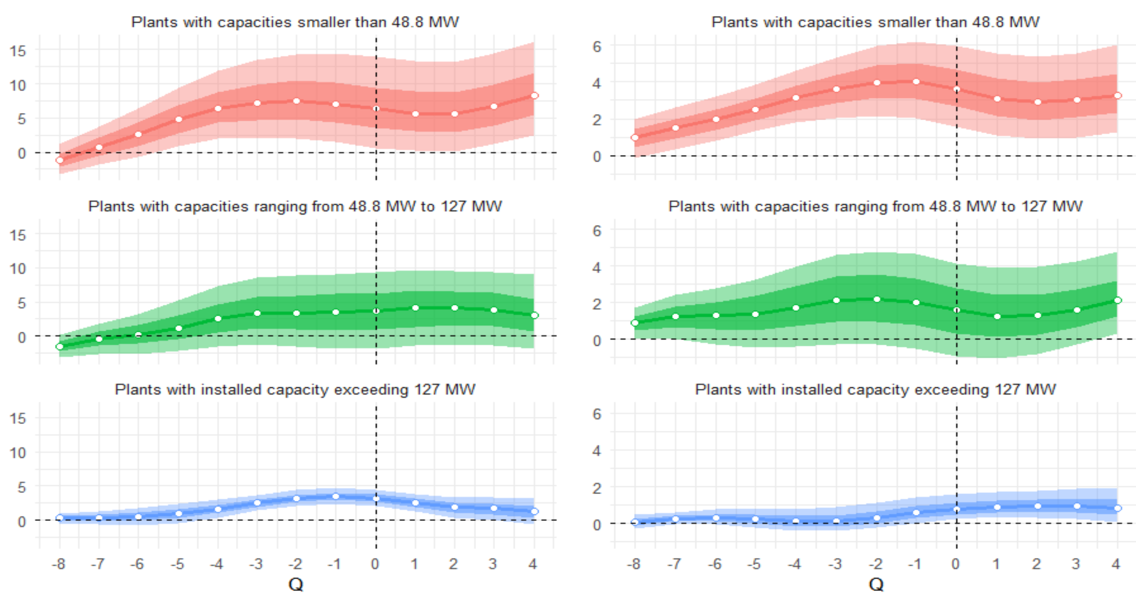
(a) Employment

(b) Renewable employment

Figure 10a presents the dynamic response of total provincial employment by plant size. The results reveal clear differences. Medium and large plants generate statistically significant positive effects, with similar timing and dynamics, peaking around the installation date, with clear anticipatory effects driven by construction activity. In contrast, the impact of small plants is only statistically significant after or close to $t = 0$, which may reflect fundamental differences in the construction processes by plant size. This result is particularly informative, as it reveals a pattern that was not fully captured in Section 6.1. Specifically, we now observe that the construction phase plays a substantial role in job creation for solar projects, a dynamic that was likely obscured in the baseline estimates due to the dominance of small scale installations in the sample. The magnitude of the employment effect is roughly 6 times larger for medium-sized plants than for large ones (46.7 vs 8 jobs per MW), suggesting that while both induce job creation, larger plants may benefit from economies of scale or greater deployment efficiency.

In terms of renewable employment (Figure 10b), only medium-sized plants show significant effects, with green jobs representing approximately one-third of total employment created. The estimates for small and large plants are not statistically significant, reinforcing the idea that medium-scale solar projects may strike a balance between capital intensity and local labor engagement.

Figure 11: *IRFs to an additional MW of solar installed capacity*



(a) Extraprovincial Employment

(b) Extraprovincial Renewable employment

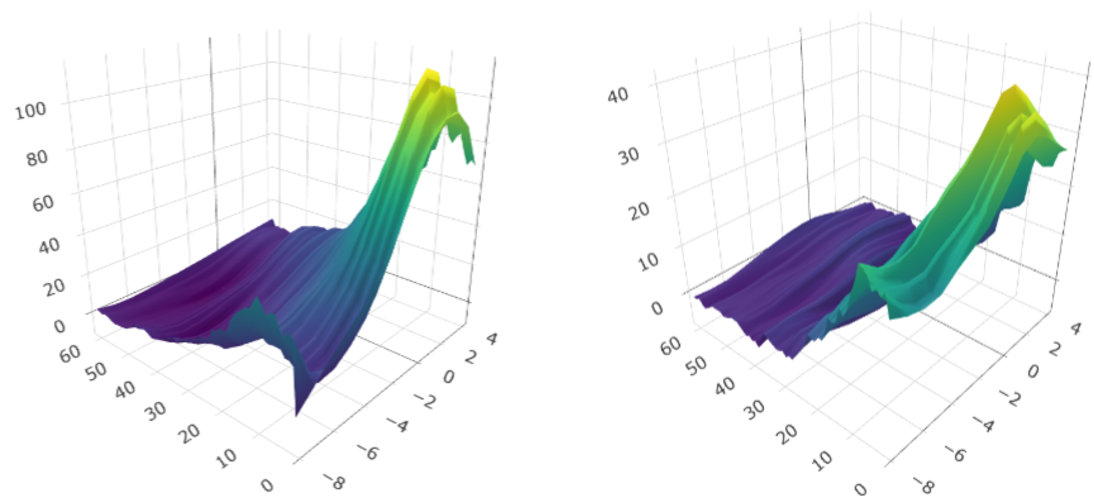
The extraprovincial results provide further insight. As shown in Figure 11a, small plants generate sizable and statistically significant employment spillovers to economically connected provinces, particularly during the construction phase. At peak, they create around 8.35 jobs per MW outside the host province -on par with the impact of medium plants but with greater statistical clarity. This suggests that small-scale projects are often executed (or complemented for medium and large plants) using external supply chains and labor, yielding indirect employment effects in trade-linked regions. This confirms the finding from Section 6.2 that solar installations generate a substantial amount of extraprovincial employment. However, statistical significance is most evident for either very large or very small plants, particularly the former, which is a pattern that appears conceptually plausible.

Finally, Figure 11b displays the dynamic response of extraprovincial renewable employment. The overall dynamics mirror those of total extraprovincial employment, but with some differences in composition. For small plants, renewable jobs account for nearly 50% of the total extraprovincial employment, a proportion that remains broadly similar for medium-sized plants. In the case of large plants, renewable employment emerges primarily after the construction phase and reaches approximately one job per megawatt installed.

Together, these results suggest that plant size plays an important role in shaping the employment impact of solar deployment. Aggregated figures, such as those reported in Section 6.1 or in Fabra et al. (2024), are heavily influenced by the characteristics of large-scale projects (although smaller plants also alter the shape of the response, they do not substantially affect its overall magnitude). Disentangling the effects by plant size reveals that small and medium installations contribute to job creation in different ways -either through local hiring or through spillovers- while large projects, though dominant in capacity, tend to generate fewer jobs per MW.

In contrast to solar, where the distribution of installed capacity is highly skewed, wind installations exhibit a much more uniform distribution across plant sizes. This characteristic allows us to explore employment effects in a more continuous fashion across the plant size spectrum. Rather than discretizing plants into a few large categories, we implement a rolling-window approach to better capture the gradual evolution of employment intensity with size. More specifically, after sorting wind plants by ascending size, we construct a set of 61 overlapping percentile windows of width 41. That is, the first group includes plants from the 0th to the 40th percentile of the size distribution, the second from the 1st to the 41st percentile, and so on, up to the final window covering percentiles 60 to 100. For each window, we estimate impulse response functions for employment outcomes. Results are presented as 3D plots: the x-axis represents event time (horizons), the y-axis represents the starting percentile of each window, and the z-axis displays the estimated number of employees per additional MW installed.

Figure 12: *IRFs to an additional MW of wind installed capacity*



(a) Employment

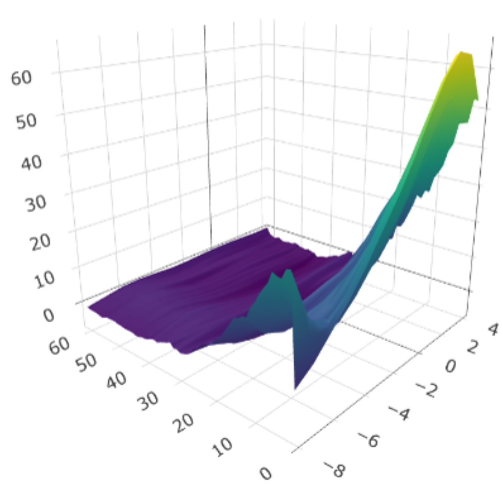
(b) Renewable employment

Figure 12a shows the results for total provincial employment. A clear and consistent temporal dynamic emerges across all plant sizes: the employment effect rises steadily until around $t = 0$, the point at which the plant becomes operational, after which it stabilizes or slightly declines. However, the magnitude of the employment effect varies sharply by size. For the largest plants (upper percentile windows), the impact reaches approximately 7 jobs per MW. In contrast, the smallest plants exhibit dramatically higher estimated impacts -up to 97 jobs per MW in the lowest percentile group (for a more detailed breakdown, refer to the tables in Appendix 3). These results suggest strong and continuous economies of scale: as plant size increases, the number of local jobs created per MW falls significantly. This is consistent with the findings of Costa and Veiga (2021), who argue that the effects of wind energy depend strongly on plant size.

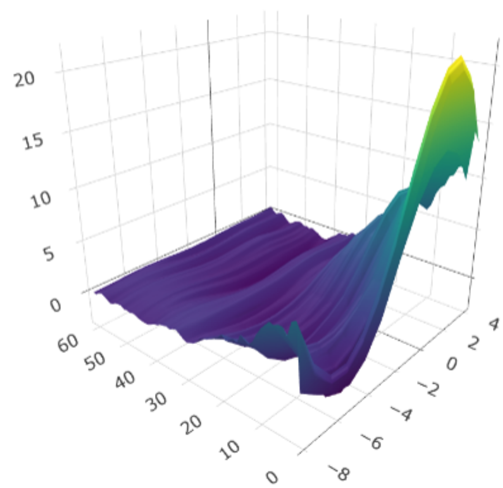
It is worth noting, however, that while effects for larger plants are statistically significant, the confidence intervals widen substantially as plant size decreases. This implies that although smaller plants may create more jobs per unit of capacity, the estimates are less precise -likely reflecting greater heterogeneity in local implementation strategies, and labor sourcing. Another contributing factor could be that many small projects were developed during the initial stages of deployment, at a time when installation technologies and processes were less mature and potentially less productive.

A similar pattern is observed in renewable employment, as shown in Figure 12b. The overall dynamics mirror those of total employment, with green jobs peaking just before commissioning and accounting for roughly 20% of total employment, consistent with baseline findings in Section 6.1. Again, larger plants generate more stable and significant effects, while smaller plants show larger but noisier estimates.

Figure 13: *IRFs to an additional MW of wind installed capacity*



(a) Extraprovincial Employment



(b) Extraprovincial Renewable employment

Turning to extraprovincial employment effects, both total and renewable, the results are slightly different from the provincial ones. As shown in Figures 13a and 13b, the estimated spillovers are close to zero for most plant sizes. This reinforces the earlier conclusion seen in the case of solar that large-scale projects tend to internalize most of their labor and supply chains within the host province. Notably, total provincial employment for large wind plants is the most robust and significant effect across all outcomes. In contrast, for smaller plants, extraprovincial employment gains become more prominent. The estimates indicate meaningful spillovers, particularly around the construction phase, effectively exporting labor demand to economically connected regions, but with greater margin of error.

In summary, smaller wind plants generate higher employment effects both within and outside the host province, albeit with greater uncertainty. These results provide further evidence of scale effects: not only do smaller plants require more labor per MW, but they also depend more heavily on extraprovincial inputs. This complements our findings for solar and confirms that aggregated figures, such as those in Section 6.1 or in Fabra et al. (2024), are heavily shaped by the characteristics of large-scale projects.

6.5 Heterogeneity by education level

One additional advantage of using microdata from the Spanish Labor Force Survey is the ability to disaggregate employment impacts by education level. This enables us to test whether the jobs created through renewable energy deployment are concentrated among more highly educated workers, or whether they are more evenly distributed. A priori, one might expect renewable-related employment, particularly in sectors like engineering or plant operation -to favor workers with higher education credentials. However, previous sections have shown that a substantial share of the observed effects are concentrated in the construction phase, and that green or specialized occupations capture only part of the total employment impact. Thus, it is not immediately obvious how education levels map onto the observed labor market response. We turn to the data to answer this question directly. For this analysis, we classify workers into three education groups:

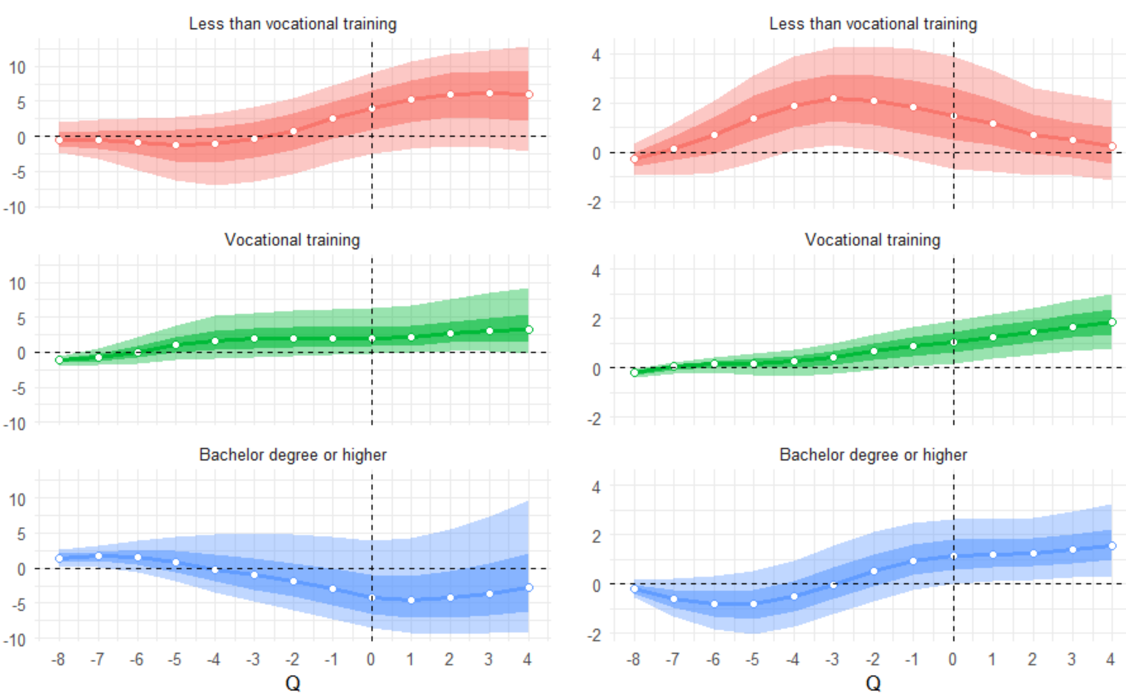
1. *Low education:* Less than vocational training,

2. *Medium education:* Vocational training,

3. *High education:* Bachelor's degree or higher.

In our sample, individuals with less than vocational training account for approximately 59.7% of the working-age population, while those with vocational training and those with a university degree or higher represent 28.3% and 12%, respectively. These proportions have evolved gradually over the past two decades, with a steady increase in the share of the population attaining vocational or higher education qualifications.

Figure 14: *IRFs to an additional MW of solar installed capacity by level of studies*



(a) Employment

(b) Extraprovincial employment

Figure 14a presents the impulse response functions for the effect of one additional megawatt of solar capacity on provincial employment, broken down by education level. We find that employment gains are more significant statistically for workers with vocational training. These effects emerge mainly during the construction phase and remain significant throughout (3 jobs per MW). In contrast, for workers with less than vocational education, we observe a slighly higher effect, around 6.2 additional jobs per MW, but with lower statistical precision (significant at the 68% confidence level but not at 84%). Interestingly, the employment response for this group is concentrated after the plant becomes operational, which may indicate that these workers are more likely to be hired for supervision or maintenance-related tasks requiring limited formal education. Finally, the employment effect for the high-education group is close to zero and statistically insignificant throughout the entire period, albeit with wide confidence bands. This may reflect greater heterogeneity in where and when highly educated workers are employed, potentially concentrated in large-scale projects, as seen in our earlier plant size analysis. When aggregating across education groups, the total estimated employment effect closely matches the baseline dynamic responses presented in Section 6.1, providing an additional layer of robustness to our core findings.

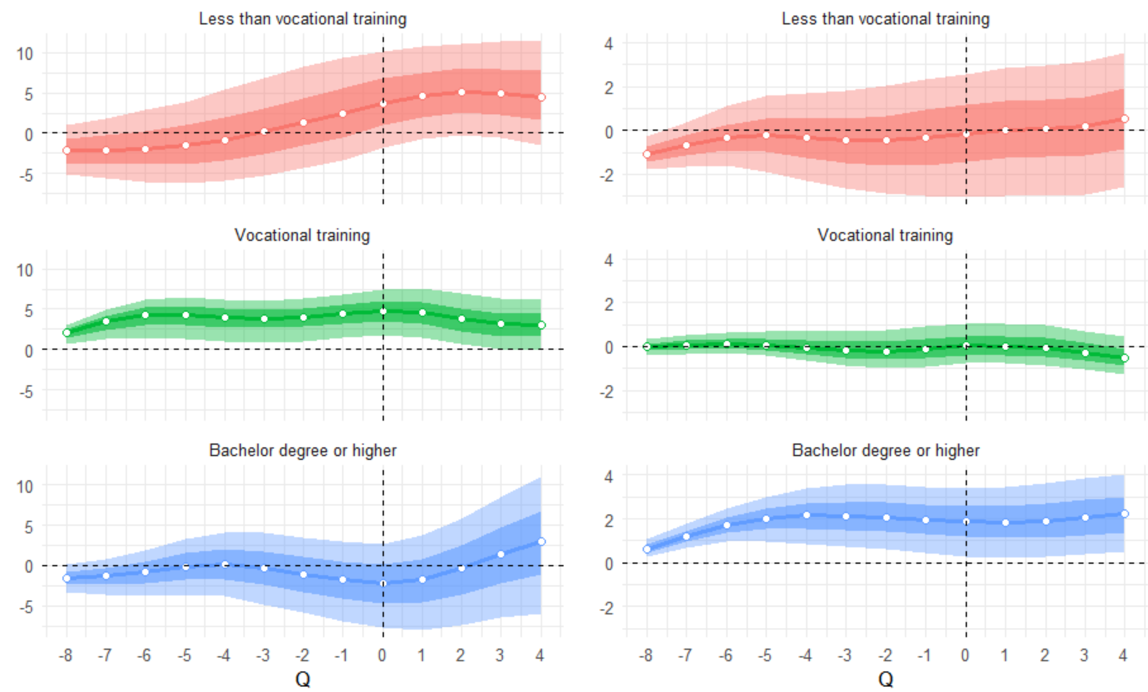
Turning to extraprovincial employment effects, the story differs. Figure 14b shows that for workers with low education, the extraprovincial impact is smaller than the provincial one, more than half as large (2.2 jobs per MW), but more precisely estimated and concentrated during the construction phase. This is consistent with the idea that workers with minimal qualifications may be temporarily contracted from neighboring regions to perform basic construction tasks, likely because specialized firms are concentrated in certain provinces. On top of that, there may also be a positive effect on extraprovincial employment stemming from jobs in solar panel manufacturing facilities, which, in most cases, do not require highly qualified workers.

In contrast, the employment effect for vocational-trained workers (1.8 jobs per MW) shifts towards the post-commissioning period. This suggests that workers with technical training may be hired in other provinces for tasks related to plant operation and maintenance, rather than construction and appear to be carried out either remotely or by workers based in other provinces who commute for work. This pattern is reinforced in the case of highly educated workers, whose extraprovincial employment effect is also close to 1.5 jobs per MW and statistically significant. This likely reflects the geographic concentration of skilled labor in specific provinces or urban centers, consistent with our earlier findings on renewable-related occupations. As previously discussed, this also reflects the fact that the headquarters of major firms are typically located in specific areas, which in turn leads to a higher share of employment contracts being formalized there.

In summary, the education-level analysis reveals a nuanced pattern. At the local level, most of the employment created after the construction phase appears to involve workers with lower levels of formal education, likely hired for routine monitoring or basic supervisory tasks. When more qualifications are required, however, hiring tends to favor individuals with vocational training. In contrast, the extraprovincial effects suggest that more highly qualified personnel, particularly those with vocational or higher education, manage, operate, or supervise the plants remotely or commuting from their home provinces, rather than relocating to the installation sites. Meanwhile, less-qualified workers are also recruited externally, either for the construction phase or to assemble the panels in manufacturing facilities located in provinces different from where the solar plants are installed. These findings align with prior work (e.g., Vona et al. 2018) showing that green employment can span a wide range of occupations and education levels, with job creation occurring both in high-skill and middle-skill segments depending on the task and phase of project deployment.

The education-level patterns for wind deployments display some important similarities with those of solar, but also reveal notable differences. Figure 15a presents the estimated provincial employment responses to one additional MW of wind capacity, disaggregated by

Figure 15: *IRFs to an additional MW of wind installed capacity by level of studies*



(a) Employment (b) Extraprovincial employment

education level. As with solar, we observe the most robust effects for workers with vocational training, approximately 5 workers per MW. The dynamic response follows a similar trajectory, with statistically significant job creation beginning during the construction phase and persisting around the time of plant commissioning. Workers with lower educational attainment (less than vocational training) exhibit a positive but statistically insignificant response, which, as in the case of solar, emerges primarily in the post-operational phase (5 jobs per MW). The key difference with respect to solar arises in the case of high-educated workers. While the effects remain statistically insignificant at 84% confidence levels, they grow larger and approach significance towards the end of the horizon (3 jobs per MW). This pattern suggests that, at the provincial level, wind projects may generate more demand for university-educated labor during the operational phase. This could be related to the complexity of managing wind installations and the more technical nature of their maintenance requirements as mentioned by International Renewable Energy Agency (2017, 2022). Importantly, the uncertainty may also reflect variation in the local supply of highly educated workers. Not all provinces have the same pool of university-trained professionals, and some projects may require drawing from labor markets beyond the immediate region. This issue has already been noted for the Spanish labor market more broadly. Gutiérrez et al. (2023) document persistent spatial mismatches between the distribution of economic activity and population across provinces.

Turning to extraprovincial employment, the dynamics differ from those observed for solar. Figure 15b shows that wind projects generate significant extraprovincial employment among highly educated workers starting as early as the construction phase. The estimated effect peaks at around 2.2 jobs per MW for university-educated workers residing in other provinces. This contrasts with solar, where high-skill employment spillovers emerge only after plants become operational. For workers with low and medium education levels, we find no statistically significant extraprovincial employment response. This may suggest that wind projects rely more heavily on local hiring for technical roles, or that external recruitment of these workers is more limited.

Overall, wind deployments appear to generate more consistent and earlier labor market impacts among highly educated workers compared to solar. Vocational-trained workers tend to benefit primarily at the local level, while university-educated workers are more likely to be recruited outside the province, particularly during the construction and early operation phases. This pattern likely reflects the high qualification requirements associated with both the assembly and supervision of wind plants, activities that can often be performed remotely or commuting from a province different from where the wind plant is physically located. Broadly speaking, the distribution of workers by education level differs substantially between technologies. In the case of solar, using the peak values of the median impulse response functions to calculate the shares, approximately 56% of the new workers fall into the low education categories, 29% in the medium education category, with the remaining 15% having higher education. In contrast, the distribution for wind is markedly different: 40% of workers have low education, 37% medium education, and 23% hold a university degree or higher. These figures suggest that the educational requirements in the renewable energy sector are generally higher than those observed in the average Spanish job -particularly in the case of wind energy.

These patterns point to the importance of regional educational supply and mobility in shaping the distribution of employment gains from the energy transition. As renewable investments expand, ensuring that local labor markets can meet the growing demand for technical and higher education profiles may become a key challenge for equitable and efficient implementation.

7 Employment from renewable expansion in Spain

7.1 Estimated historical impact of renewable deployment (2005–2024)

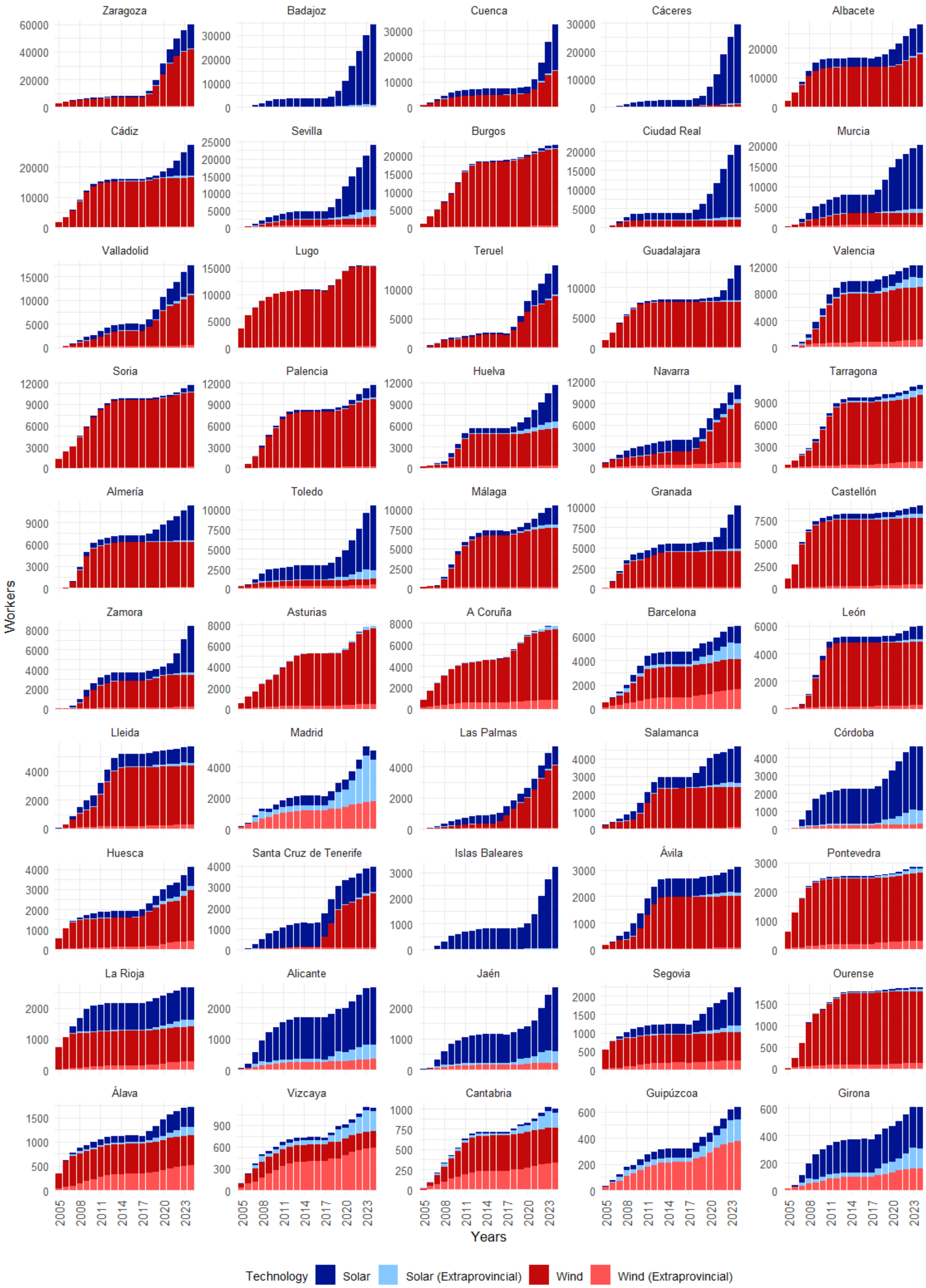
To quantify the historical employment impact of renewable energy deployment, we combine quarterly data on installed capacity by province and technology over the period 2005–2024 with the estimated impulse response function discussed in previous sections. Leveraging the analytical framework developed in this paper, we distinguish between intraprovincial and extraprovincial employment effects. Specifically, we apply the dynamic responses estimated in Section 6.1 to capture the intraprovincial effect of capacity additions within each province, and those in Section 6.2 to estimate extraprovincial effects arising through interprovincial economic linkages.

Employment effects are computed dynamically for each installation shock. Starting at quarter $t = -8$, we apply the full IRF up to $t = 4$, after which the final value is assumed to persist indefinitely. This simplifying assumption, motivated by the fact that all four IRFs remain statistically significant at t = 4, implies that employment impacts are treated as permanent from that point onward. While this assumption may lead to an upward bias, particularly for early-period installations, it provides a tractable and consistent method for long-run aggregation across provinces. It also offers a useful order-of-magnitude estimate of the cumulative labour market impact of Spain's renewable deployment.

This methodology could be understood as providing an upper-bound approximation of sustained employment creation over the full 2005–2024 period. Given the long time horizon, it is plausible that some of the jobs initially created may have been subsequently lost, either due to natural turnover, technological change, or the decommissioning of earlier projects. At the same time, our use of the median impulse response across horizons introduces an additional layer of variability. In the presence of estimation uncertainty, the realized effects are likely to lie within a distribution around this central estimate, with plausible outcomes both above and below the figures presented. To maintain tractability, we apply a single response per channel (solar/wind, provincial/extraprovincial) throughout the entire sample. This modelling choice is supported by the empirical results discussed in earlier sections, and avoids the additional complexity involved in applying dynamic responses differentiated by time period or plant size. Nonetheless, as discussed in Section 6.3, the estimated IRFs are clearly influenced by more recent installations -particularly larger projects. This may lead to a slight underestimation of effects associated with early deployments and a mild overestimation of those linked to the latter part of the sample. Figure 16 shows the cumulative employment generated by renewable deployment between 2005 and 2024, disaggregated by technology (solar vs. wind) and employment channel (provincial vs. extraprovincial). The results reveal substantial variation across provinces in both the magnitude and composition of employment creation, suggesting that applying the national average effect may lead to an overestimation of impacts in smaller, more rural provinces- and, by extension, an underestimation in the rest.

In absolute terms, Zaragoza leads with more than 60,000 cumulative jobs, followed, at

Figure 16: *Estimated historical impact of renewable deployment (2005–2024)*



some distance, by Badajoz, Cuenca, Cáceres, Albacete, Cádiz, Sevilla, and Burgos. These provinces have cumulative totals ranging from approximately 34,400 to 23,000 jobs. For a breakdown of what these figures represent relative to total provincial employment, refer to Appendix 4.

Notably, the dominant technology varies considerably across regions: e.g. wind in Zaragoza and Burgos, solar in Badajoz and Murcia. Similarly, the timing of growth is heterogeneous. For instance, Zaragoza and Badajoz experienced rapid expansion over the past 6–7 years, while others, such as Bizkaia or Alicante, exhibit more gradual and sustained growth. In nearly all provinces, the two deployment phases identified in Sections 4 and 6.3 are clearly distinguishable. In total, we estimate nearly half a million jobs (579,082) were created between 2005 and 2024 as a result of renewable deployment. Relative to the national employment level in 2024, this represents approximately 2.7 percent of total employment. The distribution by technology is relatively balanced, with 53 percent of cumulative jobs attributable to wind and 47 percent to solar. Furthermore, approximately 92.4 percent of the employment generated corresponds to direct jobs within the province where capacity was installed, while the remaining 7.6 percent, roughly 43,500 jobs, represents indirect or extraprovincial employment. Among these, several provinces stand out due to their economic centrality in the renewable value chain: Madrid accounts for 10.2 percent of all indirect jobs, followed by Sevilla (6.2 percent), Barcelona (6.5 percent), Valencia (5.8 percent), Tarragona (4 percent) and Toledo (3.7 percent).

These results are consistent with a protracted and meaningful impact of renewable energy investments on local labour markets in Spain over the past two decades. They also highlight the persistent geographical asymmetries in job creation, as well as the differentiated roles that provinces play in the deployment and support of renewable technologies.

7.2 Projected total employment from renewable expansion (2025–2030)

To quantify the potential labor market impact of Spain's renewable deployment plans, we apply our estimated employment multipliers to the expansion targets outlined in the *Plan Nacional Integrado de Energía y Clima 2023–2030* (MITECO, 2024). According to the latest figures published by Red Eléctrica de España as of June 2025 (Red Eléctrica de España, 2025), installed capacity stands at 32.5 GW for onshore wind and 34.9 GW for solar photovoltaic. These figures fall short of the PNIEC's intermediate 2025 targets, which aim for 36.15 GW of wind and 46.5 GW of solar. This represents a gap of approximately 10% in wind and 25% in solar relative to the 2025 benchmarks.

Looking ahead to 2030, reaching the PNIEC objectives would require an additional 29.55 GW of wind and 41.38 GW of solar PV capacity. Applying our total employment multipliers -defined as the median value of the IRF at horizon $h = 4$, in line with the approach discussed in Section 7.1 for capturing the permanent effect, and summing both provincial and extraprovincial impacts- we estimate 13,850 jobs per GW for wind and 11,600 for solar. Based on these figures, the expected expansion between mid-2025 and the end of 2030 would generate approximately 409,267 new jobs from wind and 480,072 from solar, for a total of 889,340 jobs. These multipliers are drawn from the dynamic responses presented in Sections 6.1 and 6.2, as they are broadly consistent with the values observed during the second investment phase, although with some differences, as discussed in previous sections, which suggest that the resulting figures may be best interpreted as an upper bound. Nevertheless, using them allows for greater consistency with the long-run interpretation in Section 7.1, balances the trade-off between simplicity and informativeness, and enables us to incorporate both within -and beyond-province employment effects.

When distributed evenly over the 5.58 years remaining until the end of the decade, the estimated figure translate into an average of approximately 159,380 local jobs per year if the plan is fulfilled. This is likely an optimistic assumption, given that deployment is already behind schedule and it is unclear whether the targets, particularly for wind, will be met, as noted by Rodríguez (2025). However, if accomplished, the estimated impact is highly consistent with the Spanish government's own projections in the PNIEC, which foresee that renewable and green hydrogen investments will generate between 138,000 and 199,000 jobs annually during this period (MITECO, 2024).[19] This number is particularly relevant when placed in context: in the last two years, 2023 and 2024, Spain created an average of 625,550 new jobs annually. Therefore, if job growth continues at a similar pace, employment linked to the energy transition would represent around 25% of total job creation, an economically significant and probably overly optimistic contribution. It is worth noting that the jobs created by renewable investments may, over a longer horizon, be offset by job losses in carbon-intensive (or "brown") sectors.[20] This would be a plausible dynamic, as fossil-based plants are not typically shut down immediately upon the entry of renewables. Rather, they are gradually displaced from the energy mix as cleaner technologies expand their market share and push conventional sources out of operation. It is also important to note that the jobs estimated here include both direct employment in renewable energy activities and indirect employment generated in other occupations, such as hospitality or local services, that benefit from increased economic activity and local income effects.

Adopting a more conservative approach by using the average multiplier across horizons, rather than the last value, leads to a lower estimate. Focusing on the mean effects, the employment multipliers fall to approximately 5,887 jobs per GW for solar and 6,509 jobs per GW for wind. Applying these to the 41.38 GW of solar and 29.55 GW of wind capacity still

[19] Our figure assumes that the delays will be made up for, so if everything had proceeded on schedule until now, the number would actually be lower.

[20] Since the EPA reports employment stocks rather than labor market flows, the data do not allow us to track individual transitions between employment states, occupations or sectos (e.g., from unemployment or inactivity to employment). As a result, we cannot directly observe whether renewable deployment leads to job creation through new hires, reactivation of inactive workers, or shifts across sectors.

to be installed yields roughly 243,595 jobs for solar and 192,340 jobs for wind. Together, this amounts to approximately 435,937 jobs, or about 49% of the 889,340 jobs estimated under the last-period multipliers. Finally, it is also informative to compare our projections with those of Fabra et al. (2024), who estimate that solar investments will generate around 5,682 local jobs per year over the decade, based on second-wave multipliers (which could reach up to 37,090 jobs per year using their county-level estimators for solar, compared to our 86,034 using our solar multiplier). The discrepancy likely reflects both methodological and definitional differences, as well as broader geographical coverage in our analysis.

Overall, our findings reinforce the view that the renewable energy transition outlined in the PNIEC holds significant potential for local employment generation. Ensuring that this potential is fully realized will depend not only on meeting capacity targets, but also on investment timing, regional execution strategies, and the distribution of project scales across Spanish provinces. Projections suggest that approximately 37,000 of the 480,072 new jobs in the solar sector, and 71,000 of the 409,267 total jobs expected from wind deployment, will be created in occupational categories identified throughout this work as particularly intensive in green skills. This implies a total of around 110,000 new green-skilled positions over the coming years, equivalent to 20,000 per year, or roughly 3% of the average annual job creation observed in Spain in recent years. At the same time, using the education-level shares estimated in Section 6.5, we can approximate how the projected employment from renewable deployment would be distributed across education groups. For solar, approximately 271,462 would correspond to workers with low education, 192,849, to those with medium education, and 15,761 jobs to workers with high education. For wind, of the 409,267 jobs projected, an estimated 155,177 would go to workers with low education, 104,061 to those with vocational training or medium education, and 150,029 to highly educated workers. In total, these figures imply that approximately 426,640 jobs would be created for workers with low education, 296,910 for those with vocational training, and 165,790 for university-educated workers.

Ensuring that the labor market can supply this volume of green-skilled workers is likely to be a major challenge, particularly given current constraints. As noted by García and Lores (2025), shortages in technically qualified labor are already a limiting factor in sectors like construction. Similarly, LinkedIn (2024) and Kaura (2024) emphasized persistent gaps between green skills demand and workforce readiness in global labor markets. In Spain, SEPE (2024) also highlights shortages in green-related management knowledge (e.g., environmental regulation compliance) and technical competencies (e.g., energy efficiency or waste management).

7.3 Projected provincial employment from renewable expansion (2025–2030)

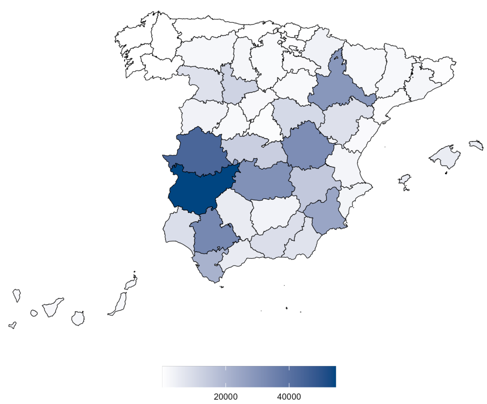
To assess the spatial implications of this transition, we allocate projected employment across provinces using the observed historical distribution of installed solar and wind capacity, distinguishing between intraprovincial and extraprovincial effects. This approach ensures that the geographic distribution of employment associated with the PNIEC aligns with deployment patterns observed thus far, which are largely driven by the availability of natural resources (solar irradiation and wind intensity) and the presence of spare transmission capacity, as emphasized by Fabra et al. (2024). Provincial employment is defined as jobs created within a province as a result of renewable capacity installed in that same province. Extraprovincial employment refers to jobs generated in a province due to capacity installed elsewhere, based on economic interdependencies across provinces, captured through interregional linkages.

The resulting estimates reveal substantial heterogeneity across both geographic space and employment channels. Figure 17 disaggregates projected employment into four categories: provincial solar, provincial wind, extraprovincial solar, and extraprovincial wind. Unsurprisingly, provinces with high historical or projected renewable deployment concentrate the bulk of provincial employment effects. For instance, Zaragoza is projected to generate nearly 81,300 new provincial jobs, of which over 52,300 are associated with wind projects. Burgos and Albacete follow, with approximately 28,400 and 22,600 intraprovincial wind jobs, respectively. In contrast, provinces such as Badajoz (54,720), Cáceres (43,855), and others including Sevilla, Cuenca, and Ciudad Real (each around 30,000) are expected to lead in solar-related provincial employment. Other provinces with projected totals above 25,000 jobs from both technologies include Cádiz, Murcia, and Valladolid.

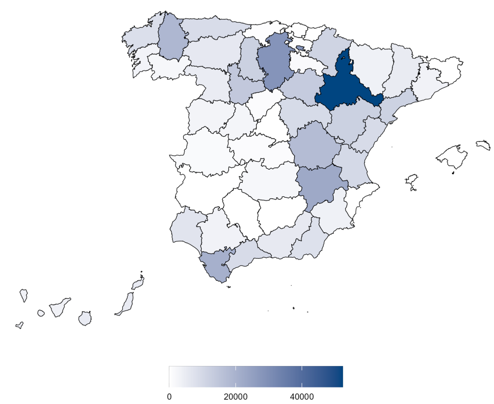
By contrast, more urbanized and industrial provinces such as Barcelona, Madrid, or Bizkaia record comparatively modest levels of intraprovincial employment -each under 5,500 jobs, and in the case of Bizkaia and Madrid, even below 1,000. This reflects both physical constraints on land availability and a lower prevalence of utility-scale renewable projects in these regions. Nevertheless, such provinces are expected to benefit significantly through indirect employment spillovers. These effects are more diffuse. For example, Madrid is projected to gain nearly 10,500 additional jobs through such indirect channels, despite its limited local deployment. Similar spillover effects are observed in Valencia, Barcelona, and Sevilla, all of which play key roles as economic hubs in the national renewable energy value chain.

In relative terms, the intensity of employment growth is best captured by annualized changes over the existing provincial labour market, as shown in Figure 18, disaggregated across the same four employment channels. Focusing first on direct effects, Cuenca emerges as the province with the highest projected average annual employment growth, reaching 8.5 percent, of which approximately 70 percent is attributable to solar deployment. Soria follows, with a 5.8 percent growth rate almost entirely explained by wind installations (close to 85 percent of the total), along with Teruel (5.2 percent, 55 percent wind-driven), Cáceres (5 percent, 96 percent solar), Albacete (3.8 percent, 64 percent wind), and Palencia (3.7 percent, 80 percent solar). These are substantial effects in the context of annual labour market dynamics, especially considering that provincial employment growth in recent years has rarely

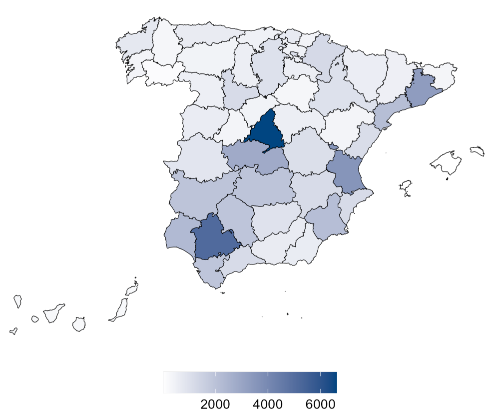
Figure 17: *Spatial distribution of total employment generated by renewable deployment under the PNIEC (2025–2030)*



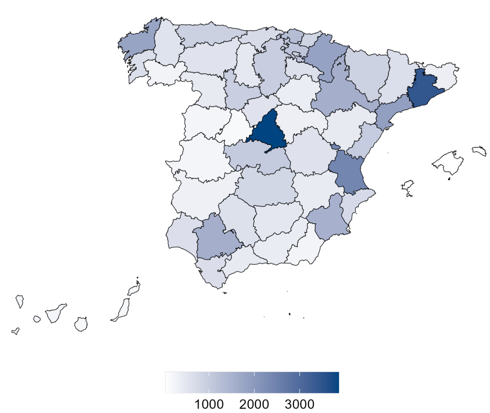
(a) Provincial solar jobs (2025–2030)



(b) Provincial wind jobs (2025–2030)



(c) Extraprovincial solar jobs (2025–2030)



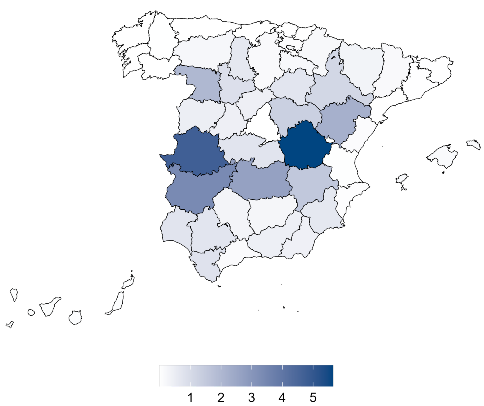
(d) Extraprovincial wind jobs (2025–2030) exceeded 3% in aforementioned provinces. This may suggest that we are likely overestimating the impact in smaller provinces, where even modest job creation could represent an unusually large percentage increase. At the same time, since our coefficients reflect the average impact across all provinces in Spain, it is also plausible that we are underestimating the true effect in larger provinces with fewer megawatts installed. Future research could explore this heterogeneity more explicitly by disaggregating impacts by province size or labour market characteristics. Another relevant consideration is that the future distribution of installed megawatts may differ from historical patterns.

All of the provinces with high annual employment growth values share two structural characteristics: a high concentration of renewable deployment and relatively small labour markets. The combination of both factors magnifies the observed employment growth rates. Other provinces with notable direct employment growth, in the range of 2 to 3.5 percent annually, include Badajoz, Zamora, Burgos, Zaragoza, Ciudad Real, Guadalajara, Lugo, and Valladolid.

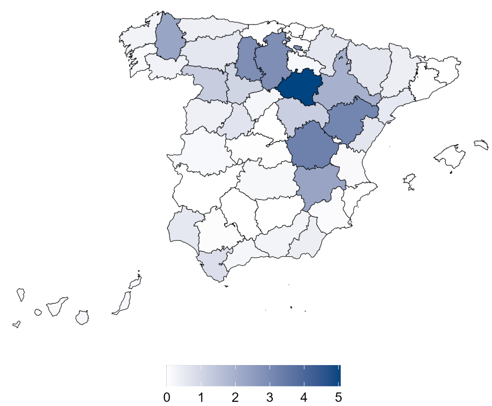
At the opposite end of the distribution, the impact of direct renewable deployment on employment remains very limited in urban provinces such as Madrid, Gipuzkoa, Bizkaia, Girona, Barcelona, Cantabria, or Alicante. In these cases, the annual employment growth attributable to direct renewable deployment does not reach 0.1 percent. This muted effect reflects a combination of large existing employment bases and limited availability of land or political space for large-scale renewable installations.

Turning to indirect employment, its relative contribution is more modest. The province with the highest projected annual growth in indirect employment is Cuenca, at around 0.3 percent, followed by Soria, Palencia, Zamora, Ciudad Real, Huesca and Huelva, each with approximately 0.25 percent. In large metropolitan areas such as Sevilla (0.15 percent), Madrid (0.06 percent), or Valencia (0.09 percent), indirect employment effects are not negligible in absolute terms, but remain limited when considered relative to total employment. These patterns reflect the more diffuse and distributed nature of extraprovincial spillovers, which tend to be diluted in large labour markets.

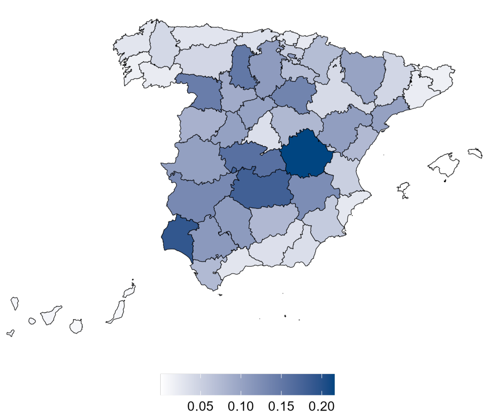
Figure 18: *Projected annual employment growth by province from renewable energy deployment under the PNIEC (2025–2030)*



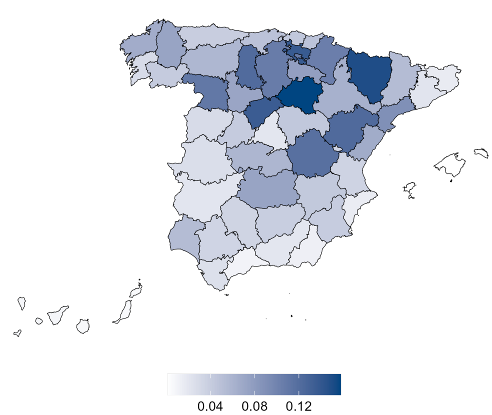
(a) Annual growth of provincial solar jobs



(b) Annual growth of provincial wind jobs



(c) Annual growth of extraprovincial solar jobs



(d) Annual growth of extraprovincial wind jobs

8 Conclusion

This paper offers an innovative assessment of the employment impacts of utility-scale renewable energy deployment in Spain, using quarterly data from the Spanish Labour Force Survey and detailed administrative records of wind and solar installations. We implement a flexible panel local projection framework to estimate dynamic responses to installed capacity shocks, disaggregated by technology, project phase, education level, and plant size.

Our findings reveal that both solar and wind energy investments generate substantial provincial employment gains, though with important differences in magnitude, composition, and spatial distribution. On average, each additional megawatt of installed solar capacity generates around 10.15 new jobs within the host province, while wind projects create approximately 12.4 provincial jobs per MW. However, the nature of these jobs differs: in the case of solar, the employment increase is concentrated in mid-skill occupations, with virtually none corresponding to renewable skill-intensive occupations as defined by the ESCO taxonomy. In contrast, for wind, approximately 2.4 out of the 12.4 provincial jobs per MW qualify as renewable-intensive, reflecting higher specialization requirements.

Beyond the host province, we also identify sizable extraprovincial spillovers. Solar investments generate an additional 2.8 jobs per MW in economically connected provinces at the peak of the response, of which at least one corresponds to a green skill-intensive occupation. Wind installations yield approximately 1.5 extraprovincial job per MW, with one-third being classified as green skill-intensive. These patterns underscore the importance of interregional labor mobility and the external sourcing of specialized tasks.

The effects exhibit strong heterogeneity across phases and technologies. This is particularly pronounced for solar, where dramatic cost reductions over time have been accompanied by a shift toward fewer but significantly larger plants. As a result, employment effects in the first deployment phase were nearly 13 times greater than in the second phase for solar, and about

2.5 times greater for wind. This evolution becomes even clearer when disaggregated by plant size. In solar, disentangling the effects by size reveals that small and medium installations contribute to job creation in different ways, either through local hiring or via spillovers, whereas large plants, though dominant in cumulative capacity, tend to generate fewer jobs per MW. For wind, smaller installations generate higher employment effects both within and beyond the host province, albeit with greater estimation uncertainty. These patterns confirm strong scale effects: smaller plants are both more labor-intensive and more reliant on external labor markets.

When examined through the lens of education, the analysis reveals a nuanced distribution of gains. For solar, local jobs created after the construction phase primarily benefit workers with lower educational attainment, likely engaged in routine monitoring and supervision. In contrast, when more technical qualifications are required, the main beneficiaries are workers with vocational training. Extraprovincially, both vocational and highly educated workers are recruited from other provinces to manage and operate solar plants, while less-qualified workers are also mobilized for the construction phase. These findings echo those of Vona et al. (2018), confirming that green employment spans multiple skill tiers and phases.

In the case of wind, employment gains display greater consistency and arise earlier for highly educated workers, particularly in extraprovincial contexts. While vocational-trained workers benefit primarily within the province, university-educated professionals are more frequently hired in other provinces, especially during the construction and early operation phases. This likely reflects the more stringent skill requirements of wind energy and the limited availability of such profiles in rural host provinces.

Relative to Fabra et al. (2024), the current benchmark in the literature, our results differ in several dimensions. First, by working at the provincial level, we are able to detect employment effects from wind that are absent in municipal-level analyses, and find larger impacts for solar. Second, we integrate an occupation-based definition of renewable or green employment and disaggregate results by education level, showing the importance of both. Third, we quantify employment multipliers by plant size and investment phase, showing that small and medium plants rely more on external labor markets and create higher employment per MW. Fourth, by leveraging interprovincial trade matrices, we provide a novel measure of extraprovincial spillovers. Finally, using microdata, we are able to distinguish the impact by education level.

These methodological advances translate into high projections of job creation under Spain's 2023-2030 Integrated National Energy and Climate Plan (PNIEC). If targets are met, we estimate the creation of approximately 889,340 local jobs, an average of 159,380 jobs per year between mid-2025 and 2030, compared to 5,682 jobs per year implied by second-wave estimates in Fabra et al. (2024). Our projections align more closely with official government figures, between 138,000 and 199,000 jobs annually. Furthermore, projections suggest that around 110,000 of the new jobs expected under the PNIEC, approximately 20,000 per year, will be created in green skill-intensive occupations, a figure equivalent to 3% of recent annual job creation in Spain. Meeting this demand poses a significant challenge given current bottlenecks in the supply of technically qualified labor, particularly in construction and energy-related occupations. Recent evidence from Spain and other labor markets highlights persistent gaps in both technical and managerial green competencies, underscoring the urgency of aligning training systems with the evolving needs of the energy transition.

Beyond forward-looking projections, our estimates also suggest that renewable deployment has already had a significant and sustained effect on employment over the past two decades. Using consistent assumptions and applying median impulse responses to historical capacity data, we estimate that nearly 579,082 jobs were cumulatively created between 2005 and 2024. This figure, which can be interpreted as an upper-bound, represents approximately 2.7 percent of total national employment as of 2024, with a roughly balanced contribution from wind (53 percent) and solar (47 percent) technologies. The vast majority of these jobs, around 92.4

percent, were generated directly within the provinces where capacity was installed.

Overall, these findings emphasize that the employment benefits of the green transition depend not only on where and how much capacity is installed, but also on the structure of the labor market, the plant size, and the strength of interregional linkages, among others. Realizing the full local employment potential of renewables will require complementary measures, such as vocational training, labor mobility support, and local hiring incentives to ensure that gains are inclusive, regionally balanced, and persistent.

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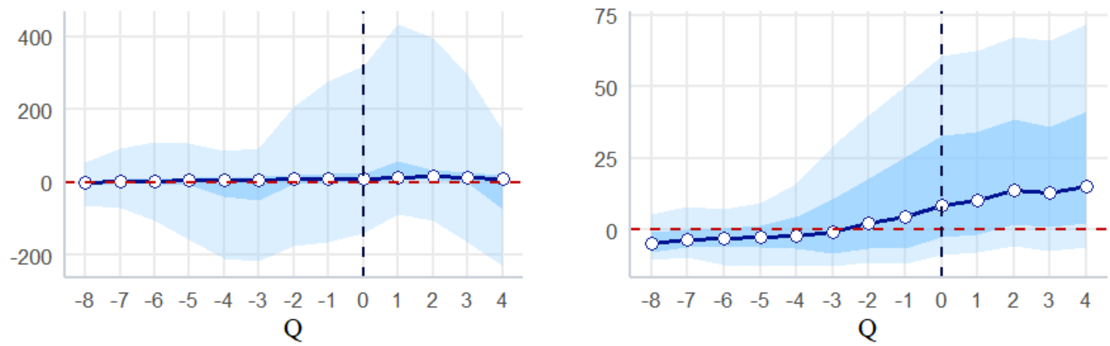
Appendix 1 Bootstrap robustness: accounting for time heterogeneity

As outlined in Section 5.4, our baseline inference procedure relies on bootstrapping across provinces by resampling full province-level panels. This approach preserves the original time structure of the data, keeping fixed the temporal sequencing and distribution of renewable installations across periods. It captures spatial heterogeneity in the response to renewable deployment, such as differences across labor markets or provincial exposure to infrastructure, but does not incorporate uncertainty stemming from the temporal dimension. In this section, we implement a more demanding inference design by incorporating a two-dimensional (2D) block bootstrap across both provinces and time. This exercise serves as a robustness check on our previous results and highlights the role of temporal idiosyncrasies in shaping uncertainty.

The rationale for including time heterogeneity is twofold. First, as documented throughout this paper, particularly in the discussion of plant size and investment phases, renewable deployment has been far from uniform over time. Specifically, the period between 2014 and 2018 saw minimal wind expansion, while solar installations were sparse between 2009 and 2019 (see Figure 1). Second, bootstrapping across time allows us to capture additional sources of uncertainty arising from period-specific shocks and institutional bottlenecks, such as permitting delays or policy moratoria.

The results of this bootstrap procedure are presented in Figure 19. As expected, introducing time heterogeneity results in noticeably wider confidence bands, especially in the case of solar (Figure 19a). This is consistent with the extended periods of low installation activity, which reduce the effective sample size in some bootstrap replications. Wind installations, while also affected, exhibit somewhat narrower bands due to more stable deployment patterns (Figure 19b).

Figure 19: *IRFs to an additional MW of installed capacity (2D Bootstrap)*

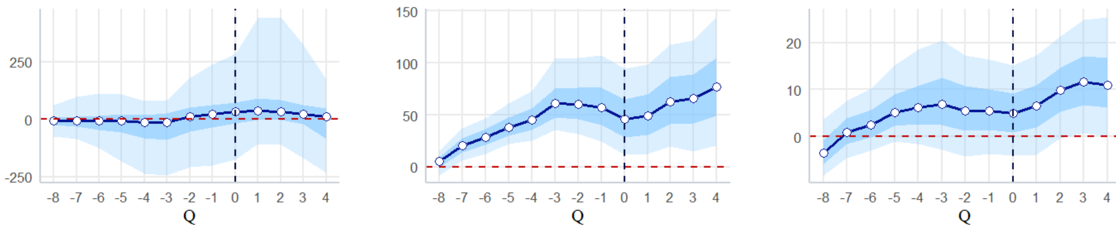


(a) Solar (b) Wind

Nonetheless, the median impulse response functions remain qualitatively similar to those obtained with the standard bootstrap. The shape of the dynamic responses is preserved, with employment peaking around the installation date and subsiding afterward. Interestingly, the magnitude of the responses under 2D bootstrapping is somewhat larger, 15.3 vs 10.15 employments for solar plants and 15.4 vs 12.4 employments for wind plants, measured one year after the shock occurs, reflecting the greater weight of small-scale deployments in the resampled panels. As shown in Section 6.4, these smaller projects tend to have stronger employment effects per MW, thereby inflating the estimated average in small plant-intensive samples.

To better understand the source of this uncertainty, we re-estimate the solar IRFs by plant size under the 2D bootstrap framework (Figure 20). The resulting pattern is illuminating. For small plants (Panel 20a), confidence intervals are extremely wide, highlighting the sparse and erratic nature of deployment over time. This confirms our earlier claim that small projects, while numerous, are unevenly distributed across quarters and heavily concentrated in specific years. Medium and large plants (Panels 20b and 20c) exhibit tighter confidence bands, albeit still wider than in the province-only bootstrap. This reflects more regular deployment and higher temporal clustering in recent years.

Figure 20: *IRFs to an additional MW of solar installed capacity by plant size (2D Bootstrap)*



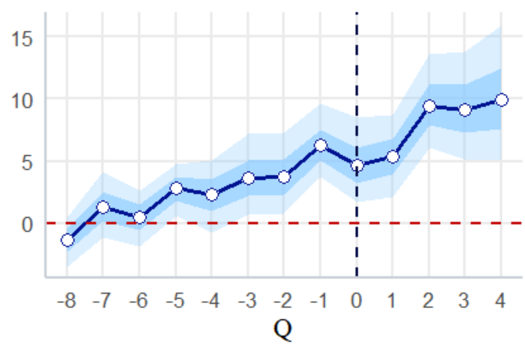
(a) Plants < 49 MW (b) 49 MW ≤ Plants < 127 MW (c) Plants ≥ 127 MW

Overall, these results support the robustness of our main findings but also underline the challenges of drawing inference in settings with significant temporal and spatial imbalance. In this context, the standard province-level bootstrap appears to strike a favorable trade-off between robustness and interpretability. While the 2D bootstrap is theoretically appealing, in our case, it likely overstates the uncertainty due to the limited number of installation events in specific years and technologies and the differences between the two renewable deployment phases. Accordingly, our preferred specification remains the province-level bootstrap, with the 2D results presented here as a robustness extension.

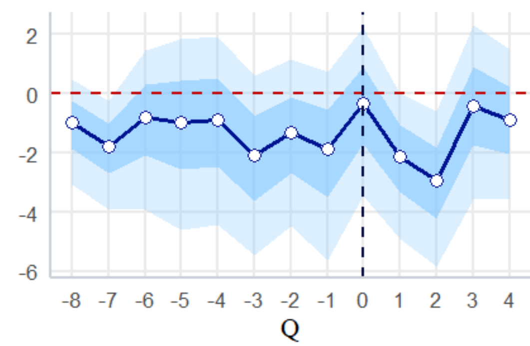
Appendix 2 Impulse response functions without smoothing adjustment

This appendix presents the raw impulse response functions corresponding to Section 6.1, prior to the application of the penalized local projections (Barnichon and Brownlees, 2019) procedure. These unsmoothed estimates preserve the original horizon-by-horizon variation and serve as a robustness check. All dynamic responses are based on the baseline specification described in Section 5.

Figure 21: *IRFs to an additional MW of solar installed capacity*

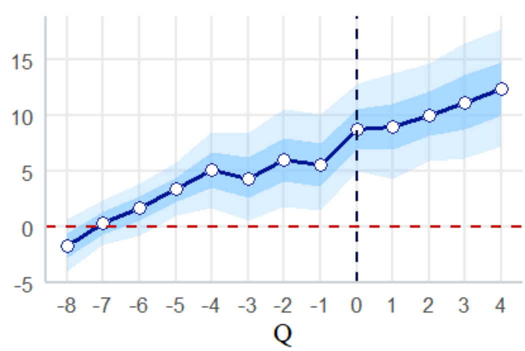


(a) Employment

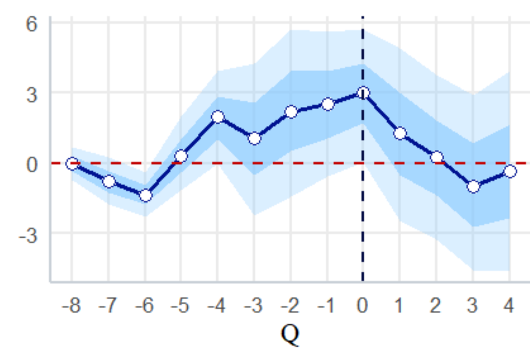


(b) Renewable employment

Figure 22: *IRFs to an additional MW of wind installed capacity*



(a) Employment



(b) Renewable employment

Appendix 3 Detailed results by wind plant size percentile

To complement the 3D visualizations presented in Figures 12 and 13, this annex reports a more detail numerical results from the rolling-window estimation of employment impacts across the wind plant size distribution. Each table shows the estimated number of jobs created per additional megawatt installed, by event time h (rows) and window starting percentile (columns). Results are reported for the 32nd percentile (lower bound), the median, and the 68th percentile (upper bound) of the distribution, reflecting estimation uncertainty. The data confirm a clear pattern of declining employment intensity with plant size, particularly around the construction phase. They also highlight the increasing role of extraprovincial labor markets in smaller-scale projects.

	Percentile 32					Median					Percentile 68				
	1	15	30	45	60	1	15	30	45	60	1	15	30	45	60
-8	0.4	2.0	-0.9	-0.7	-0.4	1.2	3.6	0.2	-0.1	-0.0	2.4	5.3	1.3	0.5	0.4
-7	-1.3	-0.2	-0.7	-0.2	-0.1	-0.1	1.0	0.1	0.3	0.2	1.5	2.1	0.9	0.7	0.5
-6	-2.8	-1.8	-1.0	-0.1	0.1	-1.2	-0.7	-0.4	0.3	0.3	0.7	0.4	0.3	0.8	0.6
-5	-3.5	-2.8	-1.5	-0.3	0.1	-1.5	-1.4	-0.8	0.1	0.4	0.8	-0.1	-0.0	0.6	0.7
-4	-2.9	-3.3	-1.8	-0.1	-0.1	-0.3	-1.6	-1.0	0.3	0.3	2.5	0.1	-0.1	0.3	0.3
-3	-1.0	-3.4	-1.9	-1.1	-0.2	2.3	-1.4	-0.9	-0.6	0.2	5.6	0.5	0.1	0.0	0.3
-2	2.2	-3.0	-1.9	-1.4	-0.3	6.3	-0.7	-0.7	-0.8	0.2	10.3	1.4	0.4	-0.2	0.2
-1	6.7	-1.9	-1.8	-1.6	-0.2	11.5	0.7	-0.9	-0.9	0.3	16.4	3.1	1.0	-0.1	0.8
0	10.8	-0.4	-1.7	-1.6	-0.2	16.3	2.6	-0.8	-0.8	0.4	22.1	5.2	1.5	0.0	1.0
1	13.5	1.1	-1.7	-1.6	-0.2	19.5	4.3	0.1	-0.7	0.5	26.0	7.2	1.8	0.2	1.1
2	14.2	2.0	-2.1	-1.8	-0.3	20.3	5.4	-0.1	-0.8	0.4	27.0	8.4	1.7	0.1	1.0
3	12.6	2.4	-2.1	-1.8	-0.4	18.4	5.5	-0.2	-0.8	0.2	24.7	8.5	1.5	0.1	0.8
4	8.8	2.0	-1.5	-1.3	-0.4	13.4	4.6	-0.0	-0.5	0.1	18.5	7.1	1.4	0.3	0.6

Table 1: Estimated jobs per additional MW installed – Provincial total employment

	Percentile 32					Median					Percentile 68				
	1	15	30	45	60	1	15	30	45	60	1	15	30	45	60
-8	16.3	7.9	-2.3	-2.0	-1.9	18.8	12.5	0.5	0.2	-0.8	21.5	17.9	3.6	2.5	0.2
-7	12.7	10.5	0.1	-2.1	-1.4	17.1	13.7	2.2	-0.7	-0.7	21.3	17.6	4.6	0.8	0.0
-6	9.9	10.9	-0.2	-2.1	-1.1	16.1	14.0	1.9	-0.9	-0.4	21.7	17.5	4.2	0.2	0.4
-5	9.0	10.4	-1.6	-1.6	-0.6	16.4	14.1	0.7	-0.3	0.2	22.9	17.9	3.2	1.0	1.3
-4	10.8	10.8	-2.7	-1.3	-0.4	18.8	15.1	-0.0	0.4	0.7	26.1	19.6	3.0	2.0	2.1
-3	12.1	10.7	-3.5	-1.4	-0.6	20.7	15.6	-0.5	0.8	0.8	28.7	20.9	3.0	2.9	2.4
-2	13.3	10.7	-3.9	-1.0	-0.7	22.6	15.9	-0.6	1.6	1.0	31.1	21.7	3.2	4.2	2.7
-1	16.1	11.3	-4.0	-0.6	-0.7	26.8	17.2	-0.5	2.4	1.2	36.4	23.7	3.6	5.6	2.8
0	18.3	11.2	-4.8	-0.7	-0.8	31.7	18.2	-0.8	2.8	1.3	43.1	25.5	3.6	6.5	3.0
1	16.9	9.1	-6.4	-1.3	-1.2	33.6	17.5	-1.7	2.7	1.1	47.0	25.8	3.2	7.1	2.9
2	13.6	5.8	-7.6	-1.8	-1.7	32.0	15.0	-2.5	2.4	0.7	46.3	23.9	2.8	7.0	2.5
3	11.0	3.3	-7.9	-2.2	-1.9	29.5	12.3	-3.0	1.8	0.2	43.7	20.9	2.1	6.1	1.9
4	11.3	4.2	-6.2	-2.2	-1.9	27.1	11.6	-2.1	1.1	-0.1	39.5	18.9	2.1	4.6	1.2

Table 2: Estimated jobs per additional MW installed – Provincial renewable employment

	Percentile 32					Median					Percentile 68				
	1	15	30	45	60	1	15	30	45	60	1	15	30	45	60
-8	2.5	10.9	-3.2	-3.2	-2.4	5.3	15.5	-0.0	-1.4	-1.2	8.1	20.1	2.9	0.2	-0.2
-7	4.9	6.6	-2.7	-1.1	-1.3	8.5	10.0	-0.5	0.1	-0.3	12.4	13.2	1.9	1.4	0.5
-6	8.7	5.2	-3.0	-0.3	-0.5	13.2	8.3	-1.0	0.8	0.4	18.0	11.4	1.3	2.0	1.3
-5	12.2	4.6	-4.0	-1.2	-0.8	18.0	8.0	-1.9	0.0	0.2	23.8	11.5	0.7	1.3	1.3
-4	16.1	4.4	-5.2	-2.8	-1.6	23.6	8.4	-2.6	-1.3	-0.4	30.5	12.3	0.2	0.1	0.8
-3	20.9	4.4	-6.0	-4.1	-2.3	30.2	9.1	-3.1	-2.2	-1.0	38.3	13.4	0.1	-0.7	0.3
-2	25.8	4.2	-6.7	-4.7	-2.4	36.6	9.6	-3.5	-2.6	-1.1	46.5	14.3	0.1	-0.9	0.4
-1	31.8	5.0	-7.0	-5.0	-2.4	44.1	11.2	-3.4	-2.7	-0.9	56.2	16.5	0.6	-0.7	0.9
0	39.0	7.5	-6.8	-5.2	-2.5	52.8	14.5	-2.6	-2.7	-0.7	67.2	20.8	1.8	-0.6	1.1
1	45.5	11.3	-6.0	-5.4	-2.8	60.4	18.8	-1.4	-2.9	-1.0	76.4	26.0	3.4	-0.5	1.1
2	50.0	14.7	-5.5	-5.8	-3.3	65.3	22.6	-0.8	-3.2	-1.5	81.7	30.5	4.5	-0.8	0.6
3	49.3	16.1	-5.0	-6.1	-3.5	64.0	23.9	-0.5	-3.6	-1.9	79.5	31.5	4.8	-1.3	0.1
4	39.9	14.3	-3.7	-5.1	-2.9	52.1	20.9	-0.0	-2.9	-1.6	65.1	27.4	4.7	-1.0	0.0

Table 3: Estimated jobs per additional MW installed – Extraprovincial total employment

	Percentile 32					Median					Percentile 68				
	1	15	30	45	60	1	15	30	45	60	1	15	30	45	60
-8	0.4	2.1	-0.9	-0.7	-0.4	1.3	3.6	0.2	-0.1	-0.0	2.4	5.3	1.3	0.5	0.4
-7	-1.3	-0.2	-0.7	-0.2	-0.1	-0.1	1.0	0.1	0.3	0.1	1.5	2.1	0.9	0.7	0.5
-6	-2.7	-1.8	-1.0	-0.0	0.1	-1.2	-0.7	-0.4	0.3	0.3	0.7	0.4	0.3	0.8	0.6
-5	-3.5	-2.8	-1.5	-0.3	0.1	-1.5	-1.4	-0.8	0.1	0.4	0.8	-0.1	-0.0	0.6	0.7
-4	-2.9	-3.3	-1.8	-0.7	-0.1	-0.3	-1.6	-1.0	-0.3	0.3	2.5	0.1	-0.1	0.3	0.7
-3	-1.0	-3.4	-1.9	-1.1	-0.2	2.3	-1.4	-0.9	-0.6	0.2	5.6	0.5	0.1	-0.0	0.6
-2	2.2	-3.0	-1.9	-1.4	-0.3	6.3	-0.7	-0.7	-0.8	0.2	10.3	1.4	0.4	-0.2	0.7
-1	6.7	-1.9	-1.8	-1.5	-0.2	11.5	0.7	-0.4	-0.9	0.3	16.4	3.1	1.0	-0.1	0.8
0	10.8	-0.3	-1.6	-1.6	-0.2	16.3	2.6	-0.0	-0.8	0.4	22.1	5.2	1.5	0.0	1.0
1	13.5	1.1	-1.7	-1.6	-0.2	19.5	4.3	0.1	-0.7	0.5	26.0	7.2	1.8	0.2	1.1
2	14.2	2.0	-2.1	-1.8	-0.3	20.3	5.4	-0.1	-0.8	0.4	27.0	8.4	1.7	0.1	1.0
3	12.6	2.3	-2.1	-1.8	-0.4	18.4	5.5	-0.3	-0.8	0.2	24.7	8.5	1.5	0.1	0.8
4	8.8	2.0	-1.5	-1.3	-0.4	13.4	4.6	-0.0	-0.5	0.1	18.5	7.1	1.4	0.3	0.6

Table 4: Estimated jobs per additional MW installed – Extraprovincial renewable employment

Appendix 4 Estimated historical impact of renewable deployment as a share of total employment

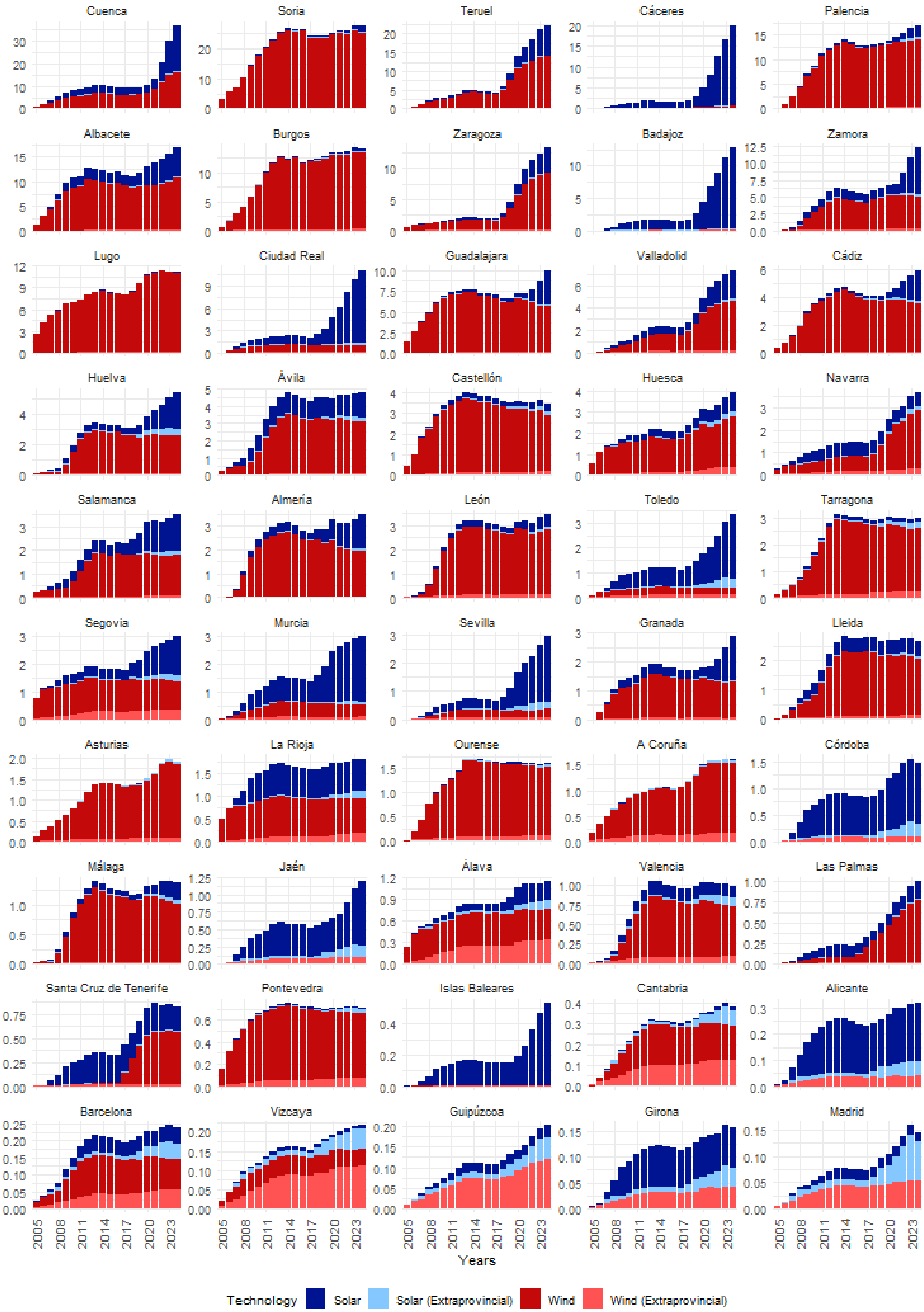
As shown in Figure 16, the provinces of Zaragoza, Badajoz, Cuenca, Cáceres, and Albacete appear to have been the most positively affected by the deployment of renewable energy in Spain. When measured as a share of total provincial employment, the rural provinces of Spain's Meseta Central stand out as key beneficiaries of this expansion, as illustrated in Figure 23.

Cuenca, in particular, displays the most pronounced effect, with renewable-related employment reaching nearly 30% of total provincial employment. This impact is driven by substantial deployment of both wind and solar technologies, with solar alone accounting for almost 60% of renewable-related jobs in recent years. It is important to note that these figures capture not only direct employment associated with the construction and operation of renewable plants, but also indirect and induced employment effects. Indirect employment refers to jobs created along supply chains and in auxiliary services essential to deployment, such as transportation, equipment provision, and component manufacturing (e.g., wind turbine blades). Induced employment, in turn, arises from increased local demand generated by the consumption of workers involved in renewable energy projects.

Figure 23 highlights the historical employment impact of renewables in provinces suffering from sustained demographic decline -typically rural areas in the Meseta with abundant natural resources, particularly solar potential. Thus, the figure illustrates the extent to which renewable energy investments have contributed, and may continue to contribute, to reversing or mitigating population loss by generating employment in territories traditionally underserved by industrial or service-sector activity.

In this context, renewable energy emerges not only as a pillar of the green transition, but also as a potential lever for regional revitalization and territorial cohesion. However, it is important to note that, for these provinces, the estimated effects could be interpreted as an upper bound, given the identification assumptions discussed in Section 7.1.

Figure 23: *Estimated historical impact of renewable deployment (2005–2024).(%)*



Working paper

2025

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