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# LEM

## WORKING PAPER SERIES

# Creating Jobs Out of the Green: The Employment Effects of the Energy Transition

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# Creating Jobs Out of the Green: The Employment Effects of the Energy Transition

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**Abstract**

The success of the green transition depends on the rapid and sustained adoption of renewable energy (RE) technologies. This paper uses a novel and detailed geo-localized dataset of RE power units deployment, across four technologies and spanning three decades, to empirically analyze the employment impacts of RE investments across European regional economies. To address the non-random deployment of renewable energy technologies, we exploit the regional physical potential for RE sources and construct an instrument for the regional exposure to technology-specific investments that is arguably exogenous to confounding economic factors. We find that the deployment of renewable energy plants has a positive and long-lasting impact on employment, generating about 40 jobs in seven years for each additional megawatt of generation capacity, primarily in the construction and agricultural sectors. We find evidence of geographical spillovers and substantial heterogeneity, with rural and low-income areas experiencing larger gains from RE deployment. The effects extend to regional output, with an RE investment multiplier exceeding unity over a 5 year horizon. Overall, these type of investments can represent an effective policy to spur local jobs and encourage rural development.

**Keywords:** Renewable Energy, Employment Multiplier, Green Stimulus

**JEL classification:** C26, H50, P18, Q20, Q43, Q52

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# 1 Introduction

A central concern about the green energy transition regards its impact on employment — that is, whether, and where, it will create or destroy jobs. This issue lies at the heart of debates on the socio-economic and political viability of a rapid decarbonization process (Bowen, 2012; Bowen et al., 2018). Indeed, addressing climate change requires a rapid shift of the energy system from fossil-intensive to renewable sources. According to the latest International Renewable Energy Agency (2023) report, annual investments in renewable energy technologies must increase at least fourfold, alongside a rapid phase-out of fossil fuels, to effectively limit global warming to 1.5°C above pre-industrial levels. Despite the urgency and policy relevance of this issue, the potential of renewable energy technologies to generate job opportunities and spur economic growth remains largely uncertain (Böhringer et al., 2013; Fabra et al., 2024). Current estimates primarily rely on model-based projections. For example, the net zero scenario of the International Energy Agency estimates a global net increase of nearly 9 million jobs by 2030 (IEA, 2021). However, this aggregate figure might hide significant sectoral and geographic disparities, which are likely inherent to any profound structural transformation (Stern and Stiglitz, 2023). First, the transition involves a significant reorganization in the spatial arrangement of the energy generation system, favoring certain regions with specific characteristics while disadvantaging others (Lim et al., 2023; Hanson, 2023). Secondly, by reshaping the composition of the energy mix via the substantial deployment of power generation facilities, the transition generates new labor demand in emerging industries, creating opportunities for some groups of workers and skillsets, while leaving others at risk of being left behind (Hanson, 2023; IRENA and ILO, 2021). Understanding the employment effects of energy decarbonization is therefore critical for designing socially informed policies that enhance the social acceptability, equity, and overall feasibility of the green transition.

In this study, we contribute to these pressing debates by presenting new empirical evidence on the employment impacts of renewable energy deployment at the regional level. Leveraging a novel dataset with detailed geographical information on power plants installations in Denmark, France, Germany and UK, we exploit the geographical and time variation in the regional energy mix to unveil systematic sectoral heterogeneity and to identify the green energy technologies that exert the most significant influence on aggregate employment.

The identification of renewable energy deployment effects is a challenging exercise. Indeed, the non-random allocation of energy capacity investments, both over years and across locations, may create endogeneity issues, potentially impacting the validity of empirical estimates. To mitigate these concerns and to estimate a causal relationship from green energy investments to employment outcomes, we adopt a research design that use a region-specific physical suitability measure of the territory for each energy technology, capturing exposure to technology-specific installations. In this regard, we use a shift-share instrument, as popularized by Bartik (1991) and Blanchard and Katz (1992), combining the differential exposure to renewable energy investments of each region with an aggregate measure of changes in the energy mix, to isolate arguably exogenous variations in local energy deployment. Using instrumental variable local projections (LP-IV, Jordà, 2005; Jordà, 2023), we identify and estimate dynamic local employment average effects resulting from renewable energy investments, measured in terms of deployment in megawatt (MW) units. Even if we can only indirectly infer a monetary value from energy power plant installations, throughout the paper, we use the terms "investments" and "installations" interchangeably, as the construction and the deployment of power plants involves the formation of fixed capital. Our results show that the effects of renewable energy installations are positive and long-lasting. In seven years, 1 MW of renewable installed capacity generates 40 new jobs, equivalent to approximately 14 jobs for $1 million spent in the development and the deployment of renewable power plants. These effects spillover to neighbouring locations and hide structural consequences for the regional economies, concentrating in the construction and agricultural sectors. Wind and solar power technologies are the main drivers of the overall effects, particularly in regions (i) with lower GDP per capita levels and (ii) that are relatively more specialized in agricultural activities. Finally, we complement our rich set of results investigating the impacts on aggregate economic activity measured by real GDP. Overall, the evidence suggests that the green investment multiplier, i.e., the dollar amount of GDP produced by a dollar of investments in renewable energy plants development, exceeds 1 after 5 years.

Our paper contributes to the blossoming research investigating the employment impacts of green energy investments. Current evidence is mainly based on input-output (IO) models, with the resulting estimates indicating sizeable positive employment effects at the national or global level (Pollin et al., 2009; Fragkos and Paroussos, 2018; Pai et al., 2021). While these models provide valuable projections of the potential net employment implications of the energy transitions, they require additional assumptions to address the granular regional and technological scope necessary for renewable energy analysis (Breitschopf et al., 2013; Jenniches, 2018). Thus, the aggregate results obtained with the IO approach may obscure heterogeneities across regions and group of workers, thus overlooking distributional issues. Indeed, renewable energy plants create employment and economic activity in a more decentralized and dispersed manner compared to the conventional energy industry, which is based on large centralized energy generation units (Jenniches, 2018; IRENA and ILO, 2021). While regions with high levels of employment in fossil fuel industries may lose their substantial relevance in favor of renewable energy generation locations (Lim et al., 2023; Hanson, 2023), locations that are not traditionally integrated in the energy system might experience gains in employment and economic growth (Creutzig et al., 2014; Clausen and Rudolph, 2020). The nature and the extent of such impacts at the regional level might depend on the energy potential and the socio-economic characteristics of the area, such as local labour availability or manufacturing capacity (Ulrich et al., 2012; Kapetaki et al., 2020). Rural areas often have a good potential for renewable energy development, as productive agricultural plots are often well-suited for development of wind and solar plants due to favorable land attributes. This has created substantial concerns about potential drawbacks to agriculture communities due to land displacement for renewable energy production (Hernandez et al., 2015). Other studies suggest that the renewable potential in rural areas is often unfulfilled or that employment benefits from renewable energy development leak outside the region because of the scarcity of skilled labour in the area (Creutzig et al., 2014; Clausen and Rudolph, 2020).

To date, there are few empirical studies estimating the local employment impacts of investing in renewable energy technologies. For the United States, Brown et al. (2012) estimate that 0.5 jobs were created per MW of wind power capacity installed over the period 2000-2008, while Hartley et al. (2015) find no job impact of wind investments for 2001-2011 in Texas. For Europe, Costa and Veiga (2021) find that wind investments reduces unemployment during the construction phase (in the range -0.39 to -0.55 jobs/MW) in Portuguese municipalities. These effects mainly benefit unskilled male workers, while the smaller, yet sustained effects during the maintenance and operations phase seem to affect mostly workers with college degrees. Using monthly data for Spanish municipalities, Fabra et al. (2024) find that solar energy investments have a positive local impact multiplier both in the phases before and during the year after the startup. They estimate that in the months following the startup date, deployment of solar technologies generates 1.47 jobs-year/MW in municipalities and 3.48 jobs-year/MW in counties, while during construction the employment multipliers are larger, at 4.55 jobs-year/MW in counties 2.47 jobs-year/MW in municipalities. As for wind, their results show that investments have no effect on rising employment, but slightly reduce unemployment during the construction and maintenance phases (-0.19 and -0.35 jobs/MW, respectively). While these studies are a relevant effort to investigate the impacts of renewable energy investments on local jobs, to our account, there are two main aspects which are still not considered. On the one hand, except for Fabra et al. (2024), they do not provide any granularity as to which industrial sectors are affected by the renewable energy investments. Understanding which sectors are affected by the energy transition is relevant to evaluate its distributional effects. On the other hand, the analysis is limited to short-term impacts, during the different development phases, and does not provide insights into the longer-term emerging macroeconomic dynamics. If the infrastructure project has cumulative impacts on local economic activity, the most important effects on economic development may appear at longer horizons. Severnini (2022), for example, find that the construction of hydro dams in the USA during the first half of the 20th century conferred a substantial boost to economic growth, increasing population density by over 50% after 30 years and by over 130% after 60 years. The author argues that hydroelectric power provision resulted in a cheap local power advantage, leading to a sustained yet dissipating long-term growth path.

Our paper also relates to the literature on the estimation of (public and private) investment multipliers. Following the recent reappraisal of the macroeconomic role of fiscal policy (Ramey, 2019), many recent contributions have exploited more granular data to estimate regional multipliers[1]. For instance, Popp et al. (2022) analyze the effects of "green component" of the American Recovery and Reinvestment Act (ARRA), across a wide spectrum of projects including renewable energy installations, R&D programs, job training for green occupations, or energy efficiency. They find that $1 million generates 15 jobs in 7 years in US commuting zones.

To the best of our knowledge, our study stands among the first to estimate the causal effects of deploying renewable energy plants on employment by adopting an empirical econometric approach within a unified framework, spanning almost three decades across different European countries. As a notable exception, Batini et al. (2022) address the impact of clean energy investments on macroeconomic dynamics by using a factor-augmented VAR model on a global panel of developed countries, estimating effects of renewable investments that are stronger and more long-lasting than their conventional counterparts. Our findings complement this, revealing similar output multipliers following renewable investments. However, as detailed in the following sections, our disaggregated approach enable us to identify, over a relatively long horizon, direct and spillover impacts, drivers, mechanism at play and relevant heterogeneity behind the average overall effects.

The rest of the paper is structured as follows. Section 2 details the description of our dataset. Section 3

[1]Example ranges from public expenditure multipliers (Nakamura and Steinsson, 2014; Auerbach et al., 2020), to infrastructure investment multipliers (Leduc and Wilson, 2017), to R&D investment multipliers (Moretti et al., 2023; Pallante et al., 2023)

illustrates the econometric specification and the research design while Section 4 shows and comments the results. Finally, Section 5 concludes.

# 2 Data

To investigate how the deployment of renewable energy (RE, henceforth) technologies affects job creation, we have assembled a new dataset covering geo-located information on energy installed capacity, encompassing four renewable and four conventional power sources. We integrate these data with measures of energy potential, employment statistics and other macroeconomic indicators at the regional (NUTS-3) level in selected countries, including Denmark, France, Germany and United Kingdom[2]. Our final dataset spans nearly three decades, from 1991 to 2018, and covers a total of 669 NUTS-3 regions.

## 2.1 Data on energy plants deployment

To construct regional variables on energy deployment, we draw on different sources of micro-data on power plant commissioning, since no other sources can directly provide us with regional-level information on green and conventional power installations. We harvest data for RE plants from the "Renewable power plants" dataset, provided by the free-of-charge data platform Open Power System Data (OPS, 2020), which combines open-source databases for a number of countries in Europe[3]. The dataset offers an exhaustive list of power plant units, along with information regarding their geolocalization, energy technology, net generation (electricity) capacity and the commissioning date. The commissioning of a power plant marks the last step of construction, which involves running and testing the plants' components and processes before the plant is set into operation. The commissioning date for the power plants is available from 1990 to 2020 and, together with geolocalization, is missing for some countries. Consequently, to exploit the time dimension of power unit installations, we restrict our dataset to four countries: Denmark, France, Germany and United Kingdom. The energy technologies are categorized into wind onshore, solar photovoltaic, hydro, and bioenergy (biofuels and biogas).

In the case of Denmark, France and Germany, OPS compiles data on all energy units with a minimum installed capacity of 1 kilowatt (kW), thus including all units that may be part of the same power plant. Consequently, we will have multiple observations for a single power plant. Conversely, in the case of United Kingdom, units are aggregated to create a single observation for each power plant with a minimum capacity 1 megawatt (MW). This distinction is particularly relevant for wind plants which typically consist of multiple wind turbines, each characterized by a specific energy capacity. In this case, the unit of observation for wind energy will be the single wind turbine. Accordingly, all UK wind power plants with less than 1 MW of installed capacity would be "selected out". To ensure that this exclusion does not introduce bias into our results, we show that our estimates are stable when excluding the United Kingdom from the analysis (see Appendix B). Moreover, we aggregate

[2]The NUTS classification (Nomenclature of territorial units for statistics) is a hierarchical system for partitioning the economic territory of the EU and the UK. The system serves as a tool for analyzing socio-economic regional outcomes, at different levels of aggregation.

[3]The latest version we are using, 2020-08-25, is available at `https://doi.org/10.25832/renewable_power_plants/2020-08-25`

power plant units by plant location to obtain power plant specific observations. Equivalent information related to conventional power plants is available in the "Power Plant Tracker" dataset, provided by Enerdata[4]. The conventional technologies in this dataset are categorized into coal, oil, natural gas, and nuclear power plants. Finally, this dataset also includes decommissioning dates for units that are no longer active.

We build our energy-investment variables by aggregating energy plant observations over years and across regions, so to provide volumes of newly installed capacity for each power source, and decommissioned capacity for conventional energy technologies. The regional installed capacity in a given year is defined as the cumulative aggregate installed capacity, subtracting eventual decommissioned capacity. A region with no observations in the sample across all energy sources is considered to be missing. If there are no observations for a single technology in a given region, the installed capacity for that technology in the region is considered to be zero.

From Enerdata, we also retrieve information about the average costs associated to the setup of a new energy power plant, also defined as overnight costs or capital expenditures (CAPEX), along with their average size (measured in kW). This data is available by country, year and technology, allowing us to assign - with a certain degree of approximation - a monetary value to every kW of installed capacity. This approach will ultimately enrich the interpretation of the effects of energy installations on jobs creation.

## 2.2 Employment data and other regional economic indicators

We source employment data from Cambridge Econometrics' European regional database ARDECO, which combines data from Eurostat and other national sources to provide historical time-series of European regional economic statistics. We have retrieved a version of the dataset updated to March 2020, which covers a period from 1980 to 2018. This allows us to collect information for the United Kingdom, no longer available in the subsequent versions of the dataset. We match data from ARDECO with our energy investments data (available for 1990-2018) and, to avoid the possible bias given by the German unification in 1990 and the subsequent integration of the post-socialist East Germany in the national statistics, we take employment data starting from 1991. The data for employment is available at NUTS-3 level and is disaggregated into six sectors consistent with NACE Rev.2 sectoral definitions, namely: Agriculture, Forestry and Fishing (A); Industry excluding construction (B-E); Construction (F); Wholesale, Retail, Transport, Accommodation and Food services, Information and Communication (G-J); Financial and Business Services (K-N); Non-market Services (O-U). Table A.1 in Appendix A provides an overlook of the sectors comprised within the ARDECO macro sectoral definition.

Finally, from the same data source, we take data on regional gross domestic product (GDP) at constant (2015) prices for our selected countries at NUTS-3 level, as well as data on gross fixed capital formation and

[4]The Enerdata dataset includes also the details related to RE sources. After conducting a thorough analysis and cross-comparison of the two datasets, we conclude that the OPS dataset provides a more comprehensive representation of green power technologies. Indeed, Enerdata includes power plant units with an installed capacity above 100 kW, whereas the minimum observed capacity for OPS is 1 kW. RE technologies are characterised by small plant units and generate energy in a decentralized manner throughout the territory (Ferroukhi et al., 2020). Therefore, ignoring all units below 100 MW might lead to underestimating the amount of renewable installed capacity and overlooking much of its crucial implications. Due to the dispersed nature of green power technologies, collecting exhaustive and detailed data, especially regarding plant coordinates, can be challenging. The Open Power System dataset excels in collecting data comprehensively and extensively, with only 0.11% of geolocalization data missing, compared to Enerdata's 43% missing entries. According to IRENA (2019), the aggregate renewable installed capacity in the four observed countries in 2018 amounted to 231.76 gigawatt (GW). Our dataset identifies 196.67 GW, while Enerdata reports 125.87 GW.

compensation of employees (wages) at NUTS-2 regional level.

### 2.3 Data on Renewable Energy Potential

We collect data on the regional potential for the installation of renewable power sources from the dataset developed by Oakleaf et al. (2019). The dataset reports a "development potential index" (DPI) which quantifies the suitability of each 1-km area of land for the development of selected technologies, ranging from 0 (low) to 1 (high). The index is measured by applying a spatial multi-criteria technique, described in Oakleaf et al. (2019), which accounts for both the resource potential of the area (such as wind-speed or solar irradiance for wind and solar energy technologies, respectively) and for land feasibility factors (such as suitable land cover and slope). We combine the 1-km spatial potential development index by energy source within each region, to obtain the overall regional potential for solar, wind, bio-energy and hydro power.

### 2.4 Descriptive Analysis

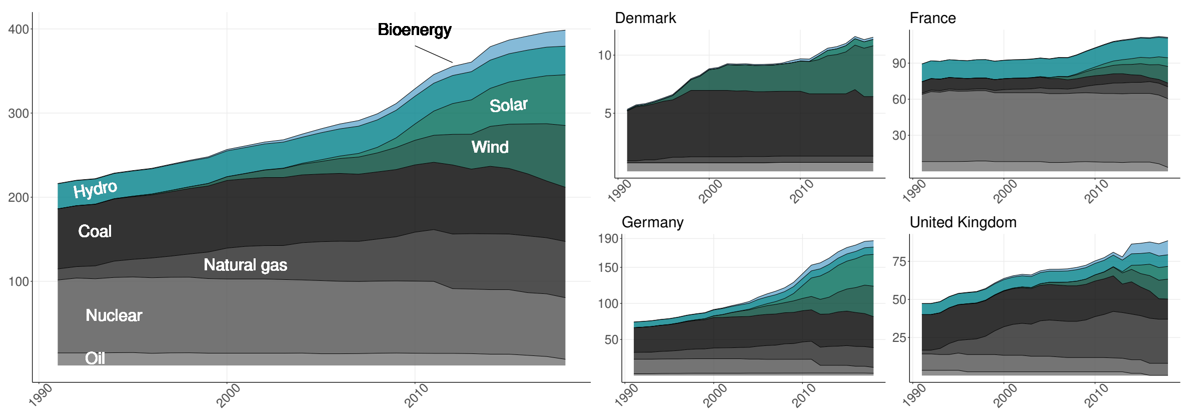
Our final dataset is a balanced panel of 18061 observations (1.6% in Denmark, 14.4% in France, 60% in Germany, 24 % in UK). Table 1 provides summary statistics regarding power plant dimensions for total renewables, as well as a breakdown by technology. Each power plant is identified by clustering the power generator units belonging to the same geo-location and plant ID. The plant size is proxied by the average installed capacity per power plant, measured in MW. Capital expenditures (CAPEX per MW) indicate the average capital costs associated to the development of a power plant. In our sample, the average plant size stands approximately at 0.8 MW. Among the different RE sources, wind power plants have the largest share of newly installed capacity, accounting for 48% of the total, while constituting only 7.5% of the new plants created. This makes wind energy the source with highest power intensity among renewable alternatives, producing an average of 4.8 MW per plant. On the other hand, solar power plants are responsible for 84% of the new renewable power generating plants. They contribute 39.6% of the new installed capacity but they are the smallest in size, with an average of 0.4 MW per plant. Less common technologies in our dataset include bionenergy and hydro, which together make up 12% of the total new installed capacity.

Table 1: Investment Metrics by Renewable Energy Technology

| | New Plants | | New Capacity | | Plant Size | Capex per MW |
|---|---|---|---|---|---|---|
| | (Thousands) | % | (GW) | % | (MW) | (Mill. $) |
| Bioenergy | 11.613 | 5.8 | 15.410 | 10.1 | 1.6 | 6.54 |
| Hydro | 5.832 | 2.9 | 3.145 | 2.1 | 0.7 | 6.61 |
| Solar | 169.047 | 83.9 | 60.251 | 39.6 | 0.4 | 2.49 |
| Wind | 15.086 | 7.5 | 73.38 | 48.2 | 4.8 | 2.23 |
| Total Renewable | 201578 | 100 | 156.595 | 100 | 0.8 | 2.79 |

The evolution of the energy mix has been shaped by a variety of factors, including demand-side drivers such as energy consumption patterns, supply-side influences like technological advancements, and, more recently,

Figure 1: Installed Capacity over the Years (GW)




energy and climate policy interventions. Figure 1 illustrates these trends.

Between 1991 and 2018, the total installed capacity in the four countries nearly doubled, going from 216 GW in 1991 to 409 GW in 2018. RE capacity accounts for 64% of this growth, contributing to 14% of the energy mix in 1991 to 48% in 2018. Conventional energy investments amount to 94.2 GW, but this is accompanied by decommissioning of 69.4 GW, resulting in a net positive variation in conventional energy of 24.8 GW. Renewable energy (RE) sources accounted for 64% of this growth, with their share in the energy mix rising from 14% in 1991 to 48% in 2018. Conventional energy investments added 94.2 GW of capacity, but this was offset by the decommissioning of 69.4 GW, resulting in a net increase of 24.8 GW. The expansion of renewables has been highly uneven, both across technologies and between countries. Wind and solar power have been the primary drivers of the energy transition, together contributing 88% of the total growth in RE capacity.

Figure 2: Localization of Conventional and Renewable Power Plants

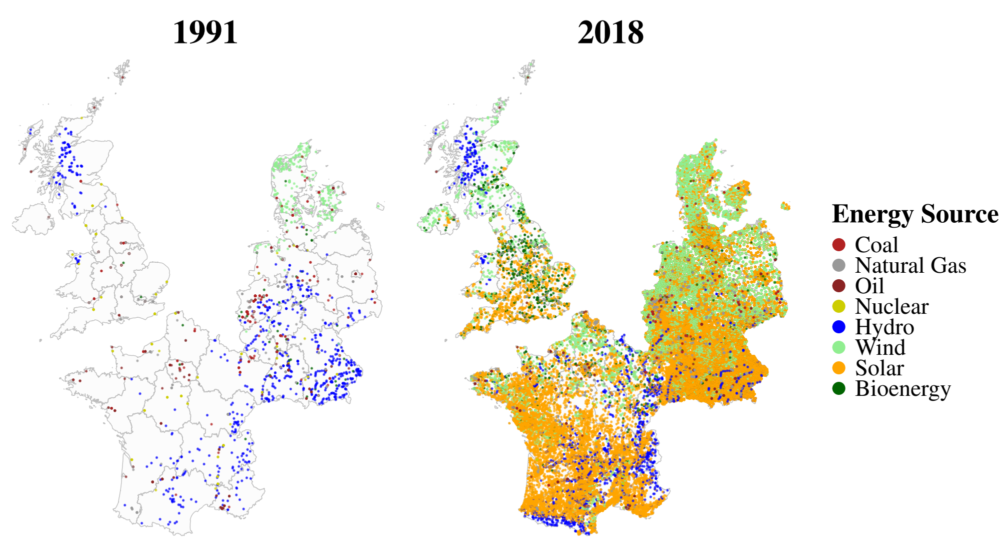



Figure 2 provides an overview of the geographical distribution of conventional and RE in the initial and final period of our sample. A clear distinction emerges between the distribution of conventional and RE unit locations:

while green technologies are widely dispersed across all regions, fossil-fuel plants are more concentrated. This evidence suggests that a green transition entails a spatial transformation of the energy system (Jenniches, 2018), with possible knock-on effects on regional economies. Finally, in line with the evidence highlighted in Figure 1, the location of energy plants reliant on conventional technologies has barely changed over both time and geography.

# 3 Empirical strategy & methods

## 3.1 Empirical Specification

We exploit the geographical and temporal variation of our data to model the employment effects of energy investment shocks using panel direct local projections (LPs). Firstly developed for univariate time series settings (Jordà, 2005), LPs have been widely implemented in panel data analysis as well (see Auerbach and Gorodnichenko, 2013; Choi et al., 2018; Jordà et al., 2020, among others). For our baseline model we run a series of regressions for different horizons, $h = \{1, ..., H\}$, as follows:

$$\frac{Y_{l,t+h} - Y_{l,t-1}}{Y_{l,t-1}} = \beta^h \frac{NewRE_{l,t}}{Y_{l,t-1}} + \sum_{r=1}^{4} \theta_r^h X_{l,t-r} + \alpha_l^h + \eta_c^h \delta_t^h + \epsilon_{l,t}^h \tag{1}$$

where $l$, $t$ and $h$ index location, time and horizon, $Y$ is regional employment, and $NewRE$ - our variable of interest - denotes the new renewable installed capacity in MW. Energy investment changes are normalized with lagged employment levels, so that the coefficient of interest $\beta^h$ can be interpreted as the $h$-period ahead cumulated employment multiplier, indicating the number of jobs generated by an extra MW of renewable installed capacity in period $t$.

We also include a vector of control variables $X$: lagged values of $NewRE$, current and lagged values of new conventional installed capacity, decommissioned energy capacity for conventional technologies, as well as growth rates of GDP, wages and total investment (measured as fixed capital formation). All variables enter with four-year lags. The selection of the maximum number of lags involves a trade-off. On the one hand, we aim to incorporate the evolution of demand patterns and productivity dynamics that could act as confounding factors. On the other hand, the inclusion of more lags comes at the cost of reducing the number of years available for analysis. This trade-off is particularly relevant given the limited size of our sample, which further decreases when focusing solely on the periods when renewable technologies penetrate the economy (see Figure 1). All specifications include location fixed effects $\alpha_l$, needed to control for unobserved regional heterogeneity. As investments in RE sources have been objective of national policy interest in the last decades, we include country-by-year fixed effects $\eta_c \delta_t$ to isolate the effects of energy investments by those that are driven by such policy interventions. The latter are especially important in our setting because the European Union, since the 2009 Treaty of Lisbon, has gained significant legislative authority also in the energy sector[5]. The choice of including just country-by-year fixed effects may omit determinants of RE investments that depend on policies carried at a more decentralized

[5]Examples include the liberalization of the energy markets, the regulation on the unbundling of utility companies and more recently, the "EU Energy Union" policy objective as well as the establishment of the EU Directive on the Emissions Trading System - ETS (Saurer and Monast, 2021).

level. Even more so for Germany, as it is the sole federal state in our sample, where each *länder* (NUTS-1 in our setting) may possess more discretion. However, the Federal Constitution of Germany gives extensive legislative power in the energy sector to the federal government and the same applies to policy measures aimed at spurring RE adoption (Saurer and Monast, 2021). This would justify our more conservative specification that features country-by-year fixed effects. Furthermore, our assumption is supported by a set of robustness checks performed in Section 4, which show that even controlling for *time-variant-NUTS-1* specific shocks, the dynamic response of employment to RE deployment remains remarkably stable. Finally, the maximum horizon over which we observe the effect of RE deployment is $H = 7$. Standard errors are clustered at NUTS-3 region level to account for the potential unobserved heterogeneity in the errors structure.

We extend our baseline specification in Equation (1) along several dimensions. Firstly, we investigate the heterogeneous impacts of aggregate RE deployment, unpacking the effects by employment sector, $i = \{1, \ldots, 6\}$:

$$\frac{Y_{i,l,t+h} - Y_{i,l,t-1}}{Y_{l,t-1}} = \beta^h \frac{NewRE_{l,t}}{Y_{l,t-1}} + \sum_{r=1}^{4} \theta^h X_{l,t-r} + \alpha_l^h + \eta_c^h \delta_t^h + \epsilon_{l,t}^h. \tag{2}$$

Secondly, we examine the total employment effect of clean energy investments by technology $k$, where $k$ can be Bioenergy, Hydro, Solar or Wind:

$$\frac{Y_{l,t+h} - Y_{l,t-1}}{Y_{l,t-1}} = \beta_k^h \frac{NewRE_{k,l,t}}{Y_{l,t-1}} + \sum_{r=1}^{4} \theta^h X_{l,t-r} + \alpha_l^h + \eta_c^h \delta_t^h + \epsilon_{l,t}^h. \tag{3}$$

In both Equation (2) and (3) employment variation and energy investments are normalised by total regional employment.

Furthermore, to unravel the nature of these effects, we explore to which extent structural economic conditions of regions under scrutiny matter in explaining the overall results. Specifically, we examine whether employment responses to investments in RE power sources differ in relatively wealthier regions, as measured by quartiles of real GDP per capita, and in regions that are relatively more rural, determined using a measure of revealed comparative advantage in agriculture (as defined in Section 4.1). To address this, we augment the baseline specification to account for potential non-linear effects of energy-investments multipliers. In particular, given the economic condition indicator $EC = \{\text{Rural}, \text{Income}\}$, calculated at the beginning of our sample, and the maximum number of categories $nEC$ for each indicator (2 for Rural and 4 when considering quartiles of real GDP-per-capita distribution), we build and interact a set of dummies $D^{EC}$ with our measure of energy investments. More formally, we estimate a regression with the following specification:

$$\frac{Y_{l,t+h} - Y_{l,t-1}}{Y_{l,t-1}} = \sum_{d=1}^{nEC} \left( \beta^h \frac{NewRE_{l,t}}{Y_{l,t-1}} \times D_d^{EC} \right) + \sum_{r=1}^{4} \theta_r^h X_{l,t-r} + \alpha_l^h + \eta_c^h \delta_t^h + \epsilon_{l,t}^h \quad EC = \{\text{Income}, \text{Rural}\}. \tag{4}$$

Finally, we want to investigate whether the RE investments in a given region benefit also the sorrounding areas, by exploring the presence of geographical spillovers. To this purpose, we estimate the following regression:

$$\frac{\tilde{Y}_{l,t+h} - \tilde{Y}_{l,t-1}}{\tilde{Y}_{l,t-1}} = \beta^h_{out} \frac{NewRE_{l,t}}{\tilde{Y}_{l,t-1}} + \sum_r \theta \tilde{X}_{l,t-r} + \alpha_l + \delta_t + \eta_c \delta_t + \epsilon_{l,t}, \quad (5)$$

where $\tilde{Y}_{l,t}$ and $\tilde{X}_{l,t}$ denote respectively the employment and the control variables for those regions that are adjacent to region $l$. More formally, $\tilde{Y}_{l,t} = d(l,l')Y_{l,t}$, where $d(l,l') = 1$ if region $l'$ is adjacent to region $l$ and 0 otherwise. The same reasoning applies for $\tilde{X}_{l,t}$. The coefficient $\beta^h_{out}$ denotes the size of the spillovers and it should be interpreted as the average cumulated effect (over horizon $h$) of an extra MW of renewable capacity installed in region $l$ on the employment of its neighbouring regions.

In the final section of the paper, we examine the broader economic impacts of RE investments by replacing employment with regional GDP as the dependent variable. We adjust the specifications in Equations (1), (3), and (5) accordingly.

The use of LPs to estimate dynamic effects has become increasingly popular, as it imposes a minimal model structure and can easily accommodate non-linearities in the form of heterogeneous treatment effects (Montiel Olea and Plagborg-Møller, 2021; Jordà, 2023). However, in order to consistently estimate these treatment effects, we need to isolate variation in energy investments that is arguably exogenous to unobserved factors that may affect regional employment dynamics. The next section discusses our approach to address the endogeneity problem associated with our measure of regional energy investments.

## 3.2 Endogeneity Issues and Identification Strategy

Our parameter of interest $\beta^h$ denotes the cumulated effect of investments in RE sources on employment growth over horizon $h$. As outlined in Section 3.1, the preferred specifications (1) - (5) include a rich lag structure, capturing the evolution of demand- and supply-side factors that may determine RE investments and also explain changes in the level of employment. For this reason, we consider lags of local wages, investment and GDP growth rates.[6,7] Moreover, our regressions feature a wide set of region and country-by-year fixed effects, thus ruling out a handful of confounding factors that would otherwise bias the estimated coefficients, such as local and global demand trends, supply shocks and country-specific policy shocks, among others).

Notwithstanding this, endogeneity concerns may still arise and undermine the validity of our estimates. For instance, regions that are already on a "green trajectory" tend to attract more green energy investments, since they often have structural characteristics associated with rapid economic growth (Popp et al., 2022). To control for this potential influence, we incorporate lags of our explanatory variable, as well as contemporaneous and lagged values of commissioning and decommissioning capacity of conventional power plants in the region. Furthermore,

[6] This is in line with the applied macro and regional economic literature since the seminal papers by Blanchard and Quah (1989) and Blanchard and Katz (1992). Additionally, although employment lags can also proxy demand shocks, we prefer not to include them. In panel settings - particularly short panels - with fixed effects, incorporating autoregressive terms of the dependent variable can introduce bias in our $\beta^h$, even when dealing with a substantial number of cross-sectional units (Nickell, 1981). Nonetheless, to assess the robustness of our findings, we also estimate specifications that incorporate the autoregressive terms, reported in Table B.1.

[7] As specified in Section 2, investments are measured with fixed capital formation, which is the expenditure on produced tangible or intangible assets that are used in the production process for more than a year. Among other components, the assets include dwellings and nonresidential buildings, civil engineering works, transport equipment, and cultivated assets (trees and livestock). Wages and capital formation are provided at NUTS-2 level. We control the robustness of our estimates both by estimating a model specification which excludes the variables from the analysis (see Table B.1) and by clustering the errors at NUTS-2 region level (see Table B.3).

our framework is well-suited to address this issue. Indeed, our panel regression with variables expressed in changes, time and region fixed effects is equivalent to a specification in levels that accounts for region-specific linear time trends. Thus, our model effectively considers the role of those factors that may correlate with green investments and also contribute to diverging regional employment trends (e.g., de-industrialization patterns). Overall, our specification is designed to control for the tendency of regions already on a "renewable investment" path to attract further investments of this sort.

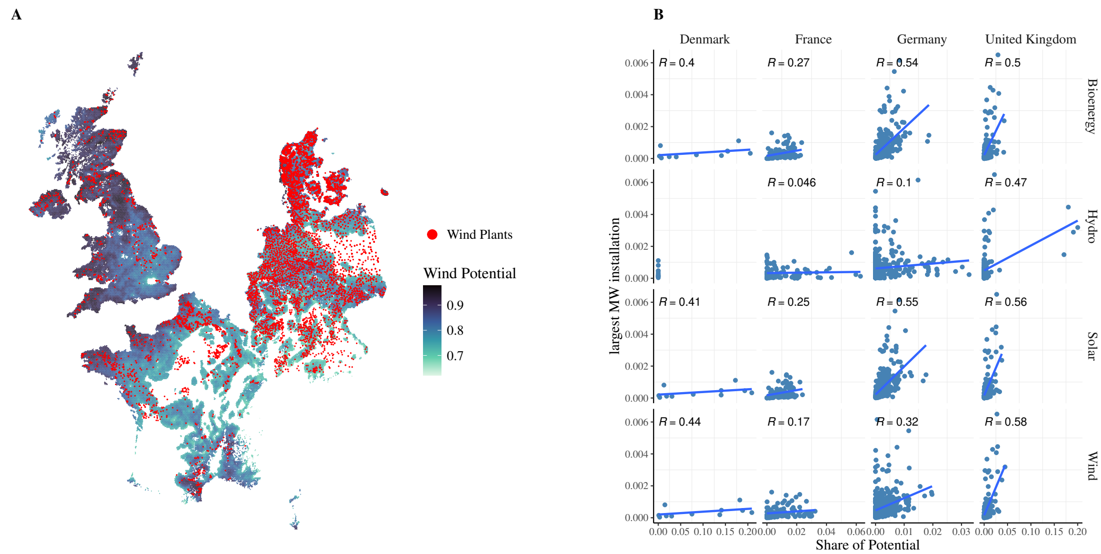
However, the amount of physical investments in energy generation that region $l$ receives at time $t$ may still be non-random after conditioning on our controls. There may be still several factors that affect both private and public green investments and local employment. If we consider solar and wind installations, for example, investments can flow in regions with lower rental costs for the land. For publicly-subsidized investments instead, it might be the case that central governments prioritize investment in municipalities with lower income or employment levels to boost development in the areas, or in regions with stronger capabilities in dealing with energy-related technologies. On the other hand, political influences may convey flows of investments to locations that would not be considered as ideal candidates. In all these cases, the so-called problem of "picking winners" or "awarding losers" would bias OLS estimates (Costa and Veiga, 2021).

In order to mitigate for the non-random allocation of investment flows across regions we propose an instrumental variable strategy that isolates a component of energy investments which is unlikely to depend on time-varying, unobserved characteristics of regions that also affect changes in employment. The instrumental variable combines a proxy for the *relative exposure* of each region with a measure of *aggregate shifts* in the RE mix. To measure the relative exposure of each region to investment shocks, we use an indicator of local RE potential, aggregating by territorial unit the granular (1-km) development potential indexes provided by Oakleaf et al. (2019), which quantify the inherent potential and development feasibility of technology-specific investments. The identification strategy rests on two key assumptions. Firstly, areas endowed with a higher RE potential are more exposed to RE investment shocks (instrument relevance). For instance, wind turbines are more likely to be installed in areas with relatively high and constant wind speeds, where each turbine generates more electricity compared to areas with lower or intermittent wind speeds (Costa and Veiga, 2021). Similarly, the potential of photovoltaics' deployment depends on solar radiation, conditional on land suitability in terms of slope and elevation. Panel A of Figure 3 provides visual evidence in support of this conjecture as the geographical distribution of wind power installations well overlaps, (yet not perfectly) with our measure of regional exposure to wind installations. Panel B of Figure 3 broadens this evidence to the other technologies we that we examine, showing that relative potential is a good predictor of the RE adoption.

Secondly, for the validity of the research design, we adopt an approach leveraging the orthogonality of the RE development potential. Conditional on our rich set of economic indicators, we argue that differences in regional exposures are unlikely to depend on other unobserved regional factors that could explain both employment dynamics and the deployment of RE generation capacity within a particular area. This ensures that the predicted level of local investment is driven solely by the physical potential of the region.[8]

[8]The index provided by Oakleaf et al. (2019) is an indicator of the renewable energy development potential that spans various dimensions of physical suitability, related to different energy technologies. We have also conducted experiments using

Figure 3: Development Potential and Plant Localization




Notes: The figures show the relationship between the development potential index for RE technologies (DPI, as in Oakleaf et al., 2019) and plant localization, showing how DPI helps predicting RE adoption. In particular, Panel **A** shows how the geographical distribution of wind power facilities well overlaps with areas characterized by higher wind potential (white spaces corresponds to areas with very low potential scores and low land suitability and availability). Panel **B** contrasts the NUTS3 share of DPI and the region-specific largest MW installation (per number of employed persons), by country and technology.

In the spirit of Bartik (1991), we then use these measures of regional potential to construct a regionally-weighted sum of national renewable energy investments as follows:

$$NewRE^{IV}_{l,t} = \frac{\sum_k s_{l,k} NewRE^{country}_{k,t}}{Y_{l,t-1}} \tag{6}$$

where $s_{l,k} = Potential_{k,l}/Potential^{country}_{k}$ is the measure of region $l$ potential as a share of the country's total potential for technology $k$, and analogously $NewRE^{country}_{k,t}$ measures the aggregate new installed capacity of the region's country. We decided to calculate shares within countries in order to avoid distortions in the way energy investments are absorbed by geographical units, as the size of NUTS-3 regions typically differs across countries (e.g., German districts vs French departments), and so their RE potential. As a consequence, we believe country-specific shares are better suited to predict the overall adoption of RE investments than those calculated over the full sample.[9] As an additional precaution, for each observation, the country-specific shift is constructed by excluding region $l$ investment contribution (leave-one-out), to avoid the potential bias that may arise from

simpler measures of relative exposures, such as solar radiation and average wind speeds. Overall, the results confirm the hypothesis that these physical features, increasing the potential for solar and wind power plants deployment, are an important and arguably exogenous mediating factors for RE investments. To further validate our choice, we inspect whether RE potential correlates with measures of regional attractiveness, a catalyst for tourism-related activities and possibly an obstacle for RE deployment. As shown in Figure B.2, there is no evidence of such correlation if we consider an indicator of tourism intensity that Eurostat published at NUTS3 level. All in all, using shares of RE potential allows us to capture regional exposure tailored to green investment shocks, in a way that is plausibly exogenous.

[9]In this regard, Figure A.12 shows the correlation between the regional ranking of solar potential and solar installed capacity, calculated either over the entire sample (A.12a) or within countries (A.12b). The figures show that, when the regional ranking is computed over the entire sample, the correlation between potential and installed capacity is 0.47. Conversely, when the ranking is calculated within countries, the correlation is sensibly higher. As a robustness check, in Table B.3, we also report our baseline specification estimates when the instrument in Equation (6) is built using shares of potential that are calculated over the entire sample. We also discuss these results more in detail in Section 4.

using own-observation information (Goldsmith-Pinkham et al., 2020).

To provide an intuition of how our IV works we compare, in Figure B.1 (Appendix B), the observed and the predicted level of RE deployment for two NUTS-3 regions, Schwäbish (DK) and Bornholm (DE). The plots suggest that every time a region receives an amount of RE investments, our measure of relative exposure helps predicting a level of RE deployment that is mediated by the regional physical potential of the region.

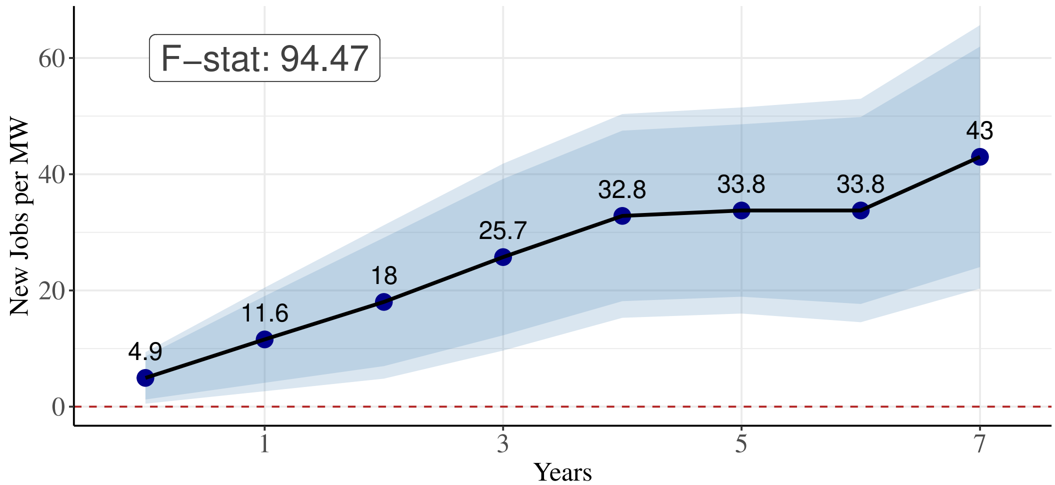
The next Section will show the results of our empirical analysis and in all Tables and Figures displaying IV regressions, we report the value of the first-stage heteroskedasticity-robust F-statistic, either averaged over horizons or shown for each local projection (Kleibergen and Paap, 2006). According to the econometric specification, we implement slight variations of the instrument defined in Equation (6). In particular, when estimating the employment multiplier generated by investing in renewable technology $k$ (cfr., Equation 3), we instrument the endogenous variable $NewRE_{k,l,t}/Y_{l,t-1}$ by isolating the $k$ component of the energy mix. Instead, when we estimate the geographical spillover effects as modelled in Equation (5), we simply normalize the new installed capacity in renewables by the lagged value of employment in the neighbouring region.

# 4 Results

We estimate models in Equation (1) to (4) using instrumental variable local projections (LP-IV). The dynamic effects of aggregate renewable investment on total regional employment, estimated using our baseline specification in Equation (1) - with $NewRE^{IV}_{l,t}$ as instrumental variable (see Equation 6) - are displayed in Figure 4, which plots the year-by-year cumulative number of jobs that, on average, are created by installing one MW of RE power sources. Employment steadily rises following RE investments, suggesting the presence of persistent and permanent long-term effects. While the initial impact is modest and not strongly significant — 4.9 jobs created in the first year — the effect grows significantly over a seven-year period, leading to the creation of 43 jobs. To contextualize these findings, the average plant capacity in our sample is 0.8 MW. This means that installing a single plant generates approximately 3.9 jobs immediately and 34.4 jobs over a seven-year period. Additionally, with capital expenditures averaging $2.79 million per MW, an investment worth $1 million in renewable energy plants results in roughly 1.8 jobs created immediately and 15.4 jobs over seven years. Our results are similar to those implied by the short-run county-level estimates of Fabra et al. (2024). A tentative explanation is that green investments stimulate regional demand directly, for example by creating jobs related to the installation, operation and maintenance of RE facilities; indirectly, if we consider employment in vertically-integrated sectors, leading to increased employment to support the expanding economic activity. This boost may also induce and trigger positive externalities due to the presence of complementarities and synergies with energy technologies, generating increasing returns to scale (Vona et al., 2019).

Even if we are convinced of the validity of the research design, we need to check whether our instrument is correlated with the endogenous regressor $NewRE_{l,t}$. Under weak instruments, IV estimates are biased towards OLS and the standard errors may provide unreliable inference. To mitigate these concerns, we report the value of the first-stage F-statistic that is well above the usual cut-off level of 10 for which an instrument is considered

Figure 4: Impact of Aggregate Renewable Energy Investments on Employment




Notes: The figure plots the dynamic effect, estimated via LP-IV, of aggregate renewable investment on total regional employment, measured as the number of jobs created for 1MW installed, according to Equation (1). The control variables include four lagged terms of GDP growth, renewable investments, wages growth, capital formation growth and conventional energy commissioning and decommissioning. The regression includes NUTS-3 region and country-by-year fixed effects. Standard errors are clustered at NUTS-3 region level. The darker and lighter shaded regions correspond to a 90% and 95% confidence level, respectively. The F-statistic reported is an average computed over the different time horizons $h$.

weak[10].

Our estimates align in magnitude with the figures presented by Popp et al. (2022), who found that 1 million dollars of the "green" component of the American Recovery and Reinvestment Act (ARRA) resulted in the creation of approximately 15 jobs over 7 years. In turn, these figures are smaller compared to the multipliers associated to ARRA fiscal package, which span from 7 to 38 jobs per year per $1M spent (Chodorow-Reich, 2019a). It's worth noting that our measure of "investment" slightly differs from those related to the ARRA. In its green component, for example, investments are not confined to RE infrastructure development, but also include energy retrofits, public transportation, and waste management. Nonetheless, our results suggest that the development of RE power generating facilities may constitute a key driver of employment stimulus in the context of the energy transition.

There are several factors that can undermine the stability of the results. To corroborate them, we perform a series of robustness checks, exploring how our main estimates are sensitive to model (miss)specification, data filtering, and identification strategy. The rich lag structure of control variables and the wide set of region and country-by-year fixed effects could potentially impose a heavy structure on the model.

As a due exercise, we explore how the main coefficient of interest $\beta^h$ changes as we progressively include current and lagged values of the control variables. The results, as shown in Table B.1, indicate that the inclusion of these controls stabilizes the estimates of $\beta^h$ within a relatively narrow range, effectively capturing demand and supply side factors as well as local energy investment decisions. Another concern relates to the shape of the dynamic response of employment, as plotted in Figure 4. Particularly, if the effects do not vanish or stabilize at

[10]Figure 4 displays the average value of F-statistic, computed across all projections. For additional details, in column (1) of Table C.2 we report the value of the first stage statistics for each horizon $h$.

longer horizon, we would be concerned that we are not properly isolating exogenous variation in local investment in RE sources. Instead, we could be capturing some preexisting trends that influence dynamics over time. Given the size of our sample and the lag structure imposed to the model, we proceed with caution when calculating and interpreting jobs multiplier at longer horizons. Nevertheless, we perform this exercise and present the results in Figure B.3a. As expected, confidence bands widen significantly, and the point estimate stabilizes after 10 years at around 100 jobs generated per MW.

Due to countries' differences in the institutional setting, some authority can be granted at the sub-national level for decisions related to renewable energy policies such as the allocation of energy investments. We have already pointed out in Section 3 that this is not the case for Germany, the only federal state in our sample. However, to rule out possible contributions that more localized energy policy may play in confounding the effects of RE deployment, we check whether our results are robust to the inclusion of *NUTS1-by-year* rather than country-by-year fixed effects (cf., Equation 1). Although not our preferred approach due to the rigidity imposed on the regression by the larger and more demanding fixed effect structure, the results show remarkable stability and consistency with those obtained with our baseline equation, as illustrated in Figure B.4, in Appendix B. This seems to suggest that in our research design, policy-related decisions at a more localized level do not appear to be a relevant confounding factor.

We conducted several additional robustness checks, as presented in Table B.3. Firstly, we examine the impact of excluding the UK from our sample due to data limitations in reporting wind energy units smaller than 1 MW, as discussed in Section 2.1. Despite this exclusion, our estimates remain remarkably stable. Another issue related to the structure of our sample pertains to bio and hydro energy installations, which constitute a smaller portion, approximately 15%, of the total newly installed capacity. Observations related to these sources can potentially act as outliers within our sample or they can affect employment outcomes through different transmission mechanisms, as they tend to be more geographically concentrated and less dispersed compared to wind and solar energy units. Moreover, as noted by Oakleaf et al. (2019), the development potential indexes (DPI) for bioenergy and hydropower may be affected by higher measurement error since it exhibits a higher degree of uncertainty. This arises because these indexes are constructed using fewer criteria compared to those for the other energy technologies. To address potential concerns related to bio-energy and hydro plants, we estimated our model excluding them from the sample. We observe that the magnitude precision of the estimates remains substantially invariant to such a data filter.

Finally, we also consider alternative specifications of the instrumental variable. First, we substitute national shares with *full-sample* shares of RE potential, and the national shift with the full-sample aggregate counterpart. Results qualitatively holds as the dynamic response of aggregate employment growth is similar to our preferred specification, although larger and with lower precision. For the other two specifications, we adapt our approach to be more in line with the traditional formulation of the Bartik instrument. Here, the shares of technology $k$ are computed with respect to the full sample installed energy capacity. Although it's more challenging to argue that the alternative shares approximate a near-random allocation of energy investments, we conduct these tests to examine the sensitivity of our estimates to instrument variations. In one of these alternative specifications, the shares are fixed at the year 2000, which is before renewables began to gain traction. In the other case, we used lagged values of the shares, creating a predicted amount of investments based on previous regional exposure. The results in Table B.3 indicate that our preferred instrument demonstrates relatively higher predictive power, as evidenced by a lower value of the other instruments' first stage F-stat. In the case of *full-sample* energy potential shares, the reason behind this is discussed in more detail in Section 3.2. When we fix the value of the shares to the "pre-green" era, we confidently argue that these shares are orthogonal to unobserved determinants of green investments. However, they provide very little variation that we aim to isolate, as many of the regions under analysis have barely any level of renewable installed capacity. Finally, the Bartik instrument variant that utilizes lagged values of the shares has a larger F-stat, indicating strong correlation with regional deployment of RE sources. However, the exclusion restriction necessary for the instrument validity is less likely to be satisfied, as previous shares of regional RE capacity can be correlated with unobserved characteristics that also predict employment dynamics.

We also assess the robustness of our results by employing alternative standard error structures. The first specification uses Conley standard errors, which account for potential spatial autocorrelation within radius of 100 km. This adjustment allows controlling for eventual spatial clustering of RE investments and for common shocks in geographically adjacent areas. The second specification clusters the standard errors at the NUTS-2 level, a broader regional aggregation compared to our baseline, which clusters at the NUTS-3 level. Clustering at the NUTS-2 level allows for arbitrary correlation within these larger regions, providing a more conservative inference when there may be region-wide shocks that affect employment outcomes across multiple NUTS-3 areas within the same NUTS-2 region.

## 4.1 Inspecting the mechanisms

In this section we empirically inspect the mechanisms behind our results, to better understand the implications of the energy transition. We exploit the nature of our dataset to further inspect the effects shown in Figure 4, seeking to understand which sectors benefit the most from the development of the RE sources and, in particular, which technology has contributed the most to this transformation.

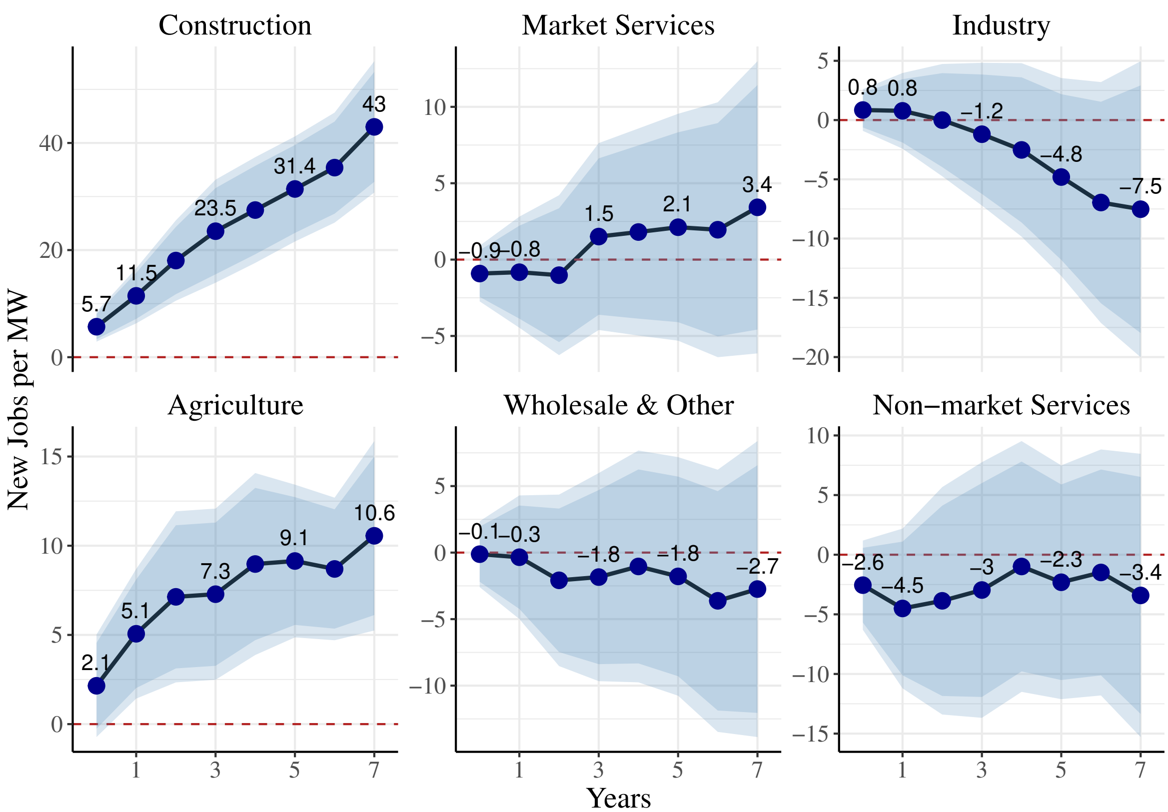
**Effects by sector**. We begin by unpacking the dynamic effects by sectoral employment, following the specification in Equation (2). The results, as shown in Figure 5, reveal that most of the jobs created by renewable energy investments are concentrated in the construction sector, in line with previous evidence (Popp et al., 2022). It is important to note that this sector includes activities such as planning, design, and maintenance of buildings, civil engineering projects, and utility infrastructure, which are essential for both the development and ongoing operation of RE power plants. Importantly, these activities extend beyond direct plant construction, involving roles in infrastructure development, operation, and maintenance. This evidence suggests that renewable energy investments can create localized jobs related to the operation and maintenance of the power plants, which helps explaining the persistence of the effect beyond the construction horizon.

We also find a small positive impact on the agriculture sector, with nearly 11 jobs generated per MW installed in 7 years. This translates to approximately 4 jobs for $1 million invested and approximately 9 jobs per plant.

Unfortunately, the lack of more disaggregated data does not allow us to input these effects to particular activities or occupations. However, it is likely that these jobs result from the increase in demand following RE investments (e.g., agricultural and forestry workers for biomass production). A more detailed discussion of these results is presented below where the mechanisms are analyzed with particular attention to the distinction between rural and non-rural areas.

Finally, although not statistically significant, renewable energy installations appear to be associated with a mild decline in industrial employment in the long term. Whether this outcome may indicate a reallocation of jobs from industry to agricultural and construction sectors, characterized by lower average remuneration, is difficult to determine within our empirical framework.

Figure 5: Impact of Aggregate RE Investments on Sectoral Employment



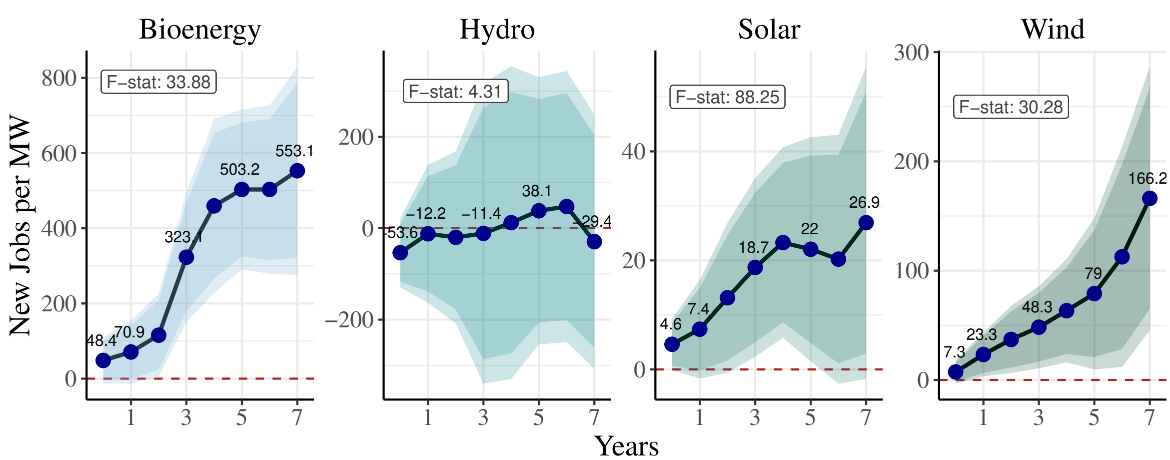

Notes: The figure plots the dynamic effect, estimated via LP-IV, of aggregate renewable investment on sectoral employment, measured in number of jobs created in each sector for 1MW installed, according to Equation (2). The control variables include four lagged terms of GDP growth, renewable investments, wages growth, capital formation growth and conventional energy commissioning and decommissioning. The regression includes NUTS-3 region and country-by-year fixed effects. Standard errors are clustered at NUTS-3 region level. The darker and lighter shaded regions correspond to a 90% and 95% confidence level, respectively. The average F-statistic for the first stage, computed over the different time horizons $h$, is 94.47.

**Effects by Power Sources**. As shown in Table 1, investments in RE vary across power technologies. Here, we test whether this heterogeneity matters in explaining the employment impacts of their deployment (See Figures 4 and 5). It is not merely a matter of which power source generates more employment, but which one explains more the aggregate effect that we are observing. Figure 6 presents the results for the specification in Equation (3), where we disentangle the effect on total employment by energy source.[11] Bionenergy deployment shows the highest employment multiplier, followed by wind and solar. Back of the envelope calculations shows that, in 7 years, every additional $1 million spent in bioenergy, solar and wind energy capacity, the number of jobs created in the regions increase by 84, 74 and 11, respectively. These effects primarily manifest in the long term, with short-term impacts being relatively modest and barely significant.

Notably, the estimates for solar and wind energy deployment closely align with the overall effect $\beta^h$ estimated for Equation (1). Given that wind and solar energy sources constitute together the majority of the total new installed capacity in the sample (48% and 40%, respectively), the aggregate results seem to be primarily driven by investments in these technologies.

For robustness, we run a series of regressions for each sector of the economy on each renewable source deployment. This additional analysis, presented in Figure C.1 in Appendix C, largely confirms that solar and wind power sources are the largest contributors to the total effects observed at aggregate level and within the construction and agricultural sectors.

Figure 6: Impact of Technology - Specific Investments on Employment




Notes: The figure plots the dynamic impact, estimated via LP-IV, of technology-specific investments on overall regional employment, measured in number of jobs created for 1MW installed, according to Equation (3). The control variables include current values of investments in the remaining non-instrumented energy technologies, and four lagged terms of GDP growth, aggregate renewable investments, wages growth, capital formation growth and conventional energy commissioning and decommissioning. Standard errors are clustered at NUTS-3 region level. The darker and lighter shaded regions correspond to a 90% and 95% confidence level, respectively. The F-statistic reported is an average computed over the different time horizons $h$, which serves as indicator of the relevance of each technology-related instrument.

**Regional Heterogeneities**. Thus far, our findings indicate that the construction and agricultural sectors have been the most affected by the deployment of wind and solar power sources, which in turn play a predominant role in explaining the aggregate effects. Motivated by the increasing deployment and the corresponding reorganization in the spatial arrangement of these RE sources, we want to see whether the effects also concentrate in more or less favored economic areas. In particular, we test the presence of non-linear dynamic effects of RE investments for regions that are i) specialized in agricultural activities, which allows us to classify regions as rural versus

[11] As recalled in Section 3.2, in estimating the effects for technology $k$, we construct the instrument using just the share of energy $k$ potential and the corresponding national aggregate shift.

non-rural; ii) relatively 'poorer' based on quartiles of the real GDP per capita distribution.

As for regional specialization, we build an index inspired by the Revealed Comparative Advantage (RCA) index in Balassa (1965). A region $l$ is comparatively specialized in sector $i$ when its ratio of employment in sector $i$ to total employment in the same sector exceeds the analogous ratio calculated for the entire sample. In this case, the region will exhibit a specialization coefficient larger than 1:

$$RCA_{l,i} = \frac{X_{l,i}/\sum_j X_{l,i}}{X_i^T/\sum_i X_i^T} \geq 1, \tag{7}$$

where the employment of sector $i$ in region $l$ is denoted by $X_{l,i}$ and $X_i^T$ is the employment in sector $i$ in the whole sample. Figure 7 displays the correlation between the regional deployment of RE over the entire period ($RE_l = \sum_{t=1991}^{2018} RE_{l,t}$) and the regional comparative specialization at the beginning of our sample in 1991.[12] We observe a strong correlation between RE plant development and initial employment shares in agriculture (0.64), suggesting that rural areas - those comparatively more specialized in agriculture and forestry activities - tend to offer more space and synergies for clean energy technologies (Clausen and Rudolph, 2020). Regions that are relatively more specialized in the construction sector also seems to attract RE investments, while regions with initial shares in the financial and business sector are associated with lower rates of RE installations. While regional specialization may indeed change over the decades, given the technological maturity of European countries, we think that this measure can be a good representation of the structural characteristics of the regional economies under scrutiny.

Figure 7: Correlation between RE Investments (1991-2018) and Initial Revealed Comparative Advantage (1991), plotted on logarithmic scales.


We categorize regions as "rural" if they reveal a comparative advantage in the agricultural sector, denoted by

[12]The correlation is plotted on logarithmic scales.

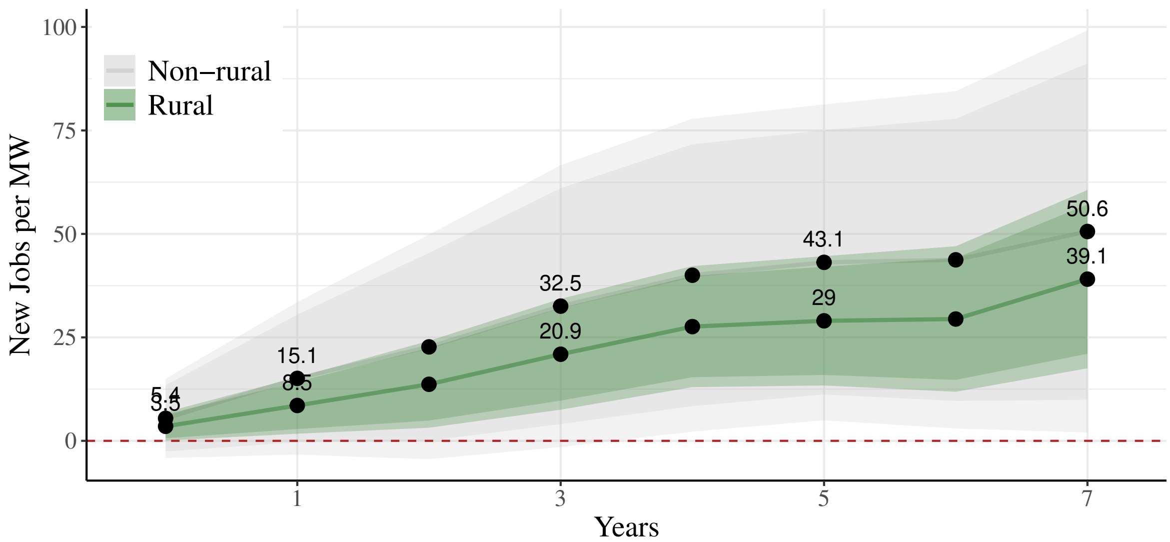
an RCA of 1 or greater, while other regions are classified as "non-rural". Approximately 38% of regions fall into the rural category, accounting for 64% of total installed RE capacity.

Using non-linear LP-IV, as detailed in Equation (4), we assess the employment effects of RE deployment in rural and non-rural regions ($EC = \{\text{Rural, Non-rural}\}$). Figure 8 displays the results, revealing positive and persistent long-term employment impacts in rural areas. The effects are slightly larger in non-rural regions, yet less precisely estimated. When we analyze the sector-specific impacts, a notable distinction emerges between rural and non-rural areas. Specifically, while the major effects in non-rural regions primarily stem from the construction sector, significant and positive effects on agriculture are mainly concentrated in rural areas (see Figure C.2 in Appendix).

This observation leads to three key interpretations. First, agricultural production, particularly crop yields, directly enters the supply chain for energy production through bioenergy, establishing a clear linkage between renewable energy deployment and the agricultural sector (IRENA and ILO, 2021). Second, the positive influence on agricultural employment may be due to the presence of input complementarities - agrivoltaic farms, for instance - which in turn increases local demand and possibly stimulate overall economic activity, extending the renewable investments effects beyond the energy sector (for instance, by fostering activities to connect the utility projects to high-voltage transmission lines). Recent experimental studies reveal that installations of wind turbines and agrivoltaic systems, for instance, can create favorable microclimatic conditions, boosting crop yields and overall agricultural productivity (Kaffine, 2019; Al Mamun et al., 2022; Mills, 2018). Third, the availability of renewable power sources in the rural areas generates a cheap local power advantage, echoing the mechanism identified in the impact of hydroelectric dams in the United States during the 20th century in USA by Severnini (2022). The availability of the cheaper energy sources lowers energy input costs for agricultural production, stimulating growth and employment in the sector over the medium and long term. Wind turbines and solar panels, can also be an additional source of income for landowners, who might choose to lease or sell land to energy providers or even become energy producers themselves. In such cases, co-locating renewable energy installations with agricultural activity can enhance farmers' revenues and improve their financial conditions, particularly during volatile weather and market conditions (Cuppari et al., 2021; Mills, 2018). Taken together, these findings address the key concern that agricultural activity can be potentially displaced by the increasing renewable energy technologies adoption (Hernandez et al., 2015). To the contrary, our results suggest that renewable energy investments can complement agricultural activity and even act as a catalyst for economic growth in the sector.

Finally, we investigate whether regions with different income levels, proxied by quartiles of real GDP per capita distribution, experience heterogeneous impacts in response to RE investments. Notably, rural regions are also (but not limited to) those characterized by lower income levels. The estimation of non-linear effects when $EC = \{Income\}$ can help dissecting whether is the sectoral or income heterogeneity that primarily drives the employment stimulus resulting from RE source deployment. Results for this specification are highlighted in Figure 9. For regions positioned above the median of the real GDP per capita distribution ($3^{rd}$ and $4^{th}$ quartiles), the deployment of RE plants does not seem to significantly spur employment growth. Conversely, regions below

Figure 8: Impact of Aggregate RE Investments on Employment in Rural and Non-Rural Areas




Notes: The figure plots the dynamic effect, estimated via LP-IV, of aggregate renewable investment on total regional employment in rural and non-rural areas, according to Equation (4). Employment is measured as the number of jobs created for 1MW installed. The control variables include four lagged terms of GDP growth, renewable investments, wages growth, capital formation growth and conventional energy commissioning and decommissioning. The regression includes NUTS-3 region and country-by-year fixed effects. Standard errors are clustered at NUTS-3 region level. The darker and lighter shaded regions correspond to a 90% and 95% confidence level, respectively. The average F-statistic, computed over the different time horizons $h$, is 88.67.

the median of the distribution ($1^{st}$ and $2^{nd}$ quartiles) experience sizable stimulus effects, with employment multipliers reaching 39 and 60, respectively, over a 7-year period.

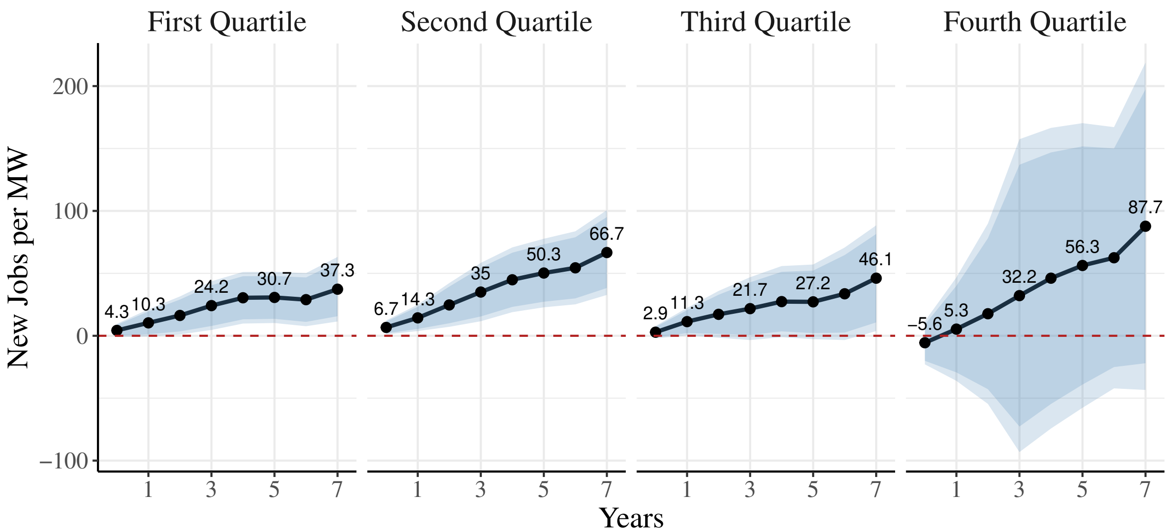
In summary, these findings suggest that RE technologies have the potential to stimulate employment and enhance economic growth, particularly in regions with relatively lower income levels. This result aligns with the macroeconomic literature on infrastructure investments, as the deployment of RE can act as a catalyst for economic expansion in areas that may lack sufficient infrastructure. On the demand side, public RE investments may help reducing the uncertainty on future rates of RE adoption, especially over the initial phase of the green transition, thus increasing the value of the investment multiplier (Gbohoui, 2021). On the supply-side instead, these investments may possess significant potential for productivity gains (Ramey, 2021).

## 4.2 Geographic Spillovers

We documented sizable average effects of regional investments in renewable power sources on local employment growth. However, these regional estimates might not necessarily hold for larger geographies, such as entire countries. NUTS-3 regions represent very small and open economies, where workers can easily move from one region to another through commuting or migration. Accordingly, flows of investment can attract workers and other entrepreneurs from surrounding regions towards regions receiving larger flows of investments in renewables. Or, they can benefit from the latter as the result of the presence of spillover effects.

To investigate whether neighboring regions can benefit from such investments, we examine the presence of

Figure 9: Impact of Aggregate RE Investments on Employment Across Regional Income Distribution




Notes: The figure plots the dynamic effect, estimated via LP-IV, of aggregate renewable investment on total regional employment in areas categorised into quartiles of real GDP per capita distribution, according to Equation (4). Employment is measured as the number of jobs created. The control variables include four lagged terms of GDP growth, renewable investments, wages growth, capital formation growth and conventional energy commissioning and decommissioning. The regression includes NUTS-3 region and country-by-year fixed effects. Standard errors are clustered at NUTS-3 region level. The darker and lighter shaded regions correspond to a 90% and 95% confidence level, respectively. The average F-statistic, computed over the different time horizons $h$, is 71.68.

geographical spillovers by estimating Equation (5), focusing on the coefficient $\beta^h_{out}$, which measures the number of jobs that are generated in region $l'$ over horizon $h$ following the development of RE plants in region $l$. Our results, displayed in Table 2, indicate that, on average, RE projects developed in one region significantly stimulate employment in surrounding regions. Over a 7-year horizon, employment steadily increases, amounting to approximately 23 jobs for each MW installed. This suggests the presence of substantial spillover effects arising from RE investments, implying that our baseline regional estimates in Figure 4 might represent a lower bound for the total effect. This finding aligns with recent evidence in the fiscal policy literature, where local-level public expenditures and investments have been found to generate substantial spillovers without signs of crowding-out effects (Chodorow-Reich, 2019a; Auerbach et al., 2020).

Table 2: Spillover Effects of Investing in Aggregate RE on Employment Levels of the Neighbouring Regions

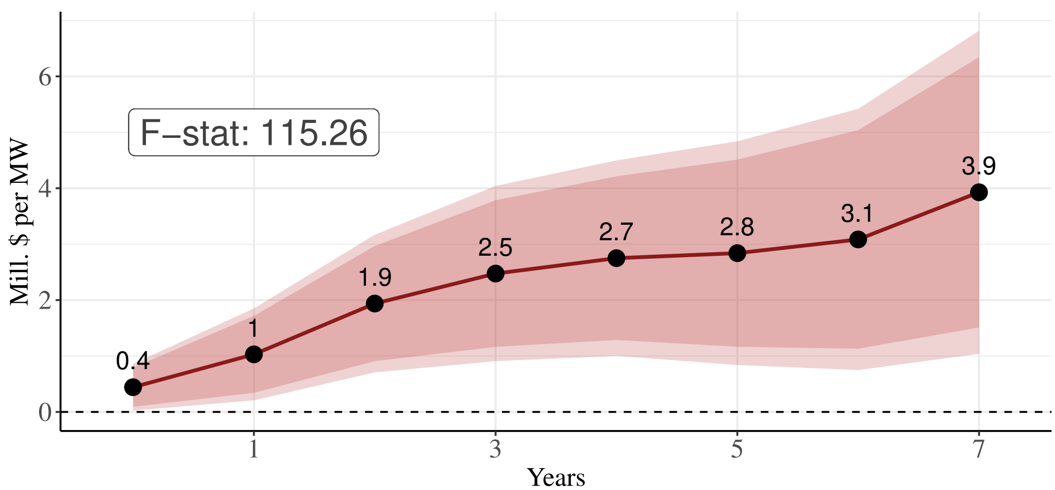
| Horizon | ($h = 0$) | ($h = 1$) | ($h = 2$) | ($h = 3$) | ($h = 4$) | ($h = 5$) | ($h = 6$) | ($h = 7$) |
|---|---|---|---|---|---|---|---|---|
| Employment | 3.501*** | 5.567*** | 8.039*** | 11.407*** | 14.933*** | 18.430*** | 19.256*** | 23.206*** |
| | (0.781) | (1.499) | (2.173) | (2.811) | (3.268) | (3.933) | (4.409) | (5.265) |
| *F-stat* | 118.73 | 125.72 | 142.98 | 118.92 | 109.72 | 94.59 | 76.64 | 59.30 |

The table reports the spillover effects of aggregate renewable investments on employment in the neighbouring regions, estimated via LP-IV according to Equation 5, for horizons $h = 0, ..., 7$. Employment is measured in number of jobs created. The control variables include four lagged terms of GDP growth, renewable investments, wages growth, capital formation growth and conventional energy commissioning and decommissioning. All regressions include NUTS-3 region and country-by-year fixed effects. Standard errors are clustered at NUTS-3 region level. The last row of the table reports the first stage F-statistic for each horizon.
p < 0.1, ** p < 0.05, *** p < 0.01

## 4.3 Effects on Regional Output

Solar and wind power technologies emerge as the primary drivers of the employment effects, particularly within sectors characterized by lower value-added activities like agriculture and construction. Moreover, it is worth noting that these two sectors differ in their labor intensity, with construction being relatively more reliant on labor, and productivity, with agriculture being relatively less productive than other industries. Hence, it is worth investigating whether RE installations can exert substantial effects on the broader regional economy. To this end, we examine the impact of RE development on economic activity, replacing the outcome variable $Y$ with regional GDP in our regressions (1), (3) and (5).[13]

Figure 10: Impact of Aggregate Renewable Energy Investments on Output




Notes: The figure plots the dynamic effect, estimated via LP-IV, of aggregate renewable investment on total regional output (real GDP), measured in million $, according to Equation (1). The control variables include four lagged terms of employment growth, renewable investments, wages growth, capital formation growth and conventional energy commissioning and decommissioning. The regression includes NUTS-3 region and country-by-year fixed effects. Standard errors are clustered at NUTS-3 region level. The darker and lighter shaded regions correspond to a 90% and 95% confidence level, respectively. The F-statistic reported is an average computed over the different time horizons $h$.

[13]Consistent with our baseline specification, where we intentionally excluded lagged terms of employment growth as controls to reduce potential bias, we adopt a similar approach in our GDP regression (Nickell, 1981). Consequently, we do not include lagged GDP growth values as controls. Robustness checks for alternative specifications are reported in Table B.2 in Appendix B.

Table 3: Impact of RE Investments on Output

| | Dependent Variable: Output Growth | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| | Explanatory Variable: Predicted RE Deployment (MW) | | | | | | | | |
| | $(h = 0)$ | $(h = 1)$ | $(h = 2)$ | $(h = 3)$ | $(h = 4)$ | $(h = 5)$ | $(h = 6)$ | $(h = 7)$ | F-stat |
| *Aggregate* | | | | | | | | | |
| Outward Spillover | 0.392*** | 0.813*** | 1.447*** | 2.025*** | 2.411*** | 2.698*** | 2.872*** | 3.367*** | 88.27 |
| | (0.078) | (0.161) | (0.247) | (0.337) | (0.432) | (0.541) | (0.639) | (0.769) | |
| *By Technology k* - Regional ($\beta_k^h$) | | | | | | | | | |
| Bioenergy | -1.023 | 1.614 | 8.098 | 14.114* | 17.750* | 19.511** | 23.573** | 29.531** | 31.9 |
| | (2.437) | (4.480) | (6.139) | (7.820) | (9.789) | (9.819) | (10.604) | (12.500) | |
| Hydro | 7.824 | 11.295 | 9.816 | 2.871 | 5.248 | 7.463 | 13.666 | 10.759 | 5.34 |
| | (5.519) | (9.447) | (7.477) | (7.361) | (8.462) | (9.061) | (10.557) | (8.420) | |
| Solar | 0.728*** | 1.826*** | 3.095*** | 3.834*** | 3.912*** | 3.453** | 2.945* | 3.526* | 94.87 |
| | (0.275) | (0.535) | (0.791) | (0.990) | (1.154) | (1.363) | (1.576) | (2.048) | |
| Wind | 0.118 | -0.140 | -0.023 | 0.282 | 1.192 | 2.910 | 6.835 | 12.007** | 33.37 |
| | (0.426) | (0.808) | (1.210) | (1.486) | (1.877) | (2.936) | (4.555) | (5.452) | |

The table outlines the effects of RE investments on output (real GDP), measured in million \$. Each row reports the estimates obtained using a different specification, for horizons $h = 0, \ldots, 7$. For all equations, the control variables include four lagged terms of employment growth, renewable investments, wages growth, capital formation growth and conventional energy commissioning and decommissioning. For technology-specific regressions, the control variables include the investments in the other, non-instrumented, RE sources. All regressions include NUTS-3 region and country-by-year fixed effects. Standard errors are clustered at NUTS-3 region level. The F-statistic reported is an average computed over the different time horizons $h$.
p < 0.1, ** p < 0.05, *** p < 0.01

Figure 10 and Table 3 report the effects of installing 1 MW of RE capacity on GDP, measured in millions of dollars. The dynamic response of GDP growth to RE investments mimics the results for employment analyzed in previous sections. On impact, GDP increases by approximately \$0.4 million and continues to rise steadily in the long run, reaching a cumulative effect of approximately \$3.9 million after 7 years.

As shown in the first line of Table 3, neighboring regions also benefit from these investments, as spillover effects increase significantly to around \$3.37 million after 7 years. Recalling that, on average, the cost of investing in 1 MW of renewable power plants amounts approximately to \$2.79M/MW (cfr., Table 1), our estimates imply that the green energy investment multiplier - i.e., the dollar amount of GDP produced by a dollar of investments in energy plants deployment - exceeds 1 after only 5 years (or 2 years if we include the spillover effects). Our estimates on impact are lower compared with the country-level evidence collected by Batini et al. (2022), who reported a "green investment" impact multiplier within the range of 1.2 to 1.5. There are two main reasons behind this. First, their measure of green investments, relative to ours, extend to networks for the transmission of electricity generated by RE sources. Second, as previously argued, our analysis focuses on local green investments, and our estimates may represent a lower-bound measure of national renewable investment multipliers (Chodorow-Reich, 2019a).[14] Finally, when we break down the effects and examine the contribution of each technology to the overall impact, we can conclude that, similar to employment, solar power sources make the most substantial

[14] In Table C.1 we report the OLS estimation results for the response of output. In contrast, Table B.4, report the same battery of robustness checks that we conduct for the employment response.

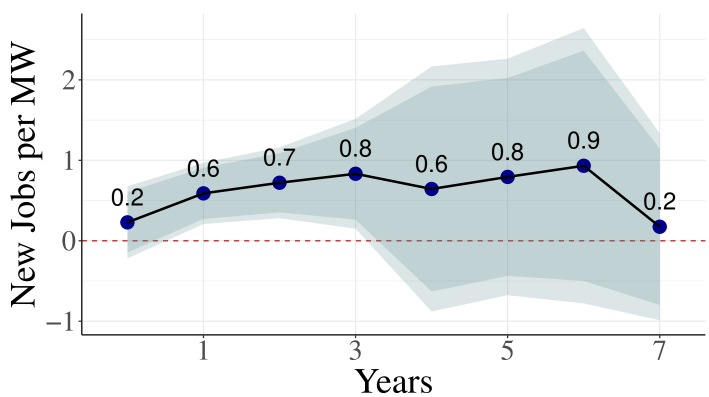
contributions.

### 4.4 Decommissioning of Conventional Power Plants

In the face of the energy transition, conventional sources are experiencing increasing decommissioning as well as waves of commissioning, mostly driven by the advancement of energy technology production based on natural gas combustion, as shown in Figure 1. While the primary focus of our study is on RE sources, our baseline model in Equation (1) controls for regional (dis-)investments associated with conventional energy sources. This inclusion allows us to investigate the relationship between these activities and employment growth. Even though our analysis does not provide estimates that can be interpreted as causal, the dynamic correlations shown in Figure 11 reveal interesting patterns.

We find that dis-investments of the conventional power plants does not lead to job displacement in the region, but is instead positively associated to small employment effects in the short term. However, we caution the interpretation of these estimates since the decommissioning of conventional power plants might reflect external factors which our specification does not account for, generating issues of endogeneity that we are not addressing here and go beyond the scope of the paper. Notwithstanding, these conditional correlations seems to discard significant negative associations between employment and phasing out of conventional power plants. To the contrary, they are suggestive of a stimulus provided by the decommissioning activities.

Figure 11: Correlations between Decommissioning Conventional Power Plants and Employment




Notes: The figure plots the effects on total regional employment ofthe decommissioning of conventional energy plants, which are included as control variables in our baseline Equation 1. The regression includes NUTS-3 region and country-by-year fixed effects. Standard errors are clustered at NUTS-3 region level. The darker and lighter shaded regions correspond to a 90% and 95% confidence level, respectively.

## 5 Conclusions

Efforts to decarbonize the energy sector primarily directed at mitigating climate change are bringing about an unprecedented transformation of the energy generation system (Jenniches, 2018). The consequences for the creation and distribution of jobs remain still unclear. Whether these actions will represent an opportunity to stimulate further investments and reduce uncertainty about climate risk, crucially hinges on the unfolding of the employment effects (Stern and Stiglitz, 2023). In this paper, we provide new empirical evidence on the effects of green energy investments on employment dynamics. Using a newly assembled dataset on renewable energy power plants commissioning covering nearly 3 decades and including 669 NUTS-3 regions across Denmark, France, Germany and UK, we estimate the dynamic causal effects of deploying RE plants on employment, using instrumental variable local projections (LP-IV, Jordà, 2005; Jordà, 2023). To the best of our knowledge, this paper is one of the first attempts to explore these effects within a unique framework, covering regional economies across different countries and allowing for an exploration of heterogeneity and underlying mechanisms. To identify investment shocks at the regional level, we employ a shift-share identification strategy. This approach relies on the differential regional exposure, measured as the regional shares of development potential for selected technologies, to national shocks in the renewable energy mix.

Our study reveals that the regional employment multiplier for green investments, measured as the number of jobs created by the installation of 1 MW of renewable energy, reaches 43 in about seven years. This figure also corresponds to approximately 15 jobs generated per $1 million spent on renewable power plants. Wind and solar power technologies drive these results, given their higher representation across European regions and wider adoption over the years. In the four countries under study, we find evidence of job gains within the construction and agricultural sectors - 43 and 11 jobs generated in seven years, respectively. These sectors are typically more labor-intensive and characterized by stronger complementarities and synergies with RE technologies. Furthermore, these effects spillover to neighboring locations, suggesting that the estimated *relative* job multiplier can be interpreted as a lower bound its national counterpart, a finding that is somewhat common in the cross-sectional fiscal policy literature (Chodorow-Reich, 2019b). Additionally, we find relevant non-linearities, as the jobs generated out of green energy installations are significant in regions with a higher specialization in agricultural activities (defined as rural areas) and in relatively poorer regions, as measured by GDP per capita levels. Finally, our results complement the national output multipliers estimated by Batini et al. (2022). We observe that following 1MW of renewable energy investments, regional output increase by approximately $3.8 million after 7 year. The output response mirrors the dynamic effects on employment, with significant direct and spillover effects, primarily driven by solar and wind technologies. Specifically, recalling that the cost of investing in 1 MW of renewable power plants amounts approximately to $2.79M/MW, the green energy investment multiplier for output - i.e., the dollar amount of GDP produced by a dollar of investments in renewable energy plants development - exceed 1 after 5 years (2 if we add the estimated spillover effects). From a policy perspective, our findings reveal that renewable energy investments can serve as in important source of local stimulus, especially in rural areas. They have the potential to reshape regional economies, effectively acting as place-based policies. Moreover, our results suggest that more stringent climate policy, such as environmental regulations that mandate the adoption or the installation of renewable power technologies, are not necessarily displacing jobs in the manufacturing sector and in polluting industries.

A necessary and complementary aspect of our analysis shall be left for further research. For sake of clarity, we have not delved into the other phase of the energy transition, namely the effects of progressive decommissioning of conventional plants on employment. We hint at this at the end of analysis. Indeed, we find that controlling for investment in conventional energy plants does not change the magnitude and the dynamics of our estimates. Furthermore, our findings suggest that the decommissioning of conventional power plants is positively correlated to local job creation in the short-term. A proper identification of these events needs to be addressed as we find preliminary results compelling.

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# Appendix A Data & Descriptives

Table A.1: Sectors of Economic Activity according to NACE Rev.2

| Macro-sector | Sectors |
|---|---|
| Agricolture, forestry and fishing (A) | Agricolture, forestry and fishing (A) |
| Industry (B-E) | Mining and Quarrying (B) |
| | Manufacturing (C) |
| | Electricity, gas, steam and air conditioning supply (D) |
| | Water supply; sewerage, waste management and remediation activities (E) |
| Construction (F) | Construction (F) |
| Wholesale etc (G-I) | Wholesale and retail trade; repair of motor vehicles and motorcycles(G) |
| | Transportation and storage (I) |
| | Accommodation and food service activities (H) |
| | Information and communication (J) |
| Financial and business services (K-N) | Financial and insurance activities (K) |
| | Real estate activities (L) |
| | Professional, scientific and technical activities (M) |
| | Administrative and support service activities (N) |
| Non-market services (O-U) | Public administration and defence; compulsory social security (O) |
| | Education (P) |
| | Human health and social work activities (Q) |
| | Arts, entertainment and recreation (R) |
| | Other service activities (S) |
| | Activities of households as employers(T) |
| | Activities of extraterritorial organisations and bodies (U) |

Table A.2: Descriptive Statistics of Socioeconomic Variables

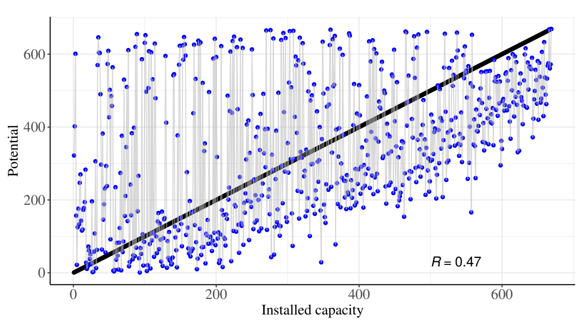
| | Mean | Std.Dev | Min | Median | Max |
|---|---|---|---|---|---|
| Growth rates (%) | | | | | |
| Total Employment | 0.54 | 2.53 | -30.63 | 0.61 | 36.11 |
| Agriculture | -0.06 | 0.63 | -16.41 | -0.01 | 29.80 |
| Construction | -0.02 | 0.63 | -10.11 | 0.00 | 10.27 |
| Industry | -0.21 | 1.18 | -25.90 | -0.08 | 10.73 |
| Wholesale | 0.23 | 0.96 | -13.19 | 0.21 | 10.26 |
| Financial & Business Services | 0.25 | 0.77 | -7.94 | 0.22 | 10.00 |
| Non-market Services | 0.36 | 0.98 | -14.43 | 0.35 | 26.34 |
| GDP (Mill. $) | 1.62 | 4.02 | -29.81 | 1.73 | 55.38 |
| Wages | 1.56 | 2.95 | -21.04 | 1.64 | 33.27 |
| Capital Formation | 1.43 | 6.80 | -28.08 | 1.68 | 169.64 |
| Levels (Thousands) | | | | | |
| Total Employment | 140.85 | 162.84 | 8.00 | 95.14 | 2036.32 |
| Agriculture | 3.08 | 3.98 | -0.20 | 1.84 | 42.33 |
| Construction | 9.45 | 9.01 | 0.00 | 6.76 | 152.66 |
| Industry | 23.01 | 20.17 | 0.92 | 16.92 | 270.93 |
| Wholesale | 37.97 | 47.45 | 2.00 | 24.28 | 637.43 |
| Financial Services | 23.29 | 41.62 | 0.00 | 11.36 | 663.47 |
| Other Services | 44.04 | 53.59 | 2.00 | 28.01 | 787.65 |
| GDP (Mill. $) | 11.41 | 16.38 | 0.60 | 6.80 | 253.74 |
| Wages | 40.02 | 36.96 | 2.49 | 29.87 | 360.60 |
| Capital Formation | 16.21 | 15.86 | 0.92 | 12.44 | 167.20 |

Table A.3: Descriptive statistics of Energy Variables

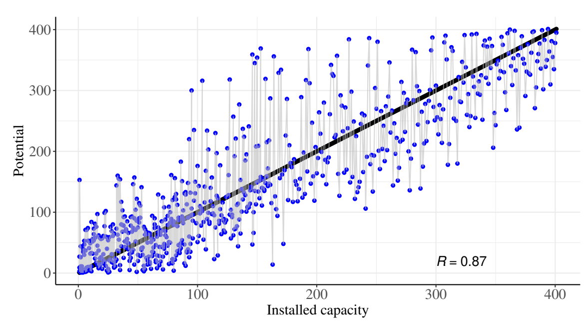
| (MW) | Mean | Std.Dev | Min | Median | Max |
|---|---|---|---|---|---|
| New Capacity | | | | | |
| Bioenergy | 0.85 | 9.91 | 0.00 | 0.00 | 673.10 |
| Solar | 3.34 | 9.95 | 0.00 | 0.04 | 233.80 |
| Hydro | 0.17 | 2.35 | 0.00 | 0.00 | 203.00 |
| Wind | 4.06 | 15.95 | 0.00 | 0.00 | 476.19 |
| Renewable | 8.43 | 22.41 | 0.00 | 0.86 | 673.10 |
| Oil | 0.14 | 4.73 | 0.00 | 0.00 | 400.00 |
| Coal | 1.22 | 33.30 | 0.00 | 0.00 | 2120.00 |
| Natural Gas | 3.36 | 51.66 | 0.00 | 0.00 | 2305.00 |
| Nuclear | 0.62 | 29.37 | 0.00 | 0.00 | 1500.00 |
| Conventional | 5.00 | 64.49 | 0.00 | 0.00 | 2305.00 |
| Decommissioned Capacity | | | | | |
| Oil | 0.57 | 26.33 | 0.00 | 0.00 | 2340.00 |
| Coal | 1.77 | 42.26 | 0.00 | 0.00 | 2400.00 |
| Natural Gas | 0.44 | 16.06 | 0.00 | 0.00 | 1350.00 |
| Nuclear | 1.01 | 33.22 | 0.00 | 0.00 | 2407.00 |
| Conventional | 3.79 | 62.18 | 0.00 | 0.00 | 2407.00 |

Figure A.12: Regional Ranking according to Solar Energy Potential and Installed Capacity

(a) Full-Sample Ranking




(b) National Ranking

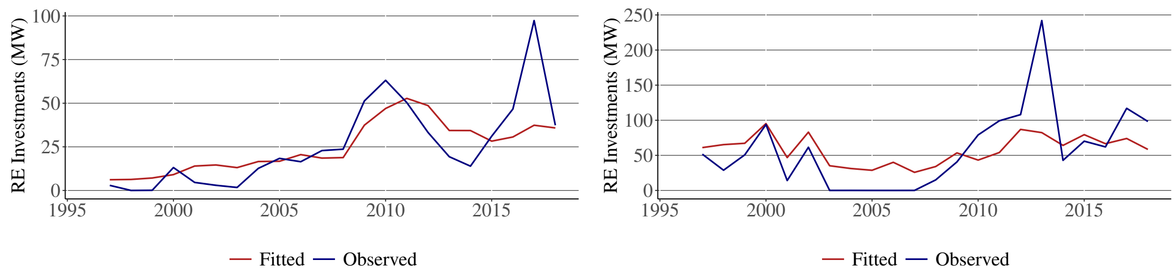



Notes: The figures plot the relation between the ranking of regions in terms of their solar potential and their aggregate solar installed capacity at the end of the sample period. In figure A.12a the positioning of each region, for both potential and capacity, is computed over the entire sample. The maximum rank in this case is 669, accounting for all the regions in the sample. The correlation between region potential and installed capacity ranking is reported at the bottom of the plot at 0.47. In figure A.12b the positioning of each region, for both potential and capacity, is computed within its country. The maximum rank in this case is 401, as the country with the largest number of observations is Germany with 401 NUTS-3 regions. The correlation between region potential and installed capacity ranking is reported at the bottom of the plot at 0.87.

# Appendix B Robustness Checks

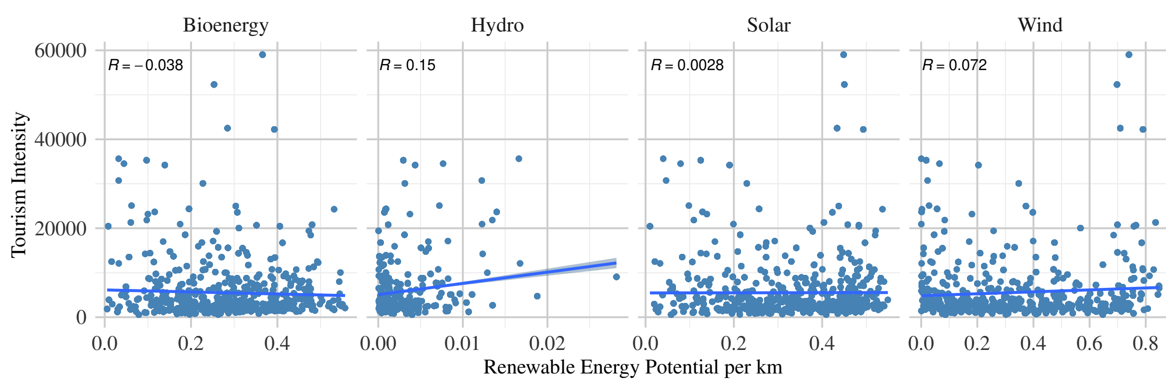
Figure B.1: Actual New Renewable Energy Investments vs Predicted First-Stage

(a) Schwäbish Hall (b) Bornholm




Notes: The figures report observed vs predicted renewable energy investments (in MW) in the Schwäbisch Hall district of the German State Baden-Württemberg in panel B.1a, and in the Bornholm province in Denmark in panel B.1b.

Figure B.2: Regional Tourism Intensity vs. Renewable Energy Potential




Notes: The figure reports the correlation between tourism intensity, measured as the number of nights spent in hospitality accommodations in 2023 per number of regional inhabitants, and renewable energy potential per km. The value for tourism intensity provided by the Eurostat database excludes values for the United Kingdom.

Table B.1: Impact of Aggregate RE Investments on Employment: Alternative Specifications

| | Dependent Variable: Employment Growth | | | | | | |
|---|---|---|---|---|---|---|---|
| | Independent Variable: Predicted Aggregate RE Deployment | | | | | | |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) |
| $(h = 0)$ | 2.059 | 4.163** | 4.215* | 4.058* | 4.902** | 4.946** | 4.381 |
| | (1.992) | (1.850) | (2.200) | (2.196) | (2.253) | (2.263) | (2.949) |
| $(h = 1)$ | -1.148 | 9.399** | 10.478** | 10.169** | 11.503** | 11.570** | 10.570* |
| | (4.260) | (3.806) | (4.564) | (4.568) | (4.531) | (4.548) | (5.723) |
| $(h = 2)$ | -4.895 | 15.007*** | 16.178** | 15.638** | 17.935*** | 18.023*** | 16.970** |
| | (6.527) | (5.766) | (6.803) | (6.804) | (6.706) | (6.736) | (8.166) |
| $(h = 3)$ | -4.501 | 21.329*** | 22.620*** | 22.017*** | 25.613*** | 25.738*** | 25.003** |
| | (7.993) | (7.056) | (8.191) | (8.191) | (8.173) | (8.206) | (9.769) |
| $(h = 4)$ | -0.608 | 28.151*** | 29.256*** | 28.465*** | 32.688*** | 32.826*** | 32.436*** |
| | (8.747) | (7.937) | (8.881) | (8.878) | (8.926) | (8.946) | (10.738) |
| $(h = 5)$ | 4.746 | 30.538*** | 29.972*** | 28.892*** | 33.594*** | 33.758*** | 34.837*** |
| | (9.975) | (8.518) | (9.085) | (9.099) | (9.040) | (9.047) | (11.045) |
| $(h = 6)$ | 8.905 | 30.106*** | 29.057*** | 27.805*** | 33.688*** | 33.760*** | 34.842*** |
| | (11.046) | (9.431) | (9.903) | (9.872) | (9.826) | (9.809) | (11.558) |
| $(h = 7)$ | 21.118 | 38.410*** | 38.234*** | 36.783*** | 42.982*** | 42.990*** | 43.439*** |
| | (13.574) | (11.457) | (11.760) | (11.708) | (11.609) | (11.566) | (13.600) |
| *Average First-stage* | *188.68* | *156.56* | *92.68* | *94.75* | *94.32* | *94.47* | *94.36* |
| **Controls** | | | | | | | |
| Output growth | | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Renewable investments | | | ✓ | ✓ | ✓ | ✓ | ✓ |
| Conventional investments and dis-investments | | | | ✓ | ✓ | ✓ | ✓ |
| Wages growth | | | | | ✓ | ✓ | ✓ |
| Capital Formation growth | | | | | | ✓ | ✓ |
| Employment growth | | | | | | | ✓ |

The table outlines the effects of predicted RE investments on regional employment, measured as number of jobs generated per 1MW installed. Each row reports the estimates obtained using a different specification, for horizons $h = 0, ..., 7$. Our baseline regression is (6). All control variables are lagged up to four periods. The regression includes NUTS-3 region and country-by-year fixed effects. Standard errors are clustered at NUTS-3 region level. The F-statistic reported is an average computed over the different time horizons $h$ for each specification.
$p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table B.2: Impact of Aggregate RE Investments on Output: Alternative Specifications

| | Dependent Variable: Output Growth | | | | | | |
|---|---|---|---|---|---|---|---|
| | Independent Variable: Predicted Aggregate RE Deployment | | | | | | |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) |
| ($h$ = 0) | 0.965*** | 0.375** | 0.422** | 0.411** | 0.444** | 0.442** | 0.202 |
| | (0.233) | (0.189) | (0.206) | (0.207) | (0.213) | (0.213) | (0.273) |
| ($h$ = 1) | 1.300*** | 0.855** | 1.023** | 1.000** | 1.026** | 1.029** | 0.664 |
| | (0.393) | (0.376) | (0.410) | (0.413) | (0.419) | (0.419) | (0.507) |
| ($h$ = 2) | 1.693*** | 1.739*** | 1.990*** | 1.950*** | 1.939*** | 1.938*** | 1.457** |
| | (0.571) | (0.574) | (0.634) | (0.637) | (0.628) | (0.628) | (0.727) |
| ($h$ = 3) | 1.912*** | 2.243*** | 2.496*** | 2.453*** | 2.462*** | 2.474*** | 1.949** |
| | (0.710) | (0.739) | (0.809) | (0.810) | (0.801) | (0.799) | (0.885) |
| ($h$ = 4) | 1.890** | 2.496*** | 2.718*** | 2.644*** | 2.718*** | 2.750*** | 2.114** |
| | (0.818) | (0.845) | (0.886) | (0.891) | (0.895) | (0.892) | (0.995) |
| ($h$ = 5) | 1.982** | 2.625*** | 2.734*** | 2.675*** | 2.814*** | 2.839*** | 2.000* |
| | (0.967) | (0.987) | (1.016) | (1.022) | (1.023) | (1.020) | (1.120) |
| ($h$ = 6) | 2.112* | 2.710** | 2.806** | 2.778** | 3.067** | 3.084*** | 2.055 |
| | (1.129) | (1.157) | (1.186) | (1.191) | (1.191) | (1.191) | (1.305) |
| ($h$ = 7) | 2.523* | 3.288** | 3.501** | 3.514** | 3.916*** | 3.927*** | 2.622 |
| | (1.441) | (1.436) | (1.462) | (1.467) | (1.473) | (1.474) | (1.596) |
| *Average First-stage* | *191.42* | *152.05* | *112.84* | *112.75* | *114.94* | *115.24* | *115.19* |
| **Controls** | | | | | | | |
| Employment growth | | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Renewable investments | | | ✓ | ✓ | ✓ | ✓ | ✓ |
| Conventional investments and dis-investments | | | | ✓ | ✓ | ✓ | ✓ |
| Wages growth | | | | | ✓ | ✓ | ✓ |
| Capital Formation growth | | | | | | ✓ | ✓ |
| Output growth | | | | | | | ✓ |

The table outlines the effects of RE investments on regional output (real GDP), measured in million $. Each row reports the estimates obtained using a different specification, for horizons $h = 0, \ldots, 7$. Our baseline regression is (6). All control variables are lagged up to four periods. The regression includes NUTS-3 region and country-by-year fixed effects. Standard errors are clustered at NUTS-3 region level. The F-statistic reported is an average computed over the different time horizons $h$ for each specification.
p < 0.1, ** p < 0.05, *** p < 0.01

Table B.3: Impact of Aggregate Renewable Investments on Employment: Robustness Checks

| | Dependent Variable: Employment Growth | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| | Explanatory Variable: Predicted RE Deployment (MW) | | | | | | | | |
| | ($h$ = 0) | ($h$ = 1) | ($h$ = 2) | ($h$ = 3) | ($h$ = 4) | ($h$ = 5) | ($h$ = 6) | ($h$ = 7) | F-stat |
| *Restricted Sample* | | | | | | | | | |
| Excluding UK | 4.603** | 8.572** | 13.555*** | 20.715*** | 27.210*** | 29.357*** | 28.389*** | 35.688*** | 90.85 |
| | (1.799) | (3.451) | (4.862) | (6.208) | (7.160) | (8.095) | (8.889) | (10.540) | |
| Wind and Solar | 4.744** | 11.595** | 17.626** | 23.176*** | 29.450*** | 29.089*** | 28.803*** | 38.703*** | 93.06 |
| | (2.203) | (4.593) | (6.897) | (8.081) | (8.807) | (9.141) | (9.838) | (11.728) | |
| *Alternative Instruments* | | | | | | | | | |
| Full-Sample Potential | 19.854* | 32.285** | 43.716** | 54.333** | 65.287** | 57.153** | 55.951* | 75.004* | 38.21 |
| | (10.651) | (15.163) | (19.229) | (24.157) | (28.812) | (27.752) | (30.903) | (39.836) | |
| Fixed Shares | 3.491 | 13.173* | 24.083* | 35.503** | 39.310** | 40.906* | 37.810 | 41.531 | 23.21 |
| | (4.128) | (7.290) | (12.490) | (15.657) | (17.607) | (21.961) | (24.294) | (27.768) | |
| Lagged Shares | 0.450 | 3.532 | 7.510 | 13.348** | 16.893** | 19.044** | 21.315** | 26.987** | 101.2 |
| | (1.819) | (3.485) | (5.075) | (6.635) | (7.778) | (8.372) | (9.241) | (10.756) | |
| *Alternative Standard Errors* | | | | | | | | | |
| Conley (100 km) | 4.946* | 11.570** | 18.023** | 25.738** | 32.826*** | 33.758*** | 33.760*** | 42.990*** | 44.67 |
| | (2.790) | (5.758) | (8.645) | (10.352) | (11.226) | (11.732) | (12.999) | (15.446) | |
| Clustered NUTS2 | 4.946* | 11.570* | 18.023** | 25.738** | 32.826*** | 33.758*** | 33.760** | 42.990*** | 62.89 |
| | (2.523) | (6.244) | (9.090) | (10.396) | (11.336) | (11.018) | (12.902) | (15.797) | |

The table outlines the effects of predicted RE investments on total regional employment, measured as number of jobs created per 1 MW installed. For all regressions, the control variables include four lagged terms of GDP growth, renewable investments, wages growth, capital formation growth and conventional energy commissioning and decommissioning. The regressions include NUTS-3 region and country-by-year fixed effects. Standard errors are clustered at NUTS-3 region level. The F-statistic reported is an average computed over the different time horizons $h$ for each specification.
Each row reports the estimates obtained using a different specification. In the first two rows, our baseline specification is regressed over a restricted sample, respectively excluding observations for the UK, and keeping only the aggregate investments for wind and solar as explanatory variable in the second one. We also adopt three different alternative instruments, where the regional shares are calculated out of the total sample and interacted with full-sample shifts in renewable energy capacity. *Full-Sample Potential* interacts regional potential as a share of the total sample potential for technology $k$ with full-sample new capacity for technology $k$. For the other two specifications, the instrument is constructed using an alternative measure of regional exposure given by the past renewable energy investments occurred in the region. In *Fixed Shares* the regional shares of investments are kept fixed at the year 2000; *Lagged Shares* uses the lagged shares of technology-specific regional investments out of the total sample. Finally, we test the robustness of our results by applying two alternative standard error structures: Conley SEs to account for spatial autocorrelation within a 100 km radius; secondly, clustering at the NUTS-2 level allows for arbitrary correlation within these larger regions.
$p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table B.4: Impact of Aggregate RE Investments on Output: Robustness Checks

| | Dependent Variable: Output Growth | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| | Explanatory Variable: Predicted RE Deployment (MW) | | | | | | | | |
| | ($h = 0$) | ($h = 1$) | ($h = 2$) | ($h = 3$) | ($h = 4$) | ($h = 5$) | ($h = 6$) | ($h = 7$) | F-stat |
| *Restricted Sample* | | | | | | | | | |
| Excluding UK | 0.505** | 1.205*** | 2.181*** | 2.806*** | 2.912*** | 2.828*** | 2.797** | 3.550** | 112.92 |
| | (0.206) | (0.388) | (0.563) | (0.745) | (0.897) | (1.051) | (1.213) | (1.485) | |
| Wind and Solar | 0.445** | 1.003** | 1.848*** | 2.380*** | 2.644*** | 2.696*** | 2.866** | 3.710** | 116.07 |
| | (0.207) | (0.422) | (0.639) | (0.809) | (0.898) | (1.031) | (1.195) | (1.483) | |
| *Alternative Instruments* | | | | | | | | | |
| Full-sample Potential Shares | 0.922*** | 1.685*** | 3.156*** | 3.677*** | 4.121*** | 4.102*** | 4.087** | 5.285** | 46.28 |
| | (0.330) | (0.632) | (0.941) | (1.186) | (1.331) | (1.520) | (1.685) | (2.107) | |
| Fixed Shares | 1.156*** | 2.149*** | 2.970*** | 3.437*** | 4.081*** | 4.517*** | 4.718*** | 5.147*** | 42.46 |
| | (0.323) | (0.562) | (0.807) | (1.007) | (1.146) | (1.303) | (1.405) | (1.691) | |
| Lagged Shares | 1.971*** | 2.918*** | 4.797*** | 5.417** | 5.608** | 5.786* | 5.876* | 6.772* | 31.67 |
| | (0.538) | (1.010) | (1.819) | (2.387) | (2.807) | (3.279) | (3.457) | (3.780) | |
| *Alternative Standard Errors* | | | | | | | | | |
| Conley (100 km) | 0.442* | 1.029** | 1.938** | 2.474*** | 2.750*** | 2.839*** | 3.084*** | 3.927*** | 44.5 |
| | (0.264) | (0.499) | (0.754) | (0.939) | (1.018) | (1.063) | (1.171) | (1.372) | |
| Clustered NUTS-2 | 0.442* | 1.029** | 1.938** | 2.474** | 2.750** | 2.839** | 3.084** | 3.927** | 70.25 |
| | (0.251) | (0.510) | (0.793) | (1.041) | (1.169) | (1.278) | (1.433) | (1.704) | |

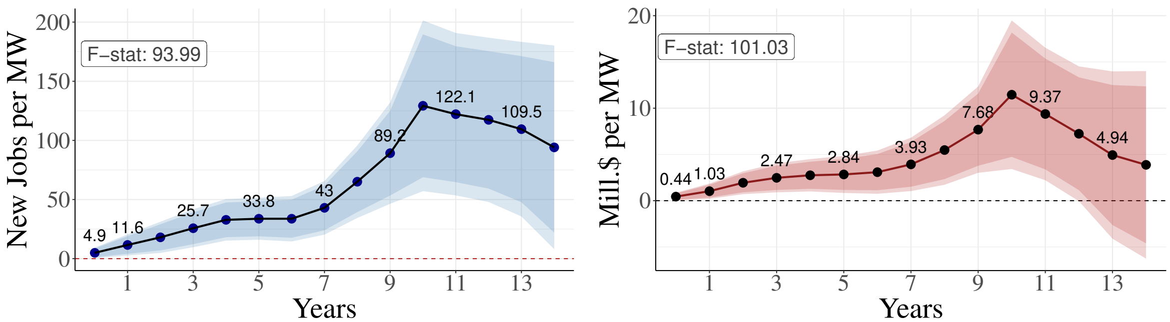
The table outlines the effects of RE investments on regional output (real GDP), measured in million $. For all regressions, the control variables include four lagged terms of GDP growth, renewable investments, wages growth, capital formation growth and conventional energy commissioning and decommissioning. The regressions include NUTS-3 region and country-by-year fixed effects. Standard errors are clustered at NUTS-3 region level. The F-statistic reported is an average computed over the different time horizons $h$ for each specification.

Each row reports the estimates obtained using a different specification. In the first two rows, our baseline specification is regressed over a restricted sample, respectively excluding observations for the UK, and keeping only the aggregate investments for wind and solar as explanatory variable in the second one. We also adopt three different alternative instruments, where the regional shares are calculated out of the total sample and interacted with full-sample shifts in renewable energy capacity. *Full-Sample Potential* interacts regional potential as a share of the total sample potential for technology $k$ with full-sample new capacity for technology $k$. For the other two specifications, the instrument is constructed using an alternative measure of regional exposure given by the past renewable energy investments occurred in the region. In *Fixed Shares* the regional shares of investments are kept fixed at the year 2000; *Lagged Shares* uses the lagged shares of technology-specific regional investments out of the total sample. Finally, we test the robustness of our results by applying two alternative standard error structures: Conley SEs to account for spatial autocorrelation within a 100 km radius; secondly, clustering at the NUTS-2 level allows for arbitrary correlation within these larger regions.

p < 0.1, ** p < 0.05, *** p < 0.01

Figure B.3: Long-run Impact of Aggregate RE Investments on Employment and Output

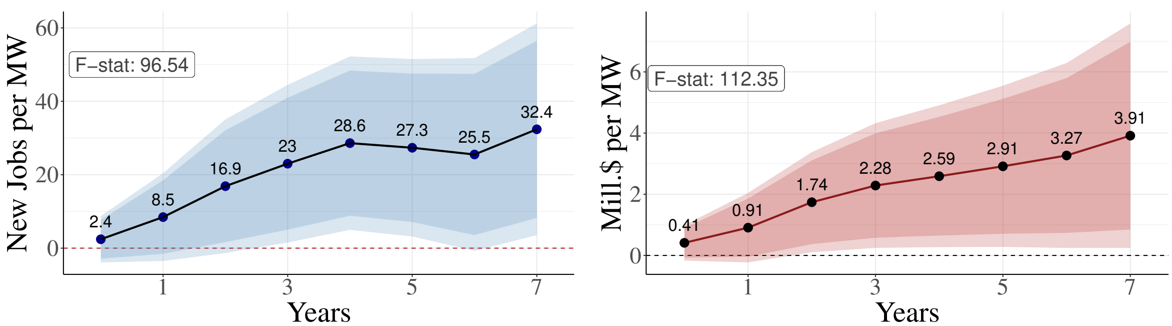
(a) Employment (b) Output




Notes: The figure plots the long-run dynamic effect, estimated via LP-IV, of aggregate renewable investment on regional employment and output (Figures B.3a and B.3b, respectively). Employment is measured as the number of jobs created, while output is measured as million $ real GDP generated. The control variables include four lagged terms of RE investments, wages growth, capital formation growth, and conventional energy commissioning and decommissioning. The regression on employment growth includes four lagged terms of GDP growth, while the regression on output growth includes four lagged terms of employment growth. The regressions includes NUTS-3 region and country-by-year fixed effects. Standard errors are clustered at the NUTS-3 region level. The darker and lighter shaded regions correspond to a 90% and 95% confidence level, respectively. The reported F statistic is an average computed over different time horizons $h$.

Figure B.4: Impact of Aggregate RE Investments on Employment and Output with Alternative Fixed Effects Structure

(a) Employment (b) Output




Notes: The figure plots the dynamic effect, estimated via LP-IV, of aggregate renewable investment on total regional employment and output (Figures B.4a and B.4b, respectively. Employment is measured in number of jobs created, while output is measured in million $ per 1MW installed. Instead of NUTS-3 and country-by-year fixed effect, as in the baseline equation (1), the regression includes NUTS-3 region and NUTS1-by-year fixed effects. The fixed effect structure allows us to control for degrees of sub-national discretionality that can potentially occur withing energy policies, as the one granted for example to the federal states in the case of Germany. The control variables include four lagged terms of RE investments, wages growth, capital formation growth, and conventional energy commissioning and decommissioning. The regression on employment growth includes four lagged terms of GDP growth, while the regression on output growth includes four lagged terms of employment growth. Standard errors are clustered at NUTS-3 region level. The darker and lighter shaded regions correspond to a 90% and 95% confidence level, respectively. The F-statistic reported is an average computed over the different time horizons $h$.

# Appendix C Other estimates

Table C.1 displays the OLS regression results of the specification in Equation (1). Overall, OLS estimates are positive yet lower than IV estimates, suggesting the predominance of omitted factors in OLS estimates that lead to downward bias.

Table C.1: Impact of Aggregate RE Investments on Employment and Output: OLS Estimates

| | Explanatory Variable: Aggregate Renewable Investments | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | ($h = 0$) | ($h = 1$) | ($h = 2$) | ($h = 3$) | ($h = 4$) | ($h = 5$) | ($h = 6$) | ($h = 7$) |
| Dependent Variable: | | | | | | | | |
| Employment | 0.345 | 2.038** | 2.476* | 3.431** | 5.348*** | 4.604* | 5.864** | 9.785*** |
| | (0.584) | (0.906) | (1.380) | (1.628) | (2.068) | (2.540) | (2.887) | (3.149) |
| Output | 0.105* | 0.281** | 0.409*** | 0.475*** | 0.412* | 0.502* | 0.651** | 0.960** |
| | (0.064) | (0.110) | (0.140) | (0.181) | (0.231) | (0.296) | (0.324) | (0.376) |

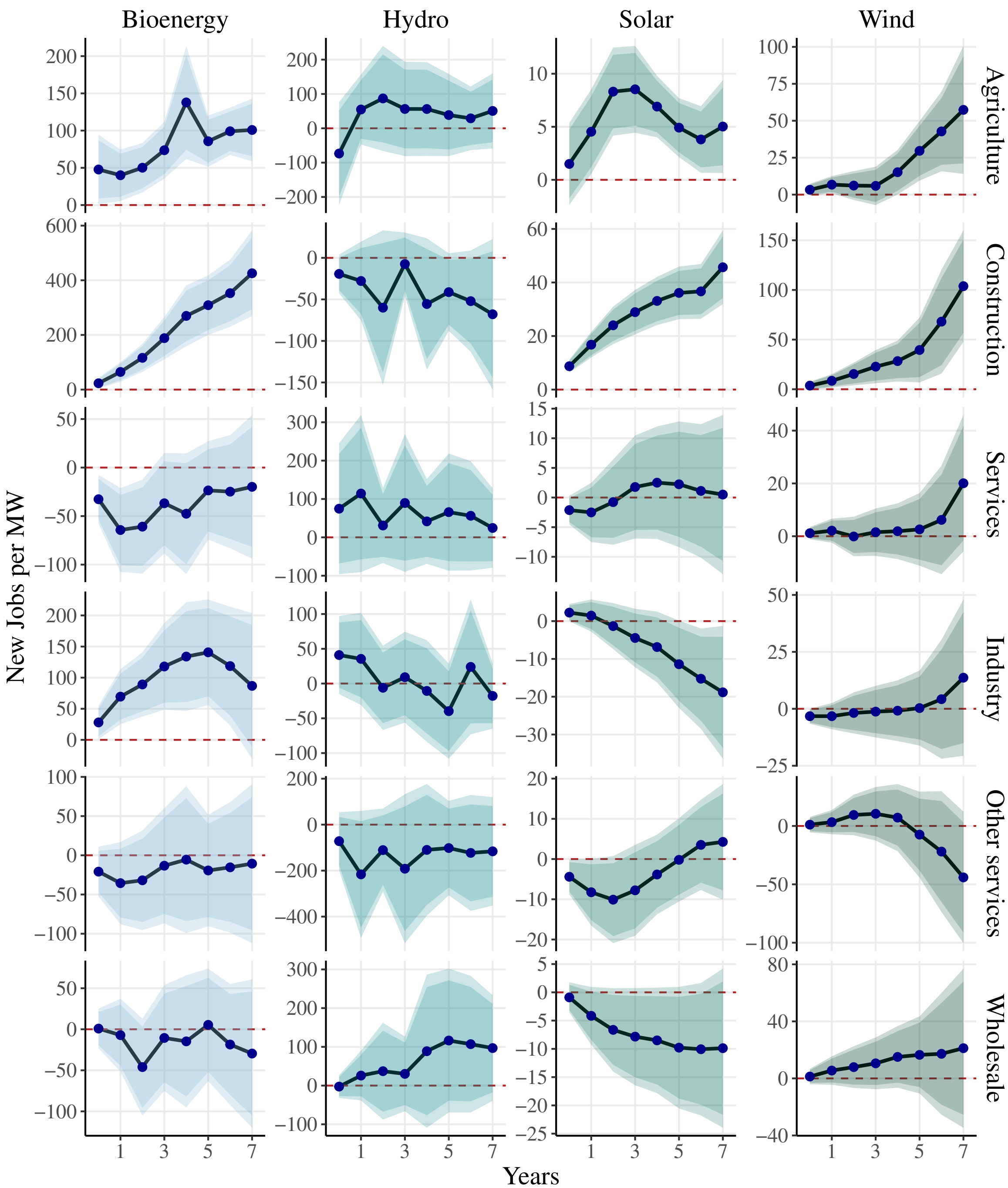
The table reports the effects of aggregate renewable investments on regional employment and output (real GDP), estimated according to Equation 1. Employment is measured in number of jobs created while output is measured in million $ per 1 MW installed. Both regressions include as controls four lagged terms of RE investments, conventional investments and dis-investments, wages growth and capital formation growth. The employment regression also includes the lagged terms of GDP growth, while the output regression controls for the lagged terms of employment growth. All regressions include NUTS-3 region and country-by-year fixed effects. Standard errors are clustered at NUTS-3 region level.
p < 0.1, ** p < 0.05, *** p < 0.01

Table C.2: First Stage Estimates

| | | Dependent Variable: New RE Capacity | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| | | Explanatory Variable: IV | | | | | | | |
| | | $h = 0$ | $h = 1$ | $h = 2$ | $h = 3$ | $h = 4$ | $h = 5$ | $h = 6$ | $h = 7$ |
| Renewable | Coef | 0.559*** | 0.565*** | 0.569*** | 0.608*** | 0.664*** | 0.716*** | 0.699*** | 0.653*** |
| | | (0.071) | (0.073) | (0.068) | (0.071) | (0.066) | (0.064) | (0.059) | (0.058) |
| | F-stat | 61.13 | 59.43 | 70.75 | 74.00 | 102.22 | 124.08 | 138.81 | 125.38 |
| Bioenergy | Coef | 0.352*** | 0.327*** | 0.412*** | 0.402*** | 0.382*** | 0.621*** | 0.620*** | 0.579*** |
| | | (0.129) | (0.082) | (0.081) | (0.080) | (0.082) | (0.079) | (0.079) | (0.080) |
| | F-stat | 7.45 | 16.02 | 25.98 | 24.95 | 21.50 | 61.47 | 61.73 | 51.92 |
| Hydro | Coef | 0.215** | 0.212** | 0.213** | 0.213** | 0.216** | 0.218** | 0.219** | 0.228** |
| | | (0.103) | (0.103) | (0.104) | (0.105) | (0.105) | (0.105) | (0.105) | (0.105) |
| | F-stat | 4.39 | 4.18 | 4.21 | 4.12 | 4.20 | 4.29 | 4.39 | 4.71 |
| Solar | Coef | 0.513*** | 0.513*** | 0.515*** | 0.539*** | 0.617*** | 0.643*** | 0.644*** | 0.562*** |
| | | (0.063) | (0.063) | (0.063) | (0.060) | (0.056) | (0.059) | (0.060) | (0.066) |
| | F-stat | 66.58 | 66.78 | 67.38 | 80.34 | 120.55 | 118.62 | 113.40 | 72.32 |
| Wind | Coef | 0.681*** | 0.715*** | 0.765*** | 0.850*** | 0.900*** | 0.916*** | 0.751*** | 0.689*** |
| | | (0.120) | (0.126) | (0.129) | (0.162) | (0.164) | (0.191) | (0.157) | (0.111) |
| | F-stat | 32.43 | 32.28 | 35.01 | 27.68 | 30.29 | 22.96 | 22.93 | 38.72 |

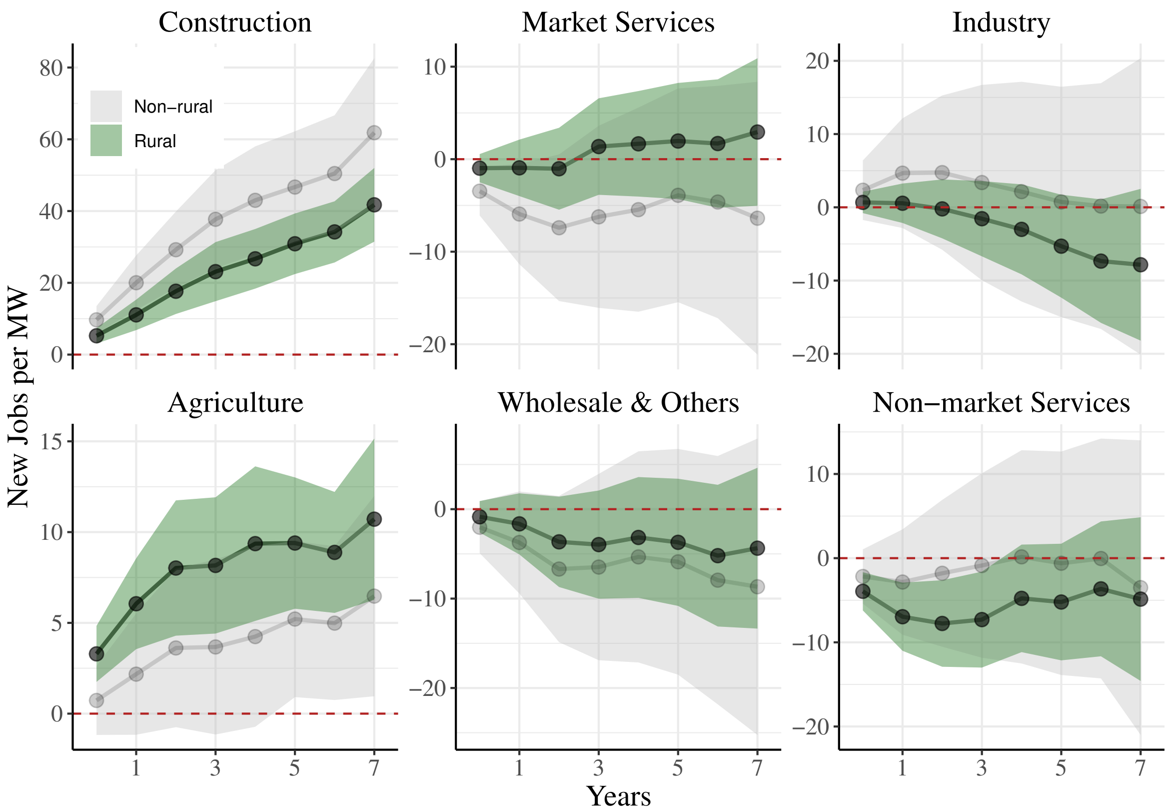
The table reports the first stage coefficients, standard errors, and F-statistic for aggregate renewable investments (equation 1) and technology-specific investments equations (equation 3). The control variables include four lagged terms of GDP growth, renewable investments, wage growth, capital formation growth, and conventional energy commissioning and decommissioning. All regressions include NUTS-3 region and country-by-year fixed effects. Standard errors are clustered at the NUTS-3 region level. Standard errors are in parentheses.
p < 0.1, ** p < 0.05, *** p < 0.01

Figure C.1: Impact of Technology - Specific Investments on Sectoral Employment




Notes: The figure plots the dynamic impact, estimated via LP-IV, of technology-specific investments $k$ on sectoral regional employment $i$, measured by the number of jobs created in each sector, combining the specification in Equations (2) and (3). The control variables include the investments in the remaining non-instrumented energy technologies, and four lagged terms of GDP growth, renewable investments, wages growth, capital formation growth and conventional energy commissioning and decommissioning. The regression includes NUTS-3 region and country-by-year fixed effects. Standard errors are clustered at the NUTS-3 region level. The darker and lighter shaded regions correspond to a 90% and 95% confidence level, respectively.

Figure C.2: Impact of Aggregate Investments on Technology-Specific Employment in Rural and Non-Rural Areas




Notes: The figure plots the dynamic effect, estimated via LP-IV, of aggregate renewable investment on sectoral regional employment in rural and non-rural areas. Employment is measured as the number of jobs created in each sector per 1MW installed. The control variables include four lagged terms of GDP growth, renewable investments, wages growth, capital formation growth and conventional energy commissioning and decommissioning. The regression includes NUTS-3 region and country-by-year fixed effects. Standard errors are clustered at NUTS-3 region level. The darker and lighter shaded regions correspond to a 90% and 95% confidence level, respectively. The average F-statistic, computed over the different time horizons $h$, is 88.67.