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

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Abstract

A rapid transition towards renewable energy sources is crucial to address climate change and improve local energy independence. However, the acceptability of this transition often faces resistance due to concerns about potential job-losses in the fossil-intensive sectors, while the employment potential of renewable energy technologies remains unclear. In this study, we address this concern by employing a novel and detailed geolocalized dataset of energy power units across four technologies and three decades, to examine the employment impacts of renewable energy investments in four large European countries. To mitigate for the possible non-random allocation of renewable energy technologies, we leverage the physical potential of each region in relation to renewable energy sources, to isolate its exposure to technology-specific investments. We find that the deployment of renewable energy plants has a positive and long-lasting impact on employment. Our central estimates suggest that 1 MW of new renewable energy installed capacity creates around 40 jobs in 7 years locally, indicating that 1 Million USD invested in renewable energy technologies generates approximately 15 jobs over the same time frame. These estimates are mostly driven by the effects generated by the solar and wind installations on the construction sector. We find evidence of substantial heterogeneities across regional features, where rural and low-income areas are the ones experiencing the largest employment effect from renewable energy deployment. Overall, our findings suggest that green energy investments can constitute as a strategic asset to spur local jobs and encourage rural development.

Keywords: renewable energy, employment multiplier, green stimulus, shift-share

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

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1 Introduction

Addressing climate change requires a rapid shift of the energy system from fossil-intensive to renewable energy sources. According to the latest International Renewable Energy Agency (2023) report, annual investments must increase at least fourfold to align with the 1.5°C Scenario, as fossil fuels currently supply 80% of the world's total energy (International Energy Agency, 2023). The recent turmoil in European energy commodity markets, triggered by geopolitical tensions and disruptions in natural gas and coal supplies, has further highlighted the relevance of renewables as strategic assets to improve local energy security, by decreasing dependence on external sources, reducing energy prices and overall inflation volatility (Cevik, 2022; Garratt and Petrella, 2022; Caldara et al., 2022). Beyond climate mitigation and energy security concerns, switching from conventional to renewable energy sources entails a change in the spatial arrangement of the energy generation system, with significant economy-wide implications (Stern and Stiglitz, 2023). One of the most debated consequences concerns the effects of decarbonization on employment in energy and related sectors, as new industries emerge and old ones decline (Pai et al., 2021). Despite the relevance that the topic occupies in policy debate, the potential of renewable energy technologies in generating job opportunities and spurring growth is still largely unknown. Model-based projections estimate that the energy transition will generate 14 million new jobs in the RE sector by 2030, while employment in oil, gas and coal fuel supply and energy generation declines by around 5 million, leading to a net increase of nearly 9 million jobs (IEA, 2021). However, the effect is still largely unclear, polarizing the political debate and leading to exaggerated claims from across the political spectrum (Bowen, 2012; Deschenes, 2018; Böhringer et al., 2013). Thus, understanding how the decarbonization of the energy sector will affect jobs is crucial to reduce climate risk uncertainty, to align policy decisions for a just transition, and to improve the social acceptability of renewable energy deployment.

In this study, we contribute to these ongoing debates by presenting new empirical evidence on the effects of the deployment of renewable energy sources on regional employment dynamics. 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.

We focus on regions as unit of analysis since global and national estimates may conceal geographically dispersed socio-economic effects. 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). Regions with high levels of employment in fossil fuel industries, especially where renewable energy potential is low, may lose their substantial relevance in favor of renewable energy generation locations. In contrast, locations that are not traditionally integrated in the energy system might experience gains in employment and economic performance following renewable energy investments. This may be particularly relevant for economically less-favored regions (Creutzig et al., 2014; Clausen and Rudolph, 2020).

Due to the presence of strategic decisions and economic coordination, the identification of renewable energy deployment effects is a challenging exercise. The non-random allocation of these installations, 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 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 overall economic activity measured by GDP. Overall, evidence suggest that the investment multiplier, i.e., the dollar amount of GDP produced by a dollar of investments in energy plants development, exceeds 1 after 4 to 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). However, while these models provide valuable projections of the potential net employment implications of the energy transitions, they heavily rely on simplifying assumptions on the the economic and technological structure (Breitschopf et al., 2013; Jenniches, 2018). First, IO tables typically do not differentiate between renewable and conventional energy sectors, necessitating additional assumptions to retrieve technology-specific estimates. Secondly, IO tables are generally provided at the national level, hence analyses at a fine regional or sub-regional level are often not available or they are derived from the national ones with additional simplifications (Bowen, 2012; Xie et al., 2023). Indeed, the aggregate results obtained with the IO approach might hide disparities across regions and group of workers, thus overlooking distributional issues. 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. However, different studies suggest that this potential 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). 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). On the other hand, renewable energy plants, especially wind turbines and photovoltaics, can become an additional source of income for landowners, who can either sell or rent land to energy providers, or directly become energy producers themselves. In these cases, co-location of renewable energy sources can increase farmers' revenues and improve financial stability during volatile weather and market conditions (Cuppari et al., 2021; Mills, 2018). Additionally, recent experimental research shows that both windmills and agrivoltaics can provide favourable microclimatic conditions which increase crop yield and productivity (Kaffine, 2019; Al Mamun et al., 2022; Mills, 2018).

To date, there are few empirical studies estimating the local employment impacts of investing in renewable energy technologies. For the US, 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 are felt mainly for unskilled male workers, while the smaller, yet sustained effects during the maintenance and operations phase seem to affect mostly workers with college degrees. Using use monthly data for Spanish municipalities, Fabra et al. (2023) 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 local 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, 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 in the long run. Severnini (2022), for example, find that the construction of hydro dams in USA in 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. 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. 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 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 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 dataset with newly geolocalated information on energy installed capacity, encompassing 4 renewable and 4 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 four 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

[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)

[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`

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 and offshore), 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 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.

[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 decentralised manner throughout the territory (IRENA, 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.

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 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 aggregate each 1-km spatial potential development index along energy source within each NUTS3, to obtain the aggregate regional potential for solar, wind, bio-energy and hydro.

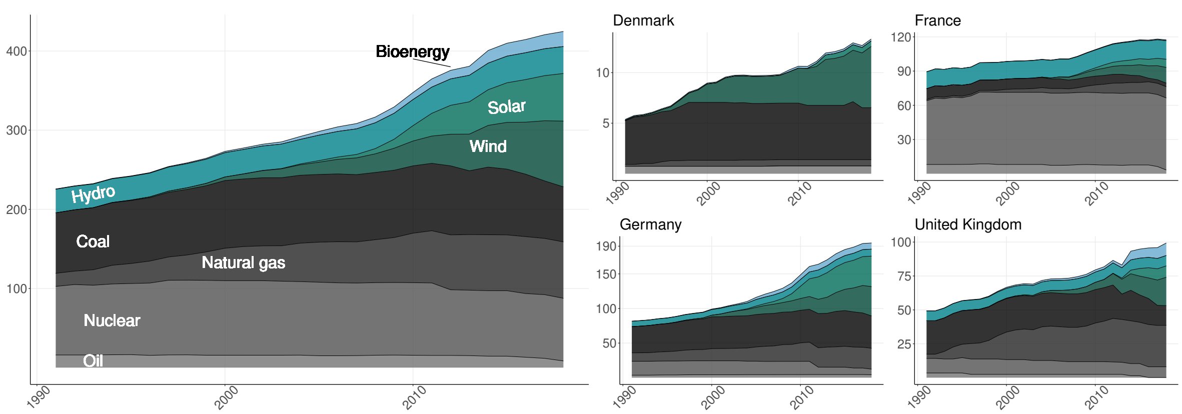
2.4 Descriptive Analysis

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 51% of the total, while constituting only 7.7% of the new plants created. This makes wind energy the source with highest power intensity among renewable alternatives, producing an average of 5.28 MW per plant. On the other hand, solar power plants are responsible for 83% of the new renewable power generating plants. They contribute 37.2% of the new installed capacity but they are the smallest in size, with an average of 0.36 MW per plant. Less common technologies in our dataset include bionenergy and hydro, which together make up 11.4% of the total new installed capacity.

Table 1: Investment Metrics by RE Technology

	New Plants		New Capacity		Plant Size	Capex per MW
	(Thousands)	%	(GW)	%	(MW)	(Mill. $)
Bioenergy	11.612	5.7	16.08	9.9	1.38	6.54
Hydro	5.908	2.8	3.17	1.9	0.54	6.61
Solar	169.173	83	60.25	37	0.36	2.49
Wind	15.791	7.7	83.33	51.2	5.28	2.23
Total Renewable	202484	100	162.82	100	0.8	2.79

Figure 1: Installed Capacity over Time (GW)



The evolution of the energy mix has been certainly determined by various aspects, including demand-side factors such as energy consumption, supply-side factors like technological change, and more recent energy and climate policy actions. Figure 1 illustrates these trends. During this period, 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. The growth in renewables exhibits large heterogeneity, both across technologies and between countries. Wind and solar are the green technologies which grew most overall, driving the energy transition so far, accounting for 86% of the total RE growth[5].

[5]See Table A.4 in Appendix A for more details

Figure 2: Installed Capacity per Capita

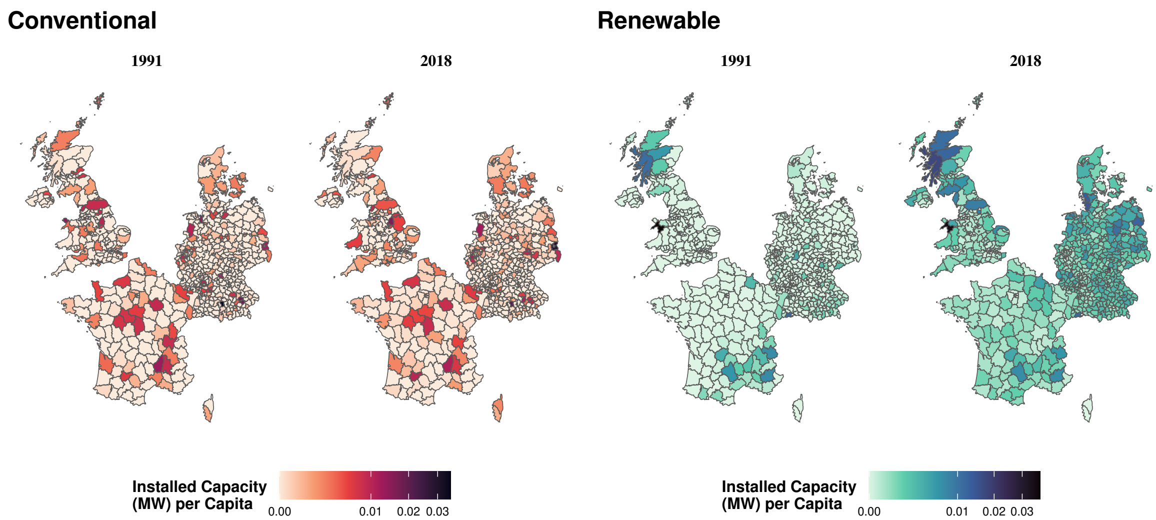


Figure 2 provides an overview of the geographical distribution of conventional and RE in the initial and final period of our sample. A clear distinction emerges between the distribution of conventional and RE unit locations: while green technologies are widely dispersed across all regions, fossil-fuel 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 normalised with lagged employment levels, so that the coefficient of interest β^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 α_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 and 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[6]. 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 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, $i = \{1, ..., 6\}$:

[6]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).

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

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 $EC = \{\text{Income}, \text{Rural}\}$, 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:

$$\frac{\tilde{Y}_{l,t+h} - \tilde{Y}_{l,t-1}}{\tilde{Y}_{l,t-1}} = \beta_{out}^h \frac{NewRE_{l,t}}{\tilde{Y}_{l,t-1}} + \sum_{r} \theta \tilde{X}_{l,t-r} + \alpha_l + \delta_t + \eta_c \delta_t + \epsilon_{l,t}, \tag{5}$$

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 β_{out}^h 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 β denotes the dynamic effect of investments in RE sources on employment growth. As specified in Section 3.1, the preferred specifications (1) - (4) include a rich lag structure that captures the evolution of demand- and supply-side factors (in line with the applied macro and regional economic literature since the seminal papers by Blanchard and Quah, 1989; Blanchard and Katz, 1992). 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, endogeneity concerns may still arise and undermine the validity of our estimates. Indeed, RE investments may respond to unobserved characteristics that also predict changes in the level of employment. For example, investments in region l could be triggered by changes in local demand factors, which are proxied by considering the evolution of wage and investment growth rates. Spikes in productivity may also spur local energy investments, and we try to accommodate for this by including lagged values of the growth rate of GDP[7,8]. Additionally, 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 lagged values of our explanatory variable, as well as data on commissioning and decommissioning capacity of conventional power plants in the region. Furthermore, 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 fact that regions on a "renewable investment" path, are consequently more likely to receive investments of this sort.

What is left is the amount of energy investments that region l receives at time t. For example, 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 "picking winners" or "awarding losers" problem would bias OLS results (Costa and Veiga, 2021).

[7] Although lagged variations in employment would better 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 β^h, even when dealing with a substantial number of cross-sectional units (Nickell, 1981).

[8] 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 one year. Among other, the assets include dwellings and non-residential 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 (results are available upon request).

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 that is orthogonal to 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 quantifies 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 aggregate RE investment shocks (instrument relevance). Secondly, differences in regional exposures do not depend on any unobserved regional factors affecting employment, such as the strategic choice to invest in RE technologies within a particular area (instrument validity). In our case, the relative exposure to aggregate changes in the RE mix is solely determined by the natural attributes of the location, specifically the presence and accessibility of the natural resources essential for the operation of the chosen energy technology. For instance, wind turbines are more likely to be installed in areas with high wind speeds, where each turbine generates more electricity compared to areas with lower wind speeds (Costa and Veiga, 2021).

Before building our instrumental variable, we aggregate the 1-km spatial development potential for each energy source within each NUTS-3 region to obtain the aggregate regional potential for solar, wind, bio and hydro energy sources. In the spirit of Bartik (1991), we then use these measures of regional potential to construct a weighted sum of new installations in energy capacity aggregated by country as follows:

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

where $s_{l,k} = Potential_{k,l}/Potential_k^{country}$ is the measure of region l potential as a share of the country's total potential for technology k, and $NewRE_{k,t}^{country}$ measures the aggregate new installed capacity of the region's country. 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 experience a sudden increase in the amount of RE deployment, our measure of relative exposure mitigates this effect, thus predicting an amount of RE investments that is conditioned by the potential of the region.

Our instrument reflects that the potential for RE investments drives investment decisions within country-specific strategies and not at a generalised EU level. For instance, although France has the highest potential for solar energy deployment, the regions receiving the largest investments in this technology are in Germany, which has relatively lower solar potential (see table A.5)[9]. To reflect this, our instrument combines country-level aggregate shifts in RE investments with each region's potential, measured as a share of its national potential.

Fortunately, our research design ensures that the method we use to calculate the shares of potential devel-

[9]In this regard we show, in Figure A.11, the correlation between the regional ranking of solar potential and solar installed capacity, calculated either over the entire sample (A.11a) or within countries (A.11b). 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 higher.

opment, which should motivate the exclusion restriction (Goldsmith-Pinkham et al., 2020), will not affect the validity of the instrument. For instrument relevance, we implement the heteroskedasticity-robust F-statistic, or Kleibergen-Paap Wald statistic, which tests for the joint significance of the first stage regressors in settings with one endogenous variable and non-homogeneous errors (Kleibergen and Paap, 2006). 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 F-statistic, either averaged over horizons or shown for each local projection.

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

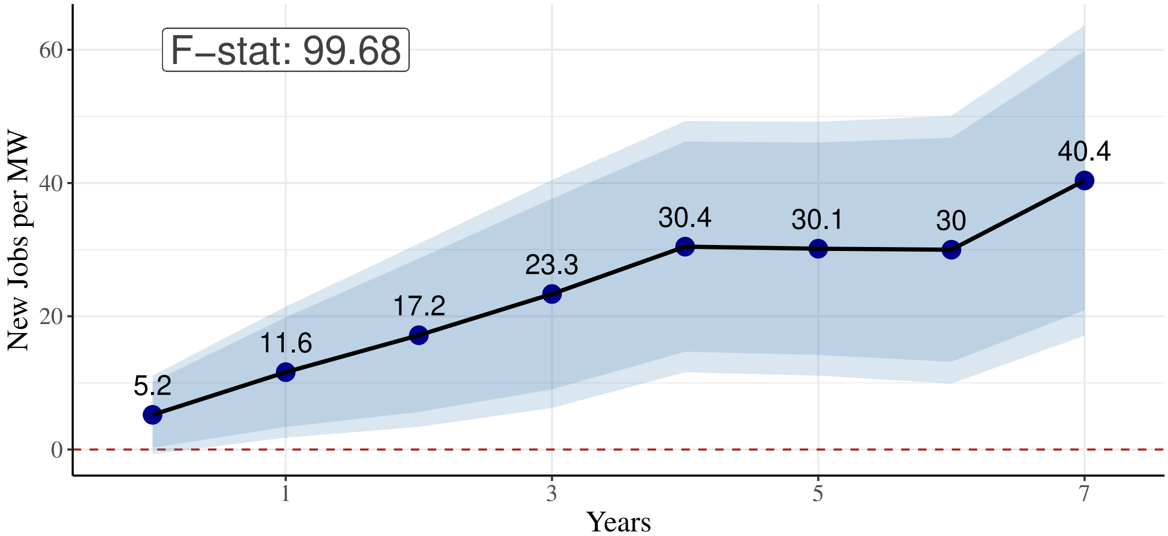
We estimate models in Equation (1) to (4) using instrumental variable local projections (LP-IV). The dynamic effects of aggregate renewable investment on total regional employment, estimated using our baseline specification in Equation (1) - with $NewRE^{IV}_{l,t}$ as instrumental variable (see Equation 6) - are displayed in Figure 3, 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 —5.2 jobs created in the first year —the effect grows significantly over a seven-year period, leading to the creation of approximately 40 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 4.2 jobs immediately and 32.4 jobs over a seven-year period. Additionally, with capital expenditures averaging \$2.79 million per MW, an investment of \$1 million in renewable energy plants results in roughly 1.9 jobs created immediately and 14.5 jobs over seven years. A tentative explanation for these results is that green investments stimulate regional demand, leading to increased employment to support the expanding economic activity. This increase is likely to 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 weak[10].

Our estimates align in magnitude with the figures presented by Popp et al. (2022), who found that 1 million

[10]Figure 3 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.

Figure 3: 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, 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.

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, β^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 β^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 3. Particularly, if the effects do not vanish or stabilize at 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.2a. As expected, confidence bands widen significantly, and the point estimate stabilizes after 10 years at around 90-100 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.3, in Appendix B. This seems to suggest that in our research design, policy-related decisions at a more localized level do not significantly alter the magnitude and the dynamical response of employment.

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 our data pertains to bio and hydro energy installations, which constitute a smaller portion, approximately 11.3%, 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 centralized and less dispersed compared to wind and solar energy units. In both scenarios, including them in the sample can potentially influence our aggregate results in Figure 3. To address this concern, we estimated our model excluding these energy sources, and observe that the magnitude and significance of the estimates remains substantially invariant to this data filter.

Finally, we also consider alternative specifications of the instrumental variable. As defined in Equation (6), our instrumental variable combines a measure of regional exposure (shares of national RE potential) with an aggregate shift in national new installed capacity. We first alter slightly our instrument specification by excluding the regional own investment observation in constructing the national shift. By removing the idiosyncratic technology-location component of the investment shift, this instrument specification, defined as leave-one-out (Goldsmith-Pinkham et al., 2020), addresses a possible finite sample bias. However, since our sample is made of 669 locations, using leave-one-out to estimate the national investment growth matters little in point estimates. Secondly, 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 with larger magnitudes and less 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 in all cases, our preferred instrument demonstrates 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. This is also suggested by the IV estimates approaching the value of OLS estimates (see Table C.1).

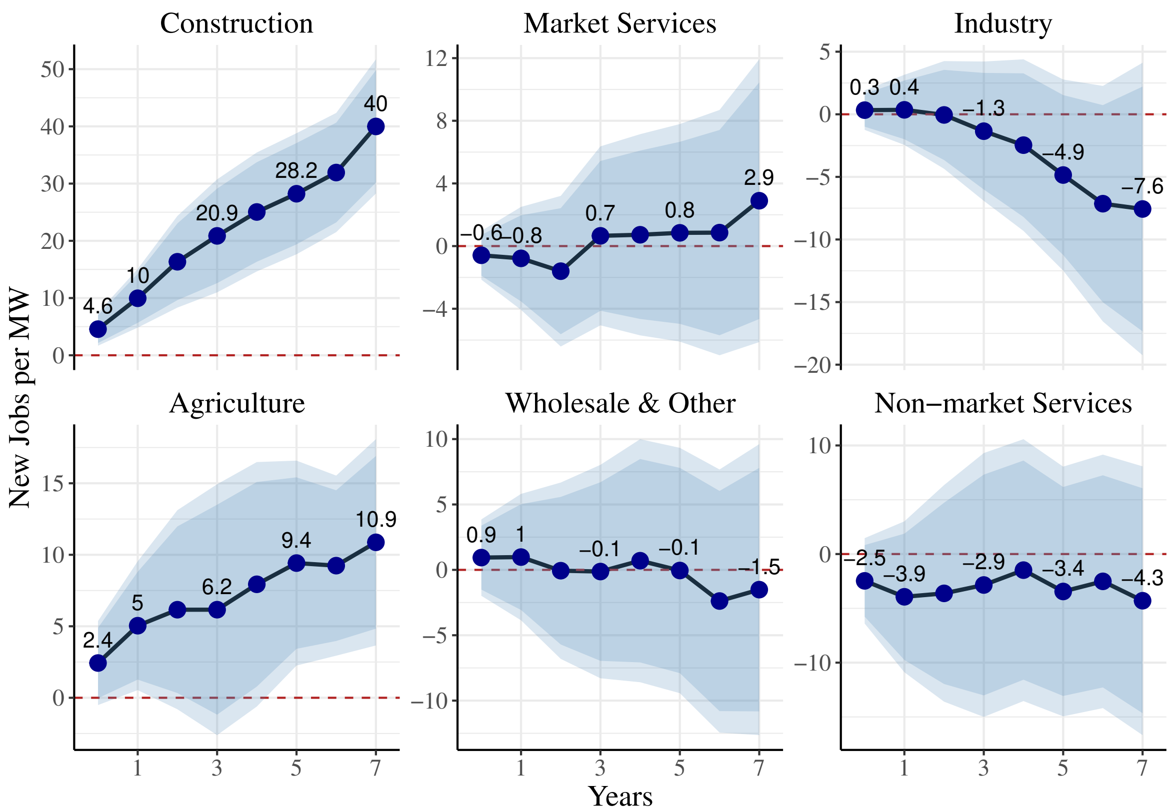
4.1 Inspecting the mechanisms

The IV estimates reveal that OLS is downward biased (Table C.1), suggesting that the effects of RE development are obfuscated by factors that explain both RE deployment and employment growth. This motivates the importance of examining the mechanisms behind our results, to better understand the implications of the energy transition. For this reason, we exploit the nature of our dataset to further inspect the effects shown in Figure 3, 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 4, reveal that the largest and most significant impacts are in the construction sector, followed by the agricultural one. In the construction sector, the installation of 1 additional MW of renewable capacity results in an immediate impact of 4.6 jobs and a cumulative increase of 40 jobs in 7 years. Back-of-the-envelope calculations suggest that, over the time horizon, RE projects generate approximately 32 jobs per plant and 14.4 jobs per $1 Million invested. It is important to note that this sector includes construction of buildings, civil engineering and utility projects, making it a significant contributor to the development of RE power plants. In the agriculture sector, the impacts are smaller but significant after 5 years, with nearly 11 jobs generated per MW installed. This translates to approximately 4 jobs for $1 Million invested and approximately 9 jobs per plant. Unfortunately, we are not able to go further in the disaggregation but if we assume that a significant portion of the workforce in the construction and agricultural sectors consists of unskilled laborers, our findings align with those of Popp et al. (2022), where green investments within the ARRA favoured unskilled workers in the construction sector.

Effects by Power Sources. As shown in Table 1, investments in RE vary across power technologies. We want to test whether this heterogeneity matters in explaining the employment impacts of their deployment (See Figures 3 and 4). It is not merely a matter of which power source generates more employment, but which one explains

Figure 4: Impact of Aggregate RE Investments on Sector-Specific Employment



Notes: The figure plots the dynamic effect, estimated via LP-IV, of aggregate renewable investment on sector-specific regional employment, measured by the number of jobs created in each sector, 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 clusterd 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 99.64.

more the aggregate effect that we are observing. Figure 5 presents the results for the specification in Equation (3), where we disentangle the effect on total employment by energy source. 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. Bionenergy is the power technology that is associated with the highest employment multiplier, reaching 407 jobs after 7 years. Wind and solar follows with an estimated employment multiplier over 7 years that equals 115 and 27, respectively. To assign a monetary value to these magnitudes, we calculate that, in 7 years, for an additional $1 million spent for the development of bioenergy, solar and wind energy sources, the number of jobs created in the regions increase by 62, 52 and 12, respectively.

The estimate for the aggregate effect of total renewables should be considered as a weighted average of estimated coefficients by energy sources. Notably, the estimates for solar and wind energy deployment closely align with the overall effect β^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 (51 and 37%, respectively), the aggregate results seems to be primarily driven by these power technologies. Additionally, the significantly larger average values of the first stage F-statistic indicate that wind and solar energy installations are more widely spread across geographies and over time (as shown in Figure 1), thus providing more variation for the identification of the local effects on employment. In constrast, the lower values of the average F-statistic for both Bionenergy and Hydro translate to very wide confidence bands, making estimates less precise compared to wind and solar[11].

For robustness checks, 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 contribute the most to the effects observed at both aggregate level and within the construction and agricultural sectors.

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. To further explore the role of regional economic structures in fueling the mechanism that brings RE deployment to spur local employment growth, we examine the non-linear dynamic effects of RE investments with respect to two economic indicators EC: regional specialization, which allows us to classify regions as rural versus non-rural, and a ranking of regions from 'poorer' to 'richer' based on quartiles of the real GDP per capita distribution.

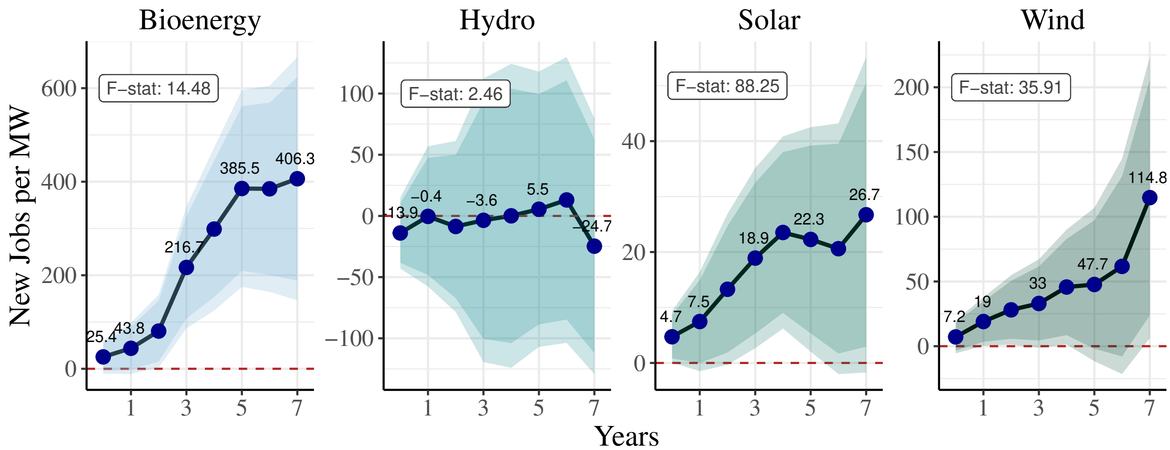
As for regional specialization, we build an index inspired by the Revealed Comparative Advantage (RCA) index in Balassa (1965). A region l is comparatively specialised in sector i when its ratio of employment in sector i to total employment in the same sector exceeds the analogous ratio calculated for 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

[11] In Table C.2 in Appendix we show the values of the first stage F-statistic for all horizons and for all the instruments implemented in our regressions.

Figure 5: Impact of Technology - Specific Investments on Employment



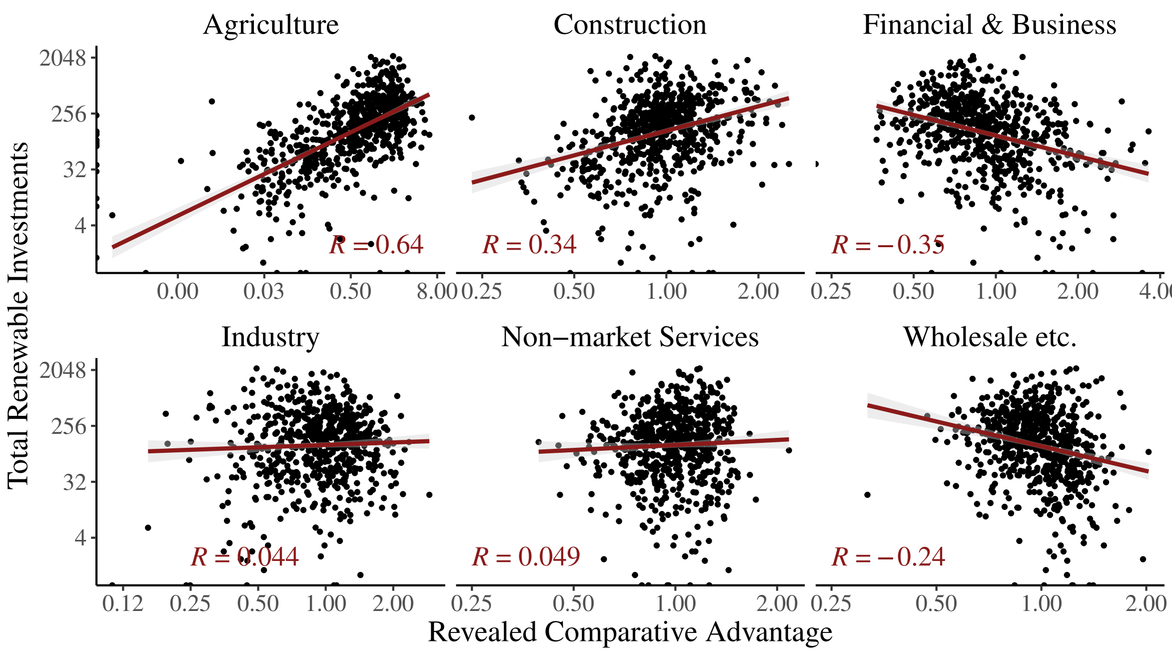
Notes: The figure plots the dynamic impact, estimated via LP-IV, of technology-specific investments on overall regional employment, measured by the number of jobs created, according to Equation (3). The control variables include current values of investments in the remaining non-instrumented energy technologies, 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.

whole sample. Figure 6 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 specialisation at the beginning of our sample in 1991. Both variables are log-transformed. We observe a strong correlation of 0.64 between RE plant development and initial employment shares in agriculture. This result aligns with expectations, as rural areas, comparatively more specialized in agriculture and forestry activities, tend to offer more space and synergies for clean energy technologies (Clausen and Rudolph, 2020). RE investments also exhibit positive correlations with initial shares in the construction sector (0.3) and negative correlations with shares in the financial and business sectors (-0.34).

Given this evidence, we want to investigate whether the rural areas are able to absorb the employment effects generated by the commissioning of green power plants. We categorize regions as "rural" if they reveal a comparative advantage in the agricultural sector, denoted by 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 (103 GW).

Using non-linear LP-IV estimation, as detailed in Equation (4), we assess the employment effects of RE deployment in rural and non-rural regions (EC = {Rural, Non-rural}). Figure 7 displays the results, revealing larger but less precise impacts in non-rural regions, possibly due to lower investment flows in these areas. Nevertheless, positive and persistent long-term employment impacts are observed in rural areas. When we analyze the sector-specific impacts (as presented in Figure C.2 in Appendix), 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, the effects on agriculture are found only in rural areas, reflecting the specialization of these regions in this particular sector. This observation leads to two key interpretations. Firstly, the positive influence on agricultural employment can be attributed to the presence of strong input complementarities - agrivoltaic

Figure 6: Correlation between aggregate regional RE investments over the period (1991-2018) and initial (1991) RCA (as defined in equation (7). Both variables taken in log

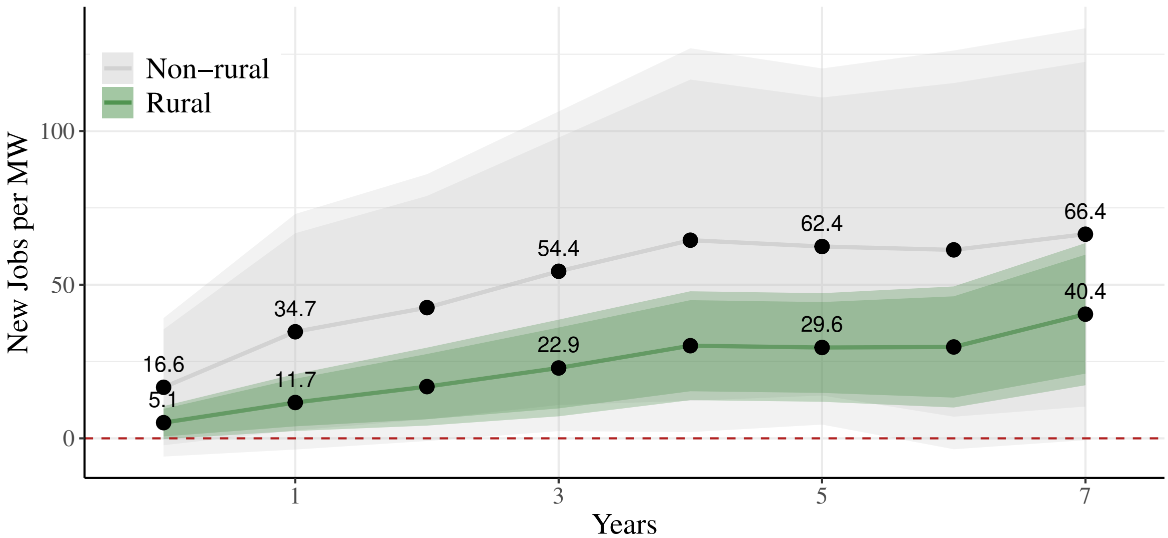


farms, for instance - which in turn increases local demand and boost overall economic activity, extending the renewable investments effects beyond the energy sector (for instance, by fostering activities to connect the utility projects to high-voltage transmission lines). Secondly, the availability of 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.

As for the second economic indicator, 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 8. 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 the median of the distribution (1^{st} and 2^{nd} quartiles) experience sizeable stimulus effects, with employment multipliers reaching 39 and 60, respectively, over a 7-year period.

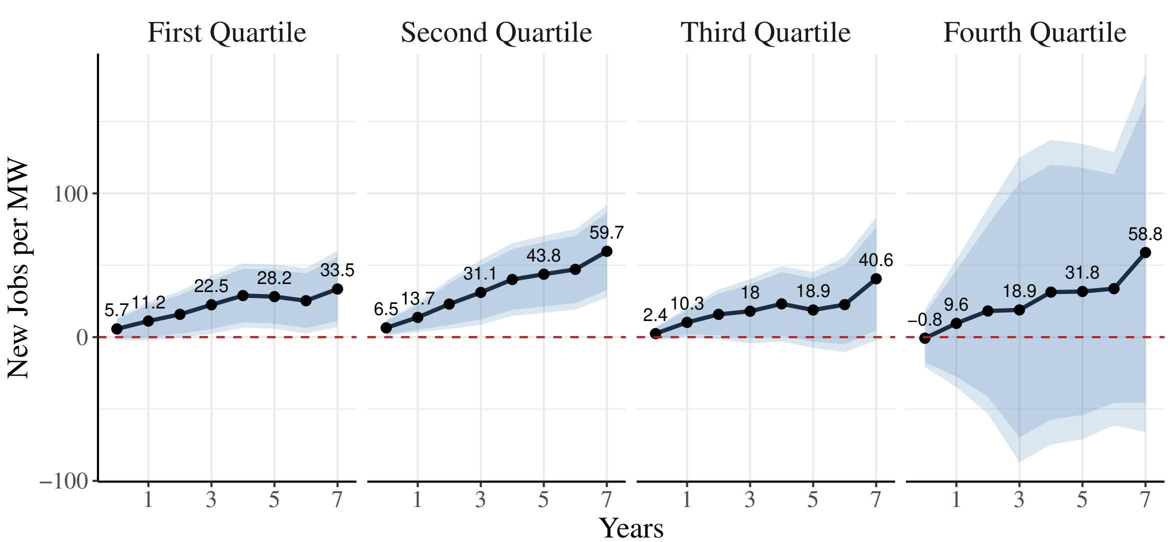
In summary, these findings suggest that RE technologies have the potential to stimulate employment and enhance economic growth, particularly in regions with lower income levels. This result is also in line with the macroeconomic literature on infrastructure investments, as the deployment of RE can act as a catalyst for economic expansion in areas that may lack sufficient infrastructure, either due to higher uncertainty in returns

Figure 7: 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. 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 clusterd 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 99.64.

Figure 8: 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 clusterd 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 99.64.

on investments (see Gbohoui, 2021) or because they possess significant potential for productivity gains following increased overall investment levels (Ramey, 2021).

4.2 Geographic Spillovers

Thus far, we documented sizeable average effects of regional investments in the deployment of renewable power sources on employment growth. However, it is important to note that 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 geographical spillovers by estimating Equation (5), focusing on the coefficient β^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 25 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 3 might represent a lower bound for their national counterpart. 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

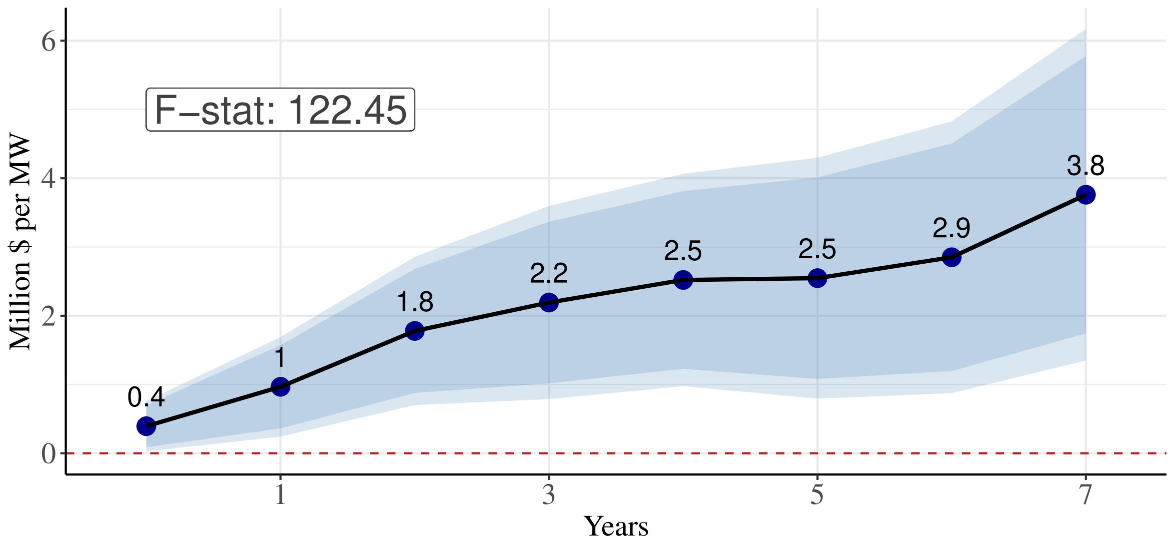
Horizon	($h = 0$)	($h = 1$)	($h = 2$)	($h = 3$)	($h = 4$)	($h = 5$)	($h = 6$)	($h = 7$)
Employment	2.073***	3.898**	6.769***	9.621***	13.394***	19.466***	19.050***	24.629***
	(0.772)	(1.564)	(2.422)	(3.129)	(3.571)	(4.707)	(5.387)	(6.536)
F-stat	132.82	171.16	259.23	229.44	187.42	204.83	176.07	145.07

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 as number of jobs created, and output is measured as $1 Million real GDP generated. 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 labour intensity, with agriculture being is less labor-intensive, especially in advanced economies like those in our sample, and construction being instead more reliant on labor. Given these insights, it is worth investigating whether the development of 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) . We apply the same research design outlined in Section 3.2, arguing that its validity and relevance still hold[12].

Figure 9: 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, measured as $1 Million real GDP generated, 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.

[12]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 (β^h_{out})	0.141*	0.476***	0.976***	1.381***	1.611***	1.890***	1.969***	2.375***	140.27
	(0.079)	(0.160)	(0.248)	(0.333)	(0.419)	(0.567)	(0.672)	(0.828)	
By Technology k - Regional (β^h_k)									
Bioenergy	-0.648	1.076	5.833	10.024*	12.143*	14.484*	17.405**	20.927**	11.85
	(1.536)	(3.083)	(4.556)	(5.858)	(7.054)	(7.856)	(8.701)	(10.281)	
Hydro	4.483	7.166	6.394*	3.975	5.414	6.889	9.155*	7.523*	4.03
	(3.071)	(4.861)	(3.588)	(4.030)	(4.555)	(4.772)	(5.451)	(4.402)	
Solar	0.722***	1.800***	3.063***	3.788***	3.860***	3.405**	2.905*	3.479*	95.05
	(0.272)	(0.529)	(0.784)	(0.979)	(1.141)	(1.350)	(1.561)	(2.033)	
Wind	0.115	0.122	0.194	0.139	0.870	1.600	3.979	8.274**	38.24
	(0.370)	(0.690)	(0.989)	(1.263)	(1.659)	(2.420)	(3.562)	(4.148)	

The table outlines the effects of RE investments on output, measured as \$1 Million real GDP generated. 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 clusterd 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 9 and Table 3 report the effects of installing 1 MW of RE capacity on GDP, measured in millions of dollars. As evident from Figure 9, the dynamic response of GDP growth to RE investments mimics the results for employment analyzed in previous sections. On impact, GDP increases by nearly \$0.4 million and continues to rise steadily in the long run, reaching approximately \$3.8 million after 7 years.

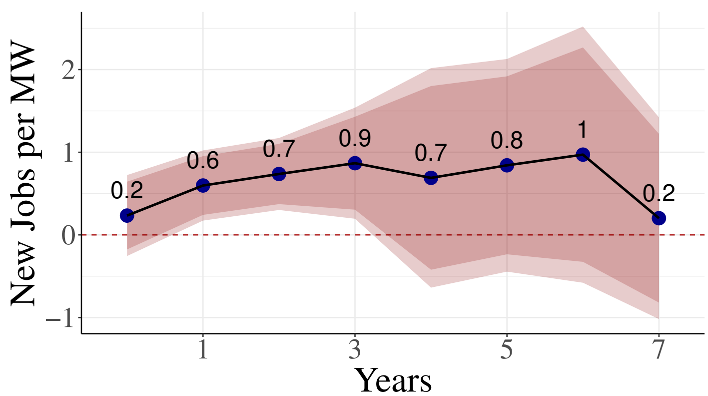
As shown in the first line of Table 3, neighboring regions also benefit from these investments, as spillover effects increase significantly to around \$2.3 million after 7 years. Recalling that, on average, the cost of investing in 1 MW of renewable power plants amounts approximately to \$2.79M/MW (cfr., 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 development - exceeds 1 after only 5 years (or 4 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. As previously argued, our analysis focuses exclusively on local green investments involving the development of renewable power facilities, suggesting that our estimates may represent a lower-bound measure of national renewable investment multipliers (Chodorow-Reich, 2019a)[13]. 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 and wind power sources make the most substantial contributions.

[13] 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.

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 Table A.4 in Appendix A. 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 10 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, this exploratory evidence seems to discard significant negative employment impacts of decommissioning, suggesting instead non-negligible positive effects on local economic activity along the energy transition that European regions are experiencing.

Figure 10: Impacts of Decommissioning Conventional Power Plants on 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 clusterd 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 spatial 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 RE 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 regional level, we employ a shift-share identification strategy. This approach relies on the differential regional exposure, measured as the regional shares of land development potential for selected technologies, to global shocks in the 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 40 in about seven years. This figure also corresponds to approximately 14 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 - 40 and 11 jobs generated in seven years, respectively. These sectors are typically more labour-intensive and characterized by stronger complementarities and synergies with RE technologies. Furthermore, these effects spillover to neighbouring 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 green investments, regional output mirrors the dynamic response of employment, with significant direct and spillover effects, primarily driven by solar and wind technologies. Specifically, 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 (4 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 dwelved 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	4.61	21.36	0.00	0.00	688.50
Renewable	8.98	26.62	0.00	0.87	691.20
Oil	0.14	4.73	0.00	0.00	400.00
Coal	1.22	33.30	0.00	0.00	2120.00
Natural Gas	3.42	52.10	0.00	0.00	2305.00
Nuclear	0.62	29.37	0.00	0.00	1500.00
Conventional	5.40	68.54	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

Table A.4: New and Decommissioned Capacity by Technology.
Values expressed in GW.

	New Capacity 1991-2018		Decommissioned 1991 -2018		Net variation
	Total	%	Total	%	
Total	260.7	100	69.4	100	191.3 ⇑
Renewable	166.5	63.9	/	/	166.5 ⇑
Bioenergy	18.7	7.2	/	/	18.7 ⇑
Hydro	4.2	1.6	/	/	4.2 ⇑
Solar	60.3	23.1	/	/	60.3 ⇑
Wind	83.3	32.0	/	/	83.3 ⇑
Conventional	94.2	36.1	69.4	100	24.8 ⇑
Coal	23.1	8.8	32.6	47	- 9.5 ⇓
Oil	2.6	1	10.2	14.7	- 7.6 ⇓
Natural gas	60.8	23.3	7.9	11.4	52.9 ⇑
Nuclear	7.7	3.0	18.6	26.8	- 10.9 ⇓

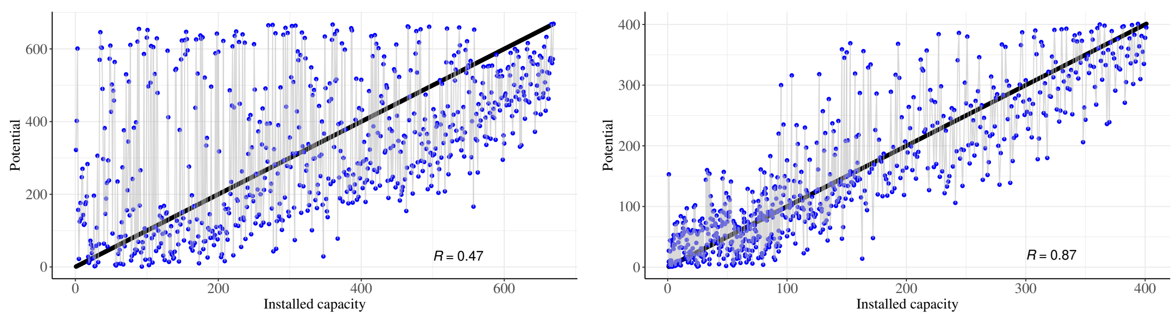
Table A.5: Top 20 Regions according to solar energy potential and installed capacity

Rank	Solar Energy Potential	Solar Energy Installed Capacity (2018)
1	FRI12 - France	FRI12 - France
2	FRI13 - France	UKK30 - UK
3	FRI11 - France	DE949 - France
4	FRC13 - France	FRI13 - France
5	FRF23 - France	UKK15 - UK
6	FRC11 - France	UKH12- UK
7	FRB01 - France	DE256 - Germany
8	DK032 - Denmark	DEA34 - Germany
9	FRK11 - France	DE228 - Germany
10	FRG02 - France	DE409 - Germany
11	FRI34 - France	DE40B - Germany
12	FRB03 - France	DE40G - Germany
13	DK050 - Denmark	DEE05 - Germany
14	FRI32 - France	DE80J - Germany
15	FRC14 - France	UKK43 - UK
16	FRG01 - France	DE227 - Germany
17	FRG05 - France	DEF0C - Germany
18	FRE21 - France	UKK23 -United Kingdom
19	FRH03 - France	DE22B - Germany
20	UKE22 - United Kingdom	DE80N - Germany

Figure A.11: Regional ranking according to solar energy potential and installed capacity

(a) Full-Sample Ranking

(b) National Ranking

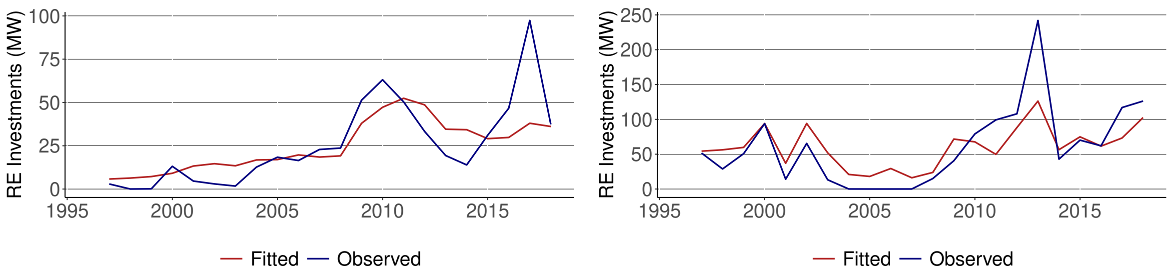


Notes: The figures plot the relation between the ranking of the sample regions in terms of their solar potential and in terms of their aggregate solar installed capacity at the end of the sample period. In figure A.11a the positioning of each region, for both potential and capacity, is computed over 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.11b 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 Predictions

(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.

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)	2.192	3.994*	4.175	4.070	5.125*	5.204*	4.980
	(2.332)	(2.381)	(2.907)	(2.912)	(2.996)	(3.010)	(3.765)
(h = 1)	0.148	9.119**	10.192**	9.973**	11.529**	11.608**	11.142*
	(4.599)	(4.192)	(5.014)	(5.034)	(4.998)	(5.015)	(6.321)
(h = 2)	-3.555	13.627**	14.800**	14.391**	17.082**	17.149**	16.916*
	(6.845)	(6.048)	(7.092)	(7.116)	(6.987)	(7.015)	(8.691)
(h = 3)	-3.345	18.497**	19.620**	19.142**	23.207***	23.343***	23.512**
	(8.536)	(7.506)	(8.726)	(8.745)	(8.685)	(8.722)	(10.652)
(h = 4)	0.693	25.229***	26.132***	25.445***	30.294***	30.447***	31.265***
	(9.355)	(8.489)	(9.524)	(9.531)	(9.575)	(9.610)	(11.952)
(h = 5)	5.975	26.309***	25.535***	24.520**	29.970***	30.141***	32.807***
	(10.672)	(9.052)	(9.671)	(9.726)	(9.705)	(9.721)	(12.421)
(h = 6)	9.579	25.681***	24.210**	22.970**	29.918***	29.988***	33.088***
	(11.799)	(9.807)	(10.278)	(10.275)	(10.262)	(10.250)	(12.621)
(h = 7)	22.232	34.955***	34.452***	32.996***	40.357***	40.369***	42.975***
	(14.359)	(11.745)	(12.010)	(11.972)	(11.907)	(11.871)	(14.340)
Average First-stage	*172.71*	*146.98*	*97.64*	*97.75*	*99.58*	*99.73*	*100.41*
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. 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)
($h = 0$)	0.851***	0.344*	0.384*	0.375*	0.396*	0.394*	0.184
	(0.231)	(0.188)	(0.203)	(0.206)	(0.213)	(0.212)	(0.276)
($h = 1$)	1.197***	0.803**	0.956**	0.935**	0.965**	0.967**	0.651
	(0.392)	(0.378)	(0.410)	(0.414)	(0.421)	(0.421)	(0.516)
($h = 2$)	1.577***	1.585***	1.810***	1.772***	1.786***	1.779***	1.353*
	(0.569)	(0.574)	(0.632)	(0.636)	(0.627)	(0.627)	(0.734)
($h = 3$)	1.789**	1.990***	2.212***	2.176***	2.189***	2.193***	1.725*
	(0.714)	(0.759)	(0.831)	(0.834)	(0.820)	(0.817)	(0.915)
($h = 4$)	1.841**	2.286***	2.484***	2.409***	2.495***	2.520***	1.942*
	(0.814)	(0.848)	(0.892)	(0.900)	(0.903)	(0.898)	(1.009)
($h = 5$)	1.938**	2.375**	2.460**	2.394**	2.522**	2.547**	1.784
	(0.957)	(0.982)	(1.013)	(1.023)	(1.023)	(1.019)	(1.119)
($h = 6$)	2.092*	2.493**	2.572**	2.537**	2.830**	2.850**	1.893
	(1.097)	(1.120)	(1.147)	(1.155)	(1.151)	(1.150)	(1.268)
($h = 7$)	2.533*	3.114**	3.307**	3.312**	3.749***	3.760***	2.529*
	(1.385)	(1.365)	(1.389)	(1.395)	(1.402)	(1.402)	(1.527)
Average First-stage	*182.71*	*152.21*	*118.93*	*118.83*	*122.16*	*122.45*	*122.76*
Controls							
Employment growth		✓	✓	✓	✓	✓	✓
Renewable investments			✓	✓	✓	✓	✓
Conventional investments and dis-investments				✓	✓	✓	✓
Wages growth					✓	✓	✓
Capital Formation growth						✓	✓
Output growth							✓

The table outlines the effects of predicted RE investments on regional output, measured as 1 Million $ real GDP generated. 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.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	4.338**	8.117**	12.806***	19.712***	26.281***	28.558***	27.669***	34.823***	123.98
	(1.722)	(3.319)	(4.684)	(5.980)	(6.930)	(7.882)	(8.679)	(10.279)	
Wind and Solar	5.169*	11.785**	17.030**	21.356**	27.866***	26.310***	25.751**	37.354***	120.29
	(3.059)	(5.149)	(7.240)	(8.754)	(9.648)	(9.974)	(10.492)	(12.280)	
Alternative Instruments									
Leave-one-out	5.735*	12.444**	18.341**	25.010***	32.419***	32.050***	31.807***	43.027***	89.950
	(3.309)	(5.428)	(7.500)	(9.305)	(10.172)	(10.195)	(10.732)	(12.395)	
Full-Sample Potential	18.413*	30.178**	40.459**	49.706**	61.061**	52.089**	51.363*	71.605*	40.46
	(10.307)	(14.325)	(17.935)	(22.846)	(27.692)	(26.283)	(29.604)	(38.863)	
Fixed Shares	5.935*	12.064**	24.946**	28.712**	32.107**	31.681*	29.966	36.230	33.46
	(3.292)	(5.650)	(10.204)	(12.625)	(14.655)	(17.566)	(19.586)	(23.684)	
Lagged Shares	3.407**	6.112*	9.943**	14.830**	17.879**	19.111**	21.983**	28.955***	101.33
	(1.734)	(3.199)	(4.952)	(6.477)	(7.429)	(7.950)	(9.042)	(10.780)	

The table outlines the effects of predicted RE investments on total regional employment, measured as number of jobs created. 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 in the first row, and keeping only the aggregate investments for wind and solar as explanatory variable in the second one. We adopt four different alternative instrument strategies. *Leave-one-out* consists in out in our baseline shift-share instrument calculated excluding the shift for the region in analysis. In the last three alternative instruments, the regional shares are calculated out of the total sample and interacted with full-sample shifts in renewable energy capacity. *Full-Sample Potential* interacts region potential as a share of the total sample potential for technology k with full-sample new capacity for technology k. For the last 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 shares of technology-specific regional investments out of the total sample, lagged one year. For all equations, 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 for each specification.

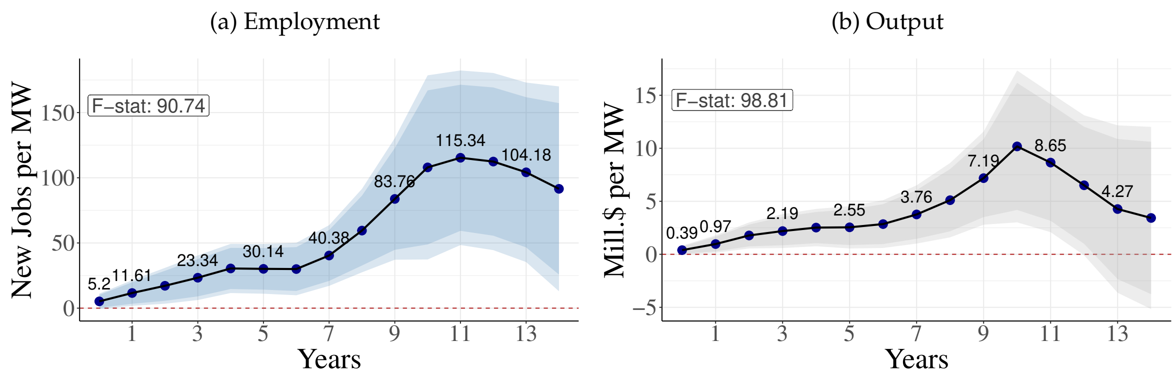
p < 0.1, ** p < 0.05, *** p < 0.01

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	0.478**	1.141***	2.077***	2.686***	2.822***	2.756***	2.729**	3.464**	120.57
	(0.197)	(0.373)	(0.543)	(0.719)	(0.870)	(1.025)	(1.185)	(1.449)	
Excluding Bio and Hydro	0.395*	0.936**	1.694***	2.088**	2.408***	2.391**	2.634**	3.557**	117.77
	(0.208)	(0.426)	(0.641)	(0.831)	(0.908)	(1.038)	(1.166)	(1.427)	
Alternative Instruments									
Leave-one-out	0.409*	0.998**	1.855***	2.277***	2.606***	2.614**	2.925**	3.857***	112.36
	(0.228)	(0.447)	(0.664)	(0.860)	(0.938)	(1.056)	(1.194)	(1.461)	
Full-sample Potential Shares	0.838***	1.638***	2.950***	3.297***	3.850***	3.750***	3.786**	4.930**	46.55
	(0.308)	(0.596)	(0.881)	(1.115)	(1.273)	(1.446)	(1.574)	(1.919)	
Fixed Shares	1.814***	2.721***	4.321***	4.868**	5.169**	5.231*	5.347*	6.460*	30.98
	(0.458)	(0.863)	(1.554)	(2.050)	(2.416)	(2.778)	(2.932)	(3.453)	
Lagged Shares	0.610***	1.105***	1.468***	1.671***	2.103***	2.502***	2.988***	3.752***	119.71
	(0.192)	(0.340)	(0.508)	(0.637)	(0.767)	(0.875)	(0.987)	(1.205)	

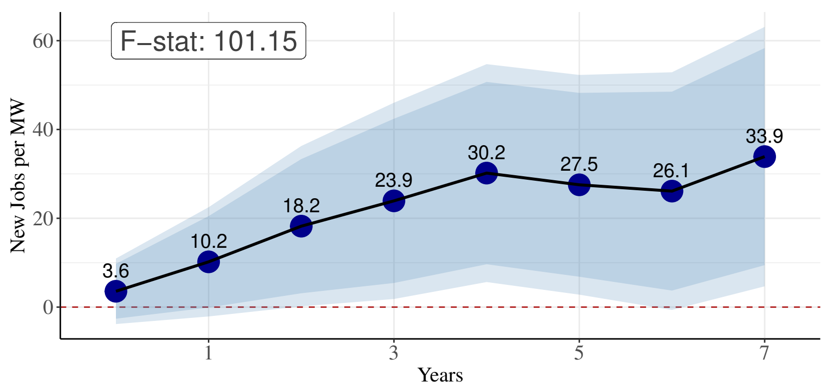
The table outlines the effects of predicted RE investments on regional output, measured as 1 Million $ real GDP generated. Each row reports the estimates obtained using a different specification. Each row reports the estimates obtained using a different specification. In the first two rows, our baseline specification is regressed over a restricted sample, respectively excluding observations for the UK in the first row, and keeping only the aggregate investments for wind and solar as explanatory variable in the second one. We adopt four different alternative instrument strategies. *Leave-one-out* consists in out in our baseline shift-share instrument calculated excluding the shift for the region in analysis. In the last three alternative instruments, the regional shares are calculated out of the total sample and interacted with full-sample shifts in renewable energy capacity. *Full-Sample Potential* interacts region potential as a share of the total sample potential for technology k with full-sample new capacity for technology k. For the last 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 shares of technology-specific regional investments out of the total sample, lagged one year. 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. The regression includes NUTS-3 region and country-by-year fixed effects. Standard errors are clusterd 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

Figure B.2: Long-run Impact of Aggregate RE Investments on Employment



Notes: The figure plots the long-run dynamic effect, estimated via LP-IV, of aggregate renewable investment on: B.2a regional employment ; B.2b regional output. Employment is measured as the number of jobs created, while output is measured as as 1 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.3: Impact of Aggregate RE Investments on Employment with Alternative Fixed Effects Structure



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. 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 in 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 GDP growth, 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.

Appendix C Other estimates

Table C.1 displays the OLS regression results using 3.1. Overall, the OLS estimations report a positive correlation between RE investments and local employment, with growing coefficients over tthe time horizon.

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	0.272	1.742**	2.705**	3.380**	4.744**	4.427*	4.024	9.517***
	(0.557)	(0.883)	(1.215)	(1.485)	(2.015)	(2.519)	(2.886)	(3.101)
Output	0.093	0.284***	0.372***	0.431***	0.401*	0.482*	0.620**	0.959***
	(0.058)	(0.100)	(0.127)	(0.164)	(0.220)	(0.281)	(0.309)	(0.370)

The table reports the effects of aggregate renewable investments on regional employment and output, estimated according to Equation 1. Employment is measured as number of jobs created while output is measured as real *Million* \$ generated. Both regressions include as controls variables four lagged terms of wages growth, capital formation growth and conventional energy commissioning and decommissioning. 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 clusterd at NUTS-3 region level.
p < 0.1, ** p < 0.05, *** p < 0.01

The table reports the effects of aggregate renewable investments on regional output, estimated according to Equation 1. Output is measured as 1 Million $ real GDP generated. 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 clusterd at NUTS-3 region level. The first stage F-statistic for each horizon is reported below the coefficients and standard errors for both outcome variables.

Table C.2: First Stage Estimates

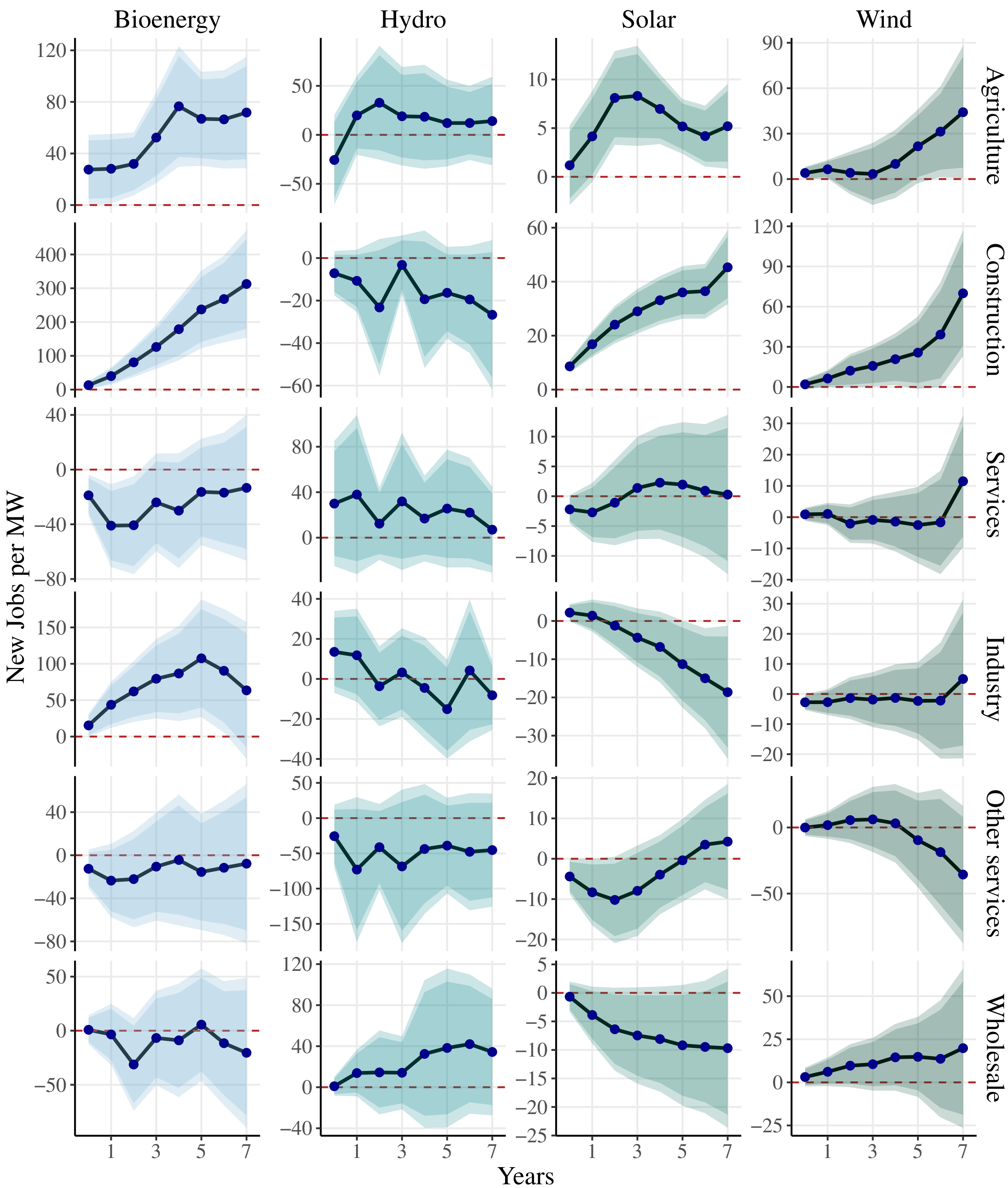
		Dependent Variable: New RE Capacity				
		Explanatory Variable: IV				
		(1) Renewable	(2) Bioenergy	(3) Hydro	(4) Solar	(5) Wind
$h = 0$	Coef	0.542***	0.623***	0.609	0.517***	0.655***
		(0.071)	(0.238)	(0.381)	(0.063)	(0.106)
	F-stat	57.54	6.82	2.55	66.47	37.96
$h = 1$	Coef	0.552***	0.514***	0.609	0.516***	0.702***
		(0.069)	(0.149)	(0.384)	(0.063)	(0.109)
	F-stat	63.37	11.84	2.52	66.36	41.38
$h = 2$	Coef	0.565***	0.597***	0.608	0.517***	0.756***
		(0.064)	(0.152)	(0.385)	(0.063)	(0.118)
	F-stat	76.96	15.43	2.50	66.82	40.98
$h = 3$	Coef	0.587***	0.595***	0.612	0.541***	0.777***
		(0.068)	(0.154)	(0.395)	(0.061)	(0.132)
	F-stat	75.08	14.93	2.39	79.52	34.77
$h = 4$	Coef	0.655***	0.586***	0.613	0.620***	0.790***
		(0.063)	(0.156)	(0.396)	(0.056)	(0.127)
	F-stat	107.24	14.00	2.41	120.36	38.89
$h = 5$	Coef	0.706***	0.812***	0.616	0.647***	0.774***
		(0.061)	(0.188)	(0.396)	(0.059)	(0.141)
	F-stat	132.92	18.55	2.42	119.63	30.25
$h = 6$	Coef	0.709***	0.816***	0.618	0.647***	0.711***
		(0.058)	(0.191)	(0.396)	(0.061)	(0.137)
	F-stat	149.16	18.30	2.43	114.18	26.75
$h = 7$	Coef	0.685***	0.787***	0.626	0.564***	0.835***
		(0.059)	(0.197)	(0.399)	(0.066)	(0.139)
	F-stat	135.17	15.93	2.46	72.63	36.26

The table reports the first stage coefficients and F-statistic for aggregate renewable investments (equation1) and technology-specific investments equations (equation 3). The control variables include four lagged terms of gdp growth, renewable investments, wages growth, capital formation growth and conventional commissioning and decommissioning. 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.
$p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table C.2, reports the predictive strength of the instrument according to the endogenous variable.

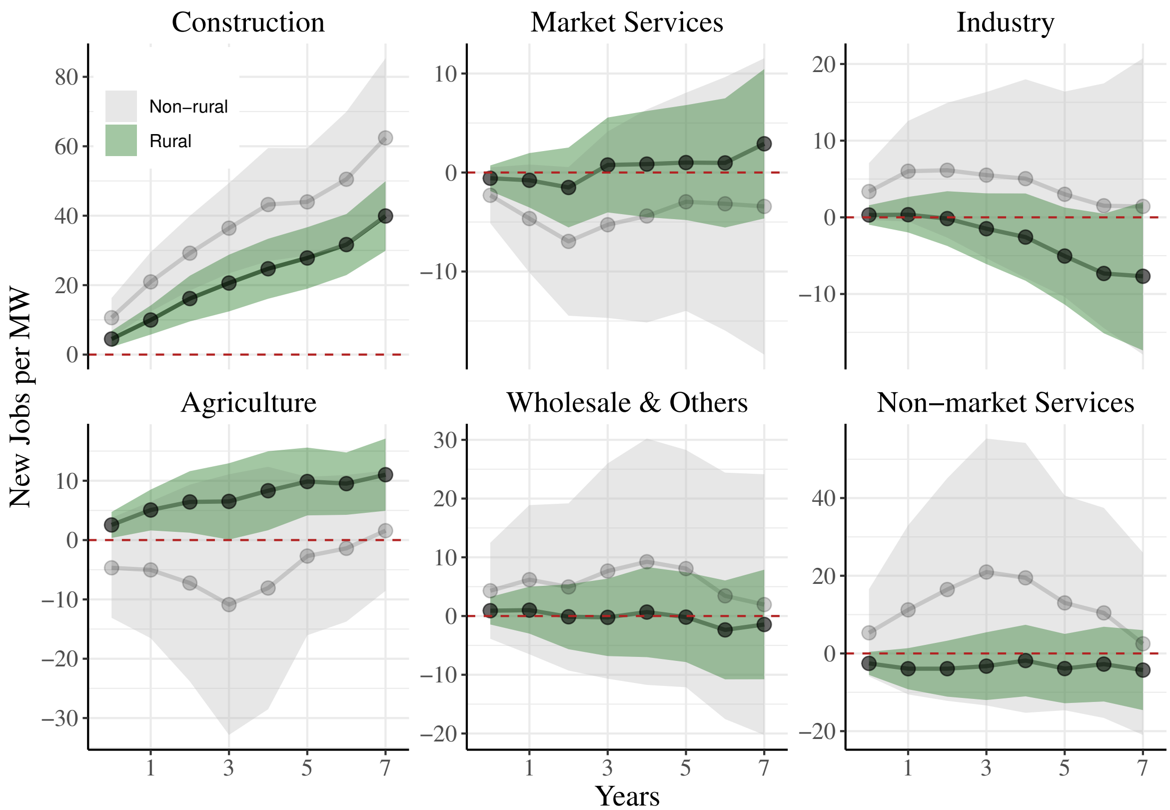
While value of the first-stage F-statistic for bioenergy averaged across time horizons is only slightly smaller compared to that computed for wind, the f-statistic for wind is always around 20 our higher, while that for bioenergy is very small (7 and 11) for the first two time horizons. The correlation between predicted and observed values is low for bioenergy and hydro and higher for solar and wind.

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 sector-specific 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 clusterd 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 sector-specific regional employment in rural and non-rural areas. Employment is measured as the number of jobs created in each sector. 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 clusterd 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 99.64.