Sun, Wind, and Sweat: Local Labor Impacts of Renewable Energy Investments

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Preliminary Version

Abstract

This paper investigates the causal effects of renewable energy investments on local jobs. We combine administrative data on renewable investments and employment in Brazil to build a municipal-level panel dataset from 2000 to 2021. Using recent advances of staggered difference-in-differences, we found that solar and wind energy investments have a positive effect on the local labor market even three years before the plants start operating. Specifically, wind energy investments increase jobs in the construction sector, while solar energy investments primarily drive employment in the services sector. Furthermore, our results show that wind energy investments lead to more low-skilled jobs, particularly among men with elementary education, whereas solar energy employs more workers with high school degrees.

Keywords: Renewable energy, employment, staggered difference-in-differences

JEL Codes: Q42, J23, C23

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1 Introduction

Debates surrounding the importance of renewable energy sources in the context of addressing climate change have become increasingly prominent. The 21st United Nations Climate Change Conference (COP21) held in December 2015 witnessed the participation of governments from around 190 countries, each presenting their respective strategies aimed at mitigating greenhouse gas emissions. These strategies placed considerable emphasis on the importance of investing in renewable energy, particularly solar and wind power. Moreover, in response to the COVID-19 pandemic, numerous countries have advocated for post-pandemic recovery plans centered around renewable energy investments, driven by the expectation that such initiatives would stimulate job creation and foster economic growth.

This study aims to assess the causal impacts of renewable energy investments, specifically in solar and wind energy, on local labor markets. Understanding the non-energy attributes associated with these energy sources can be relevant to shape public policy formulation. Factors such as the generation of local employment opportunities, community benefits, energy justice considerations, effects on human health, and economic costs associated with the implementation and operation of these technologies need to be carefully considered. By comprehending these attributes, policymakers can make well-informed decisions that maximize social and economic benefits while minimizing any adverse impacts.

Brazil provides an excellent setting for this analysis, given its vast geographical dimensions and abundant potential for harnessing wind and solar energy. The country benefits from favorable wind conditions characterized by high speed and consistency, which have been instrumental in driving the growth of wind energy projects in recent years. Additionally, Brazil possesses significant potential for solar energy exploitation. Even in regions with lower solar irradiation, it is possible to generate more electricity from solar sources than in Germany's most irradiated areas (Martins et al., 2017). According to the Brazilian Electricity Regulatory Agency (ANEEL), the country has achieved an installed capacity of 22 GW for wind energy and 21 GW for solar energy, solidifying its position as one of the world's leading producers of these source of energy.

To investigate the effects of wind and solar investments on local labor markets, we constructed a unique municipal-level panel dataset spanning from 2000 to 2021. This dataset combines information on energy investments and local labor supply. Specifically, we aggregated data from the formal sector of the labor market, which was obtained from the microdata of the Annual Social Information Report (RAIS) provided by the Ministry of Labor and Employment, and combine with energy data of operational power plants in Brazil from several ANEEL databases. Furthermore, we included geo-climatic and demographic data in our panel data.

In order to identify the causal impact of renewable energy investments on local labor markets, we employed a differences-in-differences (DID) approach. This approach leverages the staggered entry of initial investments in municipalities. As a reference point for defining the intervention period, we utilized the date of power generation initiation. However, existing literature suggests that the local effects of infrastructure investment projects occur before the operation (Simas and Pacca, 2013; Gonçalves et al., 2020; Fabra et al., 2023). Therefore, based on Callaway and Sant'Anna (2020), we relaxed the assumption of no-anticipation to identify the local effects resulting from the investments. This allows us to calculate the aggregate average treatment effect pre- and post-opening.

Recent empirical studies examining the relationship between energy sources and labor market outcomes have predominantly focused on developed countries. For instance, Fabra et al. (2023) demonstrate that solar energy investments lead to increased employment in Spain municipalities, but they do not significantly reduce unemployment, indicating that firms may hire non-resident workers. In the United States, Curtis and Marinescu (2022) find that jobs created in the solar sector are primarily concentrated in commercial activities, while jobs in the wind sector are concentrated in installation and maintenance activities. Moreover, several studies have examined the employment impacts of fossil fuel activities (Feyrer et al., 2017; Black et al., 2005; Allcott and Keniston, 2018; Bartik et al., 2019).

Regarding Brazil, the existing empirical evidence predominantly centers around the impacts of wind energy. For example, Gonçalves et al. (2020) find positive effects on employment and wages for lower-skilled workers in small and medium-sized firms. Similar results are reported by Simas and Pacca (2013) and Rodrigues et al. (2019). It is worth noting that the literature on the labor market effects of renewable energy investments in Brazil is relatively limited, particularly for solar energy. Therefore, this study aims to contribute to the existing literature by examining the specific impacts of both wind and solar energy investments on local labor markets in Brazil.

Our study shares similarities with the works of Gonçalves et al. (2020) and Fabra et al. (2023). However, unlike these studies, we employ the recent advancements in the Difference-in-Differences (DID) literature to estimate causal effects based on temporal variation and the exogenous nature of the location of power plants. In our study, we find evidence that investments in solar and wind energy have a positive effect on the local labor market three years before the commencement of plant operations. Additionally, our results indicate that the impacts of wind energy concentrate on job opportunities in the construction sector, while the impacts of solar energy concentrate in the services sector.

This work also contributes to the literature on green jobs, such as Curtis and Marinescu (2022), where we identify the characteristics of labor supply in these segments. Our results indicate that the effects of wind investments increase low-skilled labor, particularly within the construction sector. This effect is more prominent among men with elementary education degrees. On the other hand, investments in solar energy predominantly lead to a rise in employment within the services sector, which demands a higher level of skill compared to the construction industry. Consequently, solar investments lead to a rise in employment for workers with high school education degrees.

The effects of wind investments are primarily observed in an increase in the low-skilled labor, particularly within the construction sector. This effect is more prominent among men with elementary education degrees. On the other hand, investments in solar energy predominantly lead to a rise in employment within the services sector, which demands a higher level of skill compared to the construction industry. Consequently, solar investments lead to a rise in employment for workers with high school education degrees.

This study provides insights into the positive outcomes of integrating renewable energy investments into local economies. The findings highlight the significant potential for generating employment opportunities and promoting economic growth through the expansion of solar and wind energy projects. Moreover, these results can serve as a useful resource for policymakers in developing effective strategies that support a sustainable and inclusive energy future for local communities. By leveraging the benefits of renewable energy investments, policymakers can work towards creating a greener and more prosperous environment for everyone.

The remaining sections of this paper are structured as follows. Section 2 provides the institutional background, highlighting the trend of solar and wind energy investments in Brazil. Section 3 describes the data sources and outlines the construction of the municipal-level panel dataset. Section 4 presents the empirical strategy, including the methods employed to aggregate the average treatment effects and assess the temporal heterogeneity of the investments. Section 5 presents the results of the analysis. Finally, Section 6 offers concluding remarks and a discussion of the findings.

2 Background

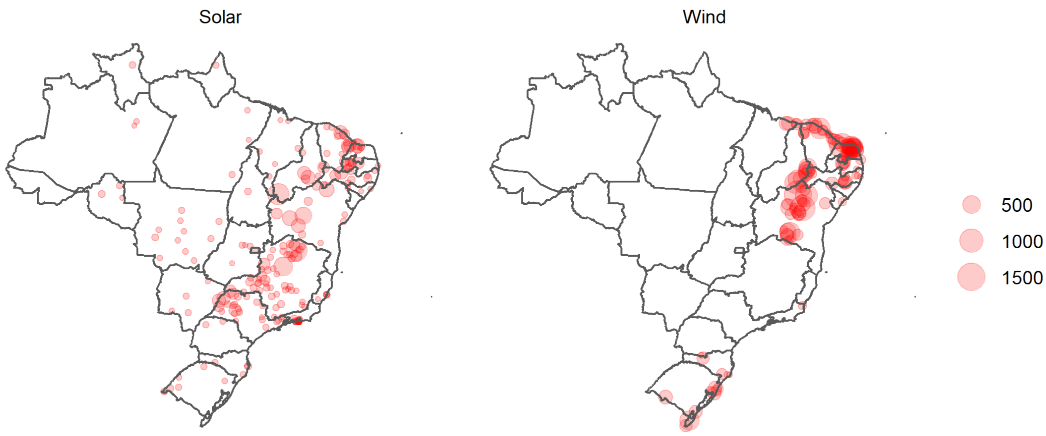
Renewable sources, primarily hydroelectricity, account for 84.4% of electricity generation in Brazil (EPE, 2021). This high reliance on hydroelectricity makes Brazil's electricity system unique. However, climatic factors determine the energy stored in reservoirs, making hydroelectricity vulnerable. During drought periods, reservoir levels can reach critical levels, necessitating the use of backup power generation from thermoelectric plants that burn fossil fuels. In this context, alternative renewable sources like wind and solar are gaining prominence.

Brazil's favorable wind conditions, characterized by high and consistent speeds, have been the main driving force behind the recent growth in wind energy projects. Moreover, Brazil has significant potential for harnessing solar energy. Figure 1 illustrates the spatial distribution of installed capacity in commercial power plants across municipalities.[1] Solar plants are predominantly located in the northeast and southeast regions, where solar irradiation is highest. Wind farms, on the other hand, are concentrated in the northeastern region, benefiting from stronger and more consistent wind speeds.

The first wind power plants began operating in the country in the early 2000s. Solar power

[1] In this paper, we consider commercial power plants as those with an installed capacity exceeding 1 MW. In Brazil, power plants with less than 1 MW are referred to as micro and mini-distributed generation, primarily used for self-consumption by households and firms.

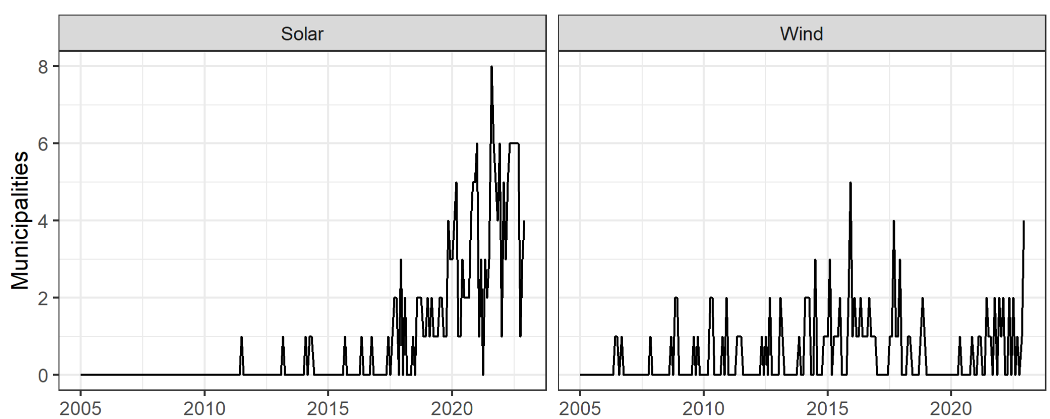
Figure 1: Spatial distribution of investments in solar and wind energy (MW)



Source: Author's own prepared from the ANEEL data.
Notes: These maps illustrate the installed capacity of solar and wind power plants at the municipal level in Brazil as of 2022. We considered power plants with an operating status and an installed capacity equal to or greater than 1 MW, as these plants are predominantly implemented for commercial purposes.

generation, on the other hand, started around 2010, primarily due to the decreasing cost of the technology, particularly in the latter part of 2016. Figure 2 illustrates the monthly count of municipalities that had their first installations implemented within their territory. From 2017 onwards, there was a significant expansion of solar power plants across a wider geographic area. In contrast, investments in wind power plants started in 2006, and their spatial expansion has followed a relatively consistent pattern over time.

Figure 2: Municipalities opening their first power plant



Source: Author's own prepared from the ANEEL data.
Notes: This figure displays the monthly count of municipalities that had their first power plant installations implemented within their territory. We included power plants with an operating status and an installed capacity equal to or greater than 1 MW, as these plants are predominantly implemented for commercial purposes.

In addition to the cost reduction of technologies, energy auctions serve as a significant tool to increase the share of renewable energy in Brazil's electricity mix. The government conducts various types of energy auctions to contract new power generation projects. One such type is the New Energy Auctions (*Leilão de Energia Nova*), which aim to secure generation projects that are not yet in commercial operation. These auctions encompass renewable energy sources like wind, solar, biomass, small hydropower plants, and energy derived from urban solid waste[2]. The timeline for a winning project in a New Energy Auction to commence operations can vary depending on the specific rules and guidelines of each auction. Typically, there is a contractual timeframe established for project completion and energy generation initiation. The duration of this timeframe depends on the project type and technical characteristics involved, ranging from a few years. These timelines are determined based on the specific attributes of each project and the requirements of the Brazilian electricity sector. New Energy Auctions with a timeframe for operation initiation of up to four years after the auction are the most common method of contracting new power generation projects in Brazil.

3 Data

The empirical exploration of the local impacts of investments in renewable plants is conducted with a municipal-level panel. This panel combines aggregated data from power plants and labor market administrative information from 2003 to 2021. In this paper, we focus on municipalities with a population size of less than 100,000 inhabitants, which account for 95% of all municipalities in Brazil. We chose this population threshold as the majority of our selected power plants are located within these municipalities. Furthermore, larger cities exhibit distinct labor market dynamics compared to medium and small-sized cities.

3.1 Power plants data

The power plant data are obtained from two administrative databases maintained by the ANEEL: the Generation Information Database and the Distributed Generation Database. The Generation Information Database contains information on large-scale power plants, which includes the energy source, project stage details, the operation start date, geographic coordinates, and the installed capacity. On the other hand, the Distributed Generation Database provides information on power plants with a capacity size of up to 5 MW. This data-set includes details such as the date of grid connection, geographic coordinates, the type of generation, and the capacity of the power plants.

Firstly, we standardized the two databases at the power plant level, ensuring consistency and compatibility. Subsequently, we selected power plants with an installed capacity exceeding

[2] In addition to New Energy Auctions, there are also Existing Energy Auctions, which award contracts to already operational power generation projects. These auctions focus on ensuring the continuity and security of the country's electricity supply. Additionally, Reserve Auctions are designed to contract energy from specific sources such as wind, solar, and biomass, among others, to diversify Brazil's energy mix and promote sustainability.

1 MW[3]. Next, we aggregated the data at the municipal level, combining information from both databases. Within each municipality, we identified the date of operation initiation for the first power plant that was installed. This specific date serves as the starting point for our intervention period, marking the beginning of the impact of renewable power plants on the local market dynamics.

We assessed the impact of renewable power plants on the local market by comparing the outcomes of treatment and control groups, as discussed in Section **??**. The treatment groups consist of municipalities with at least one solar or wind power plant with a capacity size of 1 MW or higher entering into operation by 2020. Within this group, we excluded those municipalities with the two types of power plants, solar and wind, within their territory. To ensure a cleaner control group, we excluded municipalities that had their first power plants starting operations after 2020. Additionally, we excluded municipalities with power plants under construction in 2023.

3.2 Labor market data

The labor market outcomes in this study are derived from the Annual Social Information Report (RAIS) provided by the Ministry of Labor and Employment (MLE). The RAIS serves as a data collection instrument for gathering information on employers and workers in Brazil. Companies and public agencies must provide this information annually to the MLE. The collected information includes data on the number of employees, wages, occupations, and employment relationships, among other variables. It's important to note that the RAIS data only covers the formal sector of the labor market since it is reported by firms.

Based on the annual microdata from the survey, we aggregated employment figures at the municipal level, both in total and by economic sectors, such as industry, construction, services, and agriculture. These sector categories are defined according to the groups prescribed by the Brazilian Occupational Classification (CBO). Additionally, to explore the heterogeneity within the database, we identified the number of workers by gender (males and females) and educational attainment (elementary, high school, and college degrees).

3.3 Additional data

We combine the panel constructed using the aggregated data of power plants and labor markets at the municipal level with several additional datasets. Firstly, we incorporate data on the average annual wind speed (in meters per second at a height of 50 meters) and solar irradiation (in watts per square meter), and altitude (metros above sea level) obtained from the National Institute for Space Research (INPE). Secondly, we utilize demographic data (population, urban population, and population density) from the 2010 Demographic Census conducted by the

[3]Installations with a capacity smaller than 1 MW, referred to as mini-distributed generation, are typically utilized for self-consumption by households and firms, and their impact on the labor market may be limited.

Brazilian Institute of Geography and Statistics (IBGE).

Table 1 presents the summary statistics of geo-climatic and demographic characteristics for municipalities with solar generation, wind generation, and no solar and wind generation. As expected, municipalities with solar generation exhibit higher irradiation, while municipalities with wind generation have higher wind speed. Municipalities with wind generation are located at lower altitudes, as many wind farms are situated along the coast of the northeastern region of the country. Regarding demographic characteristics, on average, municipalities with solar energy tend to be larger and have a higher urbanization rate.

Table 1: Descriptive statistic of geo-climatic and demographic variables

	Solar	Wind	None
Geo-climatic characteristics			
Wind speed	5.23	6.28	5.11
	(0.72)	(0.61)	(0.82)
Solar irradiation	5088.16	5149.2	4556.31
	(677.23)	(573.63)	(687.8)
Altitude	433.23	328.46	414.85
	(260.79)	(345.22)	(288.79)
Demographics characteristic			
Population (thousand)	30.89	23.19	15.76
	(23.96)	(20.98)	(16.57)
Density	3.96	4.29	4.57
	(6.21)	(5.38)	(10.74)
Urban (%)	73.13	55.49	62.02
	(18.39)	(21.87)	(21.32)
Municipalities	140	87	5046

Notes: This table displays the mean and standard deviation (in parentheses) for geo-climatic and demographic variables of selected samples at the municipal level. Wind speed is measured in meters per second at a height of 50 meters. Solar irradiation is measured in watts per square meter. Altitude is measured in meters above sea level. The demographic variables correspond to the year 2010.

We conducted a mean test to compare the variables of municipalities with any investment in energy generation, whether solar or wind, with municipalities without any investment. The results show that municipalities with wind generation differ significantly from other municipalities at a significance level of at least 10% for all variables, except population density. On the other hand, municipalities with investment in solar energy exhibit differences in terms of solar irradiation, total population, and urbanization rate.

4 Empirical strategy

In our empirical strategy, we explore the staggered investment in renewable power plants across municipalities. This approach allows us to leverage variations in the timing of investment in wind or solar plants to estimate the causal effects on labor market outcomes. Thus, as the identification strategy, we consider the timing of renewable plant investments is not influenced by factors that are correlated with the labor market dynamics at the municipality level.

Our objective is to estimate the average treatment effect by phase of investment. To achieve this, we employ the staggered difference-in-differences strategy proposed by Callaway and Sant'Anna (2020) (Callaway and Sant'Anna, 2020). We consider the assumption of parallel trends but relax the assumption of no-anticipation. This method is robust in the presence of arbitrary heterogeneity of treatment effects and provides transparency in selecting a comparison group[4].

To achieve this, firstly, we estimate the group-time average treatment effects by comparing the expected change in outcomes for the treated group to that never-treated control group. We assume that in the absence of treatment, the trends in the two groups would follow parallel trends. Subsequently, we aggregate the individual group-time average treatment effects estimates to derive more comprehensive causal parameters allowing us to identify the effects associated with the pre and post-power plant openings.

4.1 Group-time average treatment effects

Let G denote the treatment group, comprising municipalities where the first solar or wind generation begun in period g. The effects of renewable generation investments on the local labor market are likely to manifest before the start of operations, given that local investments typically begin during the period of land acquisition and plant construction (Simas and Pacca, 2013; Gonçalves et al., 2020; Fabra et al., 2023). Let δ denote the number of years preceding the start of generation in which the initial investments in the municipalities occur. Thus, the first period of treatment is determined by $g - \delta$.

As proposed by Callaway and Sant'Anna (2020), the group-time average treatment effect of the investment in renewable energy for the group g in year $t \geq g - \delta$ is given by:

$$ATT(g,t,\delta) = \mathbb{E}\left[\frac{G}{\mathbb{E}\left[G\right]}\left(Y_t - Y_{g-\delta-1} - m_{gt\delta}(X)\right)\right] \tag{1}$$

where Y denotes the local labor outcome, i.e., the percentage of formal workers in the population, and $m_{gt\delta}(X)$ represents the outcome regression[5] for the never-treated group ($C = 1$), conditional

[4]The effect arising from policies implemented over time is commonly estimated by Two Way Fixed Effect (TWFE) models. However, the coefficients estimated using this approach may not correctly represent the weighted average of treatment effects if treatment effects are heterogeneous over time or among groups (Roth et al., 2022; Goodman-Bacon, 2021; Sun and Abraham, 2021).

[5]See, e.g. Heckman et al. (1997).

on pre-treatment covariates X, such that:

$$m_{gt\delta}(X) = \mathbb{E}\left[Y_t - Y_{g-\delta-1} \mid X, C = 1\right] \tag{2}$$

We estimate the group-time average treatment effects in two stages. In the first stage, we estimate $m_{gt\delta}(X)$ for each group g and period t by Ordinary Least Squares (OLS), conditional on the covariates associated with the geo-climatic and demographic characteristics of the municipalities. This regression provides us with fitted values for the treated group. In the second stage, we plug these fitted values into the sample analogue of Equation 1 to obtain estimates of the $ATT(g, t, \delta)$. As our inference procedure, we employ clustered bootstrapped standard errors at municipal level[6].

4.2 Aggregations into treatment effects parameters

Given the $ATT(g, t, \delta)$ estimates, we apply partial aggregations to summarize different dimensions of treatment effect heterogeneity. In this way, we are interested in addressing the following questions: i) How does the effect of investments vary with the length of exposure to the treatment? and ii) What is the average treatment effect before and after power plant openings?

4.2.1 Average effects by length of exposure

To assess whether the treatment effect increases or decreases over time after the intervention, a way to aggregate the $ATT(g, t, \delta)$ and highlight treatment effect heterogeneity is as follows:

$$ATT^{\text{es}}(e, \bar{e}) = \sum_{g \in \mathcal{G}} 1\left\{g - \delta + \bar{e} \leq \mathcal{T}\right\} P\left(G = g \mid G - \delta + \bar{e} \leq \mathcal{T}\right) ATT(g, t, \delta) \tag{3}$$

where e represents event time, $\bar{e}$ denotes a event time limit, G represents the time period when a unit is first treated, and $\mathcal{T}$ is the number of periods. Given that the effects of the treatments occur before the start of power generation g, $e = t - g - \delta$ represents the time elapsed since treatment was adopted. Therefore, by introducing the parameter $\bar{e}$, where $0 \leq e \leq \bar{e} \leq \mathcal{T} - 2$, we limit the number of periods after treatment, ensuring balanced treated groups in terms of event time.

Thus, Equation 3 represents the average effect of the investment in solar or wind energy, e time periods after the investment began, across all groups that are ever observed to have participated in the treatment for exactly $\bar{e}$ time periods.

We limited our analysis to one year after the start of power generation operations, i.e., we defined $\bar{e} = 1$, to mitigate the effects of unobserved variables over time that may impact the

[6]See Callaway and Sant'Anna (2020) for further details on the bootstrap algorithm used to compute studentized confidence bands.

local labor market. Thus, the number of $ATT(g, t, \delta)$ estimates after treatment for each energy source is equal to $g \cdot (\delta + \bar{e} + 1) = g \cdot (\delta + 2)$. Consequently, the number of ATT^{es} estimates is equal to $\delta + 2$.

4.2.2 Average effects by phase of investment

Finally, we aim to estimate the parameters both before and after the start of the investments, specifically before and after the beginning of power generation operations. In other words, we want to estimate the average treatment effect before and after power plant openings. To accomplish this, we can define the treatment effect parameters by averaging ATT^{es} across all event times as follows:

$$ATT^{\text{pre}}(\bar{e}) = \frac{1}{\delta + 1} \sum_{e=-\delta}^{0} ATT^{\text{es}}(e, \bar{e}) \tag{4}$$

$$ATT^{\text{post}}(\bar{e}) = \frac{1}{\bar{e} + 1} \sum_{e=0}^{\bar{e}} ATT^{\text{es}}(e, \bar{e}) \tag{5}$$

Equation 4 estimates the average treatment effect pre-opening, while Equation 5 estimates the average treatment effect post-opening. These parameters allow us to determine in which phase the investment has the greatest impact on the local labor market.

5 Results

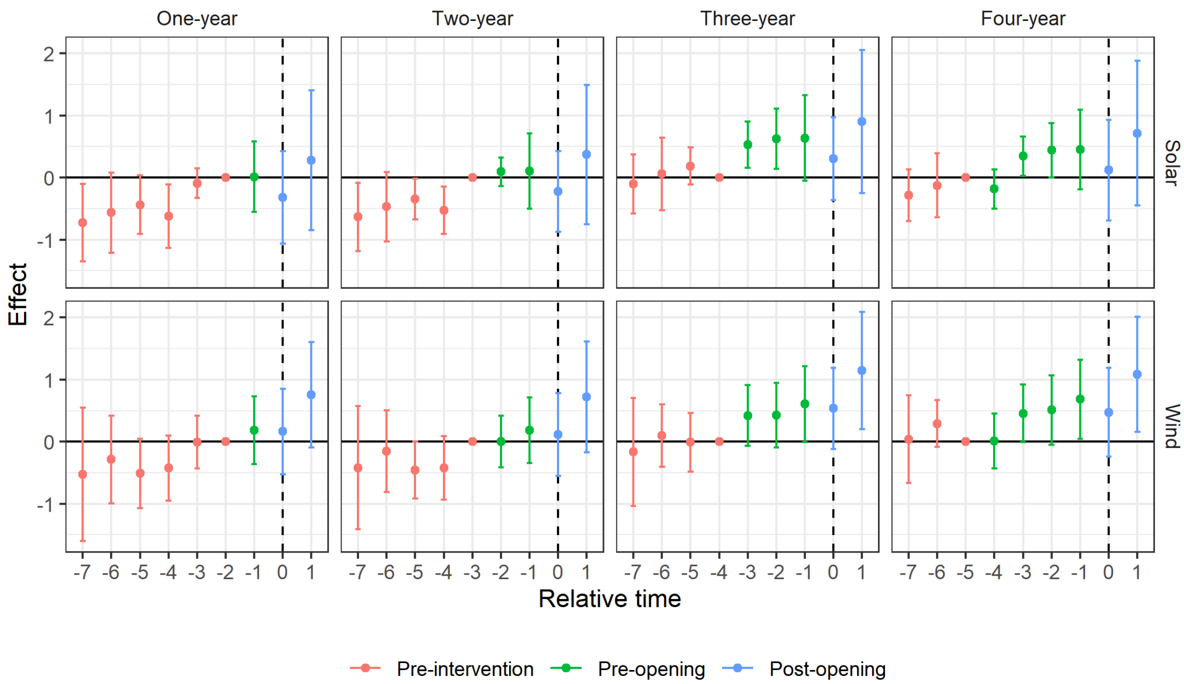
In this section, we present the results of the impact of investments in solar and wind on local labor. The dependent variable is the number of formal sector jobs per 100 inhabitants, i.e., the percentage of the population in the formal labor market sector.

5.1 Local employment effects

Figure 3 presents the effect of the investments by length of exposure. We estimate the group-time average treatment effects (Equation 1) considering $\delta \in (1, 2, 3, 4)$, which means we examine the possibility of the investment's effect starting one, two, three, or four years before the commencement of power generation ($e = 0$). Each data point represents a distinct aggregated ATT^{es} from Equation 3, accompanied by a 95% confidence interval. The figure shows the average effects for the periods before the start of investments (pre-intervention), the period after the intervention but pre-opening, and post-opening.

The figure indicates that we did not find evidence of the validity of the parallel trends hypothesis when examining the effects of investments occurring one or two years before the initiation of power generation for both solar and wind energy sources. However, we observe evidence of parallel trends when considering interventions that commence three years before

Figure 3: Local employment effects by length of exposure



Notes: The figure presents the average treatment effects values by length of exposure (ATT^{es}). The dependent variable is the number is the number of formal sector jobs per 100 people. Standard errors are clustered at the municipality level. Each data point represents a distinct ATT^{es} value along with its corresponding 95% confidence interval.

the start of power generation for both energy sources. This empirical finding aligns with the assumptions made by Gonçalves et al. (2020) and Fabra et al. (2023), where they assume that the local effects of renewable energy investments begin three years before the first power generation in the municipality. Therefore, in our preferred specification, we consider that the treatment occurs three years before the start of operations, i.e., we assume $\delta = 3$ when estimating the group-time average treatment effects.

Regarding our preferred specification (Three-year, Figure 3), the estimations indicate that investments in solar and wind generation have a dynamic impact on local jobs. Following the intervention, the figure displays a heterogeneous effect over time. For solar energy, the average treatment exhibits statistical significance at the 5% level and demonstrates a positive effect in the first year after the intervention. In the case of wind energy, although the point estimate is positive in the intervention year, the parameter achieves statistical significance at the 5% level two years after the intervention.

Table 2 presents the results of the average effects by length of exposure aggregated by investment phases: pre-opening and post-opening. As already suggested by Figure 3, we find the parameters statistically significant at least at the 10% level for our preferred specification, i.e., the specification associated with the intervention three years before the commencement of power generation.

Table 2: Local employment aggregate effects by phase of investment

	$\delta = 1$		$\delta = 2$		$\delta = 3$		$\delta = 4$	
	Pre	Post	Pre	Post	Pre	Post	Pre	Post
Panel A. Solar								
Jobs	0.012	-0.022	0.100	0.071	0.597***	0.602	0.262*	0.416
	(0.354)	(0.433)	(0.203)	(0.407)	(0.182)	(0.418)	(0.137)	(0.428)
Dep.Var.	13.99	13.99	13.99	13.99	13.99	13.99	13.99	13.99
Groups	7	7	7	7	7	7	7	7
Treated	82	82	82	82	82	82	82	82
Control	4,962	4,962	4,962	4,962	4,962	4,962	4,962	4,962
Panel B. Wind								
Jobs	0.188	0.461	0.094	0.418	0.484**	0.839***	0.416***	0.777**
	(0.332)	(0.333)	(0.205)	(0.338)	(0.191)	(0.350)	(0.162)	(0.357)
Dep.Var.	9.18	9.18	9.18	9.18	9.18	9.18	9.18	9.18
Groups	15	15	14	14	14	14	13	13
Treated	73	73	73	73	73	73	73	73
Control	4,962	4,962	4,962	4,962	4,962	4,962	4,962	4,962

Notes: The table presents the Average Treatment Effects on Treated (ATT) values. The dependent variable is the number of new installations per 100,000 households. The covariate considered is solar irradiation (log). Standard errors are clustered at the municipality level. Significance levels are denoted as *** for 1 percent, ** for 5 percent, and * for 10 percent significance levels.

The table shows that the effects of investments in solar and wind energy are distinct. For solar energy, the investment effect is statistically significant at the 1% level with a positive sign during the pre-opening period. The result indicates that during this phase, employment increases by 0.6 percentage points, corresponding to an approximately 4% increase in the proportion of the employed population.

On the other hand, the effects of investments in wind farms are positive both in the pre-opening and post-opening phases. Pre-opening, employment increases by 0.5 percentage points, resulting in an approximately 5% increase in the proportion of the employed population. Post-opening, the effect becomes even more substantial, with employment increasing by 0.8 percentage points, corresponding to a 9% increase in the proportion of the employed population.

5.1.1 Robustness

The results in Table 2 were estimated using the outcome regression (OR) approach. In this case, we model the conditional expectation of the outcome evolution for the comparison groups given their geo-climatic and demographic characteristics.

To assess the robustness of the results, we also estimated the $ATT(g, t, \delta)$ using two alternative approaches: inverse probability weighting (IPW) and double robust (DR) methods. The IPW approach relies on modeling the conditional probability of being in the group g to balance baseline characteristics of the treatment and control groups, as proposed by Abadie (2005). The DR approach, proposed by Sant'Anna and Zhao (2020), exploits both the OR and IPW components but requires that only one of those be correctly specified. However, since both approaches are potentially based on the propensity score, the validity of the overlap assumption may limit the number of observations in the treatment groups g, leading to increased uncertainty in the estimations.

Assuming the validity of the parallel trends hypothesis (see Figure A1), Table A1 presents the results for the aggregation by phase of investment using different methods, considering that the treatment occurs three years before the start of operations. The estimates suggest that the results are robust to the type of method. The point estimates obtained using IPW and DR are lower than the OR but not statistically different.

5.2 Effects by sector, gender and education

Our database allows us to explore the heterogeneities of the impact of solar and wind investment on the local labor market. Thus, we investigate the average effect by economic sector, worker gender, and education. In all estimations, we consider the intervention period to occur three years before the power plant's opening.

Table 3 presents the average effects by investment phase for the following sectors of the economy: industry, construction, services, and agriculture. For solar generation, the parameters are positive and statistically significant for the industrial and services sectors in the pre-opening phase. On the other hand, for wind generation, the parameters are positive and statistically significant for the construction and agriculture sectors in the post-opening phase. These findings are consistent with the evidence found by Curtis and Marinescu (2022) for the US. Although their work does not focus on the local effect, Curtis and Marinescu (2022) shows that about a third of solar jobs are in sales occupations, while about a third of wind jobs are in installation and maintenance occupations.

Table 4 presents the aggregated results by investment phase according to the worker's level of education: elementary, high school, and college degrees. For solar generation, the parameters are positive and statistically significant for workers with a high school education in both the pre-opening and post-opening phases. For wind generation, the parameters are positive and statistically significant for workers with an elementary and high school degree in both the pre- and post-opening. In the case of wind generation, the magnitude of the parameters is higher for workers with an elementary education compared to those with high school degrees.

Table 5 presents the aggregated results by investment phase and worker gender. The findings

Table 3: Local employment aggregate effects by treatment anticipation

	Industry		Construction		Services		Agriculture	
	Pre	Post	Pre	Post	Pre	Post	Pre	Post
Panel A. Solar								
Jobs	0.197**	0.117	0.106	-0.119	0.304**	0.511	-0.010	0.093
	(0.093)	(0.104)	(0.109)	(0.159)	(0.152)	(0.340)	(0.04)	(0.099)
Dep.Var.	13.99	13.99	13.99	13.99	13.99	13.99	13.99	13.99
Groups	7	7	7	7	7	7	7	7
Treated	82	82	82	82	82	82	82	82
Control	4,962	4,962	4,962	4,962	4,962	4,962	4,962	4,962
Panel B. Wind								
Jobs	-0.022	0.123	0.195	0.394**	0.101	0.103	0.209	0.220*
	(0.043)	(0.145)	(0.110)	(0.156)	(0.121)	(0.217)	(0.140)	(0.123)
Dep.Var.	9.18	9.18	9.18	9.18	9.18	9.18	9.18	9.18
Groups	15	15	14	14	14	14	13	13
Treated	73	73	73	73	73	73	73	73
Control	4,962	4,962	4,962	4,962	4,962	4,962	4,962	4,962

Notes: The figure presents the average treatment effects values by length of exposure (ATT^{es}). The dependent variable is the number is the number of formal sector jobs per 100 people. Standard errors are clustered at the municipality level. Each data point represents a distinct ATT^{es} value along with its corresponding 95% confidence interval.

suggest that investments in solar energy increase the labor supply for both men and women, with the treatment parameter showing a larger magnitude for men in the post-opening phase. In the case of investments in wind energy, the effect is statistically significant only for men. This implies that investment in wind energy increases the labor supply for men in both the pre- and post-opening phases.

Figures A2, A3, and A4 suggest that the parallel trends hypothesis is valid for the results associated with tables 3-5. These results provide important insights into the distinct effects on the local labor market resulting from solar and wind investments.

The effects of wind investments primarily increase the supply of low-skilled labor, particularly in the construction sector, and this effect is more pronounced among men with elementary education degrees. On the other hand, investments in solar power predominantly increase employment in the services sector, which requires more skilled labor compared to the construction sector. Therefore, in the case of solar investments, there is an increase in employment for workers with high school education degrees.

It is important to note that we did not find evidence that investments in solar or wind energy increase the availability of highly skilled workers, i.e., those with college degrees, locally. This

Table 4: Local employment aggregate effects by treatment anticipation

	Elementary		High School		College	
	Pre	Post	Pre	Post	Pre	Post
Panel A. Solar						
Jobs	0.076	-0.077	0.487***	0.691***	0.059	0.082
	(0.089)	(0.223)	(0.116)	(0.189)	(0.043)	(0.063)
Dep.Var.	6.06	6.06	6.12	6.12	1.83	1.83
Groups	7	7	7	7	7	7
Treated	82	82	82	82	82	82
Control	4,962	4,962	4,962	4,962	4,962	4,962
Panel B. Wind						
Jobs	0.378***	0.703***	0.154*	0.290*	-0.023	-0.109
	(0.143)	(0.168)	(0.081)	(0.174)	(0.055)	(0.083)
Dep.Var.	3.64	3.64	4.11	4.11	1.46	1.46
Groups	15	15	14	14	14	14
Treated	73	73	73	73	73	73
Control	4,962	4,962	4,962	4,962	4,962	4,962

Notes: The figure presents the average treatment effects values by length of exposure (ATT^{es}). The dependent variable is the number is the number of formal sector jobs per 100 people. Standard errors are clustered at the municipality level. Each data point represents a distinct ATT^{es} value along with its corresponding 95% confidence interval.

suggests that while renewable energy investments have positive effects on the local labor market, they may not necessarily lead to a substantial increase in high-skilled employment in the short term.

6 Conclusion

In this paper, we investigate the effects of investing in solar and wind energy on local labor markets. Our findings reveal that both solar and wind investments have positive effects on job creation at the local level. However, it's important to note that the impacts of these investments are diverse.

The effects of wind investments are primarily observed in an increase in the availability of low-skilled labor, particularly within the construction sector. This effect is more prominent among men with elementary education degrees. On the other hand, investments in solar energy predominantly lead to a rise in employment within the services sector, which demands a higher level of skill compared to the construction industry. Consequently, solar investments lead to a rise in employment for workers with high school education degrees.

Table 5: Local employment aggregate effects by treatment anticipation

	Males		Females	
	Pre	Post	Pre	Post
Panel A. Solar				
Jobs	0.375***	0.441*	0.142**	0.320***
	(0.123)	(0.264)	(0.063)	(0.118)
Dep.Var.	5.29	5.29	4.17	4.17
Groups	7	7	7	7
Treated	82	82	82	82
Control	4,962	4,962	4,962	4,962
Panel B. Wind				
Jobs	0.462***	0.820***	0.055	0.019
	(0.155)	(0.237)	(0.067)	(0.110)
Dep.Var.	5.29	5.29	4.17	4.17
Groups	15	15	14	14
Treated	73	73	73	73
Control	4,962	4,962	4,962	4,962

Notes: The figure presents the average treatment effects values by length of exposure (ATT^{es}). The dependent variable is the number is the number of formal sector jobs per 100 people. Standard errors are clustered at the municipality level. Each data point represents a distinct ATT^{es} value along with its corresponding 95% confidence interval.

This study sheds light on the beneficial outcomes of incorporating renewable energy investments into local economies. Our results emphasize the potential for job creation and economic growth through the expansion of solar and wind energy projects. Furthermore, the results may help policymakers to elaborate effective strategies that foster a sustainable and inclusive energy future for local communities.

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