

The Effects of Renewable Energy Communities on (Energy) Poverty in Germany

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Abstract

This paper investigates renewable energy communities and income and energy poverty in Germany. It combines county-level data on plants owned by renewable energy communities with administrative economic outcomes and household-level SOEP data, and applies staggered difference-in-differences methods. We find that community-owned biomass plants are associated with lower poverty as well as lower unemployment, higher employment, and higher disposable per capita income at the county level. By contrast, we find no effects for community-owned solar or wind plants. At the household level, although exposure to nearby renewable energy communities is associated with lower energy poverty for all three indicators considered, the magnitude and statistical precision vary across treatment definitions and energy poverty measures.

1 Introduction

There is growing policy and research interest in the socio-economic effects of the energy transition. Since the energy transition cannot be conceptualized as a purely technical process, the institutional forms in which energy is provided matter. Renewable energy communities (RECs)¹, formed by voluntary citizen initiatives, are a crucial, novel element of this landscape. They participate directly in the energy transition by investing in, owning, and operating

¹Germany defines renewable energy communities in the Erneuerbare-Energien-Gesetz (EEG, 2023) (Bundesanzeiger Verlag, 2022) as a cooperative or other form of company with at least 50 local residents with at most 10% of voting rights each, which is compatible with the EU Renewable Energy Directive (2019/944) (European Parliament and Council, 2019).

renewable energy plants. Through their local embeddedness, they might benefit the regional economy. This paper focuses on distributional outcomes, and asks concretely whether renewable energy communities can be linked to lower income and energy poverty in Germany, a leader in this field.

This question matters for policy makers, because the design of energy transition policies can address both the climate and economic and socio-economic outcomes. This people-centred approach is reflected in recent international policy frameworks, including the work of the International Energy Agency and the G20, which emphasize issues such as decent jobs, social protection, energy access, energy poverty, and social inclusion (G20, 2024; IEA, 2021a, 2021b). Importantly, these frameworks also place citizens and communities as active participants in the energy transition, giving energy communities and cooperatives particular relevance.

This study connects to two broader strands of research. First, there is a strand of literature investigating the local economic effects of renewable energy investment, without distinguishing ownership models, focusing on negative or positive externalities. The former are mostly reduced property values (Dröes & Koster, 2016; Gaur & Lang, 2023; Gibbons, 2015; Krekel & Zerrahn, 2017; Maddison et al., 2023; Schütt, 2024; Sunak & Madlener, 2016), while the latter include higher employment, income, and GDP per capita, although some studies find these gains limited to the construction phase (Brown et al., 2012; Brunner & Schwegman, 2022; Brunner et al., 2022; Costa & Veiga, 2021; de Silva et al., 2016; Fabra et al., 2024; Gilbert et al., 2024; Hartley et al., 2015; Mauritzen, 2020; Scheifele & Popp, 2025; Serra, 2023; Shoeib et al., 2021). A second strand of the literature to which this paper speaks addresses energy poverty (Boardman, 1991; Bouzarovski, 2014; Hammerle et al., 2023). This is linked to adverse health outcomes (Awaworyi Churchill & Smyth, 2021; Awaworyi Churchill et al., 2020; Buchner & Rehm, 2025; Davillas et al., 2022; Kahouli, 2020) and heightened by Germany’s rising energy costs (European Commission, 2020; German Council of Economic Experts, 2022). Again not distinguishing by ownership type, this literature finds mixed effects of renewable energy on energy poverty; global and Chinese studies have found a negative relationship (Li et al., 2023; Liu et al., 2026; Wang et al., 2026; Zhao et al., 2022; Zhou et al., 2026) while European evidence points to transition costs raising energy poverty or arrears on utility bills, at least in the early stages of adoption (Muhammad et al., 2023; Priesmann et al., 2022; Simionescu & Cifuentes-Faura, 2024; Simionescu et al., 2023).

Regarding renewable energy communities, the literature argues that they are economically beneficial (Community Energy England, 2024; Farrell, 2014;

Kienbaum et al., 2023; Lantz & Tegen, 2009; Vansintjan, 2015). Much of the existing evidence comes from case studies (Vansintjan, 2015), sector reports (Community Energy England, 2024) or modelling exercises (Farrell, 2014). However, econometric evidence is also emerging: Dilek and Bühler (2026) find positive effects of renewable energy communities on income per capita in the United Kingdom, while Hoeschle et al. (2025) show that bioenergy villages in Germany have positive effects on income and tax revenues.

Finally, this paper contributes to the literature on renewable energy communities and (energy) poverty itself, which has focused mainly on participation motives and governance structures (Bauwens et al., 2016; Cohen et al., 2021; European Committee of the Regions: Commission for the Environment, Climate Change and Energy et al., 2018; Funkhouser et al., 2015; Horstink et al., 2020; Inês et al., 2020). While it documents positive distributional effects in general and improvement of energy poverty in particular (Koukoulfikis et al., 2023), much of the evidence comes from reports of renewable energy community organizations (Kenkmann et al., 2025; REScoop.eu, 2025a, 2025b). This has led to its recognition in policy circles (European Parliament and Council, 2019); however, the academic evidence that examines the relationship between renewable energy communities and energy poverty mainly consists of qualitative comparative research and policy analysis approaches (Barroco Fontes Cunha et al., 2021; DellaValle & Czako, 2022; Hanke & Lowitzsch, 2020; Hoicka et al., 2021; Lupi et al., 2021), including surveys of members of renewable energy communities Basilico et al. (2026). For Germany, Moser et al. (2021) apply qualitative case analysis and show that collective solar schemes in multi-apartment buildings can reduce electricity costs for tenants, a group often exposed to higher risks of energy poverty.

By addressing the distributional effects of renewable energy communities, this paper contributes to the evidence-based policymaking in the “people-centred clean energy transition” field while also enriching the econometric evidence of the socio-economic effects of RECs. To the best of our knowledge, this is the first paper that studies the relationship between renewable energy communities and income poverty and energy poverty employing quasi-experimental methods.

We focus on Germany because the country is the leader in renewable energy community activity. The Renewable Energy Sources Act (Bundesanzeiger Verlag, 2000) was legislated in 2000, which guaranteed grid access, priority dispatch, and long-term feed-in tariffs for renewable generators, thereby enabling households, farmers, and local cooperatives to invest collectively in renewable generation. In 2023, renewable energy communities in Germany have a 1.1 GW

solar, 2.2 GW wind, and 98 MW biomass capacity corresponding to 1.38%, 3.47%, and 1.03% of total capacities operated by more than a thousand renewable energy communities (Federal Network Agency, 2025; Wierling et al., 2023).

Our empirical strategy is twofold. First, we investigate how community-owned solar, wind, and biomass plants affect the number of people receiving income support under SGB II using German county-level panel data. We define counties as treated once the first community-owned plant of the respective technology becomes operational² and apply the Callaway and Sant’Anna (2021) estimator to account for staggered treatment timing. We complement this analysis with employment, unemployment, and real disposable income per capita as additional outcomes. Secondly, to investigate the relationship between energy poverty and RECs, we use German-Socioeconomic Panel (SOEP) data including confidential household location information (German Institute for Economic Research (DIW Berlin), 2023). We pool REC capacity across technologies and define household exposure based on cumulative REC capacity within a 5-km radius³, estimating effects on the ten percent rule (tpr), two times median expenditure share (mtwo), and low-income high-cost (lihc) indicators⁴.

The results show that community-owned biomass capacity is associated with a significant reduction in SGB II receivers per capita, higher employment and disposable income, and lower unemployment. By contrast, we fail to find statistically significant effects of community-owned solar or wind on the county-level outcomes in our main specifications. These results are in line with Hoeschle et al. (2025) since community-owned biomass plants are linked to local production networks. Community-owned solar and wind plants may

²To estimate the effect of community-owned solar, for instance, we define the first plant operation as treatment, and we control for other community-owned renewable capacity as well as for all other renewable capacities that are not owned by RECs. The symmetric approach is applied for community wind and community biomass.

³The choice of a 5 km radius is motivated by several factors and data limitations. First, the average German municipality has a surface area of 32.6 square km; hence, a 5 km radius covers an area more than twice as large as the average municipality. This suggests that the 5 km radius is a reasonable choice for capturing local economic dynamics. Second, reducing the radius substantially decreases the number of treated households in the sample. For instance, with a 1 km radius, only 89 households have at least 1 MW of community energy capacity in their surroundings. Finally, there is a trade-off between increasing the number of treated households by enlarging the radius or lowering the capacity threshold and potentially confounding the estimates by including only mildly exposed households in the treated group. Increasing the radius beyond 5 km may therefore also increase the risk of such confounding.

⁴An alternative capacity threshold of 1 MW is also considered, and the results are reported alongside those based on the 5 MW cutoff.

not create local economic impacts significant enough to be captured in our analysis.

At the household level, the point estimates are negative for all three energy-poverty indicators. The evidence is strongest for the *mtwo* and *tpr* measures, for which some estimates are statistically significant, whereas the *lihc* estimates are not statistically distinguishable from zero. This is an indication of the effect of renewable energy communities on energy poverty reduction while we acknowledge the data limitations in this case as SOEP data does not contain direct measures of REC activity and our treatment definition based on 5 KM radius might not be a perfect proxy to measure the impact.

The remainder of the paper is organized as follows. Section 2 summarizes the German institutional context for renewable energy communities, income support, and energy poverty. Section 3 presents the data and methodology, Section 4 discusses the main results, Section 5 presents robustness checks, and Section 6 concludes.

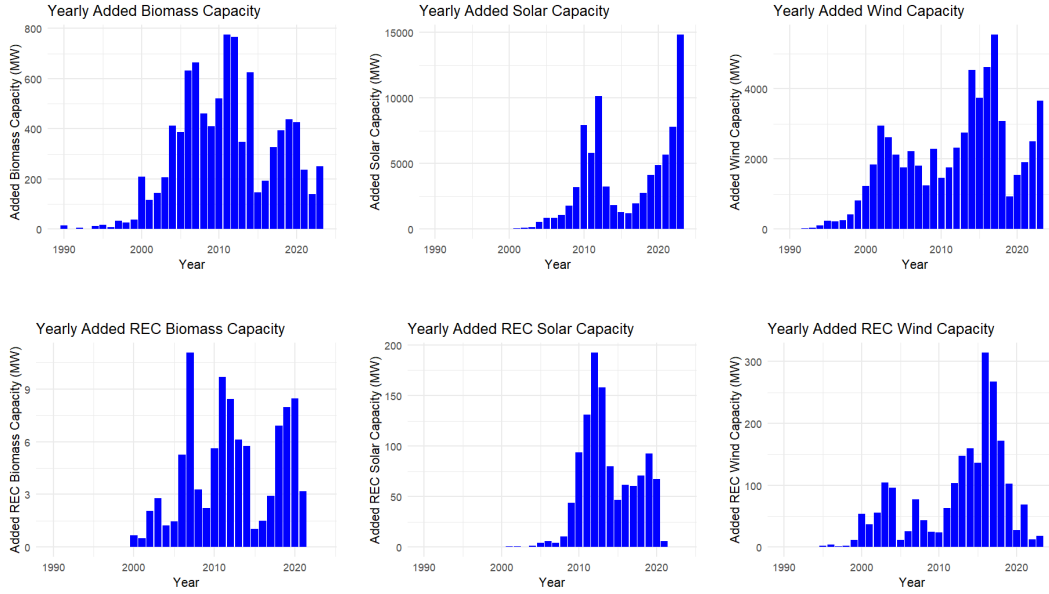
2 Institutional Context: Renewable Energy Communities, Income Support, and Energy Poverty in Germany

Germany is widely regarded as one of the pioneering countries for renewable energy communities due to the historical interaction between grassroots participation, supportive legislation, and the broader energy transition (*Energiewende*) policy framework. Citizen participation in energy production emerged from anti-nuclear social movements in the 1970s and 1980s, which promoted decentralized and democratized energy systems and later translated into strong public support for renewable energy deployment (Agora *Energiewende*, 2025). An institutional turning point was the introduction of the Renewable Energy Sources Act (*Erneuerbare-Energien-Gesetz*, EEG) in 2000, which guaranteed grid access, priority dispatch, and long-term feed-in tariffs. In 2009, Germany increased its feed-in-tariff support for offshore and onshore wind plants as well as biomass plants (International Energy Agency, 2016). This triggered a first wave of rapid expansion of investment in renewable energy plants using biomass, solar, and wind (see Figure 1, top row).

This stable policy environment allowed households, farmers, and local co-operatives to collectively invest in renewable energy generation (Future Policy Platform, n.d. Radtke & Ohlhorst, 2021), as the bottom row of Figure 1 shows.

During the early phase of the energy transition, individual citizens and cooperatives owned a notable share of renewable capacity (Clean Energy Wire, 2018). From the mid-2000s onward, hundreds of solar and wind energy communities were established, most organized as cooperatives, embedding community ownership as a structural feature of the German energy transition (Clean Air Task Force, 2024). More recently, EU energy-community directives and national regulatory reforms – including amendments to the Energy Industry Act that allows energy sharing – have formalized renewable energy communities as recognized market actors, reinforcing Germany’s long tradition of citizen energy participation within a modern European legal framework (dena – German Energy Agency, 2025; Taylor Wessing, 2025). This combination of early social mobilization, stable financial incentives, cooperative institutional traditions, and evolving EU-aligned legislation explains why renewable energy communities are a mainstay of renewable energy generation in Germany, making the country a central empirical case for their study.

Figure 1: Yearly added capacity of renewable energy plants.



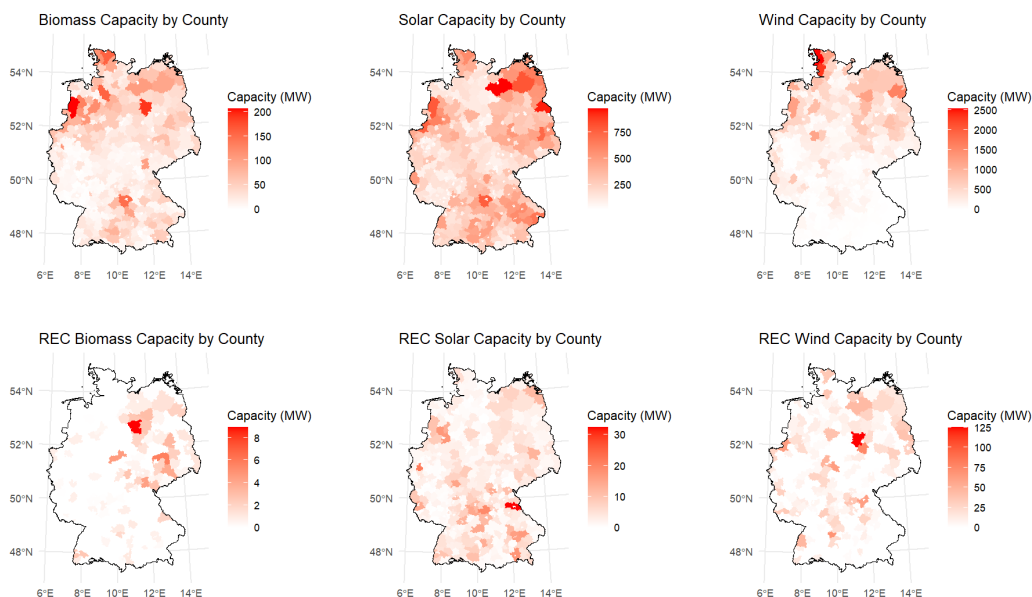
Notes: This graph shows yearly added capacities in megawatts (MW) of renewable plants in biomass, solar, and wind in Germany for the years 1990 to 2023. The top panel shows total capacity and the bottom panel shows renewable energy community (REC) plants.

Source: Own calculations, Data: Federal Network Agency (2025); Wierling et al. (2023).

The geographical distribution of renewable energy community plants across

Germany differs from that of privately-owned plants ⁵, as the comparison of the top and bottom row of Figure 2 shows. While biomass community plants are concentrated in East Germany, there are additional hotspots of privately-owned biomass plants in the agricultural regions of the North-West and the South. Solar plants, both privately- and community-owned, are prevalent across all of Germany. For wind, community wind plants are also distributed largely uniformly across Germany, while privately-owned wind plants are concentrated in the North. Compared to privately-owned plants, renewable energy communities thus appear to be located in less prosperous regions like the East, and to permeate regions more resistant to renewable energies like the South for wind.

Figure 2: Geographical distribution of renewable energy plants



Notes: This figure shows the geographical distribution of renewable energy plants for biomass, solar, and wind in megawatts (MW) in Germany at the county level at the end of 2023. The top panel shows total capacity and the bottom panel shows renewable energy community (REC) capacity.

Source: Own calculations, Data: Federal Network Agency (2025); Wierling et al. (2023)

We now turn to the German institutional context for our two main outcomes of interest: income poverty, measured through SGB II receipt, and energy poverty. SGB II provides means-tested basic income support for employable individuals whose own income and assets are insufficient to secure a

⁵The data includes households' rooftop solar systems. In the case of biomass and wind plants, small scale systems are much less common.

minimum subsistence level, as well as for members of their benefit community.⁶ It therefore covers not only unemployed job seekers, but also employed individuals with insufficient earnings and non-employable household members, such as children who live in the same benefit community. Benefits are administered by job centers and combine cash transfers for regular living expenses with support for reasonable housing and heating costs.

In 2023, around 5.5 million people in Germany received regular SGB II benefits, illustrating that the system is a central component of the German welfare state (Bundesagentur für Arbeit, 2026b). For the purposes of this study, the number of SGB II recipients at the county level is therefore an administrative indicator of local income poverty among households connected to the working-age population. We complement this indicator with additional dependent outcome variables such as the employment and unemployment rate, and real disposable income per capita is to run alternative estimations to ensure that the change in SGB II receivers is in line with other indicators and also to explore the mechanisms in which RECs reduce SGB II receivers per capita.

Our second main indicator is energy poverty. In Germany’s high-income context, energy poverty concerns less physical access to energy services but rather affordability and socially determined energy needs (Bednar & Reames, 2020). Energy-poor households face difficulties in securing adequate energy services because energy expenditures place excessive pressure on disposable income or because dwellings cannot be heated sufficiently. This makes expenditure-based indicators particularly relevant for studying energy poverty in the German context. In Germany, the affordability of household energy has been affected both by long-term structural changes associated with the energy transition and by short-term shocks to energy prices (Federal Statistical Office (Destatis), 2026b; Frondel et al., 2015). These developments have increased public and policy attention to the distributional consequences of energy costs. Survey-based evidence shows that the inability to keep homes adequately warm remains a problem in Germany (Drescher & Janzen, 2021), although less so than in other European countries (Federal Statistical Office (Destatis), 2026a).

⁶Under Hartz IV, the standard need for a single adult was 416 € per month in 2018 and 449 € in 2022, excluding accommodation and heating costs. Since January 2023, Hartz IV has been replaced by Bürgergeld, which increased benefit levels and introduced somewhat more generous asset rules (Bundesagentur für Arbeit, 2026c; Sozialpolitik aktuell, 2023).

3 Data and Methodology

3.1 Data

We construct two datasets to investigate the relationship between renewable energy communities and income and energy poverty. The first is a yearly panel containing renewable energy communities (biomass, solar, and wind), as well as income support receivers, the unemployment rate, and disposable income per capita at the county level for the years 1995 to 2023. The second dataset is a household survey panel for the years 2010 to 2023, which we augment with household’s exposure to local renewable energy community capacity.

For both data sets, the main data source for our independent variable, renewable energy community plants in Germany, comes from Wierling et al. (2023) which collects data through an initial search of the MaStR German energy market register data (Federal Network Agency, 2025). This yields the ownership entries of cooperatives (“eingetragene Genossenschaft - e.G”) and non-profit organizations (“eingetragener Verein - e.V.”). The other plants of these entities are determined using snowball sampling utilizing their websites and other web sources (Wierling et al., 2023). After cleaning Wierling et al. (2023) data⁷ by removing duplicates and imputing missing values through fuzzy matching with MaStR data based on location and plant name, we use the resulting plant level data in two ways: For the yearly panel data at the county level, we aggregate renewable energy community capacities to calculate the cumulative renewable energy community capacities by technology type. For the survey data, we use the location data for renewable energy community plants and households to calculate the cumulative renewable community capacity within 5 km radii of households and at two capacity cutoffs, 5 and 1 MW.

For the county-level data set, our main dependent variable is income poverty, measured as SGB II receivers using yearly county-level panel data (Bundesagentur für Arbeit, 2026a). Its dependents, the employment rate, unemployment rate, working age population, and total population, are based on INKAR (Indikatoren und Karten zur Raum- und Stadtentwicklung) data (INKAR, 2025); disposable income per capita comes from Statistische Ämter des Bundes und der Länder (2026) and the consumer price index and GDP deflator from Statistisches Bundesamt (2026). Due to variations in data availability of the dependent variables, this yields between 6,745 and 10,295 observations⁸,

⁷For details on this data cleaning, see Appendix A3.

⁸See the Appendix A2 for the time range of each variable.

for which Table 1 gives the summary statistics for the full sample and by energy type (biomass, wind, solar).

Table 1: Summary statistics of county panel data, Year = 2022

	Mean	SD	Min	Max
<i>Panel A. Full Sample, N = 400</i>				
<i>Capacities</i>				
REC solar capacity (MW)	2.8	3.9	0.0	32.3
REC wind capacity (MW)	5.4	12.8	0.0	125.0
REC biomass capacity (MW)	0.2	0.8	0.0	8.9
Total solar capacity (MW)	168.7	142.8	10.2	854.6
Total wind capacity (MW)	147.1	263.0	0.0	2385.6
Total biomass capacity (MW)	23.1	28.2	0.0	189.8
<i>Economic outcomes</i>				
SGB II receivers per capita	5.7	2.9	1.5	19.1
Employment rate (%)	65.1	4.2	49.0	73.4
Unemployment rate (%)	4.9	2.1	1.7	14.1
Real disp. income per capita (€)	24228	2476	17508	38005
<i>Demographics</i>				
Population	207796	243164	33264	3632853
Working age population	132523	162409	20651	2419693
<i>Panel B. REC Biomass Capacity > 0, N = 67</i>				
<i>Capacities</i>				
REC solar capacity (MW)	4.0	3.9	0.0	19.3
REC wind capacity (MW)	11.0	19.9	0.0	125.0
REC biomass capacity (MW)	1.4	1.5	0.3	8.9
Total solar capacity (MW)	235.0	152.6	18.2	854.6
Total wind capacity (MW)	256.8	300.1	0.0	1496.1
Total biomass capacity (MW)	33.5	30.7	0.5	189.8
<i>Economic outcomes</i>				
SGB II receivers per capita	5.3	2.0	2.0	11.9
Employment rate (%)	66.5	3.7	52.1	72.6
Unemployment rate (%)	5.2	1.8	2.1	11.0
Real disp. income per capita (€)	23494	2022	20127	33526
<i>Demographics</i>				

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Table 1 continued

	Mean	SD	Min	Max
Population	194263	191113	39324	1490516
Working age population	120967	130628	24151	1033987
<i>Panel C. REC Solar Capacity > 0, N = 335</i>				
<i>Capacities</i>				
REC solar capacity (MW)	3.4	4.0	0.3	32.3
REC wind capacity (MW)	6.1	13.7	0.0	125.0
REC biomass capacity (MW)	0.3	0.8	0.0	8.9
Total solar capacity (MW)	192.2	144.0	13.4	854.6
Total wind capacity (MW)	165.9	280.3	0.0	2385.6
Total biomass capacity (MW)	25.9	28.9	0.0	189.8
<i>Economic outcomes</i>				
SGB II receivers per capita	5.3	2.7	1.5	19.1
Employment rate (%)	65.4	4.2	49.0	73.4
Unemployment rate (%)	4.7	2.0	1.7	14.1
Real disp. income per capita (€)	24393	2424	17508	38005
<i>Demographics</i>				
Population	223490	259097	42251	3632853
Working age population	142572	173251	27134	2419693
<i>Panel D. REC Wind Capacity > 0, N = 136</i>				
<i>Capacities</i>				
REC solar capacity (MW)	3.6	3.7	0.0	19.3
REC wind capacity (MW)	15.8	17.9	0.5	125.0
REC biomass capacity (MW)	0.4	1.1	0.0	8.9
Total solar capacity (MW)	231.0	153.0	50.0	854.6
Total wind capacity (MW)	282.8	315.8	2.6	1925.0
Total biomass capacity (MW)	33.7	33.9	0.4	189.8
<i>Economic outcomes</i>				
SGB II receivers per capita	4.9	2.0	1.5	10.8
Employment rate (%)	66.0	3.9	49.0	73.4
Unemployment rate (%)	4.5	1.7	1.7	9.6
Real disp. income per capita (€)	24251	2083	20625	38005
<i>Demographics</i>				

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Table 1 continued

	Mean	SD	Min	Max
Population	201005	190621	39596	1832675
Working age population	126774	126651	25290	1236671

Notes: This table reports descriptive statistics of the Germany county level panel data. Renewable Energy Community (REC) capacity in megawatts (MW) covers biomass, wind, and solar production owned by renewable energy communities. Total biomass, wind, and solar capacities includes non-REC and REC plants. Monetary values are in real euros. Source: authors' calculations. Data: Bundesagentur für Arbeit (2026a); Federal Network Agency (2025); INKAR (2025); Statistische Ämter des Bundes und der Länder (2026); Statistisches Bundesamt (2026); Wierling et al. (2023)

The second dataset at the household level uses the Socio-Economic Panel (SOEP), a nationally representative household survey. We use the waves 2010 to 2023, since electricity expenditures are only consistently available after 2010. Our balanced panel contains 199,842 household-year observations from 42,249 households.

We link the SOEP data to the renewable energy community plant data using confidential household location information. For each household-year observation, we calculate cumulative REC capacity within a 5 km radius of the household location. Our main treatment indicator is equal to one once the cumulative energy production capacity of renewable energy communities within this radius reaches at least 5 MW. We exclude households in whose 5 km radius the capacity of renewable energy communities is below 5 MW and households that experience a gradual increase in treatment to 5 MW and above. Based on this definition, 511 households are treated, corresponding to 2,368 treated household-year observations, while the remaining households form the control group.⁹

In the household-level data, our outcome variables are three expenditure-based energy poverty indicators constructed from SOEP household income and energy expenditure data: the ten percent rule (tpr), the two times median expenditure share indicator (mtwo), and the low-income high-cost indicator (lihc). These three indicators capture related but distinct dimensions of energy affordability: tpr provides an intuitive absolute expenditure-share threshold, mtwo uses a relative threshold based on the distribution of energy expenditure

⁹The 5 km radius is double the surface area of average German municipalities, thus matching local economic dynamics, and it strikes a balance between the number of observations (a 1 km radius with 1 MW capacity yields 89 treated households) and mildly treated units potentially confounding the results. We also report result for 1km radius in Appendix A6.

shares, and lihc combines high energy costs with low residual income. Using all three measures allows us to assess whether the estimated effects are robust across alternative operationalizations of energy poverty. All three outcomes are binary indicators equal to one if a household is classified as energy poor.¹⁰ Household income and energy expenditures are equivalized using the modified OECD scale (OECD, 2013).

We control for home ownership, education, employment status, and family type. Table 2 reports summary statistics for the resulting household-level dataset in the full sample (first two columns), at the 5 MW cutoff (columns 3 and 4), and at the 1 MW cutoff (columns 5 and 6).

Table 2: Summary statistics of German Socio-Economic Panel data, 2010–2023

	Full Sample <i>N</i> = 199842		Treated Sample (5 MW) <i>N</i> = 2368		Treated Sample (1 MW) <i>N</i> = 16364	
	Mean	SD	Mean	SD	Mean	SD
Total REC cap. within 5 KM	257	1277	11655	7339	3410	4497
<i>Energy poverty indicators</i>						
Ten percent rule (TPR)	0.24	0.43	0.24	0.43	0.22	0.41
Two times median share (M2)	0.11	0.31	0.12	0.33	0.11	0.31
Low income high costs (LIHC)	0.09	0.28	0.10	0.30	0.09	0.28
<i>Control variables</i>						
Owner of the house	0.42	0.49	0.44	0.50	0.32	0.47
Equivalized household income (€)	1602	3922	2032	2277	1989	1812
Equivalized energy expenditures (€)	118	73	122	74	117	95
<i>Education</i>						
Less than high school	0.15	0.36	0.16	0.37	0.17	0.37
High school	0.57	0.49	0.52	0.50	0.48	0.50
More than high school	0.28	0.45	0.31	0.46	0.35	0.48
<i>Employment</i>						
Employed	0.61	0.49	0.67	0.47	0.66	0.47
Registered unemployed	0.07	0.25	0.07	0.26	0.08	0.28
Not employed	0.05	0.23	0.08	0.28	0.08	0.27
In education	0.03	0.16	0.03	0.18	0.04	0.20
Pensioner	0.24	0.43	0.13	0.34	0.14	0.35
<i>Household type</i>						
Couple without children	0.28	0.45	0.23	0.42	0.24	0.43
Single parent	0.08	0.27	0.08	0.27	0.09	0.29
1-person household	0.24	0.43	0.22	0.41	0.28	0.45
Couple with children	0.36	0.48	0.43	0.50	0.35	0.48
Other	0.03	0.17	0.05	0.21	0.04	0.20

Notes: This table shows the German Socio-Economic Panel (SOEP) data augmented with the renewable energy communities (RECs) plant data.

Source: authors' calculations. Data: German Institute for Economic Research (DIW Berlin) (2023); Wierling et al. (2023).

¹⁰See the Appendix A.1 for details on the construction of the indicators.

3.2 Methodology

We apply two difference-in-difference strategies to identify the effect of renewable energy communities on income poverty and energy poverty in Germany. The first uses Germany county-level panel data and estimates the effect on SGB II receivers per capita, also substituting the outcome variable with the employment rate, the unemployment rate, and real disposable income per capita. The second approach employs household-level SOEP data, measuring households' exposure to renewable energy communities by calculating their cumulative energy production capacity within 5 km radii of households. We estimate the effect of this exposure on three indicators of energy poverty, the ten percent rule (tpr), two times median expenditure (mtwo), and low-income high-cost (lihc).

At the county level, we define treatment as the existence of renewable energy communities' production capacity for a given renewable energy source. Thus, a German county becomes treated for solar (biomass/wind) energy once the first renewable energy community plant of the respective type becomes operational in the county. In our main estimations, we classify counties with less than 100 kW of cumulative capacity by 2023 as untreated and we exclude counties with cumulative capacities between 100 kW and 250 kW to create a buffer around the treatment threshold ¹¹.

In the second case, a household is considered treated if there is at least 5 MW (1 MW) of cumulative renewable energy community production capacity within a 5 km radius. In this approach, we do not differentiate renewable energy community capacity by energy source to preserve statistical power.

At the county level, we thus estimate the following empirical model:

$$Y_{it} = \alpha + \beta Treatment_{it} + \gamma X_{it} + \lambda_i + \theta_t + \epsilon_{it}, \quad (1)$$

where Y is the outcome variable of interest, and i and t index countries and years, respectively. Treatment is a binary variable that turns from 0 to 1 when a county starts having a positive renewable energy community production capacity of biomass, wind, or solar while counties with capacities below 100 kW by 2023 are classified as untreated and counties with capacities between 100 kW and 250 kW are excluded. X is a vector of controls that includes the other two types of renewable energy community capacities and all other plant capacities. For instance, when we estimate the effect of renewable energy communities' solar capacity, we thus control for REC wind, REC biomass,

¹¹See Section ?? for a robustness check of this cut-off.

other solar, other wind, and other biomass capacities. Finally, λ and θ are county and time fixed effects.

At the household level, we employ a similar reduced form model. Here, Y is the outcome variable of the binary energy poverty indicators (1 = energy poor, 0 otherwise), while i indexes households and t indexes years. The binary treatment variable turns from 0 to 1 when renewable energy communities' capacity within 5 km radius of a household switches from 0 to 5 MW. X is a vector of controls that includes education, employment status, and binary home ownership.

Both counties and households receive treatment at different points in time. The recent literature shows that in such cases, the estimation of two-way fixed effects (TWFE) might be biased because TWFE compares already treated with newly treated units, causing a bias when the treatment effect is heterogeneous unit- and/or time-wise (Borusyak et al., 2024; Callaway & Sant'Anna, 2021; Goodman-Bacon, 2021). For this reason, we employ the estimator proposed by Callaway and Sant'Anna (2021) (from now on CSDID estimator), which is designed for the adoption of staggered treatment and allows for heterogeneity of treatment effects across cohorts and over time.

In addition, we adopt the doubly robust estimation procedure proposed by Sant'Anna and Zhao (2020). This is particularly relevant in our setting because renewable energy communities may not be randomly located across counties. For example, the location of REC plants may be related to the existing structure of renewable energy generation. The doubly robust procedure combines outcome regression with inverse probability weighting (IPW), taking advantage of the two approaches. The outcome regression accounts for differences in the expected untreated outcome conditional on the covariates. Meanwhile, IPW reweights observations according to their probability of belonging to a treatment cohort given these covariates. Thus, the estimation uses the observed covariates to make the treated and comparison groups more comparable before estimating the treatment effect. Intuitively, the method adjusts outcomes using a model for the untreated potential outcome conditional on covariates and then reweights observations according to their propensity to receive treatment. The doubly robust property means that consistency is maintained and an unbiased estimator for the population parameter can be recovered if either the outcome regression or the treatment-probability model is correctly specified (Sant'Anna & Zhao, 2020). The CSDID estimator incorporates this doubly robust procedure into the staggered-treatment setting (Callaway & Sant'Anna, 2021).

The most important identification assumption in our analysis is (condi-

tional) parallel trends. Identification therefore requires that, conditional on the observed covariates, treated and comparison units would have experienced the same evolution in untreated potential outcomes. In our setting, this assumption means that counties that eventually receive REC capacity and counties that are not yet treated or never treated would have followed the same trend in outcomes such as SGB II receivers per capita, employment, unemployment, and real disposable income, conditional on the covariates, had the REC treatment not occurred. This assumption is plausible in the case of household-level estimations, because households in the SOEP data are selected independently of the activity of renewable energy communities, and it is unlikely that the energy poverty of households influences the installation of new renewable energy communities' power plants. At the county level, this assumption may be more demanding, because the location of renewable energy communities may be systematically related to local economic conditions. To alleviate this concern, we employ local projections difference-in-differences proposed by Dube et al. (2025), which is suitable for a staggered treatment setting and can also incorporate pre-treatment outcome variables, as a robustness check.

Since our data follow the same counties over time, the standard errors of the county-level CSDID estimates are clustered at the county level. Thus, the inference allows the estimation errors of observations belonging to the same county to be correlated across years, rather than treating county-year observations within a county as independent. This accounts for serial correlation in the estimation errors when calculating statistical uncertainty. The same principle applies to the household-level estimates, for which standard errors are clustered at the household level. Importantly, clustering affects inference rather than identification meaning that it does not imply that county- or household-specific shocks are independent of treatment adoption, nor does it establish the parallel-trends assumption.

4 Results

In this section, we first present our estimation results based on Germany county level data and then discuss the energy poverty estimations based on SOEP household level data. Both county and household level analyses show that renewable energy community plants have important positive impacts on the local economy and on local individuals.

4.1 County Level Estimations

Table 3 shows the effect of renewable energy community plants on poverty by type of energy (biomass, solar, and wind). It contains the full sample in the first column of each energy type, restricts the sample to counties with operating capacity above 1MW at the end of 2023 in the second column, and restricts the sample to rural counties in the third column. The findings suggest that biomass plants that are owned by renewable energy communities reduce poverty, measured as SGB II receivers per capita, between about 0.6 and 1 percentage points in models (1) to (3). In contrast, both solar and wind capacity are not statistically significant.

Table 3: Renewable energy communities and poverty

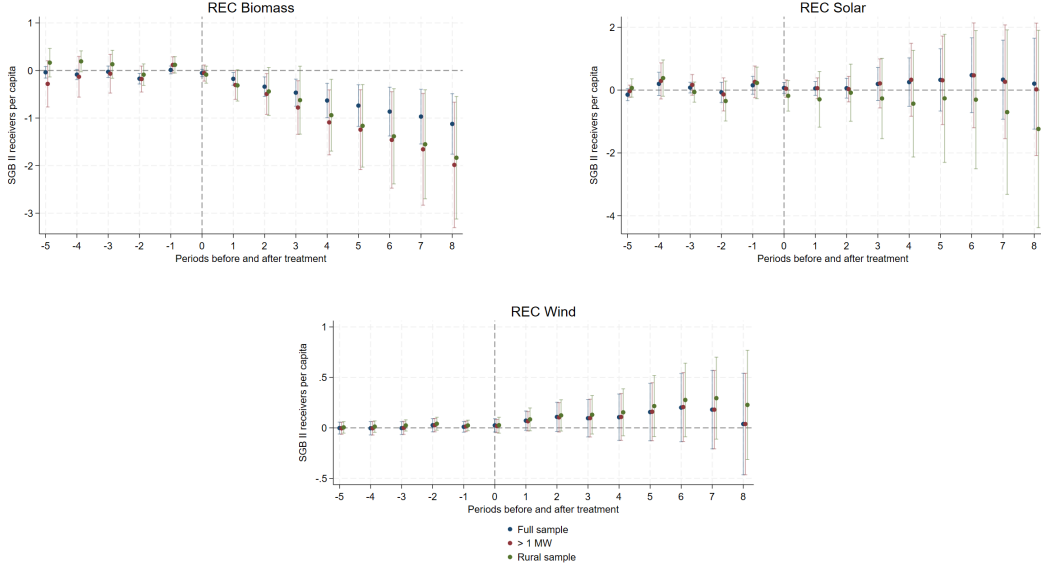
	REC Biomass			REC Solar			REC Wind		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
ATT	-0.60*** (0.175)	-1.01*** (0.346)	-0.93** (0.358)	0.22 (0.369)	0.19 (0.536)	-0.42 (0.805)	0.11 (0.120)	0.11 (0.121)	0.17 (0.129)
Capacity rest.	All	> 1 MW	> 1 MW	All	> 1 MW	> 1 MW	All	> 1 MW	> 1 MW
Rural sample	No	No	Yes	No	No	Yes	No	No	Yes
Observations	7,201	6,342	4,480	2,926	1995	1539	6,840	6,821	4,959

Notes: This table shows a DiD estimation for energy plants owned by renewable energy communities on SGB II income support receivers per capita using Germany county level panel data. Controls include total other renewable energy capacities. Columns (2), (5) and (8) restrict the sample to counties with more than 1 MW of renewable energy community capacity of the respective energy type by the end of 2023. Columns (3), (6) and (9) restrict the sample to rural counties. ATT is the Average Treatment Effect on the Treated. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Source: authors' calculations. Data: County-level panel data presented in Table 1.

Figure 3 shows the event study graphs that correspond to Table 3. Pretreatment parallel trends suggest that the German counties were moving together before the first opening of REC plants. The figure supports the conclusion from Table 3: biomass again demonstrates a convincing dynamic decrease of SGB II receivers per capita, while both solar and wind capacities do not appear to react to renewable energy communities.

Figure 3: Event study plots of renewable energy communities and poverty



Note: This figure shows the event study graphs that correspond to the estimates in Table 3 for renewable energy community (REC) owned biomass, solar, and wind power plants and SGB II recipients per capita.

Source: authors' calculations. Data: County-level panel data presented in Table 1.

Next, we explore the channels through which renewable energy community plants can affect poverty by estimating other, related outcome variables such as the employment rate, the unemployment rate, and real disposable income per capita. Table 4 presents the results, with the specifications of the three models for each energy type identical to the ones in Table 3.

In line with the estimations presented in Table 3, we find that biomass plants owned by renewable energy communities work through the three potential channels: the employment rate increases by about 0.8 to 1.3 percentage points while the unemployment rate decreases by about 0.9 to 1.4 percentage points. Furthermore, renewable energy communities' biomass capacity raises real disposable income per capita between roughly 190 and 350 Euro. In contrast, again, renewable energy communities' solar and wind capacity does not appear to affect either of our three potential channels.

Figure 4 presents the event study estimations corresponding to Table 4. They show that renewable energy communities' biomass plants have the clearest effect and that these persist statistically significantly over the period under estimation with the exception of the rural sample for income. Solar and wind plants, on the other hand, only show a few weakly statistically signifi-

Table 4: Renewable energy communities and employment, unemployment, and income

	REC Biomass			REC Solar			REC Wind		
<i>Panel A. Employment Rate</i>									
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
ATT	0.69*** (0.192)	1.33*** (0.292)	1.13*** (0.310)	-0.01 (0.242)	0.06 (0.291)	0.12 (0.336)	-0.05 (0.110)	-0.04 (0.114)	-0.16 (0.135)
Sample rest.	All	> 1 MW	> 1 MW	All	> 1 MW	> 1 MW	All	> 1 MW	> 1 MW
Rural sample	All	All	Rural	All	All	Rural	All	All	Rural
Observations	10,584	9,272	6,626	9,315	6,723	5,697	10,530	10,449	7,722
<i>Panel B. Unemployment Rate</i>									
	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)
ATT	-0.86*** (0.192)	-1.36*** (0.372)	-1.16*** (0.431)	-0.23 (0.274)	-0.46 (0.319)	-0.52 (0.448)	0.03 (0.123)	0.02 (0.129)	0.06 (0.149)
Sample rest.	All	> 1 MW	> 1 MW	All	> 1 MW	> 1 MW	All	> 1 MW	> 1 MW
Rural sample	All	All	Rural	All	All	Rural	All	All	Rural
Observations	10,192	8,927	6,379	8,736	6,266	5,356	10,062	10,010	7,410
<i>Panel C. Real Disposable Income per Capita</i>									
	(19)	(20)	(21)	(22)	(23)	(24)	(25)	(26)	(27)
ATT	190.72*** (67.132)	345.14*** (94.918)	194.18* (104.438)	-103.81 (117.250)	-191.25 (166.730)	-67.29 (99.985)	86.12 (82.841)	81.18 (84.651)	-40.77 (93.159)
Sample rest.	All	> 1 MW	> 1 MW	All	> 1 MW	> 1 MW	All	> 1 MW	> 1 MW
Rural sample	All	All	Rural	All	All	Rural	All	All	Rural
Observations	10,636	9,310	6,631	9,576	6,843	5,786	10,582	10,503	7,740

Notes: This table shows a DiD estimation of renewable energy plants owned by renewable energy communities (RECs) on the employment rate in panel A, the unemployment rate in panel B, and real disposable income per capita in Panel C, using German county level panel data. Controls include total other renewable energy capacities. Columns (2), (5) and (8) restrict the sample to counties with more than 1 MW of renewable energy community capacity of the respective energy type by the end of 2023. Columns (3), (6) and (9) restrict the sample to rural counties. ATT is the Average Treatment Effect on the Treated. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Source: authors' calculations. Data: County-level panel data presented in Table 1.

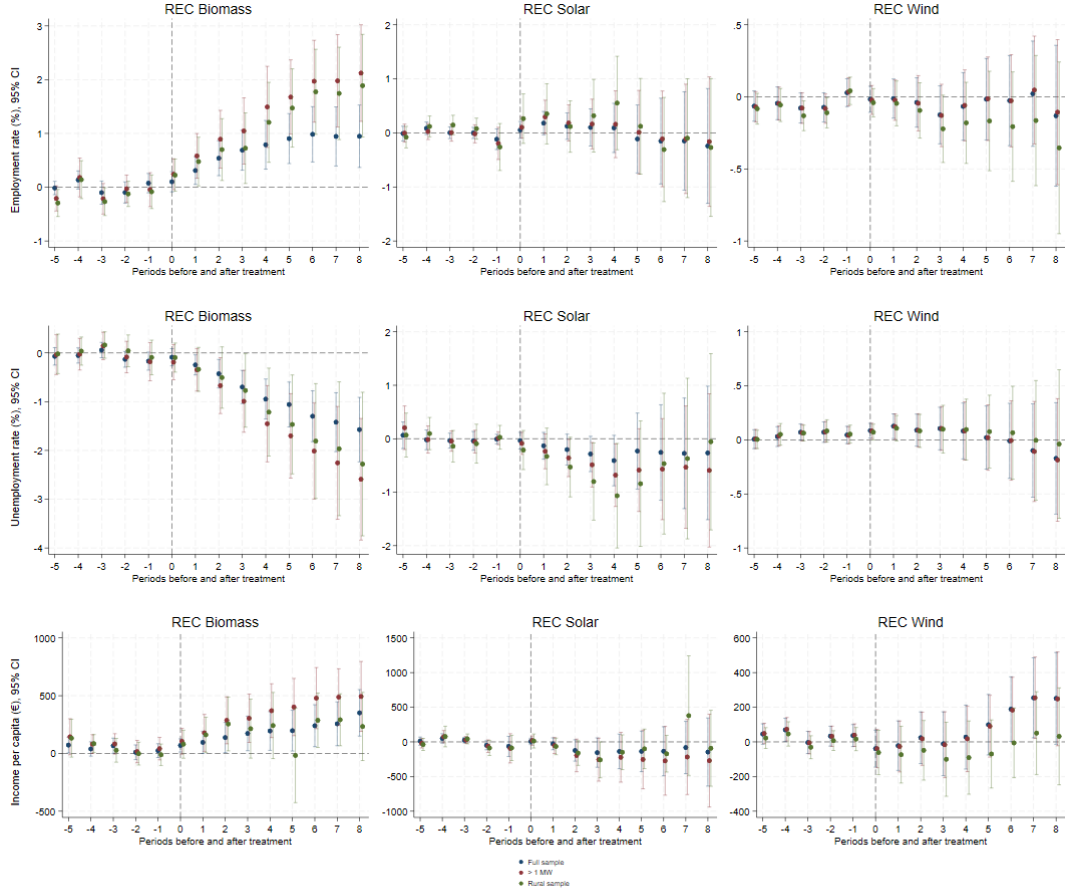
cant effects for unemployment and income, respectively, but are on the whole undistinguishable from zero.

4.2 Household Level Estimations

An important channel through which renewable energy communities might reduce poverty is energy poverty.

Turning to the household level, we see that the capacity of renewable energy communities within the proximity of households tends to reduce energy poverty indicators, although the magnitude and statistical significance vary across the estimations at the conventional levels. The most striking result is that energy poverty measured by the “mtwo” indicator capturing energy expenditures exceeding twice the median decreases by about 14 percentage points when at least 5 MW capacity of renewable energy communities is installed

Figure 4: Event study plots of renewable energy communities and employment, unemployment, and income



Note: This figure shows the event study graphs that correspond to the estimates in Table 4 for renewable energy community (REC) owned biomass, solar, and wind power plants and the employment rate, the unemployment rate, and disposable income per capita. Source: authors' calculations. Data: County-level panel data presented in Table 1.

within a 5 km radius. For the tpr indicator, which defines households as energy poor if their expenditures exceed ten percent of household income, energy poverty declines by about 7 percentage points with at least 1 MW renewable energy capacity within a 5 km radius. We interpret these findings as evidence that renewable energy communities reduce energy poverty when measured at the household level.

As Figure 5 below shows, the pre-treatment energy poverty indicators of households move largely in parallel. The trend break after the treatment is most convincing in the case of the mtwo indicator for 5 MW, and to some degree for the mtwo and tpr indicator for 1 MW.

Table 5: Renewable energy communities and energy poverty (household level)

	Low Income High Cost (lihc)		Two Times Median Energy Expenditure (mtwo)		Ten Percent Rule (tpr)	
<i>Panel A: > 5 MW REC Capacity within 5 KM</i>						
ATT	-6.30 (4.611)	-6.70 (4.538)	-14.16* (5.945)	-14.55* (5.849)	-8.03 (5.214)	-6.89 (5.438)
Controls	No	Yes	No	Yes	No	Yes
<i>Panel B: > 1 MW REC Capacity within 5 KM</i>						
ATT	-2.52 (2.591)	-2.29 (2.617)	-5.61* (2.629)	-5.27 (2.701)	-7.94* (3.174)	-6.55* (3.155)
Controls	No	Yes	No	Yes	No	Yes

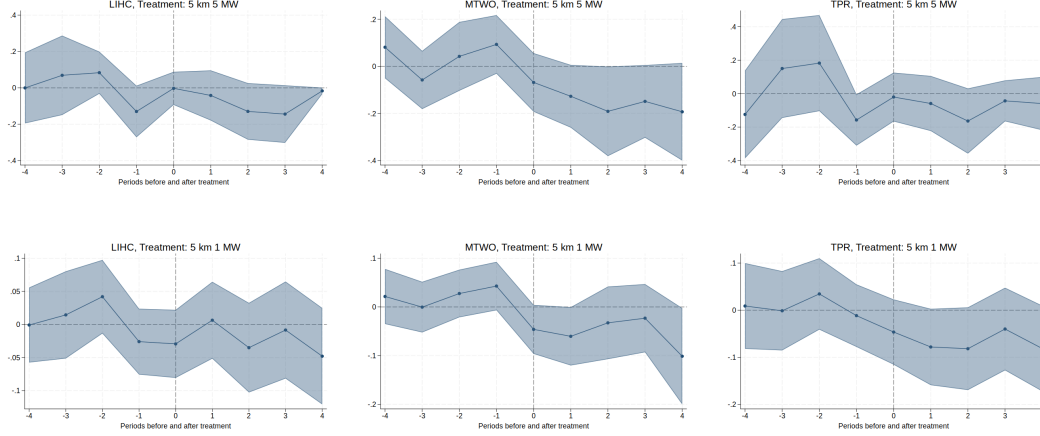
Notes: This table shows a DiD estimation of renewable energy capacity owned by renewable energy communities (REC) within 5 km of the household's location with a 5 MW (Panel A) and 1 MW (Panel B) threshold on three energy poverty indicators. These are binary variables (1 = energy poor) for low income high cost (lihc), two times median share (mtwo), and ten percent rule (tpr). ATT is the Average Treatment Effect on the Treated. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Source: authors' calculations. Data: Household-level panel data presented in Table 2.

We present energy poverty estimations at the household-level data by defining treatment as having 1 MW REC capacity within 1 km radius, and these results can be found in Appendix A6. With this treatment definition, we do not see any impact of REC capacity on energy poverty indicators (Table A6.1). However, as we mentioned, 1 km radius is very restrictive and this makes the treated units to drop to 89 households. This restrictiveness is evidenced by the event-study graphs presented in Figure A6.1. We can see that some point estimations cannot be made simply because the lack of statistical power.

To conclude, we find substantial differences at the county level for the different renewable-energy technologies. While community-owned biomass plants are associated with lower poverty and unemployment, and higher employment and income, this does not translate to solar and wind plants. This fits with the mixed literature on the economic effects of investment in renewable energy capacities (Costa & Veiga, 2021; Fabra et al., 2024; Mauritzen, 2020; Scheifele & Popp, 2025). The findings are also in line with Hoeschle et al. (2025) as they find positive effects of community biomass on income and tax revenues. It contrasts; however, with the results in Dilek and Bühler (2026) because they report some positive local economic benefits of community solar and wind capacities in the UK in terms of income while, in our study, we find positive effects coming from community biomass and we fail to detect any impacts of community wind capacity. One possible explanation for our findings

Figure 5: Event study plots of renewable energy communities and energy poverty indicators



Notes: This figure shows the event study graphs that correspond to the estimates in Table 5 for renewable energy community (REC) owned biomass, solar, and wind power plants and three energy poverty indicators. These are binary variables (1 = energy poor) for low income high cost (lihc), two times median share (mtwo), and ten percent rule (tpr). Top (bottom) row: treated = 5 (1) MW REC capacity within 5 km neighborhood. 95% confidence intervals.

Source: authors' calculations. Data: Household-level panel data presented in Table 2.

is that biomass plants typically process local farming byproducts, generating extra income for the local farm business (Hoeschle et al., 2025) while Wüste and Schmuck (2012) report positive local economic effects of biomass capacity in Germany without specifying exact mechanism. In this case, biomass energy might have an additional advantage over solar and wind energy for local economies that they rely more on local supply chains than the other two technology types.

At the household level, the exposure to nearby renewable energy communities' capacities is linked to lower energy poverty across our three indicators, although the magnitude and statistical precision of the estimates vary. This evidence countervails with the existing evidence of renewable energy and energy poverty relationship in the European context (Muhammad et al., 2023; Priesmann et al., 2022; Simionescu & Cifuentes-Faura, 2024; Simionescu et al., 2023). Although we caution that statistical power of the evidence that we present here is not conclusive, the mechanisms of renewable energy communities reducing energy poverty are plausible. Renewable energy communities provide employment, income, as well as energy saving measures, training and education (Barroco Fontes Cunha et al., 2021; Basilico et al., 2026; Lupi et al.,

2021; Young & Halleck Vega, 2024).

5 Robustness Checks

We check the robustness of our results in several ways. We investigate potential concerns regarding the endogeneity of renewable energy communities by, first, accounting for pre-treatment outcome dynamics and, second, controlling for the local economic structure. We ensure that our decisions on cut-offs do not drive the results by investigating different capacity cut-offs at the county-level and at the household level and, finally, by applying a continuous-treatment estimator.

For the first robustness check, we aim to alleviate a potential concern of self-selection of counties into treatment through investment in renewable energy communities by applying a local projections difference-in-difference estimator. This approach incorporates lags of the outcome variable (Dube et al., 2025) and thus controls for the impact of the outcome variable's pretreatment values on the selection into treatment. As Table 6 and Figure 6 show, our results are largely robust to applying local projections difference-in-differences.

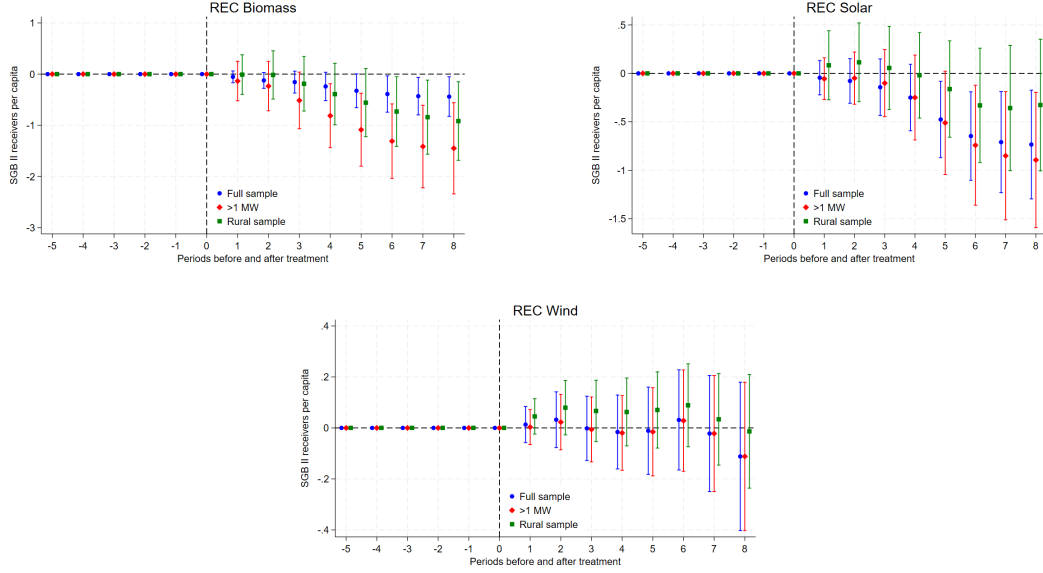
Table 6: Renewable energy communities and poverty using local projections DiD

	REC Biomass			REC Solar			REC Wind		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
ATT	-0.21*	-0.75**	-0.44	-0.28	-0.28	-0.09	-0.03	-0.03	0.03
	(0.128)	(0.352)	(0.320)	(0.169)	(0.207)	(0.221)	(0.100)	(0.100)	(0.084)
Capacity rest.	All	> 1 MW	> 1 MW	All	> 1 MW	> 1 MW	All	> 1 MW	> 1 MW
Rural sample	No	No	Yes	No	No	Yes	No	No	Yes
Observations	7,201	6,342	4,480	2,926	1995	1539	6,840	6,821	4,959

Notes: This table shows local projections DiD estimations for energy plants owned by renewable energy communities on SGB II income support receivers per capita using Germany county level panel data. Controls include total other renewable energy capacities. Columns (2), (5), and (8) restrict the sample to counties with more than 1 MW of renewable energy community capacity of the respective enrgy type by the end of 2023. Columns (3), (6), and (9) restrict the sample to rural counties. ATT is the Average Treatment Effect on the Treated. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Source: authors' calculations. Data: County-level panel data presented in Table 1.

Figure 6: Event study plots of renewable energy communities and poverty using local projections DiD



Notes: This figure shows the event study graphs that correspond to the estimates in Table 6 for renewable energy communities (REC) and biomass, solar, and wind power plants.

Source: authors' calculations. Data: County-level panel data presented in Table 1

The second robustness check aims to investigate whether German counties self-select into treatment based on their economic structure. We therefore add controls for the share of agriculture, mining-manufacturing-water supply and sewerage, and services¹² to our main estimation of renewable energy communities' capacities on poverty. Again, our results are robust to this alteration, as Table 7 and Figure 7 show.

Third, we jitter the capacity cut-off that defines our treatment variable at the county level. Concretely, we re-estimate our main result while applying a 2.5 and 5 MW cut-off instead of the original 1 MW of renewable energy communities capacity in the respective energy type for considering a county as treated. As Table 8 shows, the results are broadly robust, although biomass loses its significance in the rural sample at 2.5 MW probably due to the low number of treated observations. For the same reason, biomass cannot be estimated at the 5 MW cut-off since not a single county is treated during our period of observation.

¹²Construction is excluded to avoid multicollinearity.

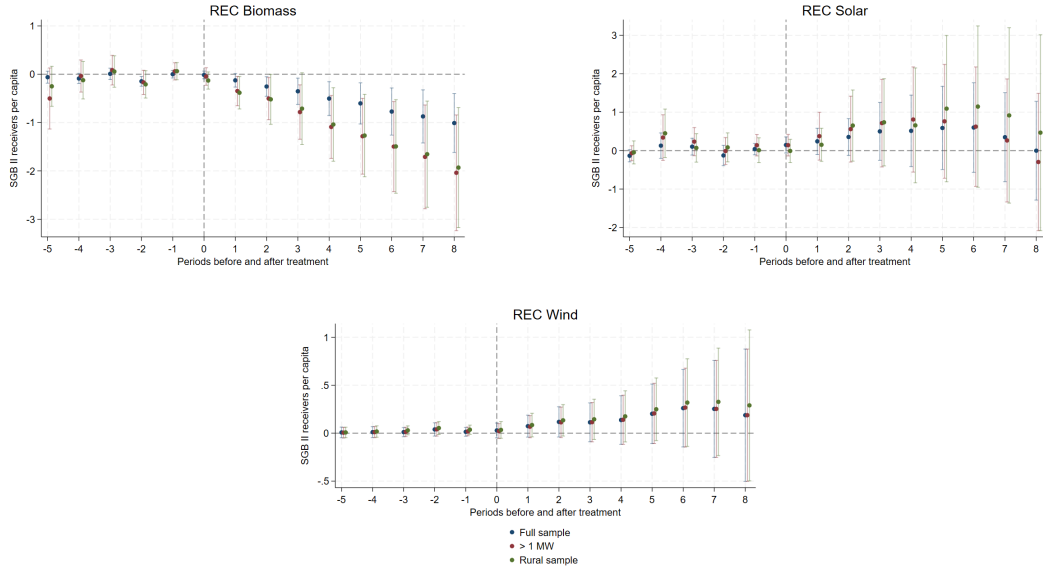
Table 7: Renewable energy communities and poverty controlling for sectors

	REC Biomass			REC Solar			REC Wind		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
ATT	-0.50*** (0.168)	-1.03*** (0.325)	-1.01*** (0.350)	0.37 (0.375)	0.44 (0.537)	0.65 (0.675)	0.15 (0.147)	0.15 (0.148)	0.20 (0.161)
Capacity rest.	All	> 1 MW	> 1 MW	All	> 1 MW	> 1 MW	All	> 1 MW	> 1 MW
Rural sample	No	No	Yes	No	No	Yes	No	No	Yes
Observations	7,201	6,342	4,470	2,919	1,984	1,539	6,840	6,821	4,959

Notes: This table shows DiD estimations for energy plants owned by renewable energy communities on SGB II income support receivers per capita using Germany county level panel data. Controls include total other renewable energy capacities and sector shares. Columns (2), (5), and (8) restrict the sample to counties with more than 1 MW of renewable energy community capacity of the respective energy type by the end of 2023. Columns (3), (6), and (9) restrict the sample to rural counties. ATT is the Average Treatment Effect on the Treated. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Source: authors' calculations. Data: County-level panel data presented in Table 1.

Figure 7: Event study plots of renewable energy communities and poverty controlling for sectors



Notes: This figure shows the event study graphs that correspond to the estimates in Table 7 for renewable energy communities (REC) and biomass, solar, and wind power plants.

Source: authors' calculations. Data: County-level panel data presented in Table 1

Fourth, we relax our assumption in the main estimations that counties with less than 100 kW of cumulative REC capacity should be classified as untreated. Table A4.1 in the Appendix shows the results when all counties with positive capacities of renewable energy communities are classified as treated.

Table 8: Renewable energy communities and poverty with different cut-offs

	REC Biomass				REC Solar				REC Wind			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
ATT	-1.0627** (0.48461)	-0.8957 (0.59746)	-	-	0.6102 (0.72580)	-0.3858 (1.09898)	0.7383 (0.86110)	-0.5746 (1.93929)	0.0617 (0.13340)	0.1188 (0.13013)	-0.0568 (0.15796)	0.0060 (0.15087)
Capacity rest.	> 2.5 MW	> 2.5 MW	> 5 MW	> 5 MW	> 2.5 MW	> 2.5 MW	> 5 MW	> 5 MW	> 2.5 MW	> 2.5 MW	> 5 MW	> 5 MW
Rural sample	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes
Observations	6,270	4,389	-	-	1,387	1,045	950	597	6,650	4,802	6,232	4,384

Notes: This table shows DiD estimations for energy plants owned by renewable energy communities on SGB II income support receivers per capita using Germany county level panel data. It drops counties with capacity in the respective energy type below 2.5 MW in columns (1-2), (5-6), and (9-10) and below 5 MW in columns (3-4), (7-8), and (11-12). Biomass at 5 MW is not reported due to data limitations. ATT is the Average Treatment Effect on the Treated. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Source: authors' calculations. Data: County-level panel data presented in Table 1.

The results are largely robust: biomass remains negative and statistically significant, with magnitudes comparable to those reported in Table 3. Solar is less stable, with a large negative and a positive coefficient. This sensitivity suggests that counties with relatively low solar capacity of renewable energy communities may introduce substantial variation into the estimates, making its effect less precisely identified. Finally, we continue to find no statistically significant correlation of wind with poverty.

Finally, we examine the role of capacity thresholds and the sensitivity of our results to low-capacity observations further by using the continuous-treatment estimator proposed by de Chaisemartin and D'Haultfoeuille (2026). This estimator identifies the average effect associated with a marginal increase of 1 kW in REC capacity at the county level. The results, reported in Table A5.1, are again broadly consistent with our main findings: Biomass is consistently associated with lower poverty while solar is inconsistent and wind is not statistically significant.

All in all, we therefore conclude that our findings for biomass appear to be highly robust to alternative specifications, while wind is consistently insignificant. For solar, we find some evidence that very low capacity counties may have an outsized impact and leads to inconsistent results.

6 Conclusion

This paper examines whether renewable energy communities contribute to reducing income and energy poverty in Germany. Combining county-level data on plants owned by renewable energy communities with administrative economic outcomes and household-level SOEP data, we study both local economic effects and household energy poverty using staggered difference-in-differences

methods.

Our county-level results point to substantial differences across renewable-energy technologies. Community-owned biomass plants are associated with lower poverty as measured by SGB II receipt as well as lower unemployment, higher employment, and higher disposable income per capita. These findings are broadly robust across alternative specifications. By contrast, we find no statistically significant effects of community-owned solar or wind plants on the county-level outcomes in our main estimations. At the household level, exposure to capacity of nearby renewable energy communities is associated with lower energy poverty across all three indicators considered (low income high cost, two times median energy expenditure, ten percent rule). The magnitude and statistical precision of these estimates vary across treatment definitions and energy-poverty measures, however, and the results should therefore be interpreted with some caution.

Several limitations should nevertheless be kept in mind. The location of renewable energy communities is not random, and although our robustness checks account for pre-treatment outcome dynamics and local economic structure, unobserved local developments may still affect both the adoption of renewable energy communities and economic outcomes. In the household analysis, nearby capacity of renewable energy communities captures local exposure rather than direct household participation, which limits conclusions about the underlying mechanisms. Finally, the household treatment depends on specific choices about the spatial radius and capacity threshold used to define local exposure to renewable energy communities. These choices involve a trade-off between capturing meaningful exposure and retaining a sufficiently large treated sample. While the results are broadly similar across alternative definitions, the estimates should therefore be interpreted as pertaining to these operationalizations of local exposure to renewable energy communities rather than to a uniquely defined treatment threshold.

Overall, despite these limitations, the findings suggest that renewable energy communities may have broader socio-economic implications, but the magnitude, mechanisms, and causal interpretation remain uncertain. Further research should examine these mechanisms more directly and assess under which conditions community energy may contribute to distributional objectives as well as to energy affordability.

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A Appendix

A.1 Construction of expenditure-based energy poverty indicators

We construct three expenditure-based energy poverty indicators using SOEP household income and energy expenditure data: the ten percent rule (TPR), the two times median expenditure share indicator (MTWO), and the low-income high-cost indicator (LIHC). In all cases, households are classified as energy poor using a binary variable. Household income and energy expenditures are equivalized using the modified OECD equivalence scale (OECD, 2013).

Let E_{it} denote equivalized energy expenditures and Y_{it} equivalized household income of household i in year t . The ten percent rule classifies a household as energy poor if its equivalized energy expenditures exceed 10 percent of equivalized household income:

$$\frac{E_{it}}{Y_{it}} > 0.10.$$

The two times median expenditure share indicator uses a relative threshold. A household is classified as energy poor if its energy expenditure share exceeds twice the median energy expenditure share in year t :

$$\frac{E_{it}}{Y_{it}} > 2 \cdot \text{median}_t \left(\frac{E_{it}}{Y_{it}} \right).$$

The low-income high-cost indicator combines an expenditure and an income criterion. A household is classified as energy poor if its equivalized energy expenditures are above the median and its residual income after energy expenditures falls below the poverty threshold, defined as 60 percent of median equivalized income:

$$E_{it} > \text{median}_t(E_{it}) \quad \text{and} \quad Y_{it} - E_{it} < 0.60 \cdot \text{median}_t(Y_{it}).$$

These indicators differ in how they capture energy affordability. TPR is intuitive and widely used, but its fixed expenditure-share threshold may classify higher-income households with high energy spending as energy poor even when they are not financially deprived (Heindl, 2015). MTWO partly addresses this by using a relative expenditure-share threshold, but it remains sensitive to the distribution of energy expenditures and does not directly account for low

income (Heindl, 2015). LIHC combines high energy costs with low residual income and therefore more directly identifies households facing both high energy burdens and limited financial resources (Buchner & Rehm, 2025; Drescher & Janzen, 2021).

A.2 Definition of variables

Table A2.1: Summary of county-level panel data variables: Definitions, codes, sources, and time spans

Category	Name	Definition	Code	Source	Time span
Treatment	REC Biomass	Cumulative biomass capacity owned by renewable energy communities in a county (MW).	enbp_biomass	Wierling et al. (2023)	1990–2023
	REC Solar	Cumulative solar capacity owned by renewable energy communities in a county (MW).	enbp_solar	Wierling et al. (2023)	1990–2023
	REC Wind	Cumulative wind capacity owned by renewable energy communities in a county (MW).	enbp_wind	Wierling et al. (2023)	1990–2023
Outcome	SGB II receivers per capita	The number of people receiving SGB II benefits in a county divided by the population of the county (per 100 persons).	peop_rec_inc_supp_pc	Bundesagentur für Arbeit (2026a)	2005–2025
	Employment rate	People who are employed divided by the working age population (per 100 persons).	employment_rate	INKAR (2025)	1997–2023
	Unemployment rate	Percentage of unemployed persons in the labor force (%).	unemployment_rate	INKAR (2025)	1998–2023
	Real disposable income per capita	Disposable income of private households including private non-profit organizations per inhabitant (EUR) adjusted to real figures using the GDP deflator.	real_disp_inc_pc	Statistische Ämter des Bundes und der Länder (2026)	1995–2023
Control	REC Bio. Per Capita	Cumulative biomass capacity owned by renewable energy communities in a county (MW) divided by the population of the county.	enbp_biomass_pc	Wierling et al. (2023)	1990–2023
	REC Solar Per Capita	Cumulative solar capacity owned by renewable energy communities in a county (MW) divided by the population of the county.	enbp_solar_pc	Wierling et al. (2023)	1990–2023
	REC Wind Per Capita	Cumulative wind capacity owned by renewable energy communities in a county (MW) divided by the population of the county.	enbp_wind_pc	Wierling et al. (2023)	1990–2023
	Total Bio. Per Capita	Total biomass capacity in a county (MW) divided by the population of the county.	mastr_biomass_pc	Federal Network Agency (2025)	1990–2023
	Total Solar Per Capita	Total solar capacity in a county (MW) divided by the population of the county.	mastr_solar_pc	Federal Network Agency (2025)	1990–2023
	Total Wind Per Capita	Total wind capacity in a county (MW) divided by the population of the county.	mastr_wind_pc	Federal Network Agency (2025)	1990–2023
	Gross value added share of agriculture	Real gross value added by NACE A sector (Agriculture, forestry logging, and fishing) divided by total real GVA.	gva_share_A	ARDECO (2026)	1995–2025
	Gross value added share of industry	Real gross value added by NACE B-E sectors (Mining, manufacturing, utilities, sewage) divided by total real GVA.	gva_share_B_E	ARDECO (2026)	1995–2025
	Gross value added share of services	Real gross value added by NACE G-U service sectors divided by total real GVA.	gva_share_G_U	ARDECO (2026)	1995–2025
Other	Population	Total number of inhabitants of a county.	population	INKAR (2025)	1995–2023
	Working age population	Number of inhabitants aged 15 to under 65 years.	working_age_population	INKAR (2025)	1995–2023

Table A2.2: Summary of household-level panel data variables: Definitions, codes, sources, and time spans

Category	Name	Definition	Code	Source	Time span
Treatment	Total REC capacity within 5 KM	Total biomass, solar, and wind energy capacities owned by renewable energy communities around 5 KM neighborhood of a household.	treatment_five_km	Wierling et al. (2023); German Institute for Economic Research (DIW Berlin) (2023)	2010–2023
Outcome	Energy poor: Ten percent rule (TPR)	Dummy variable. 1 if the household is energy poor according to this definition, 0 otherwise. Please check Appendix A1 for a detailed definition.	tpr	German Institute for Economic Research (DIW Berlin) (2023)	2010–2023
	Energy poor: Two times median share (M2)	Dummy variable. 1 if the household is energy poor according to this definition, 0 otherwise. Please check Appendix A1 for a detailed definition.	mtwo	German Institute for Economic Research (DIW Berlin) (2023)	2010–2023
	Energy poor: Low income high cost (LIHC)	Dummy variable. 1 if the household is energy poor according to this definition, 0 otherwise. Please check Appendix A1 for a detailed definition.	lihc	German Institute for Economic Research (DIW Berlin) (2023)	2010–2023
Control	Owner of the house	Dummy variable. 1 if the household owns the house that they live in, 0 otherwise.	owner	German Institute for Economic Research (DIW Berlin) (2023)	2010–2023
	Less than high school	Category variable for education status. The household head has less than high school education. The reference category is "Less than high school".	education	German Institute for Economic Research (DIW Berlin) (2023)	2010–2023
	High school	Category variable for education status. The household head has high school education. The reference category is "Less than high school".	education	German Institute for Economic Research (DIW Berlin) (2023)	2010–2023
	More than high school	Category variable for education status. The household head has more than high school education. The reference category is "Less than high school".	education	German Institute for Economic Research (DIW Berlin) (2023)	2010–2023
	Employed	Category variable for the labor market status. The household head is employed. The reference category is "Employed".	labor_force_status	German Institute for Economic Research (DIW Berlin) (2023)	2010–2023
	Registered unemployed	Category variable for the labor market status. The household head is unemployed. The reference category is "Employed".	labor_force_status	German Institute for Economic Research (DIW Berlin) (2023)	2010–2023
	Not employed	Category variable for the labor market status. The household head is not employed and not looking for a job. The reference category is "Employed".	labor_force_status	German Institute for Economic Research (DIW Berlin) (2023)	2010–2023
	In education	Category variable for the labor market status. The household head is in education. The reference category is "Employed".	labor_force_status	German Institute for Economic Research (DIW Berlin) (2023)	2010–2023
	Pensioner	Category variable for the labor market status. The household head is a pensioner. The reference category is "Employed".	labor_force_status	German Institute for Economic Research (DIW Berlin) (2023)	2010–2023
	Couple w/o a children	Category variable for the household type. The reference category is "Couple without children".	hhtype	German Institute for Economic Research (DIW Berlin) (2023)	2010–2023
	Single parent	Category variable for the household type. The reference category is "Couple without children".	hhtype	German Institute for Economic Research (DIW Berlin) (2023)	2010–2023
	1-person household	Category variable for the household type. The reference category is "Couple without children".	hhtype	German Institute for Economic Research (DIW Berlin) (2023)	2010–2023
	Couple with children	Category variable for the household type. The reference category is "Couple without children".	hhtype	German Institute for Economic Research (DIW Berlin) (2023)	2010–2023
	Other	Category variable for the household type. The reference category is "Couple without children".	hhtype	German Institute for Economic Research (DIW Berlin) (2023)	2010–2023

A.3 Data cleaning process

Wierling et al. (2023) presents REC plant data for Germany. The raw data contains unit code, unit name, founding date, capacity, energy type, street address, postal code, latitude, longitude, operational status, and owner information. However, there are missing values for each of these variables.

A.3.1 Duplicates

We reasoned that the dataset contains duplicates while the original dataset recorded these observations with distinct codes. Hence, we think that the data collectors made errors in fact. Such duplicates are around 0.2% of the dataset.

These duplicates are diagnosed by comparing their location and capacity information. For instance, Photovoltaik-Anlage Klüsserat and PV-Klüsserath are two distinct entries in the data with the same capacity (5119 kW) and the same postal code (54340). The unit names are not exactly the same and unit codes are different as well. If we check the latitude and longitude information, we see that these entries are not exactly the same; however, both locations show the same solar plant on the map. Photovoltaik-Anlage Klüsserat’s exact location is (49.85398, 6.827468) and PV-Klüsserath’s exact location is (49.853947, 6.82703). Such duplicates are removed from the dataset.

A.3.2 Missing observations

Wierling et al. (2023) dataset has important missing values for some plants. For instance, some plants do not have capacity information, founding date, or postal code and location.

These values can be imputed from MaStR German energy market register data (Federal Network Agency, 2025). MaStR data contains complete data on capacity, location, and founding date. However, the plants recorded in Wierling et al. (2023) dataset are recorded with different unit names and different unit codes than MaStR dataset. Hence, we follow a procedure to make use the most of MaStR dataset to impute missing observations in Wierling et al. (2023) dataset. The procedure can be summarized as:

- i) The plants are matched based on their exact locations. In this way, if a plant has location information but its capacity and/or founding date information is missing, we can impute it from the MaStR dataset.
- ii) After exact location match, we proceed with fuzzy matching the names of the plants in the two datasets. We use Jaro-Winkler similarity metric with

0.2 distance tolerance. After this name matching, we check further whether the two plants are "close enough" to each other. We required the distance to be 500 meters and lower to conclude that the two plants are indeed the same plant. After this matching, we can impute important missing values for the plants recorded in Wierling et al. (2023) dataset.

The above procedure can be applied for the plants that we know the location information. However, for the plants that do not have any location information, we proceed with a manual correction. The number of such plants are few: 63 biomass, 88 solar, and 38 wind plants do not have location information in Wierling et al. (2023) dataset. These plants are fuzzy matched with MaStR based on their names. However, after this fuzzy name match, we manually look the two datasets' critical information regarding each plant, such as founding date, and capacity. If we see that these entries match, then we conclude that the two plants are the same and we impute the location information from MaStR dataset.

A.4 Estimations without county exclusions

Table A4.1: Renewable energy community plants and poverty

	REC Biomass			REC Solar			REC Wind		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
ATT	-0.4556*** (0.15463)	-1.0072*** (0.34626)	-0.9264*** (0.35799)	0.0291 (0.69112)	-9.6775*** (2.24573)	0.9195*** (0.30468)	0.1091 (0.11999)	0.1087 (0.12078)	0.1701 (0.12892)
Capacity rest.	All	> 1 MW	> 1 MW	All	> 1 MW	> 1 MW	All	> 1 MW	> 1 MW
Rural sample	No	No	Yes	No	No	Yes	No	No	Yes
Observations	7,326	6,342	4,480	2,949	1,509	641	6,840	6,821	4,959

Notes: This table shows the coefficients of a DiD estimation for energy plants owned by renewable energy communities on SGB II income support receivers per capita using Germany county level panel data. Every county that has positive capacity is defined as treated. Controls include total other renewable energy capacities. Columns (2), (5), and (8) restrict the sample to counties with more than 1 MW of renewable energy community capacity of the respective energy type by the end of 2023. Columns (3), (6), and (9) restrict the sample to rural counties. ATT is the average post-treatment coefficient. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Source: authors' calculations. Data: County-level panel data presented in Table 1.

A.5 Estimations with continuous treatment

Table A5.1: Renewable energy community plants and poverty

	REC Biomass		REC Solar		REC Wind	
	(1)	(2)	(3)	(4)	(5)	(6)
ATT	-0.0009089*** (0.000)	-0.0009611*** (0.000)	-0.0000393 (0.000)	0.0004173** (0.000)	0.0000095 (0.000)	0.0000114 (0.000)
Covariates	Yes	Yes	Yes	Yes	Yes	Yes
Rural sample	No	Yes	No	Yes	No	No
Observations	6,573	4,755	1,713	1,241	6,281	4,521

Notes: This table shows the coefficients of a DiD estimation for energy plants owned by renewable energy communities on SGB II income support receivers per capita using Germany county level panel data. The estimations use de Chaisemartin and D'Haultfœuille (2026) continuous treatment. The estimated coefficients should be interpreted as “the effect of 1 kW additional capacity on SGB II receivers per capita”. Controls include total other renewable energy capacities. Columns (2) and (4) restrict the sample to rural counties. ATT is the average total effect coefficient. Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Source: authors' calculations. Data: County-level panel data presented in Table 1.

A.6 Energy poverty estimations with 1 km radius

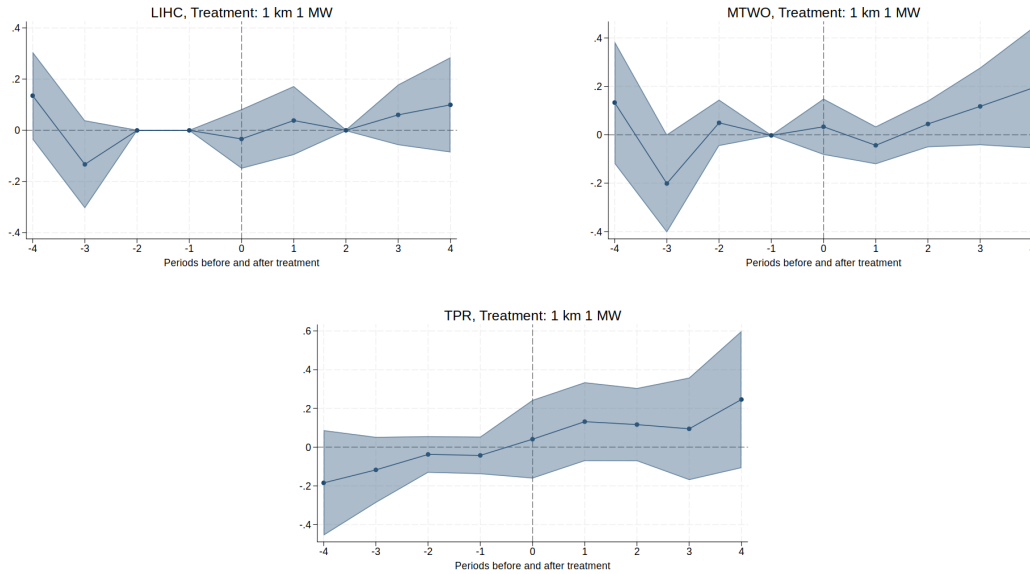
Table A6.1: Renewable energy capacity and energy poverty indicators at the household level

	Ten Percent Rule (tpr)	Low Income High Cost (lihc)	Two Times Median Energy Expenditure (mtwo)
	(1)	(2)	(3)
ATT	0.1259838 (0.08397815)	0.0327624 (0.03513537)	0.0688714 (0.03757333)

Notes: This table shows a DiD estimation of renewable energy capacity owned by renewable energy communities (REC) on four energy poverty indicators. These are binary variables (1 = energy poor) for ten percent rule (tpr), low income high cost (lihc), and two times median share (mtwo). The treatment is defined as having 1 MW REC capacity within 1 km radius of the household. ATT is the average post-treatment coefficient. Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Source: authors' calculations. Data: Household-level panel data presented in Table 2.

Figure A6.1: The event study graphs of energy poverty estimations



Notes: This figure shows the event study graphs that correspond to the estimates in Table A6.1 for renewable energy community (REC) owned biomass, solar, and wind power plants and three energy poverty indicators. These are binary variables (1 = energy poor) for low income high cost (lihc), two times median share (mtwo), and ten percent rule (tpr). The treatment is defined as having 1 MW REC capacity within 1 km radius of the household. 95% confidence intervals.

Source: authors' calculations. Data: Household-level panel data presented in Table 2.