Is Place-Based Green Industrial Policy Effective? Evidence from the Inflation Reduction Act

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Abstract

Governments around the world are turning to place-based industrial policies to spur local job creation and make the green transition more equitable. The United States' Inflation Reduction Act (IRA) provides an example of this approach through its "Energy Community" provisions, which offer additional incentives for clean energy projects in economically marginalized regions with historic ties to fossil fuel industries. We use spatially granular data on renewable energy investment, employment, and voting patterns to investigate the impact of these incentives. We show that these incentives substantially increased local solar investment, but impacts on solar-related labor demand were limited, while the incentives did not significantly impact wind investment, wind-related job creation, or political preferences in the two years after their introduction. The results suggest that place-based green industrial policies can quickly and effectively direct clean energy investment toward disadvantaged regions, but their ability to generate local job creation or improve political feasibility in the short-run may be more muted.

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1 Introduction

Regional economic disparities have deepened in many countries around the world as a result of technological progress and trade integration, leaving "left-behind" areas with population decline, stagnant employment and social distress (Austin et al., 2018; Baccini & Weymouth, 2021; Case & Deaton, 2015; Dijkstra et al., 2020; Lee et al., 2018; Rodríguez-Pose et al., 2021; Rodrik, 2021). Many of these already-vulnerable regions are also particularly exposed to labor market disruption from the green transition (Castellanos & Heutel, 2024; Shang, 2023; Vona et al., 2019). The coincidence of these challenges has contributed to a surge in place-based green industrial policies[1] designed to promote a more equitable transition, support vulnerable regions, and build political support for decarbonization (Aiginger & Rodrik, 2020; Bartik, 2020; Juhász & Lane, 2024; Rodrik & Sabel, 2020). Yet, evidence on the effectiveness of these policies remains scarce.

The Inflation Reduction Act (IRA) of August 2022 is a salient example of place-based, green industrial policy. As the largest climate policy in U.S. history, it combined ambitious clean energy subsidies with explicit place-based incentives, Energy Community provisions. In the words of former U.S. president Joe Biden, "These incentives [Energy Communities] are going to make clean energy jobs, good-paying union jobs and ensure the benefits of clean energy economy reach communities left behind". These provisions work through renewable tax credits. By providing additional bonus incentives to projects located in Energy Communities, the IRA intended to support economically marginalized regions, although its Energy Communities definition ended up covering areas across the economic spectrum.

This paper investigates whether the IRA's place-based Energy Community incentives stimulated investment in wind and solar generation, created jobs, and shifted political preferences. We focus specifically on these place-based provisions, not the broader IRA, to isolate the effects of targeted regional incentives. Energy Community incentives represent only a small portion of the IRA's overall climate-related spending, conservatively estimated at $ 392 billion and potentially exceeding $ 1.07 trillion due to the uncapped nature of the tax credits (J. E. Bistline et al., 2023).[2] Our analysis covers the period from before the IRA began in August 2022 to the end

[1] Examples of such policies include the European Union's Green Deal's Just Transition Mechanism, the U.S. Inflation Reduction Act's Energy Communities, and South Africa's Just Energy Transition Investment.

[2] Energy Community incentives are tax credits for renewable energy projects in designated "Energy Communities". As explained in section 2 they provide a bonus on top of existing federal subsidies: typically 10 percentage points for the Investment Tax Credit (ITC), which offsets construction costs, or $2.75 per megawatt-hour for the Production Tax Credit (PTC), which rewards electricity generation over the first ten years. Total ITC and PTC spending under the IRA was estimated at $127 billion out of $392 billion in climate-related spending (J. E. Bistline et al., 2023), and because the Energy Community bonus applies only to eligible projects, it represents a small share of total IRA spending.

of 2024, capturing the entire period during which the policy operated under credible commitment, as President Trump's Executive Order 14154 paused all IRA tax credits on his first day in office.

To identify the impact of these incentives, we implement difference-in-differences comparisons between Energy Communities (treated areas) and non-Energy Communities (control areas) before and after the introduction of the IRA. We compile census-tract-level investment data from the Clean Investment Monitor (2018–2024) to measure renewable investment. For employment, we start with the Quarterly Census of Employment and Wages (QCEW) to capture county-level trends, but these (and other conventional labor market data sources) are not ideally suited for examining the evolution of renewables employment, because they either aggregate multiple occupations, making it hard to isolate renewable energy jobs, or report too few jobs in smaller counties, triggering privacy restrictions that prevent their publication. To overcome these limitations, we leverage Lightcast online job vacancy data, using the raw text in online job openings to provide spatially granular measures of job openings specific to wind or solar energy. Finally, we assemble county-level election results (2000–2024) to study political outcomes at fine geographic resolution (Rhodium Group and MIT's Center for Energy and Environmental Policy Research, 2024).

We find that the Energy Community bonus substantially increased solar investment in the two years following its start date, raising the probability of solar projects in treated tracts by 0.14 percentage points, a 144 percent increase relative to the counterfactual level of investment that would have prevailed in the absence of the Energy Community provisions.[3] Wind investment, by contrast, showed no significant response to the Energy Community bonus. Despite these large investment effects, evidence of employment gains is limited. Solar-related labor demand measured as the share of online job openings mentioning solar-related keywords rose by 0.033 percentage points. This represents an increase of demand of 29% compared to the counterfactual mean, consistent with typical labor demand multipliers, though this effect is only significant at the 10% level. Wind-related labor demand was unaffected. We do not find evidence suggestive of local spillovers. One possible explanation for the divergent impacts is the design of the tax credits, which may have been more favorable to solar deployment, as discussed in sections 2 and 6. Political outcomes are unchanged, with no detectable effect on electoral results through the 2024 presidential election, indicating that the economic gains have not been accompanied by political shifts.

Back-of-the-envelope calculations in Appendix A.1 show that the implied government subsidy to abate CO_2 under the IRA's place-based provisions is substantially lower than both the Social Cost of Carbon estimated by U.S. Environmental Protection Agency (2022) and the abatement costs of other U.S. climate policies, such

[3]We define the counterfactual level as the level of investment before the IRA in treated areas plus the change in investment in control areas between the pre- and post-IRA periods.

as electric-vehicle and residential-solar subsidies (Kattenberg et al., 2023; Sheldon et al., 2023; Xing et al., 2021). Although subject to uncertainty, these short-run estimates suggest comparatively cost-effective emissions reductions, even without accounting for potential dynamic benefits. By contrast, the cost per job vacancy created appears high relative to other place-based manufacturing programs (Cingano et al., 2025; Criscuolo et al., 2019; LaPoint & Sakabe, 2021). While evidence for immediate employment effects from Energy Communities is limited, the broader solar and wind subsidies could contribute to innovation, learning-by-doing, and economies of scale in the deployment of clean energy technologies, which may generate longer-term employment impacts. Ultimately, the full value for money of the policy will hinge on long-term impacts that are yet to materialize. Our short-run estimates likely provide a conservative indication of the IRA's immediate effectiveness.

This paper builds on and contributes to several strands of literature, beginning with climate policy effectiveness. We show that spatially targeted tax incentives successfully steer renewable investment to designated regions, achieving CO_2 abatement costs below or comparable to other salient climate policies. However, we find limited evidence in the short term of these incentives spurring large-scale job creation that could counteract the localized labor market disruptions caused by the energy transition. The muted employment response could be due to the low labor-intensity of renewable energy generation,[4] the temporary nature of renewable construction jobs, the geographic concentration of fossil industries, skills mismatch between fossil fuel and green technology jobs, labor market frictions, and the concentration of green investment in places that already have a skilled green workforce (Castellanos & Heutel, 2024; Fabra et al., 2024; Popp et al., 2021; Scheifele & Popp, 2025; Shang, 2023; Vona, 2019). As public backing for climate policy is dependent on perceived fairness and local economic outcomes (Bergquist et al., 2022; Drews & Van den Bergh, 2016; Epstein & Muehlegger, 2024), the limited local gains were likely too small to generate measurable political impacts within this time horizon.

Second, we contribute to the literature on place-based industrial policy. Recent work advocates using such policies to revitalize left-behind regions (Aiginger & Rodrik, 2020; Bartik, 2020; Juhász & Lane, 2024; Rodrik & Sabel, 2020). We show that when these policies target renewable energy rather than manufacturing, the short-run fiscal cost per job created is substantially higher than comparable interventions (Atalay et al., 2023; Cingano et al., 2025; Criscuolo et al., 2019; Incoronato & Lattanzio, 2023; LaPoint & Sakabe, 2021), reflecting the capital-intensive, low-labor-intensity nature of renewable energy projects. Consequently, the Energy Community provisions do not immediately reverse long-standing patterns of population decline, economic stagnation, and social distress that characterize these regions (Austin et al.,

[4]For example, estimates of jobs supported per \$1 million in final demand range from 7.5 full-time equivalents in solar (Garrett-Peltier, 2017) to 16.5 and 14.7 in durable and nondurable manufacturing, respectively (Bivens, 2019).

2018; Baccini & Weymouth, 2021; Case & Deaton, 2015; Dijkstra et al., 2020; Lee et al., 2018; Rodríguez-Pose et al., 2021; Rodrik, 2021), even if they may help lay the groundwork for more sustainable regional revitalization over time.

Finally, we are among the first to provide ex-post evidence on the Inflation Reduction Act (Allcott et al., 2024; J. Bistline et al., 2023; J. E. Bistline et al., 2023) and, together with Ashenfarb (2024), the first to specifically examine its Energy Community provisions, which combine climate objectives with regional development goals.

The remainder of this paper is structured as follows. The next section elaborates on the IRA and the place-based incentives it offers. Section 3 introduces our data and 4 descriptive statistics. Section 5 discusses our econometric strategy. Results are presented in section 6. A final section concludes.

2 The Inflation Reduction Act and Energy Communities

2.1 Background

Signed into law on August 16, 2022, the Inflation Reduction Act (IRA) represents the largest federal investment in climate action in U.S. history. The legislation comprises three main pillars: reducing the federal budget deficit through spending reductions, lowering prescription drug prices, and investing in domestic clean energy production. This paper focuses on the environmental provisions, which constitute the bulk of the Act's spending.

Following the 2024 presidential election, President Trump issued Executive Order 14154 on his first day in office, pausing all IRA fund disbursements. Although this order was subsequently overturned in court, the Trump administration has continued to selectively modify aspects of the legislation, creating ongoing uncertainty about policy durability and implementation. Our data coverage extends through to the end of 2024, capturing the complete period during which the IRA operated under the Biden administration with credible policy commitment.

The One Big Beautiful Bill Act (OBBBA), enacted in July 2025, amended the IRA's clean energy tax credits by rapidly phasing down incentives for wind and solar generation. Under the revised rules, wind and solar tax incentives end after December 31, 2027, except for projects that begin construction by July 4, 2026. Energy Community bonus credits still exist for other technologies, such as energy storage, nuclear generation, and geothermal.

2.2 Investment and Production Tax Credits

The IRA significantly expanded long-standing U.S. clean energy tax credits: the Investment Tax Credit (ITC), introduced in 1978, and the Production Tax Credit (PTC), introduced in 1992. The ITC subsidizes capital costs for building renewable energy facilities, while the PTC provides credits based on electricity generation during the first ten years of operation. The IRA broadened eligibility by extending the ITC, previously limited to solar and offshore wind, to onshore wind, and the PTC, previously limited to wind, to solar. Our analysis focuses on the IRA's key innovation: place-based bonus rates for projects located in designated energy communities (ECs), creating spatial variation in incentives for renewable energy investment.

Although the IRA formally establishes a tiered credit structure based on project size and labor standards, only one tier is empirically relevant. Projects exceeding 1 MW that comply with prevailing wage and apprenticeship (PWA) requirements qualify for full credits of 30% ITC or $27.50/MWh PTC, while non-compliant projects receive lower rates (6% ITC or $5.50/MWh PTC). In practice, nearly all utility-scale developers are expected to meet these labor standards, making the full-credit tier the effective baseline (Congressional Budget Office, 2025). Smaller non-residential projects below 1 MW are also eligible for full credits regardless of PWA compliance, but they contribute only a minor share of generation: non-residential solar facilities under 1 MW account for roughly 10% of non-residential energy generation, and small wind projects are negligible since most turbines exceed 1 MW (U.S. Energy Information Administration, 2024a). Consequently, our empirical analysis focuses on the full-credit tier, which captures the effective policy environment for the vast majority of renewable energy development.

Crucially for our purposes, the IRA introduces the EC Bonus, which provides an additional 10 percentage points for the ITC or an extra $2.75/MWh for the PTC, and is the focus of our analysis. This translates to a 33% increase in the ITC relative to baseline, versus a 10% increase for the PTC. The value of each of these credits depends on the project's capacity factor: low-capacity-factor technologies such as solar (15–30%) benefit more from the ITC, whereas higher-capacity-factor technologies such as wind (30–60%) benefit more from the PTC.(ICF International, 2022; National Renewable Energy Laboratory, 2024, 2025) Consequently, the EC Bonus is expected to have a larger effect on solar than wind projects. Our empirical strategy leverages cross-location variation in EC eligibility to identify the impact of these place-based incentives on renewable energy development.

The IRA also introduces a Domestic Content Bonus, which offers identical additional benefits as the EC Bonus for projects that meet domestic manufacturing requirements. These bonuses[5] can be combined, potentially bringing total credits to

[5] The Low-Income Communities Bonus Credit is also available for projects smaller than 5 MW, located in Indian Land and designated low-income communities. Total annual capacity subsidized

50% ITC or $33.00/MWh PTC. However, the Domestic Content Bonus is less central to our analysis, as it does not vary across locations. A summary of possible bonuses is provided in the online appendix, Table A1.

These credits can be applied against tax liability, transferred to another taxpayer, or taken as a direct payment, provided construction commences within the policy window, defined as incurring at least roughly 5% of project costs. Eligibility is determined by the construction start date. The timing of payments differs by credit: the ITC is paid when capital costs are incurred, i.e., during facility construction, while the PTC is paid annually based on electricity generated during the first ten years of operation.

2.3 Energy Community Criteria

ECs were designed to direct benefits toward economically disadvantaged areas with historical ties to fossil fuel industries. In practice, however, the criteria cast a wide net. The EC definition covers roughly half of U.S. land area yet excludes several historically fossil-fuel-dependent regions, such as West Texas, much of Oklahoma, and large parts of North Dakota, while including areas in New England and California with few ties to these industries (Raimi and Pesek, 2022, Graham and Knittel, 2024). This mismatch between intent and coverage does not affect our empirical strategy, which exploits variation in EC designation status regardless of whether the targeted areas are genuinely fossil-fuel-dependent. The IRA defines ECs through three distinct criteria:

1. A "brownfield site" as defined in the Comprehensive Environmental Response, Compensation, and Liability Act of 1980 (CERCLA);

2. A "metropolitan statistical area" or "non-metropolitan statistical area" that has (or had at any time after 2009) either:

   - 0.17% or greater direct employment related to the extraction, processing, transport, or storage of coal, oil, or natural gas; OR
   - 25% or greater local tax revenues related to the extraction, processing, transport, or storage of coal, oil, or natural gas;

   and has an unemployment rate at or above the national average unemployment rate for the previous year;

through the LIC Bonus is capped at 1.8GW. Compared to the average size of utility-scale solar power plants in Energy Communities (127MW) the size of the LIC Bonus is limited, and its aim is to support equity rather than meaningful CO2-abatement.

3. A census tract (or directly adjoining census tract) in which a coal mine has closed after 1999 or in which a coal-fired electric generating unit has been retired after 2009.

EC designations are updated annually based on unemployment statistics, creating temporal variation in eligibility. Additionally, the definition of employment related to the extraction, processing, transport, or storage of coal, oil, or natural gas was expanded on March 22, 2024. During our study period, this resulted in three designation cohorts: communities designated starting January 1, 2023, referred to as "Cohort 1 EC", communities designated on March 22, 2024, referred to as "Cohort 2 EC" and those added on June 6, 2024, when the unemployment statistics were updated, referred to as "Cohort 3 EC". Some initial ECs lost their designation when local unemployment rates fell below national averages, while others maintained their designation throughout the period.

We observe Energy Community designations only under Criteria 2 and 3. We exclude Criterion 1 (brownfield sites) for three reasons: brownfield sites are not consistently tracked across the United States, and new sites can be discovered at any time, making it difficult to obtain reliable data; Criterion 1 likely applies to less than 0.3% of U.S. land area, compared to roughly 55% under Criteria 2 and 3 (Green, 2018); and brownfield sites have been targeted by remedial federal policy since 1995 through dedicated funding for site assessment and cleanup, which could confound our estimates.

3 Data

This paper constructs and combines various datasets[6]:

3.1 Investment Data

We use data on renewable energy investments from the Clean Investment Monitor, compiled by Rhodium Group and MIT's Center for Energy and Environmental Policy Research (2024). This dataset tracks all investments eligible for IRA tax credits, providing complete coverage from January 1, 2018, to December 31, 2024. The extended time series includes substantial pre-treatment periods and captures the full period of credible policy implementation under the Biden administration.

The investment data focuses on solar and wind energy-generating facilities eligible for the ITC and PTC. Each observation includes the census tract location, the date when the power plant first contacts the grid provider, and estimated construction costs (CAPEX) based on facility characteristics, including generating capacity, location, and technology specifications.

[6]Appendix C gives a full overview of all datasets used in this paper.

The dataset derives from the U.S. Energy Information Administration's Form 860(M) survey, which legally requires all power plants larger than 1 MW to report their information, with financial penalties for non-compliance. This regulatory framework ensures we capture the universe of utility-scale wind and solar investments in the United States. Our sample includes 4,958 solar investments and 457 wind investments between January 1, 2018, and December 31, 2024.

We construct a quarterly panel dataset at the census tract level. Given that investment levels for the most recent years are estimated using location characteristics, they may contain measurement error that could differ systematically between ECs and non-ECs. In table 1, we show for instance that solar intensity and average wind speed differ substantially between ECs and non-ECs. Hence, our preferred specification uses a binary investment indicator rather than continuous investment amounts. For each census tract i and quarter t, we observe whether any renewable energy investment in solar or wind occurs.

3.2 Labor Market Data

We measure labor market impacts using two complementary sources. First, we draw on county-level employment and wage data from the Quarterly Census of Employment and Wages (QCEW). While QCEW provides detailed coverage across NAICS industries at the county level (the lowest level of geographical disaggregation available), its usefulness for studying renewable energy is limited by a lack of occupational disaggregation and censoring due to privacy rules, which hinders the assessment of localized policy effects.

To address this limitation, we supplement our analysis with job vacancy data from Lightcast, which web-scrapes online job postings from major job boards across the United States. The dataset comprises 434,255,025 job vacancies posted between January 1, 2015, and December 31, 2024, including job descriptions, county locations, and posting dates. We construct a county-level quarterly panel measuring the share of renewable energy-related job vacancies relative to total postings in each county-quarter. Vacancy data are not subject to the same censoring concerns as QCEW and can be disaggregated by detailed occupation, making them particularly well-suited to studying place-based labor demand responses to the IRA.

We identify renewable energy-related positions through systematic keyword searches of job descriptions. Following the methodology of Bastos et al. (2024), we construct keyword lists based on the European Patent Office's technology classifications. Solar-related positions correspond to classification Y02E10/50 (Photovoltaic Energy), while wind positions align with Y02E10/70 (Wind Energy). We extract technology-related nouns from patent titles and descriptions and expand them using synonyms, hypernyms, and hyponyms from WordNet, Dictionary.com, and Google Trends.

This keyword search approach yields 372,902 job vacancies mentioning these 26 solar-energy-related keywords or their plurals and 197,584 job vacancies mentioning 6 wind-energy-related keywords or their plurals, over our analysis period.

The primary limitation of online job posting data concerns labor market representativeness, as web-based postings may not fully capture all hiring activity. Hershbein and Kahn (2018) find that Lightcast data overrepresents high-skilled positions compared to the Job Openings and Labor Turnover Survey (JOLTS), though it covers approximately 90% of JOLTS positions and maintains stable representativeness over time. Moreover, the data record job postings rather than the exact number of positions firms seek to fill. A single posting may correspond to multiple openings, which could lead to undercounting, particularly for less specialized roles. Conversely, firms may also post multiple advertisements for the same role if vacancies are difficult to fill, which could lead to double-counting. For our analysis, the key concern involves potential differential changes in representativeness between ECs and non-ECs over time. Online Appendix C presents robustness checks examining whether job vacancy-to-employment ratios, time-to-closing metrics, and the share of job vacancies with a validated NAICS code evolve differently between these areas, before the introduction of the IRA. While some statistically significant differences exist, they are economically negligible.

3.3 Election Data

We also use political outcomes data from the MIT Election Data and Science Lab (2018), providing county-level presidential election results from 2000 to 2024. The dataset includes total vote counts by party, though third-party vote totals for 2024 remain preliminary. We define Republican and Democratic vote shares as each party's proportion of the combined two-party vote at the county level.

4 Energy Communities: Characteristics and Trends

This section describes the characteristics of energy communities and documents the evolution of renewables investment and employment as well as electoral outcomes over time. Summary statistics for ECs and non-ECs are presented in Table 1, with ECs disaggregated into Cohort 1 EC, Cohort 2 EC, and Cohort 3 EC.

ECs are, on average, larger in size but less densely populated than non-ECs. Residents are less educated, with higher proportions lacking high school diplomas and lower rates of college and bachelor's degree completion. ECs are also, on average, more rural, as measured by Rural-Urban Continuum and Urban Influence codes.[7] GDP per

[7]Urban Influence and Rural-Urban Continuum Codes are ordinal values ranging from 1 to 9 and 1 to 12, respectively. In both codes, 1 stands for metropolitan areas with a population of 1 million or larger, representing the most urban category. Higher values indicate more rural areas.

capita requires caution in interpretation: several ECs, particularly in Texas, combine high natural resource output with very low population counts, generating very high average GDP per capita figures that may not be representative of the socio-economic reality in the majority of ECs.[8] Excluding natural resource and mining activities and trade, GDP per capita levels per sector are broadly comparable between ECs and non-ECs.

The energy profile of these communities reflects their historical economic base, with substantially higher electricity generation from natural gas and coal compared to non-ECs. Conversely, they have lower current solar electricity production and generally lower renewable energy potential for both solar and wind resources. These patterns suggest that while ECs receive preferential tax treatment under the IRA, they may face multiple investment barriers, including natural resource constraints and (lack of) supply of skilled labor. The geographic distribution of Energy Communities is shown in Appendix A (Figures A1, A2 and A3), illustrating their concentration in traditional fossil fuel regions, particularly in Appalachia, the Mountain West, and parts of the Midwest.

Figure 1 documents investment, employment, and electoral trends, comparing ECs with non-ECs (pooling all EC cohorts). Panels 1a and 1b[9] show that prior to the IRA, during the first Trump Presidency, and the beginning of Biden's term, ECs and non-ECs exhibited broadly similar investment trajectories for both solar and wind technologies. Solar investment in ECs increased more than in non-ECs as soon as the IRA started, even before the EC bonus became active.

The investment data captures the date when power plants first appear in the EIA 860(M) survey, which aligns broadly with initial grid provider contact rather than the start of construction. This timing allows power plant developers to respond to policy announcements before breaking ground, explaining the immediate increase in EC solar investments following the IRA's passage. The anticipatory response visible in late 2022, before the EC bonus officially took effect, provides empirical justification for dating our treatment to the IRA's initial passage rather than the bonus implementation date.

Panel 1c shows average employment by county from the last quarter of 2019 through 2024, comparing ECs and non-ECs.[10] The EC average starts at roughly

[8] In table 1, we exclude Loving County, Texas, as this county has a GDP per capita of 84 trillion and a 2020 population of 64, making it the least populated county in the U.S. Even after excluding Loving County, eight out of ten counties with the largest GDP per capita are ECs with a particularly high GDP in natural resource extraction.

[9] The Tax Cuts and Jobs Tax Relief Act (TCDTR) in late 2020 extended the ITC by two years and expanded coverage to offshore wind, though this change had a limited impact on wind projects as wind projects generally favor the PTC over the ITC due to their higher capacity factors.

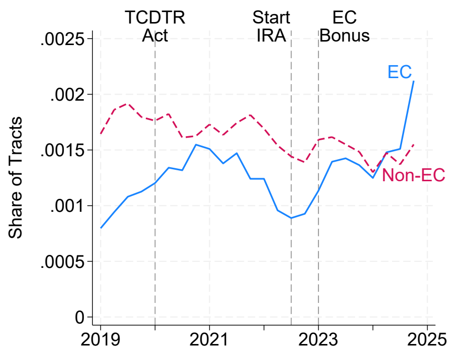
[10] ECs show higher average employment partially because the two most populous US counties, Los Angeles County and Cook County (Chicago), are classified as ECs. Appendix D.6 shows our results are not sensitive to excluding these counties from our analysis.

Table 1: Descriptive Statistics.

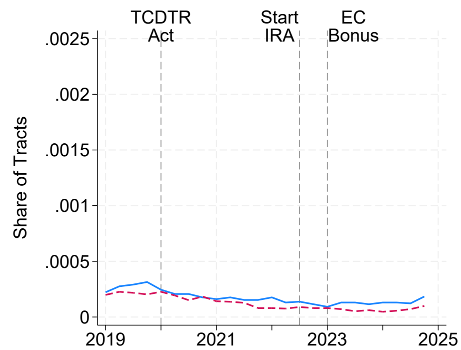
	Non-ECs	Cohort 1 EC	Cohort 2 EC	Cohort 3 EC
Panel A: Census tracts				
Area (km^2)	81,876.5 (407,347.1)	274,113.4 (2,962,130.2)***	189,367.2 (2,370,380.1)***	188,272.5 (2,393,815.7)***
Total population	3,933.5 (1,712.0)	3,698.7 (1,662.8)***	3,817.0 (1,674.1)***	3,936.2 (1,736.5)
Generation capacity:				
Total capacity (MW)	215.7 (497.0)	381.9 (611.4)***	327.8 (573.3)***	340.5 (589.2)***
Hydro (MW)	39.2 (243.4)	30.0 (167.8)	30.9 (156.8)	36.0 (182.8)
Natural gas (MW)	87.9 (284.5)	169.4 (388.1)***	144.8 (358.2)***	141.9 (354.1)***
Coal (MW)	37.6 (236.3)	146.4 (447.4)***	120.0 (416.4)***	129.8 (432.5)***
Other fossil (MW)	7.2 (39.0)	4.0 (20.9)**	3.7 (19.3)***	3.5 (18.6)***
Solar (MW)	5.1 (24.9)	1.1 (6.0)***	1.3 (5.7)***	1.2 (6.6)***
Onshore wind (MW)	12.1 (60.4)	9.8 (62.6)	7.7 (55.3)*	7.8 (55.5)*
Nuclear (MW)	25.8 (242.1)	20.4 (184.5)	18.9 (172.8)	19.7 (173.9)
Observations	52,904	17,424	27,432	27,036
Panel B: Counties				
Energy potential:				
Wind density	133.5 (69.1)	122.1 (84.1)***	122.8 (83.0)***	124.7 (87.8)***
Wind potential	4.7 (0.9)	4.5 (0.8)***	4.5 (0.8)***	4.5 (0.8)***
Solar potential	4.1 (0.3)	4.0 (0.4)***	4.1 (0.5)***	4.0 (0.4)***
Education (%):				
Some college	30.9 (5.3)	30.1 (5.1)***	30.2 (5.2)***	30.3 (5.0)***
Bachelor	25.8 (10.4)	22.5 (9.8)***	23.0 (10.0)***	23.0 (10.0)***
High school	32.6 (7.4)	35.1 (7.8)***	34.7 (7.8)***	34.8 (7.9)***
No high school	10.7 (5.4)	12.4 (5.9)***	12.1 (5.9)***	11.9 (5.5)***
County characteristics:				
Rural–urban code	4.8 (3.0)	5.4 (2.8)***	5.2 (2.9)***	5.2 (2.9)***
Urban influence	4.7 (3.5)	5.5 (3.4)***	5.2 (3.4)***	5.1 (3.4)***
Poverty rate (%)	13.4 (5.1)	15.9 (5.8)***	15.6 (5.8)***	15.6 (5.8)***
Unemployment rate (%)	3.3 (1.3)	4.1 (1.3)***	4.1 (1.3)***	4.1 (1.3)***
GDP per capita (by activity):				
GDP per capita	48.0 (41.9)	53.4 (90.5)**	53.1 (86.9)**	47.8 (54.4)
GDP trade per capita	5.4 (3.4)	4.8 (3.1)***	4.8 (3.1)***	4.8 (3.1)***
GDP transport & utilities pc	4.0 (9.2)	4.6 (13.4)	4.6 (12.9)	4.7 (13.6)
GDP manuf. & information pc	8.6 (13.3)	8.1 (10.4)	8.1 (10.1)	8.3 (9.9)
GDP nat. res. & mining pc	5.8 (33.5)	12.1 (75.9)***	11.3 (73.0)**	5.9 (25.1)
GDP government per capita	6.3 (5.4)	6.3 (5.0)	6.3 (4.9)	6.3 (5.0)
Observations	2,095	1,361	1,483	1,442

Note: Panel A reports census tract means; Panel B reports county means. Standard deviations in parentheses. Columns are non-ECs, Cohort 1 EC (eligible in 2023 and Q1, 2024), Cohort 2 EC (eligible in Q2, 2024), and Cohort 3 EC (eligible in Q3-Q4, 2024). Variable reference years: population (2020); generation capacity (2022 Q2); wind and solar potential (2019); rural–urban continuum code (2023); urban influence code (2013); poverty rate (2023); unemployment rate (2022). Standard deviations in parentheses. Stars indicate significant difference from non-ECs (two-sided t-test): * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

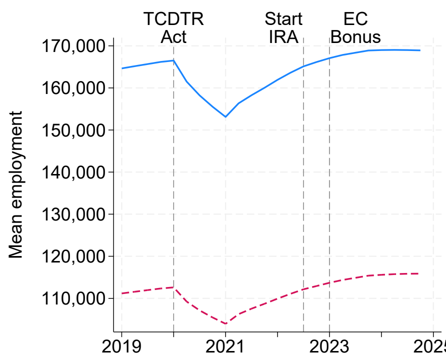
Figure 1: Evolution of Investment, Employment, and Voting
Energy Communities vs. Other Areas



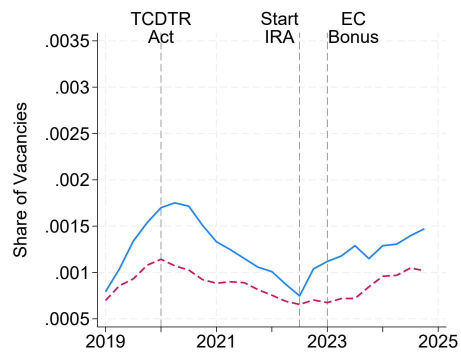
(a) Binary Solar Investment



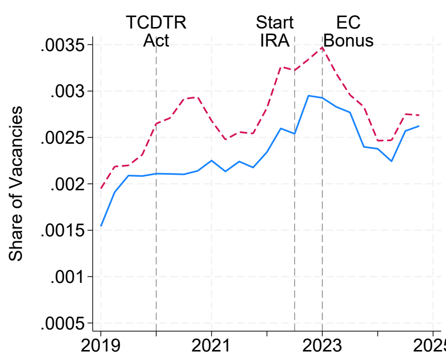
(b) Binary Wind Investment



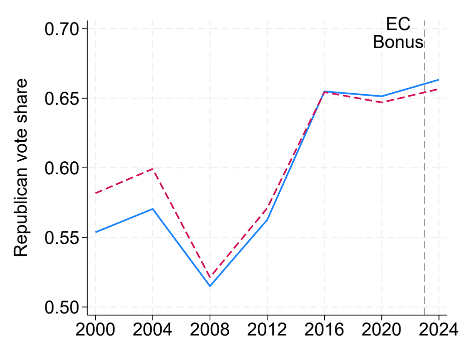
(c) Total Employment



(d) Solar Vacancies



(e) Wind Vacancies



(f) Republican Vote Share: Rust Belt

Note: The figure reports the evolution of the mean outcome variables for Energy Communities (EC) vs. other areas (non-ECs). Panels a–b plot quarterly shares of census tracts receiving solar and wind investments, smoothed with an MA(4). Panel c shows quarterly employment per county, taken from the Quarterly Census of Employment and Wages (QCEW), smoothed with an MA(4). Panels d–e plot solar and wind labor demand per county, taken from Lightcast, smoothed with an MA(4). Labor demand is measured as the share of job vacancies listing solar or wind keywords. Panel f reports Republican presidential vote shares in the Rust Belt (IL, IN, IA, KY, MD, MI, MN, MO, OH, PA, WV, WI), using only Democratic and Republican votes. Vertical dashed lines mark the passage of the Tax Cuts and Jobs Tax Relief Act (2020q1), the start of the Inflation Reduction Act (2022q3), and the introduction of the EC bonus (2023q1).

160,000 employed people per county, while the non-EC average starts at 110,000. Both groups dip sharply in 2021 following COVID and then recover to employment levels higher than their starting points. The trends run nearly parallel throughout the period, including in the pre-treatment period before 2022. The parallel pre-trends are consistent with the identifying assumptions of our difference-in-differences identification strategy.

Panels 1d and 1e show the evolution of renewables vacancies, proxied by the share of renewable energy-related job vacancies relative to total postings, and reveal distinct technology-specific responses. Solar job vacancy shares (panel c) declined between 2020 and the IRA's passage, then increased immediately in ECs. Wind-related postings (Panel 1e) showed steady growth from Biden's inauguration through the implementation of the IRA, but declined after the EC bonus took effect. This pattern is consistent with the presumption that general tax credits (particularly the PTC) matter more for wind investments than bonus provisions, while bonuses provide stronger incentives for solar development.

To conclude, Panel 1f shows Republican vote shares averaged across counties, restricting the sample to Rust Belt states (Ohio, Indiana, Illinois, Wisconsin, Michigan, Pennsylvania, Iowa, Kentucky, Maryland, Minnesota, Missouri, and West Virginia). This unweighted average yields higher Republican shares because many sparsely populated Republican counties offset fewer densely populated Democratic ones. Figure A4 in Online Appendix C shows the Republican vote shares for all U.S. counties. The data reveal significant shifts in EC political preferences over time. ECs leaned more Democratic than non-ECs in 2000, but this reversed after 2008. ECs then became consistently more Republican. This shift aligns with research on left-behind regions that moved toward Republican voting in recent decades, as documented by Rodríguez-Pose et al. (2021), Baccini and Weymouth (2021), and Rodrik (2021). While we cannot definitively identify the precise drivers of the divergent trends between ECs and non-ECs, they likely reflect underlying structural factors across regions, including industrial decline driven by trade shocks and automation, and attendant demographic changes such as out-migration of younger, educated workers (D. H. Autor et al. (2013), Pierce and Schott (2016), Acemoglu and Restrepo (2020), D. Autor et al. (2020)). Importantly, these differences do not appear to result from the policy itself and do not meaningfully affect other outcomes, such as renewable investment and labor demand, suggesting they do not invalidate treatment-control comparisons for these other outcome variables.

In our analysis of political outcomes, we restrict the sample to Rust Belt states (Ohio, Indiana, Illinois, Wisconsin, Michigan, Pennsylvania, Iowa, Kentucky, Maryland, Minnesota, Missouri, and West Virginia). In these states, ECs and non-ECs show more parallel political trends over time. This parallel trend bolsters confidence in our difference-in-differences design. It reduces the risk that unobserved political or economic differences between ECs and non-ECs bias our estimates of policy effects.

To summarize, ECs differ systematically from non-ECs in socioeconomic characteristics, energy mix, and baseline renewable capacity; yet, these structural differences are largely time-invariant. Descriptive trends show a broadly parallel, but not perfectly parallel, pre-IRA trajectory in investment and employment and, when restricted to Rust Belt states, also in political outcomes.

5 Identification

We identify the causal effects of Energy Community (EC) incentives using difference-in-differences (DID) designs. For investment and labor demand outcomes, we implement a quarterly event-study specification following De Chaisemartin and D'Haultfoeuille (2024), which is specifically designed to accommodate the non-absorbing nature of the treatment. For voting, we implement a Two-Way Fixed Effects (TWFE) estimator as the data provide only a single post period.

Investment and Labor Market Outcomes. Energy Community status is non-absorbing because it can end if local unemployment falls below the national average. Standard two-way fixed effects (TWFE) event-study regressions may be biased when treatment is reversible. The De Chaisemartin and D'Haultfoeuille (2024) method addresses the non-absorbing treatment by computing group-specific Difference-in-Differences (DiD) estimators, denoted $\text{DID}_{g,\ell}$, and then averaging them across groups. This approach is designed to isolate the effect of treatment changes while avoiding the biases that may arise in conventional TWFE designs.

The target parameter is the Actual-Versus-Status-Quo (AVSQ) effect, $\delta_{g,\ell}$:

$$\delta_{g,\ell} = E\Big[Y_{g,F_g-1+\ell} - Y_{g,F_g-1+\ell}(D_{g,1},\dots,D_{g,1})\Big], \tag{1}$$

where ℓ is the exposure length, $Y_{g,t}(d_1,\dots,d_t)$ is the potential outcome under treatment path $(d_1,\dots,d_t)$, and F_g is the first period in which the group's treatment changes. Intuitively, AVSQ compares what actually happened in group g to what would have happened if its treatment had stayed at the initial "status quo" level. It therefore captures the causal impact of the treatment change itself, independent of prior trends or other groups' dynamics.

To estimate this effect, each treated group g is compared to a set of control groups g' that (i) share the same initial treatment level $D_{g',1} = D_{g,1}$ and (ii) have not yet changed treatment by period $F_g-1+\ell$ ($F_{g'} > F_g-1+\ell$). The group-specific estimator is:

$$\text{DID}_{g,\ell} = \big(Y_{g,F_g-1+\ell} - Y_{g,F_g-1}\big) - \frac{1}{N^g_{F_g-1+\ell}} \sum_{g':D_{g',1}=D_{g,1},F_{g'}>F_g-1+\ell} \big(Y_{g',F_g-1+\ell} - Y_{g',F_g-1}\big), \tag{2}$$

where $N^g_{F_g-1+\ell}$ counts the number of eligible control groups. Identification relies on a parallel trends assumption for these groups' outcomes under the status quo.

Finally, the overall event-study effect at exposure ℓ is a weighted average of the group-specific estimates:

$$\text{DID}_\ell = \frac{1}{N_\ell} \sum_{g: F_g-1+\ell \leq T_g} S_g, \text{DID}_{g,\ell}, \tag{3}$$

where $S_g = 1\{D_{g,F_g} > D_{g,1}\} - 1\{D_{g,F_g} < D_{g,1}\}$ accounts for treatment changes in either direction, ensuring that the sign of the effect is consistent. This final average provides an unbiased estimate of the dynamic treatment effect over all groups, accommodating staggered and non-permanent treatments.

We assign treatment at the tract level for investment and at the county level for the labor market analysis due to data availability. If any tract in a county qualifies, we code the county as treated. This conservative rule likely attenuates effects, as partial exposure weakens measured responses. We cluster standard errors at the unit of analysis, i.e., census tract or county.

In our robustness checks, we assess potential spillover effects by redefining spatial treatment boundaries and examining how impacts vary across space. We define first neighbors as non-Energy Community tracts or counties directly adjacent to treated areas, while second neighbors are those adjacent to first neighbors. We estimate additional specifications that treat these neighboring areas as if they were exposed, using more distant non-Energy Communities as controls. Investment spillovers are expected to be negative, as developers may shift projects from nearby untreated areas to newly designated Energy Communities. By contrast, labor market spillovers may be positive, since firms hiring for Energy Community projects can recruit workers from a wider regional labor market.

In addition, we conduct a robustness check using propensity-score matching to pair each EC unit with a comparable non-EC control unit, thereby reducing concerns about selection on unobservables. We then re-estimate our event-study specifications on the matched sample. This exercise is documented in Appendix D.4.4.

Voting. Electoral outcomes require a different design because the data are sparse. Presidential elections occur every four years, and our window includes a single post period: 2024. We therefore estimate a two-way fixed effects difference-in-differences, coding as treated any county designated an EC by 2024, and compare 2024 to pre-policy elections with county and year fixed effects:

$$Y_{jt} = \alpha + \beta(\text{Post}_t \times \text{EC}_j) + \gamma_j + \delta_t + \mu_{jt} + \epsilon_{jt} \tag{4}$$

where Y_{jt} measures Republican vote share in county j at election t. EC_j indicates Energy Community status, Post_t denotes the post-IRA period, γ_j, δ_t, and μ_{jt} capture county, time, and state-time fixed effects[11], respectively, and ϵ_{jt} represents the error term, with standard errors clustered at the county level. We restrict the electoral analysis to Rust Belt states—Illinois, Indiana, Iowa, Kentucky, Maryland, Michigan, Minnesota, Ohio, Pennsylvania, West Virginia, Missouri, and Wisconsin—since the national sample exhibits potential non-parallel pre-trends, whereas Energy Communities and non-Energy Communities in the Rust Belt follow more comparable political trajectories over time.

6 Results

This section presents our main findings, starting with the investment and employment results before examining the impacts on voting outcomes.

Investment Results: Panels (a) and (b) of Figure 2 report event-study estimates comparing Energy Communities to non-Energy Communities, where the outcome is a tract-quarter indicator for receiving an investment in the respective technology. Energy Community designation raises solar investment in treated tracts: designated tracts experienced a 0.14 percentage point increase in the probability of solar investment in a given quarter, representing a 144% increase relative to the counterfactual mean.[12] The estimated effect grows over time, with larger coefficients in later post-designation quarters (Appendix D.1). By contrast, wind investment shows no systematic effect. Panel (b) shows some positive post-treatment estimates, but because similar values appear before treatment, we interpret this as no effect. A likely explanation is credit choice: wind projects, with higher capacity factors, typically select the PTC rather than the ITC, which reduces the marginal value of the Energy Community bonus for wind relative to solar. These conclusions are robust across a range of specification checks. Using investment levels rather than binary indicators yields a mean increase of \$185,217 per tract-quarter, representing a 133% increase relative to the counterfactual (Appendix D.3). Restricting the treated sample to communities qualifying solely under the coal-closure criterion, controlling for lagged unemployment rates, and matching on unemployment trajectories or a broader set of observables all point to a consistent range of 0.13–0.19 percentage points for solar,

[11] Additional time-varying controls are difficult to incorporate due to the limited availability of county-level data extending to recent time periods, particularly for variables that could plausibly affect both Energy Community designation and political preferences without being post-treatment outcomes themselves.

[12] We define the counterfactual level as the level of investment prior to the IRA in the treated areas plus the difference between prior and after the IRA in control areas: Counterfactual Mean $= \sum_{i=treated;t=pre} \text{investment}_{i,t} + \sum_{i=control;t=post} \text{investment}_{i,t} - \sum_{i=control,t=pre} \text{investment}_{i,t}$. The percentage growth compared to the counterfactual mean is calculated as: Percentage Growth $= \frac{\text{DID Coefficient}}{\text{Counterfactual Mean}}$.

with wind effects remaining indistinguishable from zero (Appendices D.4.1, D.4.2, D.4.3, and D.4.4). Our spillover analysis finds no evidence of investment displacement across neighboring tracts (Appendix D.5). This rules out local crowd-out but not displacement over larger distances since solar developers might evaluate sites across broad geographic areas, so projects could shift from distant non-EC locations without generating detectable local spillovers.

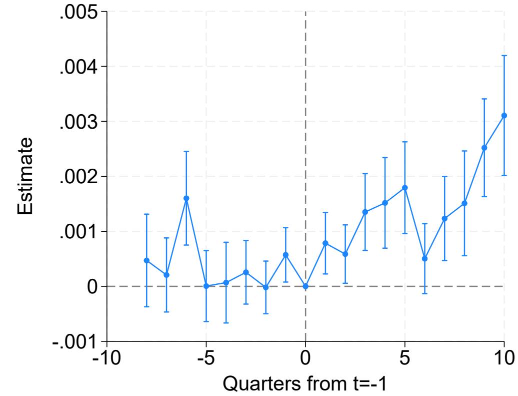
Labor Market Results: We begin by examining the policy's impact on total employment. Panel (c) of Figure 2 shows no detectable effect of the Energy Community bonus on aggregate employment measures. This null result is not surprising given that the renewable energy sectors targeted by the policy constitute a relatively small share of total employment, making it unlikely that our identification strategy would capture differences between Energy Community and non-Energy Community regions in such broad employment aggregates. We therefore turn to job openings data, which provides a more targeted measure of labor demand in the specific sectors affected by the policy.

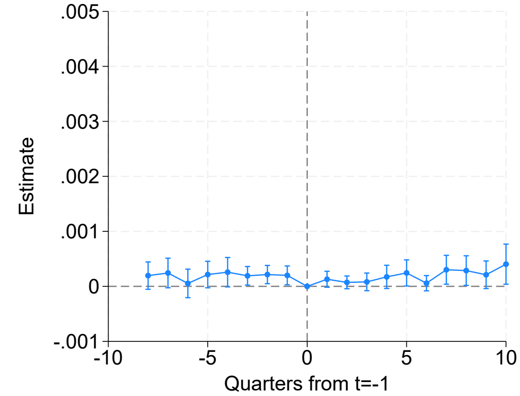
The Energy Community bonus increases solar labor demand by 0.033 percentage points but this effect is only significant at the 10% significance level. It represents a 29% rise relative to the counterfactual mean. Although this magnitude appears limited compared to the investment response, it is consistent with an auxiliary analysis linking investment to labor demand. We estimate that solar labor demand increases by 0.07 percentage points when a county receives a solar investment.[13] Given the 144% increase in investment induced by the bonus (relative to the counterfactual mean), the implied effect of 0.07 percentage points aligns with our baseline estimate. Consistent with the null investment response for wind, we find no significant effects on wind labor demand. The robustness of these labor market findings mirrors that for investment. The solar labor demand estimate rises modestly to 0.040 percentage points when matching on unemployment trajectories and falls to an insignificant 0.024 percentage points when matching on a broader set of variables, while wind remains a null result throughout (see Appendices D.4.1, D.4.2, D.4.3, and D.4.4). Spillover effects on neighboring regions are positive but statistically insignificant (Appendix D.5). Additional analyses of broader employment outcomes—including renewable energy jobs (Y02E10) and construction employment from the Quarterly Census of Employment and Wages, similarly yield no detectable effects (Appendix D.8), reinforcing our focus on the more sensitive job openings measure for detecting policy impacts in these targeted sectors.[14]

[13] Analysis provided in Online Appendix D.2.

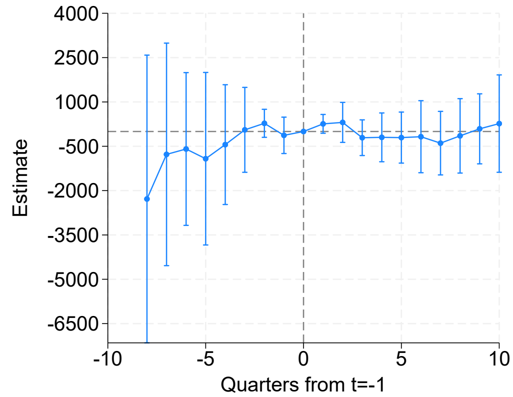
[14] We perform the same analysis on brown (i.e. fossil-fuel related) labor demand to examine potential crowding out in Appendix D.7, but problematic pre-trends prevent us from drawing strong conclusions.

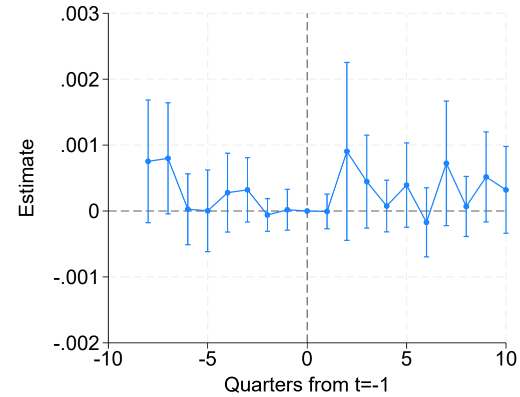
Figure 2: Event Study of the EC Bonus on Investment, Employment, and Voting



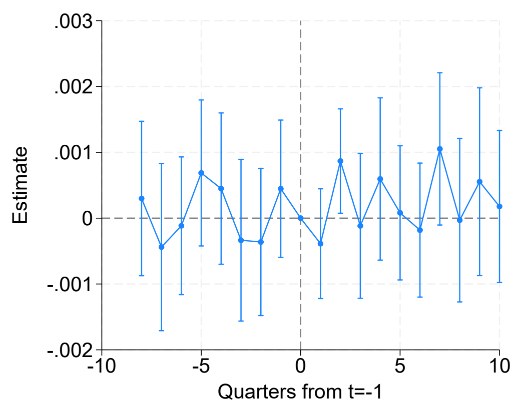


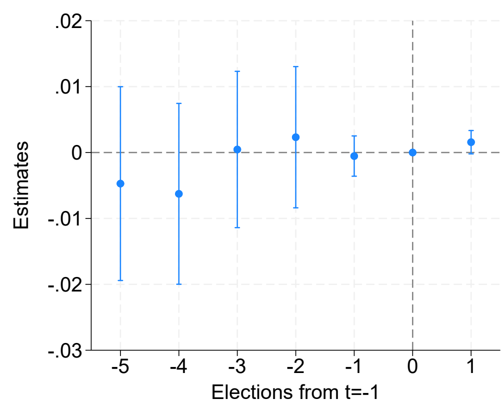
(a) Solar Investment (Extensive Margin) (b) Wind Investment (Extensive Margin)





(c) Total Employment (d) Labor Demand: Solar





(e) Labor Demand: Wind (f) Republican Vote Share: Rust Belt

Note: The figure (panels a-e) reports difference-in-differences event-study estimates, as well as 95% confidence intervals, of the impact of the introduction of Energy Community (EC) bonus provisions, estimated using the method of De Chaisemartin and D'Haultfoeuille (2024). Panels a and b report the quarterly effect of EC status on the probability of census tracts receiving solar investment and wind investment, respectively. Panel c reports the quarterly effect of EC status on total employment at the county level, measured in the QCEW. Panels d and e report the quarterly effect of EC status on solar and wind labor demand at the county-level, respectively. Labor demand is measured as the share of job vacancies listing solar or wind keywords. Panel f reports the Republican vote share effects of EC status at the county-level, estimated using a two-way fixed effects difference-in-differences estimation, including year × state fixed effects, which are not reported. Standard errors are clustered at the observation-level (panels a and b: census tract, panels c, d, e, f: county). $t = -1$ represents the period before treatment begins. For panels a-e: cohort 1: Q2-2022; cohort 2: Q1-2024; cohort 3: Q2-2024. $t = j$ ($/t = -j$) represents j periods after (/before) treatment begins. For panel f election cycles are depicted on the vertical axis, with $t = 0$ being the year treatment begins (2024).

Electoral Results: Panel 2f reports the event study for Republican vote share in Rust Belt states and shows no significant political effects of Energy Community designation. This null result is robust across specifications and sample definitions. In the full national sample, we observe clear pre-trends, consistent with the political targeting of distressed regions, while swing states display no pre-trends but likewise no treatment effects (Appendix D.9). Appendix D.9 also provides results for House and Senate elections, which show similar null-results. Analysis of county-level environmental policy attitudes using Yale Climate Opinion Maps data also yields null results across multiple policy dimensions (Appendix D.10). Overall, the evidence indicates that although the Energy Community provision successfully directed renewable investment to distressed areas, it has not altered political preferences or environmental policy support through the 2024 election cycle.

Are the place-based provisions in the Inflation Reduction Act worth it? A full answer requires assessing the policy's longer-run impacts, which is beyond the scope of this study. We focus instead on short-run costs and benefits. Appendix A.1 reports back-of-the-envelope estimates of both the cost per ton of CO_2 abated and the cost per job vacancy created. These calculations should be interpreted cautiously, as they rest on strong assumptions and capture only the near-term effects of the IRA's place-based components, not the broader legislation. Nonetheless, they indicate that the implied cost of CO_2 abatement is below the Social Cost of Carbon estimated by U.S. Environmental Protection Agency (2022) and compares favorably with other U.S. initiatives such as electric-vehicle and residential-solar subsidies. By contrast, the cost per job vacancy created is high, reflecting the low labor intensity of the renewables sector. Overall, the IRA's place-based provisions appear to deliver meaningful environmental benefits but limited immediate employment gains. Some of the broader effects of industrial policy, such as stimulating innovation, investment, and job creation, are likely dynamic and may only materialize over a longer horizon.

7 Conclusion

Regional economic divergence and the desire to mitigate adverse distributional effects of the clean energy transition have spurred the use of place-based green industrial policy, though the effectiveness of such policies remains largely unknown. This paper has examined the place-based Energy Community provisions in the Inflation Reduction Act of 2022, which were designed to promote clean energy investment and create jobs in economically marginalized areas at an elevated risk of disruption from the green energy transition.

Using spatially granular investment and job vacancy data in a difference-in-differences framework, we find that the Energy Community provisions increased the likelihood of solar investment in Energy Communities by 0.14 percentage points during the two years after their implementation, a 144% increase relative to the counterfactual level of investment that would likely have materialized without Energy Community provisions. Wind investment shows no significant response. Evidence of employment gains is limited. We find no significant impacts on aggregate employment. Solar-related online job openings rose by approximately 29% relative to the counterfactual, albeit from a low baseline. This effect is consistent with expected multipliers but significant only at the 10% level. Wind-related labor demand was not affected. These muted labor market impacts may help explain why the policy did not influence electoral outcomes.

Overall, our findings suggest that place-based incentives can quickly and effectively stimulate green investment in targeted locations but have weaker impacts on local job creation in the short-run and limited impacts on political preferences. Assessing the longer-run impact of these provisions, as well as the broader impacts of the IRA, will be important avenues for future research.

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Appendix

A.1 Back-of-the-Envelope Cost Calculations

This section presents a back-of-the-envelope calculation of the total government spending on additional CO_2 emissions abatement and job creation under the IRA's Energy Community provisions. These estimates reflect short-run effects and do not capture potential longer-term impacts. We report two cost-measures: (i) EC bonus only, which reflects the additional cost of the EC bonus relative to the baseline subsidy, and (ii) EC bonus + ITC, which reflects the total fiscal cost of the combined subsidies.

Table A.1: EC solar, 2023–2024: job creation and abatement

Panel A. Emission abatement per 127 MW plant over 20 years			
Scenario	15% CF	22.5% CF	30% CF
MWh generated (plant lifetime)	3,328,985	4,993,478	6,657,971
CAPEX per MWh	43.57	29.05	21.79
CAPEX per tCO_2	62.16	41.44	31.08
Government Expenditure (EC) per tCO_2	10.53	7.02	5.27
Government Expenditure (EC + ITC) per tCO_2	42.13	28.08	21.06

Panel B. Job Creation		
Component	EC bonus only	ITC+EC
A. Fiscal outlays	\$2.872 b	\$11.488 b
Jobs (vacancies)	10,418	10,418
Cost per vacancy	\$275,669	\$1,102,676

Note: The table reports the back-of-the-envelope calculation for government expenditure on CO_2-abatement and job creation associated with the Energy Community (EC) bonus policy. Average nameplate capacity: 127 MW; Average CAPEX (capital expenditure): \$145 m; Total CAPEX: \$28.7 b; CO_2 intensity: 0.7010 tCO_2/MWh; EC bonus: 10% of CAPEX; ITC: 30% of CAPEX. Here, b denotes billions of dollars, m millions; CF = capacity factor. MWh generated is calculated for a power plant lifetime of 20 years. Government expenditure is corrected for infra-marginality using the marginal share (1.44/2.44). Fiscal outlay is the total CAPEX multiplied by the component's rate, e.i. EC Bonus or ITC+EC.

A.1.1 Emission abatement

This section estimates direct government expenditure under the IRA's Energy Community bonuses, per metric ton of CO_2 reduced. We calculate government expenditure for emission abatement in three steps. First, we calculate the capital expenditure

(CAPEX) per MWh built in ECs from solar energy. Second, we calculate the CO_2-intensity of electricity generation from fossil sources in ECs. We assume new solar facilities displace the pre-IRA electricity generation from fossil fuels and calculate the CAPEX per tCO_2 using this CO_2-intensity. Third, we convert the CAPEX per tCO_2 to government expenditure on EC bonus and ITC per tCO_2, accounting for additionality, which gives us the total government spending per additional tCO_2 abated. The results are presented in Panel A of Table A.1.

Step 1: CAPEX per MWh. The average solar plant built in 2023–2024 in Energy Communities had a 127 MW nameplate capacity (EIA U.S. Energy Information Administration, 2024).[1] Assuming a 20-year lifetime (Friedmann et al., 2020) and capacity factors of 15%, 22.5%, and 30% (National Renewable Energy Laboratory, 2024), lifetime generation equals:

$$\text{MWh} = 127 \times \text{Capacity Factor} \times 8{,}760 \text{ hours} \times 20 \text{ years} \tag{A.1}$$

yielding 3.3, 5.0, and 6.7 million MWh, respectively. We calculate CAPEX per MWh:

$$c^{\text{MWh}} = \frac{CAPEX}{\text{lifetime MWh}} \tag{A.2}$$

With an average CAPEX of $145 million per plant built in ECs in 2023-2024 (Rhodium Group and MIT's Center for Energy and Environmental Policy Research, 2024), the CAPEX per MWh is $43.57, $29.05, and $21.79. These values align closely with IRENA's (2025) global benchmark of about $43 per MWh for utility-scale solar, lending credibility to our estimates.[2]

Step 2: CAPEX per tCO_2. We calculate a generation-weighted CO_2 emission factor using EIA Form 860(M) data from April 2022 for all electricity generators using fossil fuel in Energy Communities. For each generator we calculate:

$$\text{Annual MWh} = \text{Nameplate Capacity (MW)} \times \text{Capacity Factor} \times 8{,}760 \text{ hours} \tag{A.3}$$

$$\begin{aligned} \text{Annual tCO}_2 = {} & \text{Annual MWh} \times \text{Heat Rate (Btu/MWh)} \\ & \times \text{Emission Factor (gr CO}_2\text{/MMBtu)} \end{aligned} \tag{A.4}$$

where heat rates, emission factors, and capacity factors are from U.S. Energy Information Administration (2023a), The Climate Registry (2023), and U.S. Energy

[1] The nameplate capacity is a plant's maximum power output under standard test conditions.

[2] IRENA, a United Nations–affiliated agency with 168 member states, reports the levelized cost of energy (LCOE), which includes both capital and operating costs, while our figures reflect only upfront investment. This difference in scope explains why our estimates are slightly lower. Excluding operation and maintenance costs is appropriate since these are not subsidized under the ITC or EC bonuses. Taking O&M costs of $20/kW-year (Friedmann et al., 2020), a 127 MW solar plant running for 20 years would have total O&M costs of $50.8 million.

Information Administration (2023b) respectively. The weighted average across generators of CO_2 intensity is:

$$\text{WACO}_2 = \sum (\text{Annual tCO}_2) / \sum (\text{Annual MWh}) = 0.7010 \text{ tCO}_2/\text{MWh} \quad \text{(A.5)}$$

This lies between the natural gas (0.4354) and coal (1.0478) intensities reported by the U.S. Energy Information Administration (2024b), reflecting the Energy Community fossil fuel mix. CAPEX per ton of CO_2 is:

$$c^{\text{CO}_2} = c^{\text{MWh}}/\text{WACO}_2 \quad \text{(A.6)}$$

reported in Panel A of table A.1. The resulting estimates range from \$31/tCO_2 to \$62/tCO_2.

These estimates are broadly consistent with other studies of the IRA. Roy et al. (2022) and J. E. Bistline et al. (2023) estimate total abatement costs of the IRA at \$43–54 and \$45–61 per tCO_2, respectively. These studies use detailed energy-system and general equilibrium models to capture both private and public expenditures associated with the IRA and the resulting change in CO_2 emissions. They thus capture the economy-wide cost of abatement, not just the fiscal cost to the government, a methodological difference worth bearing in mind when comparing our results to theirs.

Step 3: Government Expenditure per tCO_2. The EC bonus (10% of CAPEX) and combined ITC+EC (40% of CAPEX) yield government expenditure per ton of CO_2 of:

$$c^{EC} = 0.10 \times c^{\text{res}}, \qquad c^{EC+ITC} = 0.40 \times c^{\text{res}} \quad \text{(A.7)}$$

We adjust for inframarginal investments by dividing by the marginal share. Solar investment increased by 144% relative to no-IRA counterfactual due to the EC bonus, taking investment from 100 units to 244 units. The first 100 units are infra-marginal under the EC bonus. However, the government pays the EC bonus for all investments in ECs representing 244 units. So, the marginal share is represented by 144 units (marginal increase) over 244 units (total investment):

$$c^{EC}_{\text{policy induced}} = c^{EC} \times (244/144), \qquad c^{EC+ITC}_{\text{policy induced}} = c^{EC+ITC} \times (244/144) \quad \text{(A.8)}$$

Panel A reports these values, which range from \$5/tCO_2 to \$42/tCO_2 and are all substantially below the EPA's social cost of carbon (\$190/tCO_2 (U.S. Environmental Protection Agency, 2022)) and considerably lower than EV subsidy costs of \$399–795/tCO_2 (Sheldon et al., 2023; Xing et al., 2021) or residential solar subsidies of \$1,036/tCO_2 (Kattenberg et al., 2023). While these comparisons strongly favor the EC bonus, it is worth noting that federal fiscal incentives for clean technologies generally aim to promote both innovation and adoption. The innovation rationale may be particularly important for EVs and rooftop solar compared with more mature technologies such as utility-scale solar. Finally, our estimates are broadly in line with but marginally lower than those of Friedmann et al. (2020), who calculate the Levelized Cost of Carbon Abatement (LCCA) for utility-scale solar, displacing the 2018 U.S. electricity grid.[3] This suggests that the EC bonus can reduce CO_2 at a somewhat lower government cost than the ITC alone.

A.1.2 Job Creation

We estimate how many job vacancies the EC bonus created and compute the total government spending per additional vacancy. Panel B of Table A.1 summarizes the results. In 2023–2024, solar employers posted 46,343 vacancies in Energy Communities. Our difference-in-differences estimate implies a 29% increase due to the EC bonus, or 10,418 additional vacancies ($46,343 - \frac{46,343}{1.29}$).

CAPEX totals \$28.720 billion across all EC plants. The combined 40% credit (30% ITC plus 10% EC bonus) applied to \$28.720 billion in CAPEX yields fiscal expenditures of \$11.488 billion. Dividing by 10,418 vacancies gives a cost per vacancy of \$1,102,676. If we isolate the EC bonus alone, this covers 10% of CAPEX, or \$2.872 billion, and the cost per vacancy is \$275,669.

For context, estimates from other place-based programs are much smaller. Cingano et al. (2025) estimate that a program subsidizing public investments in Italy generated new employment at a cost of about €180,000 per job. In the UK, Criscuolo et al. (2019) find that the UK's Regional Selective Assistance scheme, a program subsidizing firms' investments in disadvantaged areas, generated jobs at a cost ranging from \$3,541 to \$26,572. In Japan, a government policy offering high-tech manufacturing tax breaks for investing outside the main metropolis created jobs at a fiscal cost ranging from \$16,000 to \$40,000 (LaPoint & Sakabe, 2021). Closer to our setting is the study of Bombardini et al. (2024) on U.S. Buy American rules. They estimate that existing Buy American provisions for final goods created up to 100,000 jobs at a cost of \$111,500 to \$137,700 per job. Recent tightening of restrictions on foreign inputs is projected to generate fewer jobs at higher costs, between \$154,000 and \$237,800 per job.

Our lower cost estimate, including the EC bonus only, is slightly higher than the highest estimate in Bombardini et al. (2024). Note that our calculation only uses government spending on the subsidy to proxy for costs, whereas Bombardini et al.

[3] Assuming a 22.5 percent capacity factor, Friedmann et al. (2020) calculates the Levelized Cost of Carbon Abatement (LCCA) for utility-scale solar, displacing the 2018 U.S. grid as \$91 per tCO_2 unsubsidized and \$53 per tCO_2 with a 30 percent ITC, implying a fiscal cost of \$38 per tCO_2 under full additionality. Adjusting for 55.9 percent additionality, as in our case, this corresponds to \$68 per tCO_2. These values are broadly in line with our government expenditure estimates for EC bonus plus ITC but somewhat higher, reflecting the additional abatement achieved through the EC bonus, lower CAPEX in 2023–2024, and differences in the energy mix and avoided O&M and fuel costs.

(2024) measure welfare costs. In addition, we use job vacancies, while Bombardini et al. (2024) use filled positions. Taken together, these differences imply that the EC bonus created job vacancies at substantially higher cost than is typically found in the literature on place-based industrial policies. However, the IRA's goals extended beyond job creation alone. While costly in terms of labor market impacts, the policy also delivered substantial benefits in expanding clean energy infrastructure and abating CO_2 emissions, which distinguishes it from more narrowly targeted place-based employment programs.

Online Appendix for
“Is Place-Based Green Industrial Policy Effective? Evidence from the Inflation Reduction Act”

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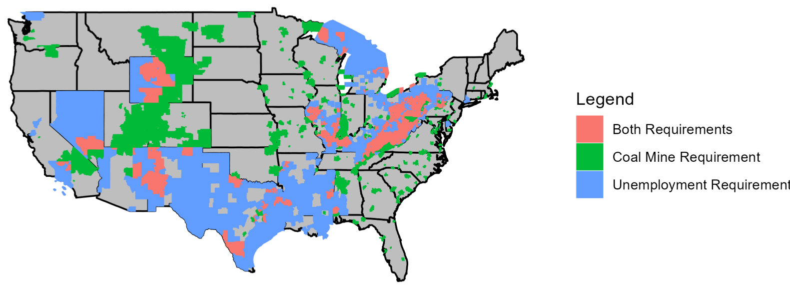
A Policy Context

Table A1: ITC and PTC rates

Project size	Base incentive	EC bonus	Domestic content bonus	Total possible
< 1 *MW*				
PTC	\$27.50/MWh	\$2.75/MWh	\$2.75/MWh	\$33.00/MWh
ITC	30%	10%	10%	50%
> 1 *MW*				
PTC	\$5.50/MWh	\$0.55/MWh	\$0.55/MWh	\$6.60/MWh
ITC	6%	2%	2%	10%
> 1 *MW with PWA*				
PTC	\$27.50/MWh	\$2.75/MWh	\$2.75/MWh	\$33.00/MWh
ITC	30%	10%	10%	50%

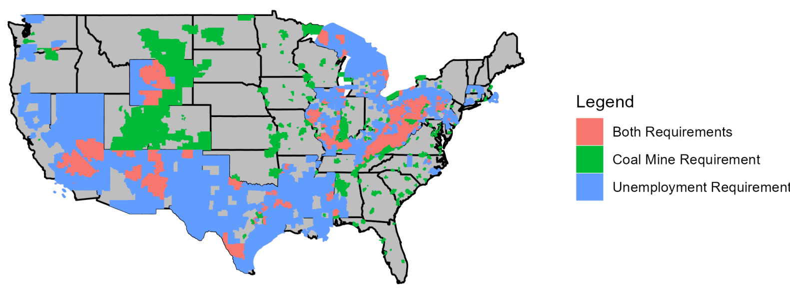
Note: The table presents the rates of the Investment and Production Tax Credits. Power plants with a nameplate capacity smaller than 1 MW receive the rates in the first row. Power plants with a nameplate capacity larger than 1 MW, receive the rates in the second or third row, depending on whether they adhere to the prevailing wage and apprenticeship requirements (PWA). ITC in percent of investment; PTC in \$/MWh. Projects built in designated Energy Communities (EC) receive the EC bonus, and projects adhering to the domestic content requirements receive the domestic content bonus. Bonuses are stackable, as reflected in the total possible column. Source: Office of Energy Efficiency & Renewable Energy (2024).

Figure A1: Energy Community Designations, January 2023–March 2024.



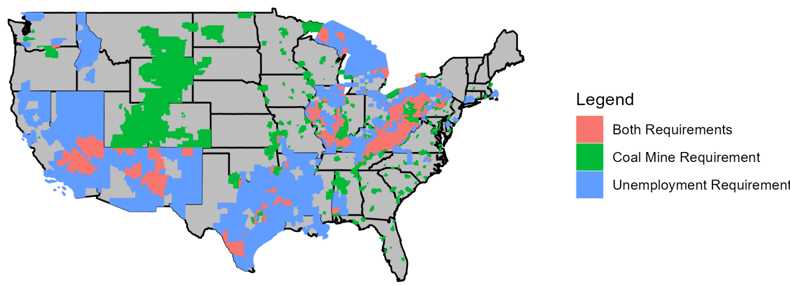
Note: The unit of observation is the census tract

Figure A2: Energy Community Designations, March 22, 2024 – June 6, 2024.



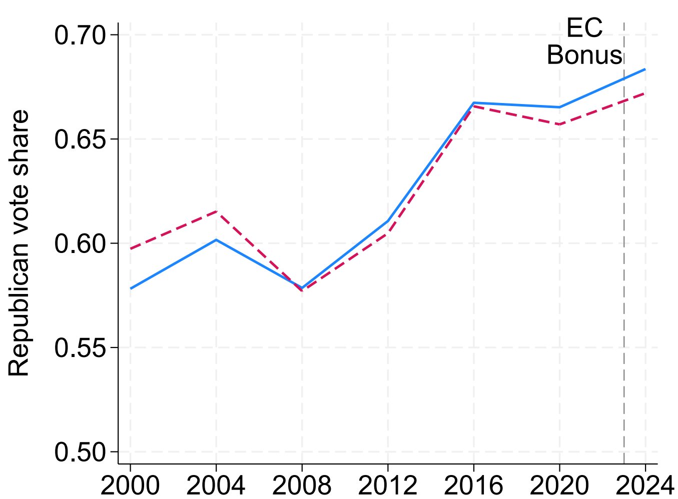
Note: The unit of observation is the census tract

Figure A3: Energy Community Designations June 6, 2024–December 31, 2024 (end of sample)



Note: The unit of observation is the census tract

Figure A4: Evolution of Voting.



Note: This figure reports county-level Republican presidential vote shares averaged across all counties, using only Democratic and Republican votes. The vertical dashed line marks the introduction of the Energy Community Bonus (Q1 of 2023).

B Data Validation

Table A2: Labor-market changes in Energy Communities (EC) vs. non-ECs.

	Job vacancies employed	Time to closing all vacancies	Share vacancies with NAICS
Year	0.002***	0.530***	-0.006***
	(0.0001)	(0.0947)	(0.0014)
Year × EC	-0.000***	-0.098	0.001
	(0.0001)	(0.0605)	(0.0009)
Observations	15,660	15,660	15,660
R^2	0.649	0.367	0.496
Adjusted R^2	0.561	0.209	0.369

Note: The table presents the results from regressions examining the representativeness of the data, and its evolution over time. Of focal interest is testing whether the quality of the labor demand data evolves similarly over time between ECs and non-ECs. The dependent variable in the first column is the ratio of job vacancies in the Lightcast data to the number of employed in the Quarterly Census of Employment and Wages. The second column uses as dependent varaiable the average number of days between the date a job vacancy was posted and the date the vacancy was closed. The third column uses as outcome variable the share of job vacancies that contain a NAICS code. All regressions are at the county-level. Year is a continuous variable, and EC is a binary indicator for counties designated as Energy Community (EC) in either cohort. *, ** and *** indicate significance at the 10%, 5% and 1% level respectively. Standard errors are clustered by county and presented in brackets. The sample spans the period from 2018 to 2022. The period in which the EC bonus became active is excluded as the treatment might affect the outcomes.

C Datasets

Table A3: Data Sources

#	Dataset	Source
1	Coal Closure Energy Communities (v2024_1)	National Energy Technology Laboratory (2025b)
2	Coal Closure Energy Communities (2023v2)	National Energy Technology Laboratory (2025a)
3	MSA/Non-MSA Fossil Fuel Employment Energy Communities (v2024_1)	National Energy Technology Laboratory (2025d)
4	MSA/Non-MSA Fossil Fuel Employment Energy Communities (2023v2)	National Energy Technology Laboratory (2025c)
5	MSA/Non-MSA FFE Energy Community Status (v2023_3)	National Energy Technology Laboratory (2025e)
6	National Sub-State Geography Database	United States Census Bureau (2025b)
7	Preliminary Monthly Electric Generator Inventory (EIA-860M)	EIA U.S. Energy Information Administration (2024)
8	Quarterly Census of Employment and Wages (County)	U.S. Bureau of Labor Statistics (2025)
9	Regional GDP and Personal Income, 2017–2022 (CAGDP9)	U.S. Bureau of Economic Analysis (2023)
10	County Presidential Election Returns, 2000–2024	Data and Lab (2018)
11	Educational Attainment for Adults 25+, 1970–2023	U.S. Department of Agriculture Economic Research Service (2025a)
12	Poverty Estimates, 2023	U.S. Department of Agriculture Economic Research Service (2025b)

Note: This table lists all datasets used in the paper.

Table A4: Data Sources 2

#	**Dataset**	**Source**
13	Unemployment and Median Household Income, 2000–2023	U.S. Department of Agriculture Economic Research Service (2025c)
14	Yale Climate Opinion Maps (YCOM 2024)	Yale Program on Climate Change Communication (2025)
15	GeoQuery Integrated Geospatial Data	Goodman et al. (2025)
16	US County FIPS–GeoQuery Crosswalk	Goodman et al. (2024)
17	Clean Investment Monitor (CIM)	Rhodium Group and MIT's Center for Energy and Environmental Policy Research (2024)
17	Clean Investment Monitor (CIM)	Rhodium Group and MIT's Center for Energy and Environmental Policy Research (2024)
18	Decennial Census Demographic Profile (DP1), 2020	United States Census Bureau (2025a)
19	Educational Attainment, ACS 5-Year Estimates, 2018–2022	United States Census Bureau (2025c)
20	Precinct-Level Election Returns, 2020	MIT Election Data and Science Lab (2026e)
21	Official House General Election Returns, 2018	MIT Election Data and Science Lab (2026d)
22	Election Context, 2018	MIT Election Data and Science Lab (2026a)
23	Official Election Returns by State, 2022	MIT Election Data and Science Lab (2026b)
24	Official Election Returns by State, 2024	MIT Election Data and Science Lab (2026c)
25	Lightcast Labor Market Data	Lightcast (2025)

Note: This table lists all datasets used in the paper.

D Additional Results

D.1 Main Regressions, Table of Coefficients

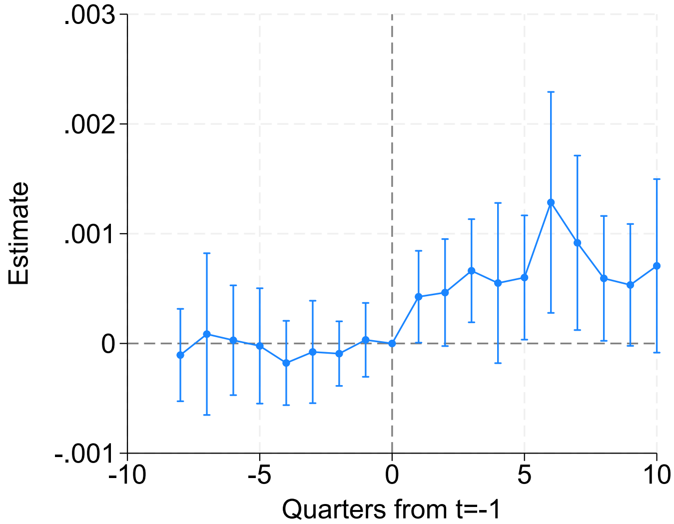
Table A5: Event Study of the EC Bonus on Investment and Labor Demand

	Investment				Labour Demand			
	(1) Solar		(2) Wind		(3) Solar		(4) Wind	
$\hat{\delta}_8^{pl}$	0.000	(0.000)	0.000	(0.000)	0.001	(0.000)	0.000	(0.001)
$\hat{\delta}_7^{pl}$	0.000	(0.000)	0.000*	(0.000)	0.001*	(0.000)	-0.000	(0.001)
$\hat{\delta}_6^{pl}$	0.002***	(0.000)	0.000	(0.000)	0.000	(0.000)	-0.000	(0.001)
$\hat{\delta}_5^{pl}$	0.000	(0.000)	0.000*	(0.000)	0.000	(0.000)	0.001	(0.001)
$\hat{\delta}_4^{pl}$	0.000	(0.000)	0.000*	(0.000)	0.000	(0.000)	0.000	(0.001)
$\hat{\delta}_3^{pl}$	0.000	(0.000)	0.000**	(0.000)	0.000	(0.000)	-0.000	(0.001)
$\hat{\delta}_2^{pl}$	-0.000	(0.000)	0.000**	(0.000)	-0.000	(0.000)	-0.000	(0.001)
$\hat{\delta}_1^{pl}$	0.001**	(0.000)	0.000**	(0.000)	0.000	(0.000)	0.000	(0.001)
$\hat{\delta}_1$	0.001***	(0.000)	0.000*	(0.000)	-0.000	(0.000)	-0.000	(0.000)
$\hat{\delta}_2$	0.001**	(0.000)	0.000	(0.000)	0.001	(0.001)	0.001**	(0.000)
$\hat{\delta}_3$	0.001***	(0.000)	0.000	(0.000)	0.000	(0.000)	-0.000	(0.001)
$\hat{\delta}_4$	0.002***	(0.000)	0.000	(0.000)	0.000	(0.000)	0.001	(0.001)
$\hat{\delta}_5$	0.002***	(0.000)	0.000**	(0.000)	0.000	(0.000)	0.000	(0.001)
$\hat{\delta}_6$	0.001	(0.000)	0.000	(0.000)	-0.000	(0.000)	-0.000	(0.001)
$\hat{\delta}_7$	0.001***	(0.000)	0.000**	(0.000)	0.001	(0.000)	0.001*	(0.001)
$\hat{\delta}_8$	0.002***	(0.000)	0.000**	(0.000)	0.000	(0.000)	-0.000	(0.001)
$\hat{\delta}_9$	0.003***	(0.000)	0.000*	(0.000)	0.001	(0.000)	0.001	(0.001)
$\hat{\delta}_{10}$	0.003***	(0.001)	0.000**	(0.000)	0.000	(0.000)	0.000	(0.001)
$\hat{\delta}$	0.001***	(0.000)	0.000***	(0.000)	0.000*	(0.000)	0.000	(0.000)

Note: The table reports difference-in-differences estimates of the introduction of the Energy Community (EC) Bonus on investment (extensive margin) and labor demand, estimated using the method of De Chaisemartin and D'Haultfoeuille (2024). Columns 1–2 show quarterly effects of EC status on the probability that census tracts receive solar or wind investment. Columns 3–4 show quarterly effects on solar and wind labor demand at the county level, measured as the share of job vacancies listing solar or wind keywords. Standard errors are clustered at the observation level (columns 1–2: census tract; columns 3–4: county) and presented in parentheses. *, ** and *** indicate significance at the 10%, 5% and 1% level respectively. $\hat{\delta}$ represents the Actual-Versus-Status-Quo effect. $\hat{\delta}_1$ represents the AVSQ the first quarter after treatment begins. For cohort 1: Q3-2022; cohort 2: Q2-2024; cohort 3: Q3-2024. $\hat{\delta}_i$ represents the AVSQ i quarters after treatment begins. $\hat{\delta}_j^{pl}$ represents the (placebo) AVSQ j quarters before treatment begins.

D.2 Auxiliary Analysis: Effect of Solar Investment on Solar Labor Demand

Figure A5: Event Study of Solar Investment on Solar Labor Demand



Note: The figure reports difference-in-differences estimates, as well as 95% confidence intervals, of the effect of solar investment on solar labor demand estimated using De Chaisemartin and D'Haultfoeuille (2024). The figure reports the impact of receiving a solar investment on quarterly solar labor demand. If a county receives a solar investment, the county is considered treated from that period onward. Solar labor demand is measured as the quarterly share of job vacancies containing solar keywords. Standard errors are clustered at the county level. $t = -1$ represents the quarter prior to treatment begins.

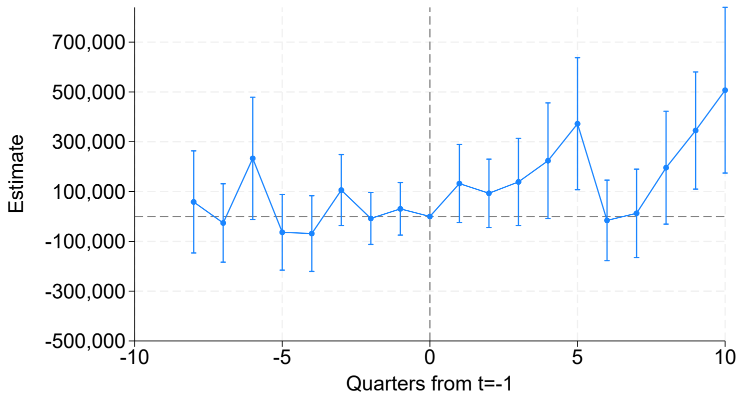
Table A6: Event Study of Solar Investment on Solar Labor Demand

	(1) Solar Labour Demand	
$\hat{\delta}_8^{pl}$	-0.000	(0.000)
$\hat{\delta}_7^{pl}$	0.000	(0.000)
$\hat{\delta}_6^{pl}$	0.000	(0.000)
$\hat{\delta}_5^{pl}$	-0.000	(0.000)
$\hat{\delta}_4^{pl}$	-0.000	(0.000)
$\hat{\delta}_3^{pl}$	-0.000	(0.000)
$\hat{\delta}_2^{pl}$	-0.000	(0.000)
$\hat{\delta}_1^{pl}$	0.000	(0.000)
$\hat{\delta}_1$	0.000**	(0.000)
$\hat{\delta}_2$	0.000*	(0.000)
$\hat{\delta}_3$	0.001***	(0.000)
$\hat{\delta}_4$	0.001	(0.000)
$\hat{\delta}_5$	0.001**	(0.000)
$\hat{\delta}_6$	0.001**	(0.001)
$\hat{\delta}_7$	0.001**	(0.000)
$\hat{\delta}_8$	0.001**	(0.000)
$\hat{\delta}_9$	0.001*	(0.000)
$\hat{\delta}_{10}$	0.001*	(0.000)
$\hat{\delta}$	0.001***	(0.000)

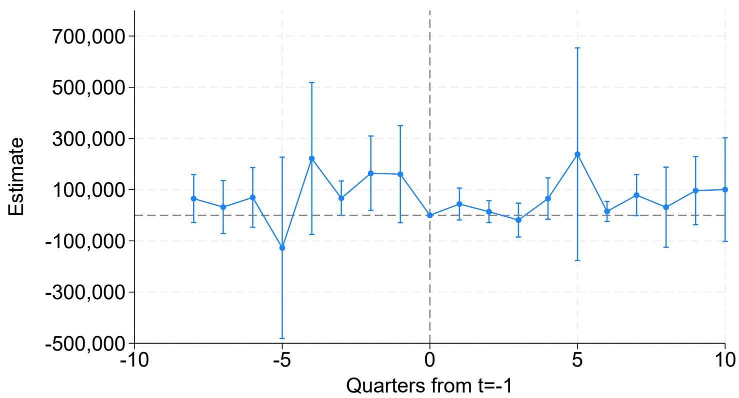
Note: The table reports difference-in-differences estimates of the effect of solar investment on solar labor demand estimated using the method of De Chaisemartin and D'Haultfoeuille (2024). The column reports the impact of receiving a solar investment on quarterly solar labor demand. If a county receives a solar investment, the county is considered treated from that quarter onward. Solar labor demand is measured as the quarterly share of job vacancies containing solar keywords. Standard errors, which are presented in parentheses, are clustered at the county level. *, ** and *** indicate significance at the 10%, 5% and 1% level respectively. $\hat{\delta}$ represents the Actual-Versus-Status-Quo (AVSQ) effect. $\hat{\delta}_1$ is the AVSQ effect one quarter after treatment begins. $\hat{\delta}_i$ represents the AVSQ i quarters after treatment begins. $\hat{\delta}_j^{pl}$ represents the placebo AVSQ j quarters before treatment begins.

D.3 Robustness: Investment in Levels

Figure A6: Event Study of the EC Bonus on Investment Levels (in USD)



(a) Solar



(b) Wind

Note: The figure reports difference-in-differences estimates and 95% confidence intervals of the effect of Energy Community (EC) status on quarterly solar (panel a) and wind (panel b) investment in USD, estimated using the method of De Chaisemartin and D'Haultfoeuille (2024). Standard errors are clustered at the census-tract level. Event time is indexed such that $t = -1$ is the quarter prior to treatment and $t = 0$ is the first treated quarter. Cohorts 1, 2 and 3 begin receiving the EC bonus in Q3-2022, Q2-2024, and Q3-2024, respectively.

Table A7: Event Study of the EC Bonus on Investment Levels (in USD)

	(1) Solar		(2) Wind	
$\hat{\delta}_8^{pl}$	58,280	(104,606)	65,147	(47,722)
$\hat{\delta}_7^{pl}$	-26,200	(80,219)	32,044	(52,858)
$\hat{\delta}_6^{pl}$	233,374*	(125,230)	69,757	(59,453)
$\hat{\delta}_5^{pl}$	-63,557	(77,510)	-127,284	(180,764)
$\hat{\delta}_4^{pl}$	-68,716	(77,398)	221,833	(151,569)
$\hat{\delta}_3^{pl}$	105,880	(72,602)	66,584*	(34,362)
$\hat{\delta}_2^{pl}$	-8,003	(53,037)	164,292**	(74,070)
$\hat{\delta}_1^{pl}$	30,505	(53,702)	160,517*	(96,792)
$\hat{\delta}_1$	132,194*	(79,859)	44,015	(31,785)
$\hat{\delta}_2$	93,163	(70,015)	13,915	(21,879)
$\hat{\delta}_3$	138,735	(89,342)	-18,720	(33,755)
$\hat{\delta}_4$	223,826*	(118,519)	65,334	(41,105)
$\hat{\delta}_5$	372,344***	(135,318)	238,411	(211,920)
$\hat{\delta}_6$	-15,799	(82,595)	15,250	(20,004)
$\hat{\delta}_7$	12,770	(90,535)	78,519*	(40,922)
$\hat{\delta}_8$	195,964*	(115,635)	31,585	(79,782)
$\hat{\delta}_9$	345,189***	(119,984)	96,421	(68,092)
$\hat{\delta}_{10}$	507,039***	(169,700)	100,321	(103,172)
$\hat{\delta}$	185,217***	(62,952)	57,215**	(24,865)

Note: The table reports difference-in-differences estimates of the effect of Energy Community (EC) status on quarterly investment in USD, estimated using the method of De Chaisemartin and D'Haultfoeuille (2024)). Columns 1 and 2 present estimates for solar and wind investment, respectively. Standard errors, shown in brackets, are clustered at the census-tract level. *, ** and *** indicate significance at the 10%, 5% and 1% level respectively. $\hat{\delta}$ represents the Actual-Versus-Status-Quo (AVSQ) effect. $\hat{\delta}_1$ represents the AVSQ the first quarter after treatment begins. For cohort 1: Q3-2022; cohort 2: Q2-2024; cohort 3: Q3-2024. $\hat{\delta}_i$ represents the AVSQ i quarters after treatment starts. $\hat{\delta}_j^{pl}$ represents the placebo AVSQ j quarters before treatment begins.

D.4 Robustness: Endogeneity

We reiterate the inclusion criteria for EC-status here:

1. A "brownfield site" as defined in the Comprehensive Environmental Response, Compensation, and Liability Act of 1980 (CERCLA);

2. A "metropolitan statistical area" or "non-metropolitan statistical area" that has (or had at any time after 2009) either:

   - 0.17% or greater direct employment related to the extraction, processing, transport, or storage of coal, oil, or natural gas; OR
   - 25% or greater local tax revenues related to the extraction, processing, transport, or storage of coal, oil, or natural gas;

   and has an unemployment rate at or above the national average unemployment rate for the previous year;

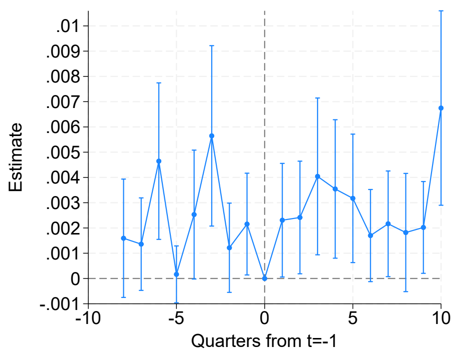
3. A census tract (or directly adjoining census tract) in which a coal mine has closed after 1999 or in which a coal-fired electric generating unit has been retired after 2009.

We do not assess ECs qualified due to brownfield sites for several reasons detailed in section 2 in the main text. Inclusion criterion 2 depends on recent economic trajectories and could possibly lead to endogeneity issues. To assess this possibility as well as its potential impacts on our results we conduct several analyses. First, we repeat the analyses in the main text but restricting the sample of treated observations to ECs qualified singularly due to criterion 3. Second, we examine a similar DiD-specification while explicitly controlling for lagged unemployment rates. Third, we perform two matching exercises; one in which we match based on unemployment rates, and one in which we match on a larger set of observables. The final matching exercise does not only examine potential endogeneity due to recent economic developments, but also for broader differences between ECs and non-ECs which could potentially violate the parallel trends assumption.

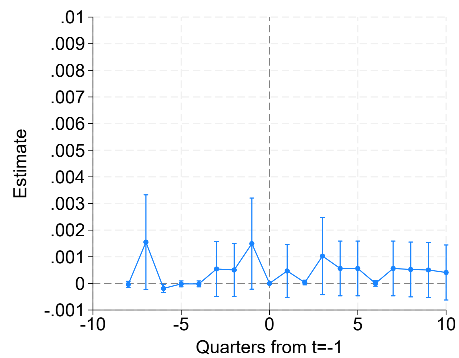
D.4.1 Robustness: Endogeneity (Criterion 3)

In this section, we perform the same DiD-specification as in our preferred specification, but limiting our sample to ECs singularly due to criterion 3. We refrain from definite conclusions using this sample due to more problematic pre-trends, especially in the solar investment specification.

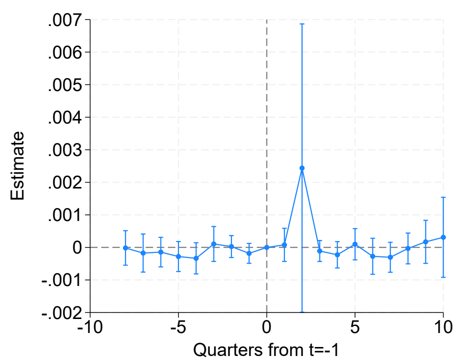
Figure A7: Event Study of the EC Bonus on Investment and Labor Demand – Sample Excluding ECs Under Criterion 2



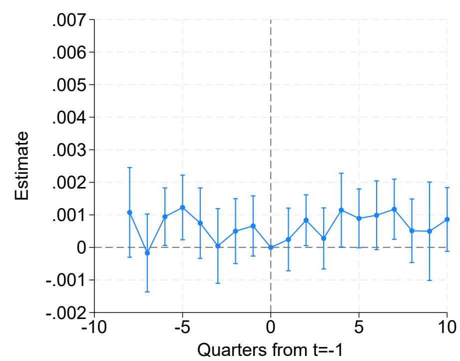
(a) Binary Solar Investment



(b) Binary Wind Investment



(c) Solar Labor Demand



(d) Wind Labor Demand

Note: The figure reports difference-in-differences event study estimates, as well as 95% confidence intervals, of the Energy Community Bonus on investment and labor demand, estimated using the method of De Chaisemartin and D'Haultfoeuille (2024) on a sample excluding ECs due to criterion 2. Panels a and b report the quarterly effect of EC status on the probability of census tracts receiving solar investment and wind investment, respectively. Panels c and d report the quarterly effect of EC status on solar and wind labor demand at the county-level, respectively. Labor demand is measured as the share of job vacancies listing solar or wind keywords. Standard errors are clustered at the observation-level (panels a and b: census tract, panels c and d: county). $t = -1$ represents the quarter prior to treatment start. For cohort 1: Q2-2022; cohort 2: Q1-2024; cohort 3: Q2-2024.

Table A8: Event Study of the EC Bonus on Investment and Labor Demand – Sample Excluding ECs Under Criterion 2

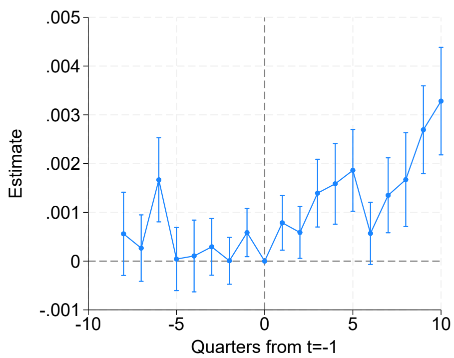
	Investment				Labour Demand			
	(1) Solar		(2) Wind		(3) Solar		(4) Wind	
$\hat{\delta}_8^{pl}$	0.002	(0.001)	-0.000	(0.000)	-0.000	(0.000)	0.001	(0.001)
$\hat{\delta}_7^{pl}$	0.001	(0.001)	0.002*	(0.001)	-0.000	(0.000)	-0.000	(0.001)
$\hat{\delta}_6^{pl}$	0.005***	(0.002)	-0.000**	(0.000)	-0.000	(0.000)	0.001**	(0.000)
$\hat{\delta}_5^{pl}$	0.000	(0.001)	-0.000	(0.000)	-0.000	(0.000)	0.001**	(0.001)
$\hat{\delta}_4^{pl}$	0.003*	(0.001)	-0.000	(0.000)	-0.000	(0.000)	0.001	(0.001)
$\hat{\delta}_3^{pl}$	0.006***	(0.002)	0.001	(0.001)	0.000	(0.000)	0.000	(0.001)
$\hat{\delta}_2^{pl}$	0.001	(0.001)	0.001	(0.001)	0.000	(0.000)	0.000	(0.001)
$\hat{\delta}_1^{pl}$	0.002**	(0.001)	0.001*	(0.001)	-0.000	(0.000)	0.001	(0.000)
$\hat{\delta}_1$	0.002**	(0.001)	0.000	(0.001)	0.000	(0.000)	0.000	(0.000)
$\hat{\delta}_2$	0.002**	(0.001)	0.000	(0.000)	0.002	(0.002)	0.001**	(0.000)
$\hat{\delta}_3$	0.004**	(0.002)	0.001	(0.001)	-0.000	(0.000)	0.000	(0.000)
$\hat{\delta}_4$	0.004**	(0.001)	0.001	(0.001)	-0.000	(0.000)	0.001**	(0.001)
$\hat{\delta}_5$	0.003**	(0.001)	0.001	(0.001)	0.000	(0.000)	0.001*	(0.000)
$\hat{\delta}_6$	0.002*	(0.001)	0.000	(0.000)	-0.000	(0.000)	0.001*	(0.001)
$\hat{\delta}_7$	0.002**	(0.001)	0.001	(0.001)	-0.000	(0.000)	0.001**	(0.000)
$\hat{\delta}_8$	0.002	(0.001)	0.001	(0.001)	-0.000	(0.000)	0.001	(0.000)
$\hat{\delta}_9$	0.002**	(0.001)	0.001	(0.001)	0.000	(0.000)	0.000	(0.001)
$\hat{\delta}_{10}$	0.007***	(0.002)	0.000	(0.001)	0.000	(0.001)	0.001*	(0.000)
$\hat{\delta}$	0.003***	(0.000)	0.000***	(0.000)	0.000	(0.000)	0.001*	(0.000)

Note: The table reports difference-in-differences estimates of the Energy Community Bonus on investment and labor demand, estimated using the method of De Chaisemartin and D'Haultfoeuille (2024) on a sample excluding ECs due to criterion 2. Columns 1–2 show quarterly effects of EC status on the probability that census tracts receive solar or wind investment. Columns 3–4 show quarterly effects on solar and wind labor demand at the county level, measured as the share of job vacancies listing solar or wind keywords. Standard errors are clustered at the observation level (columns 1–2: census tract; columns 3–4: county). *, ** and *** indicate significance at the 10%, 5% and 1% level respectively. $\hat{\delta}$ represents the Actual-Versus-Status-Quo (AVSQ) effect. $\hat{\delta}_1$ is the AVSQ effect one quarter after treatment begins. For cohort 1: Q3-2022; cohort 2: Q2-2024; cohort 3: Q3-2024. $\hat{\delta}_i$ represents the AVSQ i quarters after treatment begins. $\hat{\delta}_j^{pl}$ represents the placebo AVSQ j quarters before treatment begins.

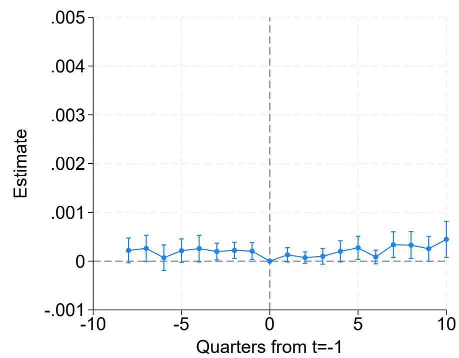
D.4.2 Robustness: Endogeneity (Controlling for Unemployment Rates)

In this section we perform our preferred specification, but including lagged unemployment rates as explicit control variables. The specific lags we include are 1, 2, and 3 years. The results are indistinguishable from our preferred specification.

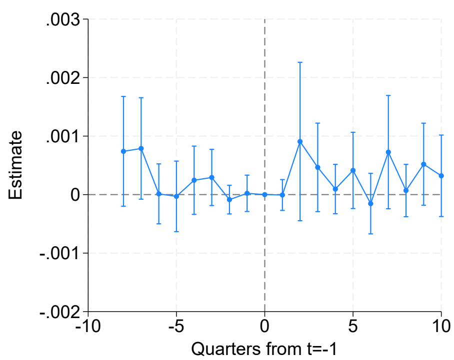
Figure A8: Event Study of the EC Bonus on Investment and Labor Demand – Controlling for 1, 2, and 3 Year Lagged Unemployment Rates



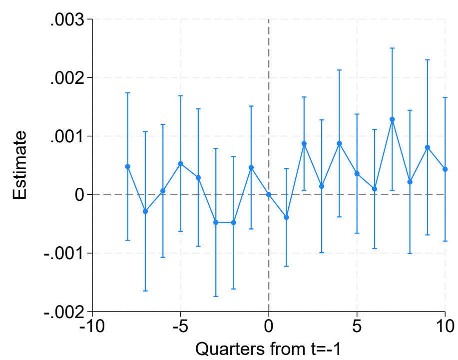
(a) Binary Solar Investment



(b) Binary Wind Investment



(c) Solar Labor Demand



(d) Wind Labor Demand

Note: The figure reports difference-in-differences event study estimates, as well as 95% confidence intervals, of the Energy Community Bonus on investment and labor demand, estimated using the method of De Chaisemartin and D'Haultfoeuille (2024) on the full sample, controlling for 1, 2, and 3 year lagged unemployment rates. Panels a and b report the quarterly effect of EC status on the probability of census tracts receiving solar investment and wind investment, respectively. Panels c and d report the quarterly effect of EC status on solar and wind labor demand at the county-level, respectively. Labor demand is measured as the share of job vacancies listing solar or wind keywords. Standard errors are clustered at the observation-level (panels a and b: census tract, panels c and d: county). $t = -1$ represents the quarter prior to treatment start. For cohort 1: Q2-2022; cohort 2: Q1-2024; cohort 3: Q2-2024.

Table A9: Event Study of the EC Bonus on Investment and Labor Demand – Controlling for 1, 2, and 3 Year Lagged Unemployment Rates

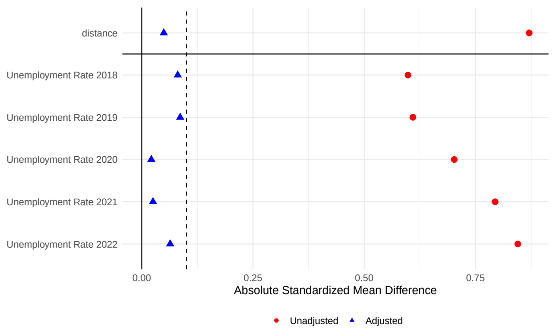
	Investment				Labour Demand			
	(1) Solar		(2) Wind		(3) Solar		(4) Wind	
$\hat{\delta}_8^{pl}$	0.001	(0.000)	0.000*	(0.000)	0.001	(0.000)	0.000	(0.001)
$\hat{\delta}_7^{pl}$	0.000	(0.000)	0.000*	(0.000)	0.001*	(0.000)	-0.000	(0.001)
$\hat{\delta}_6^{pl}$	0.002***	(0.000)	0.000	(0.000)	0.000	(0.000)	0.000	(0.001)
$\hat{\delta}_5^{pl}$	0.000	(0.000)	0.000*	(0.000)	-0.000	(0.000)	0.001	(0.001)
$\hat{\delta}_4^{pl}$	0.000	(0.000)	0.000*	(0.000)	0.000	(0.000)	0.000	(0.001)
$\hat{\delta}_3^{pl}$	0.000	(0.000)	0.000**	(0.000)	0.000	(0.000)	-0.000	(0.001)
$\hat{\delta}_2^{pl}$	0.000	(0.000)	0.000***	(0.000)	-0.000	(0.000)	-0.000	(0.001)
$\hat{\delta}_1^{pl}$	0.001**	(0.000)	0.000**	(0.000)	0.000	(0.000)	0.000	(0.001)
$\hat{\delta}_1$	0.001***	(0.000)	0.000*	(0.000)	-0.000	(0.000)	-0.000	(0.000)
$\hat{\delta}_2$	0.001**	(0.000)	0.000	(0.000)	0.001	(0.001)	0.001**	(0.000)
$\hat{\delta}_3$	0.001***	(0.000)	0.000	(0.000)	0.000	(0.000)	0.000	(0.001)
$\hat{\delta}_4$	0.002***	(0.000)	0.000*	(0.000)	0.000	(0.000)	0.001	(0.001)
$\hat{\delta}_5$	0.002***	(0.000)	0.000**	(0.000)	0.000	(0.000)	0.000	(0.001)
$\hat{\delta}_6$	0.001*	(0.000)	0.000	(0.000)	-0.000	(0.000)	0.000	(0.001)
$\hat{\delta}_7$	0.001***	(0.000)	0.000**	(0.000)	0.001	(0.000)	0.001**	(0.001)
$\hat{\delta}_8$	0.002***	(0.000)	0.000**	(0.000)	0.000	(0.000)	0.000	(0.001)
$\hat{\delta}_9$	0.003***	(0.000)	0.000*	(0.000)	0.001	(0.000)	0.001	(0.001)
$\hat{\delta}_{10}$	0.003***	(0.001)	0.000**	(0.000)	0.000	(0.000)	0.000	(0.001)
$\hat{\delta}$	0.001***	(0.000)	0.000***	(0.000)	0.000*	(0.000)	0.000	(0.000)

Note: The table reports difference-in-differences estimates of the Energy Community Bonus on investment and labor demand, estimated using the method of De Chaisemartin and D'Haultfoeuille (2024) on the full sample, controlling for 1, 2, and 3 year lagged unemployment rates. Columns 1–2 show quarterly effects of EC status on the probability that census tracts receive solar or wind investment. Columns 3–4 show quarterly effects on solar and wind labor demand at the county level, measured as the share of job vacancies listing solar or wind keywords. Standard errors are clustered at the observation level (columns 1–2: census tract; columns 3–4: county). *, ** and *** indicate significance at the 10%, 5% and 1% level respectively. $\hat{\delta}$ represents the Actual-Versus-Status-Quo (AVSQ) effect. $\hat{\delta}_1$ is the AVSQ effect one quarter after treatment begins. For cohort 1: Q3-2022; cohort 2: Q2-2024; cohort 3: Q3-2024. $\hat{\delta}_i$ represents the AVSQ i quarters after treatment begins. $\hat{\delta}_j^{pl}$ represents the placebo AVSQ j quarters before treatment begins.

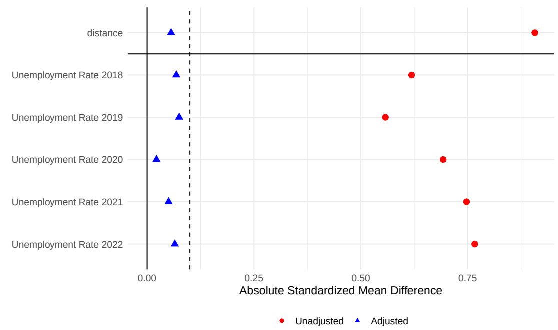
D.4.3 Robustness: Matching (Unemployment Rates)

To ensure our results are not driven by pre-existing differences between ECs and non-ECs, we perform a propensity score matching exercise. The De Chaisemartin and D'Haultfoeuille (2024) method does not accommodate matching directly, so we first perform one-to-one nearest neighbor matching without replacement to construct a restricted sample of matched observations, then apply the De Chaisemartin and D'Haultfoeuille (2024) estimator to this matched sample. In this first exercise, we match only on the unemployment rates between 2018 and 2022. The coefficient for solar investment increases substantially to 0.19 percentage point from 0.14 in our original estimate. Wind investment and labor demand remain null-effects analogous to our preferred estimate. Solar labor demand increases modestly to 0.040 percentage point from 0.033.

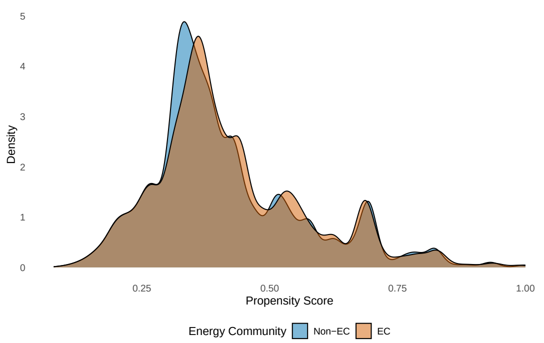
Figure A9: Matching Unemployment Rates – Specification Checks



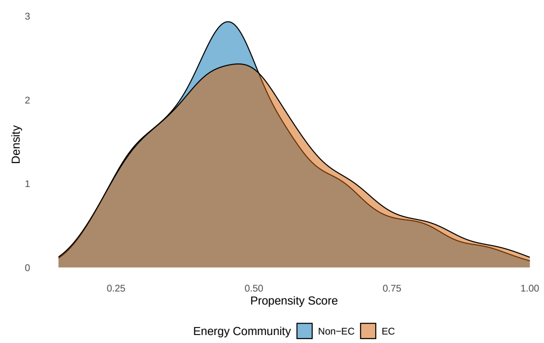
(a) Love Plot: Investment



(b) Love Plot: Labor Demand



(c) Propensity Score Density: Investment



(d) Propensity Score Density: Labor Demand

Note: The figures report the love plots and the propensity score density plot corresponding to our matching procedure. We perform one-to-one nearest-neighbor propensity-score matching without replacement, pairing Energy Communities (ECs) with comparable non-EC areas. Panels (a) and (b) report the love plots for investment and labor demand respectively. The red dots represent the pre-matching absolute standardized mean differences between the ECs and non-ECs. The blue triangles represent the post-matching differences. Panels (c) and (d) show the distribution of propensity scores for investment and labor demand respectively. The unit of observation for investment is the census tract, and for labor demand the county.

Table A10: Samples: Investment (Unemployment Rates)

Sample	N
Full Sample	83404
Energy Community Tracts	31985
Non-Energy Community Tracts	51419
Matched Sample	46724
Energy Community Tracts	23362
Non-Energy Community Tracts	23362
Dropped in Matching	36680
Energy Community Tracts	8623
Non-Energy Community Tracts	28057

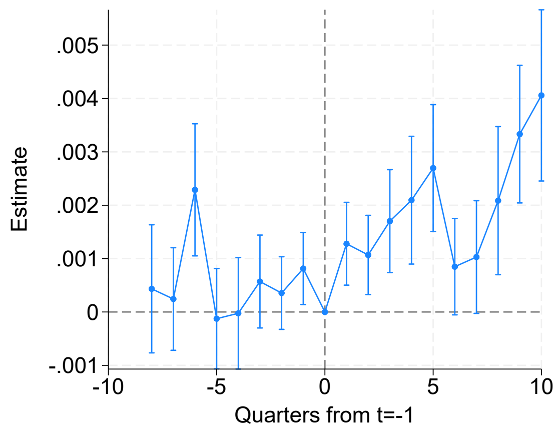
Note: The table reports the sample size for the full sample, the matched sample, and the observations dropped after matching. The unit of observation is the census tract. The matched sample is used in the investment analysis.

Table A11: Samples: Labor Demand (Unemployment Rates)

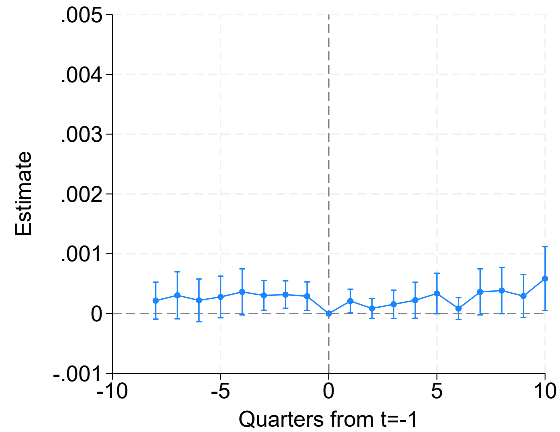
Sample	N
Full Sample	3122
Energy Community Counties	1504
Non-Energy Community Counties	1618
Matched Sample	1986
Energy Community Counties	993
Non-Energy Community Counties	993
Dropped in Matching	1136
Energy Community Counties	511
Non-Energy Community Counties	625

Note: The table reports the sample size for the full sample, the matched sample, and the observations dropped after matching. The unit of observation is the county. The matched sample is used in the labor demand analysis.

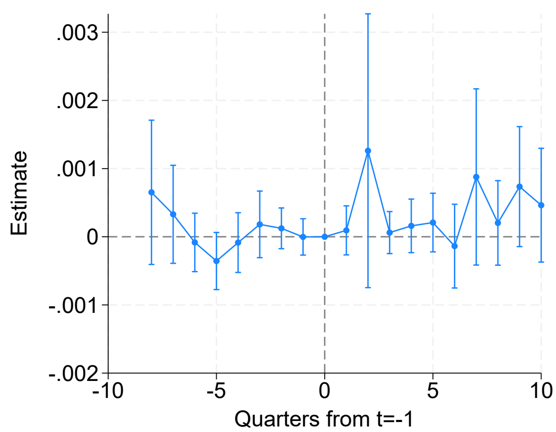
Figure A10: Event Study of the EC Bonus on Investment and Labor Demand – Matched Sample (Unemployment Rates)



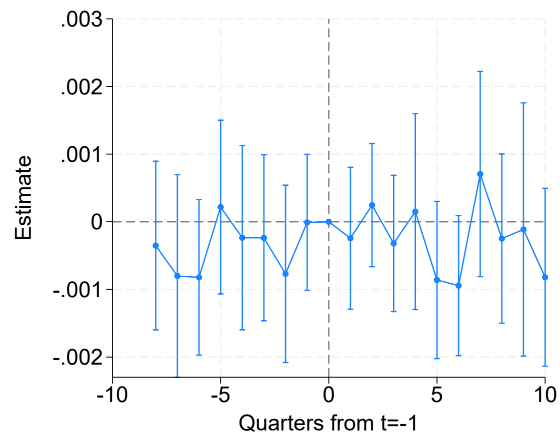
(a) Solar Investment (Extensive Margin)



(b) Wind Investment (Extensive Margin)



(c) Solar Labor Demand



(d) Wind Labor Demand

Note: The figure reports difference-in-differences event study estimates, as well as 95% confidence intervals, of the Energy Community Bonus on investment and labor demand, estimated using the method of De Chaisemartin and D'Haultfoeuille (2024) on a matched sample using unemployment rates between 2018 and 2022, selected using nearest neighbor propensity score matching without replacement prior to performing the event study analysis. Panels a and b report the quarterly effect of EC status on the probability of census tracts receiving solar investment and wind investment, respectively. Panels c and d report the quarterly effect of EC status on solar and wind labor demand at the county-level, respectively. Labor demand is measured as the share of job vacancies listing solar or wind keywords. Standard errors are clustered at the observation-level (panels a and b: census tract, panels c and d: county). $t = -1$ represents the quarter prior to treatment start. For cohort 1: Q2-2022; cohort 2: Q1-2024; cohort 3: Q2-2024.

Table A12: Event Study of the EC Bonus on Investment and Labor Demand – Matched Sample (Unemployment Rates)

	Investment				Labour Demand			
	(1) Solar		(2) Wind		(3) Solar		(4) Wind	
$\hat{\delta}^{pl}_8$	0.000	(0.001)	0.000	(0.000)	0.001	(0.001)	-0.000	(0.001)
$\hat{\delta}^{pl}_7$	0.000	(0.000)	0.000	(0.000)	0.000	(0.000)	-0.001	(0.001)
$\hat{\delta}^{pl}_6$	0.002***	(0.001)	0.000	(0.000)	-0.000	(0.000)	-0.001	(0.001)
$\hat{\delta}^{pl}_5$	-0.000	(0.000)	0.000	(0.000)	-0.000*	(0.000)	0.000	(0.001)
$\hat{\delta}^{pl}_4$	-0.000	(0.001)	0.000*	(0.000)	-0.000	(0.000)	-0.000	(0.001)
$\hat{\delta}^{pl}_3$	0.001	(0.000)	0.000**	(0.000)	0.000	(0.000)	-0.000	(0.001)
$\hat{\delta}^{pl}_2$	0.000	(0.000)	0.000***	(0.000)	0.000	(0.000)	-0.001	(0.001)
$\hat{\delta}^{pl}_1$	0.001**	(0.000)	0.000**	(0.000)	-0.000	(0.000)	-0.000	(0.001)
$\hat{\delta}_1$	0.001***	(0.000)	0.000**	(0.000)	0.000	(0.000)	-0.000	(0.001)
$\hat{\delta}_2$	0.001***	(0.000)	0.000	(0.000)	0.001	(0.001)	0.000	(0.000)
$\hat{\delta}_3$	0.002***	(0.000)	0.000	(0.000)	0.000	(0.000)	-0.000	(0.001)
$\hat{\delta}_4$	0.002***	(0.001)	0.000	(0.000)	0.000	(0.000)	0.000	(0.001)
$\hat{\delta}_5$	0.003***	(0.001)	0.000*	(0.000)	0.000	(0.000)	-0.001	(0.001)
$\hat{\delta}_6$	0.001*	(0.000)	0.000	(0.000)	-0.000	(0.000)	-0.001*	(0.001)
$\hat{\delta}_7$	0.001*	(0.001)	0.000*	(0.000)	0.001	(0.001)	0.001	(0.001)
$\hat{\delta}_8$	0.002***	(0.001)	0.000*	(0.000)	0.000	(0.000)	-0.000	(0.001)
$\hat{\delta}_9$	0.003***	(0.001)	0.000	(0.000)	0.001	(0.000)	-0.000	(0.001)
$\hat{\delta}_{10}$	0.004***	(0.001)	0.001**	(0.000)	0.000	(0.000)	-0.001	(0.001)
$\hat{\delta}$	0.002***	(0.000)	0.000***	(0.000)	0.000*	(0.000)	-0.000	(0.000)

Note: The table reports difference-in-differences estimates of the Energy Community Bonus on investment and labor demand, estimated using the method of De Chaisemartin and D'Haultfoeuille (2024) for the matched sample using unemployment rates between 2018 and 2022 as matching variables. Columns 1–2 show quarterly effects of EC status on the probability that census tracts receive solar or wind investment. Columns 3–4 show quarterly effects on solar and wind labor demand at the county level, measured as the share of job vacancies listing solar or wind keywords. Standard errors are clustered at the observation level (columns 1–2: census tract; columns 3–4: county). *, ** and *** indicate significance at the 10%, 5% and 1% level respectively. $\hat{\delta}$ represents the Actual-Versus-Status-Quo (AVSQ) effect. $\hat{\delta}_1$ is the AVSQ effect one quarter after treatment begins. For cohort 1: Q3-2022; cohort 2: Q2-2024; cohort 3: Q3-2024. $\hat{\delta}_i$ represents the AVSQ i quarters after treatment begins. $\hat{\delta}^{pl}_j$ represents the placebo AVSQ j quarters before treatment begins.

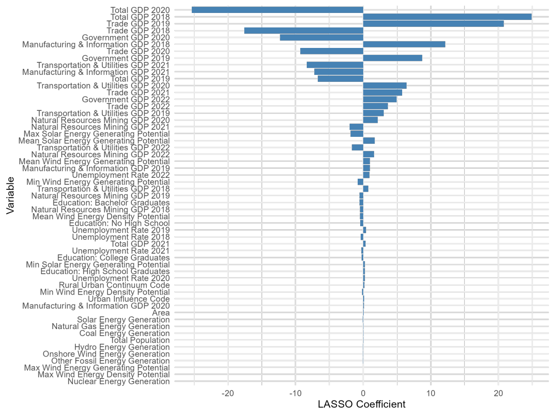
D.4.4 Robustness: Matching (Expanded Set of Variables)

In this second matching exercise, we include a very broad range of variables that could potentially violate the parallel trends trends assumption. To determine which variables to match on, we perform a LASSO regression with EC designation as the dependent variable, selecting covariates using $\lambda.1se$ (the largest penalty parameter within one standard error of the minimum cross-validation error) to ensure a parsimonious set of matching variables. Our candidate covariates include: surface area, population in 2020, solar energy generating potential (min, mean, max), wind energy generating potential (min, mean, max), wind energy density potential (min, mean, max), educational attainment shares between 2018-22 (no high school diploma, high school diploma, some college, bachelor's degree), urban influence code in 2013, rural urban continuum code in 2013, sectoral GDP shares between 2018 and 2022 (total, government, natural resources & mining, trade, transportation & utilities, manufacturing & information), energy generation by source in Q2-2022 (total, hydro, natural gas, coal, other fossil, solar, onshore wind, nuclear), and the unemployment rates between 2018 and 2022.

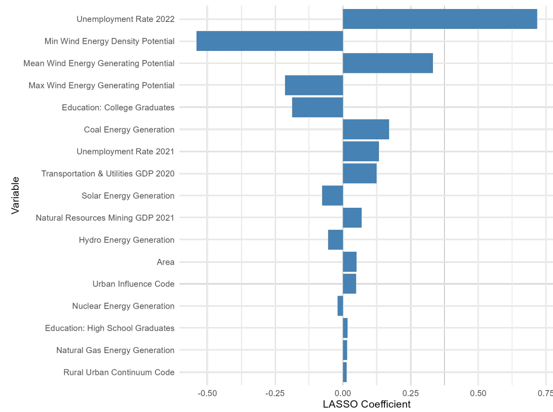
We perform the LASSO separately for investment and labor demand as the unit of observation differs between the two. Panels (a) and (b) of Figure A11 show the LASSO coefficient paths. We retain 27 variables for investment and 20 variables for labor demand. Panels (c) and (d) show the love plots, demonstrating that nearly all covariates achieve better balance after matching. Panels (e) and (f) show the propensity score density distributions, confirming adequate common support between treated and control groups. Tables A13 and A14 report the sample sizes for the matched and unmatched samples.

Figure A12 presents the event-study estimates using the matched sample. Our substantive conclusions remain unchanged. The AVSQ for solar investment decreases modestly from 0.137% to 0.129%. The solar labor demand coefficient decreases slightly from 0.033% to 0.024% and loses statistical significance, potentially due to the reduced sample size. Finally, the wind investment and labor demand shows null-results analogous to our preferred estimate.

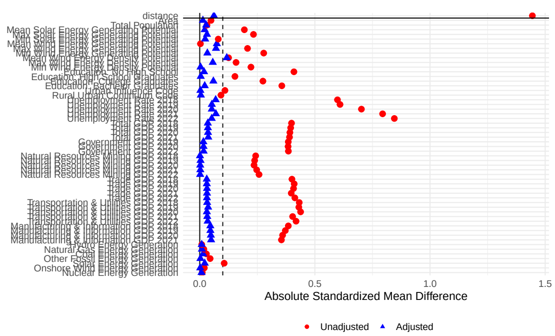
Figure A11: Matching (LASSO Selected Variables) – Specification Checks



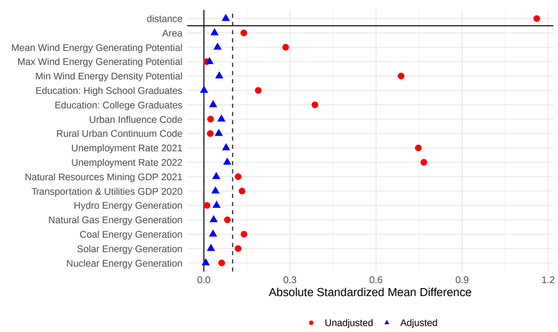
(a) Lasso Coefficients: Investment



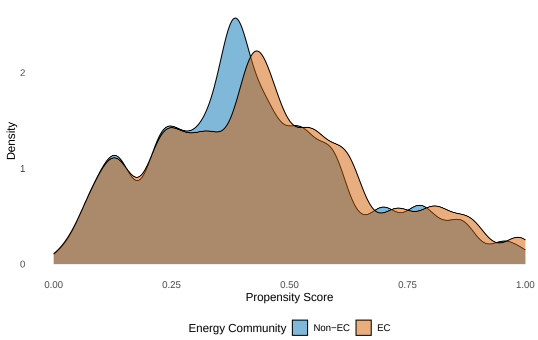
(b) Lasso Coefficients: Labor Demand



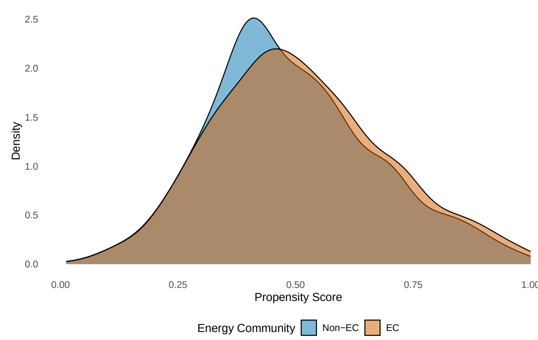
(c) Love Plot: Investment



(d) Love Plot: Labor Demand



(e) Propensity Score Density: Investment



(f) Propensity Score Density: Labor Demand

Note: The figures report the LASSO-coefficients, love plots, and the propensity score density plot corresponding to our matching procedure. We perform one-to-one nearest-neighbor propensity-score matching without replacement, pairing Energy Communities (ECs) with comparable non-EC areas. Panels (a) and (b) report the LASSO-coefficients for the investment and labor demand analyses respectively. The top variables have the largest absolute coefficients represented by the blue bars. Variables with a 0-coefficient are excluded from the figures. Panels (c) and (d) report the love plots for investment and labor demand respectively. The red dots represent the pre-matching absolute standardized mean differences between the ECs and non-ECs. The blue traingles represent the post-matching differences. Panels (e) and (f) show the distribution of propensity scores for investment and labor demand respectively. The unit of observation for investment is the census tract, and for labor demand the county.

Table A13: Samples: Investment (LASSO Selected Variables)

Sample	N
Full Sample	83404
Energy Community Tracts	31985
Non-Energy Community Tracts	51419
Matched Sample	34096
Energy Community Tracts	17048
Non-Energy Community Tracts	17048
Dropped in Matching	49308
Energy Community Tracts	14937
Non-Energy Community Tracts	34371

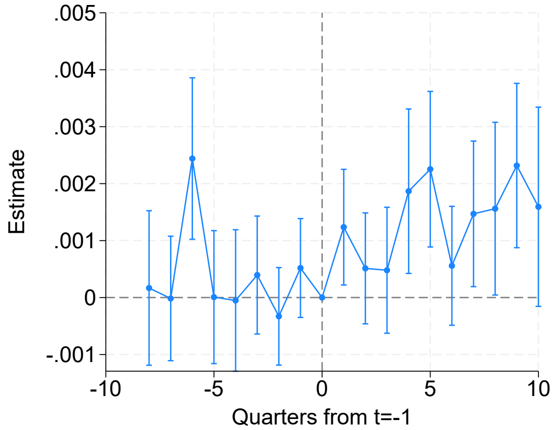
Note: The table reports the sample size for the full sample, the matched sample, and the observations dropped after matching. The unit of observation is the census tract. The matched sample is used in the investment analysis.

Table A14: Samples: Labor Demand (LASSO Selected Variables)

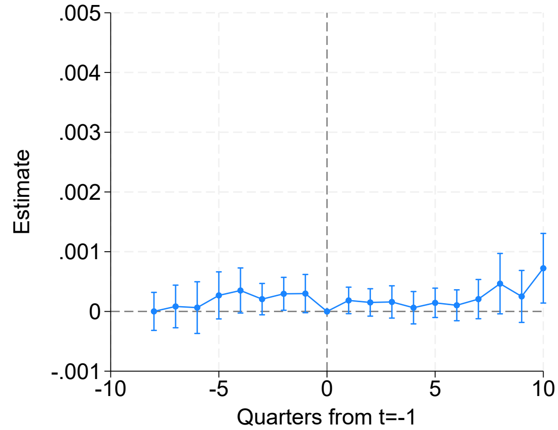
Sample	N
Full Sample	3122
Energy Community Counties	1504
Non-Energy Community Counties	1618
Matched Sample	1894
Energy Community Counties	947
Non-Energy Community Counties	947
Dropped in Matching	1228
Energy Community Counties	557
Non-Energy Community Counties	671

Note: The table reports the sample size for the full sample, the matched sample, and the observations dropped after matching. The unit of observation is the county. The matched sample is used in the labor demand analysis.

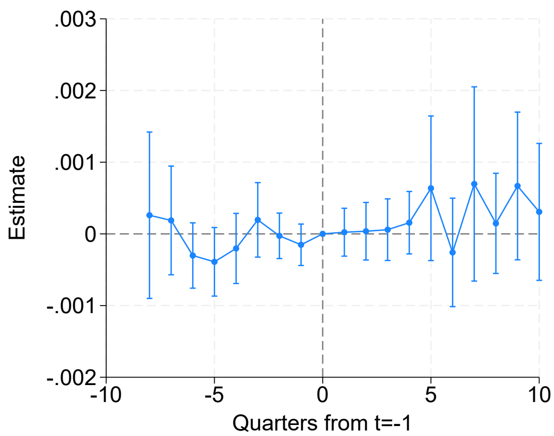
Figure A12: Event Study of the EC Bonus on Investment and Labor Demand – Matched Sample (LASSO Selected Variables)



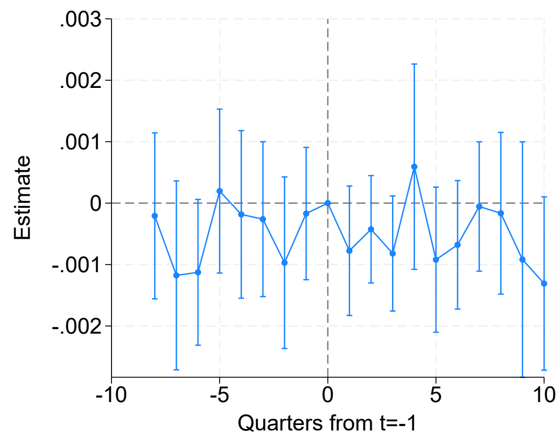
(a) Solar Investment (Extensive Margin)



(b) Wind Investment (Extensive Margin)



(c) Solar Labor Demand



(d) Wind Labor Demand

Note: The figure reports difference-in-differences event study estimates, as well as 95% confidence intervals, of the Energy Community Bonus on investment and labor demand, estimated using the method of De Chaisemartin and D'Haultfoeuille (2024) on a matched sample, selected using nearest neighbor propensity score matching without replacement prior to performing the event study analysis. Panels a and b report the quarterly effect of EC status on the probability of census tracts receiving solar investment and wind investment, respectively. Panels c and d report the quarterly effect of EC status on solar and wind labor demand at the county-level, respectively. Labor demand is measured as the share of job vacancies listing solar or wind keywords. Standard errors are clustered at the observation-level (panels a and b: census tract, panels c and d: county). $t = -1$ represents the quarter prior to treatment start. For cohort 1: Q2-2022; cohort 2: Q1-2024; cohort 3: Q2-2024.

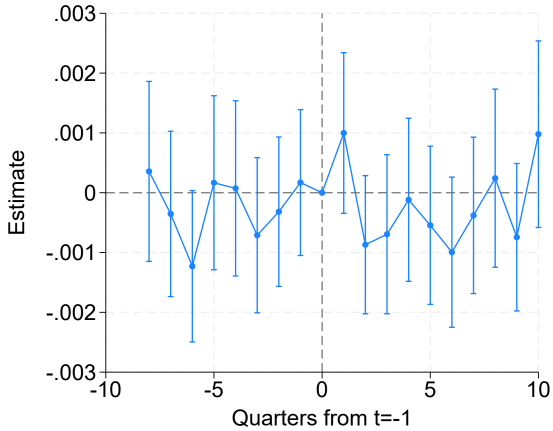
Table A15: Event Study of the EC Bonus on Investment and Labor Demand – Matched Sample (LASSO Selected Variables)

	Investment				Labour Demand			
	(1) Solar		(2) Wind		(3) Solar		(4) Wind	
$\hat{\delta}_8^{pl}$	0.000	(0.001)	0.000	(0.000)	0.000	(0.001)	-0.000	(0.001)
$\hat{\delta}_7^{pl}$	-0.000	(0.001)	0.000	(0.000)	0.000	(0.000)	-0.001	(0.001)
$\hat{\delta}_6^{pl}$	0.002***	(0.001)	0.000	(0.000)	-0.000	(0.000)	-0.001*	(0.001)
$\hat{\delta}_5^{pl}$	0.000	(0.001)	0.000	(0.000)	-0.000	(0.000)	0.000	(0.001)
$\hat{\delta}_4^{pl}$	-0.000	(0.001)	0.000*	(0.000)	-0.000	(0.000)	-0.000	(0.001)
$\hat{\delta}_3^{pl}$	0.000	(0.001)	0.000	(0.000)	0.000	(0.000)	-0.000	(0.001)
$\hat{\delta}_2^{pl}$	-0.000	(0.000)	0.000**	(0.000)	-0.000	(0.000)	-0.001	(0.001)
$\hat{\delta}_1^{pl}$	0.001	(0.000)	0.000*	(0.000)	-0.000	(0.000)	-0.000	(0.001)
$\hat{\delta}_1$	0.001**	(0.001)	0.000	(0.000)	0.000	(0.000)	-0.001	(0.001)
$\hat{\delta}_2$	0.001	(0.000)	0.000	(0.000)	0.000	(0.000)	-0.000	(0.000)
$\hat{\delta}_3$	0.000	(0.001)	0.000	(0.000)	0.000	(0.000)	-0.001*	(0.000)
$\hat{\delta}_4$	0.002**	(0.001)	0.000	(0.000)	0.000	(0.000)	0.001	(0.001)
$\hat{\delta}_5$	0.002***	(0.001)	0.000	(0.000)	0.001	(0.001)	-0.001	(0.001)
$\hat{\delta}_6$	0.001	(0.001)	0.000	(0.000)	-0.000	(0.000)	-0.001	(0.001)
$\hat{\delta}_7$	0.001**	(0.001)	0.000	(0.000)	0.001	(0.001)	-0.000	(0.001)
$\hat{\delta}_8$	0.002**	(0.001)	0.000*	(0.000)	0.000	(0.000)	-0.000	(0.001)
$\hat{\delta}_9$	0.002***	(0.001)	0.000	(0.000)	0.001	(0.001)	-0.001	(0.001)
$\hat{\delta}_{10}$	0.002*	(0.001)	0.001**	(0.000)	0.000	(0.000)	-0.001*	(0.001)
$\hat{\delta}$	0.001***	(0.000)	0.000***	(0.000)	0.000	(0.000)	-0.001	(0.000)

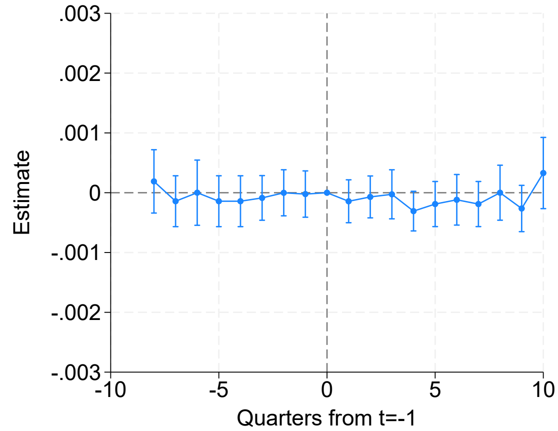
Note: The table reports difference-in-differences estimates of the Energy Community Bonus on investment and labor demand, estimated using the method of De Chaisemartin and D'Haultfoeuille (2024) for the matched sample. Columns 1–2 show quarterly effects of EC status on the probability that census tracts receive solar or wind investment. Columns 3–4 show quarterly effects on solar and wind labor demand at the county level, measured as the share of job vacancies listing solar or wind keywords. Standard errors are clustered at the observation level (columns 1–2: census tract; columns 3–4: county). *, ** and *** indicate significance at the 10%, 5% and 1% level respectively. $\hat{\delta}$ represents the Actual-Versus-Status-Quo (AVSQ) effect. $\hat{\delta}_1$ is the AVSQ effect one quarter after treatment begins. For cohort 1: Q3-2022; cohort 2: Q2-2024; cohort 3: Q3-2024. $\hat{\delta}_i$ represents the AVSQ i quarters after treatment begins. $\hat{\delta}_j^{pl}$ represents the placebo AVSQ j quarters before treatment begins.

D.5 Robustness: Spillover Analysis

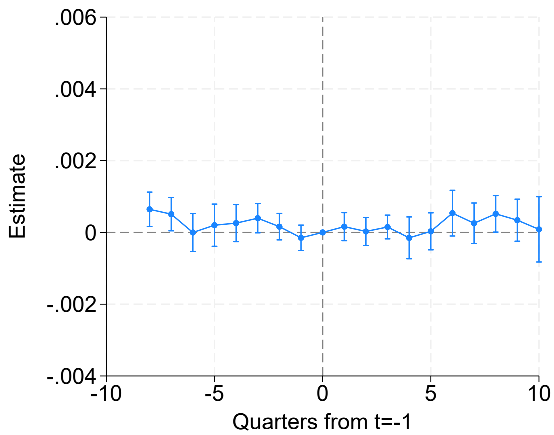
Figure A13: Event Study of the EC Bonus on Investment and Labor Demand among First and Second Neighbors



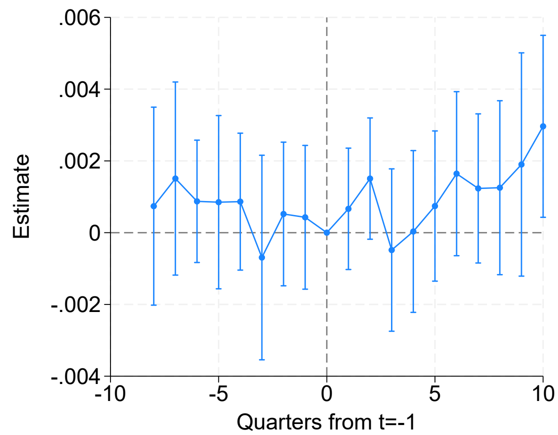
(a) Solar Investment



(b) Wind Investment



(c) Solar Labor Demand



(d) Wind Labor Demand

Note: The figure reports difference-in-differences estimates, as well as 95% confidence intervals, of the impact of the EC bonus on investment and labor demand on first and second neighbors, estimated using the method of De Chaisemartin and D'Haultfoeuille (2024). We define first neighbors as non-Energy Communities that directly border an Energy Community (EC). Second neighbors are non-ECs directly bordering first neighbors. In these spillover analyses, we exclude ECs and use first and second neighbors as treated units, comparing them to non-ECs further away. Treatment starts when the EC bordering a first neighbor receives the EC designation. Panels (a) and (b) report the effect of first and second neighbor treatment on the probability of receiving solar and wind investment, respectively. Panels (c) and (d) report the effect of first and second neighbor treatment on solar and wind labor demand, respectively. Labor demand is measured as the share of job vacancies listing solar or wind keywords. Standard errors are clustered at the observation-level (panels a and b: census tract, panels c and d: county). $t = -1$ represents the quarter prior to treatment start. For cohort 1: Q2-2022; cohort 2: Q1-2024; cohort 3: Q2-2024.

Table A16: Event Study of the EC Bonus on Investment and Labor Demand among First and Second Neighbors

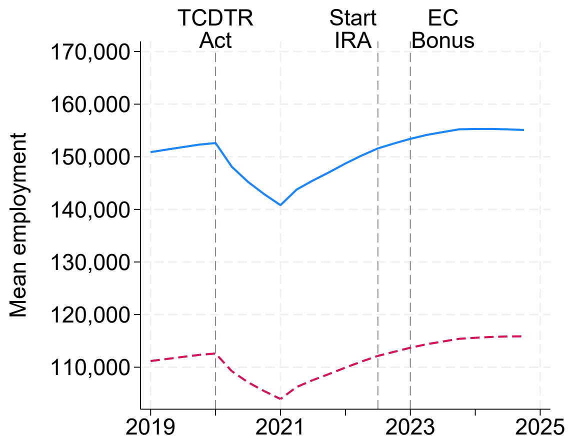
	Investment				Labour Demand			
	(1) Solar		(2) Wind		(3) Solar		(4) Wind	
$\hat{\delta}_8^{pl}$	0.000	(0.001)	0.000	(0.000)	0.001***	(0.000)	0.001	(0.001)
$\hat{\delta}_7^{pl}$	-0.000	(0.001)	-0.000	(0.000)	0.001**	(0.000)	0.002	(0.001)
$\hat{\delta}_6^{pl}$	-0.001*	(0.001)	0.000	(0.000)	-0.000	(0.000)	0.001	(0.001)
$\hat{\delta}_5^{pl}$	0.000	(0.001)	-0.000	(0.000)	0.000	(0.000)	0.001	(0.001)
$\hat{\delta}_4^{pl}$	0.000	(0.001)	-0.000	(0.000)	0.000	(0.000)	0.001	(0.001)
$\hat{\delta}_3^{pl}$	-0.001	(0.001)	-0.000	(0.000)	0.000*	(0.000)	-0.001	(0.001)
$\hat{\delta}_2^{pl}$	-0.000	(0.001)	-0.000	(0.000)	0.000	(0.000)	0.001	(0.001)
$\hat{\delta}_1^{pl}$	0.000	(0.001)	-0.000	(0.000)	-0.000	(0.000)	0.000	(0.001)
$\hat{\delta}_1$	0.001	(0.001)	-0.000	(0.000)	0.000	(0.000)	0.001	(0.001)
$\hat{\delta}_2$	-0.001	(0.001)	-0.000	(0.000)	0.000	(0.000)	0.002*	(0.001)
$\hat{\delta}_3$	-0.001	(0.001)	-0.000	(0.000)	0.000	(0.000)	-0.000	(0.001)
$\hat{\delta}_4$	-0.000	(0.001)	-0.000*	(0.000)	-0.000	(0.000)	0.000	(0.001)
$\hat{\delta}_5$	-0.001	(0.001)	-0.000	(0.000)	0.000	(0.000)	0.001	(0.001)
$\hat{\delta}_6$	-0.001	(0.001)	-0.000	(0.000)	0.001*	(0.000)	0.002	(0.001)
$\hat{\delta}_7$	-0.000	(0.001)	-0.000	(0.000)	0.000	(0.000)	0.001	(0.001)
$\hat{\delta}_8$	0.000	(0.001)	0.000	(0.000)	0.001**	(0.000)	0.001	(0.001)
$\hat{\delta}_9$	-0.001	(0.001)	-0.000	(0.000)	0.000	(0.000)	0.002	(0.002)
$\hat{\delta}_{10}$	0.001	(0.001)	0.000	(0.000)	0.000	(0.000)	0.003**	(0.001)
$\hat{\delta}$	-0.000	(0.001)	-0.000	(0.000)	0.000	(0.000)	0.001	(0.001)

Note: The table reports difference-in-differences estimates of the Energy Community Bonus on investment and labor demand among first and second neighbors of treated units, estimated using the method of De Chaisemartin and D'Haultfoeuille (2024). We define first neighbors as non-Energy Communities that directly border an Energy Community (EC). Second neighbors are non-ECs directly bordering first neighbors. In these spillover analyses, we exclude ECs and use first and second neighbors as treated units, comparing them to non-ECs further away. Treatment starts when the EC bordering a first neighbor receives the EC designation. Columns 1 and 2 report the effect of first and second neighbor treatment on the probability of receiving solar and wind investment, respectively. Columns 3 and 4 report the effect of first and second neighbor treatment on solar and wind labor demand, respectively. Labor demand is measured as the share of job vacancies listing solar or wind keywords. Standard errors are clustered at the observation-level (columns 1 and 2: census tract, columns 3 and 4: county) and presented in parentheses. *, ** and *** indicate significance at the 10%, 5% and 1% level respectively. $\hat{\delta}_1$ represents the first quarter after treatment start. For cohort 1: Q3-2022; cohort 2: Q2-2024; cohort 3: Q3-2024. $\hat{\delta}$ represents the Actual-Versus-Status-Quo (AVSQ) effect. $\hat{\delta}_1$ is the AVSQ effect one quarter after treatment begins. For cohort 1: Q3-2022; cohort 2: Q2-2024; cohort 3: Q3-2024. $\hat{\delta}_i$ represents the AVSQ i quarters after treatment begins. $\hat{\delta}_j^{pl}$ represents the placebo AVSQ j quarters before treatment begins.

D.6 Analysis Excluding LA and Cook County

L.A. and Cook County (Chicago) are the second and third most populous cities in the U.S. New York City is the largest city but divided into five counties. L.A. and Cook Counties shift the mean employment numbers of Energy Communities up by some 15.000 jobs. Below we show the employment measured through QCEW excluding L.A. and Cook counties. Additionally, we show the results of our DiD specification for investment, employment, and labor demand excluding these counties. Our results remain unchanged when excluding these counties.

Figure A14: Evolution of Employment Energy Communities vs. Other Areas Excluding LA and Cook Counties



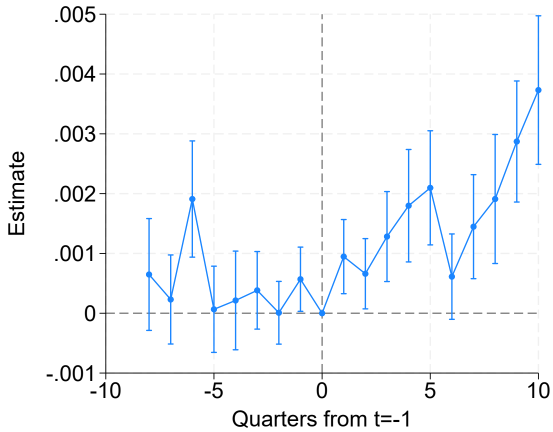
Note: The figure reports quarterly employment per county, taken from the Quarterly Census of Employment and Wages (QCEW), smoothed with an MA(4), excluding L.A. and Cook counties. Vertical dashed lines mark the passage of the Tax Cuts and Jobs Tax Relief Act (2020q1), the start of the Inflation Reduction Act (2022q3), and the introduction of the EC bonus (2023q1).

Table A17: Event Study of the EC Bonus on Employment QCEW – Excluding LA and Cook Counties

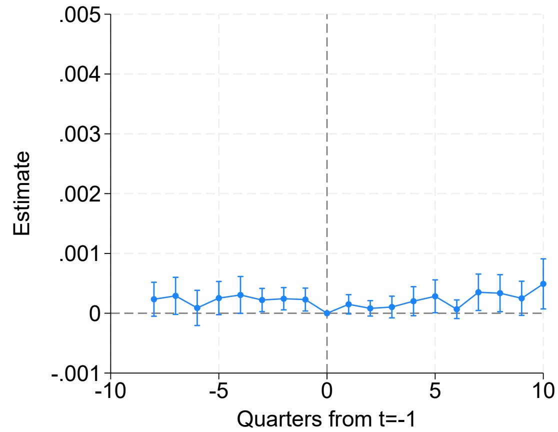
	Total Employment		Employment in Construction	
$\hat{\delta}_8^{pl}$	-296.049	(1965.155)	-0.001	(0.001)
$\hat{\delta}_7^{pl}$	803.573	(1459.852)	-0.001	(0.001)
$\hat{\delta}_6^{pl}$	492.066	(1016.557)	0.000	(0.001)
$\hat{\delta}_5^{pl}$	343.841	(1138.914)	0.000	(0.001)
$\hat{\delta}_4^{pl}$	387.586	(812.876)	0.000	(0.001)
$\hat{\delta}_3^{pl}$	623.742	(591.974)	0.000	(0.001)
$\hat{\delta}_2^{pl}$	392.698*	(225.919)	0.001	(0.001)
$\hat{\delta}_1^{pl}$	98.083	(269.756)	0.000	(0.000)
$\hat{\delta}_1$	204.534	(156.156)	-0.001*	(0.000)
$\hat{\delta}_2$	82.158	(302.945)	-0.000	(0.000)
$\hat{\delta}_3$	-170.583	(304.102)	0.001*	(0.000)
$\hat{\delta}_4$	-300.964	(404.200)	0.001	(0.001)
$\hat{\delta}_5$	-218.750	(418.722)	-0.000	(0.001)
$\hat{\delta}_6$	-415.740	(598.492)	-0.000	(0.001)
$\hat{\delta}_7$	-511.286	(540.240)	0.001	(0.001)
$\hat{\delta}_8$	-341.990	(626.880)	0.000	(0.001)
$\hat{\delta}_9$	-60.259	(593.629)	-0.000	(0.001)
$\hat{\delta}_{10}$	-128.401	(791.306)	0.001	(0.001)
$\hat{\delta}$	-177.183	(438.307)	0.000	(0.000)

Note: The table reports difference-in-differences estimates of the Energy Community Bonus on employment, estimated using the method of De Chaisemartin and D'Haultfoeuille (2024), excluding L.A. and Cook Counties. Columns 1–2 show quarterly effects of EC status on the total employment and construction employment respectively. Standard errors are clustered at the county level. *, ** and *** indicate significance at the 10%, 5% and 1% level respectively. $\hat{\delta}$ represents the Actual-Versus-Status-Quo (AVSQ) effect. $\hat{\delta}_1$ is the AVSQ effect one quarter after treatment begins. For cohort 1: Q3-2022; cohort 2: Q2-2024; cohort 3: Q3-2024. $\hat{\delta}_i$ represents the AVSQ i quarters after treatment begins. $\hat{\delta}_j^{pl}$ represents the placebo AVSQ j quarters before treatment begins.

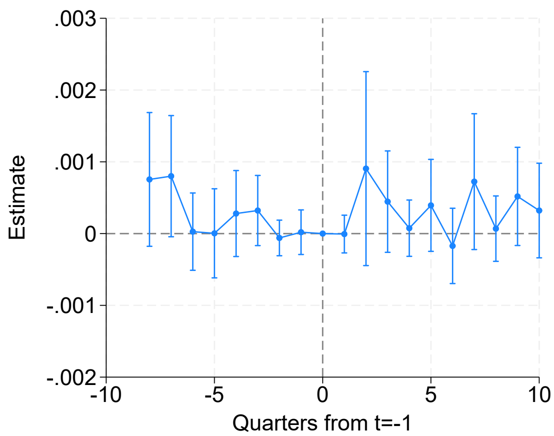
Figure A15: Event Study of the EC Bonus on Investment and Labor Demand – Sample Excluding L.A. and Cook Counties



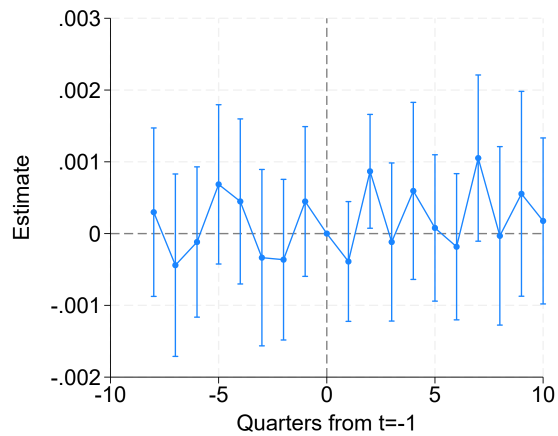
(a) Solar Investment (Extensive Margin)



(b) Wind Investment (Extensive Margin)



(c) Solar Labor Demand



(d) Wind Labor Demand

Note: The figure reports difference-in-differences event study estimates, as well as 95% confidence intervals, of the Energy Community Bonus on investment and labor demand, estimated using the method of De Chaisemartin and D'Haultfoeuille (2024) on the entire sample, excluding LA and Cook Counties. Panels a and b report the quarterly effect of EC status on the probability of census tracts receiving solar investment and wind investment, respectively. Panels c and d report the quarterly effect of EC status on solar and wind labor demand at the county-level, respectively. Labor demand is measured as the share of job vacancies listing solar or wind keywords. Standard errors are clustered at the observation-level (panels a and b: census tract, panels c and d: county). $t = -1$ represents the quarter prior to treatment start. For cohort 1: Q2-2022; cohort 2: Q1-2024; cohort 3: Q2-2024.

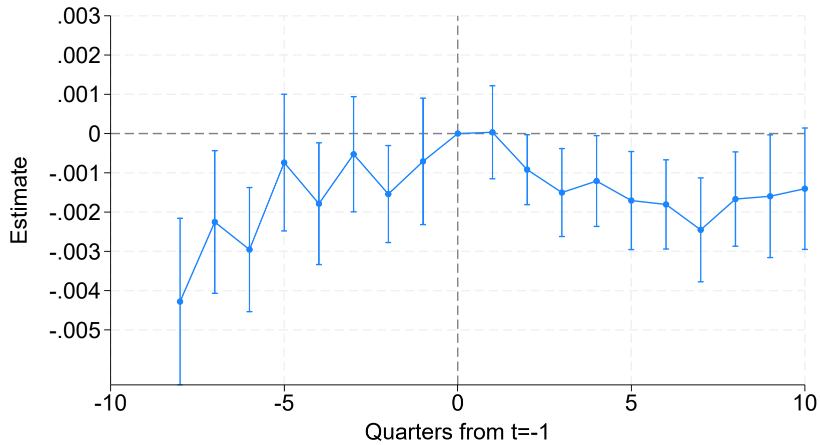
Table A18: Event Study of the EC Bonus on Investment and Labor Demand – Sample Excluding LA and Cook Counties

	Investment				Labour Demand			
	(1) Solar		(2) Wind		(3) Solar		(4) Wind	
$\hat{\delta}_8^{pl}$	0.001	(0.000)	0.000	(0.000)	0.001	(0.000)	0.000	(0.001)
$\hat{\delta}_7^{pl}$	0.000	(0.000)	0.000*	(0.000)	0.001*	(0.000)	-0.000	(0.001)
$\hat{\delta}_6^{pl}$	0.002***	(0.000)	0.000	(0.000)	0.000	(0.000)	-0.000	(0.001)
$\hat{\delta}_5^{pl}$	0.000	(0.000)	0.000*	(0.000)	0.000	(0.000)	0.001	(0.001)
$\hat{\delta}_4^{pl}$	0.000	(0.000)	0.000*	(0.000)	0.000	(0.000)	0.000	(0.001)
$\hat{\delta}_3^{pl}$	0.000	(0.000)	0.000**	(0.000)	0.000	(0.000)	-0.000	(0.001)
$\hat{\delta}_2^{pl}$	0.000	(0.000)	0.000**	(0.000)	-0.000	(0.000)	-0.000	(0.001)
$\hat{\delta}_1^{pl}$	0.001**	(0.000)	0.000**	(0.000)	0.000	(0.000)	0.000	(0.001)
$\hat{\delta}_1$	0.001***	(0.000)	0.000*	(0.000)	-0.000	(0.000)	-0.000	(0.000)
$\hat{\delta}_2$	0.001**	(0.000)	0.000	(0.000)	0.001	(0.001)	0.001**	(0.000)
$\hat{\delta}_3$	0.001***	(0.000)	0.000	(0.000)	0.000	(0.000)	-0.000	(0.001)
$\hat{\delta}_4$	0.002***	(0.000)	0.000	(0.000)	0.000	(0.000)	0.001	(0.001)
$\hat{\delta}_5$	0.002***	(0.000)	0.000**	(0.000)	0.000	(0.000)	0.000	(0.001)
$\hat{\delta}_6$	0.001*	(0.000)	0.000	(0.000)	-0.000	(0.000)	-0.000	(0.001)
$\hat{\delta}_7$	0.001***	(0.000)	0.000**	(0.000)	0.001	(0.000)	0.001*	(0.001)
$\hat{\delta}_8$	0.002***	(0.001)	0.000**	(0.000)	0.000	(0.000)	-0.000	(0.001)
$\hat{\delta}_9$	0.003***	(0.001)	0.000*	(0.000)	0.001	(0.000)	0.001	(0.001)
$\hat{\delta}_{10}$	0.004***	(0.001)	0.000**	(0.000)	0.000	(0.000)	0.000	(0.001)
$\hat{\delta}$	0.002***	(0.000)	0.000***	(0.000)	0.000*	(0.000)	0.000	(0.000)

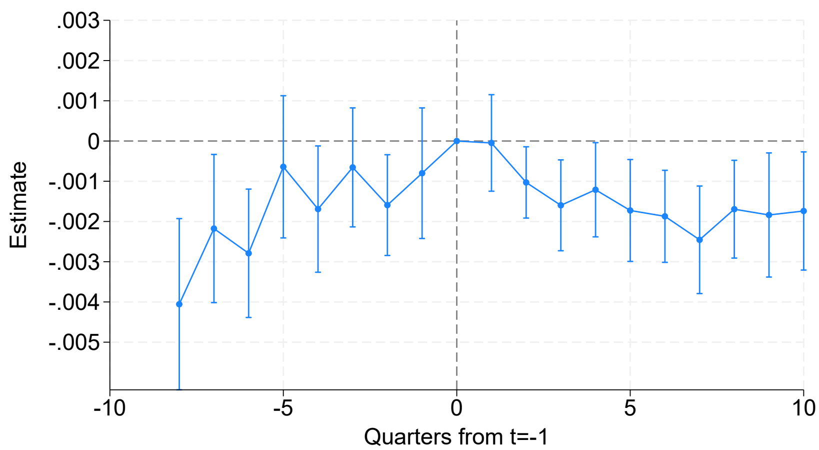
Note: The table reports difference-in-differences estimates of the Energy Community Bonus on investment and labor demand, estimated using the method of De Chaisemartin and D'Haultfoeuille (2024) on the entire sample, excluding LA and Chicago. Columns 1–2 show quarterly effects of EC status on the probability that census tracts receive solar or wind investment. Columns 3–4 show quarterly effects on solar and wind labor demand at the county level, measured as the share of job vacancies listing solar or wind keywords. Standard errors are clustered at the observation level (columns 1–2: census tract; columns 3–4: county). *, ** and *** indicate significance at the 10%, 5% and 1% level respectively. $\hat{\delta}$ represents the Actual-Versus-Status-Quo (AVSQ) effect. $\hat{\delta}_1$ is the AVSQ effect one quarter after treatment begins. For cohort 1: Q3-2022; cohort 2: Q2-2024; cohort 3: Q3-2024. $\hat{\delta}_i$ represents the AVSQ i quarters after treatment begins. $\hat{\delta}_j^{pl}$ represents the placebo AVSQ j quarters before treatment begins.

D.7 Brown Labor Demand

Figure A16: Event Study of the EC Bonus on Brown Labor Demand



(a) Total Sample



(b) Matched Sample

Note: The table reports difference-in-differences estimates of the Energy Community Bonus on brown labor demand, and 95% confidence intervals, estimated using the method of De Chaisemartin and D'Haultfoeuille (2024). Panel (a) reports the effect of EC status on the share of brown labor demand. Panel (b) reports the effect of EC status on the share of brown labor demand for the matched sample from appendix D.4.4. Brown labor demand is measured as the share of job vacancies tagged as NAICS-code 21 which represents the sector for Mining, Quarrying, and Oil and Gas Extraction. Standard errors are clustered at the county-level, which is the unit of observation. $\hat{\delta}$ represents the Actual-Versus-Status-Quo (AVSQ) effect. $\hat{\delta}_1$ is the AVSQ effect one quarter after treatment begins. For cohort 1: Q3-2022; cohort 2: Q2-2024; cohort 3: Q3-2024. $\hat{\delta}_i$ represents the AVSQ i quarters after treatment begins. $\hat{\delta}_j^{pl}$ represents the placebo AVSQ j quarters before treatment begins.

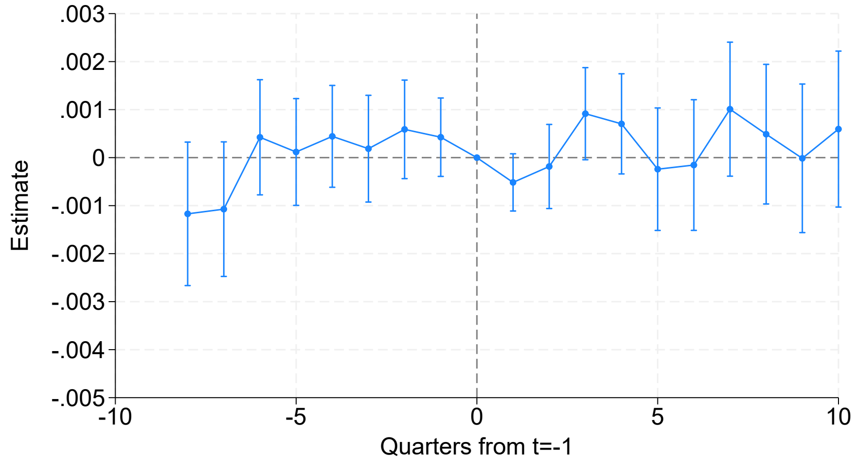
Table A19: Event Study of the EC Bonus on Brown Labor Demand

	Full Sample		Matched Sample	
$\hat{\delta}_8^{pl}$	-0.004***	(0.001)	-0.004***	(0.001)
$\hat{\delta}_7^{pl}$	-0.002**	(0.001)	-0.002**	(0.001)
$\hat{\delta}_6^{pl}$	-0.003***	(0.001)	-0.003***	(0.001)
$\hat{\delta}_5^{pl}$	-0.001	(0.001)	-0.001	(0.001)
$\hat{\delta}_4^{pl}$	-0.002**	(0.001)	-0.002**	(0.001)
$\hat{\delta}_3^{pl}$	-0.001	(0.001)	-0.001	(0.001)
$\hat{\delta}_2^{pl}$	-0.002**	(0.001)	-0.002**	(0.001)
$\hat{\delta}_1^{pl}$	-0.001	(0.001)	-0.001	(0.001)
$\hat{\delta}_1$	0.000	(0.001)	-0.000	(0.001)
$\hat{\delta}_2$	-0.001**	(0.000)	-0.001**	(0.000)
$\hat{\delta}_3$	-0.002***	(0.001)	-0.002***	(0.001)
$\hat{\delta}_4$	-0.001**	(0.001)	-0.001**	(0.001)
$\hat{\delta}_5$	-0.002***	(0.001)	-0.002***	(0.001)
$\hat{\delta}_6$	-0.002***	(0.001)	-0.002***	(0.001)
$\hat{\delta}_7$	-0.002***	(0.001)	-0.002***	(0.001)
$\hat{\delta}_8$	-0.002***	(0.001)	-0.002***	(0.001)
$\hat{\delta}_9$	-0.002**	(0.001)	-0.002**	(0.001)
$\hat{\delta}_{10}$	-0.001*	(0.001)	-0.002**	(0.001)
$\hat{\delta}$	-0.001***	(0.000)	-0.001***	(0.000)

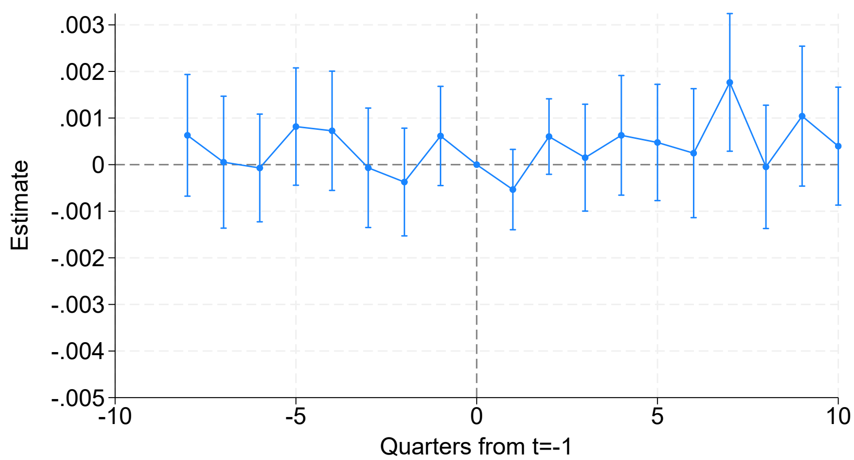
Note: The table reports difference-in-differences estimates of the Energy Community Bonus on brown labor demand, estimated using the method of De Chaisemartin and D'Haultfoeuille (2024). Column 1 reports the effect of EC status on brown labor demand for the entire sample. Column 2 reports the effect of EC status on brown labor demand for the matched sample from appendix D.4.4. Labor demand is measured as the share of job vacancies tagged as NAICS-code 21 which represents the sector for Mining, Quarrying, and Oil and Gas Extraction. Standard errors are clustered at the county-level, which is the unit of observation. *, ** and *** indicate significance at the 10%, 5% and 1% level respectively. $\hat{\delta}$ represents the Actual-Versus-Status-Quo (AVSQ) effect. $\hat{\delta}_1$ is the AVSQ effect one quarter after treatment begins. For cohort 1: Q3-2022; cohort 2: Q2-2024; cohort 3: Q3-2024. $\hat{\delta}_i$ represents the AVSQ i quarters after treatment begins. $\hat{\delta}_j^{pl}$ represents the placebo AVSQ j quarters before treatment begins.

D.8 Renewables (Y02E10) Labor Demand and Construction Employment

Figure A17: Event Study of the EC Bonus on Employment in Construction and Renewables (Y02E10) Labor Demand



(a) Employment in the Construction Sector



(b) Renewables (Y02E10) Labor Demand

Note: The figure reports difference-in-differences estimates, as well as 95% confidence intervals, of the impact of the EC bonus on employment in construction and renewables (Y02E10), estimated using the method of De Chaisemartin and D'Haultfoeuille (2024). Panel (a) reports the effect of EC status on the share of employment in construction, measured in the QCEW. Panel (b) reports the effect of EC status on renewables (Y02E10) labor demand measured as the share of job vacancies listing Y02E10 keywords. Y02E10 is the Cooperative Patent Classification code, used by the EU Patent office and the United States Patent and Trademark Office, for technologies involving renewable-energy generation as a climate-change mitigation measure. Standard errors are clustered at the county-level, and presented in parentheses. $t = -1$ represents the quarter prior to treatment start. For cohort 1: Q2-2022; cohort 2: Q1-2024; cohort 3: Q2-2024.

Table A20: Event Study of the EC Bonus on Employment in Construction and Renewables (Y02E10) Labor Demand

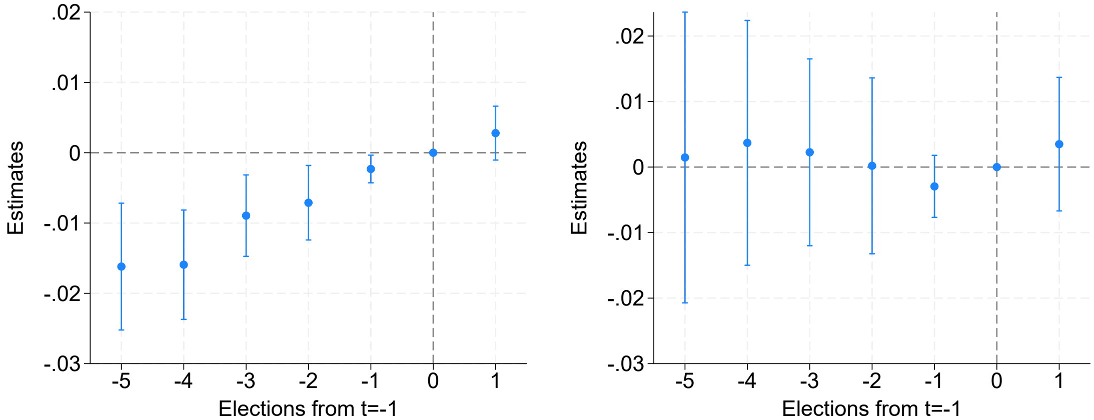
	Total Employment		Employment in Construction		Y02E10 Labor Demand	
$\hat{\delta}_8^{pl}$	-2283.149	(2483.417)	-0.001	(0.001)	0.001	(0.001)
$\hat{\delta}_7^{pl}$	-774.283	(1920.868)	-0.001	(0.001)	0.000	(0.001)
$\hat{\delta}_6^{pl}$	-591.839	(1318.590)	0.000	(0.001)	-0.000	(0.001)
$\hat{\delta}_5^{pl}$	-920.930	(1489.176)	0.000	(0.001)	0.001	(0.001)
$\hat{\delta}_4^{pl}$	-443.857	(1033.936)	0.000	(0.001)	0.001	(0.001)
$\hat{\delta}_3^{pl}$	55.817	(732.925)	0.000	(0.001)	-0.000	(0.001)
$\hat{\delta}_2^{pl}$	276.672	(241.690)	0.001	(0.001)	-0.000	(0.001)
$\hat{\delta}_1^{pl}$	-129.766	(314.035)	0.000	(0.000)	0.001	(0.001)
$\hat{\delta}_1$	258.393	(162.144)	-0.001*	(0.000)	-0.001	(0.000)
$\hat{\delta}_2$	308.112	(345.302)	-0.000	(0.000)	0.001	(0.000)
$\hat{\delta}_3$	-209.880	(307.910)	0.001*	(0.000)	0.000	(0.001)
$\hat{\delta}_4$	-197.822	(421.046)	0.001	(0.001)	0.001	(0.001)
$\hat{\delta}_5$	-206.071	(440.464)	-0.000	(0.001)	0.000	(0.001)
$\hat{\delta}_6$	-176.045	(621.861)	-0.000	(0.001)	0.000	(0.001)
$\hat{\delta}_7$	-393.873	(548.280)	0.001	(0.001)	0.002**	(0.001)
$\hat{\delta}_8$	-147.027	(642.386)	0.000	(0.001)	-0.000	(0.001)
$\hat{\delta}_9$	90.278	(604.420)	-0.000	(0.001)	0.001	(0.001)
$\hat{\delta}_{10}$	267.459	(840.611)	0.001	(0.001)	0.000	(0.001)
$\hat{\delta}$	-32.990	(450.368)	0.000	(0.000)	0.000	(0.000)

Note: The table reports difference-in-differences estimates of the Energy Community (EC) Bonus on employment in construction and renewables labor demand estimated using the method of De Chaisemartin and D'Haultfoeuille (2024). Column 1 reports the effect of EC status on total employment, measured in the QCEW. Column 2 reports the effect of EC status on the share of employment in construction, measured in the QCEW. Column 3 reports the effect of EC status on renweables (Y02E10) labor demand. Renewables labor demand is measured as the share of job vacancies listing Y02E10 keywords. Y02E10 is the Cooperative Patent Classification code, used by the EU Patent office and the United States Patent and Trademark Office, for technologies involving renewable-energy generation as a climate-change mitigation measure. Standard errors are clustered at the county-level, and presented in parentheses. *, ** and *** indicate significance at the 10%, 5% and 1% level respectively. $\hat{\delta}$ represents the Actual-Versus-Status-Quo (AVSQ) effect. $\hat{\delta}_1$ is the AVSQ effect one quarter after treatment begins. For cohort 1: Q3-2022; cohort 2: Q2-2024; cohort 3: Q3-2024. $\hat{\delta}_i$ represents the AVSQ i quarters after treatment begins. $\hat{\delta}_j^{pl}$ represents the placebo AVSQ j quarters before treatment begins.

D.9 Robustness: Electoral Results

D.9.1 Presidential Elections

Figure A18: Event Study of the EC Bonus on Republican Vote Shares



(a) Full Sample (b) Swing States

Note: The figure reports difference-in-differences estimates, as well as 95% confidence intervals, of the impact of the EC bonus on Republican vote shares estimated using two-way fixed effects. All regressions control for county and state-year fixed effects. Panels (a) and (b) report the effect of EC status on Republican vote share for the full sample, and the sample restricted to the 2024 swing states (GA, AZ, MI, NV, NC, PA, WI), using only Democratic and Republican votes. Standard errors are clustered at the county-level, which is the unit of observation. $t = -1$ represents the election prior to treatment start, which was the 2020 election.

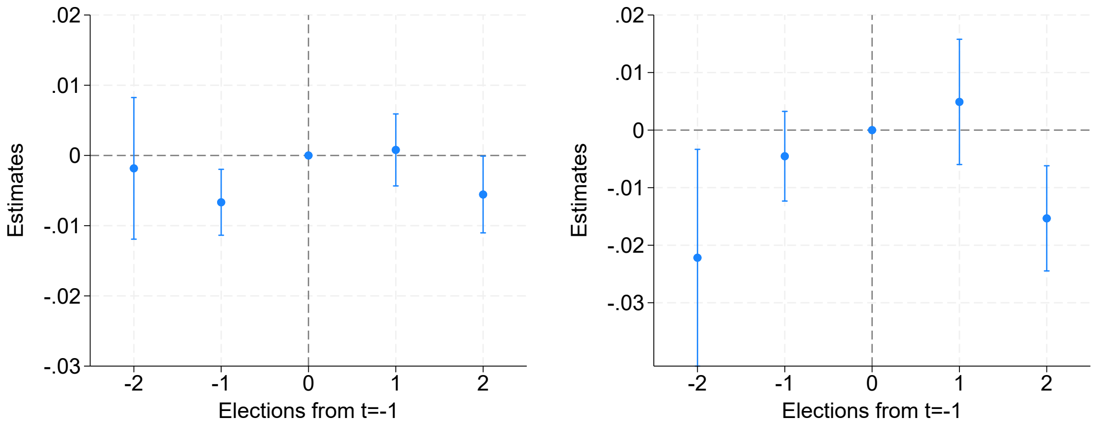
Table A21: Effect of EC bonus on Republican vote shares

	(1) Full sample	(2) Rust Belt	(3) Swing states
$\hat{\delta}^{pl}_5$ (2000)	-0.016***	-0.005	0.001
	(0.005)	(0.008)	(0.011)
$\hat{\delta}^{pl}_4$ (2004)	-0.016***	-0.006	0.004
	(0.004)	(0.007)	(0.010)
$\hat{\delta}^{pl}_3$ (2008)	-0.009**	0.000	0.002
	(0.003)	(0.006)	(0.007)
$\hat{\delta}^{pl}_2$ (2012)	-0.007**	0.002	0.000
	(0.003)	(0.005)	(0.007)
$\hat{\delta}^{pl}_1$ (2016)	-0.002*	-0.001	-0.003
	(0.001)	(0.002)	(0.002)
$\hat{\delta}_1$ (2024)	0.003	0.002	0.003
	(0.002)	(0.001)	(0.005)
R^2	0.933	0.905	0.914
Obs.	21,797	7,027	3,589

Note: The table reports difference-in-differences estimates of the impact of the Energy Community Bonus on Republican vote shares estimated using two-way fixed effects. Column 1 reports the effect of EC status on Republican vote share for the full sample. Column 2 presents the effect of EC status on Republican vote share for the sample restricted to the Rust Belt states (OH, IN, IL, WI, MI, PA, IA, KY, MD, MN, MO, WV). Column 3 presents the effect of EC status on Republican vote share for the sample restricted to the 2024 swing states (GA, AZ, MI, NV, NC, PA, WI). All regressions include year × state fixed effects, which are not reported. Republican vote share is measured using only Democratic and Republican votes. Standard errors are clustered at the county-level. *, ** and *** indicate significance at the 10%, 5% and 1% level respectively. The 2020 Republican vote share is omitted since it is the last period (i.e. event time =-1) for the period before the treatment which is the introduction of the Energy Community bonus. 2024 (i.e. event time=0, indicated here by $\hat{\delta}_1$) is the first and only year treatment takes effect.

D.9.2 House Elections

Figure A19: Event Study of the EC Bonus on Republican Vote Shares in the House Elections



(a) Full Sample (b) Rust Belt

Note: The figure reports difference-in-differences estimates, as well as 95% confidence intervals, of the impact of the EC bonus on Republican vote shares in the House estimated using two-way fixed effects. All regressions control for county and state-year fixed effects. Panels (a) and (b) report the effect of EC status on Republican vote share for the full sample, and the sample restricted to the 2024 Rust Belt States (OH, IN, IL, WI, MI, PA, IA, KY, MD, MN, MO, WV), using only Democratic and Republican votes. Standard errors are clustered at the county-level, which is the unit of observation. The dotted vertical line denotes the introduction of the Energy Community Bonus. $t = -1$ represents the election prior to treatment start, which was the 2020 election.

Table A22: Effect of EC bonus on Republican vote shares in the House Elections

	(1) Full sample	(2) Rust Belt	(3) Swing states
$\hat{\delta}^{pl}_{-3}$ (2016)	-0.002	-0.022*	-0.012
	(0.005)	(0.010)	(0.018)
$\hat{\delta}^{pl}_{-2}$ (2018)	-0.007**	-0.005	-0.005
	(0.002)	(0.004)	(0.006)
$\hat{\delta}_{1}$ (2022)	0.001	0.005	0.005
	(0.003)	(0.006)	(0.008)
$\hat{\delta}_{2}$ (2024)	-0.006*	-0.015**	-0.002
	(0.003)	(0.005)	(0.005)
R^2	0.932	0.883	0.856
Obs.	13,457	4,381	2,398

Note: The table reports difference-in-differences estimates of the impact of the Energy Community Bonus on Republican vote shares estimated using two-way fixed effects. Column 1 reports the effect of EC status on Republican vote share for the full sample. Column 2 presents the effect of EC status on Republican vote share for the sample restricted to the Rust Belt states (OH, IN, IL, WI, MI, PA, IA, KY, MD, MN, MO, WV). Column 3 presents the effect of EC status on Republican vote share for the sample restricted to the 2024 swing states (GA, AZ, MI, NV, NC, PA, WI). All estimations include year × state fixed effects, which are not reported. Republican vote share is measured using only Democratic and Republican votes. Standard errors are clustered at the county-level. *, ** and *** indicate significance at the 10%, 5% and 1% level respectively. The 2020 Republican vote share is omitted since it is the last period (i.e. event time =-1) for the period before the treatment which is the introduction of the Energy Community bonus. 2022 (i.e. event time=0, indicated here by $\hat{\delta}_1$) is the first year treatment takes effect.

D.9.3 Senate Elections

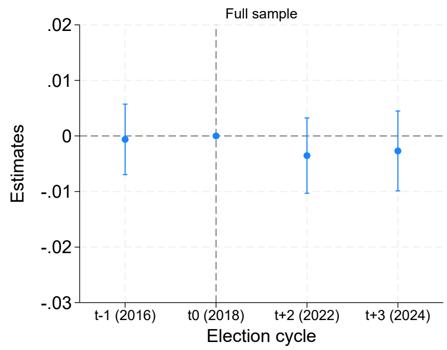
Senate Elections are slightly more difficult to estimate due to the voting system. Each state has two senators. Each seat is voted every 6 years, and the two seats of a single state are not voted simultaneously. This results in two elections in each six-year period in every state. Between 2016 and 2024, there are three potential voting sequences, Group 1: 2016, 2018, 2022, 2024; Group 2: 2016, 2020, 2022; and Group 3: 2018, 2020, 2024. We separately estimate TWFE DiD for each of these groups taking the most recent election before 2022 as the reference period.

Table A23: Effect of EC bonus on Republican vote shares in the Senate Elections: Group 1

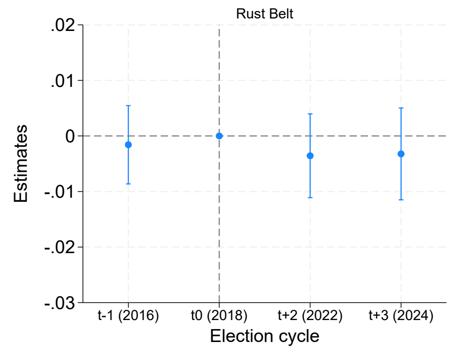
	(1) Full sample	(2) Rust Belt	(3) Swing states
$\hat{\delta}^{pl}_{-1}$ (2016)	-0.001	-0.002	0.004
	(0.003)	(0.004)	(0.004)
$\hat{\delta}_1$ (2022)	-0.004	-0.004	-0.014
	(0.003)	(0.004)	(0.010)
$\hat{\delta}_2$ (2024)	-0.003	-0.003	-0.012
	(0.004)	(0.004)	(0.010)
R^2	0.980	0.975	0.982
Obs.	1,589	1,318	355

Note: The table reports difference-in-differences estimates of the impact of the Energy Community Bonus on Republican vote shares estimated using two-way fixed effects. Column 1 reports the effect of EC status on Republican vote share for the states having senate elections in 2016, 2018, 2022, and 2024. Column 2 presents the effect of EC status on Republican vote share for the sample restricted to the Rust Belt states (OH, IN, IL, WI, MI, PA, IA, KY, MD, MN, MO, WV). Column 3 presents the effect of EC status on Republican vote share for the sample restricted to the 2024 swing states (GA, AZ, MI, NV, NC, PA, WI). All regressions include year $\times$ state fixed effects, which are not reported. Republican vote share is measured using only Democratic and Republican votes. Standard errors are clustered at the county-level. *, ** and *** indicate significance at the 10%, 5% and 1% level respectively. The 2018 Republican vote share is omitted since it is the last period (i.e. event time =-1) for the period before the treatment which is the introduction of the Energy Community bonus. 2022 (i.e. event time=0, indicated here by $\hat{\delta}_1$) is the first year treatment takes effect.

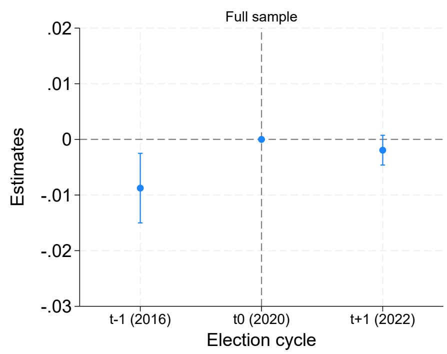
Figure A20: Event Study of the EC Bonus on Republican Vote Shares in the Senate Elections



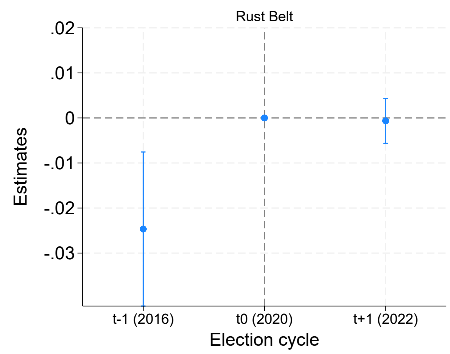
(a) Group 1: Full Sample



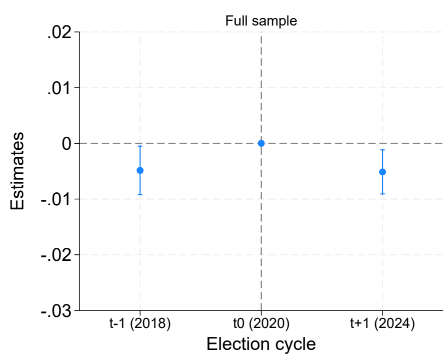
(b) Group 1: Rust Belt



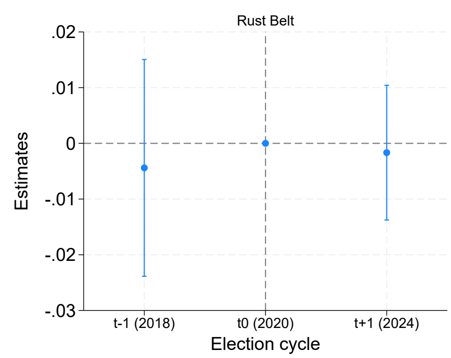
(c) Group 2: Full Sample



(d) Group 2: Rust Belt



(e) Group 3: Full Sample



(f) Group 3: Rust Belt

Note: The figure reports difference-in-differences estimates, as well as 95% confidence intervals, of the impact of the EC bonus on Republican vote shares, using only Democratic and Republican votes, in the Senate estimated using two-way fixed effects. Panels (a), (c), and (e) report the effect of EC status on Republican vote share for the full sample. Panels (b), (d), and (f) present the effect of EC status on Republican vote share for the sample restricted to the Rust Belt states (OH, IN, IL, WI, MI, PA, IA, KY, MD, MN, MO, WV). All estimations include year $\times$ state fixed effects. Standard errors are clustered at the county-level, which is the unit of observation. The dotted vertical line denotes the election prior to introduction of the Energy Community Bonus. $t = -1$ represents the election prior to treatment start, which was the 2018 or 2020 election.

Table A24: Effect of EC bonus on Republican vote shares in the Senate Elections: Group 2

	(1) Full sample	(2) Rust Belt	(3) Swing states
$\hat{\delta}^{pl}_{-2}$ (2016)	-0.009**	-0.025**	0.004
	(0.003)	(0.009)	(0.005)
$\hat{\delta}_1$ (2022)	-0.002	-0.001	-0.003
	(0.001)	(0.003)	(0.003)
R^2	0.979	0.945	0.982
Obs.	3,971	1,089	956

Note: The table reports difference-in-differences estimates of the impact of the Energy Community Bonus on Republican vote shares estimated using two-way fixed effects. Column 1 reports the effect of EC status on Republican vote share for the states having senate elections in 2016, 2018, 2020, and 2022. Column 2 presents the effect of EC status on Republican vote share for the sample restricted to the Rust Belt states (OH, IN, IL, WI, MI, PA, IA, KY, MD, MN, MO, WV). Column 3 presents the effect of EC status on Republican vote share for the sample restricted to the 2024 swing states (GA, AZ, MI, NV, NC, PA, WI). All regressions include year $\times$ state fixed effects, which are not reported. Republican vote share is measured using only Democratic and Republican votes. Standard errors are clustered at the county-level. *, ** and *** indicate significance at the 10%, 5% and 1% level respectively. The 2020 Republican vote share is omitted since it is the last period (i.e. event time =-1) for the period before the treatment which is the introduction of the Energy Community bonus. 2022 (i.e. event time=0, indicated here by $\hat{\delta}_1$) is the first year treatment takes effect.

Table A25: Effect of EC bonus on Republican vote shares in the Senate Elections: Group 3

	(1) Full sample	(2) Rust Belt	(3) Swing states
$\hat{\delta}^{pl}_{-1}$ (2018)	-0.005*	-0.004	-0.009
	(0.002)	(0.010)	(0.006)
$\hat{\delta}_1$ (2024)	-0.005*	-0.002	0.017***
	(0.002)	(0.006)	(0.005)
R^2	0.990	0.979	0.984
Obs.	3,133	588	249

Note: The table reports difference-in-differences estimates of the impact of the Energy Community Bonus on Republican vote shares estimated using two-way fixed effects. Column 1 reports the effect of EC status on Republican vote share for the states having senate elections in 2018, 2020, and 2024. Column 2 presents the effect of EC status on Republican vote share for the sample restricted to the Rust Belt states (OH, IN, IL, WI, MI, PA, IA, KY, MD, MN, MO, WV). Column 3 presents the effect of EC status on Republican vote share for the sample restricted to the 2024 swing states (GA, AZ, MI, NV, NC, PA, WI). All regressions include year $\times$ state fixed effects, which are not reported. Republican vote share is measured using only Democratic and Republican votes. Standard errors are clustered at the county-level. *, ** and *** indicate significance at the 10%, 5% and 1% level respectively. The 2020 Republican vote share is omitted since it is the last period (i.e. event time =-1) for the period before the treatment which is the introduction of the Energy Community bonus. 2024 (i.e. event time=0, indicated here by $\hat{\delta}_1$) is the first year treatment takes effect.

D.10 Robustness: Political Support Environmental Statements

Table A26: Impact of Energy Community Bonus on Attitudes (TWFE estimates) I

	(1) Full sample	(2) Rust Belt	(3) Swing states
Panel A: President Should Do More About Global Warming			
$\hat{\delta}_2^{pl}$ (2019)	0.472***	0.236	0.141
	(0.090)	(0.165)	(0.270)
$\hat{\delta}_1^{pl}$ (2020)	-0.001	0.249***	0.205
	(0.048)	(0.093)	(0.129)
$\hat{\delta}_1$ (2022)	0.137**	-0.050	0.051
	(0.057)	(0.099)	(0.140)
$\hat{\delta}_2$ (2023)	0.414***	0.059	0.040
	(0.062)	(0.117)	(0.152)
$\hat{\delta}_3$ (2024)	0.499***	-0.220	-0.054
	(0.110)	(0.197)	(0.302)
Observations	75,344	24,096	12,312
Panel B: Regulate CO_2 As Pollutant			
$\hat{\delta}_2^{pl}$ (2019)	-0.070	0.099	0.075
	(0.043)	(0.075)	(0.116)
$\hat{\delta}_1^{pl}$ (2020)	0.013	0.152**	0.126
	(0.035)	(0.064)	(0.093)
$\hat{\delta}_1$ (2022)	0.258***	0.035	0.161
	(0.047)	(0.082)	(0.115)
$\hat{\delta}_2$ (2023)	0.398***	0.086	0.166
	(0.049)	(0.084)	(0.119)
$\hat{\delta}_3$ (2024)	0.403***	0.010	0.131
	(0.081)	(0.137)	(0.203)
Observations	100,456	32,128	16,416

Note: The table reports difference-in-differences estimates, as well as standard errors reported in brackets, of the impact of Energy Community Bonus on environmental attitudes, estimated using two-way fixed effects. Panel A reports the effect of EC status on the share of people agreeing with the statement "The president should do more to address global warming". Panel B reports the effect of EC status on the share of people agreeing with the statement "Regulate CO_2 as a pollutant". . Column 2 presents the results for the sample restricted to the Rust Belt states (OH, IN, IL, WI, MI, PA, IA, KY, MD, MN, MO, WV). Column 3 shows the results for the swing states (AZ, GA, MI, NV, NC, PA, WI). All regressions control for county and year fixed effects. Columns 2 and 3 include year × state fixed effects which are not reported. Standard errors are clustered at the county-level. *, ** and *** indicate significance at the 10%, 5% and 1% level respectively. 2021 is omitted to avoid collinearity. 2022 (indicated here by $\hat{\delta}_1$) is the first year the IRA was in effect.

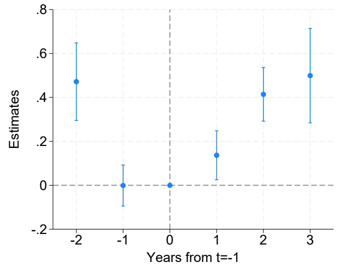
Table A27: Impact of Energy Community Bonus on Attitudes (TWFE estimates) II

	(1) Full sample	(2) Rust Belt	(3) Swing states
Panel A: President's View on Global Warming Important			
$\hat{\delta}_1$ (2022)	0.174***	0.022	0.039
	(0.067)	(0.111)	(0.183)
$\hat{\delta}_2$ (2023)	0.406***	0.144	0.054
	(0.072)	(0.129)	(0.192)
$\hat{\delta}_3$ (2024)	-0.583***	-0.670***	-0.756**
	(0.113)	(0.243)	(0.333)
Observations	50,216	16,064	8,208
Panel B: Introduce Carbon Tax			
$\hat{\delta}_3^{pl}$ (2018)	0.534***	-0.196	-0.260
	(0.083)	(0.155)	(0.243)
$\hat{\delta}_2^{pl}$ (2019)	0.385***	0.191	0.163
	(0.068)	(0.121)	(0.200)
$\hat{\delta}_1^{pl}$ (2020)	0.248***	0.226*	0.213
	(0.063)	(0.123)	(0.182)
$\hat{\delta}_1$ (2022)	0.368***	0.084	0.216
	(0.074)	(0.142)	(0.204)
$\hat{\delta}_2$ (2023)	0.652***	0.253*	0.285
	(0.079)	(0.151)	(0.215)
$\hat{\delta}_3$ (2024)	1.016***	0.211	0.098
	(0.100)	(0.161)	(0.259)
Observations	87,904	28,112	14,364

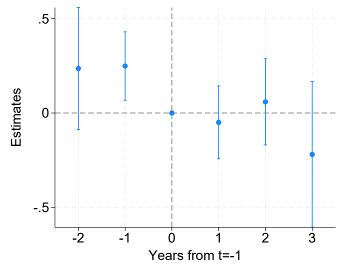
Note: The table reports difference-in-differences estimates, as well as standard errors reported in brackets, estimated using two-way fixed effects. Panel A reports the effect of EC status on the share of people agreeing with the statement "A presidential candidate's views on global warming are important to my vote". Panel B reports the effect of EC status on the share of people agreeing with the statement "Require fossil fuel companies to pay a carbon tax and use the money to reduce other taxes (such as income tax) by an equal amount". Column 1 shows the results for the full sample. Column 2 presents the results for the sample restricted to the Rust Belt states (OH, IN, IL, WI, MI, PA, IA, KY, MD, MN, MO, WV). Column 3 shows the results for the swing states (AZ, GA, MI, NV, NC, PA, WI). All regressions control for county and year fixed effects. Columns 2 and 3 include year × state fixed effects which are not reported. Standard errors are clustered at the county-level. *, ** and *** indicate significance at the 10%, 5% and 1% level respectively. 2021 is omitted to avoid collinearity. 2022 (indicated here by $\hat{\delta}_1$) is the first year the IRA was in effect.

Figure A21: Impact of Energy Community Bonus on Attitudes (TWFE estimates)

"The president should do more to address global warming"

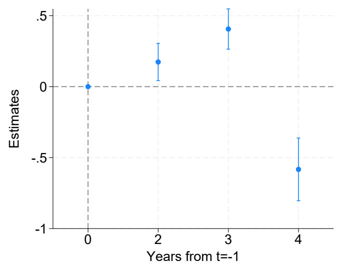


(a) Full Sample

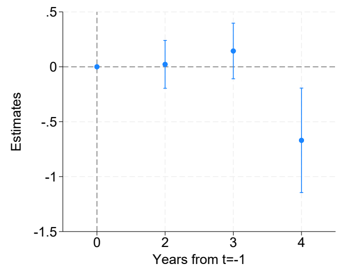


(b) Rust Belt

"A presidential candidate's views on global warming are important to my vote"

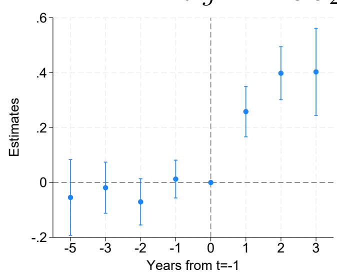


(c) Full Sample

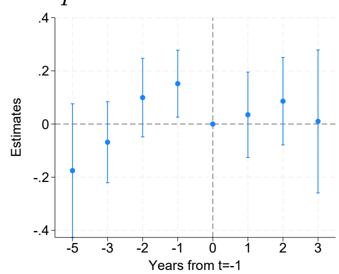


(d) Rust Belt

"Regulate CO_2 as a pollutant"

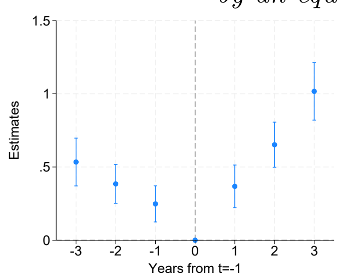


(e) Full Sample

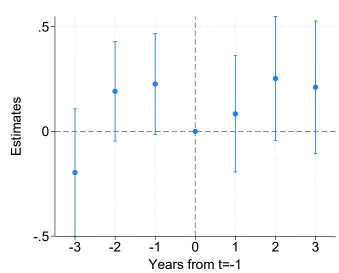


(f) Rust Belt

"Require fossil fuel companies to pay a carbon tax, using the revenue to reduce other taxes by an equal amount"



(g) Full Sample



(h) Rust Belt

Note: The figure reports difference-in-differences estimates, as well as 95% confidence intervals, estimated using two-way fixed effects. Panels (b, d, f, h) restrict the sample to Rust Belt states (OH, IN, IL, WI, MI, PA, IA, KY, MD, MN, MO, WV) and add year × state fixed effects. Standard errors are clustered at the county-level, which is the unit of observation. $t = -1$ represents the year prior to treatment start, which was 2021.

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