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

Joep Keuzenkamp[*] Jacopo Mazza[†] Bob Rijkers[‡]
Katherine Stapleton[§]

December 8, 2025

Abstract

Is place-based green industrial policy effective? We examine the Inflation Reduction Act's Energy Community provisions, which provide spatially targeted incentives for renewable energy investment. Using a difference-in-differences design with investment and job vacancy data, we find that the probability of solar investment rises 0.14 percentage points in targeted areas, equivalent to a 144% increase relative to its counterfactual level. Wind investment shows no response. Solar employment gains are modest, wind employment is unaffected, and we detect no impact on voting in the 2024 election. These findings suggest that place-based incentives can stimulate green investment in designated locations, but may be less effective at generating local job creation or political support in the short term.

JEL Codes: H81; J23; Q42; Q48; R11.
Keywords: Place-based industrial policy; Inflation Reduction Act; Renewable energy investment; Regional economic development; Labor market impacts; Political outcomes.

Acknowledgements: We thank seminar and conference participants at Utrecht University, the UK Network for Environmental Economists' Applied Environmental Economics Conference, and the Third Dutch Environmental and Resource Economics Day for useful comments and discussions. This paper has been partly supported by the Umbrella Facility for Trade trust fund (financed by the governments of the Netherlands, Norway, Sweden, Switzerland, and the United Kingdom). We also acknowledge the generous financial support from the World Bank research support budget. The findings, interpretations, and conclusions expressed in this paper are entirely those of the authors. They do not necessarily represent the views of the International Bank for Reconstruction and Development/World Bank and its affiliated organizations, or those of the Executive Directors of the World Bank or the countries they represent. The views expressed herein are those of the authors and do not necessarily reflect the views of the International Trade Centre and the United Nations. All errors are our responsibility.

[*]Utrecht University. Email: j.w.h.keuzenkamp@uu.nl
[†]Utrecht University. Email: j.mazza@uu.nl
[‡]World Bank. Email: brijkers@worldbank.org
[§]World Bank. Email: kstapleton@worldbank.org

1 Introduction

Regional economic disparities have deepened in advanced economies, leaving "left-behind" areas with population decline, stagnant employment, social distress, and rising support for populism (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 combines 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 aimed to encourage investment and job creation in economically marginalized regions.

This paper investigates whether the IRA's place-based Energy Community incentives have stimulated investment in wind and solar generation, created green 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. Our analysis covers the period from before the IRA began in August 2022 to the end 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 are not ideally suited for examining the evolution of renewables employment, because they either aggregate multiple occu-

[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.

pations, 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 presidential 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 increases 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 absent the Energy Community provisions.[2] Wind investment, by contrast, shows no significant response to the Energy Community bonus. Despite these large investment effects, labor market impacts are modest: solar labor demand measured as the share of total labor demand rises by 0.033 percentage point. This represents an increase of demand of 29% compared to the counterfactual mean, consistent with typical labor demand multipliers, though this effect is only marginally significant. Wind labor demand was unaffected. We do not find any evidence suggestive of 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 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 immediate employment effects are modest, the policy may foster innovation, learning-by-doing, and economies of scale in the deployment of clean energy technologies, which could have 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.

[2]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.

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,[3] 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; Marin & Chen, 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., 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.

[3]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).

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. Conservative estimates place climate-related expenditures at $392 billion, yet these costs could reach $1.07 trillion due to the uncapped nature of the tax credits, which depend on their actual uptake (J. E. Bistline et al., 2023).

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.

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 can be combined, potentially bringing total credits to 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. 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;

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.

3 Data

This paper constructs and combines various datasets:

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.

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 investement 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. For our analysis, the key concern involves potential differential changes in representativeness between ECs and non-ECs over time. Online Appendix B 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.[4] GDP per 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.[5] Excluding natural resource and mining activities and

[4]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.

[5]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.

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[6] 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.[7] The EC average starts at roughly 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

[6]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.

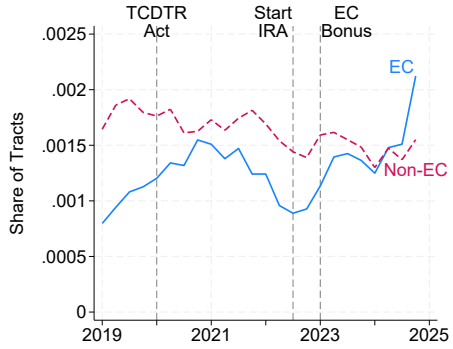
[7]ECs show higher average employment because the two most populous US counties, Los Angeles County and Cook County (Chicago), are classified as ECs.

Table 1: Descriptive Statistics.

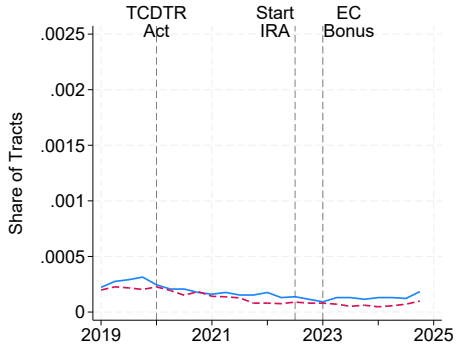
	Control	Cohort 1 EC	Cohort 2 EC	Cohort 3 EC
Panel A: Census tracts				
Area (km^2)	81,876.5 (407,347.1)	274,113.4 (2,962,130.2)***	189,367.2 (2,370,380.1)***	188,272.5 (2,393,815.7)***
Total population	3,933.5 (1,712.0)	3,698.7 (1,662.8)***	3,817.0 (1,674.1)***	3,936.2 (1,736.5)
Generation capacity:				
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 Control (not EC), 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 Control (two-sided t-test): * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

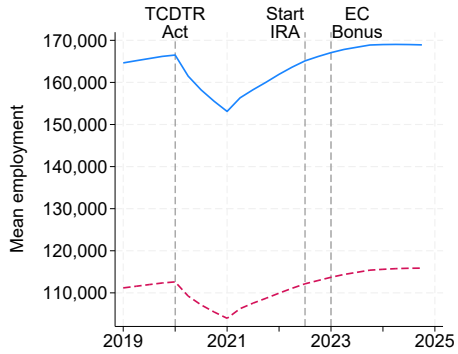
Figure 1: Evolution of Investment, Employment, and Voting
Energy Communities vs. Other Areas



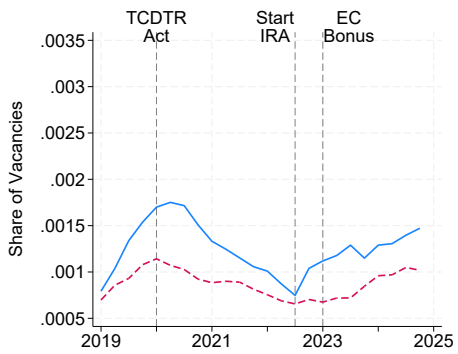
(a) Binary Solar Investment



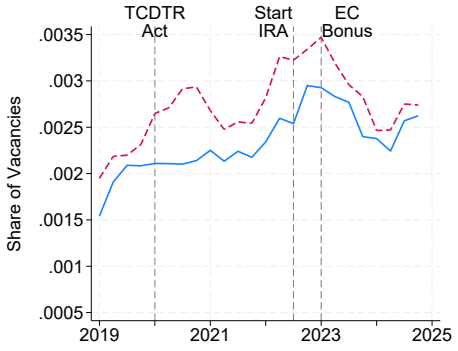
(b) Binary Wind Investment



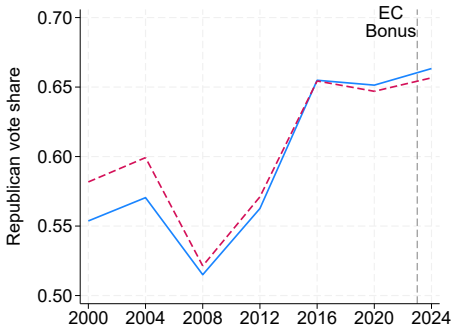
(c) Total Employment



(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, MI, OH, PA, 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).

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 B 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). In our analysis, 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, $\delta_{g,\ell}$:

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

where ℓ is the exposure length, $Y_{g,t}(d_1,\ldots,d_t)$ is the potential outcome under treatment path $(d_1,\ldots,d_t)$, 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:

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

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 C.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:

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

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 and δ_t capture county and time fixed effects, respectively, and ϵ_{jt} represents the error term, with standard errors clustered at the county level. The covariate vector X_{jt} includes state-time period fixed effects.[8] We restrict the electoral analysis to Rust Belt states—Illinois, Indiana, Michigan, Ohio, Pennsylvania, 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.

[8] 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.

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.[9] The estimated effect grows over time, with larger coefficients in later post-designation quarters (Appendix C.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. Robustness checks using investment levels rather than binary indicators and a matching exercise yield similar conclusions (Appendices C.3 and C.4). For the matched sample we find an increase of 0.15 percentage points, and for the investment in levels an increase of $185,217, representing a 133% increase compared to the counterfactual level. Our spillover analysis also finds no evidence of investment displacement across neighboring tracts (Appendix C.5), suggesting that Energy Community investments primarily represent net additions rather than relocations.

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 ($p < 0.10$), representing a 29% rise relative to the counterfactual mean. Although this magnitude appears modest compared to the investment response, it is consistent with an auxiliary analysis linking investment to employment. We estimate that solar labor demand increases by 0.07 percentage points when a county

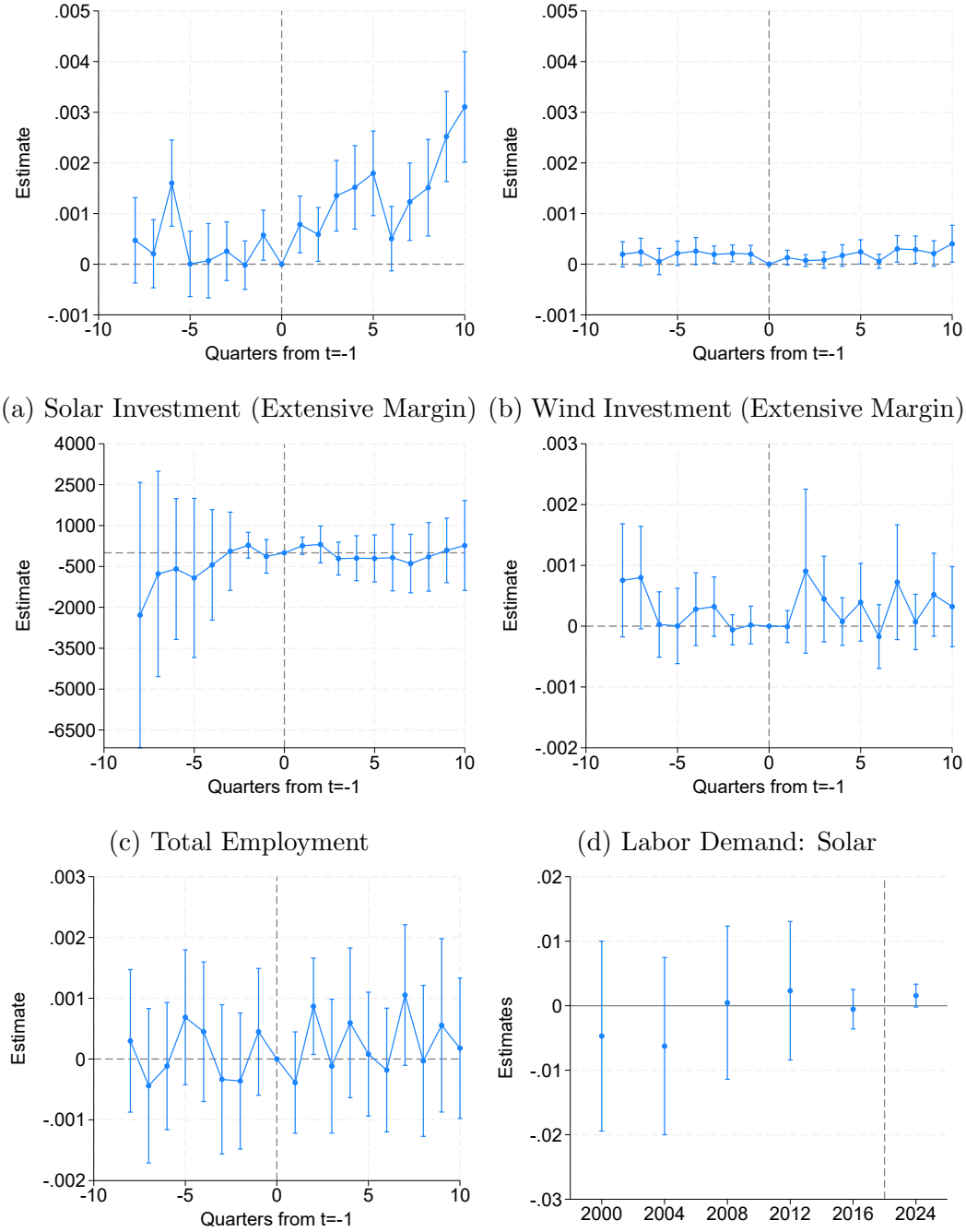
[9] We define the counterfactual level as the level of investment prior to the IRA in the treated areas plus the difference between prior and after the IRA in control areas: Counterfactual Mean $= \sum_{i=treated;t=pre} \text{investment}_{i,t} + \sum_{i=control;t=post} \text{investment}_{i,t} - \sum_{i=control,t=pre}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

receives a solar investment.[10] 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. We perform the same matching analysis for labor demand as for investment, which provides similar results (Appendix C.4 shows the average increase in solar labor demand is 0.031 percentage points). Spillover effects on neighboring regions are positive but statistically insignificant (Appendix C.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 C.7), reinforcing our focus on the more sensitive job openings measure for detecting policy impacts in these targeted sectors.[11]

[10] Analysis provided in Online Appendix C.2.

[11] We perform the same analysis on brown (i.e. fossil-fuel related) labor demand to examine potential crowding out in Appendix C.6, 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 years are depicted on the vertical axis, with 2024 being the year treatment begins.

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 C.8). Analysis of county-level environmental policy attitudes using Yale Climate Opinion Maps data also yields null results across multiple policy dimensions (Appendix C.9). 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 climate change 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, 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 likelihood of solar investment in Energy Communities increases by 0.14 percentage points, 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. Employment effects are

more modest: there are no significant impacts on aggregate employment, solar jobs rise by approximately 29% relative to the counterfactual of no Energy Community provisions, albeit from a low baseline, consistent with expected multipliers, while wind employment is unaffected. These modest labor market impacts may help explain why the policy did not influence electoral outcomes in the 2024 presidential election.

Overall, our findings suggest that place-based incentives can effectively stimulate green investment in designated locations but are less successful in generating substantial local employment gains and galvanizing political support. Assessing the longer-run impact of these provisions, as well as the broader impacts of the IRA, are interesting avenues for future research.

References

Aiginger, K., & Rodrik, D. (2020). Rebirth of industrial policy and an agenda for the twenty-first century. *Journal of Industry, Competition and Trade*, *20*, 189–207.

Allcott, H., Kane, R., Maydanchik, M. S., Shapiro, J. S., & Tintelnot, F. (2024, October). *The effects of "Buy American': Electric Vehicles and the Inflation Reduction Act* (Working Paper No. 33032). National Bureau of Economic Research. https://doi.org/10.3386/w33032

Ashenfarb, M. (2024). A place-based clean electricity subsidy and its effect on emissions. *Available at SSRN 4997027*.

Atalay, E., Hortaçsu, A., Runyun, M., Syverson, C., & Ulu, M. F. (2023). *Micro-and macroeconomic impacts of a place-based industrial policy* (tech. rep.). National Bureau of Economic Research.

Austin, B., Glaeser, E., & Summers, L. (2018). Jobs for the Heartland: Place-Based policies in 21st-century America. *Brookings Papers on Economic Activity*, 151–232. Retrieved October 7, 2025, from http://www.jstor.org/stable/26506216

Baccini, L., & Weymouth, S. (2021). Gone for good: Deindustrialization, white voter backlash, and US presidential voting. *American Political Science Review*, *115*(2), 550–567.

Bartik, T. J. (2020). Using place-based jobs policies to help distressed communities. *Journal of Economic Perspectives*, *34*(3), 99–127.

Bastos, P., Greenspon, J., Stapleton, K., & Taglioni, D. (2024). Did the 2022 global energy crisis accelerate the diffusion of low-carbon technologies? *World bank policy research wp*, *10777*.

Bergquist, M., Nilsson, A., Harring, N., & Jagers, S. C. (2022). Meta-analyses of fifteen determinants of public opinion about climate change taxes and laws. *Nature Climate Change*, *12*(3), 235–240.

Bistline, J., Blanford, G., Brown, M., Burtraw, D., Domeshek, M., Farbes, J., Fawcett, A., Hamilton, A., Jenkins, J., Jones, R., et al. (2023). Emissions and energy impacts of the inflation reduction act. *Science*, *380*(6652), 1324–1327.

Bistline, J. E., Mehrotra, N. R., & Wolfram, C. (2023). Economic implications of the climate provisions of the inflation reduction act. *Brookings Papers on Economic Activity*, *2023*(1), 77–182.

Bivens, J. (2019). *Updated employment multipliers for the US economy* (tech. rep.). Economic Policy Institute.

Bombardini, M., Gonzalez-Lira, A., Li, B., & Motta, C. (2024, September). *The increasing cost of buying american* (NBER Working Paper No. 32953). National Bureau of Economic Research. https://doi.org/10.2139/ssrn.4957407

Case, A., & Deaton, A. (2015). Rising morbidity and mortality in midlife among white non-Hispanic Americans in the 21st century. *Proceedings of the National Academy of Sciences*, *112*(49), 15078–15083.

Castellanos, K., & Heutel, G. (2024). Unemployment, labor mobility, and climate policy. *Journal of the Association of Environmental and Resource Economists*, *11*(1), 1–40.

Cingano, F., Palomba, F., Pinotti, P., & Rettore, E. (2025). Making subsidies work: Rules versus discretion. *Econometrica*, *93*(3), 747–778. https://doi.org/https://doi.org/10.3982/ECTA21319

Congressional Budget Office. (2025, April). *Business tax credits for wind and solar power* (tech. rep. No. Publication No. 61329) (Accessed: 2025-08-27). Congressional Budget Office.

Criscuolo, C., Martin, R., Overman, H. G., & Van Reenen, J. (2019). Some causal effects of an industrial policy. *American Economic Review*, *109*(1), 48–85.

De Chaisemartin, C., & d'Haultfoeuille, X. (2024). Difference-in-differences estimators of intertemporal treatment effects. *Review of Economics and Statistics*, 1–45.

Dijkstra, L., Poelman, H., & Rodríguez-Pose, A. (2020). The geography of EU discontent. *Regional Studies*, *54*(6), 737–753.

Drews, S., & Van den Bergh, J. C. (2016). What explains public support for climate policies? A review of empirical and experimental studies. *Climate Policy*, *16*(7), 855–876.

EIA U.S. Energy Information Administration. (2024). Preliminary monthly electric generator inventory (based on form eia-860m as a supplement to form eia-860) [Accessed: 2024-10-08]. https://www.eia.gov/electricity/data/eia860m/

Epstein, L., & Muehlegger, E. (2024). *Ideology, Incidence and the Political Economy of Fuel Taxes: Evidence from the California 2018 Proposition 6* (tech. rep.). National Bureau of Economic Research.

Fabra, N., Gutiérrez, E., Lacuesta, A., & Ramos, R. (2024). Do renewable energy investments create local jobs? *Journal of Public Economics*, *239*, 105212.

Friedmann, J., Fan, Z., Byrum, Z., Ochu, E., Bhardwaj, A., & Sheerazi, H. (2020). Levelized cost of carbon abatement: An improved cost-assessment methodology for a net-zero emissions world. *Columbia University SIPA Center on Global Energy Policy: New York, NY, USA*.

Garrett-Peltier, H. (2017). Green versus brown: Comparing the employment impacts of energy efficiency, renewable energy, and fossil fuels using an input-output model. *Economic Modelling*, *61*, 439–447. https://doi.org/https://doi.org/10.1016/j.econmod.2016.11.012

Hershbein, B., & Kahn, L. B. (2018). Do recessions accelerate routine-biased technological change? Evidence from vacancy postings. *American Economic Review*, *108*(7), 1737–1772.

ICF International. (2022). Solar economics: The ptc vs. itc decision. https://www.icf.com/insights/energy/solar-economics-ptc-vs-itc

Incoronato, L., & Lattanzio, S. (2023). *Place-based industrial policies and local agglomeration in the long run* (tech. rep. No. 11397). CESifo.

International Renewable Energy Agency (IRENA). (2025, July). *Tec/rpgc in 2024–2025: Trends, evolution and capacity* (Accessed: December 8, 2025). IRENA. https://www.irena.org/-/media/Files/IRENA/Agency/Publication/2025/Jul/IRENA_TEC_RPGC_in_2024_2025.pdf

Juhász, R., & Lane, N. (2024). The political economy of industrial policy. *Journal of Economic Perspectives*, *38*(4), 27–54.

Kattenberg, L., Aydin, E., Brounen, D., & Kok, N. (2023). The impact of financial incentives on technology adoption: Evidence from random allocation of solar pv subsidies. *MIT Center for Real Estate Research Paper*, (24/04).

LaPoint, C., & Sakabe, S. (2021). Place-based policies and the geography of corporate investment. *Available at SSRN 3950548*.

Lee, N., Morris, K., & Kemeny, T. (2018). Immobility and the Brexit vote. *Cambridge Journal of Regions, Economy and Society*, *11*(1), 143–163.

Marin, G., & Chen, S. Z. (2021). The employment impact of a green fiscal push: Evidence from the american recovery and reinvestment act. *Brookings Papers on Economic Activity*.

MIT Election Data and Science Lab. (2018). County Presidential Election Returns 2000-2020. https://doi.org/10.7910/DVN/VOQCHQ

National Renewable Energy Laboratory. (2024). Utility-scale pv — electricity — 2024 annual technology baseline [Accessed: 2025-08-27].

National Renewable Energy Laboratory. (2025). Renewable energy potential on federal lands analysis [Accessed: 2025-08-27].

Rhodium Group and MIT's Center for Energy and Environmental Policy Research. (2024). Clean investment monitor. https://www.cleaninvestmentmonitor.org/database-access

Rodríguez-Pose, A., Lee, N., & Lipp, C. (2021). Golfing with Trump. Social capital, decline, inequality, and the rise of populism in the US. *Cambridge Journal of Regions, Economy and Society*, *14*(3), 457–481.

Rodrik, D. (2021). Why does globalization fuel populism? Economics, culture, and the rise of right-wing populism. *Annual Review of Economics*, *13*(1), 133–170.

Rodrik, D., & Sabel, C. (2020). *Building a good jobs economy*. Harvard Kennedy School, John F. Kennedy School of Government Cambridge.

Roy, N., Domeshek, M., Burtraw, D., Palmer, K., Rennert, K., Shih, J.-S., & Villanueva, S. (2022). Beyond clean energy: The financial incidence and health effects of the ira. *Resources for the Future*.

Scheifele, F., & Popp, D. (2025). Not in my backyard? The local impact of wind and solar parks in Brazil. *Energy Economics*, 108481.

Shang, B. (2023). The poverty and distributional impacts of carbon pricing: Channels and policy implications. *Review of Environmental Economics and Policy*, *17*(1), 64–85.

Sheldon, T. L., Dua, R., & Alharbi, O. A. (2023). Electric vehicle subsidies: Time to accelerate or pump the brakes? *Energy Economics*, *120*, 106641.

The Climate Registry. (2023). 2023 default emission factors [Accessed: 2025-10-10]. https://theclimateregistry.org/wp-content/uploads/2023/06/2023-Default-Emission-Factors-Final-1.pdf

U.S. Energy Information Administration. (2023a). Average tested heat rates by prime mover and energy source, 2013–2023 [Table 8.2 in "Electricity Annual Report"].

U.S. Energy Information Administration. (2023b). Table 4.8.a. capacity factors for utility scale generators primarily using fossil fuels [Accessed: 2025-10-10].

U.S. Energy Information Administration. (2024a, October). *Electric power annual 2023* (tech. rep. No. EPA) (Accessed: 2025-08-27). U.S. Energy Information Administration.

U.S. Energy Information Administration. (2024b, December 11). *How much carbon dioxide is produced per kilowatthour of u.s. electricity generation?* [Accessed on 2025-09-03]. https://www.eia.gov/tools/faqs/faq.php?id=74&t=11

U.S. Environmental Protection Agency. (2022, November). *Report on the social cost of greenhouse gases: Estimates incorporating recent scientific advances* (External Review Draft) (Draft for public comment). U.S. Environmental Protection Agency. https://www.epa.gov/system/files/documents/2022-11/epa_scghg_report_draft_0.pdf

Vona, F. (2019). Job losses and political acceptability of climate policies: Why the 'job-killing' argument is so persistent and how to overturn it. *Climate Policy*, *19*(4), 524–532.

Vona, F., Marin, G., & Consoli, D. (2019). Measures, drivers and effects of green employment: Evidence from US local labor markets, 2006–2014. *Journal of Economic Geography*, *19*(5), 1021–1048.

Xing, J., Leard, B., & Li, S. (2021). What does an electric vehicle replace? *Journal of Environmental Economics and Management*, *107*, 102432.

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 focuses on estimating the 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:

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

$$\begin{aligned}\text{Annual } tCO_2 = {} & \text{Annual MWh} \times \text{Heat Rate (Btu/MWh)} \\ & \times \text{Emission Factor (gr } CO_2\text{/MMBtu)}\end{aligned} \tag{A.4}$$

[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.

where heat rates, emission factors, and capacity factors are from U.S. Energy Information Administration (2023a), The Climate Registry (2023), and U.S. Energy 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 45,687 vacancies in Energy Communities. Our difference-in-differences estimate implies a 29% increase due to the EC bonus, or 10,418 additional vacancies ($45,687 - \frac{45,687}{1.29}$).

CAPEX totals $28.720 billion across all EC plants (from 504 projects). 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 $1,101,676. 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 and 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.

[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.

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. (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"

Joep Keuzenkamp[§] Jacopo Mazza[¶] Bob Rijkers[‖]
Katherine Stapleton[**]

December 8, 2025

Contents

A Policy Context **2**

B Data Validation **5**

C Additional Results **6**
C.1 Main Regressions, Table of Coefficients 6
C.2 Auxiliary Analysis: Effect of Solar Investment on Solar Labor Demand 7
C.3 Robustness: Investment in Levels 9
C.4 Robustness: Matching 11
C.5 Robustness: Spillover Analysis 16
C.6 Brown Labor Demand 18
C.7 Renewables (Y02E10) and Construction Labor Demand 21
C.8 Robustness: Electoral Results 23
C.9 Robustness: Political Support Environmental Statements 25

[*]Utrecht University. Email: j.w.h.keuzenkamp@uu.nl
[†]Utrecht University. Email: j.mazza@uu.nl
[‡]World Bank. Email: brijkers@worldbank.org
[§]World Bank. Email: kstapleton@worldbank.org
[§]Utrecht University. Email: j.w.h.keuzenkamp@uu.nl
[¶]Utrecht University. Email: j.mazza@uu.nl
[‖]World Bank. Email: brijkers@worldbank.org
[**]World Bank. Email: kstapleton@worldbank.org

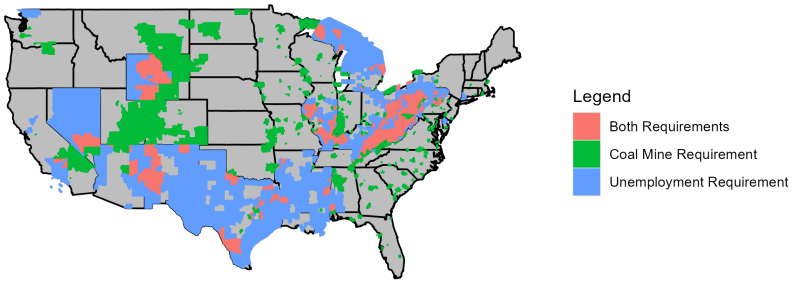
A Policy Context

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%

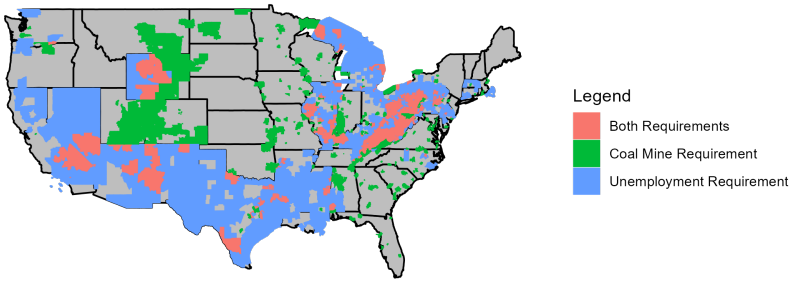
Note: The table presents the rates of the Investment and Production Tax Credits. Power plants with a nameplate capacity smaller than 1 MW receive the rates in the first row. Power plants with a nameplate capacity larger than 1 MW, receive the rates in the second or third row, depending on whether they 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.



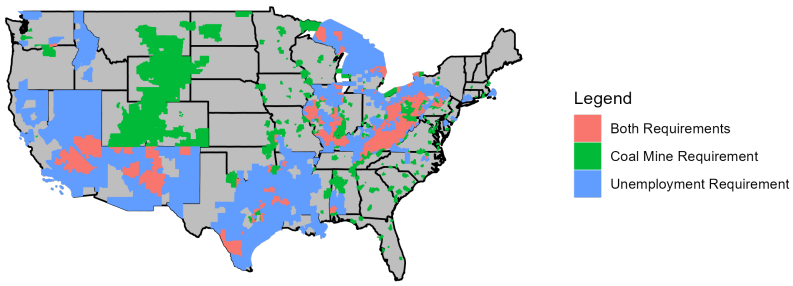
Note: The unit of observation is the census tract

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



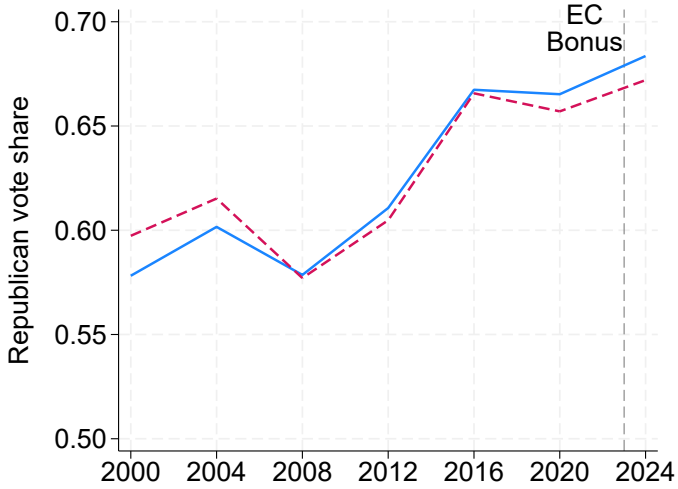
Note: The unit of observation is the census tract

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 Additional Results

C.1 Main Regressions, Table of Coefficients

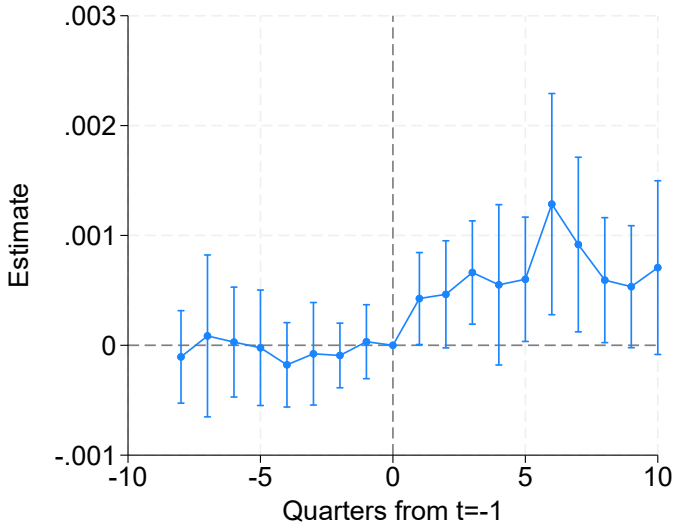
Table A3: Event Study of the EC Bonus on Investment and Employment

	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 employment, 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.

C.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. For cohort 1: Q2-2022; cohort 2: Q1-2024; cohort 3: Q2-2024.

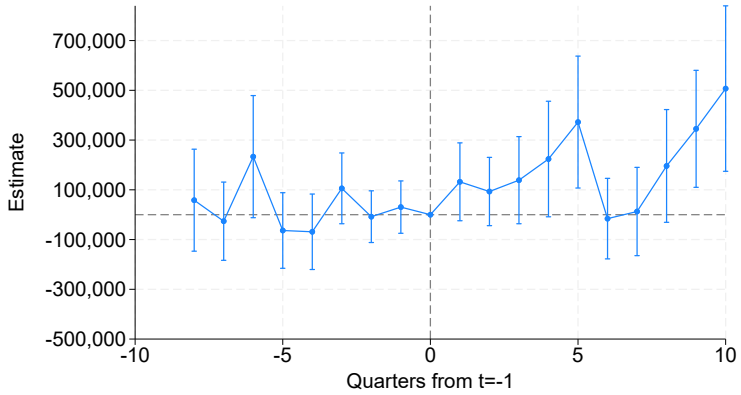
Table A4: Event Study of Solar Investment on Solar Labor Demand

	(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)

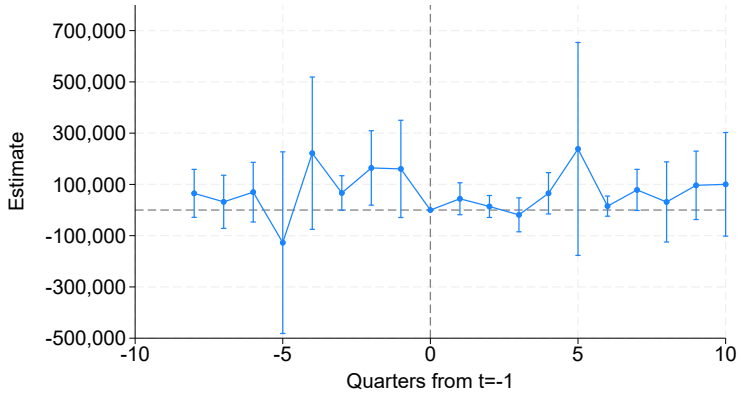
Note: The table reports difference-in-differences estimates of the effect of solar investment on solar labor demand estimated using the method of De Chaisemartin and d'Haultfoeuille (2024). The column reports the impact of receiving a solar investment on quarterly solar labor demand. If a county receives 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. 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.

C.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 Q2-2022, Q1-2024, and Q2-2024, respectively.

Table A5: 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.

C.4 Robustness: Matching

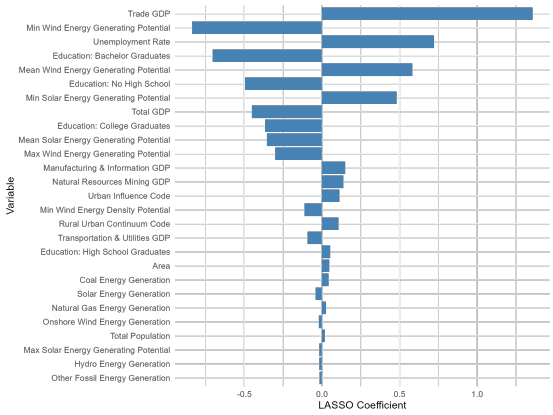
To ensure our results are not driven by pre-existing differences between ECs and non-ECs, we perform a propensity score matching exercise. The De Chaisemartin and d'Haultfoeuille (2024) method does not accommodate matching directly, so we first perform one-to-one nearest neighbor matching without replacement to construct a restricted sample of matched observations, then apply the De Chaisemartin and d'Haultfoeuille (2024) estimator to this matched sample.

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 in 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 rate in 2022.

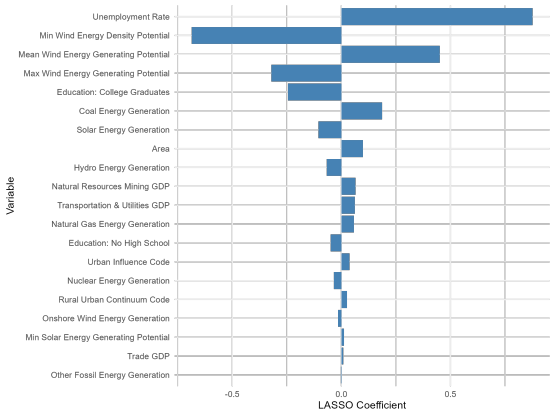
We perform the LASSO separately for investment and labor demand as the unit of observation differs between the two. Panels (a) and (b) of Figure A7 show the LASSO coefficient paths. We retain 27 variables for investment and 20 variables for labor demand. Panels (c) and (d) show the love plots, demonstrating 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 A6 and A7 report the sample sizes for the matched and unmatched samples.

Figure A8 presents the event-study estimates using the matched sample. Our substantive conclusions remain unchanged. The AVSQ for solar investment increases modestly from 0.137% to 0.147%. The AVSQ for wind investment also rises slightly from 0.017% to 0.023%. However, the positive and similarly-sized pre-treatment estimates suggest this remains a null result. The solar labor demand coefficient decreases slightly from 0.033% to 0.031% and loses statistical significance, likely due to the reduced sample size. Finally, the wind labor demand coefficient switches sign from 0.026% to -0.027%, but the comparably-sized pre-trend coefficients indicate this should also be interpreted as a null result.

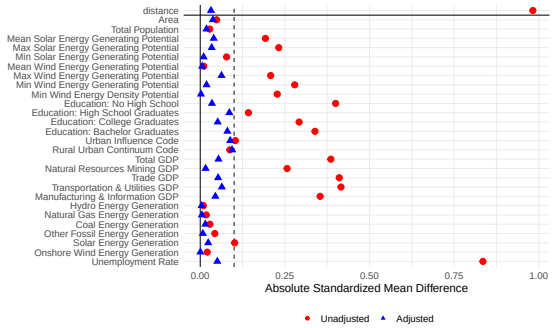
Figure A7: Matching – Specification Checks



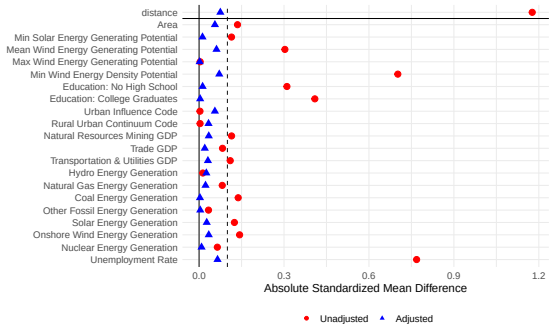
(a) Lasso Coefficients: Investment



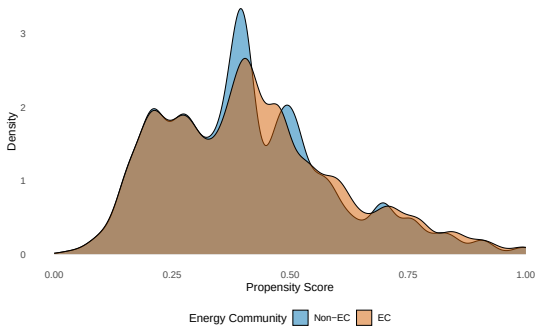
(b) Lasso Coefficients: Labor Demand



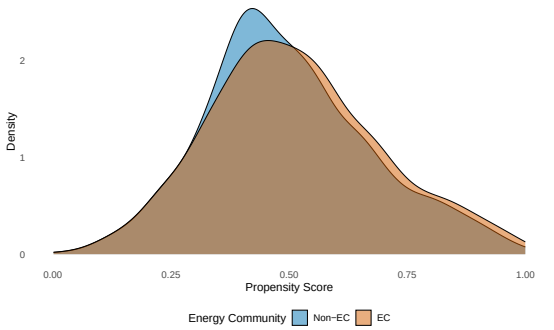
(c) Love Plot: Investment



(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 A6: Samples: Investment

Sample	N
Full Sample	82504
Energy Community Tracts	31916
Non-Energy Community Tracts	50588
Matched Sample	43968
Energy Community Tracts	21984
Non-Energy Community Tracts	21984
Dropped in Matching	38536
Energy Community Tracts	9932
Non-Energy Community Tracts	28604

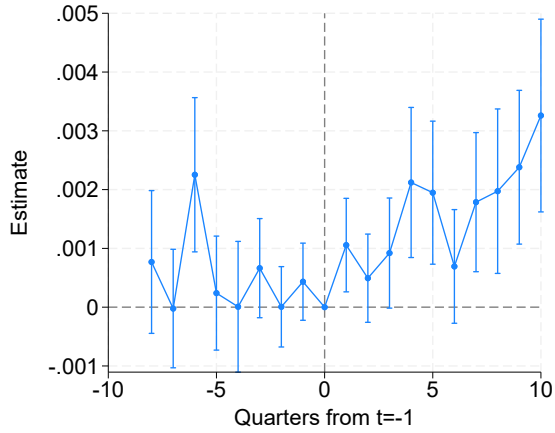
Note: The table reports the sample size for the full sample, the matched sample, and the observations dropped after matching. The unit of observation is the census tract. The matched sample is used in the investment analysis.

Table A7: Samples: Wind Investment

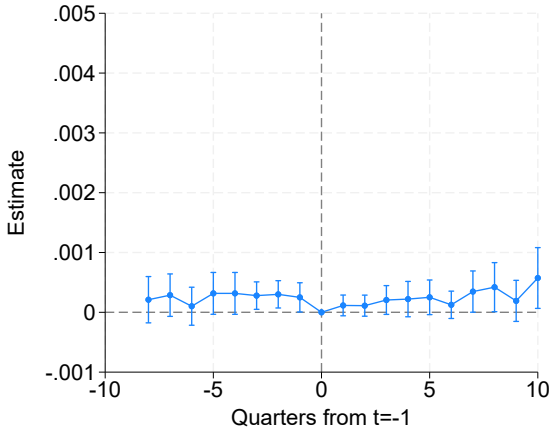
Sample	N
Full Sample	3070
Energy Community Counties	1490
Non-Energy Community Counties	1580
Matched Sample	1860
Energy Community Counties	930
Non-Energy Community Counties	930
Dropped in Matching	1210
Energy Community Counties	560
Non-Energy Community Counties	650

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.

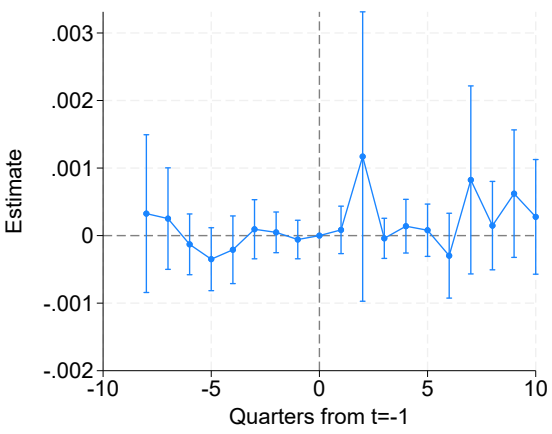
Figure A8: Event Study of the EC Bonus on Investment and Employment – Matched Sample



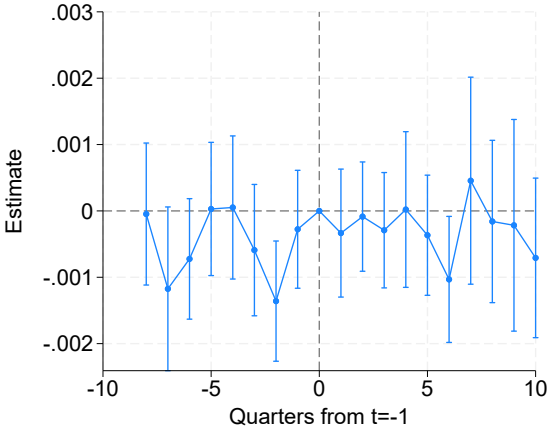
(a) Solar Investment (Extensive Margin)



(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 employment, 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.

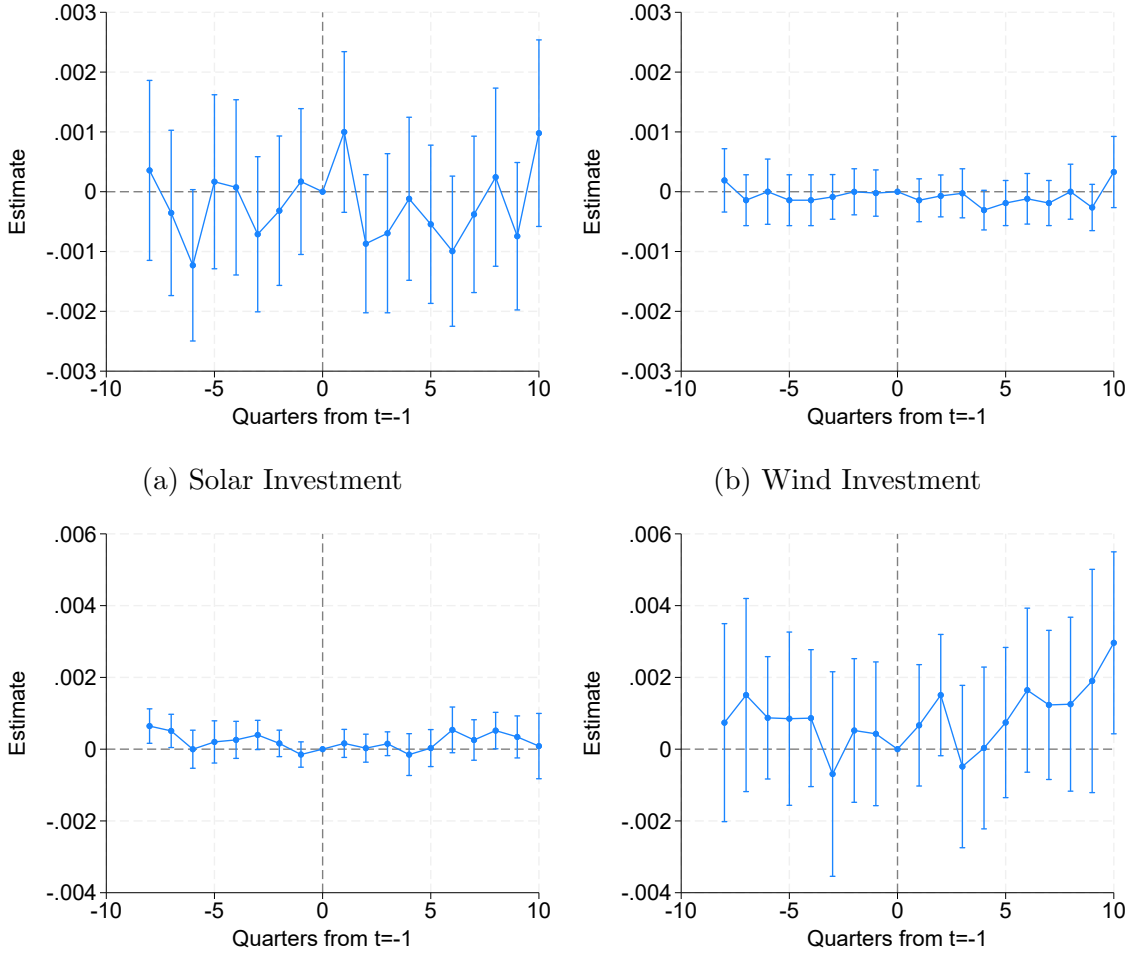
Table A8: Event Study of the EC Bonus on Investment and Employment – Matched Sample

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

Note: The table reports difference-in-differences estimates of the Energy Community Bonus on investment and employment, 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.

C.5 Robustness: Spillover Analysis

Figure A9: Event Study of the EC Bonus on Investment and Employment 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 employment 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 A9: Event Study of the EC Bonus on Investment and Employment 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 employment 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.

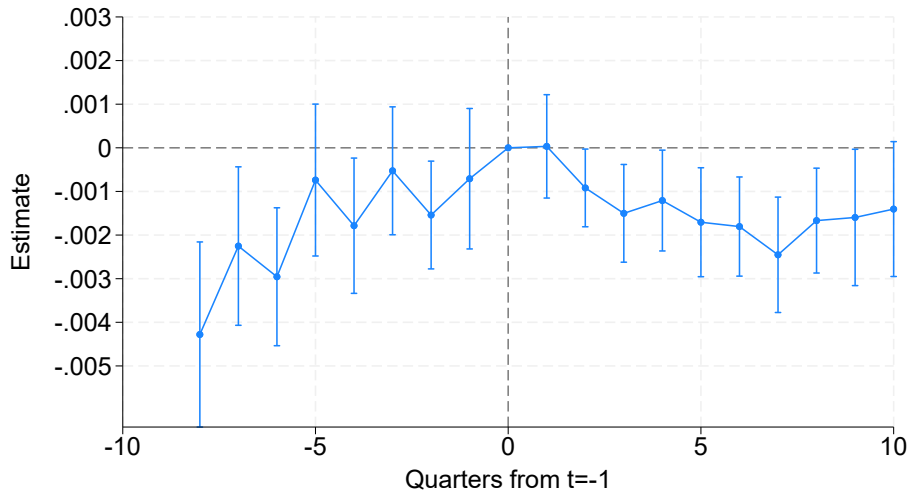
C.6 Brown Labor Demand

Table A10: Event Study of the EC Bonus on Brown Labor Demand

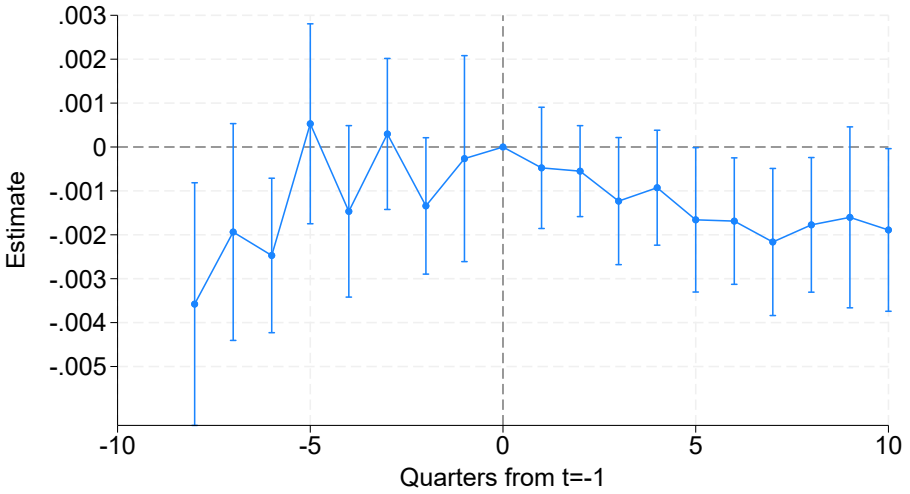
	Full Sample		Matched Sample	
$\hat{\delta}_8^{pl}$	-0.004***	(0.001)	-0.004**	(0.001)
$\hat{\delta}_7^{pl}$	-0.002**	(0.001)	-0.002	(0.001)
$\hat{\delta}_6^{pl}$	-0.003***	(0.001)	-0.002***	(0.001)
$\hat{\delta}_5^{pl}$	-0.001	(0.001)	0.001	(0.001)
$\hat{\delta}_4^{pl}$	-0.002**	(0.001)	-0.001	(0.001)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

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. 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.

Figure A10: Event Study of the EC Bonus on Brown Labor Demand



(a) Total Sample

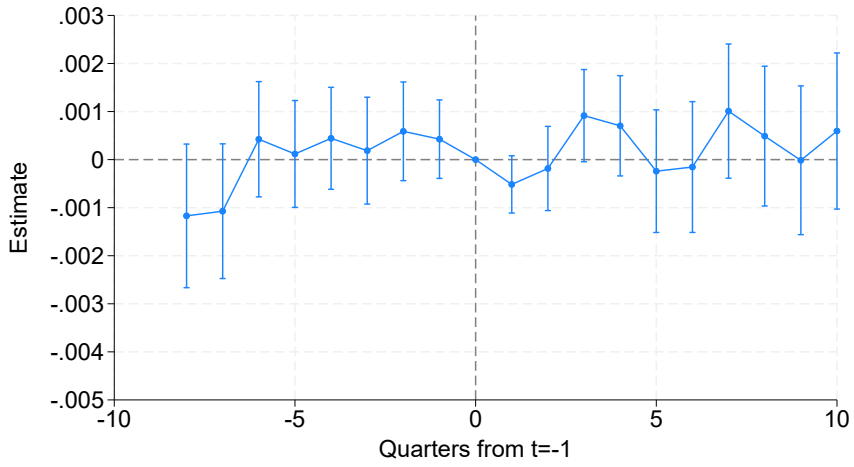


(b) Matched Sample

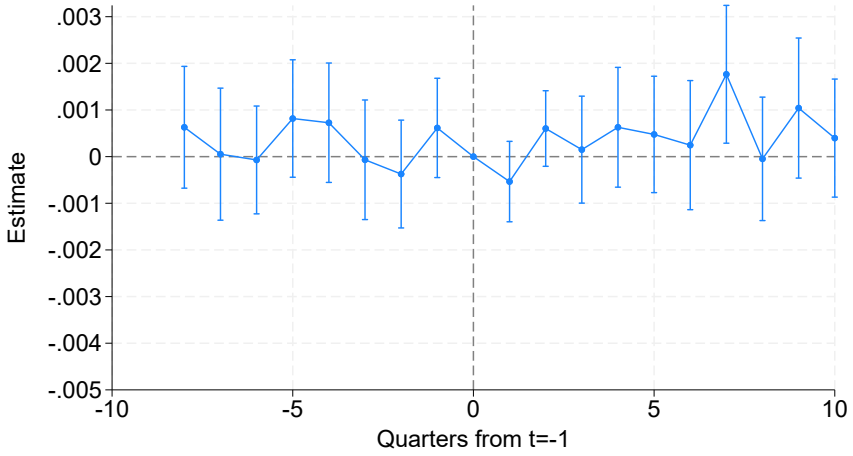
Note: The table reports difference-in-differences estimates of the Energy Community Bonus on brown labor demand, and 95% confidence intervals, estimated using the method of De Chaisemartin and d'Haultfoeuille (2024). Panel (a) reports the effect of EC status on the share of brown labor demand. Panel (b) reports the effect of EC status on the share of brown labor demand for the matched sample. 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.

C.7 Renewables (Y02E10) and Construction Labor Demand

Figure A11: Event Study of the EC Bonus on Employment in Construction and Renewables (Y02E10)



(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.

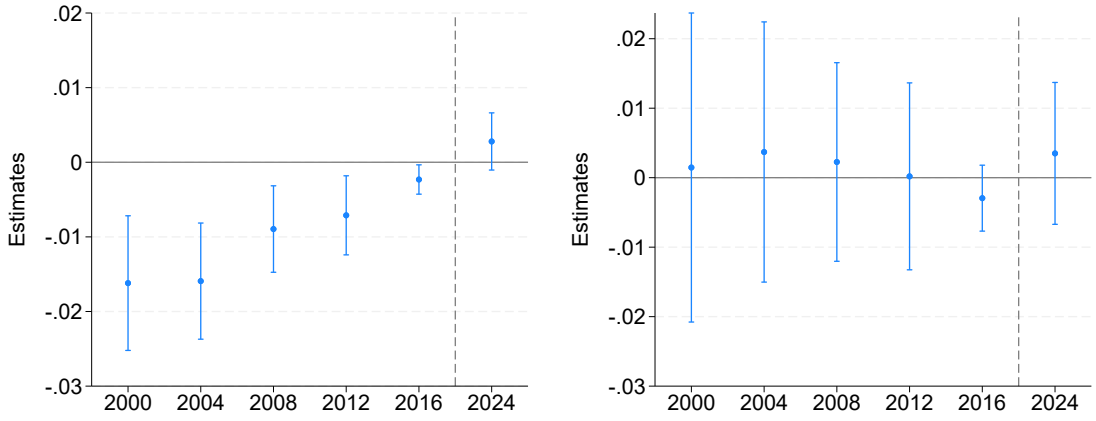
Table A11: Event Study of the EC Bonus on Employment in Construction and Renewables (Y02E10)

	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 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.

C.8 Robustness: Electoral Results

Figure A12: Event Study of the EC Bonus on Republic 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. The dotted vertical line denotes the introduction of the Energy Community Bonus.

Table A12: Effect of EC bonus on Republic vote shares

Year	Event time	(1) Full sample	(2) Rust Belt	(3) Swing states
2000	t=-6	-0.016***	-0.005	0.001
		(0.005)	(0.008)	(0.011)
2004	t=-5	-0.016***	-0.006	0.004
		(0.004)	(0.007)	(0.010)
2008	t=-4	-0.009**	0.000	0.002
		(0.003)	(0.006)	(0.007)
2012	t=-3	-0.007**	0.002	0.000
		(0.003)	(0.005)	(0.007)
2016	t=-2	-0.002*	-0.001	-0.003
		(0.001)	(0.002)	(0.002)
2024	t=0	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 Replublic 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 (IL, IN, MI, OH, PA, WI). 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), controlling for year effects. Columns 2 and 3 are estimated including year × state fixed effects, which are not reported. All regressions control for county fixed effects. 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. even time =-1) for the period before the "treatment" which is the introduction of the Energy Community bonus. 2024 (i.e. even time=0) is the first and only year treatment takes effect.

C.9 Robustness: Political Support Environmental Statements

Table A13: Impact of Energy Community Bonus on Attitudes (TWFE estimates) I

	(1) Full sample	(2) Swing states
Panel A: President		
2019	0.335***	0.089
	(0.094)	(0.276)
2020	-0.138*	0.154
	(0.072)	(0.186)
2021	-0.137**	-0.051
	(0.057)	(0.140)
2023	0.277***	-0.011
	(0.028)	(0.060)
2024	0.362***	-0.105
	(0.102)	(0.285)
Observations	75,344	12,312
Panel B: Regulate CO_2		
2019	-0.329***	-0.086
	(0.065)	(0.175)
2020	-0.246***	-0.034
	(0.062)	(0.160)
2021	-0.258***	-0.161
	(0.047)	(0.115)
2023	0.140***	0.005
	(0.014)	(0.027)
2024	0.145**	-0.029
	(0.073)	(0.181)
Observations	100,456	16,416

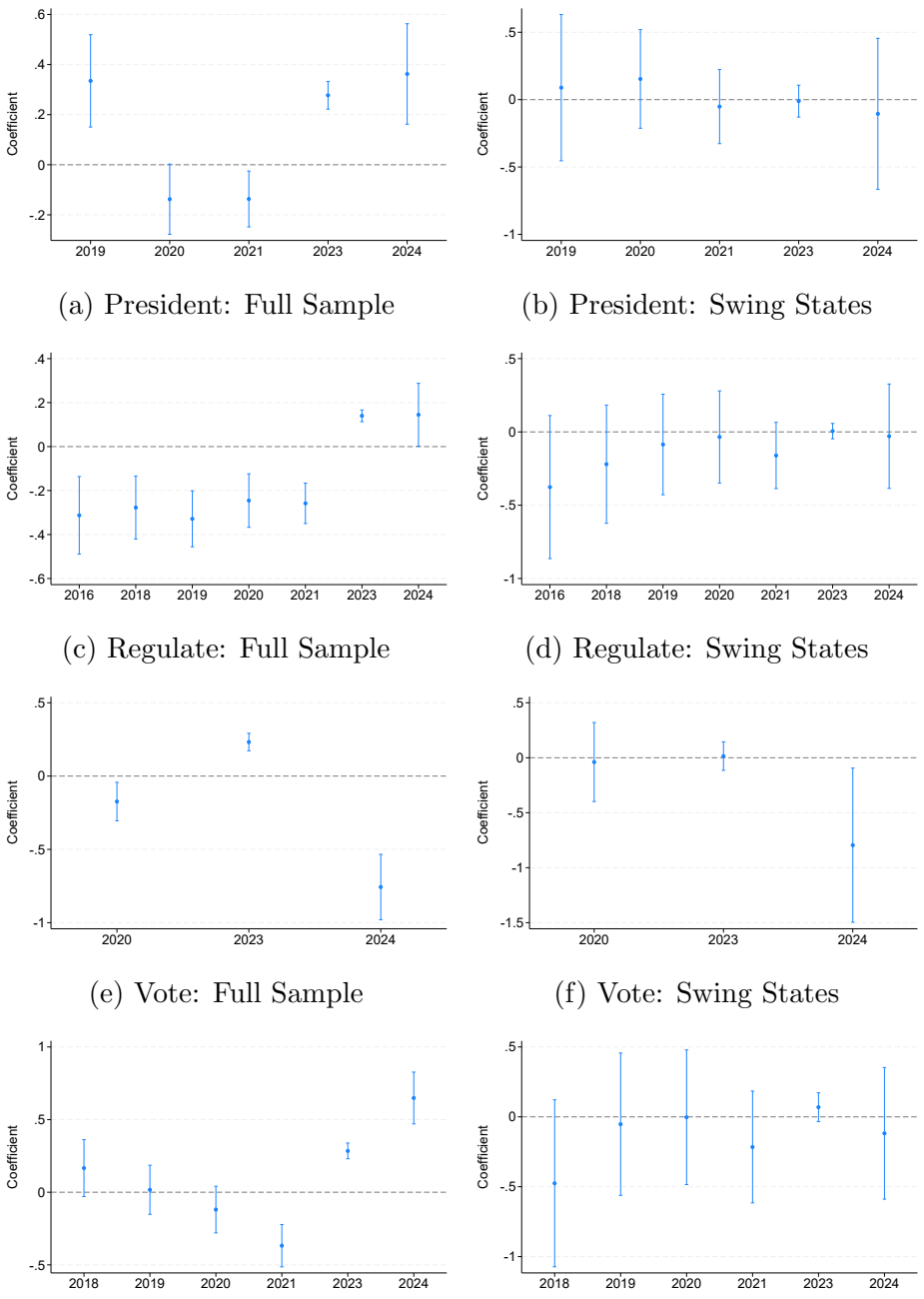
Note: The table reports difference-in-differences estimates of the impact of Energy Community Bonus on environmental attitudes, estimated using two-way fixed effects. Panel A reports the effect of EC status on the share of people agreeing with the statement "The president should do more to address global 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 1 shows the results for the full sample. Column 2 shows the results for the swing states (AZ, GA, MI, NV, NC, PA, WI). Standard errors are clustered at the county-level. *, ** and *** indicate significance at the 10%, 5% and 1% level respectively. All regressions control for county level fixed effects as well as year × state fixed effects which are not reported. 2022 is omitted to avoid colinearity. 2023 is the first year the Energy Community Bonus was in effect the entire year.

Table A14: Impact of Energy Community Bonus on Attitudes (TWFE estimates) II

	(1) Full sample	(2) Swing states
Panel A: Vote		
2020	-0.174***	-0.039
	(0.067)	(0.183)
2023	0.232***	0.015
	(0.030)	(0.066)
2024	-0.757***	-0.795**
	(0.114)	(0.357)
Observations	50,216	8,208
Panel B: Carbon tax		
2018	0.166*	-0.476
	(0.100)	(0.304)
2019	0.017	-0.053
	(0.086)	(0.259)
2020	-0.120	-0.003
	(0.082)	(0.245)
2021	-0.368***	-0.216
	(0.074)	(0.204)
2023	0.284***	0.069
	(0.028)	(0.052)
2024	0.649***	-0.118
	(0.091)	(0.240)
Observations	87,904	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 shows the results for the swing states (AZ, GA, MI, NV, NC, PA, WI). All regressions control for county level fixed effects as well as year × state fixed effects which are not reported. 2022 is omitted to avoid colinearity. 2023 is the first year the Energy Community Bonus was in effect the entire year.

Figure A13: Impact of Energy Community Bonus on Attitudes (TWFE estimates) n



(a) President: Full Sample (b) President: Swing States

(c) Regulate: Full Sample (d) Regulate: Swing States

(e) Vote: Full Sample (f) Vote: Swing States

(g) Carbon Tax: Full Sample (h) Carbon Tax: Swing States

Note: The figure reports difference-in-differences estimates, as well as 95% confidence intervals, estimated using two-way fixed effects. Panels (a) and (b) report the effect of EC status on the share of people agreeing with the statement "The president should do more to address global warming". Panels (c) and (d) report 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". Panels (e) and (f) report the effect of EC status on the share of people agreeing with the statement "Regulate CO_2 as a pollutant". Panels (g) and (h) report 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". Panels (b, d, f, h) restrict the sample to swing states (GA, AZ, MI, NV, NC, PA, WI) and add year × state fixed effects. Standard errors are clustered at the county-level, which is the unit of observation.

References for Online Appendix

De Chaisemartin, C., & d'Haultfoeuille, X. (2024). Difference-in-differences estimators of intertemporal treatment effects. *Review of Economics and Statistics*, 1–45.

Office of Energy Efficiency & Renewable Energy. (2024). Inflation reduction act tax credit opportunities for hydropower and marine energy. https://www.energy.gov/eere/water/inflation-reduction-act-tax-credit-opportunities-hydropower-and-marine-energy