Can Place-Based Incentives Accelerate the Energy Transition?

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Abstract

This paper examines the design and effectiveness of place-based industrial policy in renewable energy. We study the Inflation Reduction Act's energy-community tax credits, which offered bonus subsidies to projects located in economically vulnerable, fossil-fuel reliant areas. Reduced form estimates show no significant overall changes in interconnection requests in eligible counties but substantial heterogeneity by policy eligibility, region, and technology. We then develop and estimate a structural model of project location choice to evaluate alternative policy designs. Counterfactual simulations quantify key trade-offs between developer surplus, environmental benefits, fiscal spending, and support for vulnerable communities in the design of place-based policies.

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1 Introduction

The U.S. has a long history of place-based industrial policies designed to spur economic development in targeted geographic areas. Classic examples include state Enterprise Zones, the federal Empowerment Zone Program, the Low-Income Housing Tax Credit, and Opportunity Zones, all of which use geographically targeted incentives to influence the location of capital and jobs (Busso, Gregory, and Kline 2013; Neumark and Young 2021).[1] Yet the energy sector has seen limited place-based policy making (Mukherjee and Raimi 2023). As energy transition reshapes the distribution of energy mix across space and creates regional winners and losers, it is important to understand whether, and how, geographically targeted incentives can affect the transition.

In this paper, we study the design and effectiveness of place-based industrial policy in the energy sector. We show how these incentives affect the geography of renewable investment and lead to important trade-offs between private welfare, environmental benefits, and support for vulnerable communities. We study this in the context of the "energy community" tax credits introduced under the Inflation Reduction Act (IRA) of 2022, which provided a bonus on top of existing subsidies to renewable projects sited in locations that are economically vulnerable and reliant on fossil fuels (H.R.5376 2022). We first evaluate whether the current policy design directs renewable investment toward intended locations, followed by counterfactual analysis to examine how alternative policy designs change the distribution of investment, emissions, and welfare gains across places.

Under the IRA, a renewable energy project is eligible for an additional 10 percent bonus on the Production Tax Credit and 10 percentage points on the Investment Tax Credits if it is located in an "energy community," defined as any location that satisfied at least one of the three criteria: (i) presence of a brownfield site; (ii) local tax revenue and employment from fossil fuel extraction combined with high local unemployment rate; or (iii) recent coal mine closures or coal-fired generator retirement.

1. Freedman and Neumark (2024) provide a review of federal and state-level place-based policies across sectors in the U.S. and Berkowitz, Storper, and Herbertson (2024) provide a review of such policies in the E.U. Research on these policies has found mixed evidence regarding their effectiveness, with outcomes often varying by program design and local context (Neumark and Young 2021).

We assemble novel data on the county-level eligibility for all three energy community criteria based on IRS guidelines (Internal Revenue Service 2024), and combine them with data on transmission interconnection requests from 2020 through 2023, from Lawrence Berkeley National Laboratory. With generator interconnection being one of the first stages in project development, changes in interconnection activity provide a forward-looking measure of developers' location choices.

Our empirical analysis proceeds in two steps. First, we use a synthetic difference-in-differences (SDID) design that exploits within-county variation in eligibility to estimate the causal effect of energy-community (EC) status on renewable interconnection requests. In aggregate, EC eligibility does not lead to a statistically significant increase in interconnection requests. However, this null effect masks substantial heterogeneity by eligibility types, levels of economic vulnerability, technology (solar/wind), and geographic regions.

We find that counties qualifying only under the fossil fuel employment and local unemployment criterion experience about 83 more project requests per year than comparable control counties, corresponding to roughly 30 percent increase relative to the pre-policy mean in eligible counties. In contrast, counties satisfying all three criteria- arguably the most economically distressed and fossil-fuel dependent locations see a 36 percent decline. These patterns are driven primarily by solar projects: increases in project requests in Southeast, Texas, and the Great Plains are offset by declines in the Northeast and Appalachia. Overall, these results suggest that while the current place-based design can stimulate investment in some eligible locations, it may crowd out investment from the most distressed communities and direct it toward less constrained, yet still bonus-eligible locations.

Next, we develop a structural model of renewable project location choice as a two-level nested decision. Renewable developers first consider which balancing authority (market) to locate in and then select a county within the chosen market.[2] County level profitability driven by expected revenue, capital installation costs, land values, transmission access aggregate into market level location choices, allowing the model to capture how location specific incentives reallocate investment both within and across electricity markets. We allow preferences over revenue and costs to vary across projects and estimate the choice

2. We use balancing authority and market interchangeably throughout the paper.

experiment using random-coefficients logit models separately for solar and wind, and bootstrap standard errors across the two stages to obtain consistent parameter estimates.

Model estimates show that developers value higher expected revenues and exhibit strong disutility from higher capital expenditures and greater distance to transmission infrastructure. We allow preferences to vary with project characteristics, including whether a project is paired with battery storage, though the implied heterogeneity is modest. Furthermore, within market profitability (due to county level returns) influence market selection along with other market level factors. We use these estimates to simulate counterfactual policy designs that vary targeting rules- which counties or markets qualify, and bonus rates- the generosity of the tax-credit. For each design, we compute changes in developer surplus and carbon damages from renewable capacity reallocation across locations.[3]

The counterfactual analysis quantifies trade-offs between private developer surplus, climate benefits, fiscal costs, and support for vulnerable locations. Eliminating the energy-community bonus entirely saves roughly $3 billion in federal budget but also reduces developer surplus by $2.5 billion per year largely in the solar industry, with only modest effects on avoided carbon damages. By contrast, providing greater support to more vulnerable fossil-fuel communities reallocates roughly 6 GW of additional renewable capacity toward these locations (i.e. total investment of 24 GW in targeted locations), with moderate increases in developer surplus offset by the cost of higher fiscal spending.

Policies that target the tax-credit toward high renewable energy potential counties or high emission markets (while holding bonus rates fixed) substantially increase avoided carbon damages by roughly $0.7-0.9 billion annually. However, these policies also reduce developer surplus as projects relocate to less profitable sites. Overall, these findings reveal fundamental policy trade-offs: place-based incentives can prioritize developer rents, emission reductions, or greater renewable energy investment in fossil-fuel reliant communities, but not all simultaneously. In other words, policymakers interested in emissions reductions may have to contend with lower private returns for developers, while policies that target vulnerable communities may not deliver the largest emissions gains.

3. All welfare changes are calculated with respect to the status quo policy design of IRA 2022. We do not endogenize entry of renewable projects in response to the counterfactuals. To the extent that these policies may induce new project entry, our welfare estimates reflect the lower bound of the overall effects.

Related Literature: This paper makes several contributions to the literature. First, we add to the extant literature on the impacts of place-based industrial policy. The empirical evidence on such policies is mixed and sensitive to program design and context (Kline and Moretti 2013; Freedman and Neumark 2024). [4] Within the energy sector, evidence on place-based industrial policy is particularly scarce, in part due to lack of large scale interventions. We contribute by providing, to our knowledge, the first causal evidence on the design and effectiveness of place-based industrial policy in the energy sector.

Second, we contribute to the literature on the economics of renewable energy transition, particularly on investment dynamics within electricity markets (Holland, Mansur, and Yates 2022; Gonzales, Ito, and Reguant 2023; Gowrisankaran, Langer, and Reguant 2024; Butters, Dorsey, and Gowrisankaran 2025) and literature examining challenges and barriers to the renewable energy transition (Joskow 2019), including issues due to intermittency (Gowrisankaran, Reynolds, and Samano 2016; Wolak 2020), inadequate transmission capacity and queue delays (Davis, Hausman, and Rose 2023; Johnston, Liu, and Yang 2024; Sun 2023; Doshi 2026). We add to this literature by studying how place-based policies affect the speed and spatial pattern of the energy transition. We include factors beyond transmission infrastructure- such as local prices, costs, and eligibility rules that influence investment decisions.

Methodologically, we develop a discrete choice model of renewable project location that incorporates both market-level and within-market drivers of siting decisions, and includes incentives due to place-based subsidies. A key contribution of this framework is its generality: it allows welfare and emissions accounting for a broad class of industrial policies regardless of whether the policy incidence is at the market or county level, and applies across a range of regulatory environments including regulated and wholesale electricity markets.

Finally, we add to the nascent literature evaluating the causal impact of the IRA's energy-community tax-credits on renewable investment. Existing studies have primarily evaluated the IRA using ex-ante modeling approaches (Bushnell and Smith 2024; Bistline et al. 2023; Bistline, Mehrotra, and Wolfram 2023) and reduced-form analyses of the

4. While Busso, Gregory, and Kline (2013) find positive effects from interventions like federal Empowerment Zones, the evidence on state Enterprise Zones remains largely inconclusive (Neumark and Kolko 2010; Neumark and Young 2021). More recent evaluations of the Opportunity Zone program show limited early effects on resident outcomes (Freedman, Khanna, and Neumark 2023).

energy-community bonus on emissions (Ashenfarb 2024). We contribute by providing a comprehensive ex-post evaluation of the IRA's energy community provision that combines a reduced-form design with a structural model of renewable investment.

The rest of this article is structured as follows. Section 2 provides the institutional details of the energy community tax credits and the transmission interconnection process. Section 3 describes the data and the descriptive patterns followed by a discussion of our reduced form analysis in Section 4. Section 5 describes and estimates our structural model of project location choice and the counterfactual analysis. Section 6 concludes.

2 Institutional Details

2.1 The Energy Community Tax Credits

The Inflation Reduction Act (IRA), announced in August 2022, provides a broad array of incentives to accelerate the clean energy transition in the United States (H.R.5376 2022). Among these, the energy community tax credit represents a novel place-based policy instrument designed to provide economic incentives for renewable projects located in regions most reliant on fossil fuel activities. These additional tax credits aim to facilitate the transition to cleaner energy while alleviating the burdens associated with this shift (Raimi and Pesek 2022). Specifically, the energy community provision adds a 10 percent bonus to the Production Tax Credit (PTC) and 10 percentage point bonus to the Investment Tax Credit (ITC) for renewable energy projects built in an eligible location.[5]

Under the IRA, locations that qualify as 'Energy Communities' if they satisfy at least one of three criteria:

EC1 A "brownfield site" (as defined by IRA).[6]

5. For example, the ITC increases from 30% to 40% of installation costs when a project is sited in an energy community, and the PTC increases from $28.5 to $31.35 per MWh of production. The bonus credits apply to projects that began construction on or after January 1, 2023. However, because project siting and interconnection decisions are made well before construction begins, we use the IRA's announcement in August 2022 as the treatment date in our empirical strategy, as this is when the policy's geographic incentive structure became known to developers.

6. There is no official list of IRA qualifying brownfield energy communities. Following IRS guidance, we use the U.S. Environmental Protection Agency's Brownfield Cleanup list to identify brownfield sites that satisfy the IRA definition and then classify counties as brownfield eligible based on those sites. IRS guid-

EC2 A "metropolitan statistical area" or "non-metropolitan statistical area" which

- has 0.17% or greater direct employment or $\geq$ 25% greater local tax revenue (at or after 2009) 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;

EC3 A "census tract" (or adjacent census tract) with a coal mine closure after 1999; or a coal-fired electric generating unit retirement after 2009.

While eligibility under the unemployment-threshold criterion can vary with recent labor-market conditions, the coal-closure criterion is effectively time-invariant, as it is based on recent mine closures (post-1999) and coal-fired power plant retirements (post-2009). The eligibility rules were specified in the IRA enacted in August 2022, and we define treatment using the Department of Energy(DOE)'s official list of energy communities in our main analyses.[7]

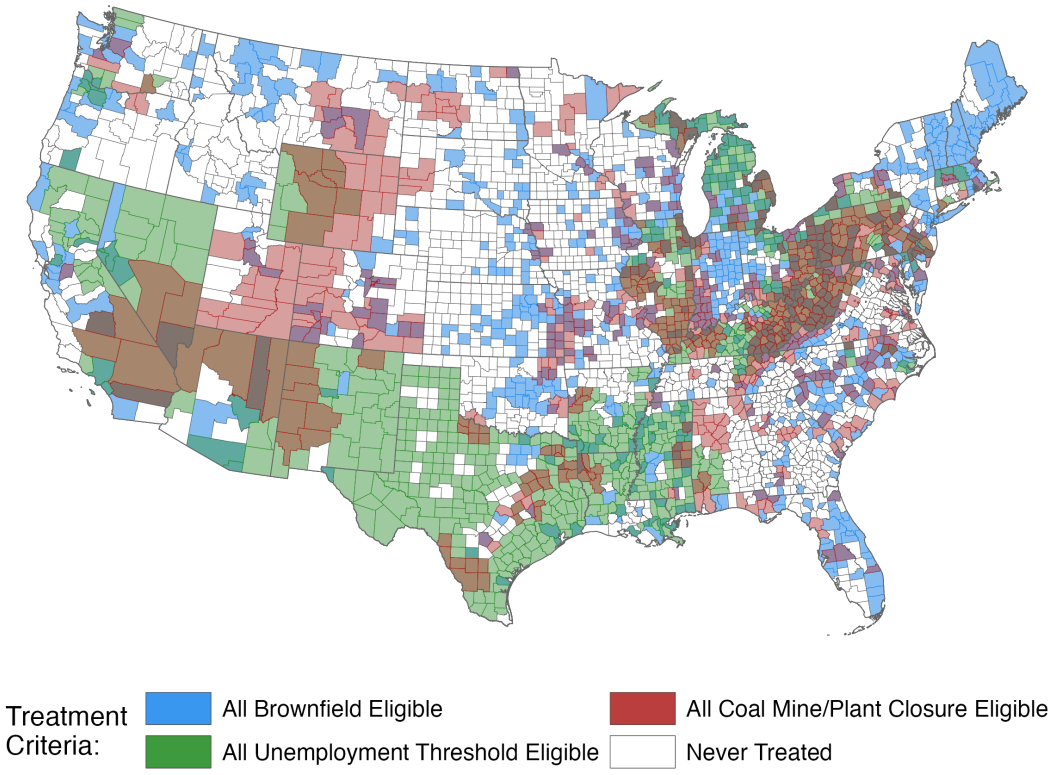
To make the comparison across the three eligibility criteria uniform, we use counties as our primary unit of analysis.[8] Figure 1 shows the spatial distribution of counties qualifying under the three energy community tax credit criteria. We observe that the energy

ance clarifies that the IRA qualifying brownfield sites are a subset of sites eligible for the EPA Brownfields Program (excluding certain statutory categories). See the EPA Brownfields site-eligibility documentation: https://www.epa.gov/sites/default/files/2018-10/documents/web-content-info-on-site-eligibility.pdf. Appendix B describes our selection and filtering procedure. Using this approach, we identify 35,102 qualifying sites and classify 1,034 counties as eligible under the brownfield criterion.

7. DOE published the official list of energy communities qualifying under the unemployment/revenue and coal-closure criteria in April 2023 via an online map and downloadable files: https://arcgis.netl.doe.gov/portal/apps/experiencebuilder/experience/?id=a2ce47d4721a477a8701bd0e08495e1d. Although released approximately three quarters after the IRA announcement, we assume that developers could anticipate eligible locations using publicly available data on fossil-fuel employment, tax revenues, recent unemployment rates, and recent coal mine closures and power plant retirements. Appendix Figure A 4 supports this assumption, showing a sharp increase in interconnection requests beginning in 2022Q3, consistent with rapid developer response following the IRA announcement. Eligibility under the unemployment threshold criterion changes slightly for a small set of counties between 2023 and 2024. To avoid discrepancies arising from time-varying unemployment thresholds, we limit our sample to 2023. We discuss the uncertainty associated with the eligibility dynamics in Section 4.4 and examine the alternative classification proposed by Raimi and Pesek (2022) in Section 4.3.

8. While the coal mine/plant closure criterion is defined at the census tract level, we aggregate to counties to align with the unemployment threshold criterion (defined at the MSA/non-MSA level) and our interconnection queue data. A county qualifies under the coal mine/plant closure if any census tract within it contains or adjoins a qualifying coal closure site.

Figure 1: Counties Eligible Under the Energy Community Tax Credits in 2023



Notes: This figure shows counties eligible under different the place-based energy-community tax credits in 2023. Never-Treated counties are not eligible under any criteria and are shown in white shade. Overlapping colors blend where counties satisfy multiple criteria. In total, 1,034 counties are eligible under the brownfield criterion (blue), 933 counties qualify under the fossil fuel employment + local unemployment threshold (green), and 798 counties qualify under the coal mine or coal-fired power plant closure criterion (red). Across all criteria, 1,914 unique counties qualify as energy communities.

community coverage is extensive and geographically heterogeneous, with each criterion concentrating eligibility in distinct regions that reflect the spatial distribution of fossil fuel economic dependence. Counties qualifying under the unemployment and fossil fuel revenue thresholds cluster in Southwest Texas and parts of the Rust Belt, including Kentucky, Illinois, West Virginia, Ohio, and Pennsylvania – regions with historical dependence on fossil fuel extraction, as well as in parts of New Mexico, Arkansas, and Louisiana, where counties exhibit relatively high unemployment rates. In contrast, coun-

ties qualifying under coal mine/plant closures concentrate in Appalachia and western coal-producing areas, particularly Utah and Wyoming (Appendix Figure A 1).

Appendix Table A1 presents baseline characteristics of counties eligible under each qualifying criterion relative to non-eligible counties. Counties qualifying under the presence of brownfields are larger, more urban, and better connected to the grid, but are otherwise economically comparable to non-eligible counties. Counties qualifying under coal mine or plant closures are more disadvantaged with slightly lower household incomes and higher poverty rates. Demographically, they are predominantly white and rural — consistent with coal-mining communities in Appalachia. On the other hand, unemployment threshold counties are the most economically distressed, with lower median household income and higher poverty and unemployment rates, consistent with oil- and gas-dependent regions, particularly in Texas. Across all three criteria, energy community counties have slightly lower renewable potential, particularly for wind, and face higher levelized costs for wind and solar generation and levelized cost of transmission relative to non-eligible counties.

As expected, substantial overlap exists between certain criteria: counties with recent coal mine closures or coal plant retirements often also meet the fossil fuel revenue threshold. Counties qualifying due to presence of brownfield sites exhibit a more dispersed pattern, reflecting the broader geographic distribution of contaminated sites eligible for EPA cleanup programs. Appendix Figure A 2 and Figure A 3 show the distribution of counties qualifying under a single criterion and under combinations of two criteria, respectively. Among the 3,111 counties in our sample, 1,914 (62 percent) qualify as energy communities under at least one criterion, with 39 percent qualifying under only one criterion, 18 percent under two criteria, and 4.6 percent under all three.

2.2 Transmission Interconnection Process

All electricity generation projects must go through the transmission interconnection process before connecting to the electricity grid. This process is administered by the balancing authorities, typically the Independent System Operators (ISOs) or Regional Transmission Organizations (RTOs) in wholesale electricity markets or vertically integrated utilities in regulated markets, to assess the impact of new capacity additions on the

transmission system. This process also helps grid operators identify necessary upgrades and system changes required to accommodate the project while maintaining grid reliability and resilience.

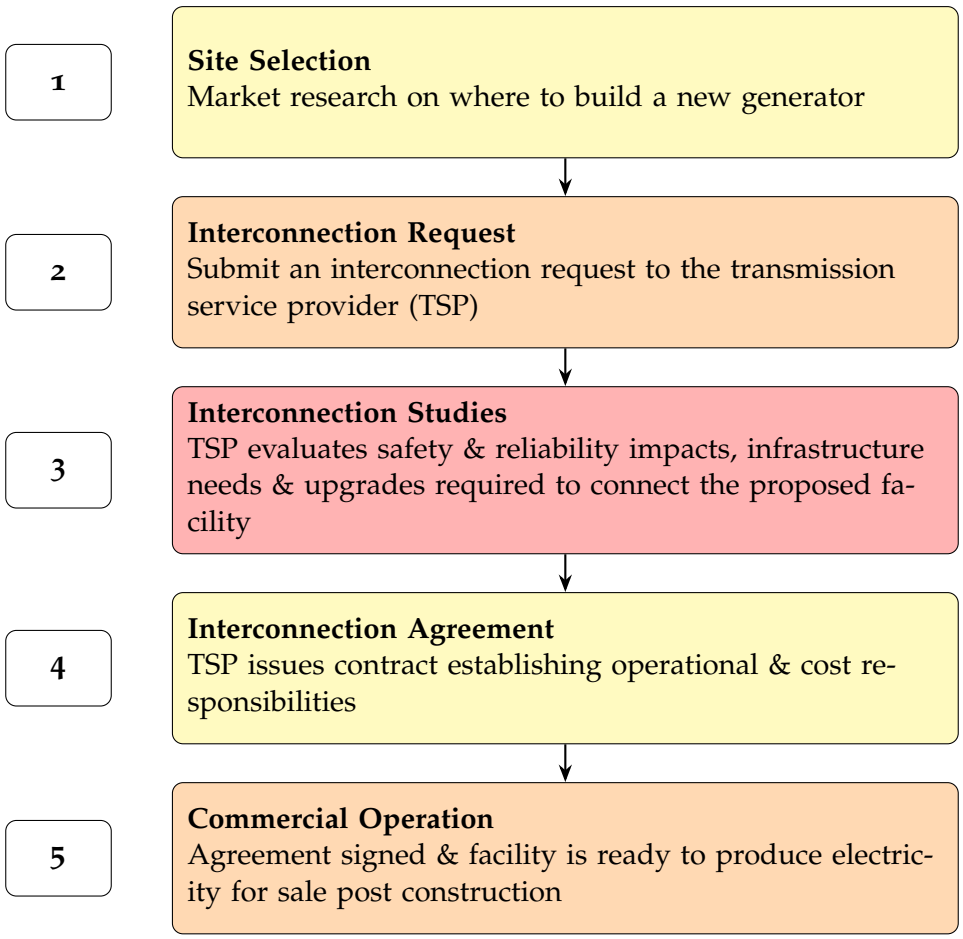
Figure 2 presents a flowchart outlining the key steps in the interconnection process. Our main outcome of interest- transmission interconnection requests-corresponds to Step 2 in the chart. At this stage, developers have already identified a preferred project site, secured necessary land permits, committed resources to preliminary development (step 1). The submission of a transmission interconnection request in Step 2 therefore reveals developers' siting preferences and represents a meaningful investment decision, making it the core focus of our analysis.

After submitting the interconnection request (Step 2), each project undergoes a series of interconnection studies (Step 3). These typically consist of three engineering studies that assess the feasibility, system impacts, and facility requirements of the proposed generation unit, and determine the local grid upgrades and other changes required for the project to be connected to the grid. Upon successful completion of these studies, developers sign an interconnection agreement with the transmission service provider (Step 4), which specifies the technical and financial terms of grid connection. Finally, once construction is complete and the interconnection agreement requirements are met, the project enters commercial operation and can deliver power to the grid (Step 5).

Entering the queue does not guarantee project completion, and completion rates vary widely across markets and technologies. Among projects requesting interconnection from 2000 and 2019, only 20% had reached commercial operation as of 2024, ranging from 8% in NYISO to 22% in ERCOT (Rand et al. 2025). Note that our analysis focuses mainly on queue entry, and not on eventual completion, though some factors driving market selection may also be correlated with project completion.

Because the entire process typically takes several years (Johnston, Liu, and Yang 2024), and projects receive the Production Tax Credit or Investment Tax Credit only after construction is complete, it is reasonable to view interconnection request submissions as reflecting developers' siting preferences in response to policy implementation. More precisely, these submissions capture an upper bound on the policy's effect on project siting decisions.

Figure 2: Flowchart of the Transmission Interconnection Study Process

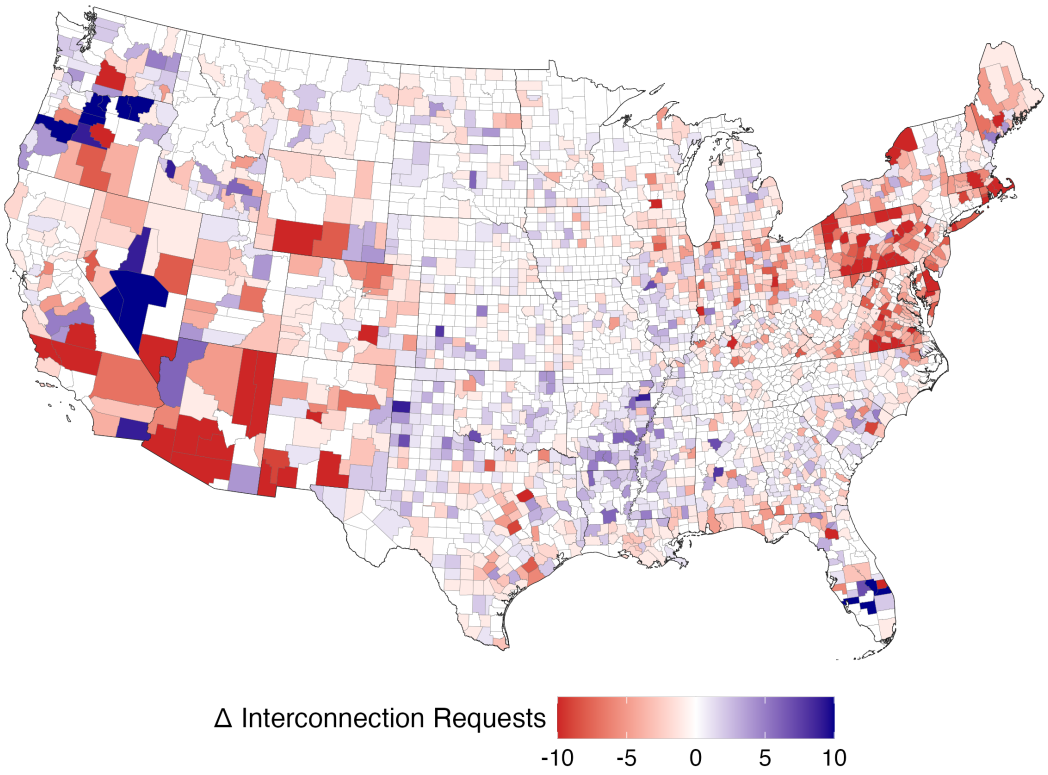


Notes: This figure illustrates the steps a project developer must complete in the interconnection process. While individual markets may differ in specific policies, the high-level process is uniform across regions. Source: FERC (2024)

3 Data and Descriptive Statistics

We obtain transmission interconnection requests submitted between 2020 and 2023 from a publicly available dataset provided by Lawrence Berkeley National Laboratory (LBNL). This dataset aggregates information from interconnection queues across all U.S. balancing authorities, documenting project-level characteristics, including fuel type, capacity, county location, transmission owner territory, requested interconnection date, and project status. We aggregate these project-level observations to the county-quarter level,

Figure 3: Change in Total Renewable Interconnection Requests Post-IRA Announcement



Notes: This figure maps the county level change in total renewable interconnection requests following the August 2022 announcement of the energy community tax credits. Changes in requests are winsorized at 10 and 10, corresponding approximately to the 1st and 99th percentiles of the distribution.

creating a panel dataset of interconnection request counts and total requested capacity by county and time period.[9]

Figure 3 shows the change in total renewable interconnection requests in each county following the August 2022 announcement of the energy community tax credits. Two main patterns emerge. First, interconnection requests decline sharply in much of the

9. Appendix Figure A 4 shows the average interconnection requests over time for counties qualifying under different energy community criteria. Requests display strong seasonality in the pre-IRA period, with higher activity in the first three quarters and a sharp decline in the fourth quarter, consistent with systematic within-year variation in development and filing behavior. We therefore seasonally adjust the outcome variable used in our reduced-form analysis. For each county, we regress total interconnection requests on quarter indicators and a linear time trend using only pre-IRA data, and use the fitted quarter effects to remove seasonal variation from both pre- and post-treatment observations.

Northeast, particularly in Pennsylvania, Virginia, and several parts of the Midwest. Several counties inthe West also experience reductions in the number of requests. Increases in projects are mainly concentrated in Texas and counties in the central U.S., as well as in some counties along the West Coast. Appendix Figure A 5 shows that change in renewable interconnection capacity follows a very similar pattern as change in requests in Figure 3.[10]

Table 1 presents summary statistics for interconnection requests, comparing energy community counties versus never-treated counties. The table is organized into three panels: Panel A covers counties qualifying under exactly one criterion, Panel B covers counties qualifying under exactly two criteria; and Panel C covers counties qualifying under all three criteria and counties qualifying under any criterion. Treatment timing is the third quarter of 2022 (the IRA announcement). Column (2) reports pre-treatment means (2020Q1 – 2022Q2) with standard deviations in parentheses, Column (3) reports post-treatment means (2022Q3 – 2023Q4), and Column (4) reports the difference in means.

Two patterns emerge from Table 1. First, interconnection requests increase by 116 percent and 80 percent, on average, in counties qualifying under one and two criteria, respectively, and these increases are statistically significant. In contrast, counties qualifying under all three criteria exhibit a modest and statistically insignificant change. Second, interconnection requests in never-treated counties also increase significantly, by approximately 75 percent over the same period.

These descriptive patterns, along with the spatial distribution of treated counties under different eligibility rules, motivate an empirical strategy that relies on comparing different eligibility criteria with a valid control group, before and after IRA announcement. This approach allows us to causally identify changes in interconnection requests attributable to energy community eligibility. To that end, we use a synthetic difference-in-differences approach, which we describe in greater detail in the next section.

10. Disaggregating the change in requests by technology in Appendix Figure A 6 shows that the geographic pattern in Figure 3 is driven primarily by solar projects, with comparatively smaller and less systematic changes for wind. The most pronounced changes in wind interconnection requests are concentrated in the Western U.S. and Texas.

Table 1: Descriptive Statistics of Renewable Interconnection Requests in IRA Qualified Counties

Treatment Criteria	# Counties	Pre-Treatment	Post-Treatment	Difference
		Mean (SD)	Mean (SD)	(3) - (2)
	(1)	(2)	(3)	(4)
Panel A: Single Criterion				
Brownfield	526	0.11 (0.65)	0.19 (0.80)	0.08***
Unemployment Thresholds	442	0.08 (0.42)	0.22 (0.79)	0.14***
Coal Mine/Plant Closure	239	0.10 (0.54)	0.20 (0.79)	0.10***
Panel B: Two Criteria				
Brownfield + Unemployment	148	0.10 (0.56)	0.20 (0.81)	0.10***
Brownfield + Coal Closure	216	0.09 (0.51)	0.17 (0.73)	0.05***
Unemployment + Coal Closure	199	0.13 (0.91)	0.24 (0.94)	0.11***
Panel C: Three Criteria and Overall				
All Three Criteria	144	0.15 (0.74)	0.16 (0.61)	0.01
Any Criteria	1,914	0.11 (0.61)	0.20 (0.79)	0.09***
Never-Treated Counties	1,197	0.08 (0.48)	0.14 (0.77)	0.06***

Notes: This table provides average and standard deviation of the number of generator interconnection requests in counties that are qualified for energy community (EC) tax credits and counties that do not qualify under any EC tax credits (never-treated counties). We include all interconnection requests submitted during our sample period between 2020 and 2023. The treatment timing is the third quarter of 2022 when the IRA was announced. 'Any Criteria' includes counties that qualify for the energy community tax-credits under any (one or more) of the three criteria- brownfield, unemployment thresholds, and coal mine and plant closures. The category, 'All Three Criteria' restricts to counties that are qualified under all of the three criteria. Significance: *** p<0.01, ** p<0.05, * p<0.1.

4 Reduced Form Analysis: Analyzing the effectiveness of place-based policies

4.1 Empirical Strategy

We employ a synthetic difference-in-differences (SDID) framework that compares changes in renewable interconnection requests between treated counties and never-treated coun-

ties. We define treated counties based on predetermined criteria from the IRA: locations of brownfield sites, coal mines or coal plant retirements, and counties meeting specific unemployment thresholds. We consider all eligible counties starting the third quarter of 2022, when the IRA announced the energy communities tax credits, as treated. Never-treated counties are those that do not meet any of these energy community qualification criteria.

Synthetic DID combines features of Synthetic Control methods (SC) and Difference-in-Differences (DID), accounting for pre-treatment outcome differences between treated energy communities counties and control non-qualifying counties. Similar to SC, SDID re-weights and matches on pre-treatment trends in the outcome to enhance the plausibility of parallel trends assumptions while maintaining invariance to additive unit-level heterogeneity and enabling valid inference like in DID (Arkhangelsky et al. 2021).[11]

Synthetic DID proceeds by solving the following optimization algorithm to recover the treatment effect of interest:

$$\left(\hat{\tau}, \hat{\mu}, \hat{\alpha}, \hat{\beta}\right) = \underset{\tau,\mu,\alpha,\beta}{\arg\min} \left\{ \sum_{i=1}^{N} \sum_{t=1}^{T} \left(Y_{it} - \mu - \alpha_i - \beta_t - W_{it}\tau\right)^2 \hat{\omega}_i^{sdid} \hat{\lambda}_t^{sdid} \right\} \tag{1}$$

where Y_{it} is the outcome variable- number of interconnection requests in county i and quarter t. W_{it} is the treatment indicator, and α_i and β_t are county and quarter-year fixed effects respectively. The coefficient of interest, $\hat{\tau}$ is the estimated treatment effect of energy communities tax credits on renewable interconnection requests.

As with the synthetic control method,unit-specific weights (ω_i^{sdid}) are chosen to minimize the mean squared difference in pre-treatment trends between the treated units (qualifying counties) and the control units. [12] Time weights (λ_t^{sdid}) are chosen such that the weighted average of pre-period outcomes in the control group mimic its average post-period outcome (up to regularization). Thus, periods with atypical (transitory) shocks

11. This approach also addresses concerns regarding potential bias in SC when pre-treatment fit is imperfect and treatment is correlated with unobserved confounders (Ferman and Pinto 2021).

12. The minimization problem in Equation 1 is subject to a regularization constraint that ensures convex weights and prevents overfitting by reducing estimator variance while balancing the bias. Mathematically, this constraint is: $\omega_i \geq 0$ and $\sum_{i=1}^{N-1} w_i = 1$ where i indexes the control units running from $i = 1$ to $N - 1$. This regularization ensures convex weights and prevents overfitting by reducing estimator variance while balancing the bias.

are down-weighted, improving comparability between pre- and post-periods when constructing the difference-in-differences comparison.[13]

The Synthetic DID specification in Equation 1 allows us to consistently estimate the causal effect $\hat{\tau}$ of the treatment W_{it} (energy community tax credits in our context), even if the parallel trends assumptions may not be plausible between all the treated and control units on average (Arkhangelsky et al. 2021; Clarke et al. 2024). The vector of non-negative unit-specific weights ω_i obtained from Equation 1 imply that the units will follow parallel pre-trends, though provided $\mu \neq 0$, not identical pre-trends.

To estimate an event-study, we follow Clarke et al. (2024) and Dench, Pineda-Torres, and Myers (2024), by calculating the difference between treated energy communities counties and control non-qualifying counties in each period relative to the difference observed in the time-weighted pre-period, and use block-bootstrap technique to construct the 95 percent confidence intervals.

4.2 Results

Table 2 shows treatment effects estimates of energy communities eligibility on renewable interconnection requests using the synthetic difference-in-differences specification in Equation 1. The treatment indicator (Energy Community Eligible) equals one for counties that qualify for the energy community tax credits in the periods following the IRA announcement. Column (1) reports estimates pooling all counties that qualify under at least one of the criterion. We also disaggregate the analysis by the specific eligibility channel, restricting the treated group to counties that qualify exclusively through the presence of a brownfield site (Column 2); fossil fuel employment and local unemploy-

13. Time weights minimize the sum of squared differences between time-weighted pre-period outcomes and the average post-period outcomes of the control units. Mathematically, $\hat{\lambda}$ are a result of the following optimization problem:

$$\hat{\lambda} = \arg\min_{\lambda} \sum_{i=1}^{N-1} \left(Y_{iT} - \sum_{t=1}^{T-1} \lambda_t Y_{it} \right)^2 + \text{regularization term} \tag{2}$$

where, i indexes the control units, from $i = 1$ to $N - 1$; t indexes the pre-treatment periods, from $t = 1$ to $T - 1$, and Y_{iT} denotes the outcomes of the control units in the post-period T. To ensure convex weights that are unique, Equation 2 is solved subject to the constraints $\lambda_t \geq 0$ and $\sum_{t=1}^{T-1} \lambda_t = 1$.

Table 2: Impact of the Energy Communities Tax Credits on Renewable Interconnection Requests

	Any Energy Comm.	Brownfield Only	Unemp. Only	Coal Closure Only
	(1)	(2)	(3)	(4)
Energy Community Eligible	-0.007	-0.007	0.047*	0.016
	(0.014)	(0.023)	(0.026)	(0.025)
County FE	✓	✓	✓	✓
Quarter-by-Year FE	✓	✓	✓	✓
Pre-treatment Mean	0.211	0.191	0.159	0.166
# Treated Counties	1,914	526	442	239
# Control Counties	1,197	1,197	1,197	1,197
Observations	49,776	27,568	26,224	22,976

Notes: This table reports the effect of eligibility under the energy community tax-credits on interconnection requests, estimated using the synthetic difference-in-differences specification in Equation 1. Dependent variable is the seasonality-adjusted number of renewable interconnection requests. Sample is county-level quarterly data from 2020 to 2023. Column (1) shows the treatment effect for counties that are eligible under any combination of the three criteria. Columns (2) - (4) show treatment effect estimates for the counties that eligible for energy community tax-credits only through one of the three criteria: presence of a brownfield site (Column 2), local unemployment and fossil fuel tax revenue thresholds (Column 3), and coal mine closure or coal plant retirements (Column 4). Pre-treatment mean is the average number of interconnection requests submitted before the IRA announcement. Control counties are counties that do not qualify for any place-based tax-credit (i.e. never-treated). Bootstrap standard errors (with 1000 replications) clustered at the county level reported in parentheses. Significance: *** p<0.01, ** p<0.05, * p<0.1.

ment threshold (Column 3); or coal mine closures or coal-fired power plant retirements (Column 4).[14]

Column (1) shows that, on average, counties eligible under any criteria do not experience a statistically significant change in interconnection requests relate to never-treated counties. However, this pooled estimate masks substantial spillovers across eligibility channels, as particular locations become relatively more or less attractive due to the bonus.

14. Appendix Figure C 10 shows the event-study estimates for Column (1), where treatment counties and their synthetic control units exhibit parallel trend prior to the IRA announcement.

Table 2 Columns (2) to (4) show important heterogeneity in treatment effects across the three eligibility criteria. We find that counties qualifying exclusively through unemployment and fossil fuel revenues thresholds (Column 3) experience a statistically significant increase in interconnection requests at the 10% critical level, corresponding to roughly a 30 percent increase relative to the pre-treatment mean. In contrast, counties qualifying only through the presence of brownfield sites or through coal closures do not show any change in interconnection requests, suggesting that these criteria alone do not drive renewable project development in those locations.

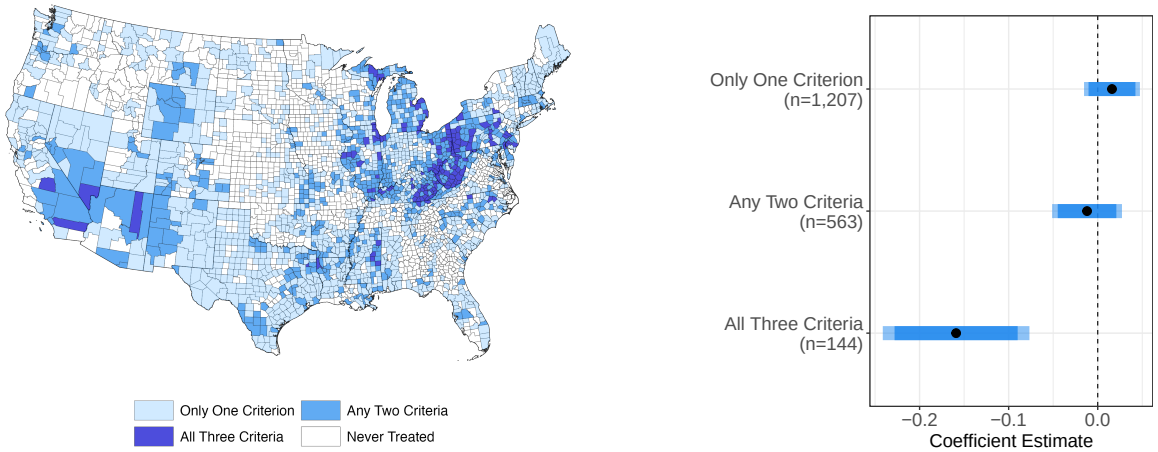
4.2.1 Do Energy Community Credits Benefit the Most Vulnerable Counties?

We next examine whether counties qualifying under multiple energy community criteria see greater levels of investments in renewable energy. Even though the tax bonus a project will receive does not depend on the number of criteria the location qualifies for, this analysis is a useful test for whether this policy induces investment in the most economically vulnerable and fossil fuel resource dominated regions.

Figure 4a shows the spatial distribution of counties that satisfy different numbers of energy-community criteria. Broad swaths of regions that meet only one criterion are mostly explained by the presence of brownfield sites or by the unemployment rate threshold criteria (e.g. counties in West Texas as shown in Appendix Figure A 2). The densest cluster of counties meeting all three criteria is in the Appalachia- often called the "coal country," due to its long legacy of coal mining which also coincides with recent coal-plant retirements (Berry 2019). Another region with a history of coal mining in the U.S. spans West- from Powder River and Wind River Region to South-Western Utah (see Appendix Figure A 1). In this Western belt, counties qualifying under two criteria most commonly qualify through the unemployment threshold or the coal mine or coal plant closure criterion (Appendix Figure A 3).

Figure 4b presents the treatment effect estimates by the number of energy community eligibility criteria a county satisfies, which we use as a proxy for local vulnerability and fossil fuel reliance. For counties that qualify under exactly one or under any two of the criteria exhibit no significant change in interconnection requests following the bonus announcement. In contrast, counties that qualify under all three criteria, arguably

Figure 4: Energy Community Eligibility and Heterogeneity by Number of Criteria



(a) Energy Community Eligibility Map (2023)

(b) Estimated Effects by # Criteria

Notes: Figure 4a shows counties eligible under different combinations of energy community tax-credit criteria. Counties qualifying under a single criterion (Only One Criterion, n=1,207) are shown in light blue. Counties qualifying under two criteria (Any Two Criteria, n=563) are shown in blue, and counties qualifying under all three criteria (All Three Criteria, n=144) are shown in dark blue. Never-treated counties (n=1,197) are not eligible under any criterion and are shown in white. Figure 4b shows the corresponding estimated effects by number of eligibility criteria. Points show coefficient estimates; shaded bands denote 95% (darker) and 90% (lighter) confidence intervals constructed from clustered bootstrap standard errors (1,000 replications) at the county level.

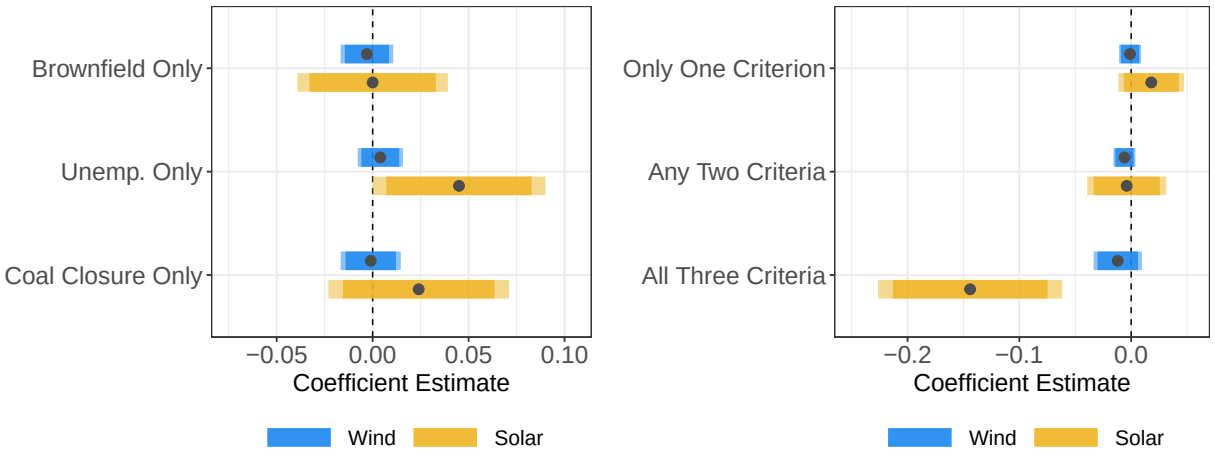
the most fossil fuel dependent and economically vulnerable regions, experience a large and statistically significant decline in interconnection requests- roughly a 36 percent reduction relative to the pre-treatment mean. This pattern suggests potential shift in developer activity away from counties meeting all three criteria to counties satisfying one or two criteria.

4.2.2 Do Energy Community Credits Affect Wind and Solar Differently?

To recap, the estimates point to substantial heterogeneity across eligibility definitions: counties qualifying solely through the unemployment and fossil fuel tax-revenue thresholds exhibit an increase in interconnection requests, whereas counties qualifying under all three criteria experience a marked decline. To assess whether these patterns are driven by projects of particular technologies, we re-estimate the synthetic difference-in-

differences separately for solar and wind interconnection requests by energy community type and number of criteria satisfied. Figure 5 summarizes the results.

Figure 5: Heterogeneity in Energy Community Effects on Interconnection Requests: Wind vs. Solar.



(a) By Type of Qualifying Criterion (b) By Number of Qualifying Criteria

Notes: Figure 5a reports estimated effects of energy community eligibility when counties qualify under exactly one criterion: Brownfield only, unemployment thresholds and fossil-fuel revenue only, or coal mine/plant closure only. Figure 5b reports estimated effects by the number of criteria a county satisfies: exactly one, any two, or all three. Points show coefficient estimates; shaded bands denote 95% (darker) and 90% (lighter) confidence intervals constructed from clustered bootstrap standard errors (1,000 replications) at the county level. Yellow corresponds to solar interconnection requests and blue corresponds to wind interconnection requests.

Figure 5 shows that the sector-specific heterogeneity is largely driven by solar rather than wind projects. Across both panels, the wind estimates are tightly centered around zero indicating no detectable change in interconnection requests across eligibility types or by the number of criteria satisfied. In contrast, the solar estimates vary across across eligibility definitions. Solar interconnection requests increase in counties qualifying only through the unemployment and fossil-fuel revenue thresholds, while declining substantially in counties qualifying under all three criteria. These results suggest that the average effects reported in Table 2 and Figure 4b primarily reflect changes in solar developer activity, with little response in the wind sector.

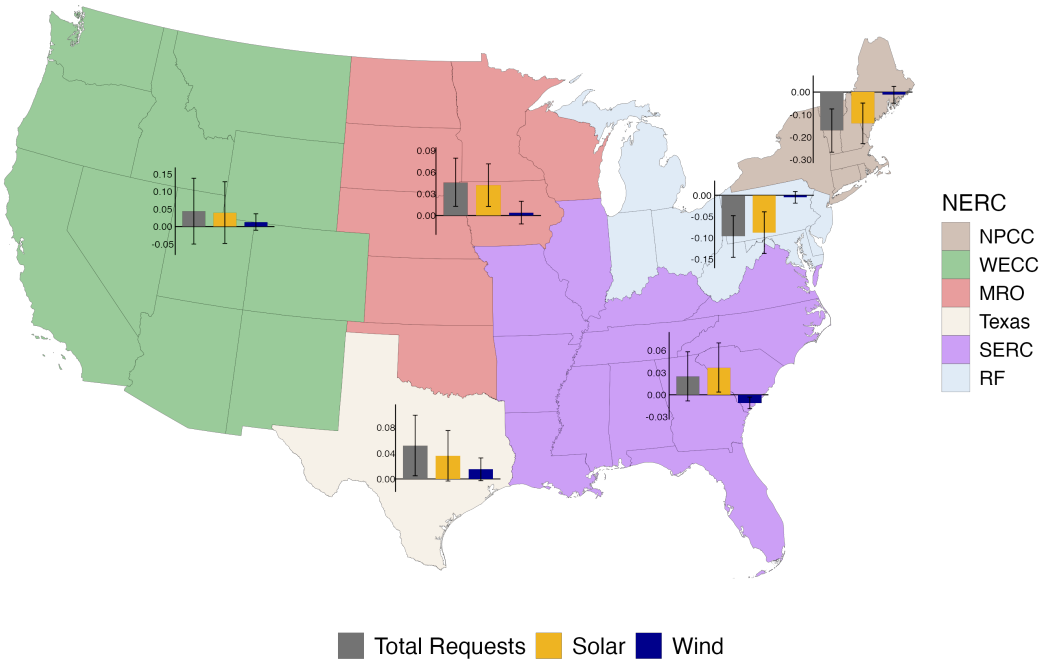
4.2.3 Do Energy Community Effects Differ Across NERC Regions?

We next examine whether the effects of the Energy Community tax credits vary across regions with different grid characteristics and renewable resource endowments. Figure 6 reports estimates by North American Electric Reliability Corporation (NERC) region, separately for total renewable interconnection requests (grey bars), solar (yellow bars), and wind (blue bars).[15] For total requests, energy communities in the Midcontinent Reliability Organization (MRO) and Texas show significant increases of 41 and 45 additional requests per year, respectively. By contrast, ReliabilityFirst (RF), which largely overlaps with PJM, and the Northeast Power Coordinating Council (NPCC) exhibit significant declines of 153 and 69 project requests per year, respectively, while the Western Electricity Coordinating Council (WECC) and Southeast Reliability Corporation (SERC) shows no detectable effects. These regional gains and losses largely offset one another, helping to explain the aggregate null effect reported in Column (1) of Table 2.

The sector-specific breakdown suggests that regional variation is primarily driven by solar. Although the total effect in SERC is not statistically significant, solar requests increase by 108 projects per year (significant at the 5% level), offset by a decline in wind projects of 32 per year (significant at the 1% level). In MRO and Texas, solar accounts for most of the total effect, an increase by 37 and 31 projects per year (significant at 1% and 10% levels respectively). By contrast, solar requests fall in the Northeast (56 fewer projects per year) and Reliability First (139 fewer projects per year). Wind responses are smaller and generally imprecise. While Texas shows a modest positive increase (13 projects per year), Southeast Reliability Corp. shows a decline (about 32 projects per year). These patterns likely reflect region-specific differences in resource quality – such as stronger solar potential in the South and Midwest than in the Northeast, as well as siting constraints and institutional factors that differentially affect solar and wind development across regions.

15. Appendix Table A3 reports the coefficient estimates from the 18 regressions. The back-of-the-envelope calculation in this paragraph is based on the numbers reported in this table.

Figure 6: Heterogeneity in Energy Community Effects by NERC Regions



Notes: This figure reports estimated effects of energy community tax credit eligibility on interconnection requests, estimated separately by NERC region and technology (i.e. 18 separate regressions). Bars show point estimates and black whiskers indicate 95% confidence intervals constructed from county-clustered bootstrap standard errors (1,000 replications). Grey bars correspond to total requests, yellow bars to solar requests, and blue bars to wind requests. NERC regions are: WECC (Western Electricity Coordinating Council), MRO (Midcontinent Reliability Organization), Texas RE (Texas Reliability Entity, corresponding to ERCOT), SERC (Southeast Reliability Corporation), RF (ReliabilityFirst), and NPCC (Northeast Power Coordinating Council).

4.3 Robustness Checks

We conduct a wide array of robustness checks to assess the sensitivity of our main results to alternative treatment timing and eligibility definitions. Appendix Table A2 reports the full set of estimates. Panel A uses outcome variables without seasonal adjustment. Panel B reclassifies brownfield eligible counties as controls, alongside never-treated counties, since site-specific brownfield eligibility may have been ambiguous for developers to identify. Panel C shifts the treatment date to April 2023, when DOE published the official

Energy Community list.[16] Panel D uses alternative unemployment threshold and coal mine/plant closure definitions from Raimi and Pesek (2022), released shortly after the IRA's announcement.[17]

Robustness results are broadly consistent with our baseline findings. In Appendix Table A2 Panels A and B, unemployment threshold eligible counties continue to show significant positive effects, while triple-qualified counties show significant negative effects. Panel D yields a similar pattern, however, single-criterion effects are less precisely estimated. By contrast, Panel C shows smaller and statistically insignificant coefficients when the treatment date is shifted to April 2023. This pattern supports using the IRA announcement date as the treatment timing indicating that developers responded quickly to the legislation rather than waiting for DOE's official guidance.

4.4 Quantifying Policy Uncertainty: Do Investment Effects Differ Near Eligibility Thresholds?

Recall that the eligibility under the fossil fuel employment and local unemployment rate criterion changes annually. To qualify, a county's unemployment rate must exceed the national average in the relevant year. Because the national unemployment benchmark is finalized only after annual statistics are released, counties with local unemployment rates close to the national average ex-ante may face uncertainty regarding their treatment eligibility status. A natural implication of this uncertainty is whether it deters developers from investment in those locations?[18]

In this section, we provide descriptive evidence on whether this policy uncertainty is associated with lower renewable investment in counties near the eligibility threshold. Table 3 presents results that compares renewable interconnection requests in counties

16. As an April 2023 treatment date leaves only three post-treatment quarters in our main sample ending in 2023Q4, we extend the data through 2024Q4 for this specification. Appendix Table A4 shows that our main results are qualitatively similar when extending the data through 2024Q4.

17. As Raimi and Pesek (2022) do not provide a clear brownfield list, we retain our brownfield eligible definition.

18. Alternatively, previously eligible counties may become ineligible in subsequent years if their local unemployment rate falls below the national average. For instance, Appendix Figure A 7 compares the distribution of counties eligible in 2023 and 2024. While the eligibility is largely similar across both years, some previously eligible counties in West Texas 2023 are no longer eligible in 2024.

Table 3: Impact of the Energy Communities Eligibility Thresholds on Renewable Interconnection Requests

	(1)	(2)	(3)
𝟙(Near Unemp. Rate Cutoff)	-0.077*	0.007	-0.009
	(0.042)	(0.032)	(0.033)
County FE	✓	✓	✓
Quarter-by-Year FE	✓	✓	✓
Far-from-cutoff counties included	✓		✓
Never treated counties included		✓	✓
Pre-treatment Mean	0.069	0.069	0.069
Observations	7,072	20,144	26,224

Notes: This table reports synthetic difference-in-differences estimates of the effect of being near the unemployment eligibility cutoff for Energy Community tax credits on renewable interconnection requests. Dependent variable is the seasonality-adjusted number of renewable interconnection requests. Near Cutoff counties are unemployment threshold eligible counties with 2022 unemployment rates within 0.1 standard deviations of the national unemployment rate; far-from-cutoff counties are the remaining unemp. threshold eligible counties. Never treated counties are ineligible for energy community tax credits. Of the 442 unemp. threshold eligible counties, 62 are near the cutoff and 380 are far-from-cutoff; 1,197 counties are never treated. Bootstrap standard errors (with 1,000 replications) clustered at the county level are reported in parentheses. Significance: *** p<0.01, ** p<0.05, * p<0.1.

near the eligibility cutoff in both the never-treated counties and those that qualify under the unemployment threshold criteria.

We first compare counties near the unemployment eligibility cutoff to counties farther from the cutoff as the control. Column (1) shows that near-cutoff counties receive about 0.077 fewer project requests per quarter than far-from-cutoff (and unemployment threshold eligible) counties. Column (2) instead uses never-treated counties as the control group. The coefficient estimate is economically small and statistically insignificant, suggesting no meaningful evidence of spillover from ex-ante near-cutoff counties to never-treated locations. Column (3) expands the control group to include far-from-cutoff counties. As in Column (2), coefficient estimate is small and statistically insignificant, with a sign consistent with Column (1).

Taken together, these results suggest that uncertainty around the eligibility in unemployment threshold criterion does not induce greater investment toward counties ineligible for any place-based tax credits. However, as Column (1) shows, developers do prefer locations with a greater degree certainty of qualifying for the tax credits. These patterns suggest that the bonus tax incentive itself is the primary driver of investment, while within eligible locations developers prefer counties with less uncertainty.[19]

Overall, our reduced-form analysis shows that the effectiveness of the place-based tax credits varies markedly across eligibility types, technologies, and regions. The incentives are most effective in counties qualifying under the fossil fuel employment and local unemployment thresholds. Strikingly, counties satisfying all three eligibility criteria- the most economically distressed and fossil fuel-dependent regions- experience a statistically significant decline in interconnection requests. Taken together, these spillovers help explain the overall null effect observed when aggregating across all energy community eligibility types.

5 A Model of Project Location Choice

We develop a structural model of project location choice as a two-level nested decision. Renewable developers first consider which balancing authority (market) and then select a county within the chosen market, conditional on expected revenues and costs. County-level profitability, together with market attributes informs the market-level location choice. This structure allows us to quantify total welfare effects and isolate the within-market effects arising from the reallocation of projects across counties within a market.

19. Our main results define counties that are near the eligibility cutoff using the 2022 unemployment rate. Appendix Table A5 reports additional results that define near cutoff counties for the 2023 unemployment rate. The results are qualitatively similar to Table 3. Note that our baseline specification uses 2020-2023 to avoid potential noise from the revised unemployment benchmark in the 2024 designation. As a robustness check, we extend the outcome window through 2024 while holding eligibility fixed at its 2023 designation. Appendix Table A4 shows results are similar to those in Table 2, which is unsurprising given that near eligibility cutoff counties make up a small share of all eligible counties (380 of 1,914).

5.1 County Choice Model

Project i chooses county j within a market m to maximize the net-present value of annual profits from its project. The static profits for a period t can be written as:

$$\pi_{ijt|m} = p_{ijt} Q_{ijt} - OM_{ijt} \tag{3}$$

where, p_{ijt} is the price per MWh of electricity received by the project i at location j in period t. The annual energy production from location j in period t is Q_{ijt} and OM_{ijt} is the technology specific (wind or solar) operations and maintenance costs incurred by the project in period t. Assuming a constant discount rate of r, the net-present value of expected profits over the life of the project (T) is,

$$\Pi_{ij|m} = \sum_{t=1}^{T} \left(\frac{1}{1+r} \right)^t \mathbb{E}\left[p_{ijt} Q_{ijt} - OM_{ijt} \right] - C_{ij} \tag{4}$$

We approximate annual energy generation Q_{ijt} by project i at site j as a product of proposed system size (nameplate capacity) and technology-specific (wind or solar) capacity factor. The uncertainty in annual (static) profits in Equation 4 is due to a combination of uncertainty in output prices and energy production. The latter is a feature of the inherent uncertainty in renewable generation whereas the former is due to wholesale market volatility or negotiated prices in a long-term contract. We make two simplifying assumptions in Equation 4. First, we assume that the energy production remains constant over the life of the project, replacing Q_{ijt} with per-period production Q_{ij}. Second, we assume that the average prices at location j reflects the value of renewable generation in that location and is not dependent on project i.

We use annual county-level averages of wholesale prices to approximate the the value of power in county.[20] Finally, C_{ij} denotes the location-specific installation (fixed) costs.

20. The county-level prices are aggregated from annual average Locational Marginal Price data from Lawrence Berkeley Lab's The Renewables and Wholesale Electricity Prices (ReWEP) Tool (Millstein, O'Shaughnessy, and Wiser 2024). The coverage includes all nodes within ISO/RTOs and prices reported by the Western Energy Imbalance Market (WEIM) and the Western Energy Imbalance Service market (WEIS). For counties falling within the footprint of an ISO/RTO, WEIM, or WEIS but without a price node, we use the balancing authority level annual averages. For counties not in an ISO/RTO or not part of the Western Energy Imbalance Market or Western Energy Imbalance Service we use REC-adjusted resale prices aggregated at the balancing authority level using data from EIA Form 923 and following Doshi and

Federal tax credits enhance profits by reducing the cost of development or increasing the revenue from power generation. Production Tax Credit (PTC) provides a tax credit for each unit of production whereas the Investment Tax Credit (ITC) provides a credit equal to 30 percent of project installation costs. Thus, the effect of energy community tax bonus depends on whether it enhances the revenue per MWh of the project (PTC) or lowers capital expenditure (ITC). We conduct the analysis with PTC as the subsidy of choice, following observation in Seel et al. (2024) that the majority of recently operational wind and solar projects take-up PTC.

Let τ^{PTC} denote the per-MWh PTC rate and δ_{jt} be the energy community bonus on the PTC. Denoting t as the period when the project makes the location choice decision, the static utility corresponding to the profit function in Equation 4 (at period t), of a project choosing PTC is,[21]

$$U_{ijt|m} = \beta_i \cdot \Big(p_{jt} + \underbrace{\big(1 + \delta_{jt} \cdot \mathbb{1}\{j \in \text{EC eligible}\}\big)\, \tau^{PTC}}_{\text{PTC with place-based tax credit}} \Big) Q_{ij} - \gamma_i \cdot C_{ij} + \Lambda \mathbf{X}_{ijt} + \epsilon_{ijt} \tag{6}$$

where, $\mathbb{1}\{j \in \text{EC eligible}\}$ is an indicator equal to one if county j qualifies for the Energy Community (EC) tax-credit under the IRA. C_{ij} is the annualized measure of project installation costs for project i in location j. While we do not observe these costs directly, we approximate costs as, $C_{ij} = (LCOE_j^{Tech} \times CF_j^{Tech} \times 8{,}760 - FOM^{Tech}) \times MW_i$, where $LCOE_j^{Tech}$ is the technology specific ($Tech$ = solar or wind) Levelized Cost of Electricity at site j, and CF_j^{Tech} and FOM^{Tech} are the technology specific capacity factor and fixed operations and maintenance expenses ($/MW) at site j respectively. These data are obtained from NREL's 2023 Annual Technology Baseline (NREL 2023). Finally, MW_i is the project nameplate capacity.

Johnston (2025) and Aldy, Gerarden, and Sweeney (2023). Appendix Figure A 8 shows the annual prices at the county level from 2020 to 2024.

21. Denoting τ^{ITC} the ITC rate and Δ_{jt} as the energy community bonus on the ITC, the equivalent specification for projects choosing ITC is,

$$U_{ijt|m} = \beta_i \cdot p_{jt} Q_{ij} - \gamma_i \cdot \Big(1 - \underbrace{\big(1 + \Delta_{jt} \cdot \mathbb{1}\{j \in \text{EC eligible}\}\big)\, \tau^{ITC}}_{\text{ITC with place-based credit}} \Big) C_{ij} + \Lambda \mathbf{X}_{ijt} + \epsilon_{ijt} \tag{5}$$

Vector $\mathbf{X}_{ijt}$ summarizes location-specific factors affecting operations and maintenance costs. We include average farm value ($/acres) to account for the value of land, and average farm size to account for average parcel size in a county. We also control for the access to transmission infrastructure by including average distance (in kilometers) from a renewable project site to the point of interconnection.

We model the project-specific marginal utility of revenue (β_i) and capital expenditure (γ_i) as a function of an indicator for whether a project is paired with a battery storage unit. These hybrid projects account for approximately 10 percent of wind projects and 39 percent of solar projects in our sample. These heterogeneous preferences are given by,

$$\begin{pmatrix} \beta_i \\ \gamma_i \end{pmatrix} = \begin{pmatrix} \overline{\beta} \\ \overline{\gamma} \end{pmatrix} + \rho \cdot hybrid_i + \Sigma \nu_i$$

where $\overline{\beta}$ and $\overline{\gamma}$ are the mean utility for annual revenue and capital expenditure respectively, ν_i are unobserved tastes, drawn from a standard normal distribution, and Σ is the variance-covariance matrix of different components of ν_i. Finally, we assume that the idiosyncratic taste shocks ϵ_{ijt} are independent and identically distributed (i.i.d.) and follow a Type I Extreme Value distribution.

5.2 Market Choice Model

The relative profitability of counties within a market affect the attractiveness of that market. We model the utility of selecting a market as a function of aggregate county-level profitability and other market level attributes. The utility specification for this choice situation is,

$$\mathcal{U}_{imt} = \lambda_i \cdot IV_{imt} + \alpha_m + \mathbf{Z}'_{mt}\Theta + \omega_{imt} \tag{7}$$

where, IV_{imt} is the project-specific inclusive value that aggregates county-level profitability within market m. With J_m counties in market m and $U_{ijt|m}$ as the utility of locating in county j from the county choice model in Equation 6, and Type I EV assumption, the

inclusive value is defined as,

$$IV_{imt} = \mathbb{E}\left[\max_{j \in J_m} U_{ijt|m}\right] = \log \sum_{j \in J_m} \exp\left(U_{ijt|m}\right) \tag{8}$$

While market attributes $\mathbf{Z}_{mt}$ shift utility directly, county-level profitability affect market choice only through the inclusive value. Markets with more high profitability counties (high revenue, low cost) will have higher inclusive values. We allow preferences for within-market profitability, summarized by inclusive value, to vary across projects according to $\lambda_i = \bar{\lambda} + \sigma\vartheta_i$, where ϑ_i is an unobserved project-specific preference shock drawn from a standard normal distribution.

We include a rich set of covariates, summarized by the vector $\mathbf{Z}_{mt}$ that include market and policy levers that may inform a project's choice to locate in a particular balancing authority m. We include load-weighted RPS target in m in year t, load-weighted residential and industrial electricity consumption shares, and a binary indicator for whether the balancing authority is a wholesale market.

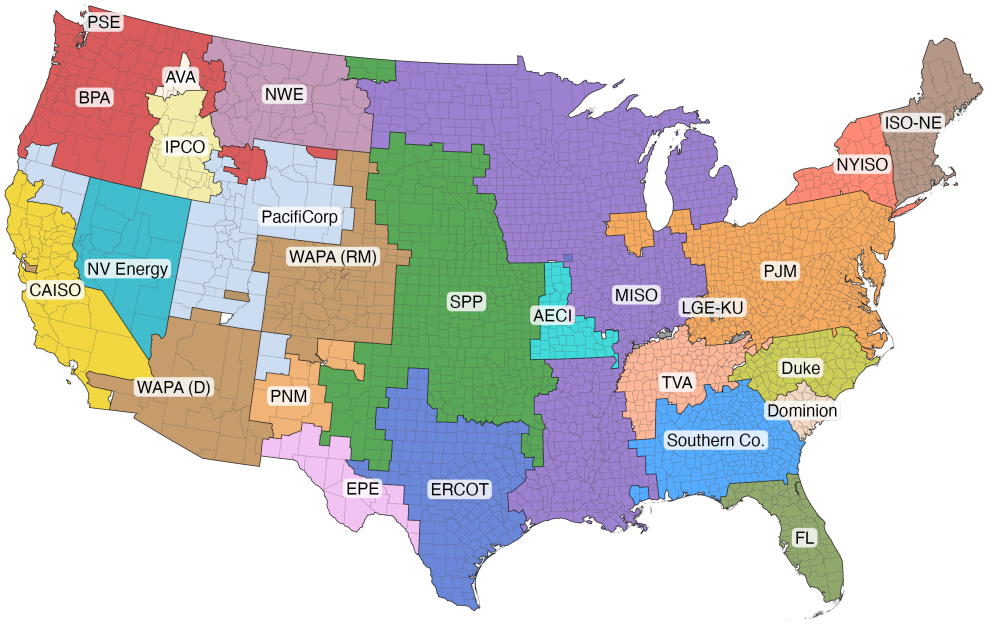
We also include region fixed effects denoted by α_m. These fixed effects include separate indicators for the seven wholesale markets, an indicator for the Southeast, and an indicator for the non-ISO West. These fixed effects account for region-specific policy and market drivers such as presence of capacity markets, interconnection queue delays and backlogs that may influence market selection. Furthermore, these fixed effects also account for any unobserved demand shifters. Finally, ω_{imt} is the random error term following a Type 1 Extreme Value distribution.

5.3 Model Estimation

Model estimation proceeds in four steps. First, we construct project-specific county choice sets and estimate the county-level location model. Second, we use the county-level estimates to compute inclusive values across all counties and markets. Third, we estimate the market-level location model with the generated inclusive values as regressors. Finally, we conduct bootstrap inference to obtain standard errors. We describe each step in turn.

We classify each balancing authority as either one of the seven ISO/RTOs with a wholesale electricity market (CAISO, ERCOT, SPP, MISO, PJM, NYISO, and ISO-NE) or as one of 18 major vertically integrated utility service areas. Each county is assigned to one of the resulting 25 balancing authorities, which constitute the markets in the model.[22] Figure 7 shows the resulting markets and the counties within those markets.

Figure 7: Balancing Authorities in the U.S.



Notes: This map shows the major Balancing Authorities we use for the market level choice model. Each county is assigned to a unique balancing authority based on EIA Form 930. Appendix Table A6 provides balancing authority names and number of counties in the respective service area for the abbreviations used in the map.

As evident from Figure 7, several markets comprise of a large number of potential county level alternatives. For example, projects in MISO may choose among more than 800 counties. Such large choice sets both make the county choice problem unrealistic and likelihood function computationally challenging to optimize. To address this issue, we implement a sampling procedure in which, for each project i, we construct a reduced choice set consisting of the chosen county and approximately 25 non-chosen alternatives

22. We use balancing authority shapefiles from EIA Form 930 to assign counties to markets. Because utility and ISO/RTO service territories often overlap, we assign each county to the balancing authority covering the largest share of the county. In the event of ties, we assign the county to the balancing authority with higher total electricity demand.

(following the sampled choice set approach in Ben-Akiva and Lerman (1985)), that are similar along key dimensions: location-specific capacity factors (solar/wind), levelized cost of electricity, average farm size and average farm value, terrain characteristics (elevation and ruggedness), local zoning laws restricting development of renewable energy and transmission infrastructure (number of substations).[23]

Using these sampled choice sets, we estimate a random coefficients logit model corresponding to the county-level utility function in Equation 6. To account for the sampling variation, we include the log of the county inclusion probability in the likelihood function, which yields consistent parameter estimates (Train 2009).

We then use the estimated county-level parameters to construct the deterministic utility component $U_{ijt|m}$ for each county-market-project combination. We construct inclusive values IV_{imt} for each project and market by aggregating predicted county-level utilities within each balancing authority (Equation 8). We estimate the market-level location model as a random coefficients logit, with the inclusive value entering as a regressor alongside observed market attributes (Equation 7).

For inference, we implement a bootstrap procedure that resamples projects and markets jointly. This approach propagates uncertainty from the county-level estimation through the construction of inclusive values and into the market-level parameters, ensuring that we obtain the correct standard errors.

5.4 Welfare and Counterfactual Analysis

We use the estimates from the market selection model (Equation 7) and the county choice model (Equation 6) to evaluate a series of policy-relevant counterfactual scenarios. For each counterfactual, we compute changes in developer surplus, renewable capacity, carbon emission damages avoided, and subsidy cost for each renewable technology.[24]

23. Specifically, we construct a similarity index based on these characteristics for all counties within a project's balancing authority and sample non-chosen counties using a probability proportional-to-size rule, where counties more similar to the chosen county are more likely to be drawn (Lohr 2021). Appendix Section D provides additional details and summary statistics on the sampled choice sets for wind and solar projects.

24. We assume the set and size of renewable projects to be fixed, i.e. we do not endogenize entry of renewable projects in response to the policy. To the extent that there could be project entry in response to the energy community tax credits, our welfare estimates will be a lower bound of the overall welfare effect.

The change in total producer welfare under counterfactual c includes welfare due to reallocating projects across counties within the chosen market as well as surplus from reallocating projects across markets (balancing authorities) under the counterfactual. Total welfare is (Small and Rosen 1981),

$$\Delta W_i^{total} = \frac{1}{\mu_i}\left[\log\left(\sum_m \exp\left(\lambda_i \cdot IV_{imt}^c + \alpha_m + \mathbf{Z}'_{mt}\Theta\right)\right) - \log\left(\sum_m \exp\left(\lambda_i \cdot IV_{imt} + \alpha_m + \mathbf{Z}'_{mt}\Theta\right)\right)\right] \quad (9)$$

where $\mu_i = \frac{\lambda_i \cdot \beta_i}{\sigma_{IV}}$ is the marginal utility of income at the market level, λ_i is the coefficient on the inclusive value, β_i is the marginal utility of revenue from the county model, and σ_{IV} is the standard deviation of inclusive values used for standardization in estimation. This expressions reflects how the dollar of revenue in the county choice propagates through the model to affect market level utility.

We compute changes in expected renewable capacity allocated to eligible counties $\mathcal{E}$ under each counterfactual c using the predicted county choice probabilities. Because project level capacity is fixed, changes in capacity allocated to eligible counties under a counterfactual arise entirely from reallocations across counties within a market.

$$\Delta\text{Capacity} = \sum_{j\in\mathcal{E}}\left[\int_i MW_i \Pr_{ij|m}^c(\nu)dF(\nu) - \int_i MW_i \Pr_{ij|m}(\nu)dF(\nu)\right] \quad (10)$$

where, MW_i is the nameplate capacity of project i, $\Pr_{ij|m}^c$ and $\Pr_{ij|m}$ denote the probability that project i locates in county j in counterfactual c and the status quo respectively, integrated over the distribution of unobservable project tastes. Under the assumption of Type I EV distribution of errors in county choice model (Equation 6), the predicted probability (conditional on project-specific coefficients) of choosing location j in market m takes the standard logit form,

$$\Pr_{ij|m}(\beta_i, \gamma_j) = \frac{\exp\left(\beta_i \cdot \tilde{p}_{jt}Q_{ij} - \gamma_i \cdot C_{ij} + \Lambda\mathbf{X}_{ijt}\right)}{\sum_{l\in J_m}\exp\left(\beta_i \cdot \tilde{p}_{ly}Q_{il} - \gamma_i \cdot C_{il} + \Lambda\mathbf{X}_{ilt}\right)} \quad (11)$$

Finally, we compute the value of carbon damages avoided due to reallocation of expected project capacity across markets under each counterfactual policy. For each project i and market m, let $\widehat{\Pr}_{im}^{c}$ denote the predicted probability that the project locates in market m under counterfactual c, and $\widehat{\Pr}_{im}$ the corresponding probability in the status quo. The contribution of each project-market pair to emissions depends on the project's nameplate capacity MW_i, market-specific average capacity factor cf_m, marginal emissions rate e_m (tons per MWh), and the social cost of carbon (SCC) which we assume to be \$185 per metric ton of CO_2 emissions (Rennert et al. 2022). The resulting change in the annual dollar value of CO_2 damages is,

$$\Delta E_{CO_2} = \sum_{m} \sum_{i \in m} MW_i \left(\widehat{\Pr}_{im}^{c} - \widehat{\Pr}_{im} \right) \text{cf}_m \cdot e_m \cdot \text{SCC} \cdot 8760 \tag{12}$$

By construction, a positive value of ΔE_{CO_2} indicates lower damages (damages avoided) in the counterfactual relative to the status quo, whereas a negative value indicates higher damages in the counterfactual.

5.5 Model Estimates

Table 4 reports estimates from the location choice model. Panel (a) presents the county-level choice parameters that govern within-market allocation, while Panel (b) reports market-level parameters that govern selection across balancing authorities.

Across both the wind and solar sectors, the coefficients in Panel (a) have the expected signs: utility increases with revenue and decreases with installation costs. The magnitudes of the capital expenditure coefficients indicate that both technologies are quite sensitive to upfront costs. While both wind and solar projects experience disutility from being located farther from a substation, the estimated disutility is substantially larger for wind projects. Broadly, the interaction terms indicate modest systematic variation in the valuation of revenue and costs across hybrid project status, for both technologies. Panel (b) shows that the within-market profitability (the inclusive value, see Equation 8) affects the market choice positively and is precisely estimated for both wind and solar projects, with substantial heterogeneity across projects.

Table 4: Estimates from the Location Choice Model

(a) County Choice Model Estimates

	Wind Projects			Solar Projects		
	Means ($\bar{\beta}$)	SD (σ)	$\times$ Hybrid	Means ($\bar{\beta}$)	SD (σ)	$\times$ Hybrid
Revenue	.035 (.005)	.037 (.008)	-.010 (.010)	.057 (.007)	.049 (.008)	.012 (.008)
Capital Expenditure	-.210 (.035)	.186 (.041)	.103 (.043)	-.256 (.032)	.121 (.047)	.037 (.044)
Log Avg. Farm Size	.710 (.070)	–		.366 (.022)	–	
Log Avg. Farm Value	.437 (.105)	–		.317 (.030)	–	
Log Dist. to Substation	-.179 (.056)	–		-.058 (.019)	–	
# of Projects		748			6,355	
Observations		18,341			155,534	
Log Likelihood		-3,637			-32,850	

(b) Balancing Authority (Market) Choice Model Estimates

	Wind Projects		Solar Projects	
	Means ($\bar{\beta}$)	SD (σ)	Means ($\bar{\beta}$)	SD (σ)
Within-mkt. profitability	.856 (.269)	.328 (.169)	1.634 (.065)	.610 (.038)
# of Projects	748		6,355	
Observations	18,700		158,875	
Log Likelihood	-1,918		-16,649	

Notes: Panel (a) shows the coefficient estimates from the random coefficient logit model for the location choice model in Equation 6. Revenue and Capital Expenditure are measured in million $. Hybrid is an indicator for whether the project includes a battery storage unit. Both specifications in Panel A. include an offset term for sampling probability with the coefficient constrained to 1. Panel (b) reports the coefficient on within-mkt. profitability (the inclusive value, see Equation 8) from the random coefficients logit balancing authority choice model in Equation 7. Both specifications in Panel (b) include load-weighted RPS target in market m, load-weighted residential and industrial electricity consumption, a binary indicator for whether the market is an ISO/RTO, and region fixed effects. Both county and market level models are estimated separately for the sample of interconnection requests for wind and solar projects, greater than 10 MW in size and entered the queue between 2020 and 2023. Robust standard errors reported in parentheses.

5.6 Counterfactual Policies

We evaluate four counterfactual policy designs that modify the eligibility criteria and/or generosity of the Energy Community (EC) tax credit: (1) complete phasing out of the

EC tax credit, (2) higher bonus to more vulnerable counties, (3) restricting the energy community bonus to counties with high renewable energy potential, and (4) targeting incentives to markets with high marginal carbon emission rates. These scenarios highlight how alternative designs trade off private producer welfare, spatial distribution of renewable investment, carbon damages, and fiscal costs relative to the status quo policy design. Table 5 reports the results separately for wind and solar industries and represent changes for requests submitted after the IRA announcement (August 2022) through December 2023.

5.6.1 Eliminating the Energy Community Tax Credit

We first consider a complete phase-out of the Energy Community bonus. This scenario mimics the current policy of elimination of IRA's place-based subsidies under the One Big Beautiful Bill Act of 2025 while keeping other federal incentives unchanged (Sidley Austin LLP 2025).

Phasing out the tax-credit generates the largest losses in developer surplus among the counterfactuals. Total producer welfare declines by $2.12 billion for solar and $0.40 billion for wind due to large declines in within-market surplus for both wind and solar projects. These reductions reflect lower returns that currently attract projects to eligible locations. From a fiscal perspective, the policy delivers large federal budget savings, approximately $3 billion, but at the cost of reduced producer welfare and investment in eligible communities.

Because the total number of projects are held fixed, the elimination of the bonus leads to substantial reallocation of capacity, about 18 GW (mainly solar) away from formerly eligible counties. Despite this shift, changes in avoided carbon damages are small.

5.6.2 Greater Support to Vulnerable Communities

Next, we consider a counterfactual policy in which projects located in the most vulnerable counties receive a larger tax credit. Recall that under the baseline policy design, projects in counties qualifying under multiple criteria receive the same credit as those in counties qualifying under only one criterion. Figure 4 shows that, under the baseline, projects shift away from these more vulnerable counties- particularly in Appalachia- to-

Table 5: Change in Developer Surplus, Renewable Capacity, Emission Damages, and Fiscal Spending Across Counterfactuals

Sector	Δ Developer Welfare (bil. $)	Δ Capacity (GW)	Avoided CO_2 Damages (bil. $)	Δ Spending (bil. $)
A. Eliminating the Energy Community Tax Credits				
Solar	-2.12	-14.64	-0.07	-2.23
Wind	-0.42	-3.10	0.07	-0.78
B. Greater Support to More Vulnerable Communities				
Solar	1.13	5.39	0.42	1.27
Wind	0.23	0.70	-0.04	0.31
C. Targeting High Renewable Potential Counties				
Solar	-0.10	5.85	0.50	-0.12
Wind	-0.05	1.76	0.17	-0.28
D. Targeting High Carbon Emissions Markets				
Solar	-1.15	21.53	0.54	-0.86
Wind	-0.28	4.18	0.35	-0.17

Notes: Results from counterfactual analysis. Sample is all solar (n = 2219) and wind (n = 352) interconnection requests ($\geq$ 10 MW) post IRA announcement (August 2022 - December 2023). Δ Developer Welfare is the total change in producer surplus across all projects (billion $), obtained from the market selection model (Equation 9). Δ Capacity is the change in expected capacity in eligible (treated) counties; total capacity across all counties is held fixed, so negative values indicate a shift of capacity from eligible to non-eligible counties and vice versa. Avoided CO_2 Damages (billion $) is the value of carbon emission avoided under the counterfactual, calculated using the market selection model. We use a Social Cost of Carbon of $185 per metric ton of CO_2 emissions (Rennert et al. 2022). Δ Spending (billion $) is the change in fiscal spending for each counterfactual policy design. All Δ's are relative to the status quo (actual) scenario: positive values indicate increases under the counterfactual.

ward the Great Plains and Texas. We therefore consider an alternative bonus schedule: projects in counties qualifying under one criterion receive a 10 percent tax credit; those qualifying under any two criteria receive a 20 percent credit; and those qualifying under all three criteria receive a 30 percent credit.

This is the only policy scenario in which producer surplus does not decline. However, these gains are offset by approximately $1.6 billion in additional federal spending. Emis-

sions benefits are modest and mainly driven by solar, with about $0.42 billion in avoided carbon damage. The most notable effect is on renewable siting in targeted communities. Eligible counties receive an additional 5.4 GW of solar and 0.7 GW of wind capacity relative to the baseline policy- bringing total renewable investment in targeted locations to roughly 24 GW when combined with the baseline investment. Overall, the policy trades higher investment in vulnerable communities and large developer welfare gains for higher fiscal costs and modest environmental benefits.

5.6.3 Targeting High Renewable Potential Locations

In the third counterfactual we restrict eligibility to counties with technology specific capacity factors above the 75th percentile. Appendix Figure A 9 maps the eligible counties for wind and solar. By directing incentives toward high productivity sites, the policy shifts investment toward locations with better renewable resource quality: solar capacity in eligible counties rises by 6 GW and wind capacity increases by about 2 GW. At the same time, this policy reduces over $0.65 billion in additional carbon damages, as investment is redirected to places where new projects displace more carbon-intensive generation (e.g., more solar in the Southeast and West, and wind in SPP).

These environmental benefits come with small declines in private surplus. Developers effectively steer toward sites with better renewable potential and environmental benefits but slightly lower private returns compared to the status quo.[25]

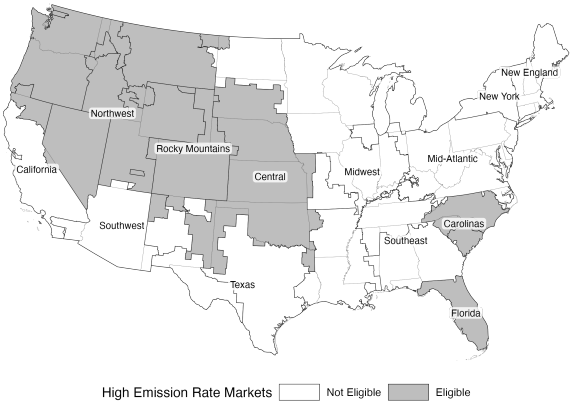
5.6.4 Targeting High Carbon Emissions Markets

Finally, we restrict eligibility to balancing authorities with marginal carbon emissions rates above the median for each technology (source: EPA (2023)). Figure 8 shows the eligible markets for wind and solar and the resulting spatial pattern of avoided damages. Many markets in the West, Central (SPP), and the Southeast qualify under this rule.

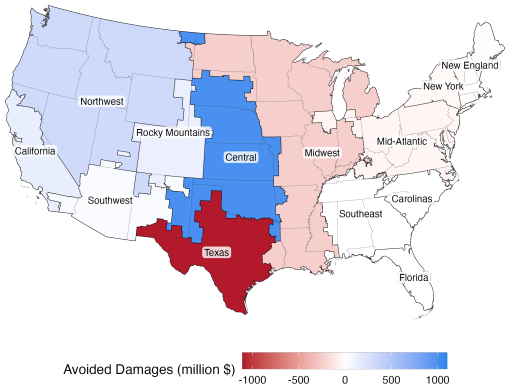
This policy directs investment toward markets where new renewable capacity will generate the large emissions reductions. Capacity in eligible markets increases by about 26

25. Alternatively, some projects that still choose their original location without the energy community tax credits will see lower private returns compared to the status quo.

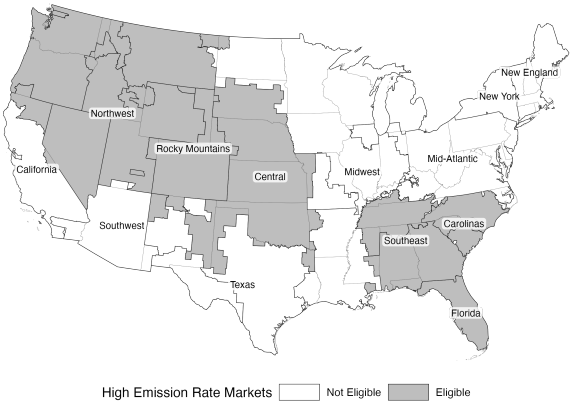
Figure 8: Targeting Markets with High Carbon Emission Rate



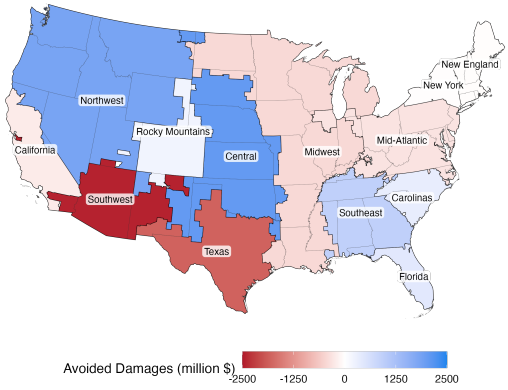
(a) Wind: Markets with High Emission Rate



(b) Wind: Avoided Carbon Emissions (million $)



(c) Solar: Markets with High Emission Rate



(d) Solar: Avoided Carbon Emissions (million $)

Notes: Thus figure shows the balancing authorities eligible under the counterfactual policy that targets the place-based tax credit to markets with high marginal carbon emission rates. Figure 8a and Figure 8c show the eligible markets for wind and solar, respectively. Differences in eligible markets across technologies are due to differences in generation profiles and the source of marginal emissions they displace. We use 2023 marginal emission rates for onshore wind and solar from EPA (2023). Markets with marginal emission rates above the median (for the relevant technology) are classified eligible. Figure 8b and Figure 8d show the implied change in avoided carbon damages (million $) under this counterfactual scenario. Blue shade indicates a decline in damages, whereas red shade indicates an increase compared to the actual scenario.

GW across solar and wind combined, and aggregate avoided damages total about $0.9 billion.[26]

26. Figure 8 also shows substantial spatial heterogeneity in emissions avoided. The Central, Northwest, and Rocky Mountain regions together experience about $2.35 billion per year in reduced CO_2 damages, and the Southeast sees a further $0.66 billion in reduced emissions due to greater solar investment. However, these benefits are partly offset by approximately $2.3 billion in additional damages in non-eligible markets where renewable investment falls.

However, these environmental gains come at the cost of lower private surplus. Developer surplus declines across both the sectors, with approximately $1.15 billion losses for solar and $0.28 billion for wind. Consistent with the design objective, the policy prioritizes environmental gains over developer rents.

5.6.5 Summary of findings

Across the four policy designs, no option simultaneously maximizes private surplus, emissions reductions, and fiscal savings. Eliminating the credit generates largest budget savings but results in substantial losses in developer surplus. Targeting vulnerable fossil-fuel communities increases renewable investment in those areas with higher fiscal spending and moderate gains in developer surplus. Targeting high renewable potential or high-emission locations yields sizable environmental benefits but reduces private surplus as investment shifts toward locations with lower private returns.

6 Conclusion

We examine the design and effectiveness of place-based industrial policy in the energy sector. Using a synthetic difference-in-differences, we find that the IRA's Energy Community tax credits, which provide geographically targeted incentives to renewable energy projects, do not lead to an overall change in renewable project development in targeted locations. These effects, however, are heterogeneous: locations qualifying through local unemployment and fossil fuel tax-revenues see increase in project requests, while locations satisfying all three criteria which are the most economically distressed places, see significant declines. These patterns are primarily driven by solar projects and vary substantially across regions.

Evaluations of place-based in other sectors such as the Opportunity Zones (Freedman, Khanna, and Neumark 2023) find limited early effects on resident outcomes in targeted areas, while evidence on state level Enterprise Zones suggests that their effectiveness depends on program design and local context (Neumark and Young 2021). These findings are consistent with the idea that place-based incentives are most effective where underlying conditions support investment. Our results extend this pattern to the energy

sector: when eligible locations face binding supply-side constraints, such as limited renewable recourse potential, high transmission costs, and challenging siting conditions, a uniform subsidy may be insufficient to overcome these barriers. Instead, the bonus redirects investment toward less constrained locations that also qualify, generating spatial displacement within the set of eligible communities.

To evaluate whether alternative designs can improve these outcomes, we develop and estimate a structural model of renewable project location choice. Our counterfactual simulations highlights the trade-offs between private developer surplus, climate benefits, and fiscal costs. We find that phasing out the energy community bonus, as envisioned under the One big Beautiful Bill Act of 2025 (Sidley Austin LLP 2025), lowers fiscal costs but also causes large losses in developer surplus and reduces investment in formerly eligible locations. By contrast, policy designs that target incentives toward areas with strong renewable potential or markets with high marginal emissions increase the value of avoided climate damages, but may also shift projects toward locations with lower private returns.

These trade-offs connect to a broader tension in the economics of energy transition. Prior work has shown that transmission constraints (Davis, Hausman, and Rose 2023) and resource intermittency (Gowrisankaran, Reynolds, and Samano 2016) create wedges between the private and social returns to renewable investment. Our results show that place-based subsidies introduce an additional spatial dimension to this wedge: the location where renewable investment would most benefit distressed communities are often not the locations where such investment is privately profitable or environmentally most valuable. Making this trade-off explicit as our framwork allows, is essential for designing policies that are transparent about their objectives.

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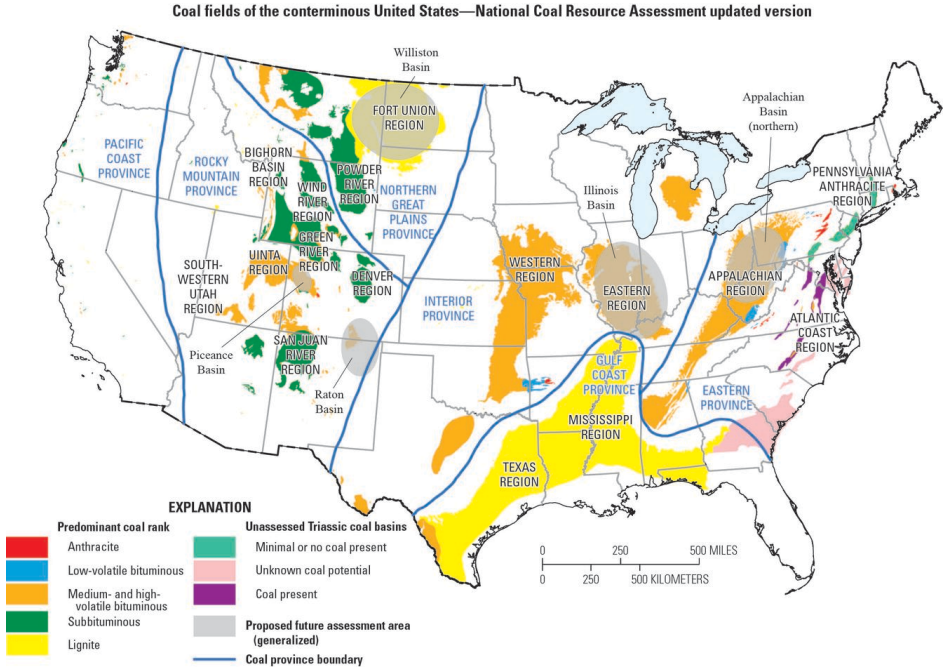
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Appendix

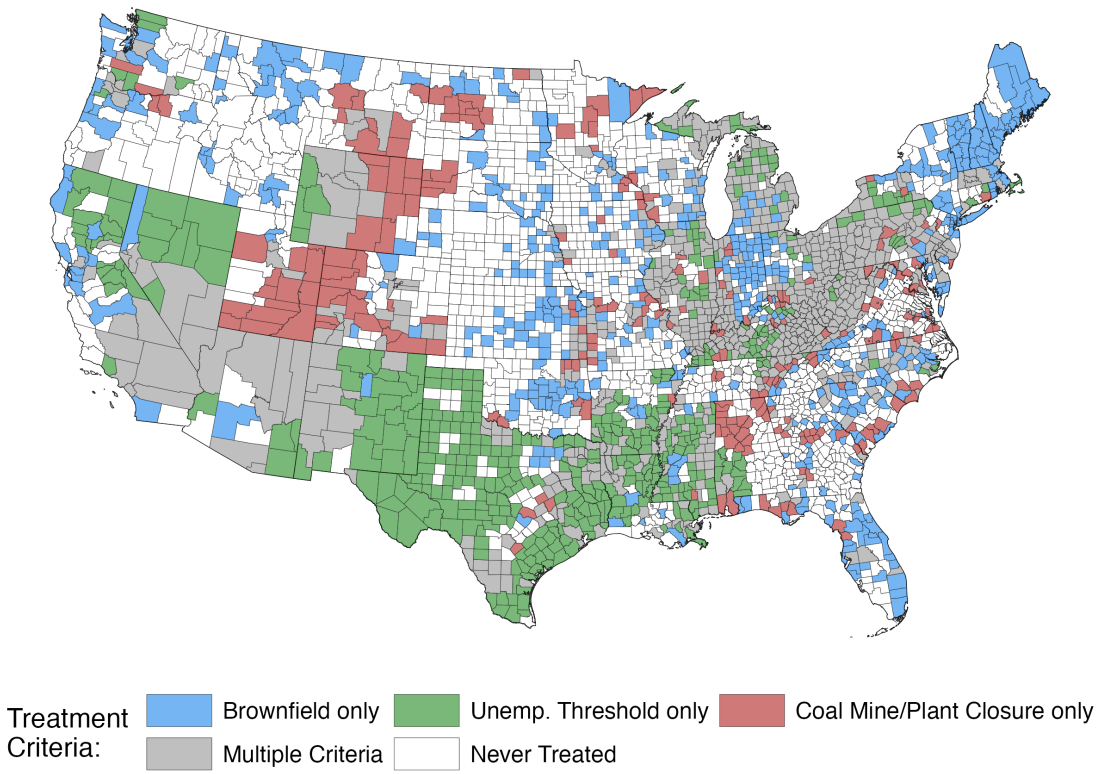
A Supplementary Figures and Tables

Figure A 1: USGS Coalfields of the Conterminous United States



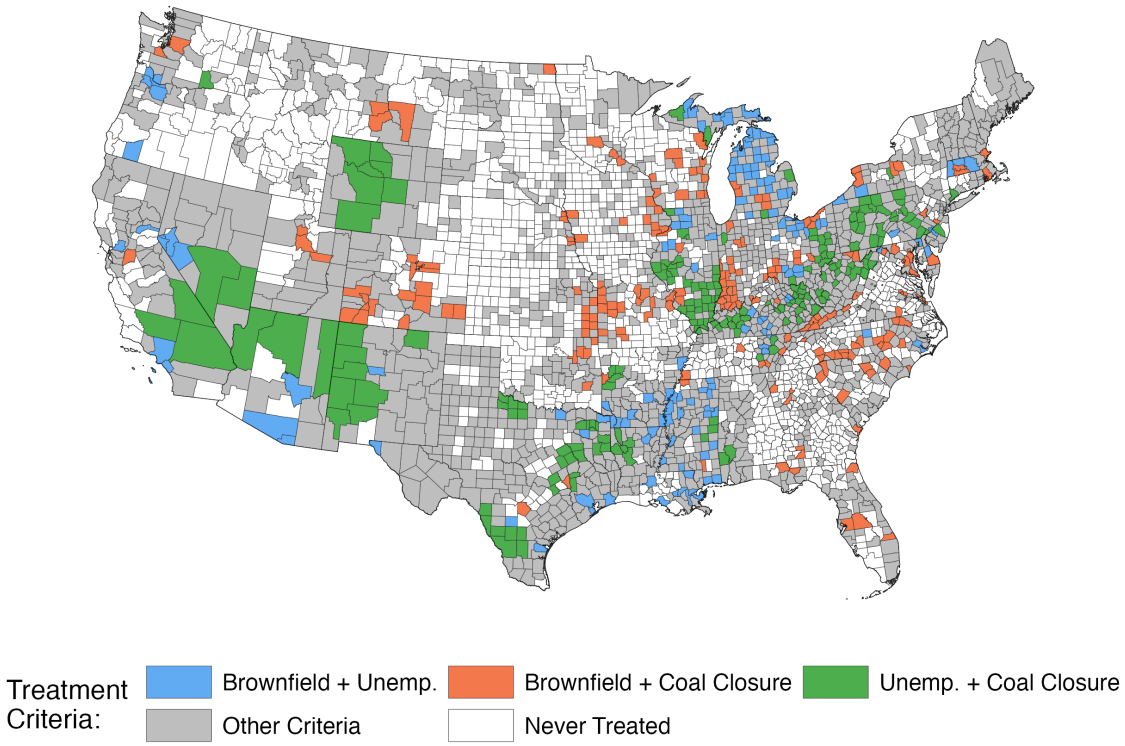
Notes: This figure shows the main coal producing regions in the U.S. Source: Central Energy Resources Science Center, USGS.

Figure A 2: Map of Counties Eligible under a Single Energy Communities Criterion in 2023



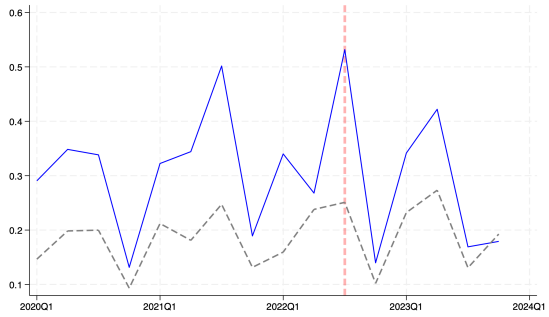
Notes: This figure shows counties eligible under a single energy community tax credits criterion. Counties in blue shade qualify under the presence of brownfield sites only. Counties in green shade qualify exclusively under the local unemployment and fossil fuel tax revenue threshold criterion, and counties in red shade qualify exclusively under the coal mine or coal plant closure criterion. Counties that qualify under combination of two criteria only or all three criteria are shown in grey shade. Never-Treated counties are not eligible under any criteria and are shown in white shade.

Figure A 3: Map of Counties Eligible under Two Energy Communities Criteria in 2023

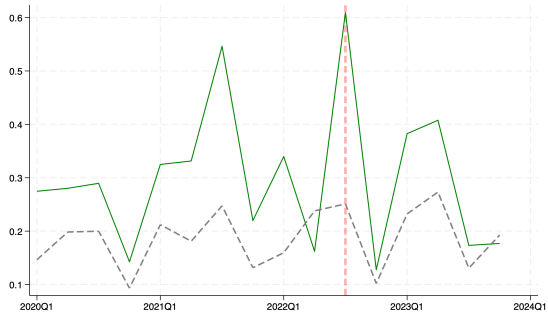


Notes: This figure shows counties eligible under various combinations of two energy community tax credits criteria. Counties in blue shade qualify under the presence of brownfield and unemployment and fossil fuel revenue threshold, counties in red shade qualify under presence of brownfield and coal mine or coal plant closure, and counties in green shade qualify under unemployment and fossil fuel revenue thresholds and coal mine or coal plant closure. Counties that qualify under a single criteria only or all three criteria are shown in grey shade. Never-Treated counties are not eligible under any criteria and are shown in white shade.

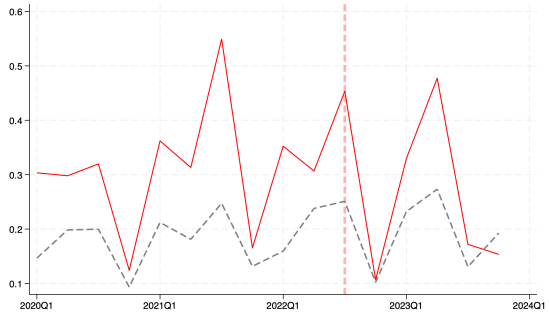
Figure A 4: Average Interconnection Requests for Different Energy Community Criteria



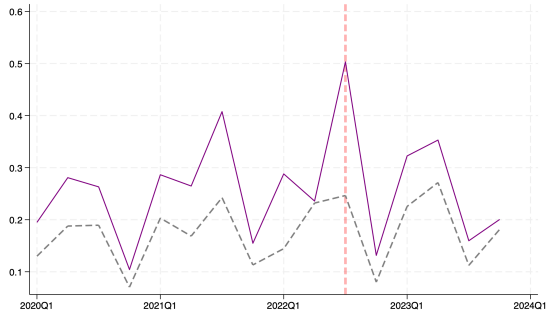
(a) All Brownfield Eligible



(b) All Unemployment Threshold Eligible



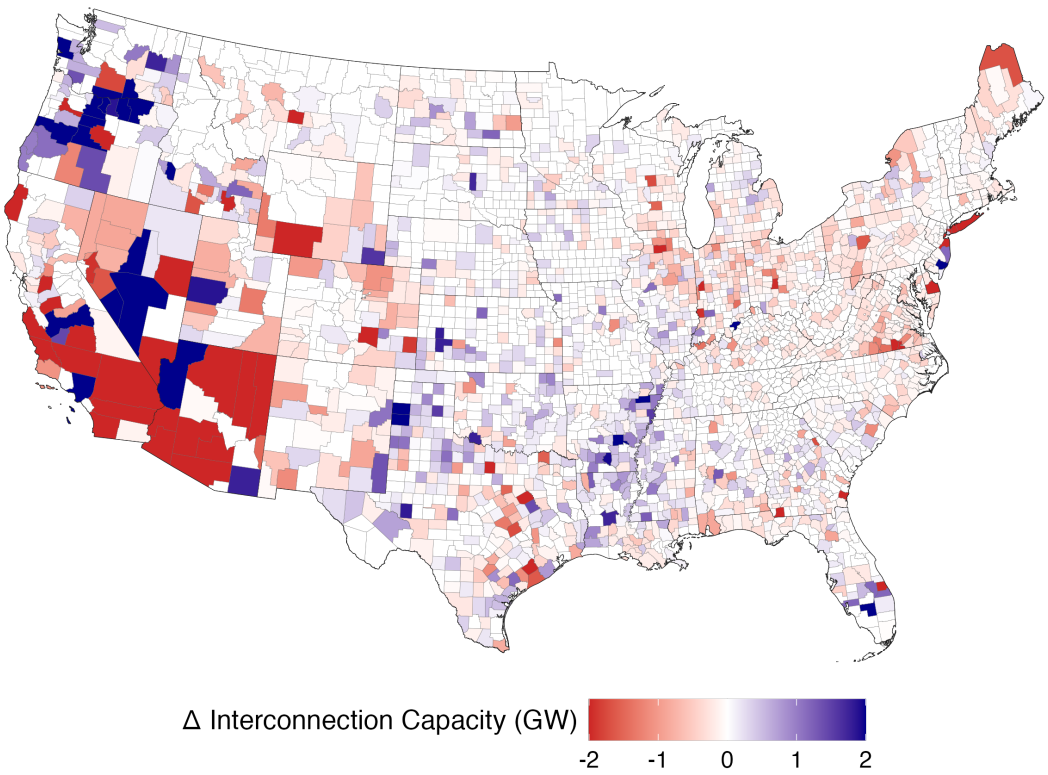
(c) All Coal Closure Eligible



(d) All Three Criteria Eligible

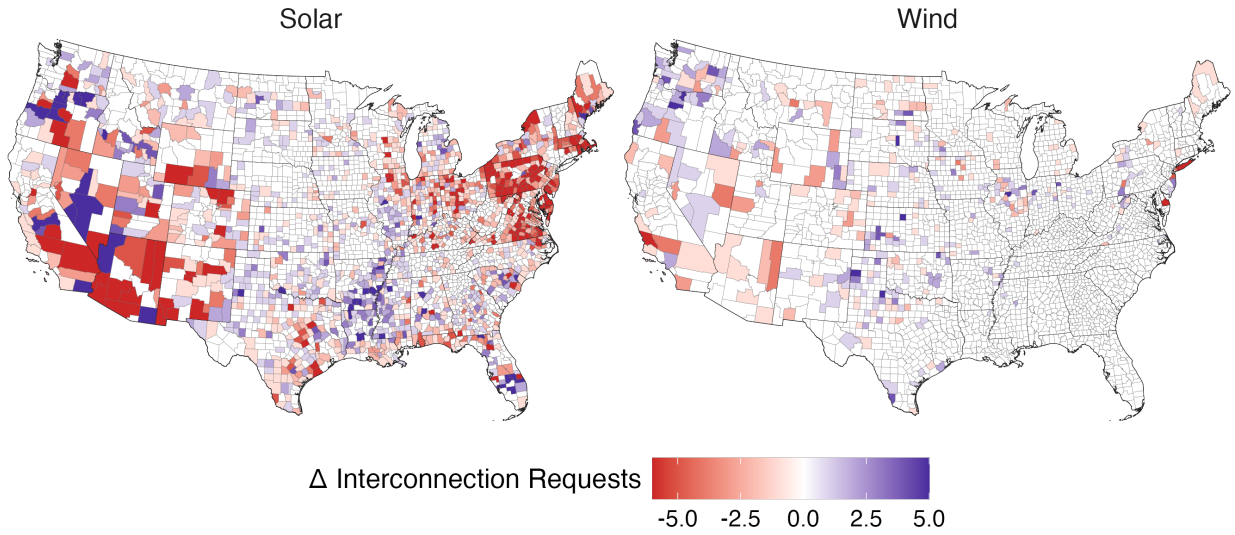
Notes: This figure plots quarterly average interconnection requests over time for counties qualifying under different energy community criteria, compared to never-treated counties (control group; gray dashed line).

Figure A 5: Change in Total Renewable Interconnection Request Capacity Post-IRA Announcement



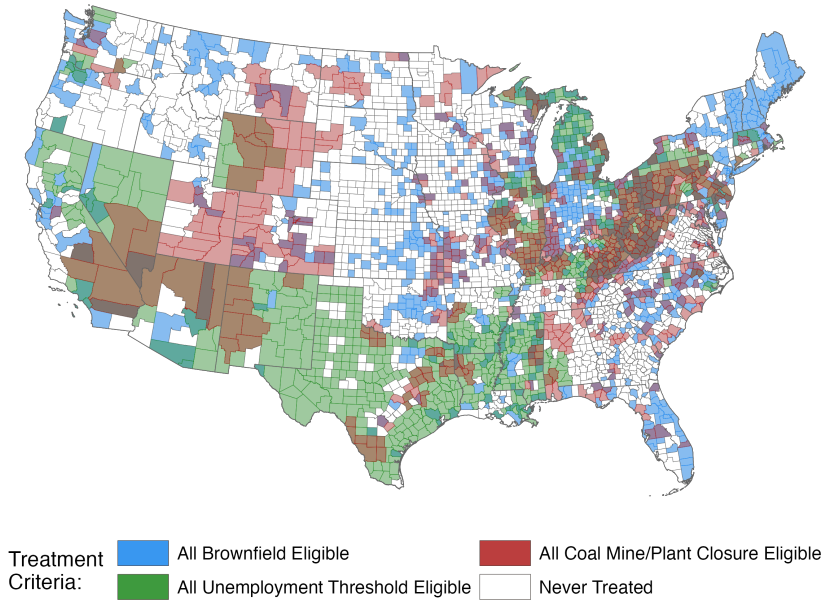
Notes: This figure maps the county level change in total renewable interconnection capacity following the August 2022 announcement of the energy community tax credits. Changes in requests are winsorized at 2 and 2, corresponding approximately to the 1st and 99th percentiles of the distribution.

Figure A 6: Change in Total Renewable Interconnection Requests By Technology

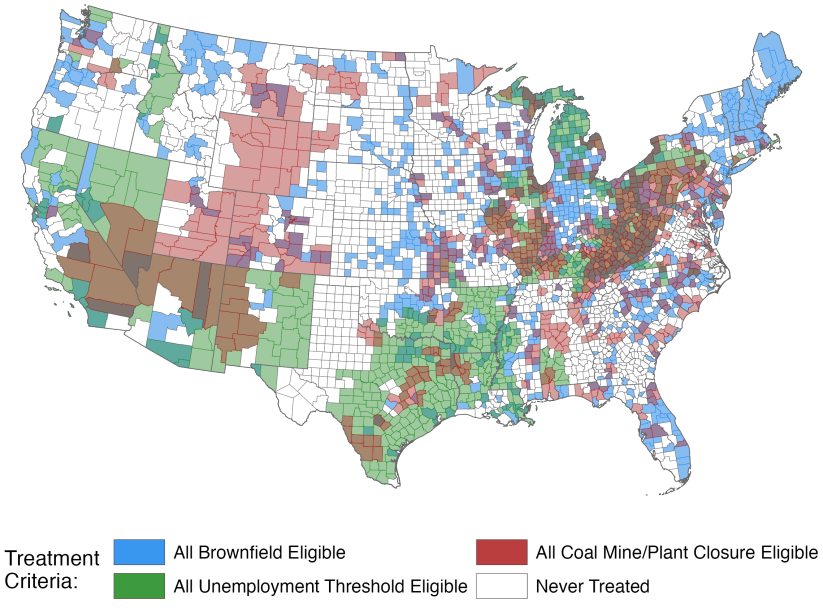


Notes: This figure maps the county level change in total renewable interconnection requests disaggregated by technology (solar and wind) following the August 2022 announcement of the energy community tax credits. Changes in requests are winsorized at 6 and 5, corresponding approximately to the 2nd and 98th percentiles of the distribution.

Figure A 7: Counties Eligible under the Energy Community Tax Credits in 2023 vs. 2024

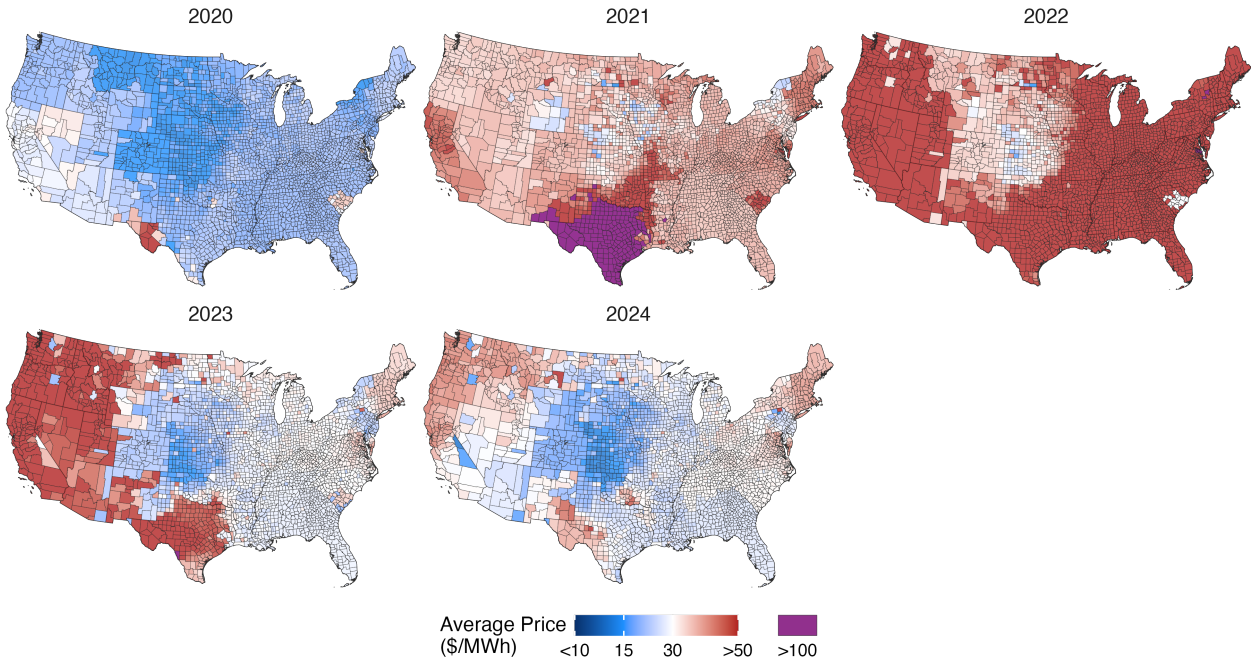


(a) Counties Eligible in 2023



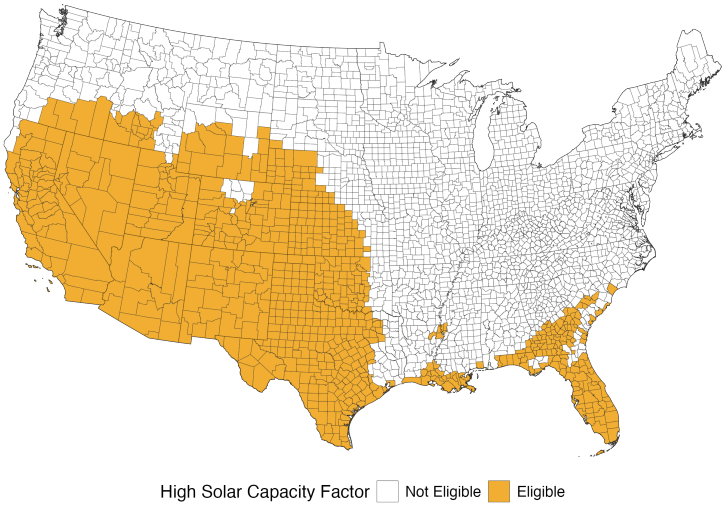
(b) Counties Eligible in 2024

Figure A 8: Wholesale Prices ($/MWh) of Electricity

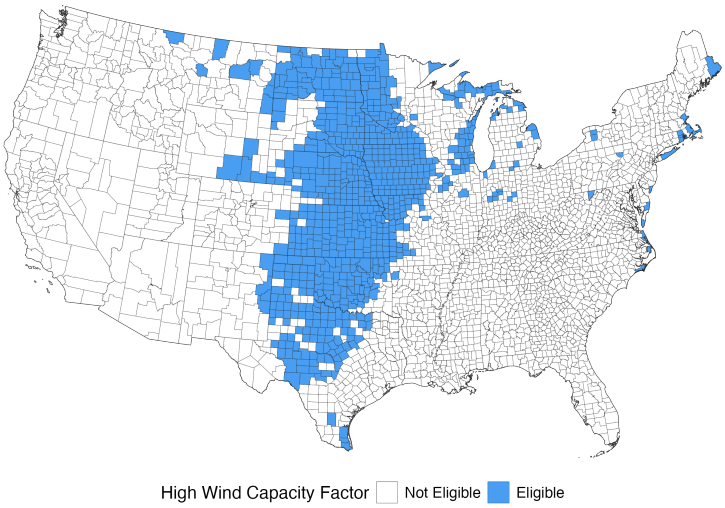


Notes: This figure shows the wholesale prices from 2020 to 2024 aggregated at the county-level. Missing county values are imputed: counties within ISO/RTO footprint or within the Western Energy Imbalance Market or the Western Energy Imbalance Service, we use the average price at the balancing authority level, while for the Southeast we use REC adjusted resale prices aggregated at the balancing authority level.

Figure A 9: Map of Counties Eligible under the counterfactual targeting counties with high wind and solar capacity factors



(a) Counties with High Solar Capacity Factor



(b) Counties with High Wind Capacity Factor

Notes: This figure shows counties eligible under the counterfactual scenario targeting counties with renewable capacity factors greater than the 75th percentile.

Table A1: Summary Statistics of EC characteristics

	Pre-Treatment Mean				Difference from Never Treated (NT)		
	Brownfield	Unemployment	Coal Closure	Never Treated	EC1-NT	EC2-NT	EC3-NT
Energy Infrastructure							
No. of substations (69kV+)	24.93	13.21	22.20	12.76	12.17***	0.46***	9.45***
	(30.71)	(19.92)	(26.96)	(12.89)	(0.14)	(0.10)	(0.13)
Dist. to substation, wind (km)	44.51	60.28	56.77	56.81	-12.30***	3.47***	-0.04
	(38.97)	(48.58)	(50.76)	(43.54)	(0.25)	(0.28)	(0.30)
Dist. to substation, solar (km)	73.38	101.02	87.51	83.35	-9.97***	17.67***	4.16***
	(63.91)	(71.64)	(72.31)	(57.73)	(0.37)	(0.40)	(0.42)
Wind capacity factor	0.39	0.39	0.38	0.40	-0.01***	-0.02***	-0.02***
	(0.08)	(0.07)	(0.07)	(0.09)	(0.00)	(0.00)	(0.00)
Solar capacity factor	0.25	0.26	0.26	0.26	-0.01***	0.00***	-0.01***
	(0.02)	(0.03)	(0.03)	(0.02)	(0.00)	(0.00)	(0.00)
Wind LCOE ($/MWh)	28.64	28.65	29.34	28.11	0.52***	0.54***	1.22***
	(7.78)	(7.32)	(7.28)	(8.18)	(0.05)	(0.05)	(0.05)
Solar LCOE ($/MWh)	45.37	43.26	44.67	43.13	2.24***	0.14***	1.55***
	(5.59)	(6.35)	(5.22)	(4.83)	(0.03)	(0.03)	(0.03)
Wind LCOT ($/MWh)	14.32	16.31	16.63	12.53	1.79***	3.78***	4.10***
	(14.92)	(15.77)	(15.98)	(11.91)	(0.08)	(0.09)	(0.09)
Solar LCOT ($/MWh)	27.06	28.40	27.51	23.50	3.56***	4.90***	4.01***
	(34.68)	(34.22)	(31.02)	(32.50)	(0.20)	(0.21)	(0.21)
Economic Characteristics							
Per capita income ($)	52,883	49,208	50,688	52,909	-25	-3,701***	-2,220***
	(13,719)	(15,149)	(13,047)	(14,645)	(193)	(207)	(205)
Median household income ($)	59,344	52,576	57,332	58,768	577***	-6,192***	-1,436***
	(15,815)	(13,756)	(15,159)	(15,634)	(211)	(205)	(223)
Poverty rate (%)	14.66	16.82	15.01	13.34	1.33***	3.48***	1.67***
	(5.93)	(6.54)	(5.74)	(5.77)	(0.08)	(0.08)	(0.08)
Unemployment rate (%)	5.48	6.09	5.45	4.50	0.97***	1.59***	0.95***
	(2.29)	(2.63)	(2.29)	(2.56)	(0.03)	(0.04)	(0.04)
Demographic Characteristics							
Population	226,177	103,395	140,744	43,268	182,908***	60,127***	97,476***
	(546,211)	(455,098)	(331,876)	(82,251)	(5,122)	(4,298)	(3,209)
Median age	40.56	41.65	41.59	42.40	-1.84***	-0.75***	-0.81***
	(4.88)	(5.26)	(4.82)	(5.57)	(0.07)	(0.08)	(0.08)
% White	79.00	80.26	83.07	83.15	-4.15***	-2.89***	-0.08
	(17.63)	(17.16)	(15.64)	(15.38)	(0.22)	(0.22)	(0.22)
% Black	10.06	9.97	8.13	8.04	2.02***	1.93***	0.09
	(14.42)	(15.90)	(12.46)	(13.94)	(0.19)	(0.21)	(0.19)
% Hispanic	8.13	13.86	7.54	7.97	0.16	5.89***	-0.43***
	(10.29)	(20.15)	(11.46)	(10.62)	(0.14)	(0.21)	(0.16)
% Bachelor's degree or higher	25.98	19.50	22.99	22.43	3.55***	-2.94***	0.56***
	(10.74)	(7.94)	(10.42)	(8.98)	(0.13)	(0.12)	(0.14)
Number of counties	1,034	933	798	1,197	2,231	2,130	1,995

Table A2: Robustness Checks with Alternative Treatment Definition and Timing

	Any Energy Comm.	Brownfield Only	Unemp. Only	Coal Closure Only	Triple EC
	(1)	(2)	(3)	(4)	(5)
Panel A: Without Seasonality Adjustment					
Energy Community Eligible	0.005	-0.003	0.052**	0.029	-0.104***
	(0.015)	(0.021)	(0.024)	(0.026)	(0.039)
Pre-treatment Mean	0.197	0.184	0.155	0.175	0.326
Observations	49,776	27,568	26,224	22,976	21,456
Panel B: Using Brownfield Eligible Counties as Control					
Energy Community Eligible	0.016	–	0.046*	0.014	–
	(0.018)	–	(0.025)	(0.025)	–
Pre-treatment Mean	0.194	–	0.159	0.166	–
Observations	41,648	–	34,640	31,392	–
Panel C: Alternative Treatment Timing: 2023 Q2					
Energy Community Eligible	-0.009	-0.012	0.012	0.007	-0.040
	(0.012)	(0.017)	(0.018)	(0.018)	(0.027)
Pre-treatment Mean	0.211	0.193	0.192	0.183	0.312
Observations	62,220	34,460	32,780	28,720	26,820
Panel D: Alternative Treatment Definition: Raimi and Pesek (2022)					
Energy Community Eligible	-0.024*	-0.017	0.029	0.022	-0.170***
	(0.014)	(0.022)	(0.036)	(0.027)	(0.048)
Pre-treatment Mean	0.227	0.191	0.224	0.172	0.438
Observations	49,776	30,768	26,416	26,896	24,304
County FE	✓	✓	✓	✓	✓
Quarter-by-Year FE	✓	✓	✓	✓	✓

Notes: This table reports robustness checks for the effect of energy community tax credit eligibility on renewable interconnection requests. The dependent variable is the number of interconnection requests per county-quarter. Panel A presents estimates using data without seasonal adjustment. Panel B uses EC1 (brownfield) counties as the control group rather than never-treated counties, under the assumption that brownfield eligibility uncertainty may have muted developer response. Panel C uses 2023Q2 (April 2023, when DOE published the official energy community list) as the treatment date rather than 2022Q3 (IRA announcement). Panel D applies alternative EC2 and EC3 definitions from Raimi and Pesek (2022), published in August 2022. Column (1) includes counties eligible under any criterion. Columns (2)(4) include counties eligible under only one criterion: brownfield (EC1), unemployment (EC2), or coal closure (EC3), respectively. Column (5) includes counties eligible under all three criteria. All specifications include county fixed effects and quarter-by-year fixed effects. Bootstrap standard errors (1,000 replications) clustered at the county level in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A3: Heterogeneity in Energy Community Effects by NERC Regions

	WECC	MRO	Texas RE	SERC	RF	NPCC
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Total Requests						
Energy Community Eligible	0.044	0.046***	0.052**	0.025	-0.097***	-0.171***
	(0.048)	(0.017)	(0.024)	(0.017)	(0.025)	(0.049)
Pre-treatment Mean	0.262	0.007	0.122	0.128	0.490	0.237
Panel B: Solar						
Energy Community Eligible	0.040	0.042***	0.036*	0.037**	-0.088***	-0.139***
	(0.045)	(0.015)	(0.020)	(0.017)	(0.025)	(0.046)
Pre-treatment Mean	0.230	0.006	0.113	0.122	0.472	0.193
Panel C: Wind						
Energy Community Eligible	0.013	0.004	0.015*	-0.011***	-0.005	-0.012
	(0.012)	(0.008)	(0.009)	(0.004)	(0.007)	(0.019)
Pre-treatment Mean	0.031	0.001	0.009	0.006	0.018	0.044
County FE	✓	✓	✓	✓	✓	✓
Quarter-by-Year FE	✓	✓	✓	✓	✓	✓
# Treated Counties	249	223	216	730	395	101
Observations	23,136	22,720	22,608	30,832	25,472	20,768

Notes: This table reports the effect of energy community (EC) tax credit eligibility on interconnection requests, estimated separately by NERC region and technology. The dependent variable is the seasonality-adjusted number of total renewable interconnection requests (Panel A), solar (Panel B), and wind (Panel C) in each corresponding region. The sample is county-level quarterly data from 2020 to 2023. Pre-treatment mean is the average number of interconnection requests in each category submitted before the IRA announcement. All specifications include county and quarter-by-year fixed effects. Bootstrap standard errors (1,000 replications) clustered at the county level in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A4: Impact of the Energy Communities on Renewable Interconnection Requests, 2020-2024

	Any Energy Comm.	Brownfield Only	Unemp. Only	Coal Closure Only
	(1)	(2)	(3)	(4)
Energy Community Eligible	-0.011	-0.016	0.056**	0.004
	(0.012)	(0.018)	(0.022)	(0.020)
County FE	✓	✓	✓	✓
Quarter-by-Year FE	✓	✓	✓	✓
Pre-treatment Mean	0.211	0.191	0.159	0.166
# Treated Counties	1,914	526	442	239
# Control Counties	1,197	1,197	1,197	1,197
Observations	49,776	27,568	26,224	22,976

Notes: This table reports the effect of eligibility under the energy community (EC) tax-credits on interconnection requests, estimated using the synthetic difference-in-differences specification in Equation 1. Dependent variable is the seasonality-adjusted number of renewable interconnection requests. Sample is county-level quarterly data from 2020 to 2024. Column (1) shows the treatment effect for counties that are eligible under any combination of the three criteria. Columns (2) - (4) show treatment effect estimates for the counties that eligible for energy community tax-credits only through one of the three criteria: presence of a brownfield site (Column 2), local unemployment and fossil fuel tax revenue thresholds (Column 3), and coal mine closure or coal plant retirements (Column 4).Pre-treatment mean is the average number of interconnection requests submitted before the IRA announcement. Control counties are counties that do not qualify for any EC based tax-credit (i.e. never-treated). Bootstrap standard errors (with 1000 replications) clustered at the county level reported in parentheses. Significance: *** p<0.01, ** p<0.05, * p<0.1.

Table A5: Impact of Energy Communities Eligibility Thresholds on Renewable Interconnection Requests (2023 UR Definition)

	(1)	(2)	(3)
𝟙(Near Unemp. Rate Cutoff)	-0.037	0.031	0.033
	(0.066)	(0.063)	(0.033)
County FE	✓	✓	✓
Quarter-by-Year FE	✓	✓	✓
Far-from-cutoff counties included	✓		✓
Never treated counties included		✓	✓
Pre-treatment Mean	0.275	0.275	0.275
Observations	7,072	20,096	26,224

Notes: This table reports synthetic difference-in-differences estimates of the effect of being near the unemployment eligibility cutoff for Energy Community tax credits on renewable interconnection requests. Dependent variable is the seasonality-adjusted number of renewable interconnection requests. Near Cutoff counties are unemployment threshold eligible counties with 2023 unemployment rates within 0.1 standard deviations of the national unemployment rate; far-from-cutoff counties are the remaining unemp. threshold eligible counties. Never treated counties are ineligible for energy community tax credits. Of the 442 unemp. threshold eligible counties, 59 are near the cutoff and 383 are far-from-cutoff; 1,197 counties are never treated. Bootstrap standard errors (with 1,000 replications) clustered at the county level are reported in parentheses. Significance: *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Table A6: Balancing Authorities used in the Location Choice Model

Balancing Authority		# Counties
Abbreviation	Name	
AECI	Associated Electric Cooperative	59
AVA	Avista Corporation	6
BPA	Bonneville Power Administration	87
CAISO	California Independent System Operator	49
DUKE	Duke Energy Carolinas	108
EPE	El Paso Electric Company	17
ERCOT	Electric Reliability Council of Texas	186
FL	Florida (Florida Power & Light, Duke Energy Florida)	58
IPCO	Idaho Power Company	23
ISNE	ISO New England	67
LGE-KU	Louisville Gas and Electric Company and Kentucky Utilities Company	11
MISO	Midcontinent Independent System Operator	811
NV Energy	NV Energy and Nevada Power Company	18
NWE	NorthWestern Corporation	45
NYISO	New York Independent System Operator	62
PacifiCorp	PacifiCorp (East and West)	57
PJM	PJM Interconnection	528
PNM	Public Service Company of New Mexico	15
PSE	Puget Sound Energy Inc.	1
Dominion	Dominion Energy South Carolina	23
Southern Co.	Southern Company Services Inc.	231
SPP	Southwest Power Pool	395
TVA	Tennessee Valley Authority	146
WAPA (RM)	Western Area Power Administration: Rocky Mountain	84
WAPA (D)	Western Area Power Administration: Desert Southwest	21

B CIMC-Based Filters for Identifying IRA Eligible Brownfield Sites and Counties

This section details our methodological approach for identifying brownfield sites eligible for the Energy Community (EC) Tax Credit under the Inflation Reduction Act (IRA) and for defining EC-eligible counties based on the brownfield criterion in our study. We systematically evaluated filters within the Environmental Protection Agency's (EPA) Cleanups in My Community (CIMC) tool, selecting those most precisely aligned with the IRA's statutory definition of qualifying brownfield sites. Table B7 explains the justification for each selected filter, demonstrating its direct correspondence to the specific language and requirements established in the IRA legislation.

Several categories of sites are explicitly excluded from qualification as brownfield sites under the IRA guidelines. The IRA specifically excludes facilities listed or proposed for listing on the National Priorities List (Superfund NPL sites), a restriction clearly stated in Section 45(b)(11)(C)(ii)(I) of the legislation. Similarly excluded are land disposal units that have filed closure notifications under subtitle C of the Resource Conservation and Recovery Act (RCRA) with specified closure requirements in permits or plans. Additionally, unlike broader federal brownfield funding definitions, the IRA does not recognize sites with petroleum-only contamination as qualifying brownfield sites unless they also contain hazardous substances, pollutants, or contaminants. Furthermore, CIMC filters related merely to cleanup status (e.g., Remedy Selected, Construction Complete), long-term cleanup attention, or control measures (e.g., Institutional Controls, Engineering Controls) are not directly relevant to qualification, as the IRA's definition focuses specifically on the initial presence or potential presence of complicating substances rather than the remediation progress of identified sites.

The selected CIMC filters are relevant because they specifically target the identification and remediation of sites with potential or confirmed hazardous substance contamination, aligning with the core of the IRA's brownfield site definition for the Energy Community Bonus Credit. However, this selection process requires caution and careful interpretation. Categories explicitly excluded either do not meet the specific criteria of the IRA definition (e.g., petroleum-only sites) or are expressly prohibited by the legislation (e.g., Superfund sites, certain landfills). Furthermore, the inclusion of a site in

the selected CIMC filters does not automatically guarantee qualification under the IRA; each site must be individually evaluated against the precise statutory definition. It is also important to note that while mine-scarred lands can qualify as brownfield sites under the IRA, the CIMC filters discussed do not specifically isolate these types of sites. Identification of mine-scarred lands would likely occur under the broader categories of assessment and cleanup if they are complicated by the presence or potential presence of a hazardous substance, pollutant, or contaminant. This conservative interpretation approach acknowledges the inherent limitations of relying solely on CIMC filters without site-specific assessment and ensures compliance with the spirit and letter of the IRA provisions.

Based on the selected brownfield sites, we define EC-eligible counties under the brownfield criterion using a county size-adjusted measure of brownfield prevalence. Specifically, we compute the number of eligible brownfield sites per unit of county land area, normalizing county size to the median U.S. county area (600 square miles). Counties with a size-adjusted brownfield density above the median are classified as brownfield-eligible. This approach accounts for systematic differences in county size between western and eastern states and avoids mechanically classifying larger counties as eligible solely due to their greater land area.

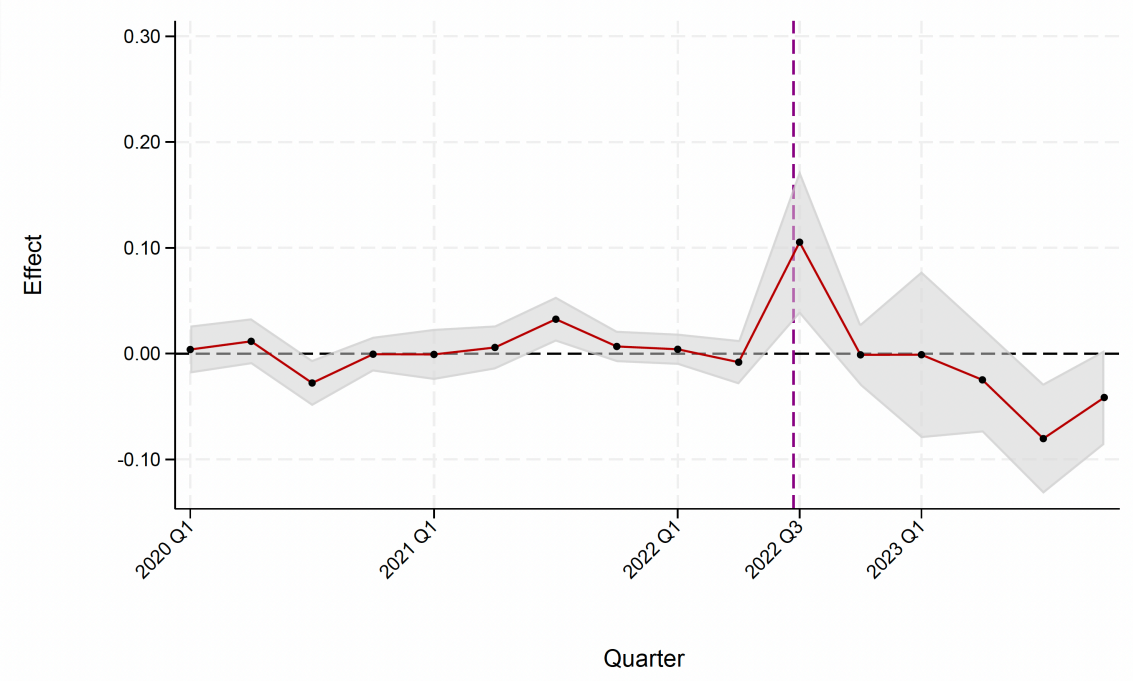
Table B7: Selected CIMC Filters and Alignment with IRA Definition

CIMC Filter	IRA EC Justification
Assessment Grants	These grants fund the initial assessment of properties to determine the presence or potential presence of contamination. This directly aligns with the IRA's definition of a **brownfield site** as "**real property, the expansion, redevelopment, or reuse of which may be complicated by the presence or potential presence of a hazardous substance, pollutant, or contaminant**." Assessment grants are often the first step in identifying such properties.
Cleanup Grants	These grants provide funding for the cleanup of properties with known contamination. This filter is pertinent as it targets sites that have already been identified as having **hazardous substance contamination**, a key component of the IRA's brownfield definition.
Revolving Loan Fund (RLF) Grants	RLF grants capitalize loan programs that provide funding for the cleanup and redevelopment of **brownfield sites**. Eligibility for these loans is predicated on a site meeting the definition of a brownfield, typically involving **hazardous substances, pollutants, or contaminants**.
Multi-Purpose Grants	These grants offer flexibility to fund a range of brownfield activities, including assessment and cleanup. Their broad scope makes them relevant to identifying sites that meet the IRA definition related to the presence or potential presence of **hazardous substances**.
Targeted Brownfields Assessments under Brownfields Properties	This program provides direct assessment services for properties suspected of being contaminated. These assessments aim to identify the presence of **hazardous substances, pollutants, or contaminants**, directly aligning with the IRA's definition of a brownfield site.

Notes: The criteria are complied by cross-referencing IRS brownfield guidelines with the EPA Brownfield Cleanup dataset. [27]

C Event-study plots for synthetic difference-in-differences specifications

Figure C 10: Impact of the Energy Community Tax Credits on Renewable Interconnection Requests



Notes: This figure presents quarterly synthetic difference-in-differences estimates and 95 percent confidence intervals obtained using block bootstrap (with 1000 replication) inference as outlined in Arkhangelsky et al. (2021). The dependent variable is the seasonality-adjusted number of renewable interconnection requests. The treatment group is if a county qualifies for any of the three energy community tax credit criteria (i.e. either through presence of a brownfield site (EC1), under unemployment thresholds (EC2), or through coal mine or coal plant closure criteria (EC3)).

D Sampling Procedure for Choice-Set Construction for the County Selection Model

We implement a sampling procedure that uses a probability-proportional-to-size (PPS) rule to draw a set of up to 25 counties (within the projects balancing authority) that are similar to the chosen county on a wide array of observable characteristics. The following algorithm describes the key steps in our sampling process:

1. **Define the choice set**: For each project i in balancing authority m, define the relevant choice set as all counties within m.
    - If the number of counties in balancing authority m is at most 25, retain the full set of counties as the choice set (i.e., no sampling).
2. **Construct a similarity index**: When the number of counties in $m > 25$, construct a feature similarity index between the chosen county and all non-chosen counties
    - We use Mahalanobis distance, which measures multivariate distance while accounting for correlation across the following characteristics: wind/solar capacity factor, average LCOE, average farm size (acres), average farm value per acre, number of substations, average terrain elevation, and terrain ruggedness.
3. **Convert similarity into sampling weights**:
    - Transform distances into sampling weights using a Gaussian kernel: counties more similar to the chosen county receive higher weight, while less similar counties receive lower weight.
    - Normalize the weights so they sum to one across non-chosen counties.
4. **Sample non-chosen counties using PPS**:
    - Draw a fixed number of non-chosen counties using probability-proportional-to-size sampling based on the kernel weights, so that the total number of alternatives retained is 25 (including the chosen county).
5. **Record inclusion probabilities for estimation**:

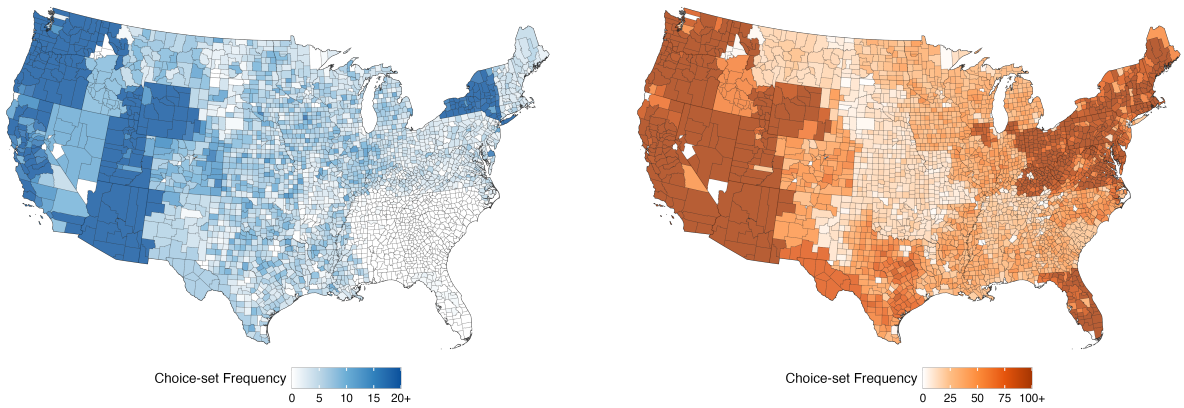
- For each sampled non-chosen county, we store its (approximate) inclusion probability implied by the PPS procedure. The chosen county is always retained, with inclusion probability equal to one.

6. **Construct an offset to correct the likelihood**:

   - Include the log of the inclusion probability for each sampled non-chosen county as an offset in the likelihood function to correct for the sampling variation.

Figure D 11 shows the choice-set size, the frequency that each county appears in the choice-set of a project. The choice-set coverage is quite extensive, with all counties appearing at least once in a project's choice-set.

Figure D 11: Choice-set Size across Wind and Solar Sectors



(a) Wind Projects (b) Solar Projects

Table D8: Summary Statistics of Annual Revenue, Capital Expenditure, and Energy Community Tax Credits for Renewable Project Requests Submitted Post IRA

	Wind		Solar	
	EC eligible	EC non-eligible	EC eligible	EC non-eligible
Annual Revenue per MW	270.92	239.80	195.92	177.08
($1,000)	(66.27)	(58.38)	(36.70)	(39.53)
Annualized CapEx. per MW	66.69	67.01	77.49	77.19
($1,000)	(7.58)	(4.48)	(5.98)	(5.20)
EC Tax Credit per MW-year	10.28	0	6.99	0
($1,000)	(2.26)		(0.86)	
Nameplate Capacity (MW)	412	318	230	184
# projects post IRA	198	147	1,497	652