Can Place-Based Incentives Accelerate the Energy Transition? Evidence from the IRA's Energy Community Tax Credits

Gaurav Doshi, Jancy Ling Liu, Xiaochen Sun*

March 2025

Abstract

We study the impact of place-based 'energy community' tax credits introduced by the Inflation Reduction Act (IRA) on renewable investment in the U.S. These credits offer a tax bonus to projects constructed in economically vulnerable, historically fossil fuel-reliant locations. We classify a county as treated if it meets one or more of three eligibility criteria: the presence of brownfield sites, fossil fuel unemployment thresholds, or historical coal mine or coal plant retirements. Using a synthetic difference-in-differences strategy, we estimate the treatment effect of different combinations of the eligibility criteria on generator interconnection requests in the county. Preliminary findings indicate that counties meeting any one of the criteria experience a statistically significant 13 percent increase in requests- equivalent to approximately 84 new renewable projects. However, counties satisfying all three criteria see a 27 percent decline in requests relative to pre-treatment levels. We attribute this negative effect in these counties as a combination of poor-economic conditions and crowding out of investment towards singly eligible counties. To further explore these mechanisms, we develop a structural model of renewable project location choice, and use it to evaluate a variety of policy-relevant counterfactuals.

*G.D., J.L. and X.S. contributed equally to this work. Gaurav Doshi: Georgia Institute of Technology, 209 Old CE Building, Atlanta, GA 30309. Email: gdoshi@gatech.edu. Jancy Ling Liu: The College of Wooster, 216 Burton D. Morgan Hall, E Pine St, Wooster, OH 44691. Email:jliu@wooster.edu. Xiaochen Sun: New Mexico State University, 1320 E University Ave, Las Cruces, NM 88003. Email: xsun@nmsu.edu.

1 Introduction

The Inflation Reduction Act (IRA) extends the Production Tax Credit (PTC) and the Investment Tax Credit (ITC) with the energy communities provision that could significantly influence the energy transition through its effects on renewable energy project siting decisions in the United States. According to Internal Revenue Service (2024), certain locations are eligible for an additional bonus of 10 percent for the PTC or 10 percentage points for the ITC if they meet any of three criteria related to: brownfield sites, certain local tax revenue from fossil fuels and unemployment rate, or the closure of coal mines or coal-fired generators. However, it is not apriori clear whether such targeted place-based incentives can successfully drive renewable energy investment toward communities that are economically vulnerable and have historically relied on fossil fuels.

This paper examines the effect of place-based implementation of the PTC and ITC under the IRA on the energy transition. Specifically, we study how different eligibility criteria affect renewable generator interconnection requests and renewable energy investment in that location. While the locations of brownfield sites and coal mines or generators are historically predetermined, the unemployment criterion varies annually based on the national average unemployment rate each year. This temporal variation creates a natural experiment to study how energy community tax credits affect the renewable energy transition in the United States. Interactions between coal mines and the generator retirement criterion, the brownfield criterion, and the unemployment criterion may create spatial variations in IRA benefits (Bistline, Mehrotra, and Wolfram 2023), potentially resulting in heterogeneous effects on the competitiveness of these locations in attracting renewable energy development.

We use transmission interconnection requests, one of the first stages of renewable project development, as our outcome of interest. Changes in transmission interconnection requests also reflect the location-specific speed of energy transition, a central focus of our analysis. Following McCrary (2007), we use the announcement date of the IRA energy community tax credit as the treatment date to account for any behavioral adjustments in project development in anticipation of the actual policy enactment. We employ a synthetic difference-in-differences (SDID) approach (Arkhangelsky et al. 2021) to estimate the effect of the announcement of energy community tax credits eligibility on interconnection requests in the treated locations. It is worth noting that projects bene-

fit from the PTC and ITC only after project construction is completed. Therefore, it is reasonable to assume that the location eligibility announcement may influence project planning, thereby capturing the upper bound of the effect.

Using the data on the brownfield cleanup list from the EPA, IRA energy community data layers from the US DOE, and IRS guidelines on IRA tax-credit eligibility, we manually construct three eligibility criteria (EC1, EC2, and EC3) under the Energy Community tax credits. A county is considered treated under the first criteria, EC1, if there are one or more brownfield sites located within the county. The second criterion, EC2, determines whether a county qualifies based on fossil fuel employment thresholds and the national average unemployment rate. Finally, the third criterion, EC3, specifies if a county qualifies under the coal mine or coal plant retirement rule.

Our paper has two main findings. First, we show that energy community tax credits lead to a 0.036 higher number of interconnection requests per county, representing a 13 percent increase compared to pre-treatment levels in qualifying counties. This translates to approximately 84 new renewable energy project requests annually. We observe similar positive effects in counties qualifying under either a single energy community criterion or a two-way combination of criteria, although some estimates for the two-criteria combinations are estimated less precisely. Second, we find that the number of interconnection requests decrease by about 0.164 in counties that qualify under all three criteria. This represents an approximately 27 percent decline in interconnection requests in these counties compared to their average pre-treatment levels.

We posit that this seemingly contradictory result is driven by how different eligibility criteria alter the relative competitiveness of eligible locations. The decline in interconnection requests in the locations qualifying under all three criteria likely reflects a complex interplay of factors such as regulatory concerns, potential investment risks and greater barriers to entry. In other words, locations qualifying under a single criteria (or even two of the EC criteria) may crowd-out or out-compete renewable investment from the most distressed communities that qualify under all three criteria.

To further explore the underlying mechanisms, we leverage a structural model to simulate the location choice of renewable projects. In this model, a renewable developer chooses a location to maximize its profits conditional on the Energy Community tax-credit, output prices, system size, resource quality, land value, and terrain charac-

teristics. Appendix Appendix B provides a detailed description of this discrete choice model. We use this model to evaluate the spatial distribution of renewable investment under three policy-relevant counterfactual scenarios. First, we examine the effect of changing location-eligibility criteria, addressing how different definitions of the EC locations, while keeping the tax-credit amount the same, would alter renewable investment patterns. Second, we analyze how location choice decisions respond to varying tax-credit amounts while keeping eligibility criteria fixed. Finally, we evaluate the combined effects of simultaneously adjusting both location-eligibility criteria and tax-credit amounts.

This paper makes three main contributions. First, we add to the growing literature on the impacts of the IRA. Recent studies have mainly evaluated the impact of the IRA using ex-ante approaches (Bushnell and Smith 2024; Bistline et al. 2023; Bistline, Mehrotra, and Wolfram 2023) and specific criteria for energy community designation (Ashenfarb 2024). Our paper builds on this literature by providing an analysis of the comprehensive energy community provision under the IRA with an ex-post approach. We offer one of the first causal estimates in the literature on the impact of the place-based tax bonus on the energy transition by combining a reduced form and a structural approach to renewable investment.

Second, we contribute to the literature on the economics of renewable energy transition. This literature has looked at challenges of the energy transition, including cost considerations (Heal 2020; Boer, Pescatori, and Stuermer 2023), intermittency of renewable energy sources (Gowrisankaran, Reynolds, and Samano 2016; Joskow 2019; Wolak 2020), challenges related to inadequate transmission infrastructure (Davis, Hausman, and Rose 2023; Doshi 2024), and interconnection delays (Johnston, Liu, and Yang 2024; Sun 2023). This paper adds to this literature by examining the impact of place-based tax credits, a novel policy, on the speed of the energy transition. Additionally, we explain factors that may influence investment decisions beyond transmission infrastructure and interconnection delays.

Finally, we build a comprehensive dataset that describes IRA-qualified brownfield sites. This addresses the major barrier of the lack of accessible information about the locations that are qualified for the tax-credits. We use hand-collected data and to compile this information to provide a map of these locations. We believe that this will advance

research in this area and provide a valuable reference for developers' project siting decisions.

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 the core empirical strategy in Section 4. Section 5 shows the results of the empirical analysis, and Section 6 provides a concluding discussion.

2 Institutional Details

2.1 The Energy Community Tax Credits

The Inflation Reduction Act (IRA) was announced in August 2022 to promote clean energy in the United States. The IRA provides a broad array of incentives and programs to accelerate the clean energy transition, among which energy community tax credits newly introduced. Energy community tax credits are designed to provide economic incentives to regions historically reliant on fossil fuel activities. It aims to facilitate them in their transition to cleaner energy and alleviate the burdens associated with this shift (Raimi and Pesek 2022).

The energy community tax bonus is a place-based tax program that qualifies locations based on three criteria. The 'Energy Communities' under the IRA are defined as (U.S. Department of Energy 2024):

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

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

    - 0.17% or greater direct employment or 25% or greater local tax revenues related to the extraction, processing, transport, or storage of coal, oil, or natural gas; and
    - has an unemployment rate at or above the national average unemployment rate for the previous year;

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

In summary, a location qualifies as an energy community (EC) is eligible for tax credits if it meets one of three criteria: designation as a brownfield site (EC1), meeting specific thresholds for local tax revenue from fossil fuels and unemployment rates (EC2), or the closure of coal mines or coal-fired generators (EC3). Based on these criteria, DOE provides the list of IRA energy communities that are qualified through EC2 and EC3. However, there is no official list of brownfield sites that qualify as energy communities under IRA. To identify brownfield sites that meet the IRA's energy community criteria, we follow IRS guidance and utilize the Brownfield Cleanup list maintained by the U.S. EPA as our initial approach for classification.[1]

Figure 1 shows the spatial distribution of counties classified as treated under the three EC tax credit criteria, with counties that do not qualify for any EC-based tax-credits shaded in white across all four panels. Panel (a) highlights counties that qualify for EC tax-credits under any of the three criteria in blue. Panels (b), (c), and (d) illustrate counties that qualify under brownfield (EC1), unemployment thresholds (EC2), and coal mine or plant closure criteria (EC3), respectively.

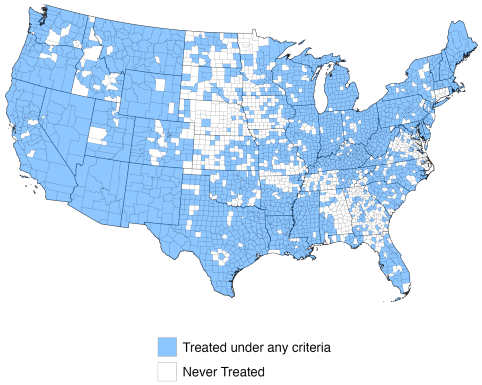
We observe that IRA energy community coverage is extensive, with the majority of counties qualifying through the brownfield criterion. Counties that qualify based on unemployment are concentrated in southwest Texas and the "Rust Belt" regions, including Kentucky, Illinois, West Virginia, Ohio, and Pennsylvania. In contrast, counties qualifying through coal mine and plant closure are more limited.[2] In addition, there is significant overlap among the three criteria. In other words, many counties qualify under

1. The IRS clarifies that IRA-designated brownfields are a subset of sites eligible for the EPA Brownfield Program: "For purposes of the energy community bonus credit, a brownfield site is limited to sites that are described in 42 U.S.C. 9601(39)(A), (B), and (D)(ii)(III), which is a subset of the sites that may qualify for federal Brownfield funding. Section 9601(39)(C) and (D) of Title 42 of the United States Code includes categories of sites that are eligible for federal Brownfield funding but do not meet the definition of a brownfield site for purposes of the energy community bonus credit." For more information, see Brownfields, US EPA and https://www.epa.gov/sites/default/files/2018-10/documents/web-content-info-on-site-eligibility.pdf. For our selection methodology and justification based on IRA definition, see Appendix C. Our filtering process identified 33,651 qualifying brownfield sites.

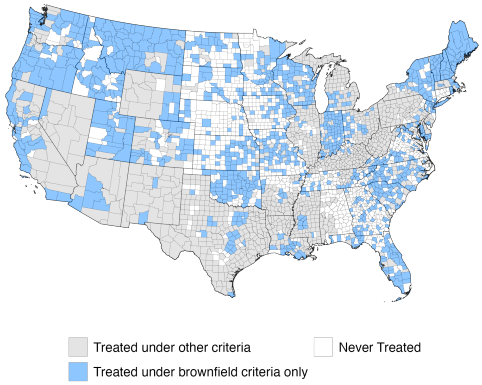
2. It is worth noting that U.S. Department of Energy (2025) provides maps for areas that qualify under EC2 and EC3. As a sanity check, we find that our maps largely align with the DOE maps for EC2 but miss some counties that qualify under EC3. We are further investigating the reasons behind this misalignment.

multiple criteria rather than just one. Appendix Figure A 1 shows the maps of counties that qualify under different combinations of the three criteria.

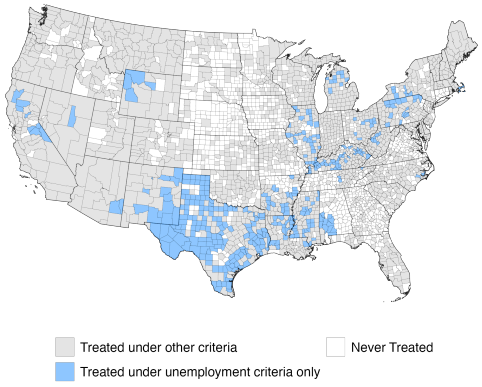
Figure 1: Counties Eligible Under the Energy Community Tax Credits



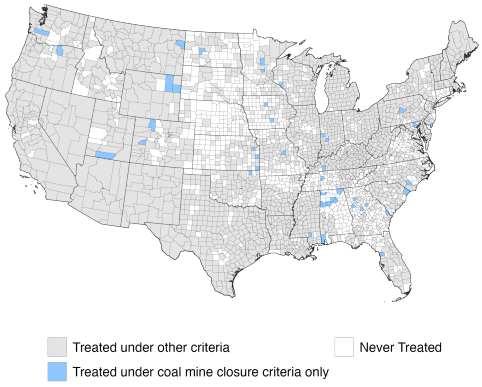
(a) Counties under any of the three criteria



(b) Counties under the brownfield criteria



(c) Counties under the unemployment thresholds



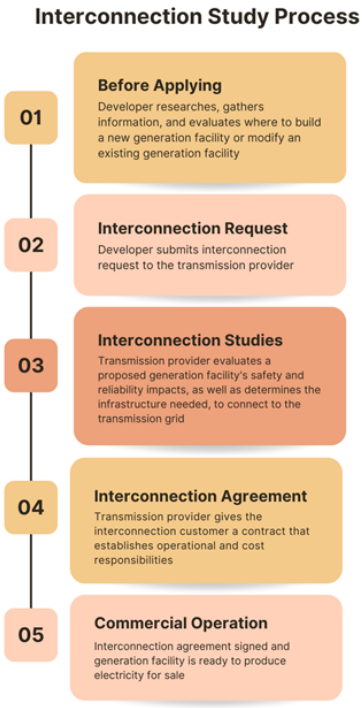
(d) Counties under coal mine or coal plant closures

Notes: This figure shows counties eligible under the energy community (EC) tax credits in blue shade (treated counties). Figure 1b shows counties that are eligible under any one (or more) of the three EC criteria, namely presence of a brownfield (EC1), unemployment thresholds (EC2), or coal mine or coal plant closure (EC3). Figure 1b shows counties eligible under brownfield criteria only. Figure 1c shows counties eligible under the unemployment thresholds criteria only, and Figure 1d shows counties eligible under coal mine or coal plant criteria only. Never-Treated counties are not eligible under any criteria and are shown in white shade. In Figure 1b, Figure 1c, Figure 1d, counties that are treated under some other criteria are shown in grey shade .

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 required by the transmission system operators, such as Independent System Operators (ISOs), Regional Transmission Organizations (RTOs), or utilities, to assess the impact of new capacity injections on the local and the overall grid. 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: Flowchart of the Transmission Interconnection Study Process



Notes: This figure illustrates the steps a project developer must follow to complete the interconnection process. While there exist subtle differences across individual markets, the process is the same at a high-level. Source: FERC (2024)

Figure 2 presents a flowchart outlining the key steps in the interconnection process. Recall, that our outcome of interest— transmission interconnection requests, corresponds to the second step in the chart. Before submitting interconnection requests, developers gather information to determine the preferred site for their project. This is

the Step 1 in Figure 2. This includes providing proof of land-use agreements for the project site, also known as "site control." Transmission interconnection request submissions (Step 2) reflect project siting preferences, which are the core focus of our study.

After submitting the interconnection request (Step 2), each project undergoes a series of interconnection studies (Step 3). These are a series of typically three engineering studies that assess feasibility, system impact, and facility requirements for the proposed generation. Upon successfully completion of these studies, developers sign an interconnection agreement with the transmission service providers (Step 4). This agreement outlines the technical and financial terms for grid connection. Finally, once construction is complete, the project can sell its power to the grid or to a off-taker(s) (Step 5). The project is now under commercial operation.

Given that the entire process typically takes several years, and considering that projects benefit from the Production Tax Credit or the Investment Tax Credit only after their construction- it is reasonable to assume that interconnection request submissions reflect project siting preferences in response to the policy implementation. More precisely, they capture the upper bound of the policy effect on project siting decisions.

3 Data and Descriptive Statistics

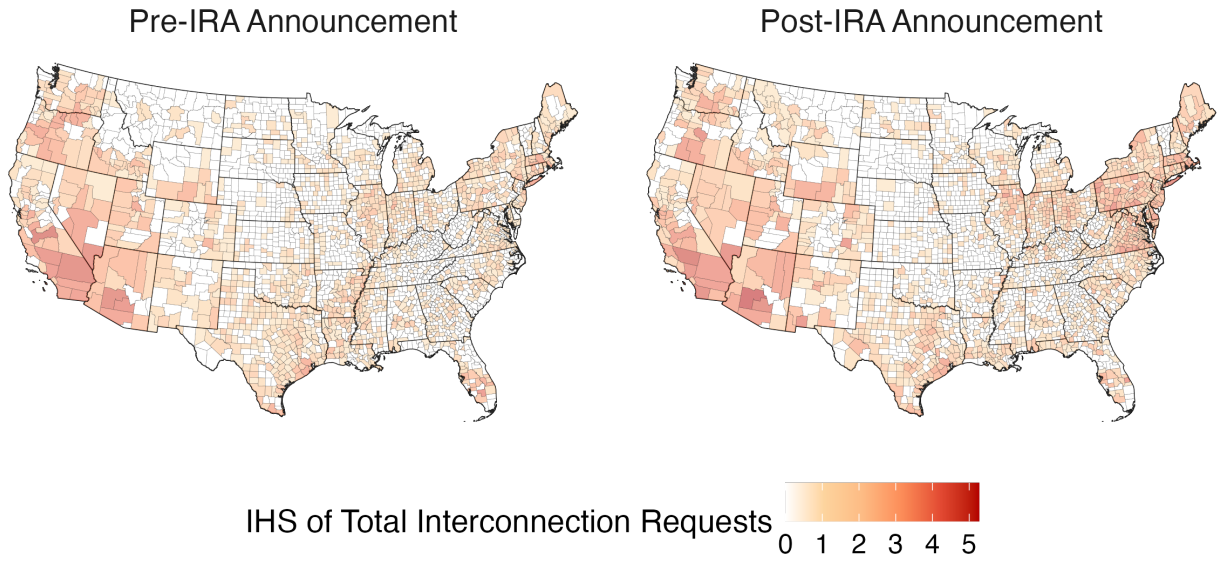
We obtain transmission interconnection requests submitted between 2020 and 2023 from a publicly available dataset provided by Lawrence Berkeley National Laboratory (LBNL). This dataset documents county-level interconnection requests with detailed generator characteristics including fuel type, capacity, county location, transmission owner territory, and project status across the entire U.S.. To reduce variance in the time series and address potential confunding effect of seasonal request patterns that might be correlated with treatment status, we deseasonalize the request data. [3]

Figure 3 shows the inverse hyperbolic sine (IHS) transformation of the total number of interconnection requests in each county before and after the announcement of the Energy Community Tax Credits in August 2022. The distribution of interconnection request

3. The seasonal adjustment procedure involves estimating separate regression models for each county, controlling for quarterly indicator variables and a linear time trend using only pre-IRA announcement data. We use the estimated coefficients to partial out the seasonal variation from the quarterly data in both the pre- and post- treatment periods.

submissions is highly uneven, with most requests concentrated in the West Coast states - California, Oregon, Nevada, Utah, and Arizona - during the pre-IRA announcement period. The East Coast states observe a moderate number of transmission interconnection requests, while the Midwest states have relatively few submissions. Interestingly, after the IRA announcement, the number of interconnection requests increases significantly in the northeastern states, particularly in Pennsylvania and Maine, whereas the West Coast and Midwest states show little change.

Figure 3: Total Renewable Interconnection Requests Pre- and Post-IRA Announcement



Notes: This figure shows the spatial distribution of the inverse hyperbolic sine (IHS) of total (renewable) interconnection requests before and after the announcement of the energy community tax credits in August 2022.

Table 1 presents summary statistics for interconnection requests, comparing EC qualifying counties against counties that do not qualify for any EC tax credits (never-treated counties). The treatment timing is set to the third quarter of 2022, when the IRA was announced. Column (2) reports the average number of interconnection requests submitted in a treatment group before the IRA announcement in August 2022, while Column (4) presents the average number of interconnection requests submitted after the announcement. Column (6) reports the difference in means between the number of interconnec-

tion requests pre- and post-announcement along with the statistical significance from the corresponding t-test of means.

Table 1: Descriptive Statistics of Interconnection Requests in Counties Qualified under the Energy Community Tax Credits

Treatment Group	# Counties	Pre-Treatment		Post-Treatment		Difference (2) - (4)
		Mean	Std Dev	Mean	Std Dev	
	(1)	(2)	(3)	(4)	(5)	(6)
Eligible under any criteria	2161	0.28	1.10	0.30	1.43	0.024*
Eligible under EC1 only	1041	0.26	1.07	0.28	1.45	0.020
Eligible under EC2 only	376	0.17	0.61	0.22	0.70	0.044**
Eligible under EC3 only	47	0.18	0.62	0.33	1.05	0.157**
Eligible under EC1 and EC2 only	432	0.37	1.48	0.42	1.98	0.055
Eligible under EC1 and EC3 only	143	0.36	1.13	0.35	1.27	-0.013
Eligible under EC2 and EC3 only	45	0.29	0.87	0.27	0.88	-0.019
Eligible under all three criteria	77	0.48	1.17	0.30	0.89	-0.184***
Never-Treated Counties	950	0.15	0.67	0.15	0.69	0.002

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. 'Eligible under any criteria' includes counties that qualify for EC tax-credits under any (one or more) of the three criteria- brownfield, unemployment, and coal mine and plant closures. EC1, EC2, and EC3 restrict the treatment definition to the counties that qualify under either brownfield, unemployment, or coal mine and plant closure criteria respectively. EC1 & EC2, EC1 & EC3, and EC2 & EC3 defines treatment as a two-way combination of the three qualifying criteria. Finally, 'Eligible under all three criteria' restricts to counties that are qualified under all of the three criteria. Significance: *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Three interesting observations emerge from Table 1. First, we observe an increase in the average interconnection requests after the announcement in counties that only qualify under a single criteria. Second, there is a slight decline in interconnection requests in counties that qualify under two- or all of the three criteria. Third, there is no difference in the mean of interconnection requests among counties that do not qualify under any criteria (never-treated counties). Further, the average requests are smaller in the never-treated counties than any of the treated counties.

The descriptive patterns in Table 1 and Figure 3 along with the spatial distribution of treated counties under different eligibility rules, as shown in Figure 1 motivate using

an empirical strategy that relies on comparing each treatment group in Table 1 with a valid control group, before and after IRA announcement. To that end, we use a synthetic difference-in-differences approach which we describe in greater detail in the next section.

4 Empirical Strategy

We employ a synthetic difference-in-differences (SDID) framework that compares changes in renewable interconnection requests between treated counties (those that satisfy energy communities criteria) and never-treated counties (those that do not). We define treated counties based on predetermined criteria from the IRA: locations of brownfield sites (EC1), coal mines or coal plant retirements (EC2), and counties meeting specific unemployment thresholds (EC3). We consider all EC 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 EC 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 large-panel inference like in DID (Arkhangelsky et al. 2021). This approach addresses concerns regarding potential bias in SC when pre-treatment fit is imperfect and treatment is correlated with unobserved confounders (Ferman and Pinto 2021).

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

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

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.

Like with the synthetic control method, ω_i^{sdid} are the unit-specific weights chosen to minimize the mean squared difference in pre-treatment trends between the treated units (energy communities counties) and the control units (non-qualifying counties). This minimization is subject to a regularization constraint that increases dispersion (or sparsity) and ensures uniqueness of the estimated weights.[4]

The time-weights, λ_t^{sdid} are chosen to minimize the sum of squared differences between time-weighted pre-period outcomes and the average post-period outcomes of the control units. This approach reduces the weights of the pre-treatment observations that deviate substantially from typical patterns observed in the post-period. In other words, these weights adjust temporary shocks that may create atypical pre-period outcomes in the control units that differ substantially from the post-period outcomes.[5]

The Synthetic DID technique 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.

For statistical inference, we employ block bootstrap technique. 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 to construct the 95 percent confidence intervals.

4. Mathematically, this constraint can be written as: $\omega_i \geq 0$ 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.

5. Mathematically, these time-weights $\hat{\lambda}$ 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 $\sum_{t=1}^{T-1} \lambda_t = 1$.

5 Results

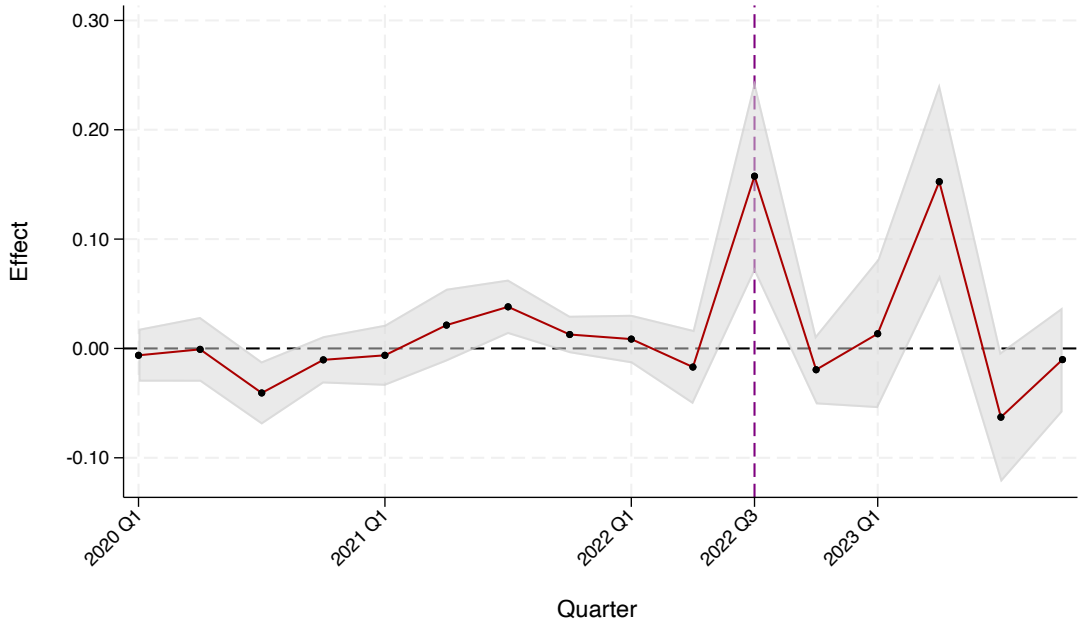
Figure 4 shows the event-study estimates for the empirical model specified in Equation 1, utilizing seasonally adjusted renewable interconnection requests. We define the treatment period as quarters beginning with Q3-2022, following the announcement of the IRA in August 2022. Our treatment group comprises all counties eligible under any energy community criterion (designated as "Either EC"). The coefficient estimates show that the treatment counties and their corresponding synthetic control units follow a parallel trend during the pre-treatment period. Following the August 2022 announcement of energy communities tax credits, we observe a clear positive treatment effect in eligible counties. The post-treatment estimates capture the treatment effects in the periods following the policy announcement in August 2022.

The results also exhibit certain seasonal patterns in Q4-2022 and Q1-2023, followed by a peak in Q2-2023. While our current data limitations prevent identification of long-term dynamics, this seasonality aligns with traditional fluctuations in interconnection requests. These seasonal trends typically occur due to factors like annual budget cycles, weather-dependent construction schedules, and fiscal year planning considerations for renewable energy developers operating in both the treated and control counties. Furthermore, these patterns are consistent with industry observations, where permitting delays and regulatory processes can impact the timing of renewable energy projects.

Table 2 shows the aggregate treatment effects estimates for the various energy communities (EC) eligibility criteria on renewable interconnection requests based on Equation 1. The treatment indicator (EC-eligible) equals one for EC counties in periods after the IRA announcement. We disaggregate results by the three eligibility criteria: EC1, EC2, and EC3 represent counties qualifying under brownfield sites, unemployment thresholds, or coal mine and plant retirements, respectively.

Table 2 Column (1) shows that on average, counties eligible under any of the three criteria saw a 0.036 increase in interconnection requests. With about 0.287 interconnection requests on average in the pre-treatment period, this represents an approximately 13 percent increase. This aggregate effect shows the overall effectiveness of this policy in stimulating renewable energy development interest in the targeted communities. Table 2 Columns (2) to (4) show that counties qualifying solely through presence of brownfield sites (EC1) saw a 16 percent increase, while counties qualifying solely through unem-

Figure 4: 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)). This is the 'Eligible under any criteria' group in Table 1.

ployment thresholds criteria (EC2) saw a 25 percent increase in interconnection requests. Most notably, counties qualifying only through coal plant or coal mine closure criteria (EC3) exhibit the largest effect: a 0.152 average increase or a 94 percent increase in interconnection requests. All of these effects are economically and statistically significant.

The substantially larger effect in counties eligible under the coal plant closure criteria likely reflects several factors. First, these areas may have existing grid infrastructure from decommissioned power plants significantly reducing interconnection costs for renewable developers. Second, these communities often have a skilled energy workforce seeking employment following plant closures. Third, local governments in these areas may be

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

	Either EC	EC1 Only	EC2 Only	EC3 Only
	(1)	(2)	(3)	(4)
EC-eligible	0.036*	0.040*	0.045*	0.155**
	(0.019)	(0.023)	(0.023)	(0.069)
County FE	✓	✓	✓	✓
Quarter-by-Year FE	✓	✓	✓	✓
Pre-treatment Mean	0.287	0.249	0.179	0.165
# Treated Counties	2,161	1,041	376	47
# Control Counties	950	950	950	950
Observations	49,776	31,856	21,216	15,952

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 interconnection requests. Sample is county-level quarterly data from 2020 to 2023. EC1, EC2, and EC3 refer to the three EC criteria, namely presence of a brownfield site, unemployment thresholds, and coal mine and plant closure criteria, respectively. EC-eligible is the treatment indicator equal one if county i is eligible for the EC tax credits in quarter-year t. Column (1) shows the treatment effect for counties that are eligible under either of the three criteria. Columns (2) - (4) show treatment effect estimates for the counties that eligible for EC tax-credits only through one of the three criteria. 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.

particularly motivated to expedite permitting processes to replace lost tax revenue from closed coal generation facilities.

Table 3 Columns (1) to (3) report estimates for counties qualifying under two-way combinations of the three criteria. Counties meeting both brownfield and unemployment criteria show an average increase of 20 percent in interconnection requests. However, other two-criteria combinations are positive but statistically indistinguishable from zero. We cannot rule out effects of the magnitude -0.103 to 0.117 for counties qualified both

from brownfield and plant closure criteria, -0.089 to 0.127 for counties qualified both from unemployment and plant closure criteria.

Table 3: Impact of the Energy Communities Tax Credits on Renewable Interconnection Requests

	EC1 & EC2	EC1 & EC3	EC2 & EC3	EC1 & EC2 & EC3
	(1)	(2)	(3)	(4)
EC-eligible	0.077*	0.007	0.034	-0.164**
	(0.046)	(0.056)	(0.063)	(0.067)
County FE	✓	✓	✓	✓
Quarter-by-Year FE	✓	✓	✓	✓
Pre-treatment Mean	0.384	0.356	0.449	0.618
# Treated Counties	432	143	45	77
# Control Counties	950	950	950	950
Observations	22,112	17,488	15,920	16,432

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 number of interconnection requests. Sample is county-level quarterly data from 2020 to 2023. EC1, EC2, and EC3 refer to the three EC criteria, namely presence of a brownfield site, unemployment thresholds, and coal mine and plant closure criteria, respectively. EC-eligible is the treatment indicator equal one if county i is eligible for the EC tax credits in quarter-year t. Columns (1) - (3) report treatment effect estimates for counties that qualify under a two-way combination of the three criteria. Column (4) shows the treatment effect estimates for the counties that qualify under all the three criteria. 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.

Interestingly, Column (4) in Table 3 shows that counties qualifying under all three criteria, experience a 26 percent decline in interconnection requests from the pre-treatment average of 0.618 requests. This effect is significant at the 5 percent level. This counterintuitive finding may reflect a confluence of several underlying mechanisms. These counties likely face the most severe economic challenges and structural barriers to development. This may translate to higher perceived risks to investments or barriers to entry for renewable developers in these locations. Second, these locations are likely to be out-competed by locations that qualify for at least one criteria. In other words, this

negative effect may be a result of crowding-out or shifting of renewable investment from these counties to other EC eligible counties that are less economically vulnerable with lower barriers to entry.

These results indicate that while the IRA energy communities tax credits generally stimulate renewable interconnection requests, the effectiveness varies substantially across qualification types. The program appears most effective in single-criteria communities, particularly those with plant closures, suggesting targeted policy design may be more effective than broader qualification approaches. The negative effect in triple-qualifying communities highlights the need for additional complementary policies beyond tax incentives in the most economically distressed areas, potentially including infrastructure investments, workforce development programs, and streamlined permitting processes to fully realize the intended benefits of the energy transition.

To further understand the underlying mechanisms driving developer decision-making, we propose a structural approach that models firms' location choice decisions based on expected profit from investing in a location which includes the effect of energy community tax credit. Appendix B describes the structural model of project location choice. We model the location choice problem of a renewable developer as a function of expected revenue (due to location specific output prices and expected energy production) and costs (e.g. due to land value, zoning, capital expenditure, and terrain characteristics). The energy community tax credits enter the profit function through their effect on expected location-specific prices a project receives for its power.

Estimating a structural model of location choice will allow us to evaluate a variety of policy relevant counterfactual scenarios. We will use the estimated model to estimate the distribution of renewable investments under alternative location-eligibility criteria, alternative tax-credit amounts, as well as a combination of alternative location and tax credit designs.

6 Conclusion

Our study of the IRA energy communities tax credits reveals economically and statistically significant effects of energy community tax-credit eligibility on renewable energy interconnection requests. Using a synthetic difference-in-differences strategy, we find

an overall 14 percent increase in interconnection requests following the IRA announcement, with the most dramatic response in counties qualifying under the coal plant or coal mine closure criteria (about a 94 percent increase) compared to more modest effects in counties qualifying under brownfield and unemployment thresholds criteria (14 and 25 percent respectively). Notably, counties qualifying under all three criteria experience a 25 percent decline in interconnection requests, suggesting that the most distressed communities face barriers that tax incentives alone cannot overcome.

These findings contribute to both energy policy and economic development literature by highlighting how geographically-targeted tax incentives affect renewable energy investment decisions. While the IRA energy communities provisions represent a promising approach to linking climate and economic goals, our results suggest that complementary policies addressing infrastructure investment, workforce development, and regulatory streamlining may be necessary in the most challenged communities. Further structural modeling of developer decision-making will help identify the precise mechanisms driving these differential responses as well as inform spatial distribution of renewable investments under a variety policy relevant counterfactual scenarios.

References

Arkhangelsky, Dmitry, et al. 2021. "Synthetic Difference-in-Differences." *American Economic Review* 111 (12): 4088–4118.

Ashenfarb, Matthew. 2024. "A Place-Based Clean Electricity Subsidy and its Effect on Emissions." *Available at SSRN 4997027.*

Bistline, John, et al. 2023. "Emissions and energy impacts of the Inflation Reduction Act." *Science* 380 (6652): 1324–1327.

Bistline, John ET, Neil R Mehrotra, and Catherine Wolfram. 2023. "Economic implications of the climate provisions of the inflation reduction act." *Brookings Papers on Economic Activity* 2023 (1): 77–182.

Boer, Lukas, Andrea Pescatori, and Martin Stuermer. 2023. "Energy Transition Metals: Bottleneck for Net-Zero Emissions?" *Journal of the European Economic Association,* jvad039.

Bushnell, James B, and Aaron Smith. 2024. *Modeling Uncertainty in Climate Policy: An Application to the US IRA.* Technical report. National Bureau of Economic Research.

Clarke, Damian, et al. 2024. "On synthetic difference-in-differences and related estimation methods in Stata." *The Stata Journal* 24 (4): 557–598.

Davis, Lucas W, Catherine Hausman, and Nancy L Rose. 2023. "Transmission impossible? Prospects for decarbonizing the US grid." *Journal of Economic Perspectives* 37 (4): 155–180.

Dench, Daniel, Mayra Pineda-Torres, and Caitlin Myers. 2024. "The Effects of Post-Dobbs Abortion Bans on Fertility." *Journal of Public Economics* 234:105124.

Doshi, Gaurav. 2024. "Chicken and Egg: Electricity Transmission and Investment in Renewable Energy." Working Paper.

Doshi, Gaurav, and Sarah Johnston. 2024. "Market Structure and Technology Adoption in Renewable Energy." Working Paper.

FERC. 2024. *Explainer on the Interconnection Notice of Proposed Rulemaking.* Retrived from: https://www.ferc.gov/explainer-interconnection-notice-proposed-rulemaking.

Ferman, Bruno, and Cristine Pinto. 2021. "Synthetic Controls with Imperfect Pretreatment Fit." *Quantitative Economics* 12 (4): 1197–1221.

Gowrisankaran, Gautam, Stanley S Reynolds, and Mario Samano. 2016. "Intermittency and the value of renewable energy." *Journal of Political Economy* 124 (4): 1187–1234.

Heal, G. 2020. *Economic aspects of the energy transition (No. 27766).* Technical report. Working paper series. National Bureau of Economic Research.

Internal Revenue Service. 2024. *Tax Credits.*

Johnston, Sarah, Yifei Liu, and Chenyu Yang. 2024. "An Empirical Analysis of the US Generator Interconnection Policy." Working Paper.

Joskow, Paul L. 2019. "Challenges for wholesale electricity markets with intermittent renewable generation at scale: the US experience." *Oxford Review of Economic Policy* 35 (2): 291–331.

McCrary, Justin. 2007. "The effect of court-ordered hiring quotas on the composition and quality of police." *American Economic Review* 97 (1): 318–353.

Raimi, Daniel, and Sophie Pesek. 2022. "What is an 'energy community'? Alternative approaches for geographically targeted energy policy." *Resources for the Future. November* 1.

Sun, Xiaochen. 2023. "Impacts of Uncertainty in Transmission Interconnection on Energy Transition." Working Paper.

U.S. Department of Energy. 2024. *Energy Community Tax Credit Bonus.* Retrived from: https://energycommunities.gov/energy-community-tax-credit-bonus/.

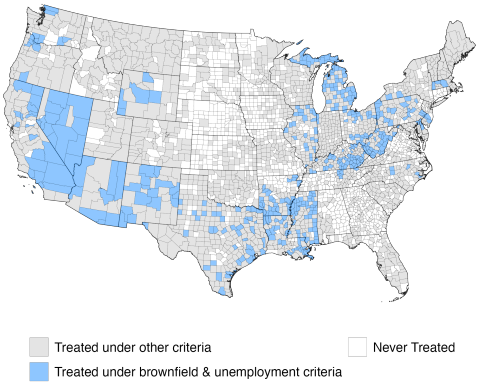
———. 2025. *Energy Community Tax Credit Bonus Map.* Retrived from: https://arcgis.netl.doe.gov/portal/apps/experiencebuilder/experience/?id=a2ce47d4721a477a8701bdoe08495e1d.

Wolak, Frank A. 2020. "Integrating renewable generation into electricity markets." *NBER Reporter,* no. 3, 16–19.

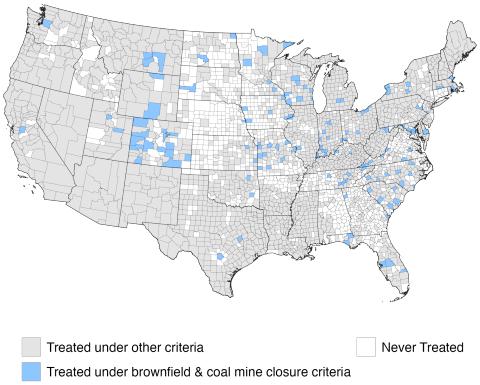
Appendix

A Supplementary Tables and Figures

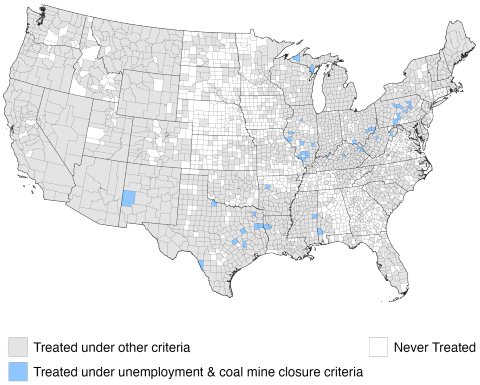
Figure A 1: Map of Counties Eligible under the Energy Community Credits



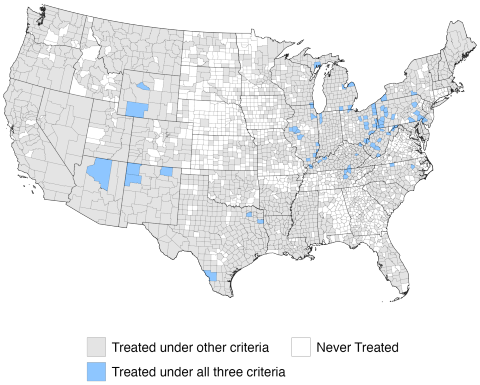
(a) Counties under brownfield & unemployment thresholds



(b) Counties under the brownfield & coal mine or coal plant closure



(c) Counties under the unemployment thresholds & coal mine or coal plant closure



(d) Counties satisfying all three criteria

Notes: This figure shows counties eligible under the energy community (EC) tax credits in blue shade (treated counties). Figure A 1a shows counties that are eligible under the brownfield and unemployment thresholds criteria only. Figure A 1b shows counties eligible under brownfield and coal mine or coal plant closure criteria only. Figure A 1c shows counties eligible under the unemployment thresholds and coal mine or coal plant closure criteria only, and Figure A 1d shows counties that are eligible under all three criteria. Never-Treated counties are not eligible under any criteria and are shown in white shade. Counties that are treated under some other criteria are shown in grey shade .

B Structural Model of Project Location Choice

In this section, we develop a theoretical model of renewable project location choice, for each technology type (solar and wind). This serves as a microfoundation for the discrete choice model.

A developer i chooses location j to maximize the net present value of annual profits from the project. The static profits for a period t can be written as:

$$\pi_{ijt} = p_{ijt}Q_{ijt} - C_{ijt} \tag{3}$$

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

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

where, F_{ij} is the location-specific fixed costs incurred at time of project siting decision. The uncertainty in annual (static) profits is due to the uncertainty in the price received by the project for its power and the uncertainty in the energy production. The latter is a feature of the inherent uncertainty in renewable resources whereas the former is due to wholesale market volatility or inflation.

Renewable developers often sign long-term contracts to sell their power to potential buyers (e.g. utilities, industrial customers, retailers etc.). These contracts generally fix price per MWh of output while allowing for pre-specified escalations to account for inflation (Doshi 2024). While this off-take decision happens after the site-selection step, we use the average of wholesale price in year t from the nearest hub to location j to approximate the effect of prices in a project's location choice problem.

We next calculate the annual energy generation Q_{ijt} for project i at site j as a product of system size (nameplate capacity) and the site specific capacity factor. This provides an approximation of the total annual energy production by the project at location j. C_{ijt} is the vector of operations and maintainable costs incurred by project each year during its

operation. This includes maintenance costs of equipments specific to each technology (solar and wind) and annual lease payments to the landowners. Finally, F_{ij} are the fixed costs associated with building a renewable project of a particular technology. These include costs of equipment procurement as well as transaction costs incurred during project siting, for instance, permit costs.

The energy community bonus credits for a site j enhance the returns from energy production at that site. Denoting the per-MWh credits at location j at period t to be τ_{jt}, the profit function in Equation 4 can be represented as,

$$\Pi_{ij} = \sum_{t=1}^{T} \gamma(r) \mathbb{E}\Big[(p_{ijt} + \tau_{jt}) Q_{ijt} - C_{ijt}\Big] - F_{ij} \tag{5}$$

where, $\gamma(r) = \left(\frac{1}{1+r}\right)^t$. Note that our goal is to model the location selection decision of a project i. To that end, we make two simplifying assumptions in Equation 5. First, we assume that the energy production remains constant over the life of the project. This allows us to replace Q_{ijt} with per-period production Q_{ij}. Second, we assume that the project takes into account the contemporaneous price at site j while making the location decision.

Denoting y as the period when the project makes the location choice decision, the static utility (at period y) corresponding to the profit function in Equation 5 is,

$$U_{ijy} = \beta \cdot (p_{ijy} + \tau_{jy} \cdot \mathbf{1}[j \in Br]) Q_{ij} + \Lambda X_{ijy} + \delta_y + \epsilon_{ijy} \tag{6}$$

where, p_{ijy} is the per-MWh price of electricity at site j and period y for project i, τ_{jy} is the tax credit in period y and $\mathbf{1}[j \in EC]$ is an indicator for whether site j qualifies for the Energy Community (EC) tax-credit under the IRA. The vector X_{ijy} summarizes factors affecting location-specific operations and maintenance costs, and location-specific fixed costs incurred during the location choice in period y. We include average farm size, average farm value, terrain elevation, terrain ruggedness (measured as the standard deviation of elevation), county level variables measuring local permitting (ordinance). Additionally, we control for the implementation of state level policies like Renewable Portfolio Standards that could influence renewable investment at a location j. Finally,

we include year fixed effects δ_y to account for common time shocks that could affect the project location choice.

B.1 Constructing project specific choice set

For each project i, we construct a choice set of potential locations J that are comparable in terms of renewable resource quality and costs of project development. Following (Doshi 2024), we use a K-Nearest Neighbor algorithm to identify sites that share key characteristics with the chosen location across multiple observable dimensions. Specifically, we use site-specific electricity prices, renewable resource potential, average farm size and value (to capture land cost), terrain elevation and ruggedness (to capture terrain type), and an indicator for the presence of local regulations that might restrict renewable project development.

Assuming that errors ϵ_{ijy} follow Type 1 Extreme Value (T1EV) distribution, the probability of choosing location j among the choice-set of J locations associated with the utility specification in Equation 6 is,

$$\Pr(ij) = \Pr(U_{ijy} \geq U_{ij'y}, \quad \forall j, j' \in J; j' \neq j) \tag{7}$$

$$= \Pr(\epsilon_{ij'y} - \epsilon_{ijy} \leq \psi_{ij'y} - \psi_{ijy}, \quad \forall j, j' \in J; j' \neq j) \tag{8}$$

$$= \frac{\exp(\psi_{ijy})}{\sum_{j \neq j'} \exp(\psi_{ij'y})} \tag{9}$$

where $\psi_{ijy} = \beta \cdot (p_{ijy} + \tau_{jy} \cdot \mathbf{1}[j \in Br])Q_{ij} + \Lambda X_{ijy} + \delta_y$. We estimate the probability of location choice in Equation 9 using a conditional logit model. Note that any project-specific costs that are location invariant will drop out of this multinomial choice situation.[6]

B.2 Evaluating policy relevant counterfactuals

Using the estimated model primitives from the utility specification in Equation 6, we evaluate market shares of renewable investment across counties under three main policy

6. This includes costs of equipment procurement for different renewable technologies, for instance, costs of solar panels and wind turbines. Because these equipments are purchased in a global market, we expect the costs to uniform across the US (Doshi and Johnston 2024).

counterfactuals.[7] First, we estimate project location choices under alternative location-eligibility criteria, while maintaining a constant tax credit amount (τ_{iy}). We construct alternative lists of eligible energy community sites and compare the resulting spatial distribution of renewable investments against the observed patterns. This analysis aims to evaluate whether modified eligibility criteria could successfully attract investment to locations that current definitions fail to reach, particularly focusing on the most economically vulneable communities.

Second, we evaluate renewable investment responses to different tax-credit designs. Under the current IRA framework, projects constructed in eligible energy community sites receive a 10 percent adder to the existing Production Tax Credit or Investment Tax Credit. Holding the list of eligible energy community sites constant, we evaluate how alternative tax credit amounts—ranging from 5 to 15 percent, for instance—affect the market shares of renewable investment in those locations, identifying potential threshold effects or diminishing returns.

Finally, we examine counterfactual scenarios that simultaneously vary both eligible sites and tax credit amounts. This scenario studies the interaction effects between eligibility criteria and incentive levels, aiming identify optimal policy combinations that maximize renewable development in fossil fuel-dependent communities while minimizing program costs.

7. Note that market shares are defined as the estimated probability of choosing a county under different policy scenarios.

C Selected CIMC Filters to Identify Brownfield Sites Eligible for the EC Tax Credit

This section details our methodological approach for identifying brownfield sites eligible for the Energy Community Tax Credit under the Inflation Reduction Act (IRA). 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 C1 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.

Table C1: 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.