Environmental Consequences of Policies that Combine Distributional and Clean Energy Goals: The Energy Community Bonus Effect on Greenhouse Gas Emissions

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Abstract

Recent United States (US) subsidies for clean technology incorporate mechanisms to promote particular geographic or socioeconomic distributions of the technologies and their environmental benefits. Examples include place-based or means-tested subsidies. But the two goals – reducing carbon emissions and distributing benefits equitably – may or may not be complementary. Redistributing subsidies could amplify or reduce their environmental benefits. This project focuses on one example, the Inflation Reduction Act (IRA) Energy Community Bonus, a place-based subsidy for clean electricity. Energy Communities are areas with local economies historically reliant on the fossil fuel industry. The Bonus is designed to steer renewable electricity investment toward those places because they are the most likely to face economic hardship from the clean energy transition. I ask how the Bonus affects the climate benefits of subsidies by changing where new clean electricity generators are built. Answering that question requires two empirical steps. The first step estimates the effect of the Energy Community Bonus on the spatial distribution of future solar and wind plants. It leverages discontinuities in the various criteria used to characterizes places as Energy Communities to create plausibly exogenous distinctions between areas designated as Energy Communities and areas that are not. The second empirical step estimates how carbon reductions from a new renewable energy generator depend on county location, time of day, and season. Combining the Bonus effect on renewable generation with the renewable generation effect on emissions produces an estimate of the Bonus effect on emissions.

1. Introduction

Recent US policies have combined climate and energy goals with distributional objectives. For example, the Inflation Reduction Act (IRA) grants subsidies to buyers of electric vehicles, but only if the buyers' incomes are below a threshold. The Weatherization Assistance Program (WAP) subsidizes

improvements to homes' energy efficiency for low-income households. Some states use Regional Greenhouse Gas Initiative (RGGI) auction proceeds to target energy efficiency and clean technologies to low-income communities. And the IRA provides a bonus tax credit for clean electricity in areas historically reliant on fossil fuels for employment and tax revenues, the Energy Community Bonus, which is the focus of this paper.

Does the Energy Community Bonus help or hinder the policy's environmental goals? The answer is not obvious. Electricity generators are built where they are most profitable, not where they have the largest environmental benefits, and place-based subsidies change the spatial distribution of profitability. So, it is possible that shifting investments to Energy Communities with a place-based subsidy will better align profitability and environmental benefits. But the reverse may also be true, such that the Bonus reduces the environmental benefits of clean electricity subsidies.[1]

More specifically, the environmental effect of the Energy Community Bonus depends on two factors. First, it depends on the extent to which the Bonus shifts renewable electricity generation to Energy Communities. If the Bonus does not steer renewable generation to Energy Communities, then it cannot have an environmental effect. Second, presuming the Bonus affects renewable generation, any resulting environmental effect depends on characteristics of local electricity grids. A solar or wind plant reduces emissions by reducing fossil fuel use. So, the environmental benefit of the Bonus depends on how much fossil fuel use it displaces, a function of the local marginal emissions rate. Accordingly, I conduct empirical analysis in two steps, the first estimating the Bonus effect on renewable generation, and the second estimating marginal emissions.

A challenge to the first step is that it is almost certainly too early to directly measure the effect of the Energy Community Bonus on electricity generation. While the Energy Community Bonus has been available since August 2022, there is a substantial time lag between planning a new renewable energy facility and connecting to the national electricity grid.[2] The median lag between connection request and commercial electricity generation for a project built in 2023 was 5 years (Rand, et al., 2024). A new electricity project is said to be "in the interconnection queue" during the time between requesting connection and commercial operation. Therefore, it is unlikely any new renewable plants coming online today were impacted by the Energy Community Bonus. Instead of directly estimating the effect of the Bonus on generation, I estimate the Energy Community Bonus effect on proposed new capacity in the interconnection queue. I then use the estimated queue effect to make inferences about future renewable generation. I expect these results of this first step to be of interest, even without the second, as they will represent the earliest empirical evidence as to whether the Energy Community Bonus is working as intended.

The second empirical step measures the variation marginal CO_2 emissions across in the US. Previous research has measured spatial variation in marginal emissions at the level of grid interconnections

[1] Put differently, unlike carbon taxes, second-best subsidy mechanisms do not inherently equalize and minimize abatement costs. The subsidies distort clean energy markets, creating a deadweight loss (DWL). The subsidies also have knock-on effects of displacing dirty energy with a net social gain. Redistributing the subsidy could be efficiency reducing or enhancing, generating more or less DWL in the clean market per social gain in the dirty market.

[2] The lifecycle of a new electricity project is first a developer makes a grid interconnection request, placing the project in the interconnection queue. Then a series of feasibility and technical studies are conducted to assess the feasibility and impact of the new facility's connection to the grid. If a project is deemed feasible, then the next step is to negotiate responsibility for the cost of interconnection, and to what extent it falls on the project developer and utility. Finally, a project is constructed, connected to the grid, and begins commercial operation.

(Holland, et al., 2022; Graff Zivin, et al., 2014), NERC regions (Siler-Evans, et al., 2012), or balancing authorities (Callaway, et al., 2018; Fell & Kaffine, 2018), assuming marginal emissions are constant within those regions. However, Energy Communities are defined at a geographic scale much smaller than any of these regions, so it is possible that the Bonus shifts renewable generation intra-regionally. It is likely that marginal emissions vary within regions because of persistent grid congestion. Therefore, I estimate county-level, hourly marginal emissions. The estimation uses exogenous variation in county-level renewable electricity generation. The result is the most geographically disaggregated econometric measure of marginal emissions estimates to date.

Finally, I combine the two steps to estimate the how the Energy Community Bonus changes the marginal emissions displaced by new renewable electricity generation. I evaluate three alternative policy counterfactuals: no bonus, a bonus everywhere, and an in-between scenario in which the same total subsidy is allocated without a place-based bonus.

2. The Energy Community Bonus

The Inflation Reduction Act of 2022 (IRA) offers two nationwide tax credits for new clean electricity. The Investment Tax Credit (ITC) subsidizes 30 percent of construction costs, and the Production Tax Credit (PTC) subsidizes 10 years' worth of electricity generation at $5.50 per megawatt-hour (MWh) in 2023, indexed to rise with inflation.[3] The credits are not combinable, so clean electricity developers must choose which to claim. The Energy Community Bonus increases the ITC by 10 percentage points and the PTC by 10 percent for projects located in eligible areas.

The IRA defines Energy Communities according to three criteria described in Table 1. The first is brownfield sites. These are parcels of land that are underutilized due to pollution, mine scars, or other residual effects of former industrial use. The second category is metropolitan statistical areas (MSAs) or non-metropolitan statistical areas (non-MSAs) that meet criteria based on fossil fuel industry employment or local tax revenues at any time after December 31, 2009, plus a criterion based on local unemployment rate in the previous year.[4] The final Energy Community category is census tracts in which a coal mine closed after December 31, 1999, or a coal-fired electricity generating unit retired after December 31, 2009.[5]

[3] The PTC value reported assumes the project meets wage and apprenticeship requirements for 10 years, and does not meet the domestic content requirement. The baseline credit value is $5.50 per megawatt-hour (MWh), multiplied by 5 for meeting wage and apprenticeship requirements, with an additional 10 percent for domestically produced construction materials and finished goods.

[4] Since designations depend on previous unemployment rates, locations may change their Energy Community status from year to year. But Energy Community Bonus eligibility for projects claiming the PTC is determined at the beginning of the projects' construction date, so they are not at risk of losing the Bonus if its location loses its Energy Community status. This applies to all projects constructed 2023 or later. Any projects placed in service August to December 2022 and claiming the PTC are at risk of losing the Energy Community Bonus if their MSA or non-MSA loses its Energy Community status.

[5] MSAs and non-MSAs are groups of counties. Counties are groups of census tracts. So, the greatest common factor of non-brownfield Energy Communities are census tracts.

(1) Brownfield site	or	**(2) Metropolitan statistical area or non-metropolitan statistical area (MSA or non-MSA) with…**			or	**(3) Census tract with…**		
		0.17% or greater direct employment related to the extraction, processing, transport, or storage of coal, oil, or natural gas at any time after Dec. 31, 2009 or 25% or greater local tax revenues related to the extraction, processing, transport, or storage of coal, oil, or natural gas at any time after Dec. 31, 2009*	and	Unemployment rate at or above national average unemployment rate for the previous year		A coal mine has closed after Dec. 31, 1999, or a census tract which is directly adjoining to such census tract	and	A coal-fired electric generating unit has been retired after Dec. 31, 2009, or a census tract which is directly adjoining to such census tract

*Although this definition is in the IRA legislation, there is currently no guidance on what data to use to quantify tax revenues, so in effect this provision is not enacted.

Table 1: Three definitions of an Energy Community. Table formatting and information from Energy Community Tax Credit Bonus - FAQs - Energy Communities.

Figure 1 maps the Energy Communities as of December 2023. Approximately 38 percent of the land area in the contiguous US is an Energy Community, with the largest concentrations in the Southwest, the Rocky Mountains, and Appalachia. The map omits brownfield sites because no single data source lists sites that qualify.[6] It also omits the areas that would qualify according to their local tax revenues because currently no Treasury guidance describes data that could identify locations meeting this qualification.

[6] The EPA produces data on brownfield sites eligible for federal Brownfield funding, but according to (IWG, 2024), "not all properties that qualify as brownfield sites eligible for federal Brownfield funding are included in the definition of brownfield site for purposes of the energy community bonus credit."

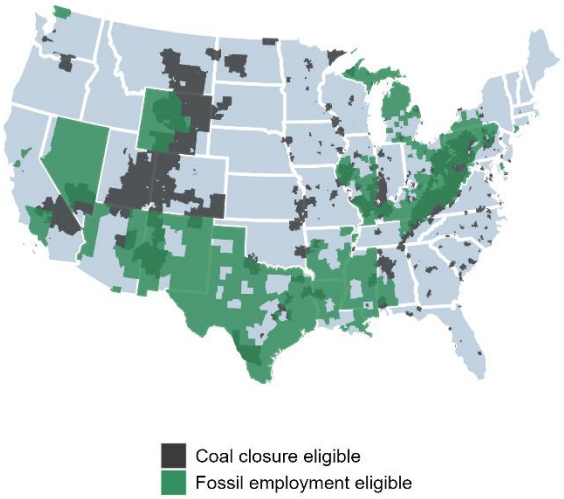


Figure 1: Energy Community census tracts, MSAs, and non-MSAs in 2023. This map uses definitions based on fossil fuel direct employment, coal mine closures, and coal electricity generator closures.

Tables 2 sketches the value of the Energy Community Bonus for a typical solar or wind electricity plant. Columns (1) and (2) show the annual value of the Energy Community Bonus for a typical plant claiming the PTC.[7] Column (1) shows the mean and median monthly generation of solar and wind plants in December 2022. Column (2) multiplies this value by the PTC value (assuming the entire plant qualifies and meets wage and apprenticeship standards), by 12 months, and by 10 percent to get the Energy Community Bonus value. For the mean solar plant, the bonus could be worth an extra $80 thousand per year, in addition to the standard production tax credit, and for the mean wind plant nearly $1 million per year. The PTC lasts for 10 years and adjusts with inflation, so the present value of locating in an Energy Community could be worth millions of dollars to prospective solar and wind developers.

Columns (3) and (4) of Table 2 show that for plants claiming the ITC, locating in an Energy Community is similarly valuable. Column (3) shows mean and median solar and wind plant capacities, and column (4) multiplies the capacity by the average construction cost per MW for solar and wind plants and by 10 percent. The mean solar plant would receive nearly $2.5 million in extra project subsidies for locating in an Energy Community, and an average wind plant an extra $16 million.[8]

[7] The baseline PTC in 2023 is $5.50 per megawatt-hour (MWh). This value is multiplied by 5 for facilities meeting wage and apprenticeship employment standards, by 1.1 for facilities meeting domestic content requirements, and by 1.1 for locating in an Energy Community. Table 2 assumes the wage and apprenticeship standards are met, but not the domestic content requirements. So the Bonus is calculated as $5.50×5×0.1=$2.75 per MWh.

[8] A caveat in interpreting these magnitudes is that the PTC and ITC subsidize generators, not plants. Plants contain many generators owned by a common entity. Nevertheless, the plant-level values are proportionate to generator-level values.

		Production Tax Credit		*Investment Tax Credit*	
		Monthly Net Generation 2022 (MWh/Month)	***Annual Bonus****	***Plant Capacity 2022 (MW)***	***Total Bonus***
		(1)	(2)	(3)	(4)
Solar	Mean	2,442	$ 80,576	15	$ 2,408,000
	Median	382	$ 12,623	3	$ 497,000
Wind	Mean	28,393	$ 936,954	108	$ 16,126,000
	Median	17,692	$ 583,828	82	$ 12,239,000

*****Assumes wage and apprenticeship requirements are met, domestic content bonus is not met, and 2023 PTC level. The PTC offers 10 years of tax credits increasing with inflation.

Table 2: The value of the Energy Community Bonus for mean and median solar and wind plants. Monthly net generation is calculated from EIA 923 forms for December 2022. Net summer capacities of are calculated from EIA 860 forms for December 2022. The ITC estimates use construction cost estimates from EIA (2022).

3. Energy Community Bonus Effect on Queued Renewable Capacity

The first part of this analysis estimates the Energy Community Bonus effect on proposed new capacity in the interconnection queue. I identify the effect using multiple strategies based on the Energy Community Bonus design. In Section 5, I use the interconnection queue effect to estimate the effect on future electricity generation.

3.A. Data to Measure the Energy Community Bonus Effect on the Interconnection Queue

Data on projects in the interconnection queue come from Rand, et al., (2024). The data include projects that enter the interconnection queue, their capacities and proposed energy types, their county locations, the date projects become operational if applicable, and the queue withdrawal date for projects that withdrew. The data track plants in the queue between 1995 and 2023. They cover all seven major Independent System Operators (ISOs) and Regional Transmission Organizations (RTOs) and 35 non-ISO utilities, accounting for approximately 85 percent of US electricity generation.

I also use the datasets described in US Treasury guidance that define Energy Communities (US Treasury, 2023; Bureau of Labor Statistics, 2022). Fossil fuel employment thresholds are defined using US Census County Business Patterns (CBP) for 2009 to 2023 (US Census, 2023). Local unemployment rates are calculated using the Local Area Unemployment Survey for 2021 and 2022 (US Bureau of Labor Statistics, 2023). Coal mine closure data are available from the US Department of Labor Mine Safety and Health Administration and coal electricity generator closures are available from the Energy Information Administration (EIA) 860 forms (MSHA, 2024; EIA, 2024).

3.B. Method to Estimate the Energy Community Bonus Effect on Interconnection Queue Entry

I use three strategies to estimate the effect of the Energy Community Bonus on the interconnection queue entry rate. Each strategy exploits a different threshold in the definition of Energy Communities, summarized in Table 3. The first strategy uses a sharp regression discontinuity design. It measures the difference in renewable projects queued in 2023 in counties within MSAs and non-MSAs with fossil fuel employment percents just above or below the 0.17% threshold.[9] I restrict the sample to exclude counties that contain census tracts qualifying for the Bonus due to a coal mine or coal generator retirement to isolate the effect of the fossil fuel employment threshold. I also restrict the sample of control counties to only those that meet the unemployment rate threshold, so they are similar in that regard to the treatment counties.

Specifically, the first strategy estimates the equation

$$Y_c = \alpha + \beta_1 D_{1m} + \gamma_{11}(MaxFFE_m - 0.17) + \gamma_{12} D_{1m}(MaxFEE_m - 0.17) + \boldsymbol{X_{1c}'\gamma_1} + \varepsilon_c, \qquad (1)$$

where Y_c is new renewable capacity entering the transmission queue in county c since the IRA passed, $D_{1m} = \mathbf{1}(MaxFFE_m \geq 0.17)$, $MaxFFE_m$ is the maximum percent of the workforce employed in fossil fuels between 2009 and 2023 of the MSA or non-MSA m that contains c, and $\boldsymbol{X_{1c}}$ are county-level controls that may determine wind or solar development. I estimate separate regressions for solar and wind, such that β_1 is the average additional wind or solar capacity in an Energy Community county.

[9] MSAs and non-MSAs are composed of counties, with counties fitting exactly into exactly one MSA or non-MSA, following the same boundaries. Counties are composed of census tracts, again with all census tracts in exactly one county, following the county boundaries. Therefore, census tract boundaries are the greatest common factor of Energy Communities. However, since interconnection queue data is at county-level spatial resolution, all analyses in this section are at the county-level.

	Treatment Sample	*Control Sample*	*Identification Strategy*
Strategy 1: Fossil fuel employment	Counties that belong to Energy Community MSAs or non-MSAs, excluding counties with coal Energy Communities.	Counties that are not Energy Communities in MSAs or non-MSAs that just miss the fossil fuel employment threshold but meet the unemployment rate threshold, excluding counties with coal Energy Communities.	Regression discontinuity. Running variable is maximum fossil fuel employment between 2009 and 2023, measuring a discontinuity is 0.17%.
Strategy 2: Unemployment rate		Counties that are not Energy Communities in MSAs or non-MSAs that just miss the unemployment rate threshold but meet the fossil fuel employment threshold, excluding counties with coal Energy Communities.	Regression discontinuity. Running variable is unemployment rate in 2023, measuring a discontinuity is 3.6%.
Strategy 3: Coal mine closure	Counties that contain Energy Community census tracts defined by coal mine closures, excluding counties with Energy Community tracts from a different definition.	Counties with no Energy Community tracts and coal mines that are not retired, excluding counties with Energy Community tracts from a different definition.	Coal mines closures are exogenous Energy Community assignments, conditional on observing county-level variables.

Table 3: Summary of strategies to identify the effect of the Energy Community Bonus on entrants to the grid interconnection queue at the county-level.

The second identification strategy relies on a discontinuity in the same eligibility criteria, but for the unemployment rate rather than the fossil fuel employment rate. MSAs and non-MSAs are Energy Communities if their local unemployment rates are at least as high as the national average for the previous year, so the sharp discontinuity for Energy Community status in 2023 is the unemployment rate in 2022, 3.6%. Analogously to the first strategy, here I restrict the set of potential control counties to only those without census tract defined as an Energy Community and that meet the 0.17% fossil fuel employment threshold, so eligibility depends solely on the local unemployment rate.

The second strategy regression is estimated similarly to the first,

$$Y_c = \alpha + \beta_2 D_{2m} + \gamma_{21}(Unemp_m - 3.6) + \gamma_{22} D_{2m}(Unemp_m - 3.6) + \boldsymbol{X'_{2c}\gamma_2} + \varepsilon_c, \qquad (2)$$

where $D_{2m} = \mathbf{1}(Unemp_m \geq 3.6)$, $Unemp_m$ is the unemployment rate of the MSA or non-MSA m that contains county c in 2022. Again, I run separate regressions for solar and wind capacity in the queue.

Figure 2 shows the counties defined as treatment and control locations from the first and second strategies. The green area shows Energy Community counties treated in 2023. The treated counties are a subset of the shaded area in Figure 1, excluding any counties that include a coal Energy Community. The yellow and brown shaded areas show counties that serve as controls for the first and second identification strategies, respectively. These counties do not contain any Energy Communities defined by MSAs, non-MSAs, or census tracts (although they may contain Energy Community brownfields). The yellow counties meet the unemployment rate threshold and just miss the fossil fuel employment threshold, with maximum fossil fuel employments since 2010 between 0.12% and 0.17%. The brown counties miss the unemployment threshold, with unemployment rates as low as 2.6%, and meet the maximum fossil fuel employment threshold of above 0.17% fossil fuel unemployment.

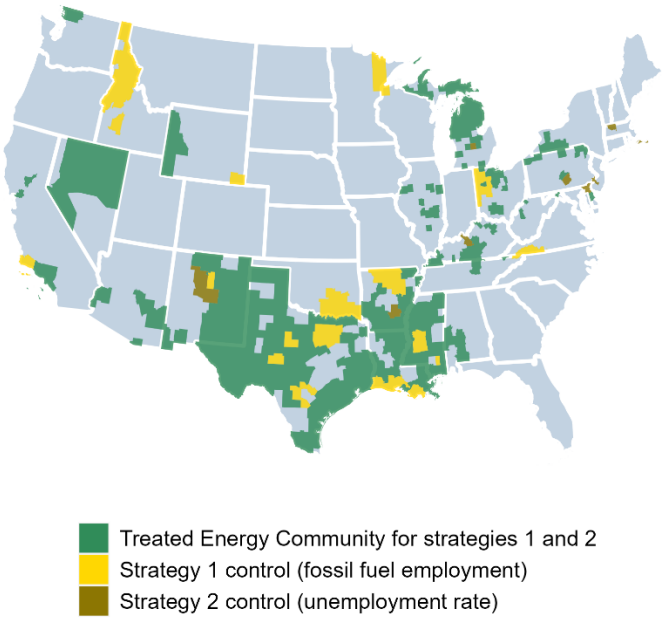


Figure 2: Counties that are treatments and control groups for strategies 1 and 2 as defined in Table 4.

The final strategy uses the Energy Community criterion that a census tract is an Energy Community if the tract or an adjoining tract has had a coal mine abandonment or coal generator retirement. But importantly, I do not use coal generator retirements. A coal-fired generator closure may itself cause new local wind and solar electricity generators to be built, confounding the Energy Community Bonus effect. Instead, I proceed only using the Energy Communities defined by coal mine abandonments, on the presumption that the presence or absence of local coal mines do not affect the profitability of nearby renewable energy generators.

Unlike the first two strategies, this third eligibility criterion is not based on a threshold level in a continuous variable. Areas have either had a coal mine abandonment or they have not. There is no possibility of identifying this third effect with a regression discontinuity to separate the effect from confounding variables. It would be problem, then, if coal mine closures were associated with local characteristics that were beneficial or adverse to development of clean energy plants. However, evidence suggests that is not a problem.

Watson et al. (2022), show that coal mine closures in the U.S. have been predominantly caused by local characteristics unlikely to be correlated with suitability for wind or solar plants: increasing mining costs, declining natural gas prices, and stagnant US total electricity demand. Mine costs, by contrast, have risen due to decreasing productivity, and to a lesser extent wage increases. Labor costs are easy to observe and control for at the county level. And declining gas prices and stagnant electricity demand are national trends unlikely to affect county-level variation in wind and solar electricity development, but regardless can also be controlled for at the county level. Overall, there is good reason to believe that the Energy Community assignment due to coal mine abandonments can be used to identify the effect of the Energy Community Bonus without worrying that the abandonments are correlated with clean electricity development.

Using coal mine closures, however, faces a different data-related challenge in that these areas are defined at the census tract level, but the interconnection queue data only list the county of the generator. Most counties are substantially larger than the census tracts they contain.[10] As a consequence, for this strategy I estimate whether renewable energy generators are more likely to locate in counties that have at least one census tract eligible for the Energy Community Bonus as a result of an eligible coal mine closure.

I limit the estimating sample to only counties that have ever had a coal mine, so that treatment and control counties are similar on that dimension. The treatment counties are those with qualifying mine closures but no other Energy Community qualifying characteristics. The control counties have coal mines that remain open today and no qualifying Energy Community characteristics. Both sets of counties are mapped in Figure 3, with the treatment counties shaded gray and the control counties shaded brown.

The regression for this third strategy is

$$Y_c = \alpha + \beta_3 CoalMineClose_c + \boldsymbol{X'_{3c}\gamma_3} + \varepsilon_c, \qquad (3)$$

where $CoalMineClose_c$ is an indicator equal to one if county c contains a coal mine closure Energy Community and zero otherwise and $\boldsymbol{X'_{3i}}$ is a vector of controls.

[10] This is a non-issue for the first two strategies because the eligibility criterion assigns an MSA or non-MSA Energy Community status, and these areas are larger than the counties they contain.

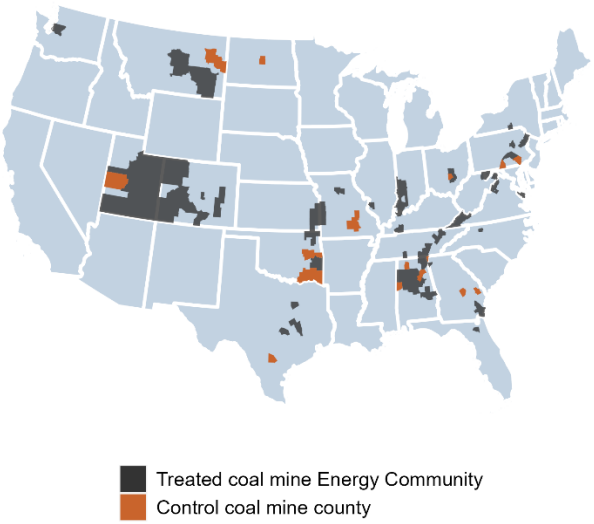


Figure 3: Treatment and control counties for strategy 3. Treatment counties have at least one census tract designated as an Energy Community due to a coal mine closure and no areas designated as an Energy Community for another reason. Control counties have operating coal mines and no area designated as an Energy Community.

All three empirical strategies – and any empirical strategy that uses a control group in the US – face a challenge that may violate the stable unit treatment values assumption (SUTVA). The Energy Community Bonus may affect the interconnection queue in three ways: (1) increase the size of renewable plants in Energy Communities, (2) create new plants in Energy Communities that would not have existed without the Bonus, and (3) shift plant locations to Energy Communities from the rest of the US. This third effect violates SUTVA if the plants are shifted from the control groups. In an extreme case, all observed treatment effect is this third type, and the Bonus merely shifts investment locations with no net increase in renewable generation.

One approach to alleviate this SUTVA concern is to implement a difference-in-discontinuities for the first two strategies, or a difference-in-differences for the third strategy. As written, the above analyses do not exploit the temporal variation in IRA enactment. But comparing the pre- and post-IRA trends for the treatment and control would allow identifying the Energy Community Bonus effect on net of its effect on non-Energy Communities.

4. Marginal Emissions Displacement Model

The next step estimates the renewable electricity generation effect on CO_2 emissions. Of course, solar and wind electricity generation have no direct effect on emissions. Their effects depend on the

degree to which additions of renewable electricity displace electricity generated from fossil fuels, or what I refer to here as the marginal emissions displaced by renewable generation.

The marginal emission varies with the time of day, the location of renewable generation, and congestion on the local grid. Previous research assumes the marginal emission is spatially constant within regions but varies across regions and over time. The regions assumed to have spatially constant marginal emissions include grid interconnections (Holland, et al., 2022; Graff Zivin, et al., 2014), within NERC regions (Siler-Evans, et al., 2012), and balancing authorities (Callaway, et al., 2018; Fell & Kaffine, 2018).

However, the marginal emission at a given time likely varies at a spatial scale smaller than any of these regions. Transmission lines often become congested, effectively splitting regional grids into many sub-regional grids. In fact, according to (PJM, 2024), "In a system as large as PJM, there is nearly always congestion somewhere on the system, and as a result there are nearly always multiple units 'on the margin.'" Congestion timing likely correlates with renewable generation (e.g., congested powerlines during sunny hours), so it is important to measure sub-regional marginal emissions for purposes of inferring the emissions effect of renewable generation.

This is especially important in the case of Energy Communities because they are much smaller balancing authorities or grid interconnections.[11] The Bonus may shift renewable development within regions, with different environmental effects depending on the local marginal emissions. Therefore, I deviate from the previous literature to estimate marginal emissions at the most precise spatial resolution that is possible under the data constraints: the county level.

4.A Data

Hourly, generator-level CO_2 emissions data come from the EPA Continuous Emissions Monitoring System (CEMS) (EPA, 2024). The CEMS data track fossil fuel generators with at least 25 MW capacity, covering about 97 percent of generation.[12] I aggregate the unit-level data to obtain hourly balancing-authority-level emissions. I collect emissions and generation data covering 2018 to 2021.

To estimate county-level marginal emissions, I use exogenous variation in solar and wind generation, as explained below. This requires nationwide data on hourly, plant-level solar and wind electricity generation. Unfortunately, no such data exists in the US. Instead, I use two datasets that model historic wind and solar generation based on observed meteorological conditions, both produced by the Lawrence Berkeley National Laboratory.

The modeled plant-level, hourly wind generation data come from PLUSWIND (Millstein, et al., 2023). PLUSWIND converts three meteorological models of hourly wind speed into three corresponding estimates of plant-level wind electricity generation. The data are available for all wind plants in the contiguous US from 2018 to 2021.

[11] Energy Communities are defined at the county level or even smaller census tract level. There are 3,143 counties and over 84,000 census tracts in the US. The smallest of the electricity regions is balancing authorities, with 66 covering the US. But previous economic research only estimates marginal emissions only for the 6 largest balancing authorities.

[12] This calculation is from comparing the generation data from CEMS to generation data tracked in EIA 923 forms.

The wind generation data are alone sufficient to identify marginal emissions in counties with wind generators. And marginal emissions estimates from wind generation are externally valid to solar generation because both are zero marginal cost. The renewable generation shifts the entire dispatch supply curve, so long as the generation is marginal, the marginal emissions are the same whether identified by marginal changes in wind generation, solar generation, or marginal changes in load.

Because most counties in the US do not have a wind generator, I need to supplement the wind generation data with another source of identifying variation. Therefore, I also obtain plant-level, hourly solar generation data from the Utility-Scale Solar (USS) initiative (Seel, et al., 2023). The USS data rely on the National Solar Radiation Database (NSRDB) based on satellite imagery from the GOES satellite and NOAA High Resolution Rapid Refresh (HRRR) data, as well as measured data from ERCOT and CAISO where available.

The solar and wind generation data will still not cover all counties and hours of the day, which means it will not be possible to measure marginal emissions for all counties in all hours. But most county-hours have some solar or wind generation, and therefore estimates of marginal emissions. Moreover, the counties without marginal emissions estimates are likely less suitable for wind and solar generation, and not important to model for this analysis because the simulations only require marginal emissions estimates in counties with interconnection queue projects.

4.B Empirical method for CO_2 emissions

I estimate county-by-season-by-hour marginal emissions. The time of generation is important because the county-specific marginal emissions may vary with load and temperature, which affect grid congestion. Hourly marginal emissions are especially important because solar and wind generation varies systematically by hour of day, so this level of temporal resolution is necessary to estimate the emissions effects of future solar and wind plants.

I estimate separate regressions for each balancing authority, each obtaining county-level marginal emissions for the counties within the balancing authority. I assume the fossil fuel emissions are only displaced in the same balancing authority as the generation. Although electricity sometimes moves between balancing authorities ("interchange"), most electricity demand in a balancing authority is satisfied by generation in the same balancing authority.

The estimating equation is

$$CO2_{bt} = \alpha_{bs\tau} + \beta_L Load_{bt} + \phi_{cs\tau} RenewGen_{ct} + \varepsilon_{bt}, \qquad (4)$$

where $CO2_{bt}$ is CO_2 emissions released in balancing authority b in day t (e.g., January 1st 2021 at 12:00am to 12:59am), $RenewGen_{ct\tau}$ is the sum of solar and wind generation in county c in balancing authority b in hour t, the τ subscript denotes the hour of the day (e.g., 12:00am to 12:59am) and the s subscript indexes season (e.g., winter). $Load_{bt}$ is electricity demand, treated as exogenous because electricity demand is inelastic. I control for load because wind generation may be correlated with load (e.g., fewer conditioners running when it is windy), and if left an omitted variable, changes to renewable generation may seem to cause emissions changes that are in fact caused by higher load. The balancing-authority-by-season-by-hour fixed effect $\alpha_{bs\tau}$ absorbs typical seasonal variation. The estimate of marginal emissions ϕ_{cs} is at the county by hour-of-day by season level.

5. Emissions Effects of the Energy Community Bonus

I combine the results of the two empirical analyses in Sections 3 and 4 to project how the Energy Community Bonus will affect CO_2 emissions. The first step is to convert the estimates of the Bonus effect on the interconnection queue, from Section 3, into a Bonus effect on annual renewable generation. This requires two sub-steps: modeling the queued projects becoming operational, and assuming capacity factors to turn new capacity into new generation. I then combine the generation estimate with the marginal emissions estimate from Section 4 to calculate emissions reductions from the new renewable electricity. I calculate emissions reductions under the baseline observed scenario and three counterfactuals: a bonus everywhere, no bonus anywhere, and an equal total subsidy with no place-based bonus. Note, the three counterfactuals are the same in that they all assume areas get the same subsidy, but are different in assuming different subsidy levels.

5.A. Converting an Effect on Queue Entrants to an Effect on Renewable Generation

Most interconnection queue entrants will drop out of the queue. The attrition rate is about 80 percent (Rand, et al., 2024). Using the historical queue data, I calculate the probability a solar or wind facility successfully begins operation after t years spent in the queue. The probability a plant is operating t years after entering the queue is $p_x(t) = \frac{oper_{xt}}{enter_{x0}}$, where $enter_{x0}$ is the number of plants of technology-type x (solar or wind) that entered in period 0 and $oper_{xt}$ is the number of plants that entered in period 0 operating t years later. I estimate $p_x(t)$ from the interconnection queue data. The average attrition rate over all technologies is about 80 percent, so the average operation probability in the limit is $\lim_{t\to\infty} p(t) = 0.2$.

This is the simplest possible model to calculate the probability of future operation after queue entry. More complicated characterizations of $p(t)$ could use duration models or condition on plant attributes such as location, local transmission, and plant size. Any approach, including the proposed, suffers from endogeneity with the Energy Community Bonus. The Energy Community Bonus could encourage less likely candidates to join the queue, increasing the dropout rate. Or the Bonus may decrease dropouts by raising expected future profits, likely the key determinant of queue survival (Johnston, et al., 2023). As a first attempt, I will use historical rates as described.

Finally, I convert capacity to generation using county-, technology-, season-, and hour-of-day-specific capacity factors from the hourly solar and wind data. Future generation from renewable plant i of technology type x (solar or wind) in county c in hour-of-day τ, seasons s, and year y is

$$Gen_{is\tau y} = p_x(y - 2023) \times CF_{s\tau xc} \times MW_i, \qquad (5)$$

where MW_i is the plant's nameplate capacity and $CF_{s\tau xc}$ is its capacity factor. $CF_{s\tau xc}$ is estimated from the wind and solar generation data by calculating the mean hourly generation divided by plant capacity in season s, hour τ, and technology x in county c.

5.B. Energy Community Bonus Emissions Effect Simulations

The estimate of annual fossil fuel emissions displaced, or emissions abatement, by renewable electricity added to the interconnection queue in county c in 2023 is

$$A_{0cy} = \frac{365}{4} \sum_{i} \sum_{s} \sum_{\tau} Gen_{is\tau y} \phi_{cs\tau}, \qquad (6)$$

where $Gen_{is\tau y}$ is the generation for plant i in county c from Equation (5) and $\phi_{cs\tau}$ is the marginal emission estimated with Equation (4), and $365/4$ is the number of days in each season. The 0 subscript on A_{0cy} denotes the baseline observed scenario.

I calculate the average Energy Community Bonus effect on a county's generation of technology type x in season s, hour τ, and year y as

$$Gen^{EC}_{xs\tau y} = p_x(y - 2023) \times CF_{s\tau xc} \times \beta_x, \qquad (7)$$

where β_x denotes the county-level Energy Community Bonus effect on new renewable capacity in the interconnection queue of technology type x, either wind or solar, measured in MW per county, as estimated with Equations (1), (2), and (3). The county-level Energy Community Bonus emissions effect is then

$$A^{EC}_{cy} = \frac{365}{4} \sum_{x} \sum_{s} \sum_{\tau} Gen^{EC}_{xs\tau y} \phi_{cs\tau}. \qquad (8)$$

The first counterfactual models all counties as Energy Communities. This means every renewable generator gets the equivalent level of ITC or PTC. I calculate the counterfactual abatement in county c as

$$A_{1cy} = A_{0cy} + (1 - EC_c) A^{EC}_{cy}, \qquad (9)$$

where EC_c is an indicator equal to one if county c is an Energy Community MSA or non-MSA or if it contains an Energy Community census tract and equals zero otherwise. This assumes the Energy Community Bonus effect on renewable capacity is constant across all counties, but varies by technology type, county-level capacity factors, and county-level marginal emissions.

The second counterfactual models emissions abatement as if no counties are Energy Communities. The abatement in this scenario in county c is

$$A_{2cy} = A_{0cy} - EC_c A^{EC}_{cy}. \qquad (10)$$

Again, the Bonus effect is assumed constant across all counties. This may result in some counties with negative emissions abatement. Specifically, A_{2cy} is negative if the average Bonus effect on emissions is larger than the emissions abated by the renewable energy added to the queue in county c in 2023.

The final counterfactual models the Energy Community Bonus subsidy disbursed equally among counties. I assume all counties respond equally to the subsidy, and therefore get the same additional renewable capacity. The equal bonus effect is

$$\tilde{\beta}_x = \frac{1}{n_c} \sum_{c} \beta_x EC_c, \qquad (11)$$

where n_c is the number of counties in the US. $\tilde{\beta}_x$ is interpreted as the new renewable capacity per county of technology x entering the interconnection queue if the Energy Community Bonus effect were

distributed equally across the US, measured in MW. The corresponding county-level change in generation is

$$Gen_{xs\tau y}^{Equal} = p_x(y - 2023) \times CF_{s\tau xc} \times \tilde{\beta}_x, \qquad (12)$$

and the resulting abatement in county c in year y is

$$A_{cy}^{Equal} = \frac{365}{4} \sum_x \sum_s \sum_\tau Gen_{xs\tau y}^{Equal} \phi_{cs\tau}. \qquad (13)$$

The county-level counterfactual emissions abatement for this scenario is

$$A_{3cy} = A_{0cy} + EC_c\left(-A_{cy}^{EC} + A_{cy}^{Equal}\right) + (1 - EC_c)A_{cy}^{Equal}, \qquad (14)$$

such that Energy Community counties' abatement subtracts the larger Energy Community Bonus effect and adds the equal subsidy effect, and the non-Energy Community counties just add the equal subsidy effect.

All counterfactual scenarios assume constant marginal emissions over time. It is possible that the new transmission lines or generator retirements change marginal emissions over time. Holland, et al. (2022) show marginal emissions are increasing slightly over time between 2010 and 2019 across the US, reflecting increased reliance on coal for marginal electricity generation. However, the time trend is relatively small. Nevertheless, it is possible to account for county-level time trends in marginal emissions by amending Equation (4).

6. Conclusion

It is an empirical question whether the Energy Community Bonus increases or decreases emission abatement, depending on how marginal emissions displaced by renewable electricity in Energy Communities compares to marginal emissions in the rest of the US. I estimate the bonus effect on emissions with two empirical steps. The first estimates the bonus effect on renewable energy, and the second estimates the renewable energy effect on emissions.

The effect of the Energy Community Bonus on renewable electricity is interesting in its own right because it is the first empirical evidence of whether the Bonus is working as intended. I offer a series of empirical strategies to measure the Bonus effect. If the Bonus is indeed creating exogenous variation in local renewable energy generation, future research may use the Energy Community Bonus as an instrumental variable for the effect of renewable energy on outcomes of interest, such as the number and quality of jobs, local air and water quality, or spillover investment to other industries. However, it is too early to measure the Energy Community Bonus effect on renewable generation, so I instead identify its effect on projects entering the interconnection queue.

I then estimate marginal emissions at the county level. This analysis constitutes the most geographically disaggregated econometric estimate of US marginal emissions to date. The disaggregation is especially important in the case of the Energy Community Bonus, as the Bonus varies across counties and census tracts throughout the US.

Finally, I combine the separate empirical analyses to project how the Energy Community Bonus will affect future CO_2 emissions. I convert the queue effect to a renewable generation effect by modeling the probability projects successfully complete the interconnection queue and their capacity factors upon completion. I compare the observed Bonus effect to scenarios with no place-based incentives. The results are useful to examine whether, in the case of this one prominent place-based environmental policy, there will be an equity-efficiency tradeoff, or whether incorporating distributional mechanisms will amplify the environmental benefits of the clean energy subsidies.

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