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RESEARCH ARTICLE

Additionality of solar tax incentives under community choice aggregation in Ohio

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Abstract
In the State of Ohio, the electric regulatory landscape permits local governments to become energy suppliers to residents and small businesses through community choice aggregation (CCA). Some CCAs provide enrollees 100% renewable electricity. Concurrently, the federal government offers an income tax credit (ITC) for the purchase of a solar array. With policy incentives, it is important to ensure they encourage behavior beyond the baseline scenario without the ITC. This is known as "additionality." Renewable aggregation programs may crowd out the benefits of the ITC, violating additionality. This paper assesses additionality of the ITC in the context of Ohio's CCA programs. The actual additionality can depend on whether renewable energy is already being supplied to the site of a solar array. Hence, we study the relationship between CCA and solar adoption probability to determine whether tax incentives are additional. Using panel data methods and post-estimation simulations, we discern if additionality is violated where these programs overlap. We find aggregation programs increase the probability of solar adoption and that $0.79 of every dollar spent on the income tax credit in Ohio is non-additional. This will help policymakers determine the efficacy of funds allocated to their programs.

Keywords: Additionality; energy policy; community choice aggregation

JEL codes: Q42; Q48; Q58

Introduction
As the United States grapples with an aging electric grid and the emergence of climate change, renewable power has become a leader of growth with new energy projects (US EIA 2024). Looking forward, renewables are expected to become the dominant capacity drivers in electricity generation (US EIA 2023). Part of this effort is to build distributed photovoltaic (PV) solar arrays. Many of these distributed solar arrays are privately owned by residents and small businesses. Federal and local authorities have engaged in the industry with a series of regulations and incentives to proliferate reliable, clean, and affordable solar generation technology. One such incentive is a federal income tax credit

(ITC) that subsidizes the purchase of a solar array (Office of Energy Efficiency and Renewable Energy, US DOE 2023).

As policymakers at various scales contribute to crafting solutions, we must remember to evaluate the efficacy of these programs and the efficiency of their respective expenditures. The economic principle of additionality can be an important metric of a program's cost effectiveness. An incentive payment for some conservation activity satisfies additionality if the environmental services for which the payment is received would not be generated absent the payment (Horowitz and Just 2013). In the case of the federal ITC for the purchase of a solar array, it should serve to promote the supply of renewable solar energy to the extent that individuals who claim it would not have supplied that renewable energy if they did not qualify for the tax incentive. If those who claim the tax credit would have supplied it anyway, or if the energy they consume already includes some renewable electricity, they risk violating additionality. The latter scenario is the case in certain jurisdictions in Ohio, where local officials operate "community choice aggregation" (CCA) programs to purchase electricity on behalf of their residents and small businesses. These programs are often coupled with "renewable defaults" that provide a guaranteed supply of 100% renewable electricity.

In this paper, we estimate the additionality of the federal ITC for the purchase of a solar array in the face of CCA where electricity may already be renewable. To do this, we estimate the effects of CCA and renewable default aggregation on solar adoption decisions among Ohio residents and small businesses—hereafter, "sites." We focus on Ohio as the prevalence of aggregation is well beyond any of the seven other states that allow it in the US (Hsu 2022). We use our estimates to calculate the total share of federal ITC dollars that generate non-additional renewable energy. We find residents and small businesses in CCA programs are more likely to adopt solar and that, on average, 79% of the expenditures in the ITC program are non-additional in the context of emissions reduction in Ohio.

Literature review

The subject of additionality has some precedent in solar policy, but it is not widely studied. We are not aware of economic analyses of additionality of the ITC in the context of aggregation, but there have been studies of the additionality of ITCs. A study of the California rebate program found that without the rebate, California would see a 53% decline in solar adoption (Hughes and Podolefsky 2015). In Europe, members of the EU created a mechanism to recognize and measure additionality of renewable energy sources to evaluate progress made towards decarbonization objectives (Acharya 2022).

While still emergent, drivers of private solar adoption among homeowners and small businesses in the US is a relatively well-studied subject with the caveat that market conditions are continually evolving. Many prior studies look at specific locations examining the effect of different policy treatments and market forces as determinants of solar adoption. Schulte et al. (2022) provides a useful meta-analysis to summarize the field of literature which seems to begin in the mid-1980s. Choice experiments, panel, and spatial data are commonly employed along with techniques including the theory of planned behavior and diffusion of innovation (Schulte et al. 2022).

Consumer choice experiments have been particularly useful to analyze determinants of adoption that are intrinsic to the buyer, including consumer preference and preference heterogeneity. A common hurdle to solar adoption may be the price premium (either perceived or real) that accompanies the purchase decision. Mamkherzi et al. (2020) find statistically significant differences in perspectives on renewable and solar energy between rural and urban communities. Specifically, they find that location and exposure to solar are factors that influence both respondents' willingness to pay for solar and support for renewable portfolio mandates on power suppliers. This analysis extends beyond the narrow perspective of rooftops or privately owned solar arrays. Additionally, they find a household willingness to pay (WTP) of $27–$30 per month for increased renewable portfolio standards of about 80% of supply (Mamkhezri et al. 2020) on their electricity bill.

A similar analysis of willingness to pay for a national renewable energy standard finds support with a household WTP of $162 per year (due to increased cost of electricity) for a renewable portfolio standard of 80% by 2035 (Aldy et al. 2012). Another inquiry corroborates respondents are WTP for solar production to substitute fossil fuel sources, but also finds the WTP cannot offset the financial premium (Heng et al. 2020). As such, Heng et al. suggest that the government has a clear role in subsidizing the adoption of solar energy in the private markets.

Inquiry into adoption patterns is also rich in the literature. PV technology has begun to diffuse through the marketplace; this has allowed researchers to estimate the impact covariates have on a buyer's decision to adopt solar, including peer effects. Bollinger and Gillingham (2012) find evidence that peer effects increase solar adoption in owner-occupied homes by 0.78 percentage points for every extra installation within that same zip code (Bollinger and Gillingham 2012). This suggests that visibility of panels and "word-of-mouth" marketing are useful means of promoting solar adoption (Bollinger and Gillingham 2012). They suspect this is due to image motivation and information transfer effects. The power of peer effects is corroborated in spatial analysis of solar adoption, including in a study in Connecticut where an incremental increase in adoption is found to promote further adoption by a neighbor in the same 0.5-mile radius block group in the next six months (Graziano and Gillingham 2014).

Spatial effects also pertain to sunlight exposure (irradiance), weather, and climate. A study in Germany found that an increase in the level of sunlight by one standard deviation from the mean yields an increase of 4.7% in PV installations in the same region (Lamp 2023). Another study found solar potential (related to sunlight exposure) increases the likelihood of adoption, but the tax credit and population of an area are not associated with adoption (Young and Sarzynski 2009). Sunlight, being the primary input to production of solar energy, is likely chief among the factors of a decision and may be associated with the risk perception in a buyer's mind.

Of course, the risk associated with the project's feasibility and financial efficacy remain. Bollinger and Gillingham (2012) also observe that maintenance guarantees and alternative sales programs, including panel leasing, are effective means of de-risking a project during the sales process. However, they warn this creates opportunity for moral hazard, where reduced risk may lead to inflation of the size of installations beyond what a purchaser may really need (effectively creating a riskier project; Bollinger and Gillingham, 2012). Another technique used to significantly de-risk a project is community solar subscription programs. These are not permitted in the State of Ohio (Heeter et al. 2021). With respect to the scope of our analysis, we will forgo discussion here.

Some of these findings are corroborated in a study employing a difference-in-differences model with group time effects (O'Shaughnessy et al. 2020). The authors find that income-specific incentives provided to lower- and middle-income households, including solar leasing and financing options based on property assessments, are associated with increased adoption of solar arrays. These findings suggest that these policy interventions could encourage adoptions beyond those eligible by acting through previously discussed peer effects to further encourage adoption in these lower- and middle-income communities.

Impacts of local energy management policy options on additionality are not well-studied. However, there has been some analysis of aggregation programs in current literature. A study of price performance of Ohio's aggregation programs found that, while savings experienced by the individual are small (2–10% of the alternative offers), the costs of the programs are far lower (Littlechild 2008). Furthermore, even when the savings are small, CCA programs are useful at promoting competition in the marketplaces (Littlechild 2008) which will ultimately benefit consumers. These savings are found to fluctuate according to prevailing market conditions (Littlechild 2008).

This paper's contribution builds on studies of aggregation to determine the additionality of the federal ITC as it interacts with aggregation programs offering renewable defaults. We are the first to estimate additionality in the context of CCA solar adoption in the State of Ohio. CCA is a unique feature of the Ohio policy landscape, and we integrate data on the existence of aggregation programs (as well as their renewable energy composition) with data on the existence of privately owned solar generation sites from Ohio's solar renewable energy credit (REC) market. Integrating these datasets helps us determine which solar arrays were purchased in areas that benefited from such programs and which did not. This inquiry will help inform policymakers at multiple scales how their policies interact with other features of the policy landscape. The conclusions drawn here will help policymakers to better understand how these policies encourage solar adoption.

Data

The Public Utilities Commission of Ohio (PUCO) maintains a Renewable Power Siting Board (RPSB) which provides public access to a dataset on certified renewable generators across Ohio, Indiana, Kentucky, Michigan, and Pennsylvania.[1] This dataset includes information on the size, location, and certification dates of the solar arrays, which is assumed to correlate to the actual period of installation. This dataset is motivated by the State of Ohio's renewable energy portfolio standard (PUCO 2023). A mandate on utility companies requires 8.5% of electricity sold in the state to be sourced from renewable generators by 2026, a benchmark which will gradually increase (PUCO 2023). State law includes an enforcement mechanism to subject utilities to a financial penalty should the standard not be met (PUCO 2023). By certifying with the RPSB, generators can enter the local REC market and sell their RECs to utility providers or other consumers in that market.

Many of the generators certified with the RPSB are small and privately owned by businesses and residents. While many arrays are not owned by utility companies, they maintain interconnection agreements providing a net-metering price tariff. Net metering establishes the price utilities will pay for excess electricity produced by the generator.[2] To certify with the State's electric portfolio, generators may voluntarily opt in and register their site with the RPSB. Certification with the RPSB allows individuals to enter the REC market. The process does not significantly belabor an individual beyond what is already required to purchase a solar array. As such, this dataset reflects a sample of the true population of solar array owners in the region. We aim to model the probability of solar adoption as a function of aggregation, local incentives, net-metering tariff rates, and fixed effects. Array data includes the address of the site and longitude and latitude data for mapping purposes. Figure 1 visualizes the array sample.

Our dependent variable is *Adoption Time*, equal to one in the period a site adopts a solar array and zero otherwise. We generated data on CCA programs from an ARCGIS dataset provided by PUCO (2024). There are roughly 480 different aggregation programs within Ohio. Five percent of these programs currently offer 100% renewable energy by

[1]Of these states, only Ohio law permits CCA.

[2]Market research suggests there is usually a limit to production around 120% annual billed usage before the interconnection agreement is void in the State of Ohio (Solar United Neighbors 2024).

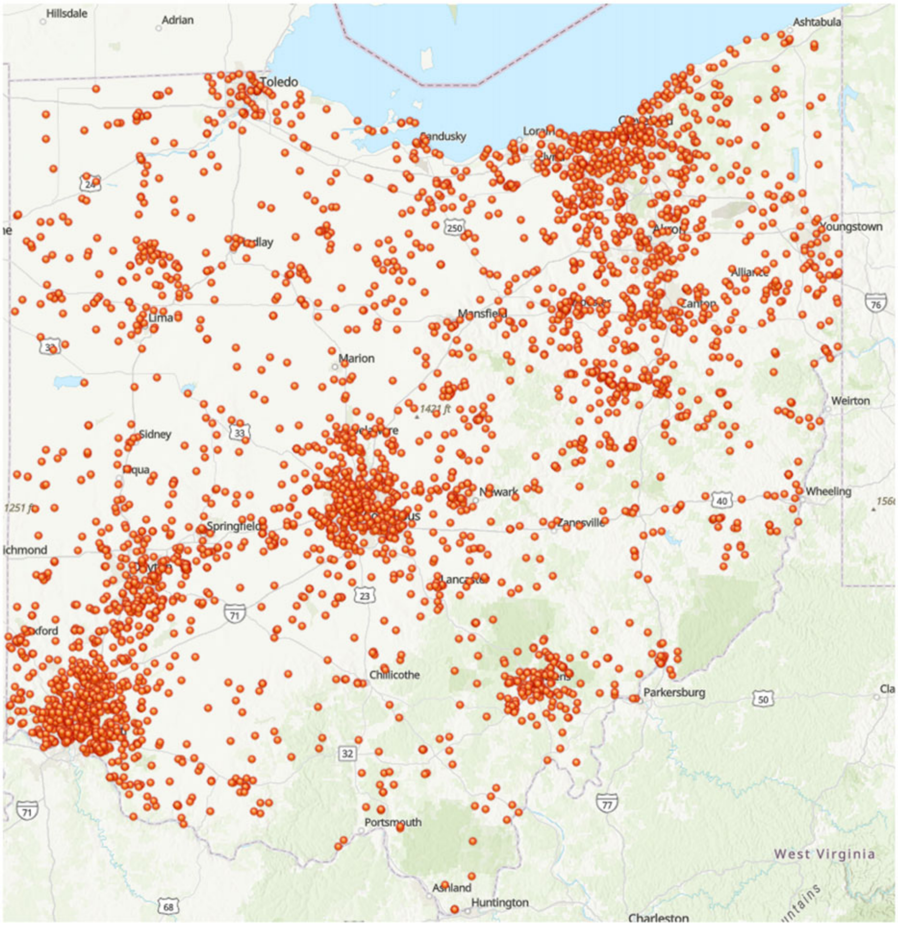

Figure 1. A map showing the location of each solar array in the dataset.

default. Using the PUCO Docketing Information System, we manually sorted each of the aggregation programs to determine when they began and if they offer 100% renewable electricity by default (PUCO DIS 2023). We then paired each solar array to its appropriate aggregation program and generated dummy variables to denote if the program existed when the array was purchased, and if the program was offering 100% renewable electricity at that time.

In an attempt to obtain time-varying information on income levels in the regions studied, we obtained annual aggregated income tax reports from the State of Ohio Department of Taxation (Ohio Department of Taxation 2023). Dividing total county reported income by number of individuals filing tax returns yields county average income by year.

The price of PV components and installation is difficult to determine for each array because certification data from the RPSB does not include this information and publicly available price data germane to the location and time of study is non-existent. To accommodate this, we use the global price of PV in the year they are adopted (Oxford

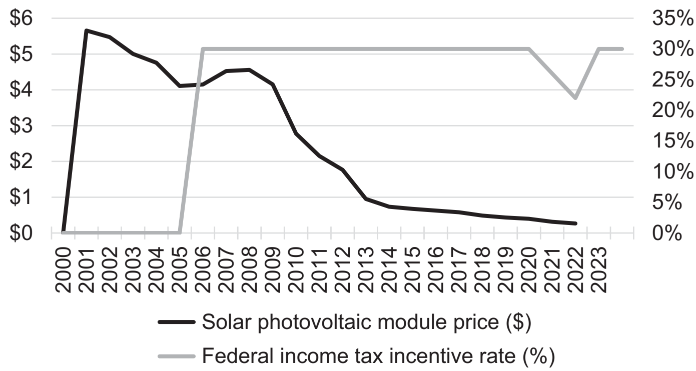

Figure 2. Photovoltaic price and federal income tax credit rate history.

Martin School 2023). Use of a global price reduces the effect of local demand shocks, effectively making our results more robust to account for exogenous shifts to factor market. We calculate the net PV price as the interaction between PV price and the quantity (1 – federal ITC) to subsume incentives offered in the observed year. Figure 2 shows the history of solar PV prices and the ITC.

The US Energy Information Administration compiles data on retail SSO electric prices by utility provider annually. Actual prices may differ from these rates because of variation due to short-run purchasing programs (Lendel and Thomas 2014), but are considered to be highly correlated to SSO prices. We are limited in determining the proper utility company for each site due to a lack of historic data on utility service areas. As such, in any given year the corresponding price is assigned to the utility service area of the site location in 2022. Electric prices were linearly interpolated to account for missing data (<5 entries) and linearly extrapolated to account for market entry and exit as well as missing data (<15 entries). Altogether, these estimations account for 6.9% of the total electric dataset.

The dataset is assembled assigning relevant characteristics to each unique solar site and then expanded to iterate regular observations for each site, beginning when observation begins on January 1, 2001, and ending when the solar array is certified with PUCO.

There are factors to the adoption decision which are excluded from our dataset. For example, net-metering tariff rates (as determined by the utility company) are seldom disclosed publicly with respect to time and lack spatial variation across utility companies. Other factors we cannot measure on our sites are climate and weather factors including irradiance, a site's presence in rural, metro, or micropolitan areas, and peer effects.

Table 1 shows descriptive statistics of our dataset. Figure 3 summarizes our dependent variable by showing differences in adoption behavior among sites with and without 100% renewable defaults using Kaplan-Meier (1958) survivor functions.[3] The survivor function for sites in renewable default aggregation programs is nearly everywhere below the function for those in nonrenewable aggregation programs. This motivates our more detailed analysis later by providing *prima facie* evidence that

[3]The survivor function is the reverse cumulative distribution function of the time to some event T—here, adoption of PV at a given site—defined as $S(t) = 1 - F(t) = \Pr(T > t)$. In this context, $S(t)$ can be interpreted as the probability that the time some site purchases a PV is at least t.

Table 1. Summary statistics of solar arrays

Variable	Obs	Mean	St dev	Min	Max
System size (kw)	2,635	16.39	22.45	0.87	249.68
Aggregated electric price (¢/kwh)	1,648	7.74	2.90	0	15.16
Aggregator = 1	2,635	0.65	0.48	0	1
Renewable Aggregator (opt-in) = 1	2,635	0.07	0.25	0	1
Default renewable aggregator = 1	2,635	0.12	0.33	0	1
Federal income tax credit at purchase (rate)	2,634	0.296	0.02	0.22	0.3
PV price at purchase ($/watt)	2,635	1.23	1.02	0.27	4.56
Price of electric at purchase (¢/kwh)	2,110	10.33	2.66	5.29	16.13
County Income ($000)	2,635	66.82	14.61	41.74	143.67
Adoption Time (Years since 2001)	2,635	15.50	4.01	8.75	22.67

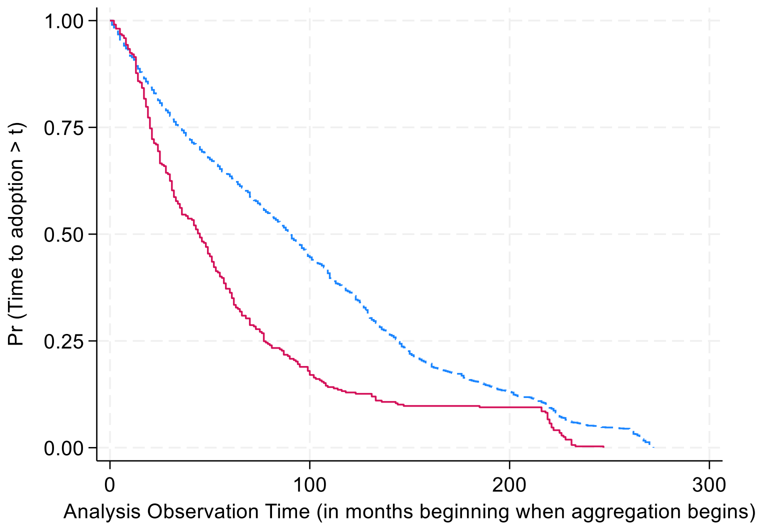

Figure 3. Kaplan-Meier Survivor Curve pooled according to existence of a renewable aggregation program at the time of purchasing a solar array for those inside (red solid line) and outside (blue dashed lien) aggregation areas with renewable defaults.

individuals in renewable aggregation programs are likely to adopt earlier than their counterparts in non-renewable aggregation programs. This is important as the tax credits received by this group are likely non-additional.

Methods

We estimate the effect of CCA using a linear probability model of adoption with one-way site fixed effects. The linear probability model will estimate the effect each of our covariates

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has on the probability of adopting a solar array while accommodating site-specific fixed effects. Using these estimates, we can perform a post-estimation simulation and measure the additionality of the income tax credit.

The fixed effects model is attractive here because the observations are in the form of a panel dataset. Further, there are both observable and unobservable qualities to each site that drive adoption. For example, prior literature suggests that a rented house or business place are less likely to have a solar array installed than an owner-occupied site (Darghouth et al. 2022). The setting of a site may have an impact including its placement in rural or urban locations as well as the level of sunlight received (irradiance). Additional site-specific factors include the age of the homeowner or business operator or the presence of a homeowners' association (which may levy rules promoting or deterring rooftop solar generation). Fixed effects allow us to control for these impacts.

The linear probability model takes the form:

$$Y_{it} = \gamma X_{it} + u_i + e_{it}, \tag{1}$$

where Y_{it} equals 1 if site i adopted a solar array in time t and zero otherwise; X_{it} is a vector of site- and time-specific predictors, including the presence of aggregation, nominal county income (in thousands of dollars), the nominal SSO price of electricity at the site's given utility company, the net PV price (equal to the global average price of PV solar panels per watt of capacity times the quantity (1 – federal ITC rate for solar adopters)); γ is a conformable vector of parameters to be estimated; u_i is the site fixed effect, and e_{it} is the overall error specific to site and time. Our data on PV price, electricity price, tax credit rates, and income is all recorded on an annual basis. Hence, we assume t denotes years.

The linear probability model is attractive due to ease of interpretation of coefficients on our predictor terms. Interpretation of our fixed effects model calls for focus on the coefficient of our predictors, γ. For each site, as a predictor variable changes along its margin, the effect is an increase or decrease in the probability of adoption at time t by $\gamma \times 100$ percentage points. Furthermore, intra-site correlation is controlled for by clustering the standard errors on sites.

Given the binary nature of our dependent variable, we include a logit model as a robustness check. Let Y_{it}^* be a latent variable denoting the utility from adoption of a solar array. If the net gains to utility from adoption are positive, then $Y_{it} = 1$. The model is

$$Y_{it}^* = \delta X_{it} + \eta_i + v_{it}, Y_{it} = 1[Y_{it}^* > 0], \tag{2}$$

where X_{it} is defined as before; δ is a parameter vector; η_i is a site fixed effect, and v_{it} is a logistic error term. Fixed effects panel logit models are available to estimate (2) but are inappropriate in this scenario because these do not estimate fixed effects directly, and hence the estimates cannot be used to calculate adoption probability. Additionally, due to the nature of the dataset, a fixed effects logit will not converge. A random effects model avoids having to estimate site-level fixed effects but assumes mean independence, $E[\eta_i|X_{it}] = \eta$, such that the unobserved individual effects are uncorrelated with X_{it}. This is unlikely to hold. As such, we estimate a correlated random effects logit model (Mundlak 1978) which assumes $E[\eta_i|X_{it}] = \theta X_{im}$, where X_{im} is a vector of the averages of time-varying variables. Adding and subtracting this relationship in (2) yields

$$\begin{aligned} Y_{it}^* &= \delta X_{it} + \theta X_{im} + v_{it} + (\eta_i - E[\eta_i|X_{it}]) \\ &= \delta X_{it} + \theta X_{im} + v_{it} + \varepsilon_i, \qquad Y_{it} = 1\left[Y_{it}^* > 0\right] \end{aligned} \tag{2}$$

where ε_i is uncorrelated with X_{it}.

We calculate the share of tax rebate expenditures that is nonadditional with estimates from the linear probability model. We simulate the adoption choices of different average individuals distinguished by different policy contexts: sites in non-aggregation areas ("group 1"), sites in aggregation areas without renewable electricity ("group 2"), and sites in aggregation areas that provide 100% renewable electricity by default ("group 3"). For each group, the probability of adoption is calculated with and without an ITC equal to 30% of the PV purchase cost. The current rate of the federal ITC is 30% and this has been the rate for most of the existence of the program (Figure 2). All other model variables are set to their sample means. Let σ_{g1} and σ_{g2} be the adoption rate among group-g sites without and with the incentive, respectively. σ_{g1} is the adoption rate for individuals who purchase even without the tax credit; in other words, these are infra-marginal adopters whose renewable energy supply is nonadditional. The share of each dollar spent on incentives for group $g = 1{,}2$ sites that is non-additional is then σ_{g1}/σ_{g2}. The share of each dollar spent on incentives for group 3 sites that is non-additional is 1 since these sites would have received 100% renewable energy regardless of whether they adopt PVs.

Results

Next, we turn to the linear probability model with one-way site-specific fixed effects described in equation (1) to estimate the effect of aggregation and renewable defaults more precisely on PV adoption decisions. Table 2 shows parameter estimates.

The positive coefficient on the aggregation dummy variable shows that aggregation programs increase the probability of adopting a solar array, all else equal, by 5.8% at a 1% level of statistical significance. Aggregation programs with a renewable default are also found to have a positive effect which is statistically significant at the 10% level. Increasing the net price of solar reduces adoption probability by 1% with every $1/watt. Recalling that the net PV price variable is PV price interacted with one minus the value of the ITC, it stands to reason that adoption will increase with the presence of the tax rebate. Increasing the price of electricity results in a similarly sized, albeit positive effect. This relationship is intuitive because electricity from the grid and solar generators can be thought of as substitute goods. Curiously, the coefficients of these two price variables have a similar absolute value. Upon reflection, this seems to be a coincidence as the respective units of these variables are not the same. Lastly, as county income rises, we see a small increase in the probability of adoption. Table 3 shows estimates from the correlated random effects logistic regression. Using a logistic regression, the interpretation of each parameter will change. In this form, coefficient estimates reflect the log-odds of the outcome. To aid interpretation, we also present marginal effects calculated at the mean of each covariate. For binary variables, the marginal effects represent a discrete change from the base level. These marginal effects are more similar to the linear model.

The logit results have many similarities in its estimated coefficients to the linear probability model with fixed effects. The presence of aggregation here increases the adoption of solar. Solar prices have a negative impact on adoption, which remains intuitive. Increases in the SSO price of electricity and in average county income also promote adoption of a solar array. One difference between the robustness check and the linear probability model is that the robustness check suggests that presence of a renewable aggregation program reduces the odds of adopting a solar array. This output invites some consideration as Figure 3 and the linear probability model would lead us to believe that individuals in the renewable default aggregation program should adopt earlier than those not in the program. However, the linear probability model finds the effect of the existence of a renewable default program on the probability of adoption is weak; within two standard deviations, the probability is negative. As such, we are inclined to believe the linear probability model, but with only a modest endorsement.

Table 2. Parameter estimates from the linear probability model of solar adoption

Dependent variable: adoption time		
Variable	Estimate[1]	Robust std error
Aggregation = 1	0.058***	0.006
Aggregation × renewable default = 1	0.02*	0.011
Net Solar PV price ($/watt)	–0.010***	0.001
Electricity price (¢/kwh)	0.010***	0.001
County income ($000)	0.005***	4.5E–4
Constant	–0.321***	0.028
Observations	40,012	

[1]Superscripts *** and * denote estimates that are significant at the 1 and 10% levels, respectively.

Table 3. Parameter estimates from the correlated random effects logistic regression

Dependent variable: adoption time				
Variable	Estimate[1]	Robust std error	Marginal effects	Std error
Aggregation = 1	0.96***	0.10	0.02***	0.002
Aggregation × renewable default = 1	–0.79***	0.16	–0.02***	0.003
Net Solar PV Price ($/watt)	–6.27***	0.11	–0.15***	0.002
Electricity Price (cents/kwh)	0.13*	0.04	0***	0.001
County Income ($0000)	0.31***	0.01	0.01***	3.04E–4
Mean Aggregation	–0.88***	0.14	–0.02***	0.003
Mean Aggregation × renewable default = 1	0.69	0.45	0.02	0.010
Mean Net Solar PV Price ($/watt)	8.58***	0.15	0.2***	0.002
Mean Electricity Price (¢/kwh)	–0.06	0.05	0	0.001
Mean County Income ($000)	–0.36***	0.02	–0.01***	.337E–4
Constant	–21.13	0.47		
Observations	40,012			

[1]Superscripts *** and * denote statistical significance at the 1% and 10% levels, respectively.

Table 4 shows estimates of σ_{g1} and σ_{g2} for each group calculated from the linear probability model. For each group, potential buyers are more likely to purchase a solar array with the tax credit than without the tax credit. However, the share of non-additional expenditure estimated herein is significant: using the share of the sample that corresponds to each group as weights, the average total share of nonadditional expenditures is $0.79 out of every dollar spent.

Table 4. Simulated probability of PV adoption by group (standard errors are included in parentheses)

Group	1	2	3
	Non-aggregation areas	Aggregation area without renewable default	Aggregation area with 100% renewable default
Description	(35% of sample)	(52% of sample)	(12% of sample)
No ITC (σ_{g1})	0.0224	0.0806	0.101
	(0.0024)	(0.0044)	(0.0096)
30% ITC (σ_{g2})	0.0341	0.0923	0.1127
	(0.0019)	(0.004)	(0.0097)
Nonadditional expenditures per rebate dollar	\$0.66	\$0.87	\$0.90
	(0.049)	(0.019)	(0.016)

Discussion and conclusion

This paper contributes to a nexus of literature on drivers of solar adoption, which is well studied, and the sparse field studying the effect of tax incentives for private renewable energy supply in the context of CCA with 100% renewable energy defaults. Our findings suggest that renewable aggregation purchasing programs generate an additionality concern in the context of the ITC and carbon emissions reduction goals. Specifically, we find that residences and small businesses under CCA are 6 percentage points more likely to adopt solar PV than sites outside CCA areas. These sites are 8 percentage points more likely to adopt if the CCA offers 100% renewable energy by default. Since these latter sites would have received renewable energy with or without PV adoption, any ITC meant to support adoption is necessarily nonadditional. Overall, we calculate the share of nonadditional tax incentives to be \$0.79 per dollar spent.

While a policymaker might hope for more "bang for our buck," there are numerous secondary and tertiary benefits from the tax credit. To the extent that it increased solar adoption (even marginally), it is successful at increasing the number of distributed generators while also promoting decarbonization and insulating individual sites from exogenous shocks in the electric markets. This is important because increasing distributed generation capacity is considered a strong step towards increasing the resilience of the electric grid across the nation (Solar Energy Technologies Office, US DOE 2023). From the point of view of residents or small businesses, the lifetime of a solar array is roughly 20 years, possibly longer. This is greater than the lifetime of a bilateral energy purchasing agreement that an aggregator would enter. Recalling our survivorship curves, which clearly show adoption rates in renewable default aggregator areas are higher than non-aggregator areas, this difference between system lifespan and aggregation contract lifespan may be impactful at the decision point for individuals installing solar. More specifically, they may not consider the fact that they currently have 100% renewable electricity when deciding to construct a solar array. Alternatively, they may lack confidence (not to mention awareness of the program itself) in the long-term survival of the 100% renewable aggregation program. While a few aggregators have terminated programs (McDonnell 2022), many of these were quickly restored (NOPEC 2023). Nonetheless, the horizon upon which a solar

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array can guarantee to provide a supply of decarbonized energy is far greater than the horizon that an aggregator can guarantee. As such, even in a case where the aggregation program provides 100% renewable electricity, the solar array is a useful device to ensure a supply of renewables to the site.

However, the results lead us to the conclusion that solar incentive money may be better spent elsewhere. This could include more direct means of incentivizing production of renewable energy generators, along with efficiency incentives including those that the Inflation Reduction Act have instituted (The White House 2023).

This research provides a novel assessment of the intersection between the federal income tax credit for solar and local electric aggregation programs in the State of Ohio. Using a linear probability model, our findings are robust to individual unobserved site-specific fixed effects. Furthermore, use of the correlated fixed effects logit model is used as a robustness check. Limitations in our study arise from difficulty obtaining site-specific, time-varying data including the true PV price, and validation of the data on the price of electric. However, collecting this information would likely require use of a survey. Furthermore, the dynamic nature of the residential and small business PV installation industry makes capturing spatially and temporally accurate price data challenging (Fu et al. 2017). As such, future research could emphasize precision in site-specific market data through an alternative data collection technique.

Data availability statement. All data used in this research is publicly available from sources cited within the text. The collection of datasets used for this research is available upon request from the corresponding author.

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