When Energy Issues are Land Use Issues: Estimating Preferences for Utility-Scale Solar Energy Siting*

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Abstract

While solar energy receives broad support in general, utility-scale solar arrays can be contentious because at the siting stage it becomes a land use issue replete with potential disamenities and tradeoffs. We conduct a choice experiment survey to estimate preferences for attributes of utility-scale solar arrays in Rhode Island, USA. Our results suggest the largest indicator of solar development approval is prior land use, with residents willing to pay an additional $10-21 in monthly utility bills for developments in commercial, industrial, brownfield, and covered landfill areas, and $13-49 to avoid developments on farm and forest land.

Keywords: Solar energy; Utility-scale solar; Willingness to pay; Contingent valuation; Choice experiment
JEL codes: Q24; Q42; Q51

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1 INTRODUCTION

Solar energy has grown immensely in the United States, with an average annual growth rate of almost 42% since 2010 (Davis et al., 2021). In 2020, the United States had over 89 gigawatts (GW) of total installed capacity, which is enough to power 16.4 million homes and accounts for 2.6% of total electricity generation (Davis et al., 2021). In the coming years, solar energy is projected to grow faster than any other renewable source in the United States, more than doubling its total installed capacity by 2025, and accounting for 47% of total renewable electricity generation by 2050 (*EIA Annual Energy Outlook*, 2021).

Despite broad support for solar energy in the United States (Carlisle et al., 2014, 2015; Farhar, 1994; Greenberg, 2009; Jacobe, 2013; Pew Research Center, 2019), the construction of utility-scale solar installations (sized 1 MW and above) is often fraught with hurdles. One key insight as to why solar can be divisive is to understand that siting of utility-scale solar is a land use issue as much as it is an energy issue. The proliferation of solar has become the largest cause of land use change in the United States (Trainor et al., 2016). On average, a solar installation with a capacity of one megawatt (MW) requires five acres of land, which is over ten times the land area required by conventional sources (Denholm and Margolis, 2008; Ong et al., 2013) and can be an obstacle to additional solar development.[1]

The debate regarding utility-scale solar siting is particularly contentious in Rhode Island (RI), which is the setting of our study. In 2004, RI adopted an ambitious Renewable Energy Standard, which set the goal of generating 38.5% of total energy from renewable sources by 2035. To this end, 80 MWs of utility-scale solar energy capacity have been built since 2013 (EIA, 2021), and the pace of development has increased recently (Kuffner, 2018). Much of the concern regarding solar energy expansion stems from the fact that the most common sites for arrays are on forest and farm lands, which combined account for 63% of RI's land area.[2] While these are the areas where development is cheapest, they offer many amenities to residents, particularly in a small state with scarce land resources, the nation's second highest population density, and strong public support for land conservation and environmental preservation (Altonji et al., 2016).

While RI is unique among states in some ways, many of the driving forces behind the land use and renewable energy tradeoffs the state is currently facing are generalizable to many states and nations. Currently, 30 U.S. states have Renewable Energy Standard legislation in force. This, coupled with falling material and construction costs for solar, means that the increasing relevance of utility-scale solar, and the emerging preference complexities that arise from solar siting, suggest that the lessons we learn from RI have important implications for researchers and policy makers in many other regions.

The purpose of this paper is to quantify the perceived externalities from utility-scale solar installations by estimating the tradeoffs people are willing to make for a set of siting attributes. We designed and administered a choice experiment (CE) survey to estimate preferences for four siting attributes of utility-scale solar installations: size of the installation, visibility, setback distance, and current land use of the proposed development site. Of these, current land use is of particular interest to us and the four land types we consider are forest land, farmland, commercial/industrial land, and brownfields/covered landfills, which represent standard siting options. The survey presents respondents with multiple hypothetical solar development plans with different attributes (including a no solar development alternative) and asks their preferred option. Each alternative is paired with a change in household electricity bill, forcing respondents to make tradeoffs between money and solar siting attributes. Through their choices, we can estimate an average monetary value (willingness to pay, or WTP) for each solar siting attribute.

Our results are consistent with expectations, but the specific magnitudes of willingness to pay yield insights into consumer priorities. The results indicate that respondents prefer larger installations and are willing to pay about $1.25 per month per additional MW of solar energy capacity, which demonstrates overall support for continued transition to solar energy. Respondents dislike visible installations and are willing to pay between $6.21 and $8.42 per month to make nearby installations not visible. Our results suggest the largest factor in determining approval is current land use of the proposed development site, with substantial heterogeneity across land types. Respondents have a preference for solar installations sited on brownfields and commercial lands, with an average WTP between $10.08 to $15.11 for brownfields and $14.48 to $20.78 for commercial areas. In stark contrast, they are willing to pay to avoid solar development on forest lands and farmlands. Conversion of forest land is most detested, and estimated WTP ranges from -$40.60 to -$49.10 per month.

While these results are consistent with expectations and sentiment expressed in town meetings and from stakeholders, they are important because they quantify resident preferences in a way that can guide statewide policy and local siting ordinances.[3] Specifically, states can offer additional subsidies for solar development on industrial/commercial areas, brownfields, and covered landfills, which are necessary to entice developers because arrays on these sites are more expensive to build and maintain. Our analysis shows that economically meaningful subsidies are highly likely to pass a benefit-cost analysis under reasonable assumptions and are thus warranted in a social welfare framework. Visual screening is another important component of development proposal and approval, and our results suggest that the significant costs borne to screen an array are also justified by the benefits of local residents not seeing the array. We discuss these policy ramifications in Section 5 in more detail.[4]

This study advances the literature in several ways. First, we provide the first estimates of the valuation of utility-scale solar siting attributes in the United States. Even beyond the United States, literature on non-market valuation of utility-scale solar energy is sparse. To date, there are only three studies that use a CE to estimate externalities from utility-scale solar attributes: Botelho et al. (2017) in Portugal, and Yang et al. (2017) and Kim et al. (2020) in South Korea,. Botelho et al. (2017) estimate a marginal WTP to avoid glare from solar panels of $5.15 per month. Yang et al. (2017) also find a negative WTP for light pollution caused by glass arrays, estimating a value of $14 per household per month. Our finding that respondents need to be compensated between $6.21 and $8.42 per month for a completely visible installation falls within the range estimated in previous studies.[5]

We additionally contribute to the understanding of solar siting preferences by explicitly distinguishing between possible prior land uses. Existing studies (Botelho et al., 2017; Kim et al., 2020; Oehlmann et al., 2021; Yang et al., 2017) that analyze the impact of solar siting on the surrounding land all find that solar installations have a negative impact on the landscape, though each defines the "landscape" attribute and its associated levels differently. Botelho et al. (2017) consider a general kind of landscape without differentiating between land use types and find that the average WTP to avoid "significant impacts on landscape" is $7.58, relative to no impact. Similarly, Yang et al. (2017) also assume a general definition of "landscape destruction" and define levels in terms of percentage decreases in "natural beauty." They estimate a WTP of $0.05 per percentage point of landscape destruction. Kim et al. (2020) capture landscape impacts on flatlands (farmlands and orchards) and mountainous areas and find that people need to be compensated $1,951 per month for solar development on flatlands, and $1,059 per month for solar on mountainous lands, compared to solar panels located on rooftops and walls. Oehlmann et al. (2021) focus mostly on proximity and do not explicitly describe prior land use. Further, the status quo still involves renewable energy development, just of an uncertain type, which makes it unclear how respondents assess land use impacts. While each study captures landscape impacts differently, none consider heterogeneity by land use types in the manner that our study does, particularly the potential positive impacts from developing solar on land types that are otherwise undesirable: brownfields and commercial areas. With this in mind, our research is the first to explicitly consider and model preferences for solar development plans based on current land use. Our findings suggest that this is a critical distinction to make as prior land use is the single largest driver of solar development approval. This is in line with Nilson and Stedman (2022) who find that survey respondents in upstate New York believe that landfill and industrial sites are more suitable for solar development than farmlands and forests.[6] An additional benefit and contribution of our approach is to demonstrate how household WTP estimates can be translated into a policy design of differential feed-in-tariffs for arrays on different land use types.

2 METHODS

2.1 Choice experiment design

In our CE, we present each respondent with six choice tasks modeled as solar development plans. Each development plan asks respondents to consider a hypothetical group of land parcels that have three main characteristics. First, all land parcels are near each other and total fifty acres. Second, they are less than fifteen minutes from the respondent's residence by car in Rhode Island. And third, each group of parcels has one of the following four different land types: brownfield, commercial, farmland, and privately owned forest.[7] The survey presents two choice tasks for both farmland and forest parcels, and one each for commercial and brownfield land types. We chose to disproportionately ask about farmland and forest land because these are more common siting locations in New England and the most contentious, so we prioritized these for precise estimates.

Our CE design differs from much of the literature by treating current land use differently than most choice attributes. In pilot testing our survey, we received feedback from stakeholders suggesting that a realistic portrayal of solar development decisions would involve different development plans on a single site (and so a single current land use) rather than development plans involving different land uses. Another concern, largely technical in nature, with the traditional CE design was that it was unclear how land use should be coded for the status quo alternative (or the no solar option) when multiple development options with different land uses were presented in a single choice. We tackle this issue by keeping current land use constant between different development plans in a given choice while varying land use between choices. Econometrically, this means we are unable to include land use variables in our choice model as one would include other attribute variables because they lack within-choice variation. However, we are still able to recover the impact of land use differences from our choice model by interacting land use indicator variables with alternative-specific constants (ASCs).

We develop a D-efficient design using the *dcreate* command in Stata (Hole, 2017), which included 30 choice sets for commercial and brownfield land types. The farm and forest land use designs included 60 choice sets, which were divided into blocks of two questions. In pilot testing the survey, both with focus groups (5 focus group meetings involving a total of 30 participants) and with a series of meetings with an advisory group of stakeholders knowledgeable about solar development in Rhode Island, we identified several areas where specific attribute levels did not make sense for certain land uses.[8] In developing our experimental design for each land use type, we specified these constraints, then allowed our software to identify the D-efficient design given these constraints.

For each choice opportunity, we present three hypothetical development plans, labeled A, B, and C. The first two plans assume that some or all of the parcels of land under consideration will be developed into utility-scale solar installations, but with varying solar installation characteristics. The final alternative (Choice C) is a status-quo option where the land will be free of solar panels and will remain in its current use 'for the time being'.

Our CE presents four solar attributes: *size of installation*, *visibility, setback*, and *change in electricity bill. Size of installation* indicates the area of land (in acres) that is converted to solar energy production, as well as how many households are capable of being powered by the installation under consideration.[9] *Visibility* refers to how visible a solar installation is from the respondents' house or from regularly traveled roads. *Setback* is the minimum distance of the solar panels from the property line of the development site. The attribute representing our payment vehicle is *change in electricity bill*, which is defined as the dollar increase or decrease in respondents' electricity bill if a specific development plan is implemented. For ease of understanding, we present the change in both monthly and annual terms. Finally, our CE also includes the attribute *probability of residential development* when the land type is either farmland or forest. This is because most farm and forest land is zoned residential in Rhode Island, and there is a possibility that it will be converted into residential housing in the future if it is not developed into solar. This attribute was added based on discussions in focus groups and represents the reality that privately held land may not remain open space indefinitely. Figure 1 shows an example choice set for the farmland land use.[10] Table 1 defines all attributes and their associated levels used in our design.

Our survey is divided into four sections. The first section provides background information about our study and the history of siting utility-scale solar installations in Rhode Island. We convey that the objective of the study is to help policy makers implement decisions that reflect the public's preferences, and that the final results will be disseminated to state and local decision makers and the public at large through outreach.[11] We also inform participants that our study is backed by an advisory group consisting of officials in state and local governments, non-profit environmental organizations, and solar development experts who have also provided guidance at various stages of the project. In the second section we ask respondents questions regarding their energy usage and attitudes about different energy sources. The third section first defines each attribute in our CE and familiarizes respondents with its overall structure using an example choice, then presents the six choice questions in a randomized order. The fourth and final section includes questions designed to assess perceived consequentiality of the survey, identify stated attribute non-attendance, and collect demographic information.

2.2 Empirical models

The choices made by respondents in our CE allow us to empirically estimate their preferences for a variety of solar siting attributes. McFadden (1974) laid the theoretical groundwork linking consumers' choices to utility maximization through the Random Utility Model (RUM). In the RUM context, the utility of individuals is assumed to have two components: an observable and an unobservable (random) component. This can be expressed as:

$$U_{im} = V_{im} + \varepsilon_{im} \tag{1}$$

where U_{im} is the utility that respondent i derives from alternative m, which is a function of his observable utility V_{im} and his random utility ε_{im} from choice m. The observable component, V_{im}, can depend on individual-specific characteristics and the attributes of alternative m.

We use the standard multinomial (conditional) logit (CL) model proposed by McFadden (1974) to model respondents' choices. The CL model requires that choices be independent of irrelevant alternatives (IIA) and makes two main assumptions: first, that all individuals have homogenous preferences, and second, that the variance of the error term is constant across individuals. In this case, that probability of individual i choosing alternative m is given by:

$$P_{im} = \frac{exp(\lambda V_{im})}{\sum_{n=1}^{N} exp(\lambda V_{in})} \tag{2}$$

where λ is a positive scale factor that is inversely proportional to the error variance, σ_ε^2:

$$\lambda = \frac{\pi}{\sqrt{6\sigma_\varepsilon^2}} \tag{3}$$

When error terms are IID, the error variance, and thus λ, are constant across individuals. Since the scale parameter cannot be directly estimated, it is typically normalized to unity, an assumption that has been called into question in the literature several times (DeShazo and Fermo, 2002; Hensher et al., 1998; J. Louviere et al., 2002; J. J. Louviere, 2001).

To allow error variances (and scale parameters) to vary across individuals and choices, we additionally employ an alternative model known as the heteroskedastic conditional logit (HCL) (DeShazo and Fermo, 2002; Hensher et al., 1998). In this model, scale parameters are represented as:

$$\lambda_{im} = exp(\boldsymbol{\varphi Z_{im}}) \tag{4}$$

where $\boldsymbol{Z_{im}}$ is a vector of individual- and choice-specific characteristics (specified as the four different land use types in our model) and φ is the parameter that describes the effect of those characteristics on the scale parameter. The probability of individual i choosing alternative m then becomes:

$$P_{im} = \frac{exp(\lambda_{im}\boldsymbol{V_{im}})}{\sum_{n=1}^{M} exp(\lambda_{im}\boldsymbol{V_{in}})} \tag{5}$$

Finally, we use the random parameters logit (RPL), or mixed logit model, which relaxes the IIA restrictions of the CL model and additionally allows for preference heterogeneity. It does this by incorporating a random parameter into the utility function that represents how much each individual's preferences deviates from the population mean. Therefore, the utility each individual i gets from alternative m in situation t can be represented as:

$$U_{imt} = \boldsymbol{X_{imt}}(\boldsymbol{\beta} + \boldsymbol{\eta_i}) + \varepsilon_{im} = \boldsymbol{X_{imt}}(\boldsymbol{\beta_i}) + \varepsilon_{im} \tag{6}$$

where $\boldsymbol{X_{imt}}$ represents the observed attributes, $\boldsymbol{\beta}$ is a vector of mean coefficient values associated with those attributes, and $\boldsymbol{\eta_i}$ is a vector of individual-specific deviation parameters that captures preference heterogeneity. Preference heterogeneity is therefore captured directly in the RPL model through the vector $\boldsymbol{\beta_i}$, which represents individual-specific preference parameters for each attribute with assumed preference heterogeneity. The probability of individual $i's$ sequence of choices $[c_1, c_2, \dots . c_T]$ is given by:

$$P_{i[c_1,c_2,\dots c_T]} = \int \dots \int \prod_t^T \left[\frac{exp(\boldsymbol{X_{imt}\beta_i})}{\sum_{n=1}^{M} exp(\boldsymbol{X_{int}\beta_i})}\right] f(\boldsymbol{\beta}) d\boldsymbol{\beta} \tag{7}$$

2.3 Estimation

Our main expected utility specification is given as:

$$\begin{aligned} V_{im} = {} & \beta_{Acres}Acres_{im} + \beta_{PartVis}PartVisibility_{im} + \beta_{FullVis}FullVisibility_{im} \\ & + \beta_{Setback}Setback_{im} + \beta_{Probability}Probability_{im} + \beta_{Cost}Cost_{im} \\ & + \beta_{FarmASC}Farm_i \times ASC_{im} + \beta_{ForestASC}Forest_i \times ASC_{im} \end{aligned}$$

$$+ \beta_{BrownfieldASC} Brownfield_i \times ASC_{im} + \beta_{CommercialASC} Commercial_i \times ASC_{im} \quad (8)$$

where $Acres_{im}$ refers to the size of the installation (in acres), $PartVisibility_{im}$ and $FullVisibility_{im}$ are indicator variables equal to 1 if the installation is partly visible and completely visible,[12] respectively, $Setback_{im}$ refers to the setback distance (in feet), $Probability_{im}$ is the probability of residential development on farm and forest land in lieu of solar development, $Cost_{im}$ is the change in respondents' monthly electricity bill, and ASC_{im} is the status-quo alternative-specific constant, or a dummy variable equal to 1 for the status-quo choice and equal to 0 for either of the solar development options (Choices A and B). $Farm_i$, $Forest_i$, $Brownfield_i$, and $Commercial_i$ are all dummy variables equal to 1 if the choice set is framed around the respective land use.

In Equation (8), each solar attribute k is associated with a preference coefficient β_k, which are estimated using maximum likelihood procedures. The interaction coefficients allow us to identify whether respondents have different preferences (and different WTP's) for each land type. The ASC_{im} term indicates respondent i's desire to choose the status-quo alternative over other solar development alternatives, which can also be interpreted as their dislike for solar arrays. The interaction of the ASC_{im} term with a land use type l will therefore represent their preferences for developing solar arrays on that particular land use type. If the coefficient associated with the interaction between land use type l and the ASC_{im} term (β_{lASC}) is positive, it implies that people prefer the status-quo option over the other alternatives, or equivalently that they dislike having solar arrays on the associated land parcel, all else equal.

These coefficient estimates can be used to make welfare calculations. We obtain the marginal WTP (MWTP) value for a one-unit increase in a particular attribute k by dividing the coefficient of that attribute with the negative of β_{Cost}, the coefficient associated with the cost variable. Mathematically:

$$MWTP_k = -\frac{\beta_k}{\beta_{Cost}} \tag{9}$$

We can also estimate the maximum willingness to pay (also called compensating variation or CV) for a specified plan by finding the price that makes the utility derived from that plan, denoted as V_i^1, equal to the utility from the status quo option, denoted $V_i^{SQ\_l}$. Note that status quo utility is indexed by land use, as our interactions of the SQ ASC with land use allows us to estimate different status-quo utilities for different land uses. From here we can estimate a unique CV for each land use type l:

$$CV_l = \frac{V^{SQ\_l} - V^{1*}}{\beta_{Cost}} \tag{10}$$

where V^{1*} is the utility of the non-price attributes associated with the solar development plan under consideration. Subtracting the CV associated with one land use type from another gives us the premium the average respondent would pay for switching solar panels from one current land use to the other.

3 DATA

3.1 Survey implementation

We use the Tailored Design Method formulated by Dillman et al. (2014) to design a mixed-mode, web-push survey. The mixed mode aspect enables us to collect data both online (using Qualtrics software) and through mail, allowing for a higher response rate and greater sample representativeness (Millar and Dillman, 2011). The web-push aspect allows us to contact potential respondents by mail and invite them to take the survey online, which lowers per-respondent cost (McMaster et al., 2017).

We drew a random sample of 3,000 individuals from the 2019 Rhode Island voter registration database, which is publicly available from the Secretary of State. These data include name, address, age, party affiliation, and whether the individual participated in the last eight elections held. 91.4% of Rhode Island's voting age population is registered to vote, and the age distribution among registered voters is similar to that of the Census (though younger people are underrepresented and older people are overrepresented). Thus, we argue that our sampling strategy is an effective way to reach a near random sample of the population. Sample selection probabilities were adjusted to increase the odds of selecting younger people, those living in rural areas, and Republicans. Republicans were oversampled because they are a smaller group in Rhode Island and have been found to be less responsive to surveys (Best and Krueger, 2012; Lang and Pearson-Merkowitz, 2022). Rural residents were oversampled because they are more likely to be impacted by solar siting decisions. We oversampled younger residents because we anticipated lower response rates from them.

We disseminated the survey in three rounds. The first round was mailed on September 4, 2020. Each envelope included an introductory letter that provided a link and unique access code to the online survey and a $2 cash incentive. Two weeks later, non-respondents were sent a follow-up postcard as a reminder, which also gave the link and access code. In the third and final round (mailed two weeks after the second round), subjects who had not responded to either of the first two rounds of mailings were sent a paper survey along with a prepaid, pre-addressed return envelope.

Of the 3,000 surveys that were mailed, 204 were returned as non-deliverable. We received 669 total responses (24% response rate), 510 of which came from the online mode and

159 from mail. We drop 13 individuals who do not answer any of the choice questions. Our final sample consists of 3,914 choices made by 656 individuals.[13]

3.2 Summary statistics

Summary statistics of respondent characteristics are presented in Table 2. The average annual household income is $109,250 and the average monthly electricity bill is $123.57. While household income is above average for the state, (EIA, 2019) reports the average electricity bill for Rhode Islanders was $122, near identical to our sample average, which bolsters our confidence for its representativeness. About 68% of the respondents have a college degree or higher, 63% are employed, and 52% are female. A large proportion of respondents are homeowners (83%), 35% have children at home, and the average tenure in their current home is over 15 years. About 5% of respondents have solar panels installed in their own homes. On average, they have a very positive attitude towards renewable energy sources (solar, wind, and hydro). Specifically, 87% of respondents have a positive view of solar energy in general. In contrast, respondents are neutral towards natural gas and dislike energy production from nuclear materials and coal. These attitudes are consistent with recent nationwide studies that find immense support for developing alternative energy over expanding fossil fuels in the U.S (McDonald et al., 2020; Pew Research Center, 2020).

Finally, about 90% of subjects find the survey to be consequential with regards to policy decisions and the payment vehicle.[14] We believe we were able to achieve such high rates consequentiality among our respondents through the detailed information we gave respondents regarding the ways in which researchers behind the survey have partnered with local and state stakeholders and policy makers in both the design of the survey and the planned dissemination of the results (Carson et al., 2014; Carson and Groves, 2007; Herriges et al., 2010). While the risk of hypothetical bias exists any time hypothetical choices are made, there is evidence in the literature that survey responses reflect actual real-world choices when the survey is perceived as consequential (Vossler and Watson, 2013, for example). As such, our primary approach to reducing the risk of hypothetical bias was through a focused effort to establish the survey as consequential both ex post and ex ante (Mamkhezri et al., 2020b).[15]

We use three key demographic variables to construct sample weights: age, political affiliation, and rural/urban residence.[16] Table A1 in the online appendix reports the demographic distribution for these three variables in our unweighted sample, the population, and the weighted sample. The unweighted sample means differ from the population means across all groups, which is due to our disproportionate sampling and various groups' propensity to respond to the survey. However, the application of sample weights balances the proportions exactly.

4 RESULTS

Table 3 reports estimation results for our main specifications. All regressions include sample weights applied using an inverse proportional weighting scheme. In Column 1 we present coefficients from the CL model. Column 2 shows coefficients derived from estimating the HCL model, along with scale parameter estimates associated with farm, forest, and commercial land use types.[17] Columns 3 and 4 report mean coefficient and standard deviation estimates, respectively, from the RPL model, which is our preferred specification because of its more realistic assumptions regarding preference heterogeneity and relaxed IIA restriction. Results are consistent across columns. We find that the coefficient on $Acres$ is positive and significant (at 1%), implying that respondents prefer large solar installations. They also dislike installations that are visible, as suggested by the negative sign on $PartVisibility$ and $FullVisibility$. However, only the coefficient on $FullVisibility$ is significant (at 1%), indicating that completely visible installations elicit a stronger negative reaction than partly visible ones. The coefficient on $Setback$ is positive across the board, insignificant in the CL and HCL models, and only weakly significant (at the 10% level) in the RPL model. This suggests that people are unaffected by setback distance when controlling for the visibility of the installation.[18] This is also likely because respondents consider setback distance to be the least important attribute while making choices (Figure A2 in the online appendix).[19] $Probability$ is negative and significant at the 1% level, which means that people are less likely to choose an option when the probability of residential development is higher. Since the only options in our design with nonzero probability of residential development are status-quo options when forests or farmlands are the current land use, the implication is that respondents are less likely to select the status-quo (and so more interested in solar development) if the land is more likely to be converted to housing in the near future, which is consistent with expectations.

We find that preferences for constructing solar installations differ by the type of land use under consideration. The positive and significant coefficient on $Farm \times ASC$ in the CL and HCL models suggests that respondents' prefer the status-quo for this land use type, and thus dislike having solar arrays built on farmlands. The corresponding mean estimate for the RPL model is positive and significant only at the 10% confidence level, though the large and significant SD value implies that people exhibit large variation in their preferences regarding solar installations on farmlands. The coefficient on $Forest \times ASC$ is positive and highly significant across all models, providing strong evidence of people's dislike for developing forest lands for solar energy. Similar to farmlands, we find evidence of large variation in respondents' preferences for converting forest land into solar installations, as indicated by the large and significant SD values associated with the $Forest \times ASC$ term. The negative and significant (at the 1% level) coefficients on the $Brownfield \times ASC$ and $Commercial \times ASC$ interaction terms indicate that, in general, people like having solar installations on brownfields and commercial land types.

Table 4 displays welfare estimates from our models. In Panel A of Table 4 we present MWTP estimates for all attributes with standard errors derived using non-parametric bootstrapping with 1,000 replications.[20] On average, respondents are willing to pay \$0.24 to \$0.28 per month for each additional acre of land to be developed for solar.[21] This translates to a monthly WTP between \$7.20 and \$8.40 for a 30 acre installation and between \$12 and \$14 for a 50 acre one, which, in a basic sense, is consistent with overall support for solar energy and general subsidies for solar energy. We find that the MWTP for a partly visible installation is negative, though insignificant, and small in magnitude. The MWTP for a fully visible installation is significant and much larger in magnitude, which suggests that respondents need to be compensated between \$6.21 and \$8.43 per month for solar installations that are completely visible, compared with not visible. Values for the $Setback$ attribute are insignificant for the CL and HCL models, and slightly significant (at the 10% level) for the RCL model. However, the magnitude is small throughout, implying that respondents are largely unaffected by setback distance. The MWTP for $Probability$ is negative and significant, indicating less compensation is needed for solar development on farm and forest lands when the probability of future residential development increases. In addition, these estimates can be interpreted as MWTP for permanent land conservation. On average, respondents are willing to pay between \$4.75 and \$11.25 per month for a 25% reduction in the probability of future residential development, and between \$9.50 and \$22.50 per month for a 50% reduction. Translating these monthly payments in perpetuity into present discounted value yields amounts that are similar to property value studies on the capitalization of conserved open space (Irwin, 2002; Lang, 2018). Our MWTP estimates are also broadly similar to various contingent valuation studies estimating the value of farmland and forest conservation across several countries (Jin et al., 2018; Lehtonen et al., 2003; Shoyama et al., 2013).

Panel B of Table 4 reports CV estimates for the development of a specific solar installation on various land types. We consider a 10 acre solar installation that is completely visible, has a setback distance of 150 feet from the property line of the development site and with a 0% probability of residential development in the future. Our results provide suggestive evidence of respondents' dislike for constructing solar panels on farmland. Estimates from the CL and HCL models suggest that people need to be compensated almost \$23 per month when farmland are converted to solar installations. In comparison, the RPL estimate of \$13.22 per month is smaller in magnitude, though it is still negative and significant. We find large negative WTP values for constructing solar on forest lands, which indicates a strong dislike for such siting. On average, people need to be compensated between \$40.58 and \$49.04 per month for the development of forest land into solar. We also find positive WTP values for $Commercial$ and $Brownfield$, implying that respondents support converting these types of lands into solar installations. Our results indicate that people are willing to pay between \$14.43 and \$20.72 per month in higher energy bills for solar development on commercial lands and range from \$10.06 to \$15.07 per month on brownfields.

Given the dominance of land use in determining project approval, we additionally investigate whether attribute preferences vary by land use. We split the sample of choice tasks by land types revealed to be desirable (commercial and brownfield) and undesirable (farmland and forest), and we estimate Equation (8) on each sample separately. Table 5 presents WTP values for solar attributes for the farm and forest subsample in Column 1 and for the commercial and brownfield subsample in Column 2.[22]

We find several differences across columns that reveal how land use impacts MWTP for attributes. While respondents are willing to pay \$0.15 (weakly significant at the 10% level) to avoid each additional acre of farm and forest land to be developed for solar, their willingness to pay for each additional acre of solar on commercial and brownfield land is over two times that amount: \$0.38. The latter translates to a monthly WTP of \$11.40 for a 30 acre installation and \$19 for a 50 acre installation. Visibility is more of a concern to respondents for farm and forest sites than on commercial and brownfield sites. Respondents are willing to pay \$5.56 to avoid seeing a partially visible installation on farm and forest lands, whereas the corresponding value for commercial and brownfields is small and statistically insignificant. While completely visible arrays are disliked regardless of the land type on which they are sited, respondents' dislike is stronger for fully visible installations on farms and forest lands. Their monthly WTP to avoid seeing fully visible installations on commercial and brownfield areas is \$5.12, but is \$13.60 for installations on farm and forest lands, which is a ratio of about 2:5. Respondents also prefer greater setback for solar in commercial and brownfield areas, though the result is only marginally significant. MWTP for reduced probability of residential development and CV estimates in Panel B are consistent with our main results.

Purely for comparison purposes, we also develop a model that does not account for land use differences and present the results in Tables A3 and A4 of the online appendix. The results present an inconsistent picture of overall approval: Total WTP switches signs across specifications. These results suggest that failure to adequately control for current land use can obscure strong preferences for and against specific types of solar development, thus underscoring the importance of including current land use in the discussion surrounding the siting of solar installations.

While we present results from multiple models here, as robustness checks we estimate the same basic model using a mixed logit in willingness-to-pay space (Train and Weeks, 2005), mixed logit models with correlated attribute distributions, generalized multinomial logit model (Fiebig et al., 2010), and a latent class model. All models give qualitatively similar results and are presented in the online appendix (Tables A5-A11). Finally, in Table A12 of the online appendix, we examine preference heterogeneity by rural/urban residence as a robustness check. We change our four ASC/Land use interactions to eight ASC/Land use/Rural-urban interactions and find only weak evidence of a rural-urban divide in preferences. Specifically, we find that no differences are statistically significant at the 5% level. However, the larger magnitude of the interaction of $Rural$ with the $Farm \times ASC$ term compared to $Urban$ and $Farm \times ASC$ interaction term suggests that rural residents are more hesitant to develop on farmland than their urban counterparts. This difference is statistically significant at the 10% level in two of our three models (though not in our preferred model, the RPL), implying that the evidence in support of a rural-urban divide in preferences is very weak.

5 POLICY RECOMMENDATIONS

In order to stimulate solar growth and achieve renewable energy targets, Rhode Island buys renewable energy from producers at a premium to offset the higher levelized cost than conventional sources.[23] However, the incentives offered to solar developers are constant regardless of the attributes of the project. Given the additional costs of developing on commercial/industrial areas, brownfields, and covered landfills, the constant incentive essentially encourages solar development on farm and forest lands. In addition, visual barriers from landscaping or other means are additional costs to developers, and thus may be inefficiently underprovided.

Several New England and Mid-Atlantic states do offer differentiated subsidies based on prior land use (see Knight et al. 2020 for a review). The most common is an additional incentive for parking lot canopies. For example, Massachusetts offers and additional $0.06/kWh and Maryland offers up to $400 per kW of installed capacity. Rhode Island undertook a pilot project in 2020 offering a $0.06/kWh adder for a single solar parking lot canopy development (*RIPUC*, n.d.). Several states similarly offer differentiated rates for solar built on brownfields and covered landfills. In the case of Massachusetts, this is a $0.03/kWh and $0.04/kWh adder, respectively. Vermont offers financial resources for assessment and cleanup of contaminated sites. Massachusetts additionally uses disincentives for solar sited on forest land. The deduction increases with the size of the installation, but as an example a 5 MW array would receive a deduction of $0.015/kWh from the standard incentive (*MA-Smart Solar*, n.d.). While these differentiated incentives are certainly in line with our estimates of preferences across land types, it is unclear whether they pass a benefit-cost test or if similar differentiated incentives enacted in Rhode Island would pass a benefit-cost test.[24]

While the results presented in Section 4 indicate welfare impacts to households from various solar siting decisions, we additionally seek to use our results to inform policy. As illustrated above, many policy actions take the form of per kWh incentives or disincentives, so that is how we structure our analysis here. Table 6 presents the logical steps of converting our household valuation results into per kWh incentives for various policy actions that are costly to developers but preferred by residents (i.e., moving development from forest land to commercial land). The goal is to develop incentives that are justified based on residents' preferences. We conduct this exercise based on a 2 MW array. Column 1 is monthly household WTP for each policy action and is calculated from Column 3, Panel B of Table 5. Column 2 is this household WTP per kWh of production. This equals Column 1 divided by 237,600 kWh, which is expected monthly electricity generation from a 2 MW array with a capacity factor of 16.5%.

The remaining columns aggregate WTP across households within a given distance (0.5, 1, 3 miles) of a hypothetical solar array. The number of households within a given distance is approximated using census data for the whole state of Rhode Island. We present multiple distances because it is uncertain what the appropriate aggregation level is. A distance of 0.5 miles might approximate the size of an area in which residents are likely to frequently encounter a solar array. Another measure of proximity stems from two studies that find that property value impacts extend to about one mile: Gaur and Lang (2020) in Massachusetts and Rhode Island, and Abashidze (2019) in North Carolina. Often solar developments are hotly debated at town meetings, and the average town in Rhode Island has an approximate radius of three miles, so we present that as an upper bound.

The results suggest that, even for conservative definitions of impacted households, substantial incentives are justified. For example, aggregating over only residents within 0.5 miles, an additional incentive of $0.07/kWh is justified if a solar array development is moved from forest land to commercial land. Similarly, an additional incentive of $0.06/kWh is justified if a solar array development is moved from forest land to a brownfield. Incentives to displace development on farmland are smaller at $0.03/kWh. Incentives for visibility screening come in around \$0.01/kWh. As the distance of impacted households grows, so do the incentives justified, reaching excessive levels for this context (i.e., \$2.47/kWh for moving a development from forest to commercial).

These incentives can additionally be altered to reflect the reality of development proposals. For instance, a developer cannot credibly declare they would build on forest land, but are now building on a brownfield, and so deserve a \$0.06/kWh added incentive. One option would be to place a \$0.03/kWh added incentive on brownfields, and a reduced feed-in-tariff of \$0.03/kWh if an array is sited on forest lands. This combination would mirror resident preferences for land types. When it comes to screening, landscaping typically is an upfront fixed cost, and thus would not need an ongoing per kWh incentive. However, vegetative (or even artificial) buffers can deteriorate over the 25 year lifetime of an array if not tended, thus an annual verification of visual screening to qualify for a small incentive (per kWh or a flat fee) could be appropriate.

As mentioned above, our calculations in Table 6 use a 2 MW capacity. As capacity grows, production grows, and subsidies decline. Since household WTP values are independent of any assumptions of solar attributes, only electricity generation will be affected when we assume an installation with a different capacity. Therefore, the WTP/kWh values will decrease in proportion to the size of the assumed installation. In Appendix Table A13, we present an analogous version of Table 6 using a 6 MW capacity installation instead. Justified incentives are substantially smaller, however, this may be appropriate as levelized cost goes down as capacity increases (*RIPUC*, n.d.).

6 CONCLUSION

This paper quantifies the externalities of utility-scale solar installations by analyzing RI residents' tradeoffs for six solar siting attributes: size of the installation, visibility, setback distance, probability of future residential development, change in electricity bill, and current land use of the proposed solar site. We collect data using a survey that was distributed to a random sample of 2,794 RI residents. Our final sample consists of 3,936 choices made by 656 respondents.

We use a CE framework and logistic regression models to estimate respondents' WTP for each attribute. MWTP values indicate that Rhode Islanders like large installations and are willing to pay $0.28 for each additional acre of land to be developed for solar energy. However, respondents dislike fully visible installations and need to be compensated $8.43 for the same. We find no significant impacts from setback distance and partly visible installations, suggesting that respondents are unaffected by these attributes. When the probability of future residential development increases, they are less likely to choose the status quo alternative of no solar development.

Assuming a 10 acre, fully visible installation with a setback distance of 150 feet and 0% probability of future residential development, we obtain total WTP values for solar development on different land types. Our results indicate substantial heterogeneity in preferences for constructing solar installations by current land use of a proposed solar site. Overall, respondents dislike solar development on farmlands and forests, and need to be compensated $13 to $49 per month for the change. However, they support solar development on brownfields and commercial land types and are willing to pay an additional $15 to $19 per month to have solar installations constructed there.

These results provide some insight into NIMBYism, which is loosely defined as a phenomenon where people approve of something in general, but do not want it near their residence. Objections to renewable energy siting are frequently characterized (and maybe dismissed) as merely NIMBYism. Devine-Wright, (2009) argues instead that local opposition is about protecting places that people are attached to and derive meaning and identity from. Boyle et al. (2019) conduct a choice experiment about onshore wind energy siting and reject a NIMBY hypothesis because those that have positive views of wind in general are more likely to choose development of wind locally. While we do not explicitly test for NIMBYism, our study provides additional insight to this debate. Our sample respondents overwhelmingly have positive attitudes towards solar energy but are more discerning when it comes to preferences for local projects, approving solar in only about 60% of choice tasks. We find that people have positive WTP for local solar on brownfields and commercial areas, but these same people require compensation for solar developed on farm and forest lands. Thus, concerns heard about solar developments in town meetings and stakeholder groups are not likely blanket NIMBY concerns, but instead are concerns about land use change and other important priorities.

We conclude with calculations and a discussion about how our results can be converted to policy relevant parameters. The incentives and disincentives will promote solar development that is consistent with residents' preferences. As Rhode Island and other states seek to meet renewable energy objectives, assessment and incorporation of residents' preferences are critical to ensure ongoing support.

This research extends the literature on both preferences for utility-scale renewable electricity generation and preferences for land conservation in a manner that is relevant to stakeholders and residents as well as actionable for policy makers. We model land use in the solar siting choice in a way that is intuitive, clear, and obviously resonant to residents. We also extend our analysis beyond traditional household WTP estimates to frame resident preferences in a way that mirrors the units of subsidy for utility scale installations. This research also hints at important future extensions in this area. Spatial heterogeneity of preferences likely exists in this area and has been shown relevant to preferences for land conservation in other contexts (Czajkowski et al., 2016). Modeling how preferences vary by spatial distance is an important extension of this work and will help shed light on which spatial aggregation ranges from Table 6 are most appropriate when determining incentives. As with any hypothetical survey, it would also be fruitful to explore to whether our findings are robust to similar choices made in incentivized contexts as well as hypothetical decisions framed as a single binary choice (Carson and Groves 2007).

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Tables and figures

Table 1: Attribute definitions and levels

Attribute	Definition	Levels
Size of installation	The size of the solar installation in acres.	10, 20, 30, 40, 50
Visibility	Visibility of a solar installation from a respondent's house or from regularly traveled roads.	Not visible, Partially visible, Completely visible
Setback[a]	Minimum distance of the solar panels from the property line.	0, 50, 100, 250
Probability of residential development[b]	The likelihood that the land being considered will be developed into residential housing in the next ten years if a solar installation is not built.	0%, 25%, 50%
Change in electricity bill[c]	The dollar increase or decrease in a respondent's monthly electricity bill if the parcel is converted to solar power generation.	-$30, -$20, -$10, -$5, $5, $10, $20, $30
Current land use[d]		
a) Farmland	The land is currently used to grow agricultural crops. In this case, solar installations would be built on the ground.	
b) Forest	The land is currently privately-owned forest land. In this case, trees will be clear cut and solar installations would be built on the ground.	
c) Commercial	The land is either currently used for business activities, including buildings and parking lots, or undeveloped land that is zoned for commercial purposes. In this case, solar installations could be built on the ground, on building rooftops, or as a parking lot canopy.	
d) Brownfield	A former industrial or commercial site where future use is affected by real or perceived environmental contamination. These could include capped landfills and quarries. In this case, solar installations would be built on the ground.	

Notes: [a] Setback level of 0 feet is excluded for farm and forest land use types.
[b] Probability of residential development is excluded when the land use type is commercial or brownfield.
[c] For the commercial and brownfield land types, the levels of -$30, -$20, and -$10 are excluded.
[d] Current land varies across choice tasks but is constant across alternatives within each choice task.

Table 2: Summary statistics of survey respondents

Variable	Mean	SD	Minimum	Maximum	Observations
Household income (000's)	109.25	50.96	15	175	601
College educated (1 = yes)	0.68	0.47	0	1	649
Children at home (1 = yes)	0.35	0.48	0	1	646
Female (1 = yes)	0.52	0.50	0	1	656
Homeowner (1 = yes)	0.83	0.38	0	1	647
Years living in current home	15.51	6.55	3	20	651
Employed (1 = yes)	0.63	0.48	0	1	650
Electricity bill ($/month)	123.57	54.88	25	200	646
Solar panels at home (1 = yes)	0.05	0.23	0	1	647
Energy attitudes (1 = positive)					
Solar	0.87	0.33	0	1	649
Offshore wind	0.80	0.40	0	1	640
Onshore wind	0.76	0.43	0	1	638
Hydro	0.68	0.47	0	1	637
Natural gas	0.52	0.50	0	1	642
Nuclear	0.26	0.44	0	1	627
Coal	0.08	0.28	0	1	638
Consequentiality (1 = positive)					
Policy	0.91	0.29	0	1	656
Payment	0.90	0.29	0	1	656

Notes: All data come from survey responses. Household income and electricity bill values come from a multiple choice question that included several ranges. We assign people the middle value of their chosen range.

Table 3: Attribute coefficients from logit regressions

Variable	Conditional Logit	Heteroscedastic Logit	Random Parameters logit	
			Mean	SD
Acres	0.010***	0.018***	0.016***	0.044***
	(0.002)	(0.004)	(0.003)	(0.004)
PartVisibility	-0.066	-0.067	-0.127	0.15
	(0.061)	(0.085)	(0.083)	(0.28)
FullVisibility	-0.313***	-0.406***	-0.546***	0.801***
	(0.074)	(0.103)	(0.111)	(0.20)
Setback (00's ft)	0.042	0.066	0.079*	0.293***
	(0.031)	(0.042)	(0.044)	(0.11)
Probability	-0.008***	-0.014***	-0.029***	0.077***
	(0.002)	(0.004)	(0.007)	(0.01)
Cost ($/month)	-0.043***	-0.065***	-0.065***	
	(0.002)	(0.007)	(0.004)	
Land use ASC interactions				
Farm × ASC	0.822***	1.407***	0.590*	3.859***
	(0.135)	(0.268)	(0.333)	(0.60)
Forest × ASC	1.596***	2.988***	2.910***	4.161***
	(0.134)	(0.465)	(0.374)	(0.560)
Brownfield × ASC	-0.793***	-0.782***	-1.232***	0.338
	(0.128)	(0.148)	(0.165)	(0.217)
Commercial × ASC	-1.035***	-1.068***	-1.517***	0.045
	(0.132)	(0.190)	(0.167)	(0.220)
Heteroskedastic variables				
Farm		-0.450***		
		(0.122)		
Forest		-0.704***		
		(0.142)		
Commercial		-0.026		
		(0.138)		
Choices	11,724	11,724	11,724	
Respondents	656	656	656	
Log likelihood	-3684.505	-3660.792	-3288.602	
AIC	7389.010	7347.585	6615.204	
BIC	7462.704	7443.387	6755.223	

Note: Acres refers to the size of the solar installation in acres. Part visibility and Full visibility are dummy variables = 1 if a solar installation is partially or completely visible, respectively. ASC is the status-quo alternative-specific constant, or a dummy variable = 1 for the status-quo choice and 0 otherwise. Cost is in terms of USD per household per month. Sample weights are applied and constructed using stepwise adjustment on three variables: age, political affiliation, and rural/urban residence. Standard errors, clustered by respondent, are in parentheses. *,**,*** indicate significance at the 90%, 95% and 99% level, respectively.

Table 4: Marginal willingness to pay estimates for solar attributes

Attribute	Conditional logit	Heteroskedastic logit	Random parameters logit
Panel A: Marginal WTP			
Acres	$0.24***	$0.28***	$0.25***
	[0.14, 0.34]	[0.19, 0.37]	[0.15, 0.35]
PartVisibility	-$1.54	-$1.03	-$1.96
	[-4.36, 1.27]	[-3.65, 1.59]	[-4.45, 0.53]
FullVisibility	-$7.30***	-$6.21***	-$8.43***
	[-10.74, -3.86]	[-9.15, -3.28]	[-11.62, -5.24]
Setback (00's ft)	$0.98	$1.01	$1.21*
	[-0.41, 2.37]	[-0.20, 2.22]	[-0.12, 2.54]
Probability	-$0.19***	-$0.22***	-$0.45***
	[-0.30, -0.08]	[-0.35, -0.09]	[-0.67, -0.23]
Panel B: Total WTP			
Farmland	-$22.54***	-$23.43***	-$13.22***
	[-23.01, -12.56]	[-23.19, -12.88]	[-23.05, -3.39]
Forest	-$40.58***	-$47.62***	-$49.04***
	[-41.22, -30.42]	[-50.21, -34.24]	[-59.56, -38.53]
Commercial	$20.72***	$14.43***	$19.32***
	[14.65, 26.78]	[9.64, 19.23]	[14.01, 24.63]
Brownfield	$15.07***	$10.06***	$14.91***
	[9.41, 20.73]	[5.57, 14.55]	[9.86, 19.96]

Notes: Welfare estimates are in USD per household per month. Estimates in Panel A represent marginal WTP values. In Panel B, the estimates represent total WTP values and assume a 10 acre, fully visible installation with a setback of 150 feet, and a 0% probability of development in the future. In both panels, confidence intervals and standard errors are calculated using the bootstrap method (with 1000 replications) and 95% confidence intervals are in parentheses. *,**,*** indicate significance at the 90%, 95% and 99% level, respectively.

Table 5: Marginal willingness to pay estimates for solar attributes estimated separately by land types

Attribute	Farm and Forest (1)	Commercial and Brownfield (2)
Panel A: Marginal WTP		
Acres	-$0.15*	$0.39***
	[-0.33, 0.03]	[0.26, 0.51]
PartVisibility	-$5.56***	-$0.29
	[-9.23, -1.90]	[-3.53, 2.96]
FullVisibility	-$13.60***	-$5.12***
	[-18.55, -8.65]	[-8.56, -1.68]
Setback (00's ft)	-$0.05	$1.63**
	[-2.4, 2.13]	[0.01, 3.25]
Probability	-$0.35***	
	[-0.53, -0.17]	
Panel B: Total WTP		
Farmland	-$11.32**	
	[-20.27, -2.36]	
Forest	-$42.18***	
	[-52.06, -32.29]	
Commercial		$15.86***
		[10.91, 20.80]
Brownfield		$12.10***
		[6.79, 17.40]

Notes: Welfare estimates are in USD per household per month. Estimates in Panel A represent marginal WTP values. In Panel B, the estimates represent total WTP values and assume a 10 acre, fully visible installation with a setback of 150 feet, and a 0% probability of development in the future. In both panels, standard errors and confidence intervals are calculated using the bootstrap method (with 1000 replications) and 95% confidence intervals are in parentheses. *,**,*** indicate significance at the 90%, 95% and 99% level, respectively.

Table 6: Developing solar siting incentives justified by residents' preferences

Policy Action	Household WTP	Household WTP/kWh	Aggregate WTP/kWh: Median households within 0.5 miles	Aggregate WTP/kWh: Median households within 1 mile	Aggregate WTP/kWh: Median households within 3 miles
	(1)	(2)	(3)	(4)	(5)
Forest to Commercial	\$68.36	\$0.00029	\$0.07	\$0.27	\$2.47
Forest to Brownfield	\$63.95	\$0.00027	\$0.06	\$0.26	\$2.31
Farm to Commercial	\$32.54	\$0.00014	\$0.03	\$0.13	\$1.18
Farm to Brownfield	\$28.13	\$0.00012	\$0.03	\$0.11	\$1.02
Fully visible to partly visible	\$6.47	\$0.00003	\$0.01	\$0.03	\$0.23
Fully visible to not visible	\$8.43	\$0.00004	\$0.01	\$0.03	\$0.30

Notes: Household WTP values in Column 1 are derived from Column 3 of Table 5. The WTP for switching solar development from one land type to another is calculated by subtracting the total WTP for the former land type from the latter. The WTP for converting a fully visible installation into a partly visible one is obtained by subtracting the WTP for a partly visible installation from the WTP for a fully visible installation, and then changing the sign from negative to positive. The WTP for making a fully visible installation not visible at all is the negative of the marginal WTP estimate of $FullVisibility$. Column 2 values are calculated by dividing Column 1 by expected monthly electricity generation from a 2 MW installation. Columns 3, 4, and 5 take the household WTP/kwh values from Column 2 and aggregate them over the median number of households within a radius of 0.5, 1, and 3 miles, respectively. Based on population density from the 2010 RI Census, we calculate the median number of households within an area equivalent to 0.5 miles from a solar array is 239, within 1 mile is 955, and within 3 miles is 8,599.

Figure 1: Example choice question

Parcel 1: Farmland

Consider a group of privately-owned land parcels that totals 50 acres and are currently used as farmland. These parcels are in Rhode Island and less than 15 minutes from your residence by car. Below are two possible solar development plans for these farmland parcels. Policy makers can approve either plan, or they can reject both plans and have no solar installation on the parcels. Please examine the three options below and indicate which option you prefer.

	CHOICE A	**CHOICE B**	**CHOICE C**
Size of installation	10 acres (generates enough power for 320 homes)	30 acres (generates enough power for 960 homes)	NO SOLAR PANELS
Visibility	Visible	Not visible	
Setback	100 ft	50 ft	
Probability of residential development	0%	0%	50%
Change in monthly electricity bill (annual)	$10 increase ($120 annual ↑)	$10 decrease ($120 annual ↓)	No change
YOUR CHOICE [Please check ONE box only]	**A** ☐	**B** ☐	**C** ☐

[1] Other concerns of residents related to solar development include glare from glass panels, ecosystem impacts, loss of scenic beauty and rural character, water pollution, and reduction in property values (Abashidze, 2019; Dröes and Koster, 2021; Farhar et al., 2010; Gaur and Lang, 2020; Gross, 2020; Jarvis, 2021; Lovich and Ennen, 2011; Qi and Zhang, 2017; Tsoutsos et al., 2005; Turney and Fthenakis, 2011).

[2] The goal of having 38.5% of total energy generated from renewable sources by 2035 may not seem to be very ambitious by global standards (or even US ones), but it certainly is so by RI standards and when placed in context. When RI adopted the RPS target in 2004, it had 0% renewables, which meant that it would have to increase the renewable share by a little over 1% every year to meet the goal in 2035. As of 2020, 16 years after adopting the target, about 12% of all in-state electricity generation came from renewables. To meet the target of 38.5% by 2035, the state would have to accelerate renewable energy generation, and this will have to happen in the wake of recent protests against solar development on farm and forest lands.

[3] The results are expected based on our attendance of town meetings, discussion with stakeholders, and input from our advisory board. In addition, many academic papers have demonstrated the value people place on open space.

[4] The small geographic scope of RI implies that respondents live in roughly similar environments which allows us to make state-wide policy recommendations.

[5] Tangentially related are Mamkhezri et al. (2020a) and Oehlmann et al. (2021), who study preferences for energy mix and renewable energy goals. Mamkhezri et al. (2020a) find that respondents in New Mexico, USA have positive WTP for more aggressive RPS targets and prefer rooftop solar over utility-scale solar to meet those targets. Oehlmann et al. (2021) find that respondents in Germany prefer solar to wind or biomass, but prefer smaller installations to larger for all three options.

[6] See Nilson and Stedman (2022) for a review of the socio-political literature on public acceptance of utility-scale solar installations.

[7] As discussed below, our brownfield land type designation includes brownfields, landfills, and quarries. Knight et al. (2020) document potential solar capacity at these types of sites. They find 63 landfill sites with a possible capacity of 90 MW and 13 quarries also with possible capacity of 90 MW. There are 700 known, remediated brownfield sites with an estimated solar potential of 650 MW. Rhode Island operates a voluntary brownfield remediation program (Lang and Cavanagh, 2018), meaning there are additional unknown sites that could also be available for solar development. While brownfields are more concentrated in urban areas and water ways, across the three categories there is potential in every RI town.

[8] The constraints to attribute levels were twofold. First, only farm and forest land were given nonzero probabilities of future residential development. This was done because farm and forest land are far more likely to be zoned for residential development than commercial and brownfield land in RI. Second, while we originally planned for eight different levels for changes in household monthly electric bills for all land use types (-$30, -$20, -$10, -$5, $5, $10, $20, and $30), our advisory group noted that the greater costs associated with developing solar on commercial and brownfield lands made development plans on these land types coupled with large decreases in monthly electric bills unrealistic. As a result, our design was constrained so that $30 and $20 decreases in monthly electric bills would not be combined with commercial and brownfield development plans. As a result of these differences, we separately derived efficient designs for each land use type, with the commercial and brownfield designs having one fewer attribute and two fewer levels for the cost attribute.

[9] Additionally, in the variable description section of our survey, we describe a 1 acre installation as being the same size as 1 football field, with the hope that respondents would find that easier to visualize.

[10] The complete survey instrument is presented in the online appendix. This includes example choice tasks for each land type, supplementing Figure 1, as well as all other questions used in the analysis.

[11] The grant that funded this work requires integration of research and extension.

[12] The omitted category is ‘not visible’.

[13] Only 36 respondents chose the status quo alternative in all six choice questions, giving us a serial non-participation rate of 5.5%, which is considerably lower than other studies (Chen et al., 2020; von Haefen et al., 2005). This finding suggests that respondents are engaging with the subject and not dismissing it outright. Figure A4 in the online appendix depicts respondents’ choice preferences for the status quo and solar development alternatives by land use.

[14] Following (Carson and Groves, 2007; Herriges et al., 2010), we use a knife-edge definition of consequentiality where policy consequentiality is an indicator variable equal to 1 if respondents believe that their answers will influence policies. Likewise, payment consequentiality is an indicator variable equal to 1 if respondents believe that they will have to pay with any positive probability. Questions are framed as probabilistic, with respondents giving a zero probability to the likelihood of payment/policy consequentiality being labeled as not consequential. 11.23% of respondents give a zero probability to the payment consequentiality question while 10.95% give a zero probability to the policy consequentiality question. Individuals who see a lack of consequentiality in one domain overwhelmingly see it in the other domain as well, as only 12.35% of respondents fall into the inconsequential category when we define it as giving a zero probability to either question.

[15] Analyses that follow include both respondents who view the survey as consequential and those that did not. Omitting inconsequential responses yields qualitatively similar results, altering compensating variation estimate by only $1 – 4 across specifications. While the non-binary repeated discrete choice elicitation format we use in our survey is very common in the literature, it is worth noting that Carson and Groves (2007) also argue that only a single binary choice design is incentive compatible and so immune to potential strategic response. While we are not aware of any research that empirically quantifies bias from strategic response using our elicitation format vs. single binary choice in a survey setting, we feel the potential for strategic response is worth noting.

[16] While income is an important predictor of WTP, we choose not to weight on this variable for two reasons. First, this information is not available to us *a priori* in the voter registration data. Second, we would have to rely on self-reported income information from the survey to create weights for income, and not everyone responds to that question. Even if we do create income weights (after dropping the 55 respondents who skip that question), we find that our CV estimates change by no more than $2 (in either direction).

[17] Coefficients for land use in "Heteroskedastic variables" portion of this model are read as the change in scale parameter (or, more specifically, the change in the exponent of the scale parameter) for the land use relative to the omitted land use, which is brownfield.

[18] As visibility is likely correlated with setback, it would not be totally correct to conclude that RI residents to not value setback. Indeed, if increasing setback is the only way (or best way) to decrease the visibility of an installation, then our findings suggest that greater setback is valued through its ability to decrease visibility.

[19] We find that our results are also robust to controlling for stated attribute non-attendance (ANA). The only major change of controlling for ANA is greater statistical significance for coefficients and welfare estimates of the partial visibility attribute.

[20] We also utilized the Carson and Czajkowski (2019) correction method and found that it leads to nearly identical results.

[21] We additionally tested whether there may be non-linear relationships between utility and the acreage attribute. We estimated models including quadratic and cubic terms, but these yielded no statistically significant nonlinearities. Models that instead used a series of dummy variables provided some evidence that utility for acreage may be nonlinear for sites exceeding 30 acres. For the purposes of this analysis, we use linear utility specifications for each attribute and restrict all welfare and policy analyses to installations less than or equal to 30 acres.

[22] The random parameters logit regression coefficients that are used to create Table 5 are presented in Table A2 of the online appendix.

[23] The vast majority of electricity in RI is generated out-of-state using natural gas (about 91%).

[24] Doing so is especially important in the context of RI since the average price of electricity (cents/kwh) within the state is already very high (the 4th highest average price of electricity in the US).