Agriculture and Solar Farms: Heterogeneous Preferences Among Local Public Officials, the General Population, Landowners and Non-Landowners

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Abstract

Utility-scale solar development has raised considerable local land use concerns. We investigate stakeholders' valuations for solar project attributes, focusing on land use trade-offs with a choice experiment in U.S. state of Iowa that incorporates information treatments and choice uncertainty. Results indicate substantial heterogeneity, with public officials and landowners valuing high-quality farmland significantly more than the general population and non-landowners. However, information treatments do not significantly affect attribute tradeoffs, though they influence overall support for solar. Rankings of land use challenges vary with respondents' farming backgrounds and solar experiences and interests. Findings highlight stakeholder-specific preferences shaping local acceptance of solar projects.

Keywords: Agricultural land use, Community acceptance, Information treatments, Land quality, Stakeholders, Utility-scale solar energy, Willingness to pay

1. Introduction

Solar energy systems produce less greenhouse gases during their life cycle than fossil fuel energy sources (NREL, 2012), representing a low-carbon renewable alternative to fossil fuels in the electricity production industry. With cost advantages in electricity generation and environmental gains (Lazard, 2020), the adoption of utility-scale solar photovoltaic (PV) energy, commonly defined as PV projects with greater than one megawatt (MW) capacity, is regarded as one of the fastest growing approaches to cutting carbon emissions and transitioning the United States towards a decarbonized power grid and a clean energy future (Solar Energy Industries Association).

The fast growth of solar has attracted considerable attention to its land use implications in the United States (Trainor et al., 2016). Given the current prevailing technology, one MW of PV solar capacity takes about 4-6 acres of land (Bolinger and Bolinger, 2022). Even though the National Renewable Energy Laboratory (NREL) estimates that the entire U.S. could be powered by utility-scale solar panels, occupying merely 0.6% of the country's land, the development of such projects and the associated land use issues are inherently localized (Majumdar and Pasqualetti, 2019; Suh and Brownson, 2016). According to a report from the USDA's Economic Research Service (ERS), over 90% of solar projects in the U.S. between 2009 and 2020 were located in rural areas, with more than 70% of these projects sited on agricultural land (Maguire et al., 2024).

The development of solar on farmland creates direct competition for land resources, potentially affecting both food production capacity and rural economies. As suggested by Maddison et al. (2023), large-scale solar farms have disamenity impacts on nearby property values. Elmallah et al. (2023) and Gaur and Lang (2023) provide further evidence of declining property values for solar developments on agricultural land and for rural homes. Therefore, despite its advantages, utility-scale solar development has caused concerns among communities about the localized impacts, especially land-use conflicts with agricultural production (Crawford et al., 2022; Gaur et al., 2023). For example, Iowa lawmakers proposed a bill in 2023 to prohibit the construction of utility-scale solar panels on land suitable for farming, limiting options for landowners and hindering the growth of solar power (McCulluough, 2023).

The localized impacts of utility-scale solar projects are crucial factors underlying individual preferences and community acceptance (Hanger et al., 2016; Majumdar and Pasqualetti, 2019; Roddis et al., 2018). One key attribute addressed in previous studies was the choice of project siting. Gaur et al. (2023) utilized a choice experiment survey in Rhode Island to estimate the trade-offs people are willing to make for a set of siting attributes. They found that residents were willing to pay \$13–\$49 more in monthly utility bills to avoid locating such projects on agricultural and forestry landscapes. Moreover, studies by Larson and Krannich (2016) in Utah and Carlisle et al. (2016) across six southern Californian counties observed reduced support among residents for projects situated in proximity to residential areas, wildlife migration routes, or breeding grounds. Nilson and Stedman (2022) suggested that support for large-scale solar development in New York was associated with potential economic opportunities, especially considering the hardships facing the agricultural communities in their study. Similarly, Pascaris et al. (2022) found that survey respondents in Lubbock County, Texas, and Houghton County, Michigan, favored projects offering economic benefits to farmers and the local community. Crawford et al. (2022) found that the most common concern in Michigan was the potential devaluation of residential property. Various perceived risks for electricity supply, including intermittency, negative impacts on rural and tribal culture, and community energy sovereignty, as well as human health, were also found to be important factors (Boudet, 2019; Mulvaney, 2017; Nilson and Stedman, 2022; Roddis et al., 2020). However, studies concerning the formal assessment of the trade-offs between localized agricultural land-use impacts of utility-scale solar projects and their associated economic and environmental implications are still limited in the existing literature.

In contrast, a large literature investigates the role of different factors influencing individuals' preferences for solar energy systems, including message-framing strategies in advertisements (Wolske et al., 2018), financial incentives (Crago and Chernyakhovskiy, 2017), dissemination of solar energy information (Palm and Lantz, 2020), and social norms and environmental concerns (Kalkbrenner and Roosen, 2016; Wolske et al., 2017). These studies primarily focus on residential solar energy. Furthermore, a handful of qualitative studies based on interviews outline the challenges hindering solar energy adoption at both residential and utility scales, including information gaps regarding the advantages and benefits of solar power, high upfront investment costs, and land availability (Burke et al., 2019; Faiers and Neame, 2006; Frate and Brannstrom, 2017; Jager, 2006; Rai and Sigrin, 2013; Schelly et al., 2021). Understanding how underlying factors and the dissemination of information influence preferences for utility-scale solar projects provides valuable insights into their acceptance—or lack thereof—within local communities.

The objective of this study is to quantify the trade-offs of agricultural land of different qualities and other factors associated with utility-scale solar systems, such as environmental outcomes and economic consequences, and examine how agricultural land is valued relative to other attributes. By disentangling the intricacies of these trade-offs, our research seeks to help outline the potential factors shaping preferences and decisions in the context of utility-scale solar project development. More importantly, we aim to explore potential heterogeneity in how different stakeholder groups – public officials, the general population, landowners, and nonlandowners – value the attributes related to utility-scale solar projects and the associated trade-offs, recognizing their diverse perspectives on land use and solar development. We also aim to study how preferences for solar projects are affected by different information treatments, given the growing controversy and differing narratives surrounding utility-scale solar projects and their land use.

To answer the research questions, we conducted a survey experiment in 2023 that targeted both public officials and the general population in the U.S. state of Iowa. Iowa has experienced rapid growth in utility-scale solar energy development in recent years. From 2016 to 2023, the state commissioned 17 utility-scale solar PV power plants, aggregating its total capacity from 3.3 MW to 262.5 MW (EIA, 2024) – a trend expected to continue, given that over 3,804 MW of additional development is in queue with Midcontinent Independent System Operator (MISO, 2025). With approximately 85% of its land dedicated to farming, Iowa is a major agricultural state, representative of the broader Midwest U.S. in terms of agricultural importance to local economies, land-use patterns, and solar energy development. This makes Iowa a particularly relevant region for studying the trade-offs related to agricultural land use and utility-scale solar energy development. The majority (over 63%) of solar projects in the U.S. between 2009 and 2020 were sited on agricultural land (Maguire et al., 2024). Given these statistics, understanding solar development in agricultural states like Iowa is crucial for informing renewable energy policy and implementation strategies across the Midwest and the nation.

Our results show all stakeholder groups value agricultural land use, but the valuations differ among different stakeholder groups. Specifically, public officials demand much higher monthly compensations in terms of savings in electricity bills ($48.73) than the general public demands ($14.81). Landowners also require significantly more ($49.60) than non-landowners ($17.13) to offset the loss of highly productive farmland for solar projects relative to less productive farmland. To put these numbers in perspective, we note that in 2022, the annual average cash rent for farmland in Iowa was $256/acre (ISU Extension 2022) and the average monthly electricity bill was $110 (EIA, 2022). We also observe notable disparities in trade-offs between agricultural land use and other attributes across stakeholders. However, the type of information presented does not statistically significantly affect individual preferences concerning land uses. An analysis of the respondents' rankings of land use as a challenge for utility-scale solar projects and a latent class analysis suggest that respondents' farm backgrounds (or lack thereof), knowledge, and personal experiences related to solar energy are likely potential drivers of the preference heterogeneity.

This paper contributes to the existing literature in three ways. First, we surveyed two distinct groups, public officials and the general population, while also analyzing differences between landowners and non-landowners, to explicitly evaluate heterogeneous preferences for siting utility-scale solar projects on farmland of different qualities. Existing studies have shown that local communities play a critical role in utility-scale solar development (e.g., Hanger et al., 2016; Majumdar and Pasqualetti, 2019; Roddis et al., 2018). However, these studies have predominantly focused on the general public. There is a lack of perspectives of public officials, who may prioritize specific attributes differently than the general population, due to the distinct roles and responsibilities they have in their communities. Public officials' perspectives are crucial because of their decision-making power and the broader and more lasting impacts their decisions have on communities (Bohner and Dickel, 2011; Macawile and Su, 2009). In addition, existing research on renewable energy perceptions (e.g., Delicado et al., 2016; Rogers et al., 2008) often focuses on the community as a whole and overlooks the differences between landowners and nonlandowners, who may have diverging priorities based on their proximity to and economic involvement in land-use decisions (Mills et al., 2019; Musall and Kuik, 2011; Roddis et al., 2018). This study addresses this gap by encompassing the perspectives of public officials vs. the general population and landowners vs. non-landowners, allowing for an understanding of how different stakeholder groups value and prioritize various aspects of utility-scale solar projects and the associated trade-offs, thereby informing the design of more effective deployment strategies at the local level.

Second, we provide quantitative estimates of the trade-offs among various aspects of localized impacts specific to utility-scale solar energy, with primary data collection, and we analyze how different information treatments affect these trade-offs. While previous studies have investigated the determinants of community acceptance and factors influencing individual preferences (e.g., Chen et al., 2025; Majumdar and Pasqualetti, 2019; Nilson and Stedman, 2022; Roddis et al., 2020; Roddis et al., 2018), there is little quantitative analysis on how local communities value different attributes of such projects and the impact of each attribute in shaping individual preferences and support behaviors. We contribute to the existing literature and policy discussions with more quantitative insights about the value of utility-scale solar projects to local communities, using non-market valuation techniques that can incorporate environmental and behavioral drivers underlying people's preferences over different attributes. Furthermore, as land use for solar projects becomes a controversial topic, there are various information sources that emphasize different effects, some positive and some less favorable. The literature has shown that negative, positive, and peer information can influence preferences differently (Allcott and Knittel, 2019; Noll et al., 2014; Sias et al., 2023). We explore how preferences for solar projects are affected by different information treatments. Our study aims to inform debates about the trade-offs related to land uses of different quality and utility-scale solar at the local community level and to help inform policymaking for future solar development.

Third, our discrete choice experiment (DCE) incorporates respondents' degrees of uncertainty and information treatments, which enables us to derive more accurate WTP estimates. The fundamental assumption of the DCE is that respondents accurately know their preferences and can make precise choices. However, in reality, the assumption may be violated, potentially leading to biased inferences due to respondents' uncertainty regarding the utility derived from different alternatives (Beck et al., 2016; Ku et al., 2017; Loomis, 2014). Ku and Wu (2018) demonstrate that the identified low-uncertainty respondents are notably consistent in their preferences. To reflect a more realistic setting with choice uncertainty, we follow the literature (Choi et al., 2018; Hofstede et al., 2014; Ku and Wu, 2018; Serenari et al., 2015) to assess how respondents' uncertainty affects WTP estimates. Consistent with existing literature (e.g., Ku and Wu, 2018; Olsen et al., 2011), we find preference inconsistency between highly certain and uncertain responses, and the exclusion of highly uncertain responses improves model fitness and the accuracy of WTP estimates. To the best of our knowledge, there are no other studies that incorporate this aspect into stated preference analysis regarding community preferences for utility-scale solar projects.

The rest of this paper is organized as follows. Section 2 details the design and implementation of the survey and experiments. Section 3 describes the empirical methodology. Section 4 presents the results, and Section 5 concludes.

2. Data and methods

To study local land use issues related to utility-scale solar projects, we design a survey questionnaire to directly collect individual- and community-level data that are not available otherwise. The survey questionnaire (included in Appendix C) incorporates six sections. Besides the discrete choice experiment that incorporates information treatments, we collect data on respondents' knowledge of utility-scale solar energy, their perceptions and attitudes towards it, the electricity profiles of their communities, and basic demographic information through different sections. Our empirical analyses are based on these data.

2.1. Discrete choice experiment with uncertainty levels

We design a discrete choice experiment to assess how local communities value various attributes related to utility-scale solar projects. After extensive discussion with extension and outreach specialists [1], survey experts, and local officials (including county supervisors, city council members, and zoning and planning professionals), we choose four attributes from a set of local impacts regarding utility-scale solar, aiming to achieve our research goal, while minimizing the number of choices required for empirical estimation. As presented in Table 1, the four attributes we consider and their corresponding levels are: (i) expected carbon emission reduction relative to coal-fired power plants at 85% and 95%[2]; (ii) expected annual lease payment to landowners of 2, 4, and 6 times prevailing cash rent[3]; (iii) expected savings on the monthly electricity bill for the household of \$5, \$25, and \$40[4]; and (iv) land quality of the occupied farmland categorized as low, medium, and high based on the measure of corn suitability rating 2 (CSR2)[5].

The factorial design yields a total of $2 \times 3 \times 3 \times 3 = 54$ attribute combinations. To reduce the number of choices each participant has to make, we utilize data from 37 respondents in pilot testing as prior information to conduct a D-optimal design[6], aiming to eliminate dominated alternatives in the design of choice sets. This process results in 12 choice scenarios (tasks), producing a D-efficiency of 0.95. The 12 choice scenarios are divided into two blocks, and participants are randomly assigned to one of the two survey blocks, each containing six scenarios. In each scenario, we present two potential plans for a typical medium-sized solar PV project (i.e., 50 MW of nameplate capacity[7]) that are under consideration within a local community; the two plans are identical except for variations in attribute levels. Participants are asked to report which plans they were more likely to support in their communities. Following Herriges et al. (2010), Vossler and Evans (2009), Vossler and Watson (2013), and Vossler et al. (2012) for ensuring consequentiality and incentivizing respondents to reveal their true preferences, we emphasize in the instructions to respondents that their choices are critical to decision-makers considering solar development policies in their regions and would inform the design of land use regulations serving local communities.[8] To reduce the risk of protest responses that occur with an explicit "opt-out" option, participants are asked to make a choice between two proposed plans without a "no choice" option. However, we ask participants to state the extent of certainty regarding their choice following each choice scenario. Such an approach helps to mitigate hypothetical bias and obtain more accurate WTP estimates (Choi et al., 2018; Ku and Wu, 2018; Loomis, 2014). An example choice scenario is presented in Figure A.1.

2.2. Information treatment experiment

Land use for solar projects has become a controversial topic, frequently making headlines in news outlets and other information sources, which might highlight either positive or negative effects. Positive coverage often emphasizes the potential to reduce carbon emissions (Rocky Mountain Institute, 2021), create jobs (Reuters, 2024), and generate tax revenues (Arevon Energy, 2024), whereas negative reporting usually highlights the large land requirements displacing prime farmland (Farm Progress, 2022). While the economics literature (e.g., Allcott and Knittel, 2019; Sias et al., 2023; Noll et al., 2014) shows that negative, positive, and peer information can influence preferences differently, less is known about how such information affects preferences and local trade-offs between land use and other attributes specific to utility-scale solar development.

We conduct an information treatment experiment in the questionnaire, which is designed with an emphasis on different categories of information: the control group receives no information, one category focuses on peer information related to peers' adoption of regulations for utility-scale solar projects, and the remaining two categories offer information highlighting either positive or negative effects of deploying utility-scale solar projects within local communities. Participants are randomly assigned to one of the four versions of the questionnaire, each with one category of information. The descriptions used for the information treatment are provided in Table A.1. To ensure respondents carefully read the provided information, we include validation questions immediately after the information content. Participants are informed that the answers to these validation questions can be found in the preceding text and that they would be excluded from our study and would not receive compensation if they failed to answer them correctly in three attempts. Our final sample size of 868, consisting of 204 to 230 observations in each of the four groups, satisfies the minimum requirement of sixty-four subjects in each group to detect one-half of a standard deviation change in the outcome variable with a power of 0.80 at the 0.05 significance level (Cohen, 2013).

2.3. Survey implementation

Our study focuses on Iowa, USA, targeting both public officials and the general population. After obtaining human subjects' approval from the institutional review board at Iowa State University, we conducted a pilot survey and held multiple consultations and discussions with extension staff and survey experts to refine our survey questionnaire. To enhance responses from public officials, we implemented the survey in a mixed mode, combining the use of the online Qualtrics platform with a traditional mail-based approach in data collection.

We compiled a comprehensive list of 599 elected and appointed officials across Iowa's 99 counties, including County Supervisors, Staff members, and Zoning and Planning Board members. Contact information was sourced from the Iowa State Association of Counties (ISAC) Directory. Our multi-phase approach began with email invitations in April 2023, where each recipient received a unique link and access code to the online survey, followed by reminder emails and postcard invitations with QR codes for non-respondents. To increase participation, we leveraged the ISAC magazine, the Iowa League of Cities member newsletter, and relevant regional conferences. In July, we mailed paper surveys to remaining non-respondents along with a prepaid and pre-addressed return envelope, followed by reminder postcards. We offered public officials a $30 e-gift card as compensation for their time in completing the survey questionnaire. However, they could decline to receive the e-gift card by not leaving an email address for any reason (e.g., state regulations barring public officials from receiving such compensation). Overall, we received a total of 182 responses from public officials, with 57 returned physical copies of the survey and 125 obtained through the online mode. The regional distribution of the responses is shown in Figure 1.

The general population survey was executed exclusively via Qualtrics from July 15 to August 15, 2023. It was administered via Dynata[9], a well-known market research company, to facilitate participant recruitment and establish a sample that was representative and balanced across regions and demographics within the state. Dynata was responsible for survey compensation, which included a combination of cash (from $5 to $10) and other means of rewards. Of 1,522 invitations[10], we received 686 completed responses, representing a 45.1% response rate. Figure 1 shows the number of responses across regions, closely reflecting the population distribution across regions in Iowa.

3. Empirical strategy

Our empirical strategy consists of three components. In this section, we first present the discrete choice model we apply to estimate preferences for utility-scale solar project attributes. A latent class analysis is then employed to identify clusters of respondents with heterogeneous preference patterns. Additionally, we investigate how respondents differ in their rating of land use as a challenge to utility-scale solar development based on an ordered logit model.

3.1. Attribute-based discrete choice model

We apply an attribute-based discrete choice model under the framework of random utility maximization (RUM) (McFadden et al., 1973; Freeman III et al., 2014). In a choice experiment setting, respondents are asked to choose between two potential plans for utility-scale solar projects within their communities, characterized by a set of attributes. The RUM model posits that an individual chooses the alternative that yields the highest expected utility among all alternatives in each given choice scenario.

Our analysis utilizes a random parameter logit (RPL) model (also called mixed logit), which accommodates preference heterogeneity and relaxes the Independence of Irrelevant Alternatives assumption[11] required by the standard conditional logit model.[12] The RPL model allows for random taste variations, unrestricted substitution patterns, and correlation in unobserved factors over time (Train, 2009). For the RPL model, the utility an individual i obtains from choosing alternative j for choice sequence (i.e., choice scenario) t is:

$$U_{ijt} = V_{ijt}(X_{ijt}) + \varepsilon_{ijt} = \boldsymbol{\beta}_i X_{ijt} + \varepsilon_{ijt} \quad (i=1, \ldots, n; j=1, \ldots, J; t=1, \ldots, T) \tag{1}$$

where V_{ijt} is the systematic component of utility, which is a function of observable attributes of the alternative j for the sequence t, X_{ijt}; $\boldsymbol{\beta_i}$ is the individual-specific random coefficients on observed attributes of alternative j to capture preference heterogeneity; and ε_{ijt} is the standard error term that captures the unobserved, stochastic element of the utility.

The probability that individual i will select alternative j ($y_{it} = j$) from a set of J alternatives is given by

$$
\begin{aligned}
P_{ijt} = P\left(y_{it} = j \mid X_{ijt}\right) &= Pr\left(U_{ijt} \geq U_{ikt},\ \forall k \neq j\right) \\
&= Pr\left(U_{ikt} - U_{ijt} \leq 0,\ \forall k \neq j\right) \\
&= Pr\left(\varepsilon_{ikt} - \varepsilon_{ijt} \leq \beta_{\mathrm{i}} X_{ijt} - \beta_{\mathrm{i}} X_{ikt},\ \forall k \neq j\right)
\end{aligned} \tag{2}
$$

Assuming that the error terms ε_{ijt} are independently and identically drawn from a type I extreme value distribution (McFadden et al., 1973), then we can obtain

$$
P_{ijt} = P\left(y_{it} = j \mid X_{ijt}\right) = \frac{exp\left(\beta_{\mathrm{i}} X_{ijt}\right)}{\sum_{j=1}^{J} exp\left(\beta_{\mathrm{i}} X_{ijt}\right)} \tag{3}
$$

In non-market valuation studies, the inclusion of an opt-out (i.e., neither) alternative is commonly adopted. By incorporating an opt-out alternative, the model can capture the value associated with accepting or rejecting the proposed changes to specific attributes (Hensher et al., 2005; Veldwijk et al., 2014). However, studies have also shown that an opt-out alternative may lead to inattentive responses, with some participants always opting out when available (Krosnick, 1991; Sandorf, 2019), resulting in limited preference information for analysis. Nonetheless, Carlsson et al. (2007) found no evidence that respondents who select the opt-out option are different from those who made trade-offs among attributes. Our study specifically focuses on the trade-offs between different project attributes when solar development is assumed to occur rather than on whether a solar project will be developed (Veldwijk et al., 2014). Hence, to elicit more preference information, we employ a forced choice format; that is, participants are asked to make a choice between two options and are not provided with a "no choice" option. Furthermore, our design realistically captures the choice setting where a community has decided to have a utility-scale solar project and is considering where the project should be located. However, respondents may not accurately know their preferences to make precise choices among presented alternatives, thereby challenging the fundamental assumption of the DCE. Thus, we ask respondents to report their certainty levels for each choice they make so that we can examine the implications of choice uncertainty. Following the recommendations in existing literature (e.g., Hofstede et al., 2014; Choi et al., 2018; Ku and Wu, 2018; Serenari et al., 2015), responses with a high level of uncertainty (i.e., certainty level = 1 or 2 out of a scale of 5 in the DCE tasks) are excluded from our analysis, as such responses provide no more information than random guesses to reflect true preference (Vossler et al., 2012). For robustness check, we assess the effects of respondents' choice uncertainty on WTP estimates in Subsection 4.4.1.

The attribute vector (X_{ijt}) consists of one of two levels of carbon emission reduction ($Carbon_{jt}$), one of three levels of lease payments to landowners ($Lease_{jt}$), one of three levels of savings on monthly electricity bills ($Bill_{jt}$), and one of three levels of land quality for the occupied farmland ($Farmland_{jt}$) (refer to Table 1 for more details). For the RPL model, V_{ijt} in Eq. (1) is specified as:

$$V_{ijt} = \beta_{C,i} Carbon95_{ijt} + \beta_{L,i} Lease_{ijt} + \beta_{B,i} Bill_{ijt} + \beta_{M,i} Farmland70_{ijt} + \beta_{H,i} Farmland85_{ijt} \tag{4}$$

where $Carbon95_{ijt}$ is an indicator, taking the value of one for carbon emission reduction of 95% relative to coal-fired plants; $Farmland70_{ijt}$ and $Farmland85_{ijt}$ are indicators for medium- and high-quality farmland, respectively, each taking the value of 1 if the corresponding quality level is present; $\beta_{C,i}$, $\beta_{L,i}$, $\beta_{B,i}$, $\beta_{M,i}$, and $\beta_{H,i}$ are random coefficients, each assumed to be normally distributed with means β_p and standard deviations σ_p, where $p = \{C, L, B, M, H\}$. Carbon emission reduction and land quality of the occupied farmland are coded as dummy variables, with the 85% reduction in carbon emissions and the low-quality farmland (average CSR2 score of 55) set as the baselines for these two variables, respectively. Lease payments to landowners and savings on the monthly electricity bills are specified as continuous variables.[13] All attribute coefficients are classified as random and normally distributed. This specification is determined through a comparison of model fit statistics. Models with different random coefficient specifications are estimated, and the model with all attributes specified as random coefficients results in the lowest Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC) values, indicating the best model fit.

Using the estimated random coefficients from Eq. (4), we can derive the marginal WTP estimates by dividing the coefficient of a non-monetary attribute, e.g., $\beta_{H,i}$, by the coefficient of the monetary attribute, $\beta_{B,i}$, i.e., $\frac{\beta_{H,i}}{\beta_{B,i}}$, a ratio that represents the WTP of locating the solar project on high-quality farmland relative to on low-quality farmland. A negative value indicates a willingness to accept (WTA) compensation for the associated attribute. The standard errors are estimated using the Delta method (Greene, 2003).[14]

We further incorporate the interactions between farmland quality and both carbon reduction and energy savings in Eq. (4) because we conjecture that the marginal benefits one derives from electricity bill savings might differ depending on the quality of farmland that is being used for the solar projects or the carbon benefits of the project. We do not consider lease payments to landowners for interaction effects because most respondents do not consider such lease payments as a significant benefit. The systematic component of utility V_{ijt} for the RPL model with these interaction terms is specified as:

$$\begin{aligned} V_{ijt} = {} & \beta_{C,i} Carbon95_{ijt} + \beta_{L,i} Lease_{ijt} + \beta_{B,i} Bill_{ijt} + \beta_{M,i} Farmland70_{ijt} + \beta_{H,i} Farmland85_{ijt} \\ & + \rho_{1,i}\left(Farmland70_{ijt} \times Carbon95_{ijt}\right) + \rho_{2,i}\left(Farmland85_{ijt} \times Carbon95_{ijt}\right) \\ & + \rho_{3,i}\left(Farmland70_{ijt} \times Bill_{ijt}\right) + \rho_{4,i}\left(Farmland85_{ijt} \times Bill_{ijt}\right) \end{aligned} \tag{5}$$

where $\rho_{1,i}$, $\rho_{2,i}$, $\rho_{3,i}$, and $\rho_{4,i}$ are random coefficients, each is assumed to follow a normal distribution with mean ρ_g and standard deviation σ_g, $g \in \{1, 2, 3, 4\}$.

3.2. Latent class analysis model

To investigate the potential source of preference heterogeneity, we conduct a latent class analysis (LCA). The LCA method enables us to identify distinct preference patterns among clusters of respondents (Sinha et al., 2021) and has advantages over other classification techniques like cluster analysis or k-means clustering, as it is model-based and allows for a mathematical assessment of how well the proposed LCA model fits the data (Nylund-Gibson and Choi, 2018). It is plausible that individuals with varying levels of knowledge about utility-scale solar energy and different personal experiences may evaluate project attributes differently and make trade-offs accordingly. Thus, we utilize data on landownership, respondents' self-rated levels of knowledge of utility-scale solar energy, the presence of utility-scale solar projects in their counties of residence, and their participation or interest in rooftop or community solar projects in determining the class assignments.

In LCA analysis, individuals are assumed to be homogeneous within each class but heterogeneous across classes. The between-class regression models the probability of an individual belonging to each latent class as a function of individual-level characteristics, typically using a multinomial logit model for class membership assignment. The within-class regression uses the conditional logit model to estimate the choice model parameters separately for each latent class. The probability that individual i chooses alternative j from a set of J alternatives ($\boldsymbol{y_{it}} = \boldsymbol{j}$), conditional on being in class s (Holmes et al., 2017), is:

$$P_{ijt}|_s = P\left(y_{it} = j | X_{ijt}, class = s\right) = \frac{exp\left(\beta_s X_{ijt}\right)}{\sum_{j=1}^{J} exp\left(\beta_s X_{ijt}\right)} \qquad (6)$$

3.3. Examining sources of heterogeneity in farmland valuation

To further shed light on preference heterogeneities about the main attributes of utility-scale solar projects, in our survey, we asked respondents to report their ratings of perceived land use challenges in the development of utility-scale solar within their communities, $Land\_use\_challenge_i$. The rating is categorized on a three-point ordinal scale (1 = "not a challenge," 2 = "somewhat a challenge," 3 = "a significant challenge"). Given the ordinal nature of the responses, we use the ordered logit model (McCullagh, 1980)[15] to examine factors that affect the perception of land use challenges.

Let $Land\_use\_challenge_i^*$ denote the unobserved continuous latent variable that determines the value of the observed ordinal outcome of $Land\_use\_challenge_i$. The latent variable $Land\_use\_challenge_i^*$ has two unobserved cutoff points, κ_1 and κ_2, where $\kappa_1 < \kappa_2$. The ordinal logit model is estimated as follows:

$$P\left(Land\_use\_challenge_i > l\right) = \frac{exp\left(\boldsymbol{\omega D}_{\mathrm{i}} - \kappa_l\right)}{1 + exp\left(\boldsymbol{\omega D}_{\mathrm{i}} - \kappa_l\right)},\ l \in \{1,2\} \tag{7}$$

where $\boldsymbol{D_i}$ represents the vector of variables for respondent i that explains $Land\_use\_challenge_i^*$ in the population; and $\boldsymbol{\omega}$ is the vector of regression coefficients to be estimated. The log odds analyzed in the model are:

$$\log \frac{P\left(Land\_use\_challenge_i \leq l\right)}{P\left(Land\_use\_challenge_i > l\right)} = \kappa_l - \boldsymbol{\omega D}_{\mathrm{i}} \tag{8}$$

For parsimony, the latent variable, $Land\_use\_challenge_i^*$, is specified as follows:

$$Land\_use\_challenge_i^* = \alpha + \omega_1 Roof_i + \omega_2 Comm_i + \omega_3 Util_i + \lambda Muni_i + \mu Z_i + \xi_i \tag{9}$$

where α, ω_1, ω_2, ω_3, λ, and $\boldsymbol{\mu}$ are model parameters; $Roof_i$ indicates respondent i's current adoption or intention to adopt rooftop solar; $Comm_i$ measures respondent i's degree of interest in participating in a community solar project; $Util_i$ represents the presence of a utility-scale solar project within the county where respondent i resides; $Muni_i$ indicates whether respondent i's electricity supplier is a municipal utility or a cooperative; vector $\boldsymbol{Z_i}$ is individual-specific demographic and socioeconomic characteristics; and ξ_i is the error term, assumed to follow a standard logistic distribution, capturing the random disturbance related to the perceived land use challenges of respondent i. Table 2 presents summary information of all these variables, which are included in Eq. (9) because they represent knowledge attainment and personal experience, and may influence individuals' views on land use challenges. Understanding the effects of these factors provides insights into the sources of preference heterogeneity on the land use aspect of utility-scale solar projects, helps inform the design of education and outreach programs to address land use concerns within local communities, and promotes more solar energy development.

4. Results

4.1. Summary statistics of sample data

We received a total of 868 responses that provided usable information. After filtering out responses with missing key information, our choice experiment yields 10,334 usable choices (including those with high uncertainty), with 864 unique respondents. Table 2 presents an overview of the sample statistics and demographics of survey respondents. Within the general population subset, 53.21% of respondents are female, and 46.5% are male, roughly reflecting the female-to-male ratio in Iowa (50.1%-49.9%) based on the 2023 U.S. Census Bureau population estimates.[16] Our general population subsample's median age is 47, which aligns with Iowa's adult population (18+), whose median age is within the range of 40-49.[17] The median age of public officials in our sample is 50, which slightly exceeds the median age range of Iowa's adult population. Because public officials constitute a distinct group, representativeness relative to the broader state population is neither expected nor necessary for the purposes of this analysis. The median household income of our general population respondents falls within the range of $61,000 to $90,000. In comparison, the reported median household income in Iowa from 2019 to 2023 was $73,147 (in 2023 dollars), which aligns with the range observed in our data. Furthermore, educational attainment in our sample (98.11% with high school education or above, 44.88% with bachelor's degrees) compares well with Iowa data of age 25+ (93.2% and 30.9% respectively), although our sample is somewhat better educated than the average Iowa resident. We conducted formal data analysis and found no evidence that the higher share of college-educated respondents in our sample affects the preference estimates (results are available upon request). Political affiliation distributions (26.09% Democrat, 36.01% Republican, 33.24% Independent, 4.66% Other) also closely mirror Iowa's voter registration data (29.20%, 32.40%, 35.56%, 2.84%).[18] The aforementioned demographic information provides evidence supporting the representativeness of our general population subsample in reflecting the broader demographic makeup of Iowa.

Consistent with another statewide survey conducted by the Tarrance Group in 2022, which reported that 68% of Iowa voters supported new solar energy projects when asked directly (BFI, 2022), our survey indicates that over 70% of respondents express moderate to extreme levels of support for their communities hosting a utility-scale solar project. The largest proportion (44.01%) shows a moderate degree of support, while 23.50% and 10.14% express strong or extremely strong support. Those showing slight support account for 14.29%, while 8.06% indicate non-support. Our survey results reveal some different levels of support for utility-scale solar projects across respondent groups. On average, public officials in Iowa score 3.02 (on a 5-point scale) in their level of support, whereas the general population scores 3.16. However, the difference is not statistically significant. On the other hand, we find a statistically significant difference in the level of support between landowners and non-landowners.[19] Landowners exhibit a relatively lower degree of support, with a mean score of 2.95, compared to 3.17 among non-landowners. Table A.2

presents the distribution of landownership across information treatment groups and subsamples (general population vs. public officials).

The US Energy Information Administration (2022) reports that 15 of the 99 counties in Iowa operate utility-scale solar projects at the time of our study. Among our respondents, 31% of the public officials report they have either adopted rooftop solar systems at their residences or plan to install solar panels in the next five years; the corresponding percentage is 26% for the general population. Most respondents (74%) express moderate interest in participating in a community solar project if one were available.

The potential impact on land use, particularly the conversion of farmland to solar installations, is considered by survey respondents as a primary challenge when it comes to adopting utility-scale solar projects. As shown in Figure A.2b, over half of the respondents (51.5%) identify land use as a significant issue for their communities adopting utility-scale solar projects. Among several potential challenges, 35% of respondents point to the potential loss of farmland as the primary challenge associated with the adoption of utility-scale solar energy systems (Figure A.2d), while 29% cite high initial investment costs, including construction costs, as the primary challenge. Despite land use concerns, a majority of respondents (71.5%) consider a reduced electricity bill for their households as an extremely important factor for their communities adopting utility-scale solar projects (Figure A.2a), followed by increased resilience during electricity-disrupting disasters (62.3%) and reduced emissions of carbon and other air pollutants (58.6%). As presented in Figure A.2c, 33% of respondents rate reduced electricity bills as the most significant benefit associated with the adoption of utility-scale solar projects within local communities, closely followed by reduced carbon and other air pollutant emissions (29%). These data suggest there are great heterogeneities in how people view the significance of different challenges and benefits of utility-scale solar projects. We will examine how these heterogeneities affect the way people make trade-offs among different attributes of a solar project.

4.2. Estimates of the values of different attributes

Column 1 of Table 3 presents results in willingness-to-pay space from the conditional logit model, while Column 2 reports the main effects in willingness-to-pay space from the random parameter logit (RPL) model, based on the model in preference space as specified in Eq. (4). These estimates represent the marginal WTP for the attributes considered in our experiment, all else equal, and conditional on the development of a utility-scale solar project. WTP is estimated as monthly energy savings on household electricity bills, with a negative WTP indicating willingness to accept (WTA). The RPL results show that respondents are willing to pay \$3.22 per month more in electricity bills for carbon emission reduction from 85% to 95% relative to coal-fired plants, to host the utility-scale solar project (as defined in our experiment). Moreover, respondents, on average, require a compensation of \$4.58 per month for adopting projects on medium-quality farmland (with an average CSR2 score above 70 and below 85) and \$20.24 per month on high-quality farmland (with an average CSR2 score of 85 or higher) relative to low-quality farmland (with an average CSR2 score of 55 or lower). We do not observe a significant mean WTP for a one-level increase in lease payments to landowners. However, the statistically significant standard deviation implies substantial variation in individual valuations: some respondents strongly favor projects with higher lease payments to landowners, while others do not or are indifferent. The positive and negative preferences might be balancing each other out in the sample. Furthermore, the standard deviations for all project attributes are statistically significant, suggesting the existence of preference heterogeneity among respondents, albeit with smaller magnitudes compared to mean WTP coefficients.

The conditional logit results are largely consistent with the RPL estimates. However, our analysis focuses on the RPL model for several methodological reasons. First, RPL allows for preference heterogeneity across respondents and provides more realistic behavioral assumptions by relaxing the restrictive independence of irrelevant alternatives (IIA) assumption inherent in conditional logit. Second, the statistically significant standard deviations of the random coefficients indicate meaningful unobserved heterogeneity in preferences across our sample. Finally, the lower AIC and BIC statistics from the RPL model suggest improved model fit relative to the conditional logit model, providing evidence that accounting for this unobserved heterogeneity better captures the underlying choice patterns in our data.

In addition to examining the main effects, we investigate interaction effects to understand how changes in farmland quality influence people's marginal WTP for carbon emission reduction and energy savings associated with the project. These results are presented in Column 3 of Table 3. Our findings reveal that when a project is proposed on medium-quality farmland rather than low-quality farmland, individuals' valuations of carbon emission reductions and energy savings decrease. Specifically, when a project is proposed on medium-quality farmland instead of low-quality farmland, respondents' average additional WTP for a one-level increase in carbon reduction (from 85% to 95%) decreases by $22.87 in monthly energy savings. This suggests that respondents become substantially more sensitive to the use of medium-quality farmland when considering the carbon reduction benefits of a solar project. In other words, individuals place a higher value on preserving medium-quality farmland, which is manifested as a lower valuation for carbon benefits when better farmland is used. However, we did not observe significant interaction effects when comparing high- and low-quality farmland, suggesting that respondents' valuations of carbon reductions and energy-saving benefits remain relatively unchanged regardless of whether the projects are located on high-quality or low-quality farmland. Several explanations may account for this finding. First, respondents may prioritize the preservation of high-quality farmland to such an extent that the potential benefits of increased carbon reduction and energy savings do not significantly influence their preferences or their expectations for compensation when considering the adoption of the project. Second, while respondents value carbon reduction and energy savings, the level of change of these two attributes may not be substantial enough to justify the switch of project siting from low- to high-quality farmland. Third, respondents may feel that most carbon reduction potential is already met, given that only 23.5% of Iowa's electricity generation came from coal in 2023 compared to about 60% from wind energy (EIA, 2023), and that additional reductions should not occur at the expense of high-quality farmland when viable options, such as wind, exist for meeting carbon reduction goals without compromising prime farmland.

The standard deviations of these interaction terms are all statistically significant, indicating heterogeneity in how individuals value carbon emission reductions and energy savings in relation to farmland quality. This suggests that the valuations for carbon reductions and energy savings are not constant but vary depending on the quality of the farmland. For instance, respondents may place a higher value on carbon reduction and energy savings when the project is located on lower-quality farmland, possibly because the opportunity cost of using such farmland for renewable energy projects is perceived as lower. Conversely, on higher-quality farmland, where agricultural productivity might be a greater concern, respondents may be less willing to sacrifice farmland for environmental and economic benefits, reflecting a more conservative valuation. In the following section, we explore the heterogeneity in preferences for project attributes among respondents.

4.3. Exploring preference heterogeneity

4.3.1. Preference heterogeneity across stakeholder groups

To explore preference heterogeneity in more detail, specifically, how preferences for project attributes vary across stakeholder groups, we incorporate interactions between project attributes and stakeholder indicators (i.e., public official indicator and landowner indicator) into Eq. (4). We later investigate factors driving heterogeneity in the valuations of farmland of different qualities across respondents, given that this study focuses on local land use issues related to utility-scale solar projects.

Table 4 presents the WTP estimates across stakeholder groups, public officials vs. the general population, and landowners vs. non-landowners. Our findings indicate that the general population and non-landowners have a statistically significant WTP as measured by $4.31 and $3.49 extra in monthly energy costs, respectively, to achieve a 95% carbon emission reduction compared to an 85% reduction. However, we observe no statistically significant differences in willingness to pay for the same carbon emission reductions between public officials and the general population, and between landowners and non-landowners. By contrast, our findings reveal notable differences in the mean valuations of land quality attributes across these stakeholder groups. Public officials and landowners are particularly concerned about the quality of the farmland occupied by solar projects, requiring statistically significantly higher compensation for adopting a 50-MW project on 375 acres of higher-quality farmland within their communities than the compensation required by either the general population or non-landowners. Specifically, public officials and landowners require an additional compensation of $14.32 and $14.26 in monthly energy savings, respectively, to offset medium-quality farmland loss and an additional compensation of $33.92 and $32.47, respectively, to offset high-quality farmland loss, compared to low-quality farmland. For context, Iowa's average annual cash rental rates in 2022 ranged from $217 per acre for low-quality land to

$297 per acre for high-quality land (ISU Extension 2022). Thus, these findings corroborate and provide further insights about the results in Table 3 that there are substantial heterogeneities in preferences concerning solar project attributes.

4.3.2. Preference heterogeneity across information treatments

To examine how preferences for project attributes are different across information treatment groups, we conduct regressions that incorporate interactions between project attributes and information treatment indicators into Eq. (4).

Table 5 presents the results for both the general population subsample (Column 1) and the full sample (Column 2), and the results in the two columns are largely the same. The WTP estimates show respondents' valuations of project attributes across the four information treatment groups: no information (control group), peer information, positive information, and negative information. The baseline results suggest that the WTP for additional carbon emission reductions and lease payments to landowners are not statistically significant for the control group. However, this group exhibits a statistically significant willingness to accept compensation, in terms of monthly energy cost savings, for proposed projects on high-quality farmland compared to low-quality farmland. The two columns show a similar willingness to accept compensation for siting projects on medium-quality farmland compared to low-quality farmland, although the WTA is statistically significant at the 10% confidence level for the full sample and not significant for the general population subsample, likely due to the loss of efficiency from the reduced sample size.

Regarding the interaction effects with information treatments, the coefficients for the peer and positive information treatments are positive across all attributes, suggesting that such information may increase respondents' valuations for carbon reductions and lease payments while reducing concern about projects on higher-quality farmland. Conversely, coefficients for the negative information treatment are negative across all attributes, potentially indicating decreased valuation of project benefits and heightened land use concerns. However, none of these interaction effects is statistically significant, providing no robust evidence that our information treatments meaningfully alter respondents' tradeoffs among project attributes. This lack of statistically discernible effects could be partly due to limited statistical power, as the inclusion of full interaction terms substantially increases the number of parameters to be estimated. Alternatively, the results suggest that respondents' underlying values and priorities regarding utility-scale solar attributes are deeply held and not easily shifted by the types of normative messaging tested in this study.

It is important to note, however, that while information treatments do not appear to affect how respondents weigh the tradeoffs among project attributes, the nature of the information can still affect people's overall attitudes toward utility-scale solar projects. For example, our survey data suggests that respondents who received positive information about solar projects expressed statistically significantly higher support (averaging 3.20 on a 5-point scale) compared to those who received negative information (averaging 3.01).

4.3.3. Latent class analysis (LCA)

To implement the LCA model as represented in Eq. (6), we first determine the number of classes to use. Based on the BIC results, we select a model with 3 classes of respondents, comprising 46.5%, 32.9%, and 20.6% of the sample, respectively.[20] The results are presented in Table A.3. Class 1 respondents are characterized primarily by significantly lower knowledge of utility-scale solar energy compared to Class 3 respondents (the reference group), without notable differences in landownership, rooftop solar adoption or future plans, or interest in participating in community solar. Class 2 respondents are more likely to be landowners and show less interest in rooftop solar adoption and community solar participation relative to Class 3 respondents.

Table A.3 illustrates distinct differences in preferences for utility-scale solar project attributes among the three respondent classes: Cost-Conscious Accepters (Class 1), who value energy savings but moderately oppose projects on higher-quality farmland; Strong Land Stewards (Class 2), defined by the strongest opposition to projects on higher-quality farmland; and Solar Advocates (Class 3), who value project benefits (carbon reduction and increased lease payment to landowners) and are supportive of locating projects on higher-quality farmland. Compared to Class 1 respondents, Class 2 respondents are less likely to support projects offering higher carbon benefits and lease payments to landowners, and less likely to support projects on medium- and high-quality farmland relative to low-quality farmland. This may reflect a prioritization of higher-quality farmland over other benefits or a general resistance to utility-scale solar projects in local communities, resulting in negative evaluations of both higher carbon benefits and financial incentives to landowners. In contrast, Class 3 respondents place a higher value on carbon emission reductions and lease payments than Class 1 respondents when deciding which projects to support. Moreover, Class 3 respondents exhibit a greater willingness to adopt projects situated on higher-quality farmland and may also prioritize the environmental and economic benefits associated with utility-scale solar projects, viewing higher-quality farmland as compatible with sustainable energy initiatives. Note that none of the classes show significant differences in the presence of county utility-scale solar. This could be attributed to the limited presence of utility-scale solar projects in Iowa during our study period. The LCA results provide evidence that landownership, respondents' knowledge, and personal experiences related to solar energy are likely important drivers of the observed preference heterogeneity in Table 3.

We also implement the covariate-free version of LCA, which groups classes of respondents simply by the observed choices (Train, 2009). This allows us to test whether distinct preferences are driven by choice patterns rather than the specific covariates included. As shown in Table A.4, the covariate-free LCA model identifies the same three distinct classes – Cost-Conscious Accepters, Strong Land Stewards, and Solar Advocates – with similar preference structures and class shares compared to Table A.3. The high alignment between the two model specifications strongly supports the robustness of the identified classes, showing that the core preference heterogeneity likely exists independently of the individual characteristics used to explain it. In Appendix B, we investigate attribute non-attendance to better understand the underlying sources of preference heterogeneity in respondents' decision processes.

4.3.4. Drivers of heterogeneity in farmland valuation

As explained in Section 3.3, we implement the ordinal logit model in Eq. (7) to provide insights regarding factors that drive the heterogeneities in the valuation of farmland quality, and present the results in Table 6.

Results in Table 6 indicate that individuals with rooftop or community solar experience, or those highly interested in participating in the near future, are significantly less likely to view land use concern as a considerable challenge to the adoption of utility-scale solar projects within their communities. Specifically, those with installed rooftop solar or adoption interest are 5.5% more likely to view land use as "Not a challenge" and "Somewhat a challenge". Their likelihood of viewing land use concern as "A significant challenge" decreases by 10.92% compared to those without rooftop solar installation or adoption interest. Similarly, individuals interested in community solar participation are 6.06% less likely to regard land use concerns as a significant barrier compared to those who express no interest. In contrast, respondents with family farm operation experience are 8.15% more likely to consider land use a significant barrier. Other demographic variables show no significant impact. These findings highlight the importance of personal experience with respect to solar energy and farming in the heterogeneous valuation of farmland quality for utility-scale solar projects and can inform policies balancing solar energy expansion with responsible land use planning.

4.4. Robustness checks

We conduct the following three types of additional analyses to assess the robustness of our primary results in Table 3. That is, we provide analyses that take into account scale heterogeneity, respondents' different uncertainty levels in their responses, protest and inattentive responses, and consistency in responses based on answers to different but related survey questions.

4.4.1. Accounting for scale heterogeneity

Our primary analysis relies on the RPL model, which assumes that the idiosyncratic error is independent and identically distributed extreme value. However, Louviere and Meyer (2017) argue that the scale of the idiosyncratic error term often differs across respondents – known as scale heterogeneity. To test the robustness of our results in Table 3 to this concern, we follow Fiebig et al. (2010), and allow the scale parameter to vary across individuals based on observed choices using the generalized multinomial logit (G-MNL) model. The G-MNL results are presented in Table A.5. The estimated significant scale parameter, τ, which represents the standard deviation of the scale factor's distribution across respondents, indicates the presence of scale heterogeneity, suggesting that respondents vary in the randomness of their choices. However, the WTP estimates from the G-MNL model are largely consistent with those from the RPL specification as presented in Column 2 of Table 3. This implies that the existence of scale heterogeneity does not significantly affect the estimation of mean parameters, and our results are robust to the choice of model.

We retain the RPL model as our main specification for several reasons. First, removing respondents who self-report high uncertainty in their choice tasks (certainty < 3) helps mitigate the primary source of scale heterogeneity arising from respondent uncertainty. Second, the BIC values are nearly identical between the G-MNL and RPL models, indicating that the additional complexity of modeling scale heterogeneity does not improve model fit. Third, the RPL model offers greater computational simplicity and parsimony compared to the G-MNL model while maintaining equivalent explanatory power.

4.4.2. Addressing respondent uncertainty in choice decisions

In addition to excluding responses with high levels of stated uncertainty (certainty level = 1 or 2 on a 5-point scale in the DCE tasks), we use two other different approaches to account for respondents' uncertainty in their choices. First, to examine whether there is a significant difference between the estimates with and without the inclusion of highly uncertain responses, we estimate the same model specification used in Eq. (4), but without excluding highly uncertain responses in the DCE choice scenarios. Second, we perform a regression using only observations from respondents who indicate a high level of uncertainty (certainty level = 1 or 2), accounting for 12.5% of observations in our dataset. These results are reported in Columns 1 and 2 of Table A.6. The estimates in Column 1 of Table A.6 are consistent with our main results in Table 3, though there are some differences in the magnitudes of the mean WTP/WTA estimates. However, the model that excludes responses with a high level of uncertainty yields less negative log-likelihood and lower AIC and BIC values than the model retaining these responses, indicating improved model fit and more accurate estimates. As suggested in Column 2 of Table A.6, none of the WTP estimates for solar attributes are statistically significant, with large standard errors for respondents who indicated high uncertainty in choice scenarios. This finding is consistent with previous studies (e.g., Ku and Wu, 2018; Vossler et al., 2012), suggesting that responses from highly uncertain individuals are unreliable for estimating true preferences.

4.4.3. Accounting for potentially unreliable responses

As another robustness check, we further account for potentially unreliable responses in the choice experiment and survey. First, protest responses in the choice experiment can lead to inconsistencies in utility estimates (Lancsar and Louviere, 2006). Therefore, we estimate the model specified in Column 2 of Table 3, which is based on Eq. (4), but exclude respondents who consistently select either Project A or Project B across all six choice scenarios. Second, we apply an additional screening criterion by removing respondents who complete the survey in less than ten minutes. Rapid survey completion times may indicate a lack of serious consideration or engagement with choice scenarios and the trade-offs presented (Uggeldahl et al., 2016). The results are presented in Table A.7, and we find that the estimates are consistent with our main results presented in Table 3, implying that our estimates are not significantly affected by the two potential issues.

4.4.4. Assess the consistency of respondents' stated preferences

We conduct a sub-sample analysis to assess the internal consistency of respondents' stated preferences and mitigate the concerns of hypothetical bias. Sub-sample construction was based on respondents' ratings of the perceived benefits and challenges associated with utility-scale solar energy systems in their local communities. The four sub-samples comprised respondents who rated each of the following as "very important" or "extremely important": carbon emission reductions, lease payments to landowners, household energy savings on electricity bills, or concerns about land use (loss of farmland). Table A.8 shows the results in preference space. Across the sub-samples, respondents exhibit a higher valuation for the attribute they deemed very or extremely important in their community contexts. For instance, those who prioritized carbon reductions, lease payments, energy savings, or farmland impacts valued the corresponding attribute the most within their respective groups. These findings suggest a high level of consistency between respondents' stated preferences in the choice scenario and their self-reported importance ratings of the key project attributes.

4.4.5. Accounting for survey distribution mode

As mentioned in Section 2.3, mixed distribution modes (online Qualtrics survey and mail-based survey) were employed to enhance the response rate from public officials, resulting in 57 physical copy responses from public officials with the rest coming from the online mode. Among these 57 physical copy responses, 28 are also landowners. To address concerns about the potential mode effects, we re-estimate models shown in Column 2 of Table 3, Columns 1 and 2 of Table 4, excluding these physical copy responses. The results, reported in Table A.9, are largely similar in terms of sign and significance for most coefficients, implying no systematic difference in preferences for project attributes based on survey distribution mode.[21]

5. Conclusion and discussion

Solar energy systems have significant potential for reducing greenhouse gas emissions and advancing a clean energy future, yet they have also become a considerable source of concern in some communities due to localized impacts. Despite the advantages of utility-scale solar photovoltaic energy, quantitative studies on how individuals perceive and make trade-offs among localized economic, environmental, and agricultural land-use impacts are still limited. Understanding these trade-offs and preferences for local solar projects is crucial for informing policies and practices that foster utility-scale solar and renewable energy development.

This study investigates how individuals perceive and make trade-offs associated with utility-scale solar energy development in their communities. Our results suggest that individuals are generally more supportive of utility-scale solar projects that can deliver greater carbon emission reductions compared to coal, lead to increased household energy savings, and are sited on less productive farmland. However, significant heterogeneities exist in valuations and trade-offs between land use and other attributes across stakeholder groups. For instance, our findings show that while the general population and non-landowners show greater willingness to accept solar projects on agricultural land in exchange for enhanced carbon emission reductions, public officials and landowners exhibit more nuanced considerations and generally require higher compensations to site utility-scale solar projects on good-quality farmland. Other factors such as knowledge level and personal experience with solar energy are also shown to be key potential factors contributing to the preference heterogeneity.

The substantial heterogeneities in land use preferences suggest complex social and economic negotiations inherent in utility-scale solar energy projects. In order to design policies that are acceptable for local communities, policymakers must recognize that stakeholder groups do not uniformly value environmental benefits, economics, or land use trade-offs. In addition, our targeted information disseminations, whether peer regulations, positive impacts, or potential challenges, do not statistically significantly alter community valuations of the tradeoffs of solar project attributes, in particular, land use related trade-offs. This suggests that people's preferences toward solar project attributes are relatively fixed, likely shaped by prior knowledge, personal values, or deeply held beliefs about energy and land use priorities. However, the nature of information can influence people's support levels for their communities hosting solar projects. Thus, the effects of information can be nuanced in terms of how it affects people's views of the inherent tradeoffs or their overall attitudes towards solar. These findings in our study point to the need for more comprehensive engagement strategies that go beyond information sharing to include participatory planning processes, stakeholder dialogue, and addressing underlying concerns about project impacts.

Our study is based on data directly collected from the stakeholder groups and provides policy relevant insights that are otherwise not available. However, we would like to outline a couple of caveats concerning the general methodology of our study. First, our choice experiment design without an opt-out option, which is intended to promote thoughtful choices by respondents, may overstate overall support for solar projects (Johnston et al., 2017; Lancsar and Louviere, 2008; Veldwijk et al., 2014) and limit the scope of our analysis. In particular, our estimates of willingness to pay (or accept) reflect conditional preferences for solar attributes, assuming a project will proceed, rather than unconditional support for solar development. Second, we note that our study is based on data collected in the U.S. state of Iowa, and thus, applying our findings beyond this sample and region requires consideration of local context and suitability. Nonetheless, we believe our insights have broader relevance—particularly given that over 63% of U.S. solar projects are located on agricultural land. While our absolute willingness-to-pay estimates are most directly applicable to U.S. Midwest, our methodological framework and findings on the relative importance of land quality can inform solar siting policies more broadly. For instance, our approach can be readily adapted to other regions by incorporating locally appropriate land quality indicators (e.g., substituting Iowa's CSR2 with region-specific measures).

References

Allcott, Hunt, and Christopher Knittel. 2019. Are consumers poorly informed about fuel economy? evidence from two experiments. *American Economic Journal: Economic Policy* 11 (1): 1–37.

Arevon Energy. (2024, October 28). *Benefits of utility-scale solar energy*. Retrieved from https://arevonenergy.com/news/blog/benefits-of-utility-scale-solar-energy/.

Beck, Matthew J, Simon Fifer, and John M Rose. 2016. Can you ever be certain? reducing hypothetical bias in stated choice experiments via respondent reported choice certainty. *Transportation Research Part B: Methodological* 89: 149–167.

Bohner, Gerd, and Nina Dickel. 2011. Attitudes and attitude change. *Annual Review of Psychology* 62: 391–417.

Bolinger, Mark, and Greta Bolinger. 2022. Land requirements for utility-scale PV: an empirical update on power and energy density. *IEEE Journal of Photovoltaics*, 12(2), 589-594.

Boudet, Hilary S. 2019. Public perceptions of and responses to new energy technologies. *Nature Energy* 4 (6): 446–455.

Brant, Rollin. 1990. Assessing proportionality in the proportional odds model for ordinal logistic regression. *Biometrics*: 1171–1178.

Bright Future Iowa. (2022, February 8). *The Tarrance Group survey memo*. Retrieved from https://brightfutureiowa.com/wp-content/uploads/2022/02/Iowa-Summary-Memo_final-Copy.pdf.

Burke, Paul J, Jinnie Widnyana, Zeba Anjum, Emma Aisbett, Budy Resosudarmo, and Kenneth GH Baldwin. 2019. Overcoming barriers to solar and wind energy adoption in two Asian giants: India and Indonesia. *Energy Policy* 132: 1216–1228.

Carlisle, Juliet E, David Solan, Stephanie L Kane, and Jeffrey Joe. 2016. Utility-scale solar and public attitudes toward siting: A critical examination of proximity. *Land Use Policy* 58: 491–501.

Carlsson, Fredrik, Peter Frykblom, and Carl Johan Lagerkvist. 2007. Consumer willingness to pay for farm animal welfare: mobile abattoirs versus transportation to slaughter. *European Review of Agricultural Economics* 34 (3): 321–344.

Carson, Richard T., and Mikołaj Czajkowski. 2019. A new baseline model for estimating willingness to pay from discrete choice models. *Journal of Environmental Economics and Management* 95: 57-61.

Chen, Jian, Hongli Feng, Elizabeth Hoffman, and Luke Seaberg. 2025. Support for utility-scale solar: Effects of information and heterogeneity among public officials, the general population, and landowners. *Journal of Environmental Management* 377: 124574.

Choi, Andy S, Stefan Gössling, and Brent W Ritchie. 2018. Flying with climate liability? Economic valuation of voluntary carbon offsets using forced choices. *Transportation Research Part D: Transport and Environment* 62: 225–235.

Cohen, Jacob. 2013. *Statistical power analysis for the behavioral sciences*. Academic press.

Crago, Christine Lasco, and Ilya Chernyakhovskiy. 2017. Are policy incentives for solar power effective? evidence from residential installations in the northeast. *Journal of Environmental Economics and Management* 81: 132–151.

Crawford, Jessica, Douglas Bessette, and Sarah B Mills. 2022. Rallying the anti-crowd: Organized opposition, democratic deficit, and a potential social gap in large-scale solar energy. *Energy Research & Social Science* 90: 102597.

Delicado, Ana, Elisabete Figueiredo, and Luís Silva. 2016. Community perceptions of renewable

energies in Portugal: Impacts on environment, landscape and local development. *Energy Research & Social Science* 13: 84–93.
Elmallah, Salma, Ben Hoen, K. Sydny Fujita, Dana Robson, and Eric Brunner. 2023. Shedding light on large-scale solar impacts: An analysis of property values and proximity to photovoltaics across six US states. *Energy Policy*, 175, p.113425.
Faiers, Adam, and Charles Neame. 2006. Consumer attitudes towards domestic solar power systems. *Energy policy* 34 (14): 1797–1806.
Farm Progress. (2022, August 15). *Solar factors into loss of prime farmland*. Retrieved from https://www.farmprogress.com/commentary/solar-factors-into-loss-of-prime-farmland.
Fiebig, Denzil G., Michael P. Keane, Jordan Louviere, and Nada Wasi. 2010. The generalized multinomial logit model: accounting for scale and coefficient heterogeneity. *Marketing Science* 29 (3): 393-421.
Finney, D. J. 1971. A statistical treatment of the sigmoid response curve. *Probit analysis. Cambridge University Press, London* 633.
Frate, Claudio Albuquerque, and Christian Brannstrom. 2017. Stakeholder subjectivities regarding barriers and drivers to the introduction of utility-scale solar photovoltaic power in Brazil. *Energy Policy* 111: 346–352.
Freeman III, A Myrick, Joseph A Herriges, and Catherine L Kling. 2014. *The measurement of environmental and resource values: theory and methods*. Routledge.
Gaur, Vasundhara, and Corey Lang. 2023. House of the rising sun: The effect of utility-scale solar arrays on housing prices. *Energy Economics*, 122, p.106699.
Gaur, Vasundhara, Corey Lang, Gregory Howard, and Ruth Quainoo. 2023. When energy issues are land use issues: estimating preferences for utility-scale solar energy siting. *Land Economics* 99 (3): 343–363.
Greene, William H. 2003. Econometric analysis. *Pretence Hall*.
Greene, William H, and David A Hensher. 2010. *Modeling ordered choices: A primer*. Cambridge University Press.
Hanger, Susanne, Nadejda Komendantova, Boris Schinke, Driss Zejli, Ahmed Ihlal, and Anthony Patt. 2016. Community acceptance of large-scale solar energy installations in developing countries: Evidence from Morocco. *Energy Research & Social Science* 14: 80–89.Hensher, David A, Andrew T Collins, and William Greene. 2013. Accounting for attribute non-attendance and common-metric aggregation in a probabilistic decision process mixed multinomial logit model: A warning on potential confounding. *Transportation*, *40*(5), 1003-1020.
Hensher, David, Nina Shore, and Kenneth Train. 2005. Households' willingness to pay for water service attributes. *Environmental and Resource Economics* 32: 509–531.
Herriges, Joseph, Catherine Kling, Chih-Chen Liu, and Justin Tobias. 2010. What are the consequences of consequentiality? *Journal of Environmental Economics and Management* 59 (1): 67–81.
Hirschberg, Joe, and Jenny Lye. 2010. A Geometric Comparison of the Delta and Fieller Confidence Intervals. *The American Statistician* 64 (3): 234–41.
Hofstede, Stefanie N, Leti van Bodegom-Vos, Manon M Wentink, Carmen LA Vleggeert-Lankamp, Thea PM Vliet Vlieland, Perla J Marang-van de Mheen, and DISC Study Group. 2014. Most important factors for the implementation of shared decision making in sciatica care: Ranking among professionals and patients. *PloS one* 9 (4): e94176.
Holmes, Thomas P, Wiktor L Adamowicz, and Fredrik Carlsson. 2017. Choice experiments. *A*

primer on nonmarket valuation: 133–186.

Iowa Farmer Today. 2021. *Too early to tell how solar farms impact land value*. Retrieved from https://agupdate.com/iowafarmertoday/news/state-and-regional/too-early-to-tell-how-solar-farms-impact-land-value/article_1aa9cf14-bd94-11eb-af18-af769bd02582.html.

Iowa Solar Energy Trade Association. 2020. *Iowa Solar Energy Fact Sheet*. Retrieved from https://www.iaenvironment.org/webres/File/Iowa%20Solar%20Energy%20Fact%20Sheet%20January%202020.pdf.

Iowa State University Extension and Outreach (ISU Extension). 2022. *Cash Rental Rates for Iowa 2022 Survey*. Retrieved from https://www.extension.iastate.edu/agdm//wholefarm/pdf/c2-10_2022.pdf.

Jager, Wander. 2006. Stimulating the diffusion of photovoltaic systems: A behavioural perspective. *Energy Policy* 34 (14): 1935–1943.

Johnston, Robert J., Kevin J. Boyle, Wiktor Adamowicz, Jeff Bennett, Roy Brouwer, Trudy Ann Cameron, W. Michael Hanemann et al. 2017. Contemporary guidance for stated preference studies. *Journal of the Association of Environmental and Resource Economists* 4 (2): 319-405.

Kalkbrenner, Bernhard J, and Jutta Roosen. 2016. Citizens' willingness to participate in local renewable energy projects: The role of community and trust in Germany. *Energy Research & Social Science* 13: 60–70.

Krosnick, Jon A. 1991. Response strategies for coping with the cognitive demands of attitude measures in surveys. *Applied cognitive psychology* 5 (3): 213–236.

Ku, Yu-Cheng, Tsun-Feng Chiang, and Sheng-Mao Chang. 2017. Is what you choose what you want?—outlier detection in choice-based conjoint analysis. *Marketing letters* 28: 29–42.

Ku, Yu-Cheng, and John Wu. 2018. Measuring respondent uncertainty in discrete choice experiments via utility suppression. *Journal of Choice Modelling* 27: 1–18.

Lancsar, Emily, and Jordan Louviere. 2006. Deleting 'irrational' responses from discrete choice experiments: a case of investigating or imposing preferences?. *Health economics*, *15*(8), 797-811.

Lancsar, Emily, and Jordan Louviere. 2008. Conducting discrete choice experiments to inform healthcare decision making: a user's guide. *Pharmacoeconomics* 26 (8): 661-677.

Larson, Eric C, and Richard S Krannich. 2016. "A great idea, just not near me!" understanding public attitudes about renewable energy facilities. *Society & Natural Resources* 29 (12): 1436–1451.

Lazard. 2020. *Lazard's Levelized Cost of Energy Analysis.* Retrieved from https://www.lazard.com/media/451419/lazards-levelized-cost-of-energy-version-140.pdf.

Loomis, John B. 2014. 2013 WAEA keynote address: Strategies for overcoming hypothetical bias in stated preference surveys. *Journal of Agricultural and Resource Economics*: 34–46.

Louviere, Jordan J., and Robert J. Meyer. 2017. Formal choice models of informal choices: What choice modeling research can (and can't) learn from behavioral theory. *Review of marketing research*. Routledge: 3-32.

Macawile, Janet, and Glenn Su. 2009. Local government officials perceptions and attitudes towards solid waste management in Dasmarinas, Cavite, Philippines. *Journal of Applied Sciences in Environmental Sanitation* 4 (1): 63–69.

Maddison, David, Reece Ogier, and Allan Beltrán. 2023. The disamenity impact of solar farms: a hedonic analysis. *Land Economics* 99 (1): 1–16.

Maguire, Karen, Sophia J Tanner, Justin B Winikoff, and Ryan Williams. 2024. Utility-scale solar and wind development in rural areas: Land cover change (2009–20). *USDA Economic Research*

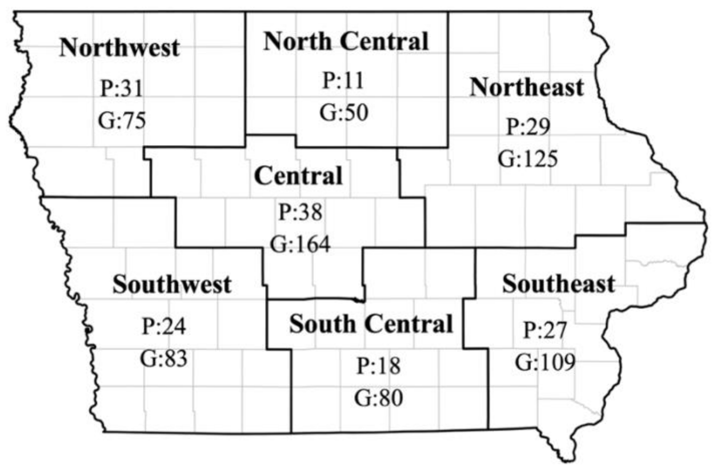
Report (330).
Majumdar, Debaleena, and Martin J Pasqualetti. 2019. Analysis of land availability for utility-scale power plants and assessment of solar photovoltaic development in the state of Arizona, USA. *Renewable energy* 134: 1213–1231.
McCullagh, Peter. 1980. Regression models for ordinal data. *Journal of the Royal Statistical Society: Series B (Methodological)* 42 (2): 109–127.
McCulluough, Caleb. 2023. Iowa Bill Would Limit Commercial Solar Panel Construction. Retrieved from https://www.thegazette.com/state-government/iowa-bill-would-limit-commercial-solar-panel-construction/.
McFadden, Daniel, et al. 1973. Conditional logit analysis of qualitative choice behavior.
Mehedi, Tanveer Hassan, Eskinder Gemechu, and Amit Kumar. 2022. Life cycle greenhouse gas emissions and energy footprints of utility-scale solar energy systems. *Applied Energy* 314: 118918.
Midcontinent Independent System Operator. (2025, September). Generator Interconnection Queue. Retrieved from https://www.misoenergy.org/planning/resource-utilization/GI_Queue/.
Mills, Sarah Banas, Douglas Bessette, and Hannah Smith. 2019. Exploring landowners' postconstruction changes in perceptions of wind energy in Michigan. *Land Use Policy* 82: 754–762.
Mulvaney, Dustin. 2017. Identifying the roots of green civil war over utility-scale solar energy projects on public lands across the American Southwest. *Journal of Land Use Science* 12 (6): 493–515.
Musall, Fabian David, and Onno Kuik. 2011. Local acceptance of renewable energy—a case study from southeast Germany. *Energy policy* 39 (6): 3252–3260.
Nilson, Roberta S, and Richard C Stedman. 2022. Are big and small solar separate things?: The importance of scale in public support for solar energy development in upstate New York. *Energy Research & Social Science* 86: 102449.
Noll, Daniel, Colleen Dawes, and Varun Rai. 2014. Solar community organizations and active peer effects in the adoption of residential PV. *Energy Policy* 67: 330–343.
NREL. 2012. Life cycle greenhouse gas emissions from solar photovoltaics. Technical report, National Renewable Energy Laboratory.
Nugent, Daniel, and Benjamin K Sovacool. 2014. Assessing the lifecycle greenhouse gas emissions from solar PV and wind energy: A critical meta-survey. *Energy Policy* 65: 229–244.
Nylund-Gibson, Karen, and Andrew Young Choi. 2018. Ten frequently asked questions about latent class analysis. *Translational Issues in Psychological Science* 4 (4): 440.
Olsen, Søren Bøye, Thomas Hedemark Lundhede, Jette Bredahl Jacobsen, and Bo Jellesmark Thorsen. 2011. Tough and easy choices: Testing the influence of utility difference on stated certainty-in-choice in choice experiments. *Environmental and Resource Economics* 49: 491–510.
Palm, Alvar, and Björn Lantz. 2020. Information dissemination and residential solar PV adoption rates: The effect of an information campaign in Sweden. *Energy Policy* 142: 111540.
Pascaris, Alexis S, Chelsea Schelly, Mark Rouleau, and Joshua M Pearce. 2022. Do agrivoltaics improve public support for solar? A survey on perceptions, preferences, and priorities. *Green Technology, Resilience, and Sustainability* 2 (1): 8.
Phaneuf, Daniel J. 2013. Heterogeneity in environmental demand. *Annual Review of Resource Economics* 5 (1): 227–244.
Rai, Varun, and Benjamin Sigrin. 2013. Diffusion of environmentally-friendly energy

technologies: buy versus lease differences in residential PV markets. *Environmental Research Letters* 8 (1): 014022.
Rocky Mountain Institute. (2021, January 26). *Renewables offer rural America the economic development opportunity of a generation*. Retrieved from https://rmi.org/renewables-offer-rural-america-the-economic-development-opportunity-of-a-generation/.
Roddis, Philippa, Katy Roelich, Katherine Tran, Stephen Carver, Martin Dallimer, and Guy Ziv. 2020. What shapes community acceptance of large-scale solar farms? A case study of the UK's first 'nationally significant' solar farm. *Solar Energy* 209: 235–244.
Roddis, Philippa, Stephen Carver, Martin Dallimer, Paul Norman, and Guy Ziv. 2018. The role of community acceptance in planning outcomes for onshore wind and solar farms: An energy justice analysis. *Applied Energy* 226: 353–364.
Rogers, Jennifer C, Eunice A Simmons, Ian Convery, and Andrew Weatherall. 2008. Public perceptions of opportunities for community-based renewable energy projects. *Energy policy* 36 (11): 4217–4226.
Reuters. (2024, September 17). *U.S. solar jobs rise 6% in 2023, study says*. Retrieved from https://www.reuters.com/sustainability/us-solar-jobs-rise-6-2023-study-says-2024-09-17/.
Sandorf, Erlend Dancke. 2019. Did you miss something? inattentive respondents in discrete choice experiments. *Environmental and Resource Economics* 73 (4): 1197–1235.
Schelly, Chelsea, Don Lee, Elise Matz, and Joshua M Pearce. 2021. Applying a relationally and socially embedded decision framework to solar photovoltaic adoption: A conceptual exploration. *Sustainability* 13 (2): 711.
Serenari, Christopher, M Nils Peterson, Christopher E Moorman, Frederick Cubbage, and Suzanne Jervis. 2015. Application of choice experiments to determine stakeholder preferences for woody biomass harvesting guidelines. *Journal of Sustainable Forestry* 34 (4): 343–357.
Sias, Richard, Laura T Starks, and Harry J Turtle. 2023. The negativity bias and perceived return distributions: Evidence from a pandemic. *Journal of Financial Economics* 147 (3): 627–657.
Sinha, Pratik, Carolyn S Calfee, and Kevin L Delucchi. 2021. Practitioner's guide to latent class analysis: methodological considerations and common pitfalls. *Critical care medicine* 49 (1): e63–e79.
Steinmann, Zoran JN, Mara Hauck, Ramkumar Karuppiah, Ian J Laurenzi, and Mark AJ Huijbregts. 2014. A methodology for separating uncertainty and variability in the life cycle greenhouse gas emissions of coal-fueled power generation in the USA. *The International Journal of Life Cycle Assessment* 19: 1146–1155.
Suh, Jangwon, and Jeffrey RS Brownson. 2016. Solar farm suitability using geographic information system fuzzy sets and analytic hierarchy processes: Case study of Ulleung Island, Korea. *Energies* 9 (8): 648.
Train, Kenneth E. 2009. *Discrete choice methods with simulation*. Cambridge University Press.
Trainor, Anne M, Robert I McDonald, and Joseph Fargione. 2016. Energy sprawl is the largest driver of land use change in United States. *PloS one* 11 (9): e0162269.
Uggeldahl, Kennet, Catrine Jacobsen, Thomas Hedemark Lundhede, and Søren Bøye Olsen. 2016. Choice certainty in discrete choice experiments: Will eye tracking provide useful measures?. *Journal of Choice Modelling*, *20*, 35-48.
US Energy Information Administration. 2022. *2022 Average Monthly Bill- Residential*. Retrieved from https://dee.nebraska.gov/sites/default/files/energy/145_Residential.pdf.
US Energy Information Administration. 2022. Preliminary monthly electric generator inventory. *Inventory of Operating Generators as of July*.

US Energy Information Administration. 2023. Form EIA-923 detailed data with previous form data (EIA-906/920).
US Energy Information Administration. 2024. Preliminary monthly electric generator inventory. *Inventory of Operating Generators as of December*.
Veldwijk, Jorien, Mattijs S Lambooij, Esther W de Bekker-Grob, Henri¨ette A Smit, and G Ardine de Wit. 2014. The effect of including an opt-out option in discrete choice experiments. *PloS one* 9 (11): e111805.
Vossler, Christian A, Maurice Doyon, and Daniel Rondeau. 2012. Truth in consequentiality: theory and field evidence on discrete choice experiments. *American Economic Journal: Microeconomics* 4 (4): 145–171.
Vossler, Christian A, and Mary F Evans. 2009. Bridging the gap between the field and the lab: Environmental goods, policy maker input, and consequentiality. *Journal of Environmental Economics and Management* 58 (3): 338–345.
Vossler, Christian A., and Sharon B. Watson. 2013. Understanding the consequences of consequentiality: Testing the validity of stated preferences in the field. *Journal of Economic Behavior & Organization* 86: 137-147.
Vrieze, Scott I. 2012. Model selection and psychological theory: a discussion of the differences between the Akaike information criterion (AIC) and the Bayesian information criterion (BIC). *Psychological Methods* 17, no. 2: 228.
Williams, Richard. 2006. Generalized ordered logit/partial proportional odds models for ordinal dependent variables. *The Stata Journal* 6 (1): 58–82.
Woli, Krishna P, C Lee Burras, Lori J Abendroth, and Roger W Elmore. 2014. Optimizing corn seeding rates using a field's corn suitability rating. *Agronomy Journal* 106 (4): 1523–1532.
Wolske, Kimberly S, Paul C Stern, and Thomas Dietz. 2017. Explaining interest in adopting residential solar photovoltaic systems in the United States: Toward an integration of behavioral theories. *Energy Research & Social Science* 25: 134–151.
Wolske, Kimberly S, Annika Todd, Michael Rossol, James McCall, and Benjamin Sigrin. 2018. Accelerating demand for residential solar photovoltaics: Can simple framing strategies increase consumer interest? *Global Environmental Change* 53: 68–77.
Zhang, Wendong. 2022. *2022 Iowa State University Land Value Survey: Overview*. Retrieved from https://farmland.card.iastate.edu/files/inline-files/2022-ISU-Land-Value-Survey-Overview.pdf.

Figures and tables

Figure 1. Regional Distribution of Survey Responses from Public Officials and the General Population



Note: The top letter 'P' represents public officials, and 'G' represents the general population. There were 4 responses from public officials that did not report county information, so they are not included in the counts on this map. The division of regions followed the classification used by the Iowa League of Cities.

Table 1: Attributes and Levels in the Discrete Choice Experiment

Attributes	Levels
Expected carbon emissions reduction relative to coal-fired power plants	85%; 95%
Expected annual lease payment to landowners	2 times prevailing cash rent 4 times prevailing cash rent 6 times prevailing cash rent
Expected savings on the monthly electricity bill for your household	\$5; \$25; \$40
Land quality of the occupied farmland	Low (CSR2=55) Medium (CSR2=70) High (CSR2=85)

Note: Corn suitability rating 2 (CSR2) is an index designed to measure soil productivity based on soil profile, slope characteristics, and weather conditions. The index is scaled from 5 for the least productive soils to 100 for the most productive.

Table 2: Sample Statistics and Demographics (N = 868)

Variable	Definition	Description	No. of Obs (%)
Stakeholder	Indicator of the respondent's stakeholder group.	Public official	182 (20.97%)
		General population	686 (79.03%)
		Non-landowner	724 (83.60%)
		Landowner	142 (16.40%)
Information treatment	Indicator of the version of information provided to the respondent.	No information	221 (25.46%)
		Peer info treatment	230 (26.50%)
		Positive info treatment	213 (24.54%)
		Negative info treatment	204 (23.50%)
Support	Degree of support for utility-scale solar projects in local communities.	1=Not at all	70 (8.06%)
		2=Slightly	124 (14.29%)
		3=Moderately	382 (44.01%)
		4=Very	204 (23.50%)
		5=Extremely	88 (10.14%)
Land_use_challenge	The degree to which the respondent rates land use as a challenge for hosting utility-scale solar projects within their community.	1=Not a challenge	123 (14.22%)
		2=Somewhat a challenge	297 (34.34%)
		3=A significant challenge	445 (51.45%)
Knowledge_utility_solar	Self-reported knowledge level regarding utility-scale solar energy.	1=Low	692 (79.91%)
		2=Medium	162 (18.71%)
		3=High	12 (1.39%)
County_utility_solar	Whether there is a utility-scale solar project in the county where the respondent resides.	0=No	724 (83.41%)
		1=Yes	144 (16.59%)
Rooftop_adopt_plan	Whether the respondent has installed rooftop solar panels or plans to adopt them in the next five years.	0=No	634 (73.04%)
		1=Yes	234 (26.96%)
Community_part_int	Degree of interest the respondent has in participating in community solar projects, if available.	1=Not at all interested	223 (25.69%)
		2=Somewhat interested	498 (57.37%)
		3=Very interested	147 (16.94%)
Municipal_cooperatives	Whether the respondents' electricity supplier is a municipal utility or a cooperative.	0=No	511 (58.87%)
		1=Yes	357 (41.13%)
Gender		1=Male	439 (50.58%)
		2=Female	426 (49.08%)
Age		<=24	46 (6.71%)
		25-34	110 (16.03%)
		35-44	152 (22.16%)
		45-54	128 (18.66%)
		55-64	115 (16.76%)
		65+	135 (19.68%)
Education		12th grade or less/no diploma	17 (1.96%)
		High school diploma or GED	131 (15.13%)
		Some college, or Associate's degree	315 (36.37%)
		Bachelor's degree	276 (31.87%)
		Graduate or Professional degree	127 (14.67%)
Political affiliation		1=Democrat	210 (24.25%)
		2=Republican	304 (35.10%)
		3=Independent	313 (36.14%)
		4=Others	39 (4.50%)
Household income		$0-$30,000	157 (18.17%)
		$31,000-$60,000	191 (22.11%)
		$61,000-$90,000	185 (21.41%)
		$91,000-$120,000	151 (17.48%)
		$120,000+	180 (20.83%)
Farm operation	Whether the respondent's family operates a farm.	0=No	728 (83.97%)
		1=Yes	139 (16.03%)

Table 3: Estimates of Attribute Coefficients in Willingness-to-Pay Space

	Conditional Logit	Random Parameter Logit	
Variable	(1)	(2)	(3)
Mean parameters			
Carbon emission reduction 95%	5.3104***	3.2164**	14.9460***
	(1.1787)	(1.3396)	(3.9124)
Lease payment to landowners	0.5120	0.2948	1.5509***
	(0.4246)	(0.4325)	(0.4372)
Medium quality farmland	-6.4551***	-4.5762***	14.4865***
	(1.5186)	(1.4508)	(4.0322)
High quality farmland	-23.9987***	-20.2377***	-22.4219**
	(2.2136)	(2.5059)	(9.1070)
Medium quality farmland × Carbon emission reduction 95%			-22.8724***
			(6.3867)
Medium quality farmland × Energy saving			-0.3640***
			(0.0781)
High quality farmland × Carbon emission reduction 95%			-0.6537
			(7.7114)
High quality farmland × Energy saving			0.0813
			(0.2084)
Standard deviation parameters			
Carbon emission reduction 95%		1.4266***	4.6335***
		(0.1236)	(0.5183)
Lease payment to landowners		0.4378***	0.5196***
		(0.0378)	(0.0566)
Medium quality farmland		1.5572***	4.5349***
		(0.1391)	(0.5264)
High quality farmland		3.3019***	8.1456***
		(0.3282)	(1.1050)
Medium quality farmland × Carbon emission reduction 95%			7.0948***
			(0.8338)
Medium quality farmland × Energy saving			0.1024***
			(0.0110)
High quality farmland × Carbon emission reduction 95%			7.7441***
			(0.8421)
High quality farmland × Energy saving			0.2031***
			(0.0228)
Log likelihood	-2,956	-2,661	-2,641
AIC	5922.158	5342.334	5317.445
BIC	5957.720	5413.457	5445.466
Certainty level ≥ 3	Yes	Yes	Yes
Number of respondents	816	816	816
Observations	9066	9066	9066

Note: Robust standard errors clustered at the individual level in parentheses, * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 4: Random Parameter Logit Models in Willingness-to-Pay Space: Estimates Across Stakeholder Groups

Variable	(1)	(2)
Mean parameters		
Carbon emission reduction 95%	4.3135***	3.4851**
	(1.4647)	(1.4043)
Lease payment to landowners	0.1080	0.2766
	(0.4840)	(0.4584)
Medium quality farmland	-2.1616	-3.1220**
	(1.6117)	(1.5352)
High quality farmland	-14.8066***	-17.1263***
	(2.6432)	(2.4547)
Carbon emission reduction 95% × Public official	-5.2905	
	(3.4394)	
Lease payment to landowners × Public official	1.1496	
	(1.0969)	
Medium quality farmland × Public official	-14.3176***	
	(4.1549)	
High quality farmland × Public official	-33.9172***	
	(8.8950)	
Carbon emission reduction 95% × Landowner		-0.8582
		(4.3585)
Lease payment to landowners × Landowner		0.6190
		(1.4781)
Medium quality farmland × Landowner		-14.2596**
		(6.1472)
High quality farmland × Landowner		-32.4714**
		(13.4699)
Standard deviation parameters		
Carbon emission reduction 95%	1.6123***	1.5127***
	(0.1479)	(0.1357)
Lease payment to landowners	0.4859***	0.4636***
	(0.0445)	(0.0416)
Medium quality farmland	1.6604***	1.6185***
	(0.1514)	(0.1453)
High quality farmland	3.2295***	3.2252***
	(0.3175)	(0.3155)
Log likelihood	-2,634	-2,649
AIC	5298.574	5328.306
BIC	5405.258	5434.990
Certainty level ≥ 3	Yes	Yes
Number of respondents	816	816
Observations	9066	9066

Note: Robust standard errors clustered at the individual level in parentheses, * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 5: Random Parameter Logit Models in Willingness-to-Pay Space: Estimates Across Information Treatment Groups

	General population	Full sample
Variable	(1)	(2)
Mean parameters		
Carbon emission reduction 95%	3.8206	1.5805
	(2.3260)	(2.3633)
Lease payment to landowners	-0.3137	0.3081
	(0.8003)	(0.7924)
Medium quality farmland	-3.8120	-4.8522*
	(2.6990)	(2.5564)
High quality farmland	-14.5888***	-18.0799***
	(4.5837)	(4.7110)
Carbon emission reduction 95% × Peer information	0.3695	2.1535
	(3.6826)	(3.4831)
Lease payment to landowners × Peer information	0.8314	-0.0100
	(1.1918)	(1.1201)
Medium quality farmland × Peer information	4.1024	3.5936
	(4.1405)	(3.7538)
High quality farmland × Peer information	0.7338	-0.1295
	(6.5422)	(6.5357)
Carbon emission reduction 95% × Positive information	4.7963	5.3651
	(3.7298)	(3.4235)
Lease payment to landowners × Positive information	1.1624	0.4219
	(1.3257)	(1.1920)
Medium quality farmland × Positive information	6.5055	1.2127
	(4.7313)	(4.1418)
High quality farmland × Positive information	4.8835	-0.3804
	(7.3606)	(6.8955)
Carbon emission reduction 95% × Negative information	-2.6316	-1.0612
	(3.9411)	(3.9700)
Lease payment to landowners × Negative information	-0.0795	-0.5625
	(1.3979)	(1.3346)
Medium quality farmland × Negative information	-4.2683	-5.0122
	(4.2969)	(4.1098)
High quality farmland × Negative information	-7.8449	-11.1071
	(7.3942)	(7.8107)
Standard deviation parameters		
Carbon emission reduction 95%	2.5017***	2.4363***
	(0.3448)	(0.3436)
Lease payment to landowners	0.7886***	0.8050***
	(0.1112)	(0.1142)
Medium quality farmland	2.8542***	2.7603***
	(0.3936)	(0.4037)
High quality farmland	5.3931***	5.5936***
	(0.7840)	(0.9120)
Log likelihood	-2,138	-2,652
AIC	4322.704	5355.362
BIC	4495.081	5533.169
Certainty level ≥ 3	Yes	Yes
Number of respondents	654	816
Observations	7296	9066

Note: Robust standard errors clustered at the individual level in parentheses, * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 6: Heterogeneity Analysis: Marginal Effects of Factors Influencing the Ranking of Land Use Challenges

Variable	Not a challenge	Somewhat a challenge	A significant challenge
County_utility_solar	0.0208	0.0208	-0.0417
	(0.0211)	(0.0212)	(0.0423)
Rooftop_adopt_plan	0.0546***	0.0546***	-0.1092***
	(0.0192)	(0.0189)	(0.0374)
Community_part_int	0.0303**	0.0303**	-0.0606**
	(0.0133)	(0.0130)	(0.0259)
Municipal_cooperatives	0.0031	0.0031	-0.0062
	(0.0164)	(0.0164)	(0.0328)
Gender = Female (baseline: male)	0.0011	0.0011	-0.0022
	(0.0167)	(0.0168)	(0.0335)
Age	-0.0003	-0.0003	0.0005
	(0.0006)	(0.0006)	(0.0011)
Education	-0.0135	-0.0135	0.0271
	(0.0088)	(0.0087)	(0.0174)
Baseline: Democrat			
Political affiliation = Republican	-0.0293	-0.0282	0.0575
	(0.0226)	(0.0215)	(0.0438)
Political affiliation = Independent	-0.0210	-0.0193	0.0404
	(0.0221)	(0.0198)	(0.0417)
Political affiliation = Others	-0.0345	-0.0342	0.0687
	(0.0445)	(0.0507)	(0.0950)
Household income	-0.0102	-0.0102	0.0203
	(0.0066)	(0.0065)	(0.0131)
Farm operation	-0.0407*	-0.0407**	0.0815**
	(0.0212)	(0.0202)	(0.0411)
Log likelihood	-826		
AIC	1679.355		
BIC	1745.903		
Observations	857		

Note: Robust standard errors in parentheses, * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Footnotes

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[1] These professionals work directly with rural communities and have extensive field experience with renewable energy project implementation and community engagement in Iowa. Their expertise was invaluable in ensuring our attributes reflected real-world concerns and decision-making factors relevant to local communities. Our attribute selection process was iterative. We initially proposed a broader set of potential attributes, including tax revenue to local government and job creation opportunities, among others. Through several rounds of discussion with these extension specialists and survey methodology experts, we refined our selection based on several criteria: 1) relevance to actual community decision-making processes, 2) policy relevance, 3) measurability and credibility to survey respondents, and 4) experimental design constraints. After these extensive consultations, we ultimately focused on the four attributes presented in our study as they best captured the primary dimensions of community concern while maintaining experimental feasibility and respondent comprehension.

[2] According to estimates by Nugent and Sovacool (2014) and Mehedi et al. (2022), utility-scale solar energy systems produce life-cycle greenhouse gas (GHG) emissions ranging from 98.3 to 149.3 g CO_2 eq/kWh, with a mean value of 123.8 g CO_2 eq/kWh. In contrast, life-cycle GHG emissions from coal-fired power plants range from 0.97 to 1.69 kg CO_2 eq/kWh (Steinmann et al., 2014). Thus, we calculate the lower bound of the expected carbon emission reduction relative to coal-fired power plants as 85% and the upper bound as 95%.

[3] The annual lease payment to landowners for installing utility-scale solar in Iowa ranged from $600 to $1,100 per acre (Iowa Farmer Today, 2021; Iowa Solar Energy Trade Association, 2020), approximately 2 to 4 times the average cropland cash rent ($256/acre) paid to Iowa landlords in 2022, as reported by ISU Extension (2022). We established three levels to accommodate variations in per-acre annual cropland cash rent and lease payments for installing utility-scale solar in Iowa.

[4] Based on data from the '2022 Average Monthly Bill – residential' reported by the Energy Information Administration (EIA, 2022), Iowa households had an average monthly electricity consumption of 888 kWh and a bill of $110. The savings on the levelized cost of energy by utility-scale solar photovoltaic were estimated to be between $0.004 to $0.046 per kWh compared to a gas combined cycle, which was the least-cost fossil fuel source (Lazard, 2020). This suggests an expected saving on Iowa household electricity bills ranging from $3.6 to $41 when transitioning to utility-scale solar. We construct three levels at $5, $25, and $40, representing approximately 5%, 23%, and 36% of the average monthly electricity bill for a household, respectively.

[5] Corn suitability rating 2 is an index designed to measure soil productivity based on soil profile, slope characteristics, and weather conditions. The index is scaled from 5 for the least productive soils to 100 for the most productive (Woli et al., 2014). According to the Iowa State University Land Value Survey (Zhang, 2022), the estimated average CSR2 for low-, medium-, and high-quality land in Iowa is 56, 70, and 83, respectively. We made slight adjustments to these numbers in the choice experiment.

[6] The D-optimal design employed in this study focuses on main effects and does not explicitly account for interaction effects. For the purposes of this study, we prioritized the main effects to

maintain a manageable design size and interpretability.

[7] We chose to study a 50 MW solar project because it is considered a medium-sized, utility-scale project. A project of this size is not too large, which may help gather more diverse opinions regarding its land use impacts from respondents compared to an extremely large or small project.

[8] Our choice experiment design did not incorporate explicit payment consequentiality questions. However, our focus was primarily on establishing policy consequentiality through informing respondents about how their responses would inform extension and outreach programs, which we believed would be the most relevant form of consequentiality for this particular research context. In addition, respondents' choices were directly linked to specific savings on monthly electricity bills, grounding choices with realistic financial implications.

[9] More details can be found at https://www.dynata.com.

[10] We received a total of 1187 attempts for the online survey. Among these attempts, 501 participants failed the attention-checking questions and were automatically excluded from the survey.

[11] The assumption states that the relative odds of choosing between any two alternatives are independent of the presence or characteristics of other alternatives in the choice set.

[12] The standard conditional logit model has been employed in many studies, which assumes homogeneous preferences across respondents, implying constant taste parameters. However, previous studies have shown that heterogeneity is a defining feature of non-market environmental valuations (Phaneuf, 2013) and the conditional logit model may misspecify the taste distribution and inaccurately represent the value of attributes appealing to specific population subsets (Phaneuf, 2013; Train, 2009).

[13] In our analysis, energy savings and lease payments are treated as continuous variables, while farmland quality is modeled using dummy variables. This distinction reflects both the nature of the attributes and our research goals. Energy savings and lease payments, being monetary attributes, are assumed to have a linear relationship with utility, allowing for a straightforward interpretation of marginal effects. In contrast, farmland quality, a central focus of our research, is coded as a dummy variable to account for possible non-linear effects, enabling us to capture how respondents' trade-offs might differ based on the project's location on farmland of varying quality. This approach offers a more detailed understanding of preferences across different farmland quality levels.

[14] Carson and Czajkowski (2019) highlight that the Delta method can produce unreliable confidence intervals when the denominator (the negative of the cost parameter) is not sufficiently far from zero in a statistical sense. As they note, the Delta method is considered adequate only when the t-statistic on the denominator exceeds 8.75 - a threshold that is not typically met in some applied economic works. The t-statistics for our cost parameter denominators are greater than 10, which are substantially greater than the threshold of 8.75 often cited in the literature (Carson and Czajkowski, 2019; Finney, 1971; Hirschberg and Lye, 2010). These values indicate that our cost

parameters are highly statistically significant and sufficiently far from zero to ensure reliable Delta method approximation.

[15] In practice, the proportional odds (PO) assumption required by the standard ordered logit model might be violated, necessitating the use of a generalized ordinal logit model, such as the partial proportional odds model (Greene and Hensher, 2010; Williams, 2006). To address concerns regarding potential violations of the PO assumption, we conducted the Brant test (Brant, 1990) to determine whether the PO assumption holds for each individual explanatory variable as shown in Eq. (6). The results of the Brant test indicate that the PO assumption holds for all explanatory variables in our study. Therefore, we utilized the standard ordered logit model (PO model) in this analysis.

[16] More details on population, age, household income, and education attainment estimates for the Iowa population can be found on the U.S. Census Bureau's QuickFacts for Iowa at https://www.census.gov/quickfacts/fact/table/IA/.

[17] The U.S. Census Bureau estimates that around 22.8% of the Iowa population in 2023 was under 18 years old, with the median age of the adult population (18+) falling in the range of 40-49 years.

[18] According to Iowa voter registration data updated in June 2025, which can be found at https://independentvoterproject.org/voter-stats/ia.

[19] The *p*-value for the two-sided *t*-test for the mean difference in the level of support between landowners and non-landowners is 0.0256, indicating the rejection of null hypothesis of no significant difference between these two groups at a 5% significance level.

[20] We estimate the Bayesian Information Criterion (BIC) for models with 2 to 10 classes, as BIC is widely used in latent class analysis for model selection due to its consistency property—it will asymptotically select the true model when the true model is among the candidate models considered. BIC achieves this through a stronger penalty for model complexity compared to other information criteria such as the Akaike Information Criterion (AIC) (Vrieze, 2012). The BIC decreases substantially from 2 classes (5538) to 3 classes (5437) but increases to 5467 for 4 classes and 5508 for 5 classes, indicating that the 3-class model provides the optimal balance between model fit and parsimony. Additionally, the model encountered convergence issues when specifying 6 or more classes, likely due to model over-parameterization.

[21] When 57 physical copy responses are excluded, the estimates for the interaction terms of attributes and the public official indicator are only significant at 5% confidence level, and landowners' valuations on medium-quality farmland for solar projects are not statistically significantly different from those of non-landowners, likely reflecting the loss of efficiency from a reduced sample size.