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Support for Utility-Scale Solar: Effects of Information and Heterogeneity among Public Officials, the General Population, and Landowners

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Abstract

In the United States, utility-scale solar initiatives face growing local resistance despite their cost-competitiveness and potential in mitigating greenhouse gas emissions. This study investigates the marginal effects of knowledge levels related to solar, information treatments, and their interconnections with peoples' attitudes toward utility-scale solar energy systems and explores some key drivers of the different knowledge levels. We designed and implemented a survey targeting both public officials and the general population in the U.S. state of Iowa. Among 862 respondents, 79.8% self-reported having a low level of knowledge about solar energy. Additionally, 77.7% expressed at least moderate support for hosting such projects in their community. Our empirical results suggest that individuals with a higher level of knowledge of utility-scale solar energy tend to express a higher degree of support for adopting such projects within their community. Individuals' attitudes are more responsive to the negative information treatment. Notably, there are significant differences between public officials and the general population in attitudes and responsiveness to information treatments. We also find that landowners' support for utility-scale solar projects is unlikely to change regardless of knowledge levels, while non-landowners show increased support with higher levels of knowledge. This study provides insights for developing context-specific outreach programs to enhance public awareness and support for utility-scale solar projects and promote future solar development.

Keywords: Attitudes, Information treatment, Knowledge, Ordinal logit, Partial proportional odds, Utility-scale solar

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1. Introduction

The transition to renewable energy sources is a critical global challenge to mitigate climate change and ensure a sustainable future. Among the various renewable energy technologies, utility-scale solar projects play a significant role in reducing greenhouse gas emissions and meeting energy demand. Over the past two decades, solar energy systems have improved dramatically in efficiency with substantially reduced installation costs and currently represent the most economical option for electricity generation, according to the U.S. Energy Information Administration (EIA, 2023). By the end of 2023, the U.S. had developed a cumulative utility-scale solar capacity of 89.5 gigawatts (GW), with 18.4 GW installed that year alone.

The successful deployment of utility-scale solar projects often relies on public support and acceptance due to the nature of land use regulations in the U.S. (Crawford et al., 2022; Majumdar and Pasqualetti, 2019). Research from the U.S. National Telephone Survey indicated strong public support for the construction of utility-scale solar facilities, with 70% of respondents viewing solar development as a symbol of government commitment to renewable energy (Carlisle et al., 2015). Nonetheless, utility-scale solar initiatives have encountered growing local resistance in the United States (Roddis et al., 2018), leading to instances where communities have either imposed temporary moratoriums on such projects or banned their development outright (Abashidze and Taylor, 2023; Dickerson, 2018). An analysis by USA TODAY reveals that 116 U.S. counties have implemented bans or construction impediments to utility-scale solar plants, with half of these restrictions enacted in 2023 alone (Weise and Bhat, 2024). Notably, 2023 marked the first year when the number of counties limiting new solar installations nearly equaled those adding their first solar farm (Weise et al., 2024). This rapidly growing trend of resistance can potentially have significant consequences for renewable energy development and warrants close attention. Local communities have raised concerns regarding utility-scale solar projects, including issues related to their intermittency, aesthetic impacts, perceived negative effects on rural and tribal culture, and community energy sovereignty,

and potential risks to wildlife and human health (Roddis et al., 2020; Mulvaney, 2017; Nilson and Stedman, 2022; Boudet, 2019).

Clearly, people across different communities and even within the same communities have diverse views and attitudes toward utility-scale solar. While many factors affect perceptions and attitudes, one's knowledge about utility-scale solar might be a particularly relevant factor for policy making. In particular, if more knowledge means more acceptance, then education and outreach efforts might be an effective strategy for promoting utility-scale solar. Palm and Lantz (2020) provided a valuable perspective by investigating the impact of a Swedish information campaign aimed at solar knowledge dissemination. Their study revealed that information campaigns yielded a significantly positive effect on adoption rates of residential solar facilities. Levy (2021) found that exposure to counter-attitudinal news can reduce negative attitudes toward opposing political parties, indicating the potential of knowledge dissemination in reshaping public viewpoints. However, the relationship between knowledge dissemination and attitudes is inconclusive in the existing literature, for example, Needham et al. (2018) did not find significant effects of newfound knowledge on individuals' valuation of specific goods. While there is a large literature on perceptions and attitudes, there are few studies that examine people's knowledge of local electricity generation and supply and utility-scale solar energy systems, and the connection between such knowledge and attitudes in the context of utility-scale solar deployment is not well understood.

The objective of this paper is to examine the potential roles of knowledge levels in peoples' attitudes toward utility-scale solar energy systems and identify likely factors underlying the diverse knowledge levels among different stakeholder groups within the same local community. Our analysis draws on data from a 2023 survey with an information treatment experiment targeting both public officials and the general population in the state of Iowa, USA. Participants were randomly assigned to a control group or one of three information treatment groups, each emphasizing a specific type of information: peers' adoption of regulations for utility-scale solar projects, positive effects, or negative effects of utility-scale solar on the local community. In our design, peer informa-

tion included local zoning regulations regarding utility-scale solar energy systems. Land use and zoning regulations contain specific requirements, such as setbacks from property lines, proximity to residential areas, land cover management, and decommissioning plans, which determine the key characteristics and impacts of solar projects and so are often of considerable concern to stakeholders. Knowledge level is measured in two ways: self-rated levels, or constructed levels based on answers to different factual questions to reflect the multifaceted nature of knowledge.

This paper contributes to existing literature in the following respects. First, we contribute to the body of knowledge-attitude literature by differentiating four stakeholder groups: public officials versus the general population, and landowners versus non-landowners, and exploring the potential heterogeneity in their knowledge-attitude linkages. There is an extensive literature examining the driving factors of perceptions and attitudes regarding solar at both utility and residential scales and other renewable energy, such as large-scale wind farms (e.g., Crawford et al., 2022; Gaur et al., 2023; Larson and Krannich, 2016; Li et al., 2021; Parkins et al., 2022). However, previous studies predominantly focused on the perspectives of the general population and landowners, and few studies include explicit contrasts and comparisons between these groups and public officials and non-landowners. In particular, to the best of our knowledge, there is no such study specifically targeting public officials. Public officials' perspectives are critical because they are generally better educated and informed, and, more importantly, they are likely to have greater impacts on the local decisions made in their communities (Macawile and Su, 2009; Bohner and Dickel, 2011). We bridge this research gap by incorporating the perspectives of public officials alongside those of the general population. This allows for a comparison between knowledge levels and attitudes of influential decision-makers and the broader public, providing insights for tailoring outreach to different stakeholder groups.

Second, our study empirically investigates the linkage between knowledge levels and attitudes by using both subjective and objective measures of knowledge levels. Building on the literature that commonly uses self-rated knowledge levels (e.g., Casaló et al.,

2019; Hadar et al., 2013; Needham et al., 2018; Shou and Olney, 2021; Wong-Parodi and Rubin, 2022), we consider both self-rated overall knowledge levels and constructed knowledge levels that are created based on responses to specific, fact-based questions such as whether there are utility-scale solar projects or community solar farms in their county or city. While Hanger et al. (2016) investigated the relationship between self-rated knowledge levels and attitudes toward utility-scale solar, a critical challenge with self-assessments is their potential lack of accuracy. Research has consistently shown that individuals may inaccurately rate their own knowledge due to cognitive biases or lack of self-awareness (Braun et al., 2012; Jahedi and Méndez, 2014; Tadesse et al., 2020). Thus, objective measures based on answers to factual questions are generally regarded as a more robust assessment of knowledge levels compared to subjective self-assessments (Shi et al., 2016; Van der Linden, 2015). By using two measurements of knowledge, our study aims to more precisely examine the knowledge-attitude relationship.

Third, we contribute to the knowledge-attitude literature concerning utility-scale solar, an area that has been subject to increasing research studies. While recent years have seen a growing body of research on utility-scale solar, including people's perceptions and attitudes toward utility-scale solar, studies examining the role of people's knowledge in renewable technology adoption have largely focused on residential solar energy facilities and wind energy (Palm and Lantz, 2020; Parkins et al., 2022; Rai and Beck, 2017; Wolske et al., 2018). However, the knowledge-attitude relationship observed in residential solar and wind energy contexts might not necessarily be transferable to utility-scale solar, which involves significant land use conflicts and other local community impacts. To our best knowledge, no study has examined this knowledge-attitude linkage in the setting of utility-scale solar, with the exception of Hanger et al. (2016), who conducted research involving interviews in Morocco, revealing a low level of knowledge regarding utility-scale solar and a positive relationship between knowledge and attitudes. However, their findings might not be applicable to contexts with different socioeconomics and natural environments (e.g., the U.S. Midwest region in our study), and our study identifies the diverse effects of knowledge levels on individuals' attitudes across target audiences

and examines the patterns of different knowledge levels. Utility-scale solar is set to grow rapidly (Bolinger et al., 2023), and so understanding the knowledge-attitude relationship in the setting of utility-scale solar is critical for shedding light on the current controversies surrounding such solar projects.

Our empirical results suggest heterogeneous effects of knowledge and information treatments on support for utility-scale solar projects across different stakeholder groups. Specifically, as knowledge level increases by one level (from low to medium or from medium to high), the odds of showing a higher degree of support for utility-scale solar projects rise by 27% for the general population. However, such an effect is not statistically significant among public officials. Moreover, public officials who received peer information demonstrated a 97% increase in the odds of higher support compared to the control group. The general population's attitudes are significantly more responsive to negative information, with a 42% decrease in the odds of expressing a higher degree of support when presented with negative information. We also find that the effectiveness of information treatments varies across knowledge groups for both public officials and the general population. Furthermore, landowners' support remains consistent across knowledge levels, while non-landowners exhibit increased support with higher knowledge level and decreased support when presented with negative information.

The remainder of this paper proceeds as follows. Section 2 reviews existing literature and formulates research hypotheses. Section 3 provides details on the survey, experimental design, and empirical methods. Section 4 presents the results, and Section 5 concludes.

2. Literature review and research hypotheses

Public preferences are critical in the development of utility-scale solar energy. Many studies have investigated factors impacting public stances on such projects. Gaur et al. (2023) find that residents of Rhode Island prefer utility-scale solar projects that avoid the use of farmland and forested areas. Carlisle et al. (2015) suggest that demographic and socio-economic factors, including property value, race, and age, significantly influence

residents' support or opposition to utility-scale solar development in the U.S. In a related vein, Li et al. (2021) identify household, family, and farm characteristics, production conditions, and the social environment as key factors influencing support behaviors. Furthermore, a stream of studies has investigated the perceived local impacts of utility-scale solar projects on residents' support or opposition. For example, Crawford et al. (2022) delve into the aspects of aesthetic, economic, land use, environmental, and energy impacts of such projects and point to the most common concern being the potential devaluation of residential property. Empirical evidence from Elmallah et al. (2023) and Gaur and Lang (2023) also supports these property value concerns. They find that the construction and proximity to utility-scale solar facilities have negative impacts on housing prices, indicating that local disamenities from such projects may help explain community opposition to siting decisions. Additionally, Larson and Krannich (2016) and Carlisle et al. (2016) find that proximity to residential areas and effects on wildlife are also significant. Various perceived risks, including intermittency, aesthetics, negative impacts on rural and tribal culture, and community energy sovereignty, as well as risks to wildlife, productive farmland, biodiversity, and human health, are also found to be important factors affecting peoples' attitudes toward utility-scale solar (Roddis et al., 2020; Mulvaney, 2017; Nilson and Stedman, 2022; Boudet, 2019).

While many studies have explored the relationship between knowledge levels and individuals' attitudes in general, there is limited empirical evidence regarding the impacts of the amount of knowledge on the degree of support for utility-scale solar energy. Given the potential benefits of such projects, one might expect greater support as people acquire more information about them. However, a notable gap exists in research concerning how individuals' knowledge affects their perceptions and attitudes towards local electricity and energy systems. Three key questions arise when examining knowledge and attitudes in the context of utility-scale solar energy systems, which are generally considered as crucial in our transition to a low-carbon economy. First, does a higher knowledge level correlate with a greater degree of support? Second, is negative information more impactful than positive information in shaping individuals' attitudes toward

utility-scale solar energy systems? Third, are individuals with lower levels of knowledge directly related to solar less responsive to information treatments? Our study aims to address these questions.

The existing knowledge-attitude literature across various contexts shows no consensus about the nature of the linkage between knowledge and attitudes. According to Cameron and Englin (1997), individuals with higher levels of prior knowledge and experience regarding an environmental good exhibit a substantially higher willingness to pay (WTP) for that good. In contrast, Needham et al. (2018) conduct a stated preference experiment on an environmental project and find a negative relationship between prior knowledge level and individuals' valuation of the public good. Their findings indicate that posterior knowledge levels do not significantly impact valuations conditional on ex-ante knowledge. Newell and Siikamäki (2014) and Chan et al. (1999) find that insufficient knowledge can lead to the undervaluation of energy efficiency and public goods. Allcott and Taubinsky (2015) indicate that having sufficient knowledge about the energy efficiency of fluorescent lightbulbs significantly enhances consumer purchases. Hanger et al. (2016) conduct 232 face-to-face interviews in Morocco, demonstrating that a higher self-reported knowledge level related to utility-scale solar energy leads to a higher level of acceptance. Nevertheless, their findings might not be directly applicable to developed countries, such as the U.S., where the socioeconomic and natural conditions differ significantly. Against the backdrop of existing literature findings discussed above, we propose to test the following hypothesis:

Hypothesis 1: *People who indicate having more knowledge related to utility-scale solar energy tend to exhibit higher support for utility-scale solar projects than people with less knowledge.*

Information provision experiments are a widely used method in existing research. Haaland et al. (2023) provided a survey of the emerging literature using information treatments in economics and discussed best-practice recommendations on how to measure

beliefs and design the information intervention. The way information is disseminated, including both content and format of information, can affect people's knowledge level, perspectives (Guess et al., 2021; Levy, 2021), and decision-making (Calvó-Armengol and De Martï, 2007). For instance, Mahadevan et al. (2023) found that an information treatment, intended to alleviate information asymmetries between sales agents and potential customers, increased potential customers' intent to adopt rooftop solar systems. Carley et al. (2019) suggest that people who received an information treatment showing them that electricity is sourced from wind or solar are significantly more supportive of constructing new local transmission lines compared to the control group. Moreover, participation in informational sessions has been shown to strengthen individuals' support for commercial wind energy (Bidwell, 2016). Wolske et al. (2018) find that re-framing the financial benefits of PV does not significantly impact the appeal of residential PV. Park et al. (2023) note significant variations in consumer responses to gain- and loss-framing information concerning the economic benefits of purchasing high-efficiency appliances. Davis and Metcalf (2016) find that state-specific energy guide labels lead to significantly improved consumer choices and investment efficiency. Beattie et al. (2022), Jessoe and Rapson (2014), and Allcott and Knittel (2019) also find positive information significantly increase consumers' willingness to buy or consumption of energy-efficient products. Allcott and Taubinsky (2015) suggest that positive and balanced information increases the market share of compact fluorescent lightbulbs at market prices by about 12 percentage points. In our study, we show how information treatments can influence individuals' decisions in terms of support or not support for utility-scale solar projects in their local community as they weigh the benefits and costs of such projects.

There is also a large literature on the effects of negative information and peer information. Baumeister et al. (2001) and Sias et al. (2023) find that individuals tend to be more responsive to negative information. Research conducted by Kabunga et al. (2012) reveals that negative information spreads faster and more widely than positive information, influencing technology adoption. The peer effect, referred to as the correlation between individual and peer group outcomes (Angrist, 2014), is also an important factor

influencing individuals' technology perceptions and adoption behaviors (Beaman et al., 2021). For instance, Bollinger and Gillingham (2012) and Noll et al. (2014) show that peer information regarding adoption has a significantly positive impact on the uptake of residential solar PV technologies. Parkins et al. (2022) find that vignettes regarding compensation to neighboring landowners and community involvement significantly enhance landowners' acceptance of large-scale wind projects. Furthermore, individuals' perceptions of social norms and the views of valued peers significantly shape their decisions to adopt new technologies (Wilson and Dowlatabadi, 2007). Studies have also investigated how adoption decisions can be affected by the effects of social networks which are closely related to peer effects. For example, Schelly (2014) find that social networks and communities of information are critical in the adoption decision of residential solar technology. Similarly, local communication networks enhance awareness of and attention to renewable energy programs, with adoption decisions being positively related to the availability and strength of communication ties (Weenig and Midden, 1991).

Thus, based on the existing literature, we propose the following hypotheses in the context of utility-scale solar for testing:

Hypothesis 2: *Negative information has a larger effect than positive information in shaping peoples' attitudes regarding utility-scale solar projects.*

Hypothesis 3: *Peoples' attitudes towards solar exhibit peer effects, in that if one is informed of their peers' choices, one is likely to make a choice similar to peers'.*

Knowledge level has been shown to have the potential to be a crucial factor in shaping individuals' preferences for technology adoption. In a study concerning owl conservation, Loomis and Ekstrand (1998) show that respondents with a higher level of knowledge about the subject exhibited greater certainty in their preferences. Hasselström and Håkansson (2014) observe notable variations in WTP among respondents with low level of knowledge exposed to either "detailed" or "fuzzy" information sets. However, no

such divergence was observed among those with high familiarity. Eshchanov et al. (2021) suggest that cognitive abilities associated with social knowledge of renewable energy systems are important for household acceptance of such systems. Moreover, Bashiri and Alizadeh (2018) find that individuals' knowledge of renewable energies positively correlates with the probability of residential solar adoption. Nonetheless, to our knowledge, no study has explored the connection between knowledge level and the effectiveness of information treatment on the level of support for renewable technology. Therefore, we formulate the fourth hypothesis as follows:

Hypothesis 4: *As to the effects on the degree of support for utility-scale solar energy, information treatments have larger effects on people who indicated a higher level of related knowledge.*

While we do not develop formal theoretical models to formulate hypotheses, our research hypotheses are based upon findings of existing studies, which sometimes conflict with each other and remain inconclusive and so a new study like ours can contribute to new perspectives on the topic. For a hypothesis that seems to have clear evidence in other contexts, our empirical estimation can show whether the hypothesis holds up in our context and the extent of heterogeneities among different treatment groups.

3. Data and methods

3.1. Experiment and questionnaire design

In order to test the four hypotheses explained in the previous section, we conducted a survey that included an information treatment experiment. The information treatments were designed with an emphasis on three types of information: one type focused on information related to peers' adoption of regulations for utility-scale solar projects; the remaining two types provided information highlighting either the positive or negative effects of deploying utility-scale solar projects within local communities. In our design,

peer information focused on local zoning regulations regarding utility-scale solar energy systems, differing from that of most existing studies such as Bollinger and Gillingham (2012) and Noll et al. (2014), which focus on peers' adoption of residential solar panels. Our experimental design reflects the critical role of local zoning regulations in the deployment of these projects within local communities. Local zoning rules specify key land use requirements, including setbacks from property lines, proximity to residential areas, land cover management, and decommissioning plans – issues that are often concerns for stakeholders. Additionally, we use common practices[1] in the region (i.e., Midwest) to represent peers because there were only very few utility-scale solar projects in Iowa when the survey was implemented and using common practices in nearby counties would not be feasible.

The descriptions used for information treatment are provided in Table A.2. For comparison purposes, we included a control group that received no information. Thus, we had four versions of survey questionnaire. Participants were randomly assigned to one of the four groups, one control and three treatment groups, each of which has a different type of information treatment. To ensure respondents carefully read the provided information, we included attention-checking questions[2] immediately after the information content. Participants were informed that the answers to these questions could be found in the preceding text and that they would not receive compensation if they failed to answer them correctly in three attempts.[3] Based on Cohen's D-statistics (Cohen, 2013), a minimum of sixty-four subjects in each group was required to detect one-half of the standard deviation change in the outcome variable with a power of 0.80 at the 0.05

[1] We acknowledge that some participants might feel the setback distances and decommissioning bond with negative connotation about solar projects. On the other hand, these regulations are contained in a Solar Model Ordinance and other participants might view them as reassurance that solar projects will be set up within reasonable rules, i.e., will be "done the right way." Thus, the information is not likely to have one-sided effects.

[2] For positive and negative information treatments, we asked one question regarding the positive or negative effects of utility-scale solar. For peer information, since the content is related to peers' adoption of regulation, there are two questions: one about the percentage of local jurisdictions having utility-scale solar zoning ordinances, and the other about the average decommissioning bond requirement. There was no attention-check question for the control group.

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

significance level. Our final sample size of 868, consisting of 204 to 230 observations in each of the four groups, ensures sufficient statistical power in analysis.

The questionnaire had other sections designed to collect information on basic demographics, the electricity profiles of a respondent's communities, and the respondent's knowledge, related perceptions and attitudes pertaining to utility-scale solar energy. The survey questionnaire is detailed in Appendix B.

3.2. Survey implementation

We implemented the survey within the state of Iowa[4] in the United States targeting both public officials and the general population. We obtained approval for human subjects research from the institutional review board at Iowa State University.[5] Following this, we carried out a pilot survey and held over four online meetings with extension staff and survey experts. The questionnaire was revised based on feedback from both the pilot testing participants and these extensive online discussions. Our distribution methodology involved a mixed-mode approach, combining the use of the online Qualtrics platform with a traditional mail-based approach in data collection. The mixed mode was implemented to enhance responses.

For public officials, we initially assembled a contact list containing 599 email and

[4] The U.S. state of Iowa has two characteristics that make it a particularly relevant study region to examine utility-scale solar related issues. First, Iowa is a major agricultural state, with approximately 85% of its land dedicated to farming operations. It is representative of the broader Midwest U.S. regarding agricultural importance in local economies, land-use patterns, and solar energy development. 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). Given these statistics, understanding solar development in agricultural states like Iowa is crucial for informing renewable energy policy and implementation strategies. Second, Iowa presents an intriguing situation in renewable energy adoption patterns that are also shared by other states (e.g., Kansas, North Dakota, and Oklahoma). The state has achieved remarkable success in wind energy deployment, leading the nation with more than 60% of its electricity generation derived from wind power. However, utility-scale solar development has progressed much more slowly, facing increasing local resistance and moratoriums, despite the state's substantial solar power potential. That is, the state has demonstrated its ability to rapidly expand one type of renewable energy, but appears to be facing barriers when it comes to large-scale solar deployment. Exploring the role of knowledge in the perceptions and community acceptance of utility-scale solar in Iowa could offer valuable lessons and insights for accelerating the adoption of utility-scale solar energy across the Midwest and the country.

[5] The IRB number is IRB-22-306.

physical mailing addresses of elected and appointed officials in Iowa. This comprehensive list included county supervisors, staff members, and members of zoning and planning boards across all 99 counties in the state. These contact details were obtained from the publicly accessible Iowa State Association of Counties Directory and included information such as names, email addresses, office addresses, and political affiliations. We started survey distribution with an email invitation in April 2023, where each recipient received a unique link and access code to the online survey. A follow-up reminder email was sent two weeks later to encourage participation. For those who remained unresponsive, a postcard invitation was sent, which had the unique link and QR code to access the online survey. In an effort to increase participation, we also disseminated survey information through the Iowa State Association of Counties magazine and the Iowa League of Cities member newsletter, and actively engaged with relevant regional conferences, such as the American Planning Association Iowa Chapter annual conference, to recruit participants. Subsequently, in July, individuals on the contact list who had not yet responded were sent a paper survey along with a prepaid and pre-addressed return envelope. This was followed by a reminder postcard sent two weeks later. 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). In total, we collected 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.

For the general population in Iowa, the survey was exclusively executed online through the Qualtrics platform from July 15 to August 15. It was administrated via Dynata[6], 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. A total of

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

1,522 survey invitations were distributed to the general population of Iowa[7], resulting in 686 completed responses, implying a 45.1% response rate. Figure 2 shows the regional distribution of the survey responses, closely reflecting the population distribution across regions in Iowa.

3.3. Empirical analysis

3.3.1. Knowledge, information treatments, and attitude

The central topic of our analysis and the key variable to the four hypotheses identified in the previous section is the degree of support for utility-scale solar projects. In our survey data, the degree of support is a categorical variable. Specifically, let $Supp_i$ denote the degree of support of respondent i concerning the adoption of a utility-scale solar project within their community. As the responses are categorized on a five-point ordinal scale (1 = 'not at all', 2 = 'slightly', 3 = 'moderately', 4 = 'very', 5 = 'extremely'), the ordinal logit model is an appropriate modeling choice for analysis (McCullagh, 1980).

In the ordinal logit model, we have an observed ordinal variable Y, which is a 5-level discrete variable, $Supp_i$, in our setting. We assume that there is an unobserved continuous latent variable, Y^* (i.e., $Supp_i^*$), that determines the value of the observed ordinal variable Y. In the population, Y^* is equal to:

$$Y_i^* = \beta X_i + \epsilon_i \tag{1}$$

where X_i is the vector of explanatory variables for respondent i; ϵ_i is the error term, assumed to follow a standard logistic distribution; and β is the vector of regression coefficients to be estimated. The continuous latent variable Y^* has 4 unobserved cutoff points, κ_1, κ_2, κ_3, and κ_4, where $\kappa_1 < \kappa_2 < \kappa_3 < \kappa_4$.

The ordinal logit model is estimated as follows:

$$P(Y_i > j) = \frac{exp(X_i\beta - \kappa_j)}{1 + exp(X_i\beta - \kappa_j)} \quad j \in \{1, 2, 3, 4\} \tag{2}$$

[7] A total of 1,522 survey invitations were distributed based on Dynata's estimated response rates from past survey campaigns and demographic information specific to Iowa. The target was to achieve 600 completed responses from the Iowa general public, which would provide a statistically sufficient sample size in the state for empirical analysis. The actual response rate was higher than our expectations.

The log odds being considered in the analysis are:

$$log\frac{P(Y_i \leq j)}{P(Y_i > j)} = k_j - X_i\beta \tag{3}$$

The above model is based on the proportional odds (PO) assumption, which assumes no explanatory variable has a disproportionate effect on a specific category of the response variable (O'Connell, 2006). In other words, the coefficient β across all response categories is assumed the same, regardless of which cutoff point is considered. However, the PO assumption may be violated in practice, meaning the effect of explanatory variables varies at different levels of the ordinal outcome, and the use of the PO model in estimation can lead to biased inference (Fullerton and Xu, 2012; Williams, 2006). To address concerns on the potential violation of the PO assumption, we utilize the generalized ordinal logit (GOL) in estimation (Greene and Hensher, 2010; Williams, 2006),

$$P(Y_i > j) = \frac{exp(X_i\beta_j - \kappa_j)}{1 + exp(X_i\beta_j - \kappa_j)} \quad j \in \{1, 2, 3, 4\} \tag{4}$$

In the GOL model, there are four sets of coefficients, denoted by $\beta_j (j \in \{1, 2, 3, 4\})$, corresponding to our five-category response variable. The parameters κ_j are model intercepts. Note that the PO model is a specific case of the GOL when the PO assumption holds. In the circumstance where the PO assumption is violated for one or more explanatory variables, the partial proportional odds (PPO) model is estimated, which assumes that one or more coefficients differ across equations while others remain the same (Williams, 2016). The PPO model is specified as:

$$P(Y_i > j) = \frac{exp(X_i\beta + Z_i\beta_j - \kappa_j)}{1 + exp(X_i\beta + Z_i\beta_j - \kappa_j)} \quad j \in \{1, 2, 3, 4\} \tag{5}$$

Here, X_i represents the explanatory variables that satisfy the PO assumption and have the same coefficient β across four different values of j; Z_i represents the explanatory variables that violate the PO assumption and have different coefficients when j takes different values. To reduce the number of estimators and the difficulties in interpretation,

we conduct the Brant test (Brant, 1990) to determine whether the PO assumption holds for each individual explanatory variable, i.e., $\beta_j = \beta$ for $j \in \{1, 2, 3, 4\}$. This test helps us decide whether to use the PO model or the PPO model in our estimation. See more details of Po and PPO models in Appendix C.

In our study, $Supp_i^*$ denotes the continuous latent dependent variable (i.e., Y_i^*) that determines the observed ordinal outcome of $Supp_i$ (i.e., Y_i). For parsimony, we specify the following model as our baseline for testing Hypotheses 1, 2, and 3,

$$Supp_i^* = \eta Know_i + \delta_1 Peer_i + \delta_2 Posi_i + \delta_3 Nega_i + \gamma C_i + \epsilon_i \tag{6}$$

where $Know_i$ represents respondent i's level of knowledge regarding utility-scale solar energy; $Peer_i$, $Posi_i$, and $Nega_i$ are indicators for the three types of information treatments: peer information, positive information, and negative information related to utility-scale solar regulation and its local impacts, respectively; the group presented with no information is utilized as the control group; C_i is a set of control variables, including demographic information specific to respondent i, such as gender, age, education, political affiliation, annual household income, and farmland operation experience; ϵ_i is the error term, assumed to follow a standard logistic distribution, capturing the random disturbance related to the attitude of respondent i; η, δ_1, δ_2, δ_3, and γ are parameters to be estimated, which can have four different coefficients when applying the PPO model for variables that violate the PO assumption; and the values of δ_1, δ_2, and δ_3 are relative to the control group. If η is found to be significantly positive, there is evidence in support of Hypothesis 1. If the coefficients derived from Eq. (6) show the absolute value of δ_3 exceeds that of δ_2, there is evidence supporting Hypothesis 2. Additionally, if δ_1 is found to be significantly different from zero, there is evidence in support of Hypothesis 3.

To test Hypothesis 4, we incorporate the interactions between constructed knowledge levels ($Know_i$) and indicators for the three types of information treatments (i.e., $Peer_i$, $Posi_i$, and $Nega_i$) into Eq. (6). The constructed knowledge level is categorized into three levels (low, medium, high) based on the total number of 'I don't know' and incorrect

responses to knowledge-related questions. The estimation equation is outlined as follows,

$$\begin{aligned} Supp_i^* = & \sum_j \rho_1^j Know_i^j \times Peer_i + \sum_j \rho_2^j Know_i^j \times Posi_i \\ & + \sum_j \rho_3^j Know_i^j \times Nega_i + \gamma C_i + \zeta_i \end{aligned} \tag{7}$$

where $Know_i^j$ denotes the level of utility-scale solar energy knowledge j for respondent i, $j = \{L, M, H\}$; ρ_1^j, ρ_2^j, and ρ_3^j are parameters of interest; ζ_i is the updated error term. If ρ_1^j, ρ_2^j, or ρ_3^j is found to be significantly different from zero, it provides empirical evidence supporting Hypothesis 4.

3.3.2. Knowledge and some key drivers

In addition to examining the impacts of knowledge, information treatments, and their interconnections on individuals' attitudes, it is critical to understand the knowledge base and factors affecting diverse knowledge levels. Drawing upon the literature surveyed in Section 2, we use the following model to examine how knowledge level is related to some important variables, including local practice and personal experience directly related to solar, potential sources of knowledge, and individual demographics. The choice between the PO or PPO model depends on whether the PO assumption holds for all explanatory variables. The latent variable model is specified as:

$$Know_i^* = \omega_1 Roof_i + \omega_2 Comm_i + \omega_3 Util_i + \lambda Muni_i + \mu C_i + \varepsilon_i \tag{8}$$

where $Know_i^*$ is the latent dependent variable that determines the observed respondent i's level of knowledge with respect to utility-scale solar energy, $Know_i$, a three-point ordinal scale ranging from 1 to 3, representing low-, medium-, and high-level of knowledge, respectively; ω_1, ω_2, ω_3, λ, and μ 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. Understanding the effectiveness of these diverse factors will help the development of education and outreach programs aimed at enhancing public perceptions and

preferences toward solar energy. ε_i is the error term or white noise in the model. We estimated the parameters of the PO and PPO models using Stata/MP 17.0, employing the "ologit" and "gologit2" commands, respectively.

4. Results

4.1. Summary statistics of variables

Table 1 details demographic information about our respondents. Within the general population subset, 53.21% of respondents are female, and 46.5% are male, reflecting the female-to-male ratio in Iowa (50.3% - 49.7%) as reported by the U.S. Census Bureau. The average age of our respondents is 48.12, higher than the Iowa average of 38.3 years. This variance might be due to the exclusion criterion of age 18 during participant recruitment.[8] The median household income of our respondents in this subset falls within the range of $61,000 to $90,000. Comparatively, the American Community Survey of 2021 reported the median household income in Iowa as $65,429, which aligns with the range observed in our data. These demographic information provide evidence supporting the representativeness of our general population sample in reflecting the broader demographic makeup of Iowa.

Our survey indicates that the majority of respondents showed at least a moderate degree of support for their communities hosting a utility-scale solar project, with 44.01%, 23.50%, and 10.14% expressing moderate, strong, and extremely strong support for the project. Those showing slight support accounted for 14.29%, while 8.06% indicated non-support. Table 1 presents the definition of the variables and the summary statistics of survey respondents. On average, public officials in Iowa scored 3.02 (out of a scale of 5, from 1 to 5) in their degree of support for utility-scale solar projects, whereas the general population scored 3.16.

In our survey, respondents were asked to rate their current knowledge level about utility-scale solar energy development, choosing from three options (levels): low, medium,

[8] The U.S. Census Bureau estimates that around 23.7% of the Iowa population is under 18 years old.

and high levels of knowledge. The mean self-rated knowledge levels regarding utility-scale solar energy were slightly higher among public officials (1.47 out of a scale of 3, indicating low, medium, and high knowledge levels) than the general population (1.15). Nevertheless, overall the self-rated knowledge level was low for both groups with minimum deviation. Our survey included five questions that were related to knowledge concerning some specific aspects of utility-scale solar energy and electricity supply. Each question provided the option of "I don't know" or "Not sure". To complement the self-rated knowledge level, we also constructed respondents' knowledge levels on a scale from 1 to 3, representing low to high levels of knowledge, based on the frequency of "I don't know" responses and incorrect answers to the knowledge questions. A score of 1 indicates that at least four "I don't know" or incorrect responses were selected by the respondent, while a score of 3 means no more than one such response. See more details in Table A.1 in the Appendix. Thus, in contrast with the self-rated knowledge level, which concerns overall knowledge about utility-scale solar energy, the constructed knowledge level is based on responses to five specific and concrete aspects of utility-scale solar. Despite their differences, these two measures of knowledge levels are correlated. Since both self-rated and constructed knowledge levels are ordinal variables, we employed the Spearman rank correlation test (Spearman, 1987) to assess their correlation. The result suggests a moderate and statistically significant correction of 0.301 (Spearman's rho = 0.301, p-value < 0.0001) between the two knowledge variables. Consistent with their self-rated knowledge levels, public officials were observed to be more knowledgeable, with a mean score of 2.38 (out of a scale of 3), compared to the general population's 1.57. This difference is greater than that the difference in self-rated knowledge levels (i.e., 0.32).

With regard to the current local practice of utility-scale solar projects, as per EIA (2022), 15 counties in Iowa currently operate utility-scale solar projects. Among our respondents, 31% of the public officials demonstrated they have either adopted rooftop solar systems at their residence or plan to install solar panels in the next five years; this percentage stands at 26% for the general population. Most respondents expressed moderate interest in participating in a community solar project if one were available.

We also report the results of the test for mean differences in variables between treatment and control groups, as well as the differences between public officials and the general population. Table 2 presents the p-values derived from a two-sided t-test. Notably, for the vast majority of the explanatory variables, we do not observe significant differences between the control and treatment groups. However, seven significant mean differences are noted in Table 2. Most of them (4 out of 7) are related to the presence of a utility-scale solar project within the county where respondents reside. This is attributed to the limited presence of utility-scale solar projects in Iowa, with 15 counties out of a total of 99 currently hosting such projects. The remaining three statistically significant differences pertain to age and political affiliation. However, they are not considered crucial from a decision-making perspective. In our estimation, we control for these differences when comparing the treatment groups with the control group.

4.2. Main results

With the empirical methods explained in the previous section, we examine the effects of the level of knowledge on local communities' attitudes toward utility-scale solar projects using both self-rated knowledge levels and constructed knowledge levels. Based on the Brant test results, we found that knowledge level, age, and farm operation in Models 1 and 2 of Table 3 (which are based on Eq. (6)) violate the proportional odds (PO) assumption. For these models, the partial proportional odds (PPO) estimation is utilized. All other models specified in this paper satisfy the PO assumption.[9] The main results based on PO or PPO model estimation are presented in Tables 3 and 5. Recognizing that public officials and the general population may possess distinct knowledge bases and have different knowledge-generating processes, we also conducted regression using the full sample while incorporating interaction terms between the explanatory variables and an indicator that differentiates public officials and the general population.[10] The

[9] Following the Bonferroni correction criterion (Napierala, 2012; Wang et al., 2020), we chose a p-value of $\frac{0.05}{\text{Number of explanatory variables}}$ to check whether the PO assumption holds for all explanatory variables.

[10] The subsample regression for public officials (with 182 observations) might lack sufficient statistical power to detect the effects of information treatments, due to the relatively small sample size in each treatment group. To address the issue, we incorporated full interaction terms between the explanatory

robust standard errors are used to account for heteroscedasticity.

4.2.1. Testing Hypothesis 1 – Support for utility-scale solar and related knowledge level

We first test Hypothesis 1, which is about whether individuals with higher knowledge levels related to solar have a higher degree of support than people with lower knowledge levels regarding the adoption of utility-scale solar projects. As shown in Table 3, our results from Model 1 suggest a significant positive relationship between individuals' knowledge and their degree of support for hosting utility-scale solar projects within their communities. Specifically, as self-rated knowledge increases by one unit, such as from a low to medium level, the odds of being in a higher support category increased by 56% to 147%[11]. Panel A of Table 4 shows the marginal effects of the explanatory variables on the categorical responses indicating the degree of support for utility-scale solar projects based on the results from Model 1 of Table 3. The results indicate that as self-rated knowledge directly related to utility-scale solar energy increases by one unit, respondents are 7.6% more likely to fall into the 'extremely support' category and 7.9% less likely to fall into the 'moderately support' category for adopting utility-scale solar projects within their communities.

We use two types of variables to represent knowledge levels: self-reported vs. constructed. Self-reported variables are widely used in research, for example, Brown et al. (2000), Hanger et al. (2016), and Tenenberg and Murphy (2005). However, self-rated knowledge levels, as subjective measures in the survey, have inherent limitations. These responses can be influenced by factors such as cognitive errors, social desirability, and

variables and an indicator that differentiates public officials and the general population. This approach allowed us to examine the effects across both groups within a single regression model, which is more efficient due to the increased degree of freedom with larger sample sizes and avoids the potential loss of statistical power compared with subsample regressions (Negi and Wooldridge, 2021). This approach also allows contrast to the difference between public officials and the general population within the same regression model. We also tested for the goodness of fit for the interaction model of the ordered logit model (Fagerland and Hosmer, 2017), including the Hosmer-Lemeshow test and the Lipstiz likelihood ratio test, both of which focus on overall predictive performance and indicate no statistical evidence of lack of fit.

[11] These percentage changes are calculated using the formula $(e^{\beta} - 1) \times 100\%$, where β is the coefficient from the ordinal logit model. For example, 56% is derived from $(e^{0.442} - 1) \times 100\%$.

contextual influences, which may lead to inaccuracies in assessing respondents' actual knowledge levels and introduce estimation biases (Jahedi and Méndez, 2014; Tadesse et al., 2020). To address these concerns, we incorporate objective knowledge-based questions to construct a more reliable measure of respondents' knowledge levels, aiming to mitigate such biases and provide more robust assessments (Fischer and Sousa-Poza, 2009; Shi et al., 2016; Van der Linden, 2015). As shown in Model 2 of Table 3, similar positive effects are observed when considering constructed knowledge levels derived from knowledge-related questions and the frequency of "I don't know" and incorrect responses. For every one-unit increase in the level of constructed knowledge, the odds of being in a higher support category increased by 28% to 57%. Results in Panel B of Table 4 show that with a one-unit increase in constructed knowledge, respondents become 3.9% more likely to be categorized as "extremely support" and 7.4% less likely to be categorized as "moderately support" for utility-scale solar projects in their communities. These findings provide evidence in support of Hypothesis 1, suggesting that enhancing people's knowledge would lead to greater support for local utility-scale solar projects.

The discussions in the previous paragraph are for the overall average effects, which contain both public officials and the general population. Table 3 also presents the results for these two respondent groups, derived from the full-sample regression incorporating interaction terms for public officials and the general population by adding interaction terms to Eq. (6). Similar positive effects are observed when focusing on the general population in Iowa. Specifically, a one-unit increase in constructed knowledge level is associated with a 27% increase in the odds of expressing higher support for utility-scale solar projects. However, no significant impacts are observed for public officials. This disparity between public officials and the general population could stem from different priorities, or inherent institutional perspectives that might mitigate the influence of knowledge on public officials' support for such initiatives. Public officials are often more aware of the different priorities of their communities and the inherent trade-offs, potentially leading to a situation where a higher personal level of knowledge regarding utility-scale solar energy does not necessarily equate to higher support for such projects.

4.2.2. Testing Hypotheses 2 & 3 – Effects of information treatments on support for utility-scale solar

We incorporated three information treatment indicators in the regression model to test the effects of various information framing on individuals' attitudes. Results based on Models 1 and 2 of Tables 3 indicate that individuals exposed to information about the negative local impacts of utility-scale solar projects exhibit a significant decrease in their degree of support for hosting such projects in their communities, with a 0.30 decrease (Models 1 and 2) compared to those who did not receive negative information. Specifically, those who were exposed to negative information are 2.5% and 3.2% more likely to show no support or only slight support, respectively, and 4.1% and 3.0% less likely to exhibit very or extreme support for hosting a utility-scale solar project in their communities (Panel A of Table 4). Additionally, respondents who received negative information treatment are 3.1% less likely to show extreme support, as reported in Panel B of Table 4 using constructed knowledge. However, there are no statistically significant impacts from the treatment of positive information. Our results support Hypothesis 2, implying that peoples' attitudes are more responsive to negative information in the context of utility-scale solar energy. This finding aligns with previous studies (e.g., Baumeister et al., 2001; Sias et al., 2023). The effects of peer information treatment, which is not statistically significant in our case, are likely because the peer information presented is about zoning rules and regulations, not directly stated as the level of support in peer communities. Consequently, the effects of the peer information as we presented might not be strong. The results do not provide evidence in support of Hypothesis 3.

While the preceding analysis encompassed the full sample, including both public officials and the general population, it is important to note the differences between these subgroups. Among the general population, we observe similar impact patterns of information treatments as Model 1. Specifically, negative information treatment results in a statistically significant 42% decrease in the odds of showing a higher degree of support for host utility-scale solar projects among the general population. For public officials, we

do not observe statistically significant differences between positive and negative information treatment and non-treatment groups. As we explained earlier, this may be because public officials are likely more alert on biases, either positive or negative, in information, and are more used to forming judgments based on comprehensive information. The insignificant effects of positive and negative information treatments on public officials might also be due to our small sample size and so cautions are needed when interpreting our estimation results. However, public officials who received peer information are more supportive of hosting utility-scale solar projects within their community, with the odds of expressing a higher degree of support increasing by 97% compared to the control group. Peer information regarding local zoning regulations likely alleviates public officials' concerns regarding the siting and land use issues associated with utility-scale solar projects.

The effects of individual demographics are detailed in Table A.3 in Appendix A. Specifically, our findings indicate that female public officials tend to hold more favorable views regarding the adoption of utility-scale solar projects in their communities. The effects of age on the degree of support range from zero to slightly negative. Moreover, a higher level of education and a lower level of annual household income are correlated with a higher degree of support, although the relationship between household income and degree of support is statistically insignificant except for public officials. Respondents whose families currently operate a farm show a negative association with the level of support for the overall sample. Additionally, Republicans, Independents, and those identifying with other political affiliations express less support for utility-scale solar compared to Democratic respondents. This finding is consistent with the commonly-held belief that Democrats are generally more inclined to support renewable energy compared with Republicans (Lyon and Yin, 2010; Maguire and Munasib, 2016).

4.2.3. Testing Hypothesis 4 – Interaction of knowledge level and information treatment on support for utility-scale solar

We further investigate how individuals, with varying knowledge levels related to utility-scale solar, respond to different types of information treatments, i.e., we empirically test Hypothesis 4 stated earlier. Note that our respondents demonstrated limited variation in self-rated knowledge levels, with approximately 79.8% rating their knowledge as low, 18.7% as medium, and 1.5% as high. Therefore, we focus on the knowledge level we constructed based on respondents' answers to knowledge-related questions.

Table 5 presents the estimation results based on Eq. (7). As shown in Model 1, the negative information treatment is effective for respondents with low levels of knowledge related to utility-scale solar energy. As we explained earlier in Section 2, previous studies (e.g., Hasselström and Håkansson, 2014; Loomis and Ekstrand, 1998) have shown that individuals with higher knowledge levels tend to exhibit greater certainty in their attitudes and perceptions, making them less likely to be affected by additional information. One plausible explanation is prior bias (Alfaro et al., 2023). Individuals with higher knowledge levels related to solar may possess a more nuanced understanding or familiarity with the benefits and challenges associated with utility-scale solar projects, including their potential long-term implications on local communities, the economy, and the environment. When new information conflicts with prior beliefs, it may trigger a 'boomerang effect,' causing individuals to strengthen their opposing attitudes (Hart and Nisbet, 2012). Conversely, when the information we provided aligns with individuals' existing beliefs, it reinforces their existing preferences (Alfaro et al., 2023). This reinforcement could lead to a more favorable attitude and increased support among the high-knowledge group, even when presented with negative information. On the other hand, we do not observe statistically significant effects from peer or positive information treatments across the three knowledge groups.

In comparison with the results from Model 1 of Table 5, the findings, as presented in Model 2 by adding interaction terms to Eq. (7), indicate that the effects of different

types of information treatments vary across three knowledge groups when distinguishing between public officials and the general population. Public officials with a medium knowledge level demonstrate increased support for utility-scale solar projects when exposed to peer and positive information treatments. Conversely, peer information is ineffective across all knowledge groups for the general population. As we explained earlier, the peer information presented in our study focused on zoning rules and regulations for utility-scale solar energy systems, rather than the level of support for these systems. Public officials are likely to be much more aware of the impacts of such specific zoning regulations than the general population. Additionally, among the general population, those with high knowledge levels show increased support when presented with positive information, whereas negative information is effective among low- and medium-knowledge groups, resulting in decreased support for utility-scale solar projects. Thus, based on the results as presented in Table 5, we find mixed empirical evidence for Hypothesis 4 in the sense that how the effects of information treatments vary across knowledge levels seems to differ by different stakeholder groups.

4.3. Perspectives of Landowners

Landowners, with a direct stake in the use of agricultural land for utility-scale solar projects, might possess greater knowledge of utility-scale solar energy and be more aware of the local impacts. Consequently, their attitudes toward utility-scale solar projects and responses to information treatments may differ from non-landowners. To explore these differences, we conducted sub-sample analyses categorized by landowner status. The results are presented in Tables 6.

Landowners' support for utility-scale solar projects does not vary significantly across different knowledge levels and information treatments, suggesting their views are unlikely to change regardless of how much they learn about utility-scale solar. This could stem from a strong preference for keeping land in agriculture as it is. The insignificant effects of information treatments could also be due to the lack of statistical power. Conversely, among non-landowners, there is a positive correlation between increased knowl-

edge levels related to utility-scale solar energy and greater support for such projects in their communities. In addition, negative information treatments tend to diminish non-landowners' degree of support for these projects. Furthermore, our findings reveal that non-landowners with low and medium knowledge levels exhibit a significant decline in support for utility-scale solar projects when exposed to negative information. Such treatment effects are absent among landowners. This disparity can be attributed to the fact that landowners generally possess greater prior knowledge about utility-scale solar energy and associated land use issues compared to non-landowners. As directly involved stakeholders, increased knowledge among landowners may indicate a greater familiarity with potential land use conflicts and negative local impacts associated with the project.

4.4. The role of personal experience and community energy profile

We investigate the roles of personal experience, community energy profiles, and individual demographics on individuals' knowledge related to solar energy. Note that we only study the marginal effects of some key drivers that are relevant to our study, not the overall effects of all drivers. Table 7 presents the estimates obtained by using both self-rated knowledge and constructed knowledge as the dependent variables in the regression. Small disparities exist between the two knowledge variables chosen as dependent variables, likely stemming from scale differences. As mentioned earlier, there is insufficient variation in respondents' self-rated knowledge levels, particularly with a limited number of observations in the high knowledge group. Therefore, the analysis in this section will focus on the effects of different drivers on the constructed knowledge related to solar.

As shown in Table 7, our results suggest that the presence of a utility-scale solar project at the county level does not contribute significantly to the development of utility-scale solar knowledge. This is likely attributed to the fact that the majority of counties in Iowa (84 out of 99) do not currently have a utility-scale solar project in operation. Moreover, our survey reveals that approximately 62% of respondents are uncertain about the existence of utility-scale solar projects within their local communities. However, it is noteworthy that higher knowledge levels are correlated with rooftop solar adoption,

future installation plans, and increased interest in participating in a community solar project for both the full sample and the general population sub-sample. Despite the distinction between distributed solar energy systems, such as rooftop solar and community solar, and utility-scale solar, these local practices demonstrate an association between direct personal experience with solar technologies and elevated knowledge levels.

Publicly-owned utilities' electricity generation decisions are driven by local communities' interests of affordability, reliability, and environmental responsibility (American Public Power Association, 2016). This implies that local communities may place more trust in their providers and possess a better understanding of the local electricity systems. Our findings, based on both the full sample and the general population sample, indicate that respondents who get electricity services from municipal utilities or cooperatives are inclined to exhibit a significantly higher level of constructed knowledge regarding utility-scale solar energy than those who get their electricity from investor-owned utilities.

Regarding demographic factors, our results show that female respondents demonstrate lower levels of knowledge about utility-scale solar energy, possibly due to less confidence in the subject-related questions. This result is consistent with findings in some other studies (e.g., Reilly et al., 2022; Tranfaglia et al., 2024) and confidence is mentioned as a reason for this gender difference. Age and annual household income are positively associated with knowledge levels in both the full sample and sub-samples, whereas respondents' highest level of education is positively linked to their knowledge in the full sample. Additionally, Republican and Independent respondents tend to exhibit higher knowledge regarding utility-scale solar energy and local electricity systems, possibly due to a slight correlation between Republicans and farmers in our Iowa-focused sample (Gowen and Johnson, 2020; Janzen et al., 2023). Conversely, there is no observed difference in knowledge levels among public officials with different political affiliations. Furthermore, respondents whose families currently operate a farm in Iowa demonstrate higher levels of knowledge in the full sample. One explanation is that utility-scale solar projects may compete with existing land use, particularly agricultural land use in the state of Iowa. As a result, individuals involved in farming are more attentive to

utility-scale solar-related issues and more actively gather such information.

5. Conclusion and discussion

Utility-scale solar energy plays a critical role in the shift from conventional to renewable energy and a continued successful build-out of additional solar energy facilities is crucial in mitigating greenhouse gas emissions and climate change. According to EIA (2023), utility-scale solar energy currently represents the lowest levelized cost of energy. Nevertheless, in the United States, initiatives for utility-scale solar energy have faced growing local resistance and moratoriums. To what extent is this resistance related to insufficient knowledge among local communities? Understanding knowledge gaps and attitudes related to such energy systems will help inform policymaking pertaining to the development of utility-scale solar in local communities.

We investigate the impacts of knowledge, information, and their interconnections on local communities' attitudes toward utility-scale solar energy systems and explore some key drivers of different knowledge levels. With a survey targeting both public officials and the general population in Iowa, we find that individuals with a higher level of knowledge about utility-scale solar energy tend to express a higher degree of support for adopting such projects within their community. Individuals' attitudes are more responsive to the negative information treatment. Notably, similar effects of knowledge levels and information treatments on support for utility-scale solar are observed in the general population in Iowa, but not among public officials. Moreover, our findings suggest that the effectiveness of information treatments on attitudes toward utility-scale solar energy varies across knowledge groups for both public officials and the general population. Furthermore, while landowners' support for utility-scale solar projects stays about the same regardless of knowledge levels, non-landowners show increased support with higher knowledge levels about utility-scale solar energy and decreased support when exposed to negative information treatment.

The findings of this study have several policy implications for designing extension and outreach programs to foster utility-scale solar energy development in local com-

munities. First, effective outreach strategies must be tailored to different stakeholder groups. For the general population, which demonstrated lower solar-related knowledge, policymakers should create accessible information campaigns, workshops, and seminars on utility-scale solar energy to enhance public awareness and alleviate their concerns regarding the negative local impacts. For public officials, outreach programs can leverage professional social networks and provide education and training focusing on utility-scale solar zoning regulations to mitigate concerns about land use conflicts within local communities. Notably, for landowners, increased knowledge does not necessarily translate to increased support, suggesting that outreach efforts should prioritize direct communication channels that specifically address their land use concerns and solicit their unique perspectives. Second, communication strategies should account for different audience knowledge levels and susceptibility to different types of information. Outreach efforts should prioritize peer-based communication and positive framing, especially when engaging medium-knowledge public officials. In addition, when communicating the challenges of utility-scale solar projects to local communities, policymakers and developers should be aware of the strong impact of negative information on general public attitudes among low- and medium-knowledge groups.

Furthermore, effective collaborations and information-sharing initiatives between utility providers and local communities may contribute to positive public attitudes toward utility-scale solar energy. Publicly-owned utilities, with their community-oriented focus, can serve as valuable conduits for disseminating information and increasing public engagement by leveraging their community ties. It is also critical to tailor extension and outreach materials and programs to local contexts, such as the specific land use situations, utility ownership structure (whether investor-owned, municipal, or cooperative), existing community solar initiatives, and the extent of rooftop solar adoption. The observed heterogeneities among local stakeholder groups, as well as the influence of factors such as personal experience and demographic characteristics, indicate that a one-size-fits-all approach to community engagement may be ineffective. Outreach materials should be customized to address the specific concerns of different stakeholder groups.

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Figures and tables

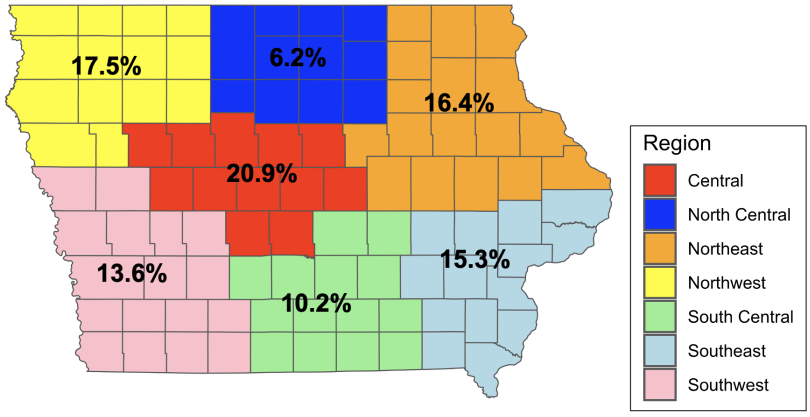

Figure 1. Regional Distribution of Survey Responses from Public Officials

Note: The division of regions followed the classification used by the Iowa League of Cities.

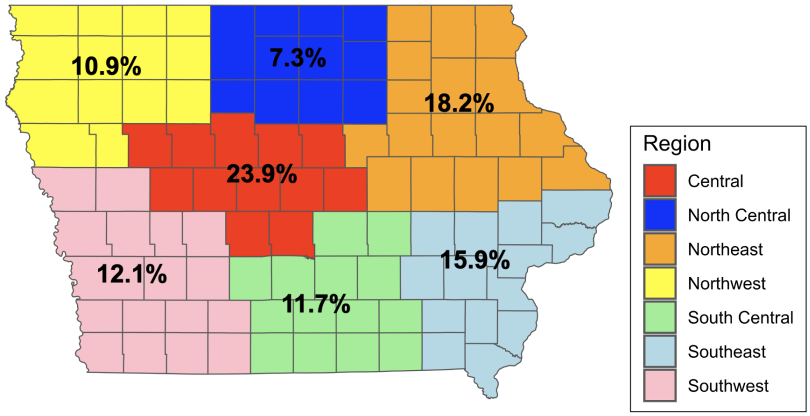

Figure 2. Regional Distribution of Survey Responses from the general population

Table 1: Definition of Variables and Summary Statistics

			Public officials			General population		
Variable	Definition	Description	Obs	Mean	Std. Dev.	Obs	Mean	Std. Dev.
Support	Degree of support for utility-scale solar projects in local communities.	1=Not at all; 2=Slightly; 3=Moderately; 4=Very; 5=Extremely	182	3.02	1.10	686	3.16	1.03
Knowledge (self-rated)	Self-reported knowledge level regarding utility-scale solar energy.	1=Low; 2=Medium; 3=High	181	1.47	0.60	686	1.15	0.37
Knowledge (constructed)	Knowledge level constructed by the authors based on the number of "I don't know" responses and incorrect answers to knowledge questions.	1=Low; 2=Medium; 3=High	182	2.38	0.64	686	1.57	0.63
Information treatment	Indicates the version of information provided to the respondent.	Control group: No information	47			174		
		Peer info treatment	45			185		
		Positive info treatment	43			170		
		Negative info treatment	47			157		
County_utility_solar	Whether there is a utility-scale solar project in the county the respondent resides.	0=No; 1=Yes	182	0.18	0.38	686	0.16	0.37
Rooftop_adopt_plan	Whether the respondent has installed rooftop solar panels or plans to adopt them in the next five years.	0=No; 1=Yes	182	0.31	0.46	686	0.26	0.44
Community_part_int	Degree of interest the respondent has in participating in community solar projects, if available.	1=Not at all interested; 2=Somewhat interested; 3=Very interested	182	1.85	0.65	686	1.93	0.65
Municipal_cooperatives	Whether the respondents' electricity supplier is a municipal utility or a cooperative.	0=No; 1=Yes	182	0.41	0.49	686	0.20	0.40
Gender		0=Other gender identities; 1=Male; 2=Female	182	1.35	0.49	686	1.54	0.50
Age		Age in years	179	49.22	14.29	684	48.12	15.86
Education		1=12th grade or less/no diploma; 2=High school diploma or GED; 3=Some college, or Associate's degree; 4=Bachelor's degree; 5=Graduate or Professional degree	181	3.62	0.87	685	3.37	1.00
Political affiliation		1=Democrat	31			179		
		2=Republican	76			226		
		3=Independent	66			247		
		4=Others	7			32		
Household income		1=$0-$30,000; 2=$31,000-$60,000; 3=$61,000-$90,000; 4=$91,000-$120,000; 5=$120,000+	178	3.87	1.10	686	2.78	1.38
Farm operation	Whether the respondent's family operates a farm.	0=No; 1=Yes	181	0.39	0.49	686	0.10	0.30
Own agricultural land	Whether the respondent owns agricultural land.	0=No; 1=Yes	180	0.38	0.49	686	0.11	0.31

Table 2: Two-sided t-test for the Mean Difference in Explanatory Variables by Treatments and Target Population

	Control-Peer Info			Control-Positive Info			Control-Negative Info		
	Full sample	Public officials	General population	Full sample	Public officials	General population	Full sample	Public officials	General population
Knowledge (self-rated)	0.347	0.800	0.089	0.631	0.930	0.391	0.567	0.565	0.271
Knowledge (constructed)	0.364	0.854	0.428	0.636	0.381	0.978	0.834	0.400	0.668
County_utility_solar	**0.006**	0.943	**0.003**	**0.016**	**0.023**	0.141	0.372	0.251	0.730
Rooftop_adopt_plan	0.343	0.926	0.247	0.154	0.462	0.211	0.171	0.822	0.095
Community_part_int	0.523	0.158	0.964	0.905	0.713	0.735	0.206	1.000	0.171
Municipal_cooperatives	0.470	0.312	0.735	0.232	0.900	0.194	0.299	0.406	0.531
Gender	0.068	0.107	0.240	0.161	0.341	0.284	0.259	0.180	0.478
Age	0.284	**0.029**	0.851	0.311	0.347	0.506	0.361	**0.000**	0.477
Education	0.465	0.382	0.702	0.076	0.396	0.123	0.355	0.970	0.347
Political affiliation	0.922	0.484	0.686	**0.047**	0.424	0.070	0.078	0.439	0.112
Household income	0.311	0.164	0.660	0.872	0.388	0.784	0.731	0.468	0.950
Farm operation	0.333	0.109	0.875	0.540	0.228	0.803	0.411	0.182	0.791
Own agricultural land	0.177	0.196	0.488	0.097	0.496	0.100	0.297	0.700	0.162

Note: The numbers presented in Table 2 are p-values, with the numbers in bold indicating statistical significance at the 5% level.

Table 3: The Effects of Knowledge and Information Treatment on Attitude (Estimates of Coefficients of Model in Equation 6.)

	Dependent variable: Degree of support for utility-scale solar projects			
	Model 1:	Model 2:	Model 3:	
			Public officials	General population
Knowledge (self-rated)	[a] -0.274			
	(0.267)			
	[b] 0.061			
	(0.203)			
	[c] 0.442***			
	(0.168)			
	[d] 0.904***			
	(0.225)			
Knowledge (constructed)		[a] -0.221	-0.252	0.238*
		(0.173)	(0.252)	(0.128)
		[b] -0.152		
		(0.127)		
		[c] 0.248**		
		(0.114)		
		[d] 0.453***		
		(0.159)		
Peer information	0.035	0.055	0.676*	-0.047
	(0.171)	(0.171)	(0.367)	(0.190)
Positive information	0.083	0.086	0.660	-0.039
	(0.191)	(0.190)	(0.422)	(0.208)
Negative information	-0.355*	-0.353*	0.441	-0.545***
	(0.181)	(0.180)	(0.399)	(0.203)
Controls	Yes	Yes	Yes	
Log likelihood	-1144.595	-1147.228	-1148.597	
Chi2	135.174	134.030	351.903	
Observations	862	862	862	

Note: For variables violating the proportional odds assumption, superscript a refers to coefficients for response (i.e., level of support for utility-scale solar projects) of 2, 3, 4, 5 vs. 1; superscript b refers to coefficients for responses of 3, 4, 5 vs. 1, 2; superscript c refers to coefficients for responses of 4, 5 vs. 1, 2, 3; superscript d refers to coefficients for responses of 5 vs. 1, 2, 3, 4, where 1 = 'not at all', 2 = 'slightly', 3 = 'moderately', 4 = 'very', 5 = 'extremely'.

All models are estimated using the full sample; however, to retain statistical power, Model 3 incorporates interaction terms instead of subsample regressions to evaluate the effects across public officials and the general population. In Model 3, the effects for both public officials and the general population are identified through interaction terms in the full sample regression.

We present the estimates from Model 3 side by side for public officials and the general population to enhance readability. The estimates of control variables are reported in Table A.3. Robust standard errors in parentheses, * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 4: Marginal Effects of Degree of Support for Utility-scale Solar Projects (For the Estimation Results of Models 1 and 2 in Table 3.)

	Degree of support for utility-scale solar projects				
	Not at all	Slightly	Moderately	Very	Extremely
Panel A: Model 1 of Table 3					
Knowledge (self-rated)	0.019	-0.029	-0.079**	0.013	0.076***
	(0.019)	(0.025)	(0.038)	(0.027)	(0.018)
Peer information	-0.002	-0.003	-0.001	0.004	0.003
	(0.012)	(0.016)	(0.007)	(0.020)	(0.014)
Positive information	-0.006	-0.008	-0.003	0.010	0.007
	(0.013)	(0.017)	(0.008)	(0.022)	(0.016)
Negative information	0.025*	0.032**	0.014	-0.041**	-0.030*
	(0.013)	(0.016)	(0.014)	(0.021)	(0.015)
Gender (reference: male)					
Female	0.012	0.015	0.007	-0.019	-0.014
	(0.009)	(0.012)	(0.006)	(0.017)	(0.011)
Other gender identities	-0.067*	-0.087*	-0.038	0.112*	0.081*
	(0.039)	(0.050)	(0.042)	(0.063)	(0.045)
Age	0.001*	-0.001	0.000	0.001	-0.001**
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Education	-0.015***	-0.020***	-0.009	0.025***	0.018***
	(0.005)	(0.006)	(0.009)	(0.009)	(0.006)
Political affiliation (reference: Democrat)					
Republican	0.110***	0.142***	0.063	-0.183***	-0.132***
	(0.017)	(0.019)	(0.056)	(0.023)	(0.018)
Independent	0.068***	0.088***	0.039	-0.114***	-0.082***
	(0.014)	(0.016)	(0.034)	(0.022)	(0.016)
Others	0.051**	0.066**	0.029	-0.085**	-0.061**
	(0.023)	(0.030)	(0.031)	(0.036)	(0.028)
Household income	0.003	0.004	0.002	-0.005	-0.003
	(0.004)	(0.005)	(0.002)	(0.006)	(0.004)
Farm operation	0.045**	0.030	-0.077*	0.075*	-0.073**
	(0.020)	(0.028)	(0.041)	(0.041)	(0.032)
Panel B: Model 2 of Table 3					
Knowledge (constructed)	0.015	0.009	-0.074*	0.011	0.039***
	(0.012)	(0.016)	(0.039)	(0.023)	(0.015)
Peer information	-0.004	-0.005	-0.002	0.006	0.005
	(0.012)	(0.015)	(0.008)	(0.019)	(0.015)
Positive information	-0.006	-0.008	-0.004	0.010	0.007
	(0.013)	(0.017)	(0.012)	(0.022)	(0.016)
Negative information	0.025*	0.032*	0.015	-0.041	-0.030*
	(0.013)	(0.016)	(0.040)	(0.026)	(0.016)
Gender (reference: male)					
Female	0.013	0.017	0.008	-0.021	-0.016
	(0.010)	(0.013)	(0.021)	(0.021)	(0.012)
Other gender identities	-0.047	-0.061	-0.028	0.078	0.058
	(0.038)	(0.049)	(0.072)	(0.061)	(0.045)
Age	0.001	-0.001	0.001	0.001	-0.002***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Education	-0.016***	-0.020***	-0.009	0.026**	0.019***
	(0.005)	(0.007)	(0.024)	(0.012)	(0.006)
Political affiliation (reference: Democrat)					
Republican	0.111***	0.143***	0.065	-0.184***	-0.136***
	(0.017)	(0.019)	(0.175)	(0.068)	(0.021)
Independent	0.070***	0.090***	0.041	-0.116**	-0.086***
	(0.014)	(0.017)	(0.107)	(0.047)	(0.017)
Others	0.051**	0.066**	0.030	-0.084**	-0.062**
	(0.024)	(0.031)	(0.079)	(0.042)	(0.030)
Household income	0.004	0.005	0.002	-0.006	-0.005
	(0.004)	(0.005)	(0.006)	(0.006)	(0.004)
Farm operation	0.041**	0.020	-0.060	0.070*	-0.071*
	(0.021)	(0.029)	(0.042)	(0.042)	(0.036)

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

Table 5: The Linkage of Information Treatment and Knowledge on Shaping Attitude (Estimates of Coefficients of Model in Equation 7.)

	Dependent variable: Degree of support for utility-scale solar projects		
	Model 1:	Model 2:	
		Public officials	General population
Knowledge^L× Peer information	-0.107	-0.645	-0.196
	(0.220)	(0.921)	(0.231)
Knowledge^M× Peer information	0.207	0.963*	0.023
	(0.229)	(0.504)	(0.257)
Knowledge^H× Peer information	0.204	0.511	0.784
	(0.347)	(0.470)	(0.628)
Knowledge^L× Positive information	-0.178	0.437	-0.321
	(0.235)	(0.912)	(0.246)
Knowledge^M× Positive information	0.324	1.439***	0.063
	(0.238)	(0.517)	(0.267)
Knowledge^H× Positive information	0.288	-0.165	1.533***
	(0.383)	(0.514)	(0.574)
Knowledge^L× Negative information	-0.530**	0.621	-0.663***
	(0.239)	(1.123)	(0.251)
Knowledge^M× Negative information	-0.361	0.058	-0.477*
	(0.243)	(0.477)	(0.286)
Knowledge^H× Negative information	0.162	0.750	-0.182
	(0.326)	(0.512)	(0.466)
Control variables	Yes	Yes	
Log likelihood	-1159.305	-1139.450	
Chi2	117.888	157.599	
Observations	862	862	

Note: The terms Knowledge^L, Knowledge^M, and Knowledge^H are dummy variables that categorize low, medium, and high levels of knowledge regarding utility-scale solar energy, respectively.

Both Models 1 and 2 are estimated using the full sample. In Model 2, the effects of different information treatments on attitudes for both public officials and the general population across different knowledge groups are identified through interaction terms in the full sample regression.

We present the estimates from Model 2 side by side for public officials and the general population to enhance readability. Robust standard errors in parentheses, * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 6: Effects of Knowledge and Information Treatments on Attitude by Landowner

	Dependent variable: Degree of support for utility-scale solar projects			
	Model 1:		Model 2:	
	Nonlandowner	Landowner	Nonlandowner	Landowner
Knowledge (constructed)	0.194*	-0.171		
	(0.11)	(0.23)		
Peer information	0.035	0.045		
	(0.19)	(0.41)		
Positive information	0.035	0.002		
	(0.20)	(0.44)		
Negative information	-0.472**	0.138		
	(0.20)	(0.42)		
Knowledge^L× Peer information			-0.209	0.502
			(0.24)	(0.66)
Knowledge^M× Peer information			0.229	-0.339
			(0.26)	(0.52)
Knowledge^H× Peer information			0.413	-0.027
			(0.40)	(0.72)
Knowledge^L× Positive information			-0.22	-0.275
			(0.25)	(0.76)
Knowledge^M× Positive information			0.23	0.254
			(0.26)	(0.57)
Knowledge^H× Positive information			0.431	-0.44
			(0.44)	(0.79)
Knowledge^L× Negative information			-0.637**	-0.063
			(0.25)	(0.86)
Knowledge^M× Negative information			-0.456*	-0.156
			(0.27)	(0.55)
Knowledge^H× Negative information			0.084	0.302
			(0.40)	(0.56)
Control variables	Yes		Yes	
Log likelihood	-1144.796		-1141.055	
Chi2	141.843		149.326	
Observations	861		861	

Note: Both Models 1 and 2 are estimated using the full sample. In Model 1, the effects for both landowners and non-landowners are identified through interaction terms in the full sample regression. In Model 2, the effects of different information treatments on attitudes for both landowners and non-landowners across different knowledge groups are identified through interaction terms in the full sample regression.

We present the estimates from Model 2 side by side for non-landowners and landowners to enhance readability. Robust standard errors in parentheses, * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 7: Driving Factors of Utility-scale Solar Knowledge (Estimates of Coefficients of Model in Equation 8.)

	Dependent variable:					
	Knowledge (self-rated)			Knowledge (constructed)		
	(1)	(2)	(3)	(4)	(5)	(6)
Local and own practices:						
County_utility_solar	-0.113	-0.400	-0.057	-0.109	-0.134	-0.110
	(0.229)	(0.439)	(0.282)	(0.174)	(0.401)	(0.200)
Rooftop_adopt_plan	0.387*	0.203	0.355	0.323**	-0.159	0.335*
	(0.197)	(0.360)	(0.251)	(0.162)	(0.353)	(0.190)
Community_part_int	0.403***	0.156	0.619***	0.217*	0.275	0.299**
	(0.146)	(0.280)	(0.188)	(0.111)	(0.267)	(0.130)
Source of knowledge:						
Municipal_cooperatives	0.132	-0.543	0.304	1.176***	-0.075	1.454***
	(0.206)	(0.372)	(0.265)	(0.160)	(0.338)	(0.196)
Demographics:						
Gender (reference: male)						
Female	-0.685***	-1.370***	-0.192	-0.672***	-0.771**	-0.480***
	(0.187)	(0.410)	(0.228)	(0.141)	(0.353)	(0.161)
Other gender identities	-14.808	-15.655	-10.758	0.730	14.841	-12.211
	(1178.714)	(1060.941)	(474.282)	(1.285)	(1041.284)	(732.605)
Political affiliation (reference: Democrat)						
Republican	-0.012	-1.129**	0.372	0.314*	-0.053	0.402*
	(0.246)	(0.489)	(0.306)	(0.188)	(0.452)	(0.215)
Independent	0.033	-0.860*	0.250	0.426**	0.651	0.368*
	(0.235)	(0.493)	(0.291)	(0.182)	(0.466)	(0.205)
Others	-0.110	-0.542	-0.196	0.138	0.422	-0.077
	(0.503)	(0.969)	(0.661)	(0.370)	(0.883)	(0.427)
Age	-0.012**	-0.017	-0.011	0.013***	0.030***	0.014***
	(0.006)	(0.012)	(0.007)	(0.005)	(0.012)	(0.005)
Education	0.060	-0.029	0.132	0.133*	0.228	0.127
	(0.101)	(0.196)	(0.127)	(0.077)	(0.184)	(0.089)
Household income	0.046	0.062	-0.146	0.354***	0.515***	0.222***
	(0.071)	(0.159)	(0.093)	(0.056)	(0.155)	(0.064)
Farm operation	0.849***	0.807**	0.125	0.724***	0.286	0.339
	(0.224)	(0.358)	(0.366)	(0.188)	(0.334)	(0.262)
Log likelihood	-446.216	-131.665	-282.285	-765.778	-147.311	-557.971
Chi2	56.197	32.166	27.945	226.436	34.199	126.180
Observations	862	178	684	862	178	684

Note: Columns (1) and (4) pertain to the full sample, while columns (2) and (5), and columns (3) and (6) use samples from public officials sample and the generation population sample, respectively. Robust standard errors in parentheses, * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Appendix A: supplemental figures and tables

Table A.1: Formulation of Constructed Knowledge Levels

	Code of knowledge level (constructed)	Number of times "I don't know" or incorrect answers a respondent checked
Low	1	5 4
Medium	2	3 2
High	3	1 0

Note: Since respondents may be confident yet incorrect when answering knowledge questions, we verified all responses except 'I don't know' against factual information using 2022 electric generator inventory data from the U.S. Energy Information Administration (i.e., Form EIA-860). Incorrect answers were treated as equivalent to 'I don't know' responses, indicating a lack of knowledge for these questions.

Knowledge-related questions in the questionnaire:

- What is the type of utility you pay your electricity bill to?
- Is there a community solar project in your jurisdiction/county/city?
- Is there a utility-scale solar project in your jurisdiction/county/city?
- Are there any utility-scale solar projects in adjacent jurisdictions/counties/cities?
- Among the following energy sources of electricity generation, which one was the top energy source in your jurisdiction/county/city in 2022?

Table A.2: Experimental Design of Information Treatments

	Control group	Treatment groups		
		Treatment 1	Treatment 2	Treatment 3
Treatment	No information	Peers' information	Positive information	Negative information
Description	No	Approximately 25% of the townships/counties in Midwestern states have zoning ordinances regarding utility-scale solar systems, and increasingly more jurisdictions have adopted utility-scale solar zoning ordinances. According to the Solar Model Ordinances published by the Great Plain Institutes, the most commonly used setback distance from the property line of a non-participating parcel in Midwestern states is 150 feet. The requirement for a decommissioning bond (financial assurance to restore the land to its original status) is project specific. Based on our studies, the decommissioning bond to cover the full restoration cost is approximately $3,500 per acre on average across the Midwest.	While some people oppose building utility-scale solar systems, studies have shown that such systems provide great benefits in reducing greenhouse gas (GHG) emissions (90% CO2 emissions reduction relative to coal-fired electricity generation), mitigating other air pollutants such as NOx (2.4 lbs/MWh from coal-fired electricity generation), creating job opportunities and tax revenues, reducing energy costs, and dependency on fossil fuels.	While some people support building utility-scale solar systems, studies have shown that such systems result in adverse impacts to local communities, such as interference with existing land uses (e.g., occupying prime farmland, 5-10 acres per MW), alteration of topsoil conditions and drainage channels during construction (e.g., increased runoff and erosion), loss of wildlife habitats, and aesthetic issues to neighbors.
Questions	Knowledge questions			
	Perception and preference questions			

Note: Participants were randomly assigned to one of four groups (1 control, 3 treatment groups), with each participant seeing only one information description. Following the information description, respondents were tested about the information provided to ensure that they had read the information provided. Specifically, each individual was presented with two questions concerning the information provided, the survey instrument explicitly stated that the answers to these questions appeared in the paragraph of description. Three attempts were allowed, those who failed the test after all 3 attempts were not allowed to continue the survey and so were excluded from our study. Respondents who passed the test were presented with questions about their knowledge, perceptions, and attitudes regarding utility-scale solar energy.

Table A.3: The Effects of Knowledge and Information Treatment on Attitude (Estimates of Control Variables.)

	Dependent variable: Degree of support for utility-scale solar projects			
	Model 1:	Model 2:	Model 3:	
			Public officials	General population
Control variables:				
Gender (reference: male)				
Female	-0.166	-0.184	-0.977***	0.001
	(0.134)	(0.137)	(0.315)	(0.149)
Other gender identities	0.959*	0.671	1.052	0.906
	(0.545)	(0.534)	(0.764)	(0.675)
Age	[a] -0.017*	[a] -0.015	-0.005	-0.006
	(0.010)	(0.009)	(0.010)	(0.004)
	[b] -0.003	[b] -0.002		
	(0.005)	(0.006)		
	[c] -0.002	[c] -0.005		
	(0.005)	(0.005)		
	[d] -0.017**	[d] -0.022***		
	(0.007)	(0.007)		
Education	0.215***	0.222***	0.488***	0.182**
	(0.071)	(0.072)	(0.184)	(0.076)
Political affiliation (reference: Democrat)				
Republican	-1.563***	-1.585***	-2.013***	-1.507***
	(0.186)	(0.189)	(0.437)	(0.202)
Independent	-0.971***	-1.001***	-1.982***	-0.771***
	(0.171)	(0.173)	(0.409)	(0.183)
Others	-0.728**	-0.725**	-0.950	-0.731**
	(0.327)	(0.342)	(0.657)	(0.371)
Household income	-0.039	-0.055	-0.244*	-0.015
	(0.050)	(0.051)	(0.147)	(0.056)
Farm operation	[a] -0.638**	[a] -0.586**	-0.168	-0.336
	(0.287)	(0.297)	(0.294)	(0.262)
	[b] -0.465**	[b] -0.379*		
	(0.219)	(0.224)		
	[c] 0.010	[c] -0.003		
	(0.211)	(0.214)		
	[d] -0.866**	[d] -0.824**		
	(0.386)	(0.406)		
Log likelihood	-1144.595	-1147.228	-1148.597	
Chi2	135.174	134.030	351.903	
Observations	862	862	862	

Note: For variables violating the proportional odds assumption, superscript a refers to coefficients for response (i.e., level of support for utility-scale solar projects) of 2, 3, 4, 5 vs. 1; superscript b refers to coefficients for responses of 3, 4, 5 vs. 1, 2; superscript c refers to coefficients for responses of 4, 5 vs. 1, 2, 3; superscript d refers to coefficients for responses of 5 vs. 1, 2, 3, 4, where 1 = 'not at all', 2 = 'slightly', 3 = 'moderately', 4 = 'very', 5 = 'extremely'. All models are estimated using the full sample; however, to retain statistical power, Model 3 incorporates interaction terms instead of subsample regressions to evaluate the effects across public officials and the general population. We present the estimates from Model 3 side by side for public officials and the general population to enhance readability. Robust standard errors in parentheses, * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Appendix B: Survey Questionnaire

Section 1: About Your Jurisdiction

1. Which state do you live in? ☐ Iowa ☐ Others, please specify: _____

2. What type of jurisdiction do you represent (i.e., are your job responsibilities related to)? Please also specify your jurisdiction's name.

   ☐ County _____ ☐ Township _____

   ☐ City _____ ☐ Others _____

3. a. Does your jurisdiction have either a zoning regulation or a zoning ordinance? ☐ Yes ☐ No

   b. Do your job responsibilities include either planning or zoning related activities? ☐ Yes ☐ No

   c. Which of the following **best** describes your zoning-related role in your jurisdiction?

   ☐ County Supervisor/City Manager or Councilor ☐ Zoning Board of Adjustment member

   ☐ Planning and Zoning Commission member ☐ Others, please specify: _____

   ☐ Staff member

Section 2: Solar Zoning Ordinance in Your Jurisdiction

4. Does the zoning ordinance in your jurisdiction mention **utility-scale** (large-scale, i.e., greater than 1 MW) solar systems?

   ☐ Yes ☐ No (skip 5, go to ➔ 6)

5. Please describe the **utility-scale solar zoning ordinance** in your jurisdiction by responding to the following questions:

   a. What is the setback requirement from **a non-participating parcel** to the solar array?

   ☐ No setbacks ☐ 1 – 50 feet ☐ 51 – 100 feet

   ☐ 101 – 200 feet ☐ > 200 feet ☐ Not sure

   b. What are the ground cover requirements beneath solar arrays? **(check all that apply)**

   ☐ Perennial ground cover (e.g., grass) ☐ Concrete/gravel type cover

   ☐ Native/pollinator plantings ☐ Others, please specify: _____

   ☐ Annual crops ☐ No requirement

   c. Are developers required to have a decommissioning bond (financial assurance to restore the land to its original status)?

   ☐ Yes ☐ No ☐ Not sure

6. a. How would you rate the following challenges to your jurisdiction's adoption of solar zoning regulations regarding utility-scale solar systems?

Challenges	Not a challenge	Somewhat of a challenge	A significant challenge
A. Lack of staff with technical knowledge of utility-scale solar	☐	☐	☐
B. Lack of demand for solar as an energy source in your community	☐	☐	☐
C. Lack of money to hire a consultant	☐	☐	☐
D. Differing opinions concerning zoning for utility-scale solar	☐	☐	☐
E. Not enough solar radiation in your community	☐	☐	☐

b. Which of the above challenges do you think is **the most important** for your jurisdiction?

☐ A ☐ B ☐ C ☐ D ☐ E

Section 3: Your Zoning Decisions

7. While some people oppose building utility-scale solar systems, studies have shown that such systems provide great benefits in **reducing greenhouse gas (GHG) emissions** (90% CO_2 emissions reduction relative to coal-fired electricity generation), **avoiding other air pollutants** such as NO_x (2.4 lbs/MWh from coal-fired electricity generation), **creating job opportunities and tax revenues**, **reducing energy costs** and **dependency on fossil fuels**.

Our research depends on you reading our survey carefully. To check whether you have read the above text, we ask one question below. You will receive no compensation if you incorrectly answer this question, the answer to which is in the text.

i. Which of the following benefits of utility-scale solar projects was stated in the paragraph?

☐ Improving topsoil conditions

☐ Protecting wildlife habitat

☐ Reducing greenhouse gas (GHG) emissions

a. How strongly do you support your jurisdiction to have a zoning ordinance regarding utility-scale solar systems?

☐ Not at all ☐ Slightly ☐ Moderately

☐ Very ☐ Extremely

Decommissioning bond is the financial assurance to restore the land to its original status.

b. What range would you prefer to be the minimum amount of the decommissioning bond for a utility-scale solar system?

☐ $1 – 2,000 per acre ☐ $2,001 – 5,000 per acre ☐ $0 (no decommissioning bond)

☐ $5,001 – 10,000 per acre ☐ Above $10,000 per acre ☐ I don't know

c. Whether or not your jurisdiction has adopted zoning regulations for utility-scale solar systems, what in your opinion is the ideal setback from a non-participating parcel to the solar array?

☐ 0 feet ☐ 1 – 50 feet ☐ 51 – 100 feet

☐ 101 – 200 feet ☐ 201 – 300 feet ☐ Above 300 feet

8. Suppose your jurisdiction is considering a **utility-scale solar project** that will have **50 MW** of nameplate capacity, run for 25 years, generate electricity to serve about 8,500 homes, and occupy 375 acres of farmland.

There are 2 potential plans, Plan A and Plan B, for the solar project that are the same except for the **life-cycle carbon emissions reduction**, **lease payment to landowners**, **savings on the electricity bill**, and **land quality of the occupied farmland**. Based on data from the Energy Information Administration, the average monthly electricity bill for residential customers in Iowa is $110. Land quality is based on the index, Corn Suitability Rating 2 (CSR2) that ranges from 5 to 100. The state average CSR2 values for high-, medium- and low-quality land are about 85, 70, and 55, respectively.

In the following, we ask you to choose whether you prefer Plan A or Plan B in 6 scenarios.

Scenario 1	Plan A	Plan B
Expected carbon emissions reduction relative to coal-fired power plants	85%	95%
Expected annual lease payment to landowners	6 times prevailing cash rent	4 times prevailing cash rent
Expected savings on the monthly electricity bill for your household	$25	$40
Land quality of the occupied farmland	Low (CSR2=55)	Medium (CSR2=70)
Which plan are you more likely to support in your jurisdiction?	☐	☐

How certain are you of your choice, on a scale of 1 to 5? (1 = very uncertain; 5 = very certain)

☐ 1 ☐ 2 ☐ 3 ☐ 4 ☐ 5

Scenario 2	Plan A	Plan B
Expected carbon emissions reduction relative to coal-fired power plants	85%	95%
Expected annual lease payment to landowners	4 times prevailing cash rent	6 times prevailing cash rent
Expected savings on the monthly electricity bill for your household	$25	$5
Land quality of the occupied farmland	Medium (CSR2=70)	High (CSR2=85)
Which plan are you more likely to support in your jurisdiction?	☐	☐

How certain are you of your choice, on a scale of 1 to 5? (1 = very uncertain; 5 = very certain)

☐ 1 ☐ 2 ☐ 3 ☐ 4 ☐ 5

Scenario 3	Plan A	Plan B
Expected carbon emissions reduction relative to coal-fired power plants	95%	85%
Expected annual lease payment to landowners	4 times prevailing cash rent	6 times prevailing cash rent
Expected savings on the monthly electricity bill for your household	$5	$40
Land quality of the occupied farmland	Low (CSR2=55)	High (CSR2=85)
Which plan are you more likely to support in your jurisdiction?	☐	☐

How certain are you of your choice, on a scale of 1 to 5? (1 = very uncertain; 5 = very certain)

☐ 1 ☐ 2 ☐ 3 ☐ 4 ☐ 5

Scenario 4	Plan A	Plan B
Expected carbon emissions reduction relative to coal-fired power plants	85%	95%
Expected annual lease payment to landowners	4 times prevailing cash rent	2 times prevailing cash rent
Expected savings on the monthly electricity bill for your household	$5	$25
Land quality of the occupied farmland	Low (CSR2=55)	Medium (CSR2=70)
Which plan are you more likely to support in your jurisdiction?	☐	☐

How certain are you of your choice, on a scale of 1 to 5? (1 = very uncertain; 5 = very certain)

☐ 1 ☐ 2 ☐ 3 ☐ 4 ☐ 5

Scenario 5	Plan A	Plan B
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
Expected savings on the monthly electricity bill for your household	$25	$5
Land quality of the occupied farmland	Medium (CSR2=70)	High (CSR2=85)
Which plan are you more likely to support in your jurisdiction?	☐	☐

How certain are you of your choice, on a scale of 1 to 5? (1 = very uncertain; 5 = very certain)

☐ 1 ☐ 2 ☐ 3 ☐ 4 ☐ 5

Scenario 6	Plan A	Plan B
Expected carbon emissions reduction relative to coal-fired power plants	85%	95%
Expected annual lease payment to landowners	2 times prevailing cash rent	6 times prevailing cash rent
Expected savings on the monthly electricity bill for your household	$40	$5
Land quality of the occupied farmland	High (CSR2=85)	Medium (CSR2=70)
Which plan are you more likely to support in your jurisdiction?	☐	☐

How certain are you of your choice, on a scale of 1 to 5? (1 = very uncertain; 5 = very certain)

☐ 1 ☐ 2 ☐ 3 ☐ 4 ☐ 5

Section 4: Your views and Information

9. a. Do you personally use solar PV panels at your place of residence?

☐ Yes (skip 9.b, go to ➔ 10) ☐ No

b. Do you plan to install solar PV panels at your place of residence in the next five years?

☐ Yes ☐ No

Community solar projects refer to local solar facilities shared by subscribers within a community. Community members can subscribe to a portion of the shared solar energy systems and receive credit on their electricity bill based on their subscribed share.

10. a. Is there a community solar project in your jurisdiction?

☐ Yes ☐ No (skip 10.b, go to ➔ 10.c)

☐ I don't know (skip 10.b, go to ➔ 10.c)

b. Have you joined a community solar project?

☐ Yes (skip 10.c, go to ➔ 11) ☐ No

c. How interested would you be in joining a community solar project?

☐ Very interested ☐ Somewhat interested ☐ Not at all interested

11. a. Is there a **utility-scale solar project** in your jurisdiction?

☐ Yes ☐ No ☐ Not sure

b. How strongly do you support your jurisdiction hosting utility-scale solar projects?

☐ Not at all ☐ Slightly ☐ Moderately

☐ Very ☐ Extremely

12. Are there any utility-scale solar projects in adjacent jurisdictions?

☐ Yes ☐ No ☐ Not sure

13. a. Whether or not your jurisdiction has a utility-scale solar project under operation, how do you rate the importance of the following benefits associated with utility-scale solar projects as applied **to your jurisdiction**?

Potential benefits	Not important	Moderately important	Extremely important
A. Increased job opportunities for your local community	☐	☐	☐
B. Reduced carbon and other air pollutants emissions	☐	☐	☐
C. Increased lease payment for landowners	☐	☐	☐
D. Increased resilience during electricity-disrupting disasters	☐	☐	☐
E. Increased tax revenues	☐	☐	☐
F. Reduced electricity bill	☐	☐	☐
G. Increased community reputation as a champion of solar energy deployment	☐	☐	☐

b. Of the above benefits you rated, which one do you think is **the most important** for your jurisdiction?

☐ A ☐ B ☐ C ☐ D

☐ E ☐ F ☐ G

14. a. Whether or not your jurisdiction has a utility-scale solar project under operation, how do you rate the following potential challenges associated with utility-scale solar projects as applied **to your jurisdiction**?

Potential challenges	Not a challenge	Somewhat a challenge	A significant challenge
A. High initial investment costs including construction costs	☐	☐	☐
B. Concerns about land use (loss of farmland)	☐	☐	☐
C. Concerns about negative effects on the environment	☐	☐	☐
D. Lack of utility companies' support	☐	☐	☐
E. Lack of favorable public opinions	☐	☐	☐
F. Lack of staff with technical knowledge regarding utility-scale solar	☐	☐	☐
G. Lack of a clear solar zoning ordinance	☐	☐	☐

b. Of the above challenges you rated, which one do you think is **the most important** for your jurisdiction?

☐ A ☐ B ☐ C ☐ D

☐ E ☐ F ☐ G

15. Based on your knowledge, what are the average setbacks from any non-participating parcels to utility-scale solar arrays in **your adjacent jurisdictions**?

_____ Feet ☐ Not sure

16. How do you rate your current knowledge level about utility-scale solar developments?

☐ Low level of knowledge ☐ Medium level of knowledge

☐ High level of knowledge

Section 5: Electricity Profile

17. Who is the **largest** electricity supplier in your jurisdiction?

☐ Investor-owned utility ☐ Municipal utility ☐ Cooperative

☐ I don't know ☐ Others, please specify: _____

18. Based on your **perception**, please rate the importance of the factors that you think the **electricity suppliers** in your jurisdiction have considered when determining the use of energy sources in electricity generation.

Factors	Not important	Moderately important	Extremely important
Cost of energy	☐	☐	☐
Land use concern (loss of farmland)	☐	☐	☐
Stability of the power grid	☐	☐	☐
Existing transmission system	☐	☐	☐
Natural resource potential	☐	☐	☐
Environmental concern	☐	☐	☐
Community's preference for solar/renewable energy	☐	☐	☐

19. a. Among the following energy sources of electricity generation, which one was the **top source** in your jurisdiction in 2022?

☐ A. Fossil fuels (coal, natural gas, or oil) ☐ D. Nuclear

☐ B. Wind ☐ E. Others, please specify: _____

☐ C. Solar ☐ I don't know

b. Among the 5 energy sources (**A - E**) listed above **(Question 19.a)**, which are the **top 3** energy sources that you would like electricity suppliers to invest in in your jurisdiction in the future?

Rank	Energy source				
1st choice:	☐ A	☐ B	☐ C	☐ D	☐ E
2nd choice:	☐ A	☐ B	☐ C	☐ D	☐ E
3rd choice:	☐ A	☐ B	☐ C	☐ D	☐ E

c. Among the 5 energy sources (**A - E**) listed above **(Question 19.a)**, which are the **top 3** energy sources you think your electricity suppliers will likely invest in in your jurisdiction in the future?

Rank	Energy source				
1st choice:	☐ A	☐ B	☐ C	☐ D	☐ E
2nd choice:	☐ A	☐ B	☐ C	☐ D	☐ E
3rd choice:	☐ A	☐ B	☐ C	☐ D	☐ E

Section 6: More About You and Your Jurisdiction

20. What is your gender or gender identity? (Select one or more options)

☐ Male ☐ Female ☐ Gender identity not listed above: _____

21. What is your age? _____ Years old

22. What is the highest level of education you have completed?

☐ 12th grade or less/no diploma ☐ Bachelor's degree

☐ High school diploma or GED ☐ Graduate or Professional degree

☐ Some college, or Associate's degree

23. Which of the following best describes your political affiliation?

☐ Democrat ☐ Independent

☐ Republican ☐ Self-describe: _____

24. What is your total annual household income?

☐ $0-$30,000 ☐ $91,000-$120,000

☐ $31,000-$60,000 ☐ $120,000+

☐ $61,000-$90,000

25. a. Do you or does your family operate a farm? ☐ Yes ☐ No

b. Do you own agricultral land? ☐ Yes ☐ No

Thank you for taking the time to complete our questionnaire. Please enter your name, and the email address where you would like to receive the electronic gift card. Or, if you cannot accept or wish not to receive honoraria, you may leave the field blank.

First name: _____ Last name: _____

Email address: _____

* Please record any further comments you have regarding utility-scale solar PV zoning decisions.

Appendix C: More details of PO and PPO model

While we cannot observe Y_i^* in Eq. (1), we observe the categories of response:

$$Y_i = \begin{cases} 1 & \text{if } Y^* \leq \kappa_1 \\ 2 & \text{if } \kappa_1 < Y^* \leq \kappa_2 \\ 3 & \text{if } \kappa_2 < Y^* \leq \kappa_3 \\ 4 & \text{if } \kappa_3 < Y^* \leq \kappa_4 \\ 5 & \text{if } Y^* > \kappa_4 \end{cases} \tag{C.1}$$

Let $\Lambda(\cdot)$ be the cumulative distribution function of the logistic distribution. We can derive the probabilities for each category:

$$\begin{aligned} P(Y_i = 1|X_i) &= P(Y_i^* \leq \kappa_1|X_i) = P(\beta X_i + \epsilon_i \leq \kappa_1|X_i) \\ &= P(\epsilon_i \leq \kappa_1 - \beta X_i|X_i) = \Lambda(\kappa_1 - \beta X_i) \end{aligned} \tag{C.2}$$

$$\begin{aligned} P(Y_i = 2|X_i) &= P(\kappa_1 < Y_i^* \leq \kappa_2|X_i) = P(Y_i^* \leq \kappa_2|X_i) - P(Y_i^* < \kappa_1|X_i) \\ &= \Lambda(\kappa_2 - \beta X_i) - \Lambda(\kappa_1 - \beta X_i) \end{aligned} \tag{C.3}$$

$$\cdots\cdots$$

$$P(Y_i = 5|X_i) = 1 - \Lambda(\kappa_4 - \beta X_i) \tag{C.4}$$

Our analysis utilizes both Proportional Odds (PO) and Partial Proportional Odds (PPO) models. The key assumption of the PPO model is the partial relaxation of the PO assumption (Williams, 2006). Unlike the standard PO model, the PPO model allows certain explanatory variables to have varying effects across different thresholds of the ordinal outcome while maintaining proportional odds for others that satisfy the PO assumption. The PPO model is preferred over the simpler PO model when the PO assumption is violated for some explanatory variables but not all, which is a common situation in real-world ordinal data. Using the PO model in such situations would result in biased estimates. Moreover, the PPO model offers improved flexibility and model

fit compared to the PO model (Eluru and Yasmin, 2015; Williams, 2016), and provides advantages over the fully generalized ordinal logit model by enhancing the interpretability of explanatory variable effects across specific response variable thresholds (Williams, 2014).

Consider variables $x_k \in X$ (for which the PO assumption holds) and $z_m \in Z$ (for which the PO assumption is violated), the marginal effects on the probability of response categories $l \in \{1, 2, 3, 4, 5\}$ are as follows:

$$\frac{\partial P(Y_i = l|X_i, Z_i)}{\partial x_{ik}} = [P(Y_i > l-1)(1-P(Y_i > l-1)) - P(Y_i > l)(1-P(Y_i > l))]\beta_k \quad \text{(C.5)}$$

$$\frac{\partial P(Y_i = l|X_i, Z_i)}{\partial z_{im}} = [P(Y_i > l-1)(1-P(Y_i > l-1)]\beta_{l-1,m} - [P(Y_i > l)(1-P(Y_i > l))\beta_{l,m}] \quad \text{(C.6)}$$

where β_k is the coefficient for x_k, which remains constant across categories; $\beta_{l,m}$ is the coefficient for z_m in Eq. (5), taking $l-1$ different values; $P(Y_i > 0) = 1$ and $P(Y_i > 5) = 0$. Therefore, for $l = 1$, only the second term in Eqs. (C.5) and (C.6) applies, for $l = 5$, only the first term in Eqs. (C.5) and (C.6) applies.