

Scholars' Mine

Doctoral Dissertations

Student Theses and Dissertations

Spring 2024

Contextualizing Renewable Energy Adoption: An Examination of the Role of Community Choice Aggregation

Ankit Agarwal Missouri University of Science and Technology

Follow this and additional works at: https://scholarsmine.mst.edu/doctoral_dissertations

Part of the Operations Research, Systems Engineering and Industrial Engineering Commons Department: Engineering Management and Systems Engineering

Recommended Citation

Agarwal, Ankit, "Contextualizing Renewable Energy Adoption: An Examination of the Role of Community Choice Aggregation" (2024). *Doctoral Dissertations*. 3303. https://scholarsmine.mst.edu/doctoral_dissertations/3303

This thesis is brought to you by Scholars' Mine, a service of the Missouri S&T Library and Learning Resources. This work is protected by U. S. Copyright Law. Unauthorized use including reproduction for redistribution requires the permission of the copyright holder. For more information, please contact scholarsmine@mst.edu.

CONTEXTUALIZING RENEWABLE ENERGY ADOPTION: AN EXAMINATION OF THE ROLE OF COMMUNITY CHOICE AGGREGATION

by

ANKIT AGARWAL

A DISSERTATION

Presented to the Graduate Faculty of the

MISSOURI UNIVERSITY OF SCIENCE AND TECHNOLOGY

In Partial Fulfillment of the Requirements for the Degree

DOCTOR OF PHILOSOPHY

in

ENGINEERING MANAGEMENT

2023

Approved by:

Casey I. Canfield, Advisor Mahelet G. Fikru, Co-advisor Jinling Liu Suzanna Long Robert J. Marley

© 2023

Ankit Agarwal

All Rights Reserved

PUBLICATION DISSERTATION OPTION

This dissertation consists of the following four articles, formatted in the style used by the Missouri University of Science and Technology:

Paper I, found on pages 9–31, has been published in the proceedings of American

Society of Engineering Management in Tampa, FL, in October 2020.

Paper II, found on pages 32-63, has been submitted to Renewable Energy Journal.

Paper III, found on pages 64–105, is intended for submission to Solar Energy

Journal.

Paper IV, found on pages 106–157, is intended for submission to Energy

Research and Social Science Journal.

ABSTRACT

The rapid expansion of renewable energy generation in the U.S., both through distributed and utility-scale facilities, is largely driven by top-down policy measures and the growing engagement of residential consumers on both individual and community levels. Previous studies on motives behind residential renewable energy adoption have examined procurement options in isolation and within a static context, primarily focused on intrinsic attributes like economic incentives, emission reductions, and peer popularity. This research introduces a novel context, assessing renewable procurement options in the presence of Community Choice Aggregation (CCA), a more prevalent and accessible alternative. This dissertation makes four pivotal contributions, offering insights into the importance of contextual factors when examining renewable energy adoption. The first contribution identifies shared attributes across various renewable procurement options using a discrete-choice experiment, and consumer classes in residential renewable market. The second contribution evaluates the impact of these attributes on procurement decisions when the default electricity supply either meets or surpasses state mandates. The third contribution employs an empirically-grounded agent-based model to forecast PV adoption rates under two scenarios: with and without the CCA context. The fourth contribution delves into how a greener default electricity supply within the CCA context influences the foundational beliefs prompting PV adoption. The insights gleaned from these contributions enables policymakers with valuable information to design targeted incentives and engineering managers to devise a strategic plan for the future development of the U.S. electricity grid with a focus on renewable generation infrastructure.

ACKNOWLEDGMENTS

First and foremost, I wish to express my profound gratitude to my advisor, Dr. Casey Canfield. Her constant motivation, ambition-inspiring guidance, and patient mentoring have been pivotal in shaping my research journey. Our meetings always concluded with an infusion of energy, pushing me to strive further. A special acknowledgment goes to my co-advisor, Dr. Mahelet Fikru. Venturing into a new domain was daunting, but her profound knowledge, invaluable resources, and steadfast support ensured I gained expertise in an impressively short time. My sincere thanks go out to my committee members - Dr. Jinling Liu, Dr. Suzanna Long, and Dr. Robert Marley. Their valuable time, critical evaluations, and constructive guidance have been indispensable in enhancing my research. I extend my thanks to the dedicated department support staff -Theresa, Karen, Jeanette, and Kimberly. Their assistance ensured that the administrative facets of my journey were seamless. My heartfelt appreciation goes to my family. Their belief in my potential and their support in my decision to study in the US laid the foundation for my academic achievements. To my wife, Mrs. Sai Sruti, words may fall short in expressing my gratitude. Her unyielding support, both mentally and emotionally, has been my anchor. Always there in my moments of need, she has been my rock. My friends have been the source of countless cherished memories during my Ph.D., and I am grateful for their presence in my life.

Lastly, I humbly offer my thanks to the Almighty, who watched over me, ensuring that the aspects beyond my grasp unfolded in the best way possible.

TABLE OF CONTENTS

PUBLICATION DISSERTATION OPTION i
ABSTRACTii
ACKNOWLEDGMENTS iv
LIST OF ILLUSTRATIONS
LIST OF TABLES
SECTION
1. INTRODUCTION1
1.1. MOTIVATION 1
1.1.1. Residential PV
1.1.2. Green Electricity
1.1.3. Community Choice Aggregation.
1.2. RESEARCH OBJECTIVES AND CONTRIBUTIONS5
PAPER
I. DISCRETE CHOICE EXPERIMENT TO STUDY CONSUMER PREFERENCES FOR RENEWABLE ENERGY PROCUREMENT OPTIONS
ABSTRACT
1. INTRODUCTION
2. METHODOLOGY AND DATA
2.1. DISCRETE CHOICE MODELING14
2.2. CHOICE TASK
2.3. SURVEY DESIGN AND MEASURES 17

2.4. MODEL SPECIFICATIONS	19
3. RESULT	20
3.1. SAMPLE DESCRIPTION	20
3.2. MULTINOMIAL LOGIT MODEL ESTIMATES	21
3.3. LATENT CLASS ANALYSIS	24
3.4. CONCLUSIONS AND RECOMMENDATIONS	26
ACKNOWLEDGEMENTS	29
REFERENCES	29
II. ROLE OF GREENER DEFAULT OPTIONS ON CONSUMER PREFERENCES FOR RENEWABLE ENERGY PROCUREMENT	32
ABSTRACT	32
1. INTRODUCTION	33
1.1. RESEARCH AIMS	36
1.2. LITERATURE REVIEW	39
2. MATERIALS AND METHODS	42
2.1. STUDY DESIGN	42
2.2. ANALYSIS	44
2.3. DATA COLLECTION	46
3. RESULTS	48
3.1. SAMPLE	48
3.2. PREFERENCES FOR ELECTRICITY PROCUREMENT	49
3.3. DISTRIBUTION OF ELECTRICITY PROCUREMENT CHOICES	52
3.4. DISTRIBUTION OF CONSUMER CHOICES	53
4. DISCUSSIONS	56

vi

5. CONCLUSIONS	0
REFERENCES	2
III. FORECASTING RESIDENTIAL SOLAR UPTAKE IN THE ERA OF UTILITY- SCALE RENEWABLE GENERATION: AN AGENT-BASED ANALYSIS	4
ABSTRACT	4
1. INTRODUCTION	5
1.1. BACKGROUND	5
1.2. LITERATURE REVIEW	9
1.2.1. Modeling PV Adoption	9
1.2.2. Agent Social Network71	1
1.2.3. ABM-DCE Integration	3
2. METHOD	6
2.1. MODEL OVERVIEW	б
2.2. AGENT INITIALIZATION	7
2.3. MODEL ENVIRONMENT INITIALIZATION	9
2.4. SIMULATION	0
3. RESULTS	3
3.1. PREDICTING PV ADOPTION FOR A SAMPLE OF CALIFORNIA HOUSEHOLDS	3
3.2. PREDICTING PV ADOPTION FOR HIGH SOLAR ADOPTERS COMMUNITY	5
3.3. SENSITIVITY ANALYSIS	б
4. CONCLUSION	1
REFERENCES	6

vii

IV. GO BIG OR GO HOME: HOW UTILITY-SCALE RENEWABLES AND COMMUNITY CHOICE AGGREGATION MIGHT ECLIPSE RESIDENTIAL SOLAR
ABSTRACT106
1. INTRODUCTION
2. LITERATURE REVIEW
2.1. ROLE OF CONTEXT ON PV ADOPTION
2.2. MODERATING EFFECTS OF CONTEXT ON PV ADOPTION 113
2.3. ADDITIONAL FACTORS TO PREDICT PV ADOPTION 117
3. METHOD
3.1. DESIGN
3.2. SAMPLE
3.3. MEASURES
3.4. STIMULI
3.5. PROCEDURE
3.6. ANALYSIS
4. RESULTS AND DISCUSSION
4.1. SAMPLE
4.2. DESCRIPTIVE FINDINGS
4.3. REGRESSION RESULTS 136
5. CONCLUSIONS145
REFERENCES149
SECTION
2. CONCLUSIONS AND FUTURE WORK

APPENDIX	165
BIBLIOGRAPHY	170
VITA	176

LIST OF ILLUSTRATIONS

SECTION	
Figure 1.1: The CCA Model (image courtesy UCS)	. 4
PAPER I	
Figure 1: Sample Choice Task	19
Figure 2: Respondents were willing to pay more for more electricity options that provide generous incentives.	26
PAPER II	
Figure 1: Proposed framework consistent with Schulte et al. (2021)	37
Figure 2: Sample Choice Task	43
Figure 3: Probability of support for each level of Renewable Content. Errors bars mark the upper and lower 95% confidence intervals.	54
PAPER III	
Figure 1: Model Flowchart	82
Figure 2: PV adoption percentage distribution for 1000 simulations for a sample of California households.	84
Figure 3: Distribution of PV adoption over 1000 runs for a sample of households in LaCosta Ridge Community, Carlsbad CA	86
Figure 4: Relationship between simulation steps and the model output for baseline inputs	88
Figure 5: Relationship between PV Adoption vs. a) Renewable content, b) Average Change in Annual Electricity Cost, c) Procurement Effort, and d) Procurement Duration	91

PAPER IV

Figure 1:	Six groups were informed about renewable content through postcards out of which only three included a CCA context. Another group was given a CCA context without the inclusion of renewable content in the postcard	125
Figure 2:	PV ad received after electricity provider's messages	125
Figure 3:	Distribution of Interest and Intention across the sample	133

LIST OF TABLES

PAPER I
Table 1: Attributes and levels. Status quo levels are marked in bold
Table 2: Logit model estimates, where *p<0.05, **p<0.01, ***p<0.001
Table 3: Relative importance of attributes 23
Table 4: Latent Class model estimates
Table 5: Relative Importance of Attributes 25
PAPER II
Table 1: DCE Attributes and Levels 45
Table 2: Characteristics across experimental conditions 49
Table 3: Multinomial Logit Model Estimates. *p<0.05, **p<0.01, ***p<0.001
Table 4: Relative attribute importance as (a) estimated by the multinomial logit model and (b) self-reported by participants. 52
Table 5: Frequency of choices (a) including and (b) excluding the default option 53
Table 6: Marginal utility estimates from a 3-segment latent class analysis.
Table 7: Relative Attribute Importance Across Classes 57
PAPER III
Table 1: Part-worth utilities to initialize agents 77
Table 2: Sensitivity of input variables without CCA context 89
Table 3: Sensitivity of input variables with CCA context 90
PAPER IV
Table 1: Dependent and Independent Variables. All Likert scale questions were measured using a 7-point scale. 122

Table 2:	Demographical characteristics of the sample ($N = 1039$). Unlike other characteristics expressed as percentages, Age and Average Electricity bills are expressed in terms of mean and standard deviation	. 130
Table 3:	Descriptive statistics of latent variables	135
Table 4:	OLS Regression results with Interest as dependent variable	140
Table 5:	OLS Regression Results with Intention as dependent variable	. 144

1. INTRODUCTION

1.1. MOTIVATION

Renewable energy is a pivotal solution in our ongoing battle against climate change. A striking testament to its efficacy is that in 2021, renewables overtook coal as the second-largest source of US electricity, a transformative shift toward a greener future (EIA, 2023). Compared to conventional fossil fuels, sources like solar, wind, biomass, and hydroelectric power release negligible carbon dioxide, offering a pathway to curbing greenhouse gas emissions. The rapid decline in costs, especially of solar modules which saw an 89% drop over the last decade (NREL, 2021), has further accelerated their adoption. This transition doesn't merely reduce our carbon footprint; it also mitigates the environmental repercussions linked with fossil fuel extraction, such as land degradation and water pollution. As the energy demand escalates worldwide, renewables present a viable and expanding solution. A testament to this is the fact that global renewable energy installation capacity grew by a record 10% in 2022 alone (IRENA, 2023). Such investments promise not only environmental dividends but also socio-economic ones, like job creation and energy security. By pivoting to renewables, we embrace a model that harmonizes growth with sustainability, amplifying our resistance against the looming threats of climate change.

The fight against climate change is multifaceted, and while large-scale initiatives and policies play a crucial role, individual and community actions are equally significant. Residential consumers are no longer passive participants; instead, they are actively shaping the energy landscape. Through residential solar PV installations, opting for utility-scale green electricity, and participating in or supporting Community Choice Aggregations, they are demonstrating a collective will to transition towards a more sustainable and renewable future.

1.1.1. Residential PV. Residential Solar PV systems have gained immense popularity among homeowners looking to tap into clean energy directly from the sun. These systems consist of solar panels, usually installed on rooftops, that capture sunlight and convert it into electricity. Over time, the initial investment in solar PV can lead to significant reductions in electricity bills. As the cost of solar panels has plummeted over the past decade, their return on investment has become even more attractive. The U.S. residential PV sector has nearly 6 gigawatts (GW) installed as of 2023 and is projected to grow by nearly 30% in the next five years (Wood Mackenzie & SEIA, 2022). Governments and local municipalities often offer incentives, tax credits, and rebates to encourage homeowners to install solar systems, making the financial proposition even more compelling. Beyond the economic benefits, households are increasingly recognizing the environmental advantages of solar, reducing their carbon footprint and playing a direct role in mitigating greenhouse gas emissions."

1.1.2. Green Electricity. Utility-scale green electricity refers to the power generated from large-scale renewable energy facilities, usually managed by power companies or specialized renewable energy providers (Dagher et al., 2017). Residential consumers can now often choose to purchase green electricity directly from these utilities: Many utilities offer green tariff options that allow consumers to opt for electricity generated exclusively from renewable sources. While there might be a slight premium attached to such options, they provide a straightforward way for households to

support and consume renewable energy. Some utilities provide green energy certificates or credits, allowing consumers to certify that a portion or all of their electricity comes from renewable sources. These certificates not only foster renewable energy production but also serve as a testament to a household's commitment to sustainability. By choosing utility-scale green electricity, consumers demonstrate their preference for clean energy, influencing utilities to further invest in renewable infrastructure and technologies.

1.1.3. Community Choice Aggregation. Community Choice Aggregation is a system where local governments or coalitions aggregate the buying power of individual consumers within their jurisdiction to secure alternative energy supply contracts on a community-wide basis (Shaughnessy et al., 2019). This approach offers several benefits to residential consumers. CCAs make up the bulk of renewable energy sales to residential customers due to high participation rates (Dagher et al., 2017). With CCA, communities can choose their energy sources, often opting for greener, more sustainable options than those provided by traditional utilities. This means that a group of residents can collectively decide to prioritize renewable energy sources over fossil fuels. By pooling their buying power, communities can often negotiate better, more competitive rates for green energy, making it affordable for all members of the community (see Fig 1). Different communities have varied needs and priorities. CCAs provide the flexibility to customize energy solutions, whether it's emphasizing local solar projects, wind farms, or other renewable ventures, in alignment with the community's values and resources. Similar to traditional utilities, CCAs also offer green tariff subscriptions to residential customers.



Figure 1.1: The CCA Model (image courtesy UCS)

The adoption of Residential Solar PV, Utility-scale green electricity, and CCA often interplay in the dynamic renewable energy landscape, sometimes creating a competitive environment. While Residential Solar PV offers individual homeowners autonomy and direct control over their energy generation, CCA provides collective bargaining power to secure greener energy at competitive prices for communities. On the other hand, Utility-scale green electricity acts as a bridge, allowing those unable to install solar panels or not under a CCA to still opt for renewable energy. Studying solar PV adoption in the context of CCA is crucial because a surge in residential solar installations might reduce the collective purchasing power of a community, as fewer households would rely on the aggregated energy supply. Furthermore, if a CCA emphasizes local renewable projects, it might influence residents to favor community-based initiatives over individual installations. Understanding these intricate relationships ensures that residential solar adoption and community energy initiatives complement rather than cannibalize each other, fostering a cohesive approach to a sustainable future.

1.2. RESEARCH OBJECTIVES AND CONTRIBUTIONS

The main contribution of this dissertation is to provide a new context for residential renewable procurement, the presence of CCA. This is done by establishing attributes for fair comparison between utility-scale and residential renewable procurement options, observing the role of greener default options in altering the influence of these attributes, developing a predictive tool for residential PV under different contexts, and delving into the effect of greener default options on the foundational beliefs that drive residential solar PV adoption.

Publication 1: The research employs a discrete choice experimental approach to assess the impact of various attributes, such as the source of electricity, pricing, benefits, acquisition efforts, and carbon offset, on residential renewable energy procurement decisions. An online panel facilitated the enlistment of 300 participants for the experiment. The findings indicate a heightened sensitivity among consumers towards pricing, the effort of procurement, and perceived benefits. They favor options with competitive pricing, greater incentives, and minimal acquisition effort compared to standard alternatives. There's also a noticeable increased propensity among consumers to invest more in electricity sources rich in renewable content. This research can guide engineering managers in devising low-carbon electricity procurement strategies that align with residential consumer preferences, thus enhancing the renewable quotient in the power grid.

Publication 2: This research employs a discrete choice experimental framework to assess the impact of factors such as renewable content, solar PV installation costs, fluctuations in electricity expenses, consumer engagement, and procurement duration on

5

household-level decision-making. A sample of 600 participants were randomly allocated to either a 15% or a 30% renewable default option. This study has three major findings. First, renewable content and cost are primary determinants, overshadowing procurement duration and engagement level, irrespective of the renewable content in the default setting. Second, cognitive biases, including status quo bias, satisficing, and the decoy effect, significantly shape procurement decisions, especially when the default option presents a higher proportion of green electricity. Third, there exist three distinguishable consumer classes, with the ratio of these classes being influenced by the volume of green electricity in the default offering. This study holds potential implications for enhancing program designs that promote the uptake of various renewable energy forms, facilitating informed grid planning, and offering insights into consumer decision processes.

Publication 3: This research assesses how messages about high renewable content, emanating from various sources, influence consumers' intentions and perceptions regarding PV adoption. Utilizing a 2 x 4 factorial design, participants were presented with messages that conveyed four distinct renewable content levels, both within and external to a CCA framework. The objective was to discern potential shifts in their inclination towards individual PV installations, propensity to engage with local installation entities, and overall perception of PV. We established multiple linear regression models with both interest and intention as the dependent variables, aligned against the promotional content and other pivotal adoption drivers. The findings delineate a significant inverse association between elevated renewable content and interest in PV adoption. Interestingly, CCA-centric promotional content did not markedly alter perceptions about PV. This study offers a fresh perspective on how residential consumers evaluate PV, holding considerable implications for the renewable energy industry.

Publication 4: While previous research has forecasted solar adoption based on variables such as tax incentives, net-metering schemes, and time-of-use tariffs, scant attention has been paid to the impact of simplified procurement through avenues like utility-scale renewables and CCA. This study presents an empirically-grounded ABM to forecast residential PV adoption in environments with both CCA and traditional electric utilities. The model initializes agents using data from a discrete-choice experiment and explores adoption dynamics under two contrasting scenarios: presence and absence of CCAs. Model predictions' reliability is reinforced through analysis of a sample of suburban California households and a pro-residential solar community in San Diego currently under CCA service. Sensitivity analysis reveals that beyond annual electricity costs and procurement effort, the duration of PV procurement emerges as a crucial factor influencing adoption rates. This simulation underscores the value of such models for engineering managers in projecting future renewable sources. Moreover, it emphasizes to policymakers the importance of maintaining robust financial incentives and strategies to expedite the residential PV procurement process to boost adoption rates.

Assessing consumer preferences for renewable energy adoption within an external context offers valuable insights to engineering managers. Such knowledge aids in strategically planning the U.S. electricity grid expansion, ensuring a balanced integration of both distributed and centralized renewable generation. Additionally, it equips policymakers with the means to promote the generation methods most favored by consumers, thus expediting the shift towards renewables. These contributions come out step by step from papers I to IV. Supplementary materials are available in the Appendix at the end of the dissertation.

PAPER

I. DISCRETE CHOICE EXPERIMENT TO STUDY CONSUMER PREFERENCES FOR RENEWABLE ENERGY PROCUREMENT OPTIONS

Ankit Agarwal

Department of Engineering Management and Systems Engineering, Missouri University of Science and Technology, Rolla, MO 65409

ABSTRACT

As the cost of renewables has decreased, options for energy procurement have proliferated to meet consumer demand. In addition to installing distributed energy resources such as rooftop solar, consumers can subscribe to centralized green energy pricing programs through their utility or competitive electricity supplier. However, it is unclear how these options to procure renewable energy from the grid influence household-level decisions to install solar and vice versa. This study uses a discrete choice experiment to measure the influence of attributes including electricity source, cost, benefits, procurement effort, and carbon reduction, on household-level renewable energy procurement decisions. Three hundred participants were recruited through an online panel to participate in the experiment. The analysis suggests that consumers are most sensitive to costs, procurement effort, and benefits. Lower prices, higher incentives and lower effort options are preferred over default options. Consumers also expressed a higher willingness to pay for electricity sources with higher renewable content and benefits. This study can help engineering managers create low- carbon electricity procurement options which are preferred by residential consumers and increase the overall renewable content in the grid.

1. INTRODUCTION

As the share of renewable energy in the grid is increasing, low-carbon electricity products have become increasingly accessible at the household level. Since 2010, renewable energy generation costs have fallen dramatically with wind energy costing 70% less and solar photovoltaics (PV) becoming 89% cheaper on average (Forbes, 2020). With a steep fall in prices of solar PV and state regulations incentivizing centralized renewable generation, the options for residential consumers to cut emissions have multiplied. Solar PV installation may require initial costs for acquiring panels, renovating residential structures for efficiency, and labor (Rai & Beck, 2015). Solar PV provides the freedom to generate and consume renewable electricity while also allowing consumers to send additional power to the utility grid (distributed generation). Despite the initial costs and effort, solar panels have seen an increase in demand as they help consumers cut their electricity procurement costs, decrease dependency on utility companies and reduce carbon footprint. Almost 6% of households in the US have already installed solar panels and 46% say they have seriously considered installing them (Kennedy, 2019). Apart from purchasing rooftop solar panels, consumers can also subscribe to 100% green electricity through their utility companies (centralized generation). Many utility companies provide 100% green electricity options at a premium rate without needing any upfront payments

or infrastructure at the customers' end. Green electricity can be sourced not only from large-scale utility companies but also from locally owned community solar programs. As of 2017, residential green pricing programs, which supply a higher percentage of electricity from renewable sources than the state mandate, account for about 10% of all voluntary renewable energy purchasing in the United States (Knapp et al., 2020). This study investigates consumer preferences for distributed and centralized renewable energy options.

In the literature, there is mixed evidence regarding preferences for renewable energy options. Some studies suggest there is a negative correlation in preferences for centralized and distributed renewable procurement options. A recent study suggested that customers treat green electricity as an alternative to solar PV but not the other way round in a community choice aggregation (CCA) program (local governments procure power on behalf of their residents) in Massachusetts (Fikru & Canfield, 2022). An empirical study also concluded that higher levels of homeownership (in contrast to renting) are associated with low participation in green electricity programs. This outcome may reflect a confounding factor: higher homeownership is associated with higher rates of adoption of rooftop solar PV (Knapp et al., 2020). Customers that have already adopted rooftop solar PV may be less inclined to participate in green pricing programs, as they may perceive that their carbon reduction goals are already fulfilled. A survey of 900 Australian consumers, found that households that were already engaged in energy-efficient behavior (which included installed solar) tended to not subscribe to green electricity (Hobman & Frederiks, 2014).

However, there is also evidence that solar PV and green electricity demands may be positively correlated depending on the households' need to increase the share of renewable shares in their electricity supply. Prior work on the foot-in-the-door effect suggests that it is easier to convince someone to take a big step (e.g., install solar) after taking a small step (e.g., choosing to opt up in a CCA) because it aligns their selfperception with action (Freedman & Fraser, 2017; Souchet & Girandola, 2013). A survey conducted on 330 Portland residents concluded that customers enrolled in green pricing programs are more likely to be willing to enrol in community solar programs (Weaver, 2017). This suggests that consumers may be interested in acquiring both distributed and centralized renewable electricity products to meet their carbon reduction and monetary saving goals.

Distributed and centralized sources of renewable electricity differ by the amount of effort the consumer has to put into procurement (Schulte et al., 2021). While there is a general consensus that solar PV adoption requires significant effort (Rai & Beck, 2015; Rai & Robinson, 2013), green tariff programs have not shown any significant relation between initial effort and adoption decision (Ozaki, 2011; Schulte et al., 2021). However, these behavioral studies did not include renewable product attributes as an influencing factor in the adoption decision framework. Therefore, these findings may not paint a clear picture of the influence of effort on adoption decisions when two low-carbon technologies, which differ not only by effort but also in other financial attributes, are presented to a consumer. Effort may be an influential factor as well as interact with expense and incentives to influence consumers' choice among two or more procurement options.

An experiment where consumers make direct trade-offs between distributed, centralized, and combined options based on certain common attributes, can provide valuable insights into their perception of renewable electricity products. This can be accomplished using a discrete choice experiment (DCEs) (Louviere & Hensher, 1982). The appeal of DCEs is that they create hypothetical choices similar to real-life choices that consumers find themselves in while buying a product. DCE is a stated preference method that has been applied to elicit consumer preferences in fields such as healthcare (Kjær, 2005), dietary choices (Gracia et al., 2014; Troiano et al., 2016), urban green initiatives (Fruth et al., 2019a) and transportation (Zarwi et al., 2017). Generally, respondents select one out of two or more alternatives involving two or more attributes (one of which is a cost attribute). An "attribute" is a characteristic or feature of an alternative, while a "level" represents the numerical or qualitative value of the attribute in each alternative. An alternative is a combination of two or more attributes. A "choice set" refers to the set of alternatives that individuals can choose from. A single choice task includes two or more alternatives with at least one attribute having different levels between alternatives, one of which may be a status quo option.

Previously, DCEs have been used to study adoption behavior for solar PV (Bao et al., 2020; Islam, 2014) and centralized green electricity (Danne et al., 2021; Motz, 2021). However, these studies focused solely on one type of procurement method. One study attempted to compare distributed versus centralized solar energy generation preferences in New Mexico, however, the focus was on the overall share of centralized and distributed generation in the state's grid, not at the residential level (Mamkhezri et al., 2020). To address this gap, this study uses a DCE where participants choose among three electricity procurement options which vary by attributes related to financial outcomes, resources needed and environmental impact. Ultimately, the following research questions are addressed:

- 1) Which attributes explain preferences towards centralized, distributed, and combined electricity procurement options?
- 2) How much are people willing to pay for each attribute of renewable energy procurement?

This study investigates the competition between different procurement methods at the individual level. The findings can help engineering managers make better decisions to facilitate the increased diffusion of low-carbon technologies and reduce the dependency on fossil fuels. This study has been pre-registered in the open-science framework (link - https://osf.io/p8ux4/)

2. METHODOLOGY AND DATA

2.1. DISCRETE CHOICE MODELING

DCE is grounded in the random utility theory which states that consumers make choices to maximize their utility (McFadden, 1973). When the alternative *i* is chosen by

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

where V_{in} is the deterministic component of the model or the observed utility that is estimated from the choice *i* and a random error component ε_{in} captures the unexplained utility that cannot be measured through the choice task. The deterministic component can be further expanded as:

$$V_{in} = \beta_0 ASC + \beta_i x_i \tag{2}$$

where β_0 is the coefficient for the alternative-specific constant which represents the status quo option to capture the business-as-usual effect (Mamkhezri et al., 2020). $\beta_i =$ $(\beta_1, \beta_2, \beta_3 \dots \beta_k, \beta_p)$ is the vector of utility estimate of attributes $x_i = (x_1, x_2, \dots, x_k, x_p)$ where *p* subscript denotes the price attribute. Utility estimates are abstract values which can only be interpreted relative to each other and therefore a more valuable way of interpreting the consumer's derived utility is willingness to pay (WTP). In an alternative *i* having *n* attributes where price attribute is x_{ip} , the WTP for any attribute x_{ik} is given as,

$$WTP_k = -\frac{\beta_k}{\beta_p} \tag{3}$$

The negative sign denotes that the price attribute has a negative coefficient, which means consumers derive less utility from higher-priced alternatives. This allows the determination of the price that a consumer is willing to pay for a unit increase in the level of an attribute. The above willingness to pay estimation methods may result in inaccurate measures of standard error. Therefore, the utility model in (2) is fit in willingness to pay space as shown below,

$$V_{in} = \lambda (\omega x_{in} - x_p) + \varepsilon_{in} \tag{4}$$

where ω represents the willingness to pay for each non-price attribute, and λ represents the scale of the deterministic portion of the utility relative to the standardized scale of the random error term. In simpler terms, ω represents the ratio of coefficients in (3).

2.2. CHOICE TASK

After interviewing 9 solar PV enthusiasts recruited from the American Solar Energy Society (ASES) and conducting a literature review, five attributes were chosen to be included in the choice tasks -1) Electricity Source, 2) Monthly Expense, 3) Carbon Reduction, 4) Monetary Benefit, and 5) Setup Effort (see Table 1). The Electricity Source attribute describes which procurement method is available to the respondent. The status quo level for this attribute is "Basic" which is the basic supply containing only the statemandated percent of renewable electricity from the renewable portfolio standard. The centralized option to procure electricity from renewable sources is represented by "Green Electricity". The distributed option is represented by "Rooftop Solar" level, which implies that it is a solar PV system that is grid-tied to basic utility supply. The combined option is represented by "Rooftop Solar + Green Electricity" level where the household would have a solar PV grid-tied to a 100% green electricity supply. Monthly Expense informs respondents about the average monthly electricity cost that can be expected for a given procurement option (Danne et al., 2021). The calculation for monthly cost incorporates both the retail rate of conventional and utility green supplies. Additionally, it also includes the net per kWh rate that is paid after net-metering credits are earned from a 4kW system. The Carbon Reduction attribute informs the net emission reduction achieved by the procurement choice in lbs./year (Islam, 2014; Sergi et al., 2018). Previous studies have also included financial benefits received from renewable electricity as an attribute. For green electricity, it could be a switching bonus (Danne et al., 2021) and for solar it could be savings in 25 years (Bao et al., 2020) and payback through netmetering (Islam, 2014). Therefore, we included a Monetary Benefit variable with discrete

levels as the incentive received for each procurement choice might vary across different regions. Behavioral studies have incorporated initial and long-term efforts of procuring low-carbon technology in frameworks that predict adoption behavior (Schulte et al., 2021). The attribute Setup Effort qualitatively provides respondents with information about time and resources needed to acquire electricity from a source.

Attribute	Definition	Levels
Electricity Source	Defines the distributed and	Basic, Rooftop Solar,
	centralized procurement	Utility-Green, Rooftop
	options	Solar + Utility-Green
Monthly Expense	The cost per kWh times the	\$85, \$100, \$120
	average consumption of a	
	US household (800 kWh)	
Monetary Benefit	The levels of savings	No Benefit, Low, High
	possible from the	
	procurement method	
Setup Effort	The level of engagement	Low, Medium, High
	needed on the consumer's	
	side to procure from a	
	source	
Carbon Reduction	This defines the amount of	1900 , 2500, 2800, 3200
	carbon in lbs./year your	
	household can reduce	
	through your choice	

Table 1: Attributes and levels. Status quo levels are marked in bold.

2.3. SURVEY DESIGN AND MEASURES

The survey included four sections - 1) scenario and attribute description, 2) choice tasks, 3) respondent characteristics, and 4) demographics. First, the participants were given a hypothetical scenario where they choose an electricity source for their new home. Each electricity source was defined in terms of the overall renewable content in the supply and the sources of generation. The other attributes were detailed to the respondents using illustrations and questions were included to measure participants' attention. Second, the respondents were presented with 16 choice tasks. The choice sets were designed using Sawtooth Lighthouse Studio software and profiles were generated using the complete enumeration method (Sergi et al., 2018). Each choice task had three alternatives out of which one was constant in every choice task – the basic electricity (see Option C in Figure 1). In each choice set, respondents were asked to select their preferred alternative based on the levels of the attributes and the monthly cost of the procurement method. The inclusion of a constant or status quo option prevents forced choices between alternatives that may not be valuable to them (Kjær, 2005). The third section had questions that captured the general characteristics of respondents in the context of electricity choices. The survey captured if the respondent subscribed to 100% green electricity or owned solar PV. Respondents also reported their average electricity bill and homeownership status. Lastly, the respondents reported their income, age, education levels, political beliefs, and gender. The survey was deployed using Prolific, an online recruitment platform. In terms of data quality measures such as attention and comprehension rates, Prolific performs better compared to other online platforms (Eyal et al., 2021).



Figure 1: Sample Choice Task

2.4. MODEL SPECIFICATIONS

The first research question in this study – "Which attributes explain preferences towards centralized and distributed and combined electricity procurement options?" was answered using two conditional logit models. Model 1 (Eq. 1) consisted of only the main effects and Model 2 (Eq. 2) included interaction effects of Setup Effort with Monthly Expense and with Monetary Benefits. The levels for Electricity Source were dummy-coded and "Green Electricity" was used as a reference level. Both models were estimated in preference space using 1,000 Halton draws. The levels of Setup Effort and Monetary Benefit were also dummy-coded, and the status quo levels were set to zero for reference. The analysis was done using the logitR package (Helveston, 2021). The results for the second research question – "How much are people willing to pay for each attribute of

renewable energy procurement?" was obtained by fitting Model 1 in willingness to pay

space to produce better estimates of standard errors.

$$V_{in} = \beta_0 ASC + \beta_1 ElectricitySource_{RooftopSolar} + \beta_1 ElectricitySource_{RooftopSolar} + \beta_2 ElectricitySource_{RooftopSolarGreenElectricty} + \beta_3 MonthlyExpense + \beta_4 MonetaryBenefit_{Low} + \beta_5 MonetaryBenefit_{High} + \beta_6 SetupEffort_{medium} + \beta_7 SetupEffort_{medium} + \beta_8 SetupEffort_{high} + \beta_9 CarbonReduction$$
(5)

$$\begin{split} V_{in} &= \beta_0 ASC + \beta_1 ElectricitySource_{RooftopSolar} + \beta_1 ElectricitySource_{RooftopSolar} GreenElectricity + \beta_3 MonthlyExpense + \\ &+ \beta_2 ElectricitySource_{RooftopSolarGreenElectricty} + \beta_3 MonthlyExpense + \\ &+ \beta_4 MonetaryBenefit_{Low} + \beta_5 MonetaryBenefit_{High} + \\ &+ \beta_6 SetupEffort_{medium} + \beta_7 SetupEffort_{medium} + \beta_8 SetupEffort_{high} \\ &+ \beta_9 CarbonReduction + \beta_{10} SetupEffort_{medium} * MonthlyExpense + \\ &+ \beta_{11} SetupEffort_{high} * MonthlyExpense + \\ &+ \beta_{12} MonetaryBenefit_{Low} * SetupEffort_{medium} \\ &+ \beta_{13} MonetaryBenefit_{Low} * SetupEffort_{high} \\ &+ \beta_{14} MonetaryBenefit_{High} * SetupEffort_{medium} \\ &+ \beta_{15} MonetaryBenefit_{High} * SetupEffort_{high} \end{split}$$

3. RESULT

3.1. SAMPLE DESCRIPTION

The responses received through the online survey (N = 300) have wide variation in terms of demographics and respondent characteristics. The annual income of a participant varies from under \$25,000 to above \$200,000, M =\$75,781, SD = \$60,584. The median of the sample was in the \$50,000 – 75,000 range having skewness very similar to the U.S. national income distribution (U.S. median income = \$67,541, US Census 2020). The age distribution (M = 34, SD = 13) suggests that the distribution is right-skewed. The sample's gender was unevenly distributed due to a higher proportion of females compared to the national average (62% compared to 50.5%). Most of the respondents were democrat-leaning (63%) and had college degrees (52%). The racial spread was similar to the national distribution with a majority of white respondents (68% vs 62% according to US Census, 2020).

The respondent characteristics provided contextual information about their choices. Only 38% of the sample self-reported as homeowners and spent \$133 per month on average for electricity. Solar PV owners and green electricity subscribers made up only 3% of the sample. A majority of respondents were unaware of green electricity options available to them and 21% were uncertain about their ability to install solar PV. Approximately half of the participants thought it was feasibility to install solar at their residences. Overall, respondents picked the status quo alternative (Basic Electricity) 18% of the time. The participants who repeatedly chose the status quo alternative were included for coefficient estimation.

3.2. MULTINOMIAL LOGIT MODEL ESTIMATES

In model 1, the significant negative coefficient for the alternative-specific constant (ASC) parameter indicates that respondents preferred the basic electricity option less over the sources with higher renewable content (see Table 2). Electricity Source (Green Electricity) was set as a reference level, so there was no significant difference in utility for the Electricity Source (Green Electricity + Rooftop Solar) option. Electricity Source (Rooftop Solar) was less preferred than the green electricity sources. Monthly Expense had a negative coefficient suggesting that for every dollar increase in monthly cost the utility was lowered by 0.064 units. The preference for Setup Effort (High)
decreased steeply in comparison to Setup Effort (Medium) from the base level. This suggests that time intensive procurement methods were not desirable for respondents. The respondents perceived Monetary Benefit (Low) as only slightly more than the base level (no benefit), however there was a high utility associated with Monetary Benefit (High). The Carbon Reduction estimate suggests that for every additional 100 lbs. per year of reduced carbon emissions the utility increases by 0.09 units.

In model 2, the main effect results were consistent except for Monetary Benefit (Low). In addition, there were multiple interaction effects. The Monthly Expense*Setup Effort (High) interaction suggests that for options that require higher effort to procure, the utility decreases less for every dollar increase in monthly cost compared to other lower effort options. There was also a significant interaction between the dummy-coded levels of monetary benefit and effort attribute. The higher estimates for Monetary Benefit (High)*Setup Effort (Medium) and Monetary Benefit (High)*Setup Effort (High) suggest that high procurement effort can be justified by higher benefit.

In addition, the utility estimates from model 1, were used to calculate the relative importance of each attribute towards the overall utility. The difference between the utilities of the highest and the lowest levels is summed for all five attributes and normalized between 0 to 1. As reported in Table 3, the respondents' utility was most sensitive to monthly expense, monetary benefit, and setup effort (in descending order).

	Model 1	Model 2
	β (SE)	β (SE)
Alternative-Specific Constant (ASC)	-0.78 (0.1) ***	-1.09(0.1) ***
Electricity Source (Green Electricity +	0.08(0.06)	0.08(0.06)
Rooftop Solar)		
Electricity Source (Rooftop Solar)	-0.32(0.06) ***	-0.31(.06) ***
Monthly Expense	-0.064(0.002) ***	-0.073(0.004) ***
Monetary Benefit (Low)	0.13(0.06) *	-0.09(0.92)
Monetary Benefit (High)	1.45(0.06) ***	1.18(0.19) ***
Setup Effort (Medium)	-0.27(0.05) ***	-1.31(0.5) *
Setup Effort (High)	-1.00(0.06) ***	-3.48(0.54) ***
Carbon Reduction (100 lbs./year)	0.09(0.1) ***	0.09(0.008) ***
Monthly Expense*Setup Effort (Medium)		0.008(0.005)
Monthly Expense*Setup Effort (High)		0.021(0.005) ***
Monetary Benefit (Low)*Setup Effort		0.33(0.16) *
(Medium)		
Monetary Benefit (High)*Setup Effort		0.36(0.17) *
(Medium)		
Monetary Benefit (Low)*Setup Effort (High)		0.39(0.17) *
Monetary Benefit (High)*Setup Effort (High)		0.5(0.17) **
AIC	7003.28	6984.16
Adjusted McFadden R ²	0.29	0.29
Log-Likelihood	-3492.64	-3477.08
Null Log-Likelihood	-4943.75	-4943.75

Table 2: Logit model estimates, where *p<0.05, **p<0.01, ***p<0.001

Table 3: Relative importance of attributes

Attribute	Relative Importance
Monthly Expense	39%
Monetary Benefit	25%
Setup Effort	18%
Carbon Reduction	11%
Electricity Source	7%

The results for the second research question – "What are consumers willing to pay for attributes of different electricity procurement options?" were obtained using a

conditional logit model fit in WTP space. The estimates suggest that on average respondents would be willing to pay \$12.25 less for basic electricity and \$5 less for electricity sourced through rooftop solar (Figure 2). The willingness to pay increased for sources with higher renewable content, however it was not found to be significantly different from 0. The respondents would pay an average of \$22.60 for a procurement option that provides generous incentives compared to lower incentive options. The increase in setup effort had a significant negative effect on WTP. The respondents were also willing to spend \$1.30 for every 100 lbs. increase in carbon reduction per year.

3.3. LATENT CLASS ANALYSIS

Table 4 and 5 report the marginal utilities and relative importance of attributes of the three classes estimated through latent class analysis. Members of the Deal Seekers group exhibit less variability in preference across procurement options compared to the Carbon Savers and Money Savers, which display distinct contrasts. The status quo option is notably and significantly disfavored by Carbon Savers members, while the Money Savers group exhibits a strong preference for the status quo option.

Green electricity emerges as the most favored choice among Deal Seekers members. This preference may stem from the fact that Deal Seekers belong to middleincome households, for whom green electricity serves as a viable substitute for solar photovoltaic (PV) systems. In contrast, Carbon Savers members exhibit a strong inclination toward a combination of solar PV and green electricity (complementary options). This preference pattern could be attributed, in part, to the presence of higher-income individuals within the Carbon Savers group.

Variable	Money Savers (Class 1)	Carbon Savers (Class 2)	Deal Seekers (Class 3)
Class Membership	22.3%	46.8%	30.9%
ASC (Status Quo)	2.24***	-3.3***	-0.24***
Rooftop Solar	-0.24***	-0.29***	-0.21***
Green Electricity	-0.03	0.09***	0.14***
Rooftop Solar + Green	0.28***	0.19***	0.07
Electricity			
Expense	-1.77***	-0.43***	-1.01***
Low Benefit	-0.05***	0.17***	0.1***
High Benefit	0.86***	1.31***	2.7***
Medium Effort	0.3***	0.09***	0.24***
High Effort	-1.96***	-0.80***	-1.4***
Carbon Reduction	0.05***	0.11***	0.06***

Table 4: Latent Class model estimates

Table 5: Relative Importance of Attributes

Attribute	Money Savers	Carbon Savers	Deal Seekers
Class Membership	30.9%	46.8%	22.3%
Carbon	5.25	9.87	4.17
Expense	62.00	30.57	41.71
Effort	9.16	16.53	31.19
Benefit	19.58	16.31	17.64

Members of the Money Savers group are most adversely affected by increased expenses, followed by Carbon Savers and Deal Seekers members, as indicated by the attribute importance table. Notably, Carbon Savers members demonstrate lower aversion to options requiring substantial effort. This observation further supports the notion that these respondents are willing to go above and beyond to reduce their carbon footprint (as evidenced by their highest utility for carbon reduction), particularly through the combination of green electricity and solar PV.



Figure 2:Respondents were willing to pay more for more electricity options that provide generous incentives.

3.4. CONCLUSIONS AND RECOMMENDATIONS

In this study, we investigated the influence of attributes on the electricity procurement choices of consumers as well as willingness to pay. The significant negative effect of Monthly Expense and positive effect of Monetary Benefits on utility that economic outcomes significantly influence consumers' choices in the electricity market. These findings are consistent with previous literature where financial considerations and benefits were positively linked to the adoption of low carbon technologies (Schulte et al., 2021). There is also a significantly higher preference and willingness to pay for electricity sources that have higher renewable content. In previous studies, the desirability for greener sources of electricity such as rooftop solar PV has been linked to younger age, higher level of education, and liberal political views (Islam, 2014; Schelly, 2014). The online sample in this study does have a higher representation of young, liberal, and more educated participants. Along with this, the presence of high renewable content options explains the higher preference for centralized and combined procurement methods compared to solar PV. The effort required to set up has a significant negative effect on the choices, which is contrary to the findings of previous studies where initial and long-term effort had no significant effect in the adoption decision of low-carbon technologies (Ozaki, 2011; Schulte et al., 2021). It may be noted that previous literature lacked data where consumers are presented with options that vary by effort along with other attributes. According to this study's findings, reduced preferences toward high effort sources may be balanced by generously incentivizing the adoption of both centralized and distributed renewable energy options. Consistent with literature, informing consumers about the carbon savings that can be achieved through their choices significantly increases their preference for a greener energy mix in the grid (Schelly, 2014; Sergi et al., 2018).

Quantitative analysis of choice data may assist engineering managers in increasing the overall renewable energy content in the grid and meeting the carbon reduction goals of the future. These efforts can be expedited by providing consumers with options that help them reduce their household's carbon footprint while also being easily accessible. Removing barriers that prolong the duration of acquiring greener electricity products, providing higher incentives for distributed generation, and making centralized generation available to households at reasonable rates are important to meeting emission goals of the future.

In this choice experiment, information on the centralized and distributed sources are included in the same attribute (electricity source). As a result, the analysis is limited to determining preferences for each procurement method. This choice experiment design makes it difficult to interpret any demand correlation that may exist between them and should be investigated in future work. The generalizability of the findings is limited to population with higher percentage of young, liberal, and educated individuals. This can be improved by using a more diverse sample where mean education level attained, age and political lineage are closer to the U.S. national average. Another limitation of this study is that the levels of monetary benefit are defined qualitatively and do not separate the benefits of distributed sources (tax credits, compensation for excess generation, etc.) from centralized sources (switching bonus). This may not sufficiently inform the consumers of the expected financial gains from their preferred choice. Future choice experiments on residential renewable options may include separate attributes for centralized and distributed generation to facilitate better interpretation of preferences. It would also be helpful to define monetary benefit by dollar amount to produce more meaningful WTP estimates.

ACKNOWLEDGEMENTS

This study received financial support from the Sloan Foundation (G-2020-13916). The experiment design and analysis were mentored by Dr. Casey Canfield and Dr. Mahelet Fikru at Missouri University of Science and Technology.

REFERENCES

- Bao, Q., Sinitskaya, E., Gomez, K. J., MacDonald, E. F., & Yang, M. C. (2020). A human-centered design approach to evaluating factors in residential solar PV adoption: A survey of homeowners in California and Massachusetts. *Renewable Energy*, 151, 503–513. https://doi.org/10.1016/j.renene.2019.11.047
- Danne, M., Meier-Sauthoff, S., & Musshoff, O. (2021). Analyzing German consumers' willingness to pay for green electricity tariff attributes: a discrete choice experiment. *Energy, Sustainability and Society, 11*(1), 1–16. https://doi.org/10.1186/s13705-021-00291-8
- Fikru, M. G., & Canfield, C. (2022). Demand for renewable energy via green electricity versus solar installation in Community Choice Aggregation. *Renewable Energy*, 186, 769–779. https://doi.org/10.1016/j.renene.2022.01.008
- Forbes. (2020). Renewable Energy Prices Hit Record Lows: How Can Utilities Benefit From Unstoppable Solar And Wind? https://www.forbes.com/sites/energyinnovation/2020/01/21/renewable-energyprices-hit-record-lows-how-can-utilities-benefit-from-unstoppable-solar-andwind/?sh=7b2ac9782c84
- Freedman, J. L., & Fraser, S. C. (2017). Compliance without pressure: The foot-in-thedoor technique. Social Psychology in Natural Settings: A Reader in Field Experimentation, 4(2), 217–232. https://doi.org/10.4324/9781315129747
- Fruth, E., Kvistad, M., Marshall, J., Pfeifer, L., Rau, L., Sagebiel, J., Soto, D., Tarpey, J., Weir, J., & Winiarski, B. (2019). Economic valuation of street-level urban greening: A case study from an evolving mixed-use area in Berlin. *Land Use Policy*, 89(August), 104237. <u>https://doi.org/10.1016/j.landusepol.2019.104237</u>
- Gracia, A., Barreiro-Hurlé, J., & López-Galán, B. (2014). Are Local and Organic Claims Complements or Substitutes? A Consumer Preferences Study for Eggs. *Journal of Agricultural Economics*, 65(1), 49–67. https://doi.org/10.1111/1477-9552.12036
- Hobman, E. V., & Frederiks, E. R. (2014). Barriers to green electricity subscription in Australia: "love the environment, love renewable energy … but why should i pay more?" *Energy Research and Social Science*, 3(C), 78–88. https://doi.org/10.1016/j.erss.2014.07.009
- Islam, T. (2014). Household level innovation diffusion model of photo-voltaic (PV) solar cells from stated preference data. *Energy Policy*, 65, 340–350. https://doi.org/10.1016/j.enpol.2013.10.004

- Kennedy, B. (2019). *More U.S. homeowners say they are considering home solar panels*. Pew Research. https://www.pewresearch.org/fact-tank/2019/12/17/more-u-shomeowners-say-they-are-considering-home-solar-panels/
- Kjær, T. (2005). A Review of the Discrete Choice Experiment With Emphasis on its Application in Healthcare. *Health Economic Papers*, *1*, 1–139.
- Knapp, L., O'Shaughnessy, E., Heeter, J., Mills, S., & DeCicco, J. M. (2020). Will consumers really pay for green electricity? Comparing stated and revealed preferences for residential programs in the United States. *Energy Research and Social Science*, 65, 0–26. https://doi.org/10.1016/j.erss.2020.101457
- Mamkhezri, J., Thacher, J. A., & Chermak, J. M. (2020). Consumer preferences for solar energy: A choice experiment study. *Energy Journal*, 41(5), 157–184. https://doi.org/10.5547/01956574.41.5.JMAM
- McFadden, D. (1973). *Conditional logit analysis of qualitative choice behavior*. https://doi.org/10.1080/07373937.2014.997882
- Motz, A. (2021). Consumer acceptance of the energy transition in Switzerland: The role of attitudes explained through a hybrid discrete choice model. *Energy Policy*, *151*, 112152. https://doi.org/10.1016/j.enpol.2021.112152
- Ozaki, R. (2011). Adopting sustainable innovation: What makes consumers sign up to green electricity? *Business Strategy and the Environment*, 20(1), 1–17. https://doi.org/10.1002/bse.650
- Peer, E., Rothschild, D., Evernden, Z., Gordon, A., & Damer, E. (2021). Data Quality of Platforms and Panels for Online Behavioral Research Data Quality of Platforms and Panels for Online Behavioral Research. *Behavior Research Methods*, August, 1–46.
- Rai, V., & Beck, A. L. (2015). Public perceptions and information gaps in solar energy in Texas. *Environmental Research Letters*, 10(7). https://doi.org/10.1088/1748-9326/10/7/074011
- Rai, V., & Robinson, S. A. (2013). Effective information channels for reducing costs of environmentally- friendly technologies: Evidence from residential PV markets. *Environmental Research Letters*, 8(1). https://doi.org/10.1088/1748-9326/8/1/014044
- Schelly, C. (2014). Residential solar electricity adoption: What motivates, and what matters? A case study of early adopters. *Energy Research and Social Science*. http://dx.doi.org/10.1016/j.erss.2014.01.001

- Schulte, E., Scheller, F., Pasut, W., & Bruckner, T. (2021). Product traits, decisionmakers, and household low-carbon technology adoptions: moving beyond single empirical studies. *Energy Research and Social Science*.
- Sergi, B., Davis, A., & Azevedo, I. (2018). The effect of providing climate and health information on support for alternative electricity portfolios. *Environmental Research Letters*, 13(2). https://doi.org/10.1088/1748-9326/aa9fab
- Souchet, L., & Girandola, F. (2013). Double foot-in-the-door, social representations, and environment: Application for energy savings. *Journal of Applied Social Psychology*, *43*(2), 306–315. https://doi.org/10.1111/j.1559-1816.2012.01000.x
- Troiano, S., Marangon, F., Tempesta, T., & Vecchiato, D. (2016). Organic vs local claims: Substitutes or complements for wine consumers? A marketing analysis with a discrete choice experiment. *New Medit*, *15*(2), 14–21.
- Weaver, A. (2017). The Social Acceptance of Community Solar: A Portland Case Study. *ProQuest Dissertations and Theses*, 175. http://193.60.48.5/docview/1964910246?accountid=15997%0Ahttp://resolver.ebsco host.com/openurl?ctx_ver=Z39.88-2004&ctx_enc=info:ofi/enc:UTF-8&rfr_id=info:sid/ProQuest+Dissertations+%26+Theses+A%26I&rft_val_fmt=info: ofi/fmt:kev:mtx:dissertation&rft.genre=di
- Zarwi, F. El, Vij, A., & Walker, J. L. (2017). A Discrete Choice Framework for Modeling and Forecasting The Adoption and Diffusion of New Transportation Services Feras El Zarwi (corresponding author) Department of Civil and Environmental Engineering University of California at Berkeley 116 McLaughli. *Transportation Research Part C: Emerging Technologies*, 1–32. https://doi.org/10.1016/j.trc.2017.03.004

II. ROLE OF GREENER DEFAULT OPTIONS ON CONSUMER PREFERENCES FOR RENEWABLE ENERGY PROCUREMENT

Ankit Agarwal¹, Casey Canfield¹, and Mahelet Fikru²

¹Engineering Management and Systems Engineering, Missouri University of Science and Technology, Rolla, MO 65409

²Department of Economics, Missouri University of Science and Technology, Rolla, MO 65409

ABSTRACT

As options for renewable procurement have proliferated to meet consumer demand, it is more complicated for consumers to navigate the available choices. In addition to installing distributed energy resources such as solar photovoltaics, consumers can subscribe to green electricity programs through their utility or competitive energy supplier. Depending on the electricity supplier, the default amount of renewable content will vary. For example, Community Choice Aggregation is a business model that can shift toward offering greener electricity by default. There are also options to purchase greener options, such as 100% renewable electricity. However, it is unclear how these options to procure renewable energy from the grid influence household-level decisions to install solar and vice versa. This study uses a discrete choice experiment to determine the influence of renewable content, solar PV installation, change in electricity costs, engagement level, and procurement duration on household-level decisions. Data were collected from 600 participants randomly assigned to either a 15% renewable default option or a 30% renewable default option. The results suggest that 1) renewable content and cost take precedence over procurement duration and engagement level regardless of the amount of renewable content in the default option, 2) cognitive biases such as status quo bias, satisficing, and decoy effect influence procurement decisions when there is more green electricity offered by default, and 3) while there are 3 distinct classes of consumers, the proportion of each class is influenced by the amount of green electricity offered by default. This research may improve program design to encourage adoption of multiple kinds of renewable energy, inform long-term grid planning, and better explain consumer decision-making.

1. INTRODUCTION

Efforts to transition to sustainable energy sources are underway globally, with renewable energy accounting for approximately 30% of global electricity generation in 2021. Key contributors to renewable energy growth include China, the U.S., the E.U., and India (IEA, 2021a). In the U.S., the power sector, responsible for nearly 32% of the country's carbon emissions, now produces 21.5% of its electricity from renewable sources (EIA, 2023). The increase in renewable energy's share is attributed to policy interventions reducing renewable technology prices, consumer awareness about greenhouse gas emissions, and nationwide deployment of distributed and centralized renewable electricity generation systems (Energy Star, 2022; EPA, 2020; DOE, 2022).

Rooftop solar photovoltaic (PV) remains the favored distributed electricity generation option for residential consumers. The IEA recently reported that the installed PV capacity led to savings of over 860mt of CO2 (IEA PVPS, 2021). Residential solar PV installations account for nearly 28% of global electricity generation (IEA, 2021b). The U.S. residential solar PV demand is projected to have 37% year-on-year growth in residential solar installations for 2022-23 (Wood Mackenzie & SEIA, 2022). Tax incentives and net-metering credits contribute to reducing installation costs and providing long-term energy bill savings. However, obstacles such as financing challenges, unfavorable policies, technical barriers, administrative hurdles, and uncertainty regarding property relocation hinder widespread adoption of solar PV among households (Schulte et al., 2022).

The increase in renewable content within the electricity grid can be attributed to utilities' centralized renewable generation projects and the growing demand for voluntary green power programs in the retail electricity market. Voluntary green power programs allow retail electricity customers to purchase renewable electricity separately from the renewable energy used to fulfill mandates such as renewable portfolio standards. In 2020, approximately 7.5 million customers procured nearly 192 million MWh of green electricity through utility green pricing, community choice aggregation (CCA), unbundled renewable energy certificates (RECs), power purchase agreements, and competitive suppliers, marking a nearly six-fold increase in the past decade (O'Shaughnessy et al., 2021). Utility green pricing subscriptions, which allow customers to support renewable generation projects by paying a premium rate, can be easily obtained from local utilities (Knapp et al., 2020). However, low participation rates are often observed due to limited customer awareness and aversion to switching costs. (O'Shaughnessy et al., 2021, Ozaki, 2011).

In contrast, CCA exhibits higher residential customer participation rate among voluntary procurement options. CCA offers an innovative approach to overcome barriers in solar PV and green electricity adoption. This program allows cities and counties to procure or generate electricity for their communities, with the utility company partnering with each CCA to deliver electricity through their transmission and distribution system. CCAs prioritize meeting the renewable energy needs of entire communities, offering flexibility in rate structures and renewable procurement, and allowing for greater local decision-making (Michaud, 2018). In cases where local renewable generation is insufficient, CCAs purchase RECs from other regions to meet consumer demand for greener sources (O'Shaughnessy et al., 2019). CCA programs operate within a state framework, enabling local organizations (often non-profits working closely with municipalities) to obtain electricity for specific territories. These CCA entities are not classified as electric utilities but rather as "electric service providers." Presently, 11 U.S. states have enacted legislation enabling CCAs, typically as opt-out programs where ratepayers are automatically enrolled (O'Shaughnessy et al., 2019). Currently, CCAs are active in 11 states, supplying approximately 4.7 million customers with 13 billion kWh of electricity (O'Shaughnessy et al., 2021). It is projected that CCAs will expand to serve 11-18 million customers within the next decade (O'Shaughnessy et al., 2019). The CCA model has been popular among residential customers as market trends suggest that they have a customer retention rate of 85%-95% (Shaughnessy et al., 2019).

The discussed renewable energy procurement options, including solar PV, utility green pricing programs, and CCAs, offer similar environmental benefits and support sustainable energy consumption. However, they vary in the level of effort and time required from consumers. Solar PV necessitates finding installation agencies, negotiating netmetering contracts, securing financing, and potentially making property renovations. This exhaustive process involves navigating bureaucratic and technical barriers. Utility green pricing provides a simpler way to power residential properties with renewable energy through virtual procurement (phone, online, or mail-in applications). The utility company assumes responsibility for selecting, constructing, and maintaining the renewable energy projects. However, the accessibility of these programs varies nationwide, and voluntary participation is limited. CCAs eliminate the need for consumers to actively select a sustainable electricity source as they procure carbon-free electricity in most regions by default. While it has been argued that perceived efforts may have an influence on adoption in some contexts (Schulte et al., 2021), current literature on renewable energy adoption lacks a comprehensive comparison of the effort required by these procurement options. Additionally, the attractiveness of solar PV/utility green pricing as an option may diminish if the default electricity supply of a community becomes carbon neutral. Such a comparison would inform the preferred procurement method for residential consumers and aid policymakers in designing programs that promote the adoption of favored options. This, in turn, would increase demand for renewables, decrease reliance on fossil fuels, and enhance the carbon neutrality of the electricity grid.

1.1. RESEARCH AIMS

This study aims to examine consumer preferences for renewable energy options in the context of a higher renewable default supply and effort-related attributes. It addresses two key gaps in literature. Firstly, it explores the competition or complementarity between solar PV installation and green tariff subscriptions, considering their substantial differences in costs and non-monetary factors. Understanding consumer decision-making regarding these options can inform marketing strategies for decarbonizing the energy industry and grid planning. Secondly, the study acknowledges the changing context of renewable content as the default option in the market, which can impact consumer preferences as norms shift with increased interconnection of renewables. This research expands existing theory on low-carbon technology adoption by accounting for contextual influences when choosing among distinct technologies with a similar purpose.



Figure 1: Proposed framework consistent with Schulte et al. (2021)

To achieve this objective, this study proposes a framework (Figure 1) that builds upon previous research on solar PV and green tariff adoption attributes (Schulte et al., 2021; Wolske et al., 2017). The framework focuses on environmental, financial, and effort attributes, while leaving the consideration of norms for future investigation. Consumer preferences may vary between these attributes and products, and such variations are expected to be influenced by the contextual factor of renewable share in the default electricity supply.

The study addresses three primary research questions:

1. How do the attributes of cost, environment, and effort influence the perceived utility of green electricity and/or solar PV?

2. How does the context of renewable content offered by default impact the perceived utility of green electricity and/or solar PV?

3. How do these effects vary based on consumer characteristics?

To investigate these questions, participants were randomly assigned to two groups with different levels of renewable content in the default electricity supply (15% vs. 30%). Through a discrete choice experiment, participants evaluated options based on attributes such as Renewable Content, PV Installation (environmental attributes), Change in Annual Electricity Cost (cost attribute), Procurement Duration, and Engagement Level (effort attributes). The findings indicate that cost and environment attributes exerted greater influence than effort attributes. Higher Procurement Duration and Engagement Level negatively affected preferences for greener electricity options. Participants showed a preference for the default option over alternatives with higher renewable content, demonstrating higher support for the greener default option. Furthermore, participants could be segmented into three distinct classes based on similarities in preferences regarding cost and renewable content.

The remainder of the article is structured as follows: Section 1.2 provides a literature review, Section 2 outlines the materials and methods employed, Section 3 presents the results, Section 4 discusses the findings, and Section 5 concludes the study.

1.2. LITERATURE REVIEW

Consumers assess renewable procurement options based on both monetary and non-monetary attributes, often guided by behavioral frameworks such as the Theory of Planned Behavior. Financial outcomes, including initial investment, premium tariff, and energy cost savings, as well as environmental benefits such as emission reduction, play a crucial role in shaping consumer attitudes toward renewable procurement (Schulte et al., 2021). Subjective norms, reflecting social support, and perceived behavioral control factors, encompassing effort, technical requirements, information availability, and switching costs, are also significant components in understanding consumer interest (Wolske et al., 2017).

These attributes have been widely employed in studies investigating solar PV and green tariff adoption. For instance, a discrete choice experiment on PV system design and installation examined preferences based on attributes such as reviewer rating, collaboration style, equipment technology, project time, warranty, savings over 25 years, panel efficiency, panel visibility, inverter type, reliability, and emission reduction. The study revealed that savings over 25 years, warranty, reliability, and customer ratings held the highest relative importance (greater than 15%). On the other hand, effort-related attributes such as installer-customer collaboration styles (independent or collaborative) and project completion time exhibited lower relative importance (less than 7%) (Bao et al., 2020). Another choice experiment focused on solar PV adoption in Canada incorporated attributes such as initial investment, energy savings, emission reduction, payback period, incentives, net-metering rewards, policy change probability, inflation, and the percentage of households already adopting the system. The study identified initial

investment, energy savings, emission reduction, and net-metering rewards as attributes with a relative importance of at least 10%, while payback period, inflation, incentives, and social norms demonstrated lower importance (less than 5%) (Islam, 2014).

In the case of green tariff adoption, choice experiments have been conducted to explore attributes including energy source, tariff structure (monthly cost or per kWh rate), share of renewables, switching bonus, price guarantee, and blackout frequency (Danne et al., 2021; Motz, 2021). German consumers exhibited a significant positive willingness to pay for electricity sourced predominantly from wind or solar, switching bonus incentives, and rate guarantees. A similar study conducted in Switzerland introduced the share of renewables as a discrete variable, reporting a significant positive willingness to pay for a 100% share (compared to alternative levels of 40% and 80%), and a significant negative coefficient for blackout frequency.

Overall, these studies underscore the importance of various attributes in shaping consumer preferences for renewable energy adoption, shedding light on the relative importance of financial, environmental, and effort-related factors.

Most studies have focused on solar PV and green tariff programs individually, rather than considering them as alternative options. Although a U.S. study explored preferences for distributed versus centralized solar generation, the emphasis was on the share of these options in the state's Renewable Portfolio Standard (RPS), rather than on individual procurement (Mamkhezri et al., 2020). Adopting rooftop solar PV or green electricity entails substantial initial effort, time, and costs, both short-term and long-term (Korcaj et al., 2015; Ozaki, 2011; Rai & McAndrews, 2012). Due to this overlap, it becomes challenging to anticipate how individuals will weigh trade-offs across cost, environmental, and effort attributes.

Residential solar PV systems offer homeowners energy independence and longterm savings but require significant investments of time and money (Korcaj et al., 2015). On the other hand, utility-scale green tariff programs provide a convenient and low-effort option for consumers willing to pay a premium for renewable energy. The weight given to attributes when deciding between these procurement options may vary, complicating predictions of which option is more favorable and why. Some participants have shown willingness to combine solar PV and green tariff options (Weaver, 2017), while evidence also suggests that purchasing either product satisfies consumers' goals of carbon savings and sustainable behavior (Ma & Burton, 2016).

In addition to product attributes, consumer adoption decisions are influenced by individual characteristics and the broader context. Individuals with liberal political beliefs, higher income, and college degrees tend to perceive renewable energy more positively (Sigrin et al., 2015; Weaver, 2017). Consumer preferences also differ based on geographical factors, with rural residents favoring centralized generation and urban dwellers expressing interest in more rooftop solar (Mamkhezri et al., 2020). Currently, consumers interested in higher levels of renewable energy can choose between or combine centralized and distributed options, but these decisions are influenced by a combination of external and internal factors, making them context-specific. For instance, when there is an economic incentive to combine options, early adopters are more likely to exhibit complementary behavior by adopting both rooftop solar PV and green electricity (Fikru & Canfield, 2022a). Conversely, without an economic incentive, customers tend to

demonstrate substitutive behavior, opting for green electricity when unable to install solar PV (Fikru & Canfield, 2022b). Therefore, more insights may be needed about the heterogeneity in consumer behavior in different contexts.

2. MATERIALS AND METHODS

2.1. STUDY DESIGN

This research utilizes a Discrete Choice Experiment (DCE) to compare solar PV and utility green pricing programs, considering the default option for consumers uninterested in renewable energy. It focuses on effort-related attributes and draws on DCE's ability to simulate real-life choices (Louviere & Hensher, 1982). DCE has been used in healthcare, dietary choices, urban green initiatives, and transportation (Kjær, 2005; Gracia et al., 2014; Troiano et al., 2016; Fruth et al., 2019; Zarwi et al., 2017). Respondents choose one alternative from a set with multiple attributes, including cost. Attributes represent characteristics, while levels indicate attribute values. Choice sets include at least one attribute with varying levels, including a potential default option.

Participants were randomly assigned to two experimental conditions: 15% and 30% renewable content in the default option. The former reflects the state's Renewable Portfolio Standard (RPS) requirement, representing the incumbent provider. The latter simulates automatic enrollment in a higher default renewable content community choice aggregation (CCA) program. Following assignment, participants completed the same DCE. This design has been used in prior energy studies to evaluate the impact of climate

and health information on electricity preferences and the influence of tailored information on energy efficiency choices (Sergi et al., 2018; Davis & Metcalf, 2014).

Each discrete choice task presented three alternatives, including a default option. Consistency was maintained across all choice sets, aligning with participants' assigned condition. Including a default option allows for genuine preference-based choices, avoiding forced decisions and capturing the business-as-usual effect (Kjær, 2005; Mamkhezri et al., 2020).



Figure 2: Sample Choice Task

The attributes shown in Fig. 2 are defined in Table 1. Higher levels of renewable content represent opt-up options available under utility green pricing programs (Danne et al., 2021; Sagebiel et al., 2014). PV installation is used as a binary attribute, if selected it

means that participant is interested in combining solar PV with opt-up options (when available). The Annual Electricity Charge attribute is motivated from previous DCE studies where it is presented in terms of percentage change(Knapp et al., 2020; Sergi et al., 2018). The levels described in this study include per KWH cost of PV installation (10 years life-cycle) provided by previous studies (Liu et al., 2014). Effort-related attributes are motivated by the DCE design by Bao et. al which included project duration and collaboration style. Engagement defines the nature of customer interaction with the solar installer/utility. The duration includes administrative processes including application review, approval, tax paperwork, and billing changes, while technical processes involve designing the rooftop solar system and home renovations. The choice task used Sawtooth Software with a full-factorial design (Sawtooth Software, 2017). Attribute levels were randomized for each participant using a complete enumeration method.

2.2. ANALYSIS

Discrete choice data were fit using the random utility model described in Equation 1 where U_{in} is the total utility of alternative *i* for individual *n*, V_{in} is the observed utility, and ε_{in} is an error term.

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

The observed utility was calculated by fitting the discrete choice data using a multinomial logit (MNL) model as shown in Equation 2 where β represents the marginal utility of each attribute. The alternative-specific constant (ASC) regressor reflects consumer preferences for the default option and gives evidence for status quo preference in the retail electricity market (Pichert & Katsikopoulos, 2008; Mamkhezri et al., 2020).

Renewable Content is a continuous measure of the marginal utility of the percent of renewables. PV is a binary variable which takes the value 1 if solar PV is installed. Annual Electricity Cost is a continuous measure of the marginal utility due to percent change in costs. Engagement High and Engagement Medium are binary variables which take the value 1 when either of these levels of engagement are present in a choice task. Procurement Duration is a continuous measure of the marginal utility of the number of days needed for collecting information and setting up the electricity supply. An interaction term for Renewable Content and PV measures the marginal utility of combining both options.

$$V_{in} = \beta_0 ASC + \beta_1 RenewableContent + \beta_2 PV + \beta_3 AnnualElectricityCost + \beta_4 Engagement_{medium} + \beta_5 Engagement_{high} + \beta_6 ProcurementDuration + \beta_7 RenewableContent * PV$$
(2)

Attributes	Levels	Definition
Renewable Content PV Installation	15%, 30%, 60%, and 100% Ves. No	Represents the percentage of renewable energy in the grid electricity.
Annual	0% (default) 20%	solar PV.
Electricity Costs	40%, and 60%	electricity costs, considering factors like tax rebates, net-metering benefits, green tariff premiums, and upfront investment for solar PV over 10 years.
Engagement Level	Low (online form), Medium (phone calls/mail-in), and High (in-person meetings)	Represents the effort consumers need to interact with the electricity provider and/or PV installer.
Procurement Duration	3 days (default), 10 days, 30 days, and 60	Indicates the time for information gathering and administrative/technical
	days.	processes.

Table 1: DCE Attributes and Levels

A Latent Class model (LCM) was then estimated to over- come the limitations of the MNL model and to better understand whether the insignificance of the organic attribute was due to heterogeneity in the sample. The definition of the best number of classes in LCM models is an exogenous process and there is not a univocal rule to be followed to this end.

2.3. DATA COLLECTION

Participants (n=600) were recruited from the online participant pool, Prolific, known for its superior data quality measures (Peer et al., 2021). The sample size of 600 (300 per condition) ensured standard errors below 0.05 for marginal utility estimates. To ensure representativeness, participants were recruited to match the demographics (gender, age, and race) of the overall US population. Eligible participants were US residents over 18 years old. Informed consent was obtained, and participants were compensated \$3 for their participation.

In the experiment, participants were instructed to imagine moving to a new home and needing to set up electricity. Four electricity options were presented based on their Renewable Content. In each experimental condition, participants were introduced to the default option (15% or 30%) and subsequently shown the other levels of Renewable Content. Participants were informed that the default option (15% or 30%) was preselected for them, and whether it met or exceeded state-mandated requirements. Participants were also informed about the availability of rooftop solar PV installation options.

Participants were informed that their electricity choices could vary in terms of Annual Electricity Costs, Engagement Level, and Procurement Duration, with each attribute defined and explained. Instructions for completing the choice task were provided, along with three attention check questions to ensure understanding of the experimental manipulation and task instructions. The first attention checks assessed understanding of the Renewable Content options, the second attention check measured understanding of the attributes, and the third attention check utilized the same choice set as the instructions but with a clear dominant choice. Performance on these questions was summed to create an attention score. The choice task consisted of 15 randomized choice sets for each participant. After completing the choice task, participants responded to additional questions regarding individual differences and demographics. They rated the importance of each attribute on a 5-point scale and indicated their level of agreement with statements related to perceived environmental benefits and trust in electric utilities and green electricity supply options. Awareness of renewable energy options, energy efficiency improvements, and ownership of low-carbon technologies were also assessed. Participants reported homeownership status, type of home, average monthly electricity bill, state of residence, household income, highest level of education, political ideology, political party affiliation, age, gender, and race.

3. RESULTS

3.1. SAMPLE

No significant differences were found between the two experimental groups in the sample (see Table 2). The sample is representative of the U.S. population in terms of gender, age, and race. Income levels were not significantly different between the groups, with the majority falling within the \$50,000-75,000 range, consistent with national income distribution. Most participants held a college degree or higher and identified as Moderate to Very Liberal Democrats. The majority were homeowners residing in singlefamily homes. Participants demonstrated high attention, correctly answering at least more than two attention check questions on average. Most participants were aware of renewable energy options and had made energy efficiency investments. The median monthly electricity bill was \$120, with no significant differences between groups. A majority of participants were aware of solar PV installation options, while a smaller percentage had already installed it. Awareness of green electricity options was lower overall, but a higher percentage (than PV) had subscribed to it. Energy-efficient technologies, particularly efficient appliances and lighting were common investments. Most participants did not own low-carbon products, but a small percentage reported owning heat pumps, hybrid vehicles, and electric vehicles. Participants showed high awareness of environmental benefits in both groups. Further details by experimental group can be found in Appendix A.

Measure	Levels	15% Default	30% Default
Gender	Male	49%	52%
	Female or Non-	51%	48%
	Conforming		
Age	Mean (SD)	45 (16)	46 (15)
Race	White	76%	75%
	Black	9%	14%
	Asian	7%	3%
	Mixed Race	5%	5%
	Hispanic	2%	1%
	Native American	0%	0.3%
	Native Hawaiian	0%	0%
Income	<\$50,000	39%	41%
	\$50,000 - \$100,000	31%	34%
	>\$100,000	30%	25%
Education	Less than Bachelor's	45%	44%
	Bachelor's or Higher	elor's or Higher 55%	
Homeownership	Homeowner	vner 60% 55	
-	Renter or Other	40%	45%
Home Type	Single-Family Home	66%	68%
	Other	34%	32%
Ideology	Very Liberal	18%	16%
	Liberal	31%	39%
	Moderate	22%	23%
	Conservative	16%	12%
	Very Conservative	8%	5%
Political	Democrat	46%	51%
Affiliation	Republican	21%	14%
	Independent or Other	29%	29%
Attention (out of 3)	Mean (SD)	2.8 (0.4)	2.7 (0.5)

Table 2: Characteristics across experimental conditions

3.2. PREFERENCES FOR ELECTRICITY PROCUREMENT

Table 3 shows that the default option (estimated by ASC) had a significant positive impact on estimated utility, indicating a preference for the default option across both experimental conditions. Furthermore, the greener (30%) default condition was associated with higher perceived utility for the default option.

Participants also derived higher utility from the Renewable Content and PV Installation attributes in the 30% renewable content default condition. The estimate for Renewable Content was positive and significant in both groups, indicating that higher renewable content was linked to higher utility. Participants showed a stronger preference for renewable content when the default was greener (30%). In the 15% default group, PV Installation did not significantly influence estimated utility. However, in the greener 30% default group, participants reported significantly higher perceived utility when PV installation was present. There was no significant interaction between Renewable Content and PV Installation in either group, suggesting that combining procurement options did not provide additional utility perceived by participants.

As cost, engagement level, and procurement duration increased, participants' perceived utility decreased (see Table 3). In general, participants were sensitive to cost, which was a significant negative influence on estimated utility. This is consistent with previous research on electricity procurement decisions in the context of both solar and green electricity (Danne et al., 2021; Islam, 2014; Motz, 2021), as well as other DCEs where a price attribute is included (Fruth et al., 2019b). For Engagement Level, decreased utility was associated with high (i.e., in-person) engagement, but there was no difference in utility for low (i.e., online form) vs. medium (i.e., phone call) engagement, consistent with Bao et al. (2020).

In addition, high engagement was perceived more negatively in the 15% default group. For Procurement Duration, as the number of days increased, the perceived utility decreased. This suggests that participants preferred to not wait for the implementation of their procurement choices (Ozaki, 2011; Schulte et al. 2021). Table 4 presents the relative attribute importance, reflecting participants' self-reported ratings of attribute importance and its alignment with their choice behavior. The consistency observed between the importance ratings and choices suggests that participants made conscious decisions and trade-offs based on these attributes, enhancing the reliability of the model estimates.

Variable	15% Default	30% Default	
	B (SE)	B (SE)	
ASC (Default)	0.72 (0.03)***	1.7 (0.04)***	
Renewable Content	0.15 (0.008)***	0.27 (0.01)***	
PV Installation	0.08 (0.04)	0.14 (0.06)*	
Annual Electricity Cost	-0.46 (0.01)***	-0.48 (0.01)***	
Engagement Level (Medium)	-0.06 (0.06)	-0.03 (0.08)	
Engagement Level (High)	-0.31 (0.06)**	-0.22 (0.08)**	
Procurement Duration	-0.1 (0.01)***	-0.12 (0.01)***	
Renewable Content x PV	0.008 (0.006)	0.008 (0.004)	
AIC	7828.73	6529.71	
Adjusted McFadden R ²	0.21	0.34	
Log-Likelihood	-3907.36	-3257.85	

Table 3: Multinomial Logit Model Estimates. *p<0.05, **p<0.01, ***p<0.001

Overall, participants displayed the highest sensitivity to Annual Electricity Cost, followed by Renewable Content and Procurement Duration. In the greener (30%) default group, participants exhibited reduced sensitivity to cost (although it remained the most important attribute) and placed higher importance on renewable content. This indicates that participants prioritized renewable content more when comparing alternatives, particularly when a greener default option was available.

	Estir	nated	Self-Reported		
Attribute	15% Default	30% Default	15% Default	30% Default	
Annual Electricity Cost	58%	46%	4.43 (0.87)	4.49 (0.76)	
Renewable Content	22%	36%	3.58 (1.12)	3.64 (1.00)	
Procurement Duration	12%	12%	2.82 (1.19)	2.89 (1.29)	
Engagement Level	6%	4%	2.7 (1.09)	2.69 (1.16)	
PV Installation	2%	2%	2.57 (1.14)	2.61 (1.12)	

Table 4: Relative attribute importance as (a) estimated by the multinomial logit model and (b) self-reported by participants.

3.3. DISTRIBUTION OF ELECTRICITY PROCUREMENT CHOICES

Participants in the greener (30%) default group exhibited a higher likelihood of choosing the default option and opting for greener electricity (60% or 100% renewable content) when deviating from the default, as depicted in Table 5. Few participants in the greener default group selected the "opt-out" option of 15%, indicating a preference for options with higher renewable content than the default. Excluding default choices, the 100% renewable option was most frequently chosen, particularly when the change in Annual Electricity Cost was a 20% increase or less. In the greener (30%) default group, participants selected the 100% renewable option 28% of the time with no change in cost and 16% of the time with a 20% cost increase. Similarly, in the 15% default group, participants chose the 100% renewable option 20% of the time with no cost change and 14% of the time with a 20% cost increase. The likelihood of choosing the 100% renewable option decreased as Annual Electricity Cost increased. To compare preferences between the two groups, simulated choices were employed to calculate the probability of support for each level of Renewable Content while holding other attributes constant. In Figure 2, simulated choices illustrated a scenario with a 20% cost increase, no solar PV, high Engagement Level, and a Procurement Duration of 10 days. The

greener default group exhibited a higher probability of choosing the default option (84%) compared to the 15% default group (67%). Moreover, the greener default group demonstrated a greater probability of supporting the 60% and 100% Renewable Content levels (58% and 80% respectively) compared to the 15% default group (39% and 54% respectively). This indicates that having a greener default systematically elevates preferences for renewable energy overall.

	Including De	fault Choices	Excluding De	fault Choices
Options	15% Default	30% Default	15% Default	30% Default
Default	43%	60%		
30% / 15%	120/	20/	21%	6%
Renewable Content	13%	290		
60% Renewable	10%	16%	34%	39%
Content	1970	1070		
100% Renewable	25%	22%	45%	54%
Content	2370	2270		
Total Number of	4 500	4 500	2,585	1,824
Choices	4,300	4,300		

Table 5: Frequency of choices (a) including and (b) excluding the default option.

3.4. DISTRIBUTION OF CONSUMER CHOICES

Latent class analysis reveals three distinct participant classes: Money Savers, Carbon Reducers, and Deal Seekers, consistent with prior research (Agarwal, 2022). Demographic analysis did not identify clear patterns for predicting group membership (see Appendix B). Table 6 and Table 7 represent the latent class model estimates and relative importance of attributes for each class respectively. Money Savers had a significant positive utility estimate for the default option and displayed the least consideration for Renewable Content. This behavior aligns with the "cost-sensitive conservatives" class (Sagebiel & Rommel, 2014), class 3 in a Canadian PV study (Islam, 2014), and the "price-sensitive democrat" in a German green tariff study (Sagebiel et al., 2014).



Figure 3: Probability of support for each level of Renewable Content. Errors bars mark the upper and lower 95% confidence intervals.

The greener (30%) default group showed some utility associated with higher Renewable Content. The proportion of Money Savers was similar across both conditions (~30%). In contrast, Carbon Reducers exhibited a strong willingness to procure electricity with higher renewable content. They had the highest preferences for Renewable Content and PV Installation while being less sensitive to cost.

	15% Default			30% Default		
	Class 1	Class 2	Class 3	Class 1	Class 2	Class 3
	Money	Carbon	Deal	Money	Carbon	Deal
	Savers	Reducers	Seekers	Savers	Reducers	Seekers
Variable	B (SE)	B (SE)	B (SE)	B (SE)	B (SE)	B (SE)
ASC (Default)	4.56***	-1.53***	1.60***	4.55***	-0.77***	2.72***
	(0.25)	(0.1)	(0.1)	(0.22)	(0.09)	(0.1)
Renewable Content	0.03	0.22***	0.19***	0.11*	0.28*	0.48***
	(0.03)	(0.01)	(0.02)	(0.02)	(0.01)	(0.02)
PV Installation	-0.23	0.14*	0.18	-0.22	0.3*	0.24
	(0.17)	(0.06)	(0.1)	(0.17)	(0.08)	(0.1)
Annual Electricity	-	-0.27***	-	-	-0.17***	-1.1***
Cost	0.99***	(0.01)	1.23***	0.88^{***}	(0.02)	(0.04)
	(0.08)		(0.04)	(0.07)		
Engagement Level	-0.51	0.13	-0.17	-0.47	-0.03	-0.09
(Med)	(0.24)	(0.1)	(0.16)	(0.24)	(0.14)	(0.14)
Engagement Level	-0.6*	-0.19*	-0.67*	-0.83*	0.02	-0.51*
(High)	(0.26)	(0.1)	(0.16)	(0.25)	(0.14)	(0.14)
Procurement	-0.44*	-0.069*	-0.21*	-	-0.05*	-
Duration	(0.06)	(0.01)	(0.03)	0.50***	(0.02)	0.22***
				(0.06)		(0.02)
Membership	28%	34%	38%	32%	19%	49%

Table 6: Marginal utility estimates from a 3-segment latent class analysis.

Default options were least preferred by this group. Similar behavior was observed in class 1 consumers (Islam, 2014) and "change makers" (Sagebiel et al., 2014). The greener (30%) default group perceived lower utility for the default option and showed a stronger preference for options with PV installations. Fewer participants were classified as Carbon Reducers in the greener default group compared to the 15% default group.

The remaining participants were classified as Deal Seekers, displaying a strong preference for low-cost renewable energy. They favored options with high renewable content as long as they were cost-effective. This class was even more cost-sensitive than the Money Savers class and aligned with "green participators" (Sagebiel et al., 2014), class 2 (Islam, 2014), and "green conservatives" (Sagebiel & Rommel, 2014). In the

greener (30%) default group, stronger preferences for Renewable Content were observed. More participants were classified as Deal Seekers in the greener default group compared to the 15% default group. This suggests a shift from Carbon Reducer behavior to Deal Seeker behavior in the presence of a greener default. These consumers aim to procure renewable energy but are unwilling to pay price premiums, potentially viewing green electricity programs as an alternative to installing solar PV (Fikru & Canfield, 2022b).

4. DISCUSSIONS

This study investigates how people make trade-offs between renewable energy options under different default conditions. This was accomplished using a discrete choice experiment with attributes including renewable content, PV installation, change in annual electricity cost, engagement level, and procurement duration. Participants were randomly assigned to either a 15% or 30% renewable content default option. There are three key findings from these results, (1) effort is a relatively minor factor in renewable procurement decisions even when comparing PV adoption versus green electricity, (2) relative perceptions of renewable procurement options strongly depend on the default level offered by an electricity provider, and (3) some consumers are more sensitive to the default level and will shift their behavior accordingly. On average, our sample exhibited a significant negative influence of Procurement Duration and Engagement Level (in-person engagement) in both experimental conditions, consistent with prior research (Bao et al., 2020).

Attribute		15% Default			30% Default	
	Money	Carbon	Deal	Money	Carbon	Deal
	Savers	Reducers	Seekers	Savers	Reducers	Seekers
Renewable	2%	39%	12%	10%	60%	32%
Content						
PV	2%	4%	2%	2%	7%	2%
Installation						
Annual	60%	42%	68 %	52%	25%	52%
Electricity						
Cost						
Engagement	11%	5%	6%	8%	1%	4%
Level						
Procurement	25%	10%	12%	28%	7%	10%
Duration						

Table 7: Relative Attribute Importance Across Classes

Despite reporting high awareness of environmental benefits, the relative importance of effort-related attributes was low. Previous studies have shown that greater awareness of environmental benefits is associated with increased interest in renewables (Danne et al., 2021; Motz, 2021; Wolske et al., 2017). However, segmentation analysis revealed a class in both experimental conditions that was highly sensitive to procurement duration (Money Savers). This finding aligns with semi-structured interviews conducted by Ozaki (2011), where participants who had the option to switch to green tariff programs chose to stick with the status quo due to information collection difficulties, inconvenience of switching, and additional costs. In contrast, participants who had already switched to a green tariff program perceived the effort as low (Ozaki, 2011). This pattern was observed in the Carbon Savers and Deal Seekers groups, who expressed greater interest in higher renewable procurement and exhibited lower sensitivity to effortrelated attributes (Engagement Level and Procurement Duration). The decision framework proposed by Schulte et al. (2021) suggests caution in interpreting the
relationship between effort and adoption, as decision-makers' characteristics may influence perceived effort. In our study, consumers who prioritize higher renewable content in their electricity procurement may be less sensitive to effort-related attributes.

Consistent with Figure 1, the evidence indicates that consumers are sensitive to the decision context, particularly the levels of the default option provided by the electricity provider. This sensitivity manifests in two ways: (a) a strong preference for the default option, especially when it is greener, and (b) a perception of higher utility for greener options (e.g., 100% renewable) when the default option is greener. Consequently, participants consistently make greener choices when the default option is greener, which aligns with decision heuristics like status quo bias, satisficing, and the decoy effect.

Across both experimental conditions, participants predominantly chose the default option (refer to Table 4), suggesting that they anchored on the default and only deviated if an alternative appeared more appealing. This effect was even more pronounced when the default option had a greener composition (30% renewable content). This behavior can be attributed, in part, to status quo bias, where consumers prefer a pre-selected option to avoid perceived losses (Tversky & Kahneman, 1991). Similar phenomena have been observed in other studies, showing a strong tendency (>90%) to adopt the default option despite the availability of greener alternatives that customers claimed to prefer (Frederiks et al., 2015; Pichert & Katsikopoulos, 2008). In our study, default adoption rates were lower (43-60%), possibly because it was a hypothetical scenario where participants tend to overestimate their willingness to take action (Frederiks et al., 2015; Kjær, 2005). Additionally, the stronger preference for the greener default option suggests that participants may have been satisficing, choosing the easiest option they deemed "good enough" when faced with excessive or complex information (Simon, 1955). When the default option had 30% renewable content instead of 15%, participants were more inclined to choose the default option, indicating it was perceived as sufficiently good when greener. These findings underscore the potency of defaults as mechanisms for promoting voluntary renewable energy procurement, aligning with the CCA model.

Moreover, a greener default option influenced perceptions of the available options, heightening interest in greener alternatives overall. This effect resembles the decoy effect, where the introduction of an inferior product alters preferences for other products in a choice set (Slaughter et al., 1999). By presenting a decoy option, the 15% renewable choice, which was costlier and more cumbersome to procure (akin to opting out of the CCA), the 30% default option consistently emerged as the cheapest and least effort option while also offering higher renewable content. Furthermore, the presence of the 15% renewable option potentially increased participants' preference for the 100% renewable option whenever other attributes were comparable. For instance, if a 100% renewable option was only 20% more expensive than the 15% renewable option, it may have been perceived as having higher utility. This suggests that interest in paying a price premium for 100% green electricity may rise when actively compared to an inferior option (less renewable, more expensive), even if it is not the default. In other words, CCAs could potentially market 100% green power more effectively.

Thirdly, consumer sensitivity to the default level varies among individuals. Our findings support the existence of three consumer classes: Money Savers, Carbon Reducers, and Deal Seekers, which aligns with previous research in the energy domain (Islam, 2014; Sagebiel et al., 2014; Sagebiel & Rommel, 2014). Money Savers prioritize

the cheapest option without considering its environmental impact, while Carbon Reducers prioritize environmental friendliness regardless of cost. Deal Seekers seek green products without price premiums. These groups exhibit differences in their perception of influential attributes. Carbon Reducers and Deal Seekers perceive greater utility as renewable content increases, whereas Money Savers and Deal Seekers are more cost-sensitive. Carbon Reducers are the least sensitive to effort, whereas Money Savers are the most sensitive. Comparing the experimental conditions, Carbon Reducers exhibit even stronger preferences for renewable energy when a greener default option is present. Furthermore, the distribution of class membership varies. In the 15% default condition, participants are roughly evenly distributed among the classes. However, in the 30% default condition, participants show a shift from Carbon Reducers to Deal Seekers, indicating a greater tendency to satisfice when a greener default option is available.

5. CONCLUSIONS

These findings have implications for electricity retail markets where providers offer multiple procurement options, such as the competition between CCAs and IOUs in residential supply. CCAs, established to increase renewable procurement at the municipality level, have achieved success partially due to the opt-out model and the influence of defaults. As observed in this study, a greener default option stimulated more consumers to purchase competitively priced green electricity, particularly when compared to less desirable options (i.e., more expensive, less renewable). Energy organizations can utilize these findings to enhance their existing green electricity products and their marketing strategies. While the CCA opt-out structure effectively boosts the sales of voluntary renewable energy, additional efforts are needed to promote green premium programs where the default option only marginally surpasses the state RPS. Targeting price-sensitive customers by designing marketing messages that compare 100% renewable products to the incumbent utility's default options could be an effective strategy to increase sales of premium options.

However, this study has certain limitations that warrant attention in future research. Firstly, the sample of customers used in this study exhibited characteristics of being more liberal, environmentally conscious, and leaning towards democracy compared to current trends in the U.S. While this may limit the generalizability of the results, these characteristics align with the typical motivations of consumers in the market for greener electricity options. Secondly, the choice task in this study does not incorporate social norms as a factor influencing procurement decisions. This omission is based on mixed evidence regarding the influence of social norms on the adoption of green tariffs offered by IOUs/CCAs and the lack of visibility advantage that green tariffs have compared to solar PV, which is known to play a role in norm-driven adoption. Lastly, the use of a stated preference approach in this study may result in inflated estimates of preferences that may not always align with participants' actual behavior in the electricity market. Previous studies on renewable energy have highlighted a value-action gap, explaining why consumers, despite having positive views on the environmental benefits of renewables, are often not motivated to adopt greener products. While substantial status

quo bias was observed, the percentage of customers actively seeking greener electricity

options may be smaller in the real world.

REFERENCES

- Bao, Q., Sinitskaya, E., Gomez, K. J., MacDonald, E. F., & Yang, M. C. (2020). A human-centered design approach to evaluating factors in residential solar PV adoption: A survey of homeowners in California and Massachusetts. *Renewable Energy*, 151, 503–513. https://doi.org/10.1016/j.renene.2019.11.047
- Danne, M., Meier-Sauthoff, S., & Musshoff, O. (2021). Analyzing German consumers' willingness to pay for green electricity tariff attributes: a discrete choice experiment. *Energy, Sustainability and Society*, *11*(1), 1–16. <u>https://doi.org/10.1186/s13705-021-00291-8</u>
- Fruth, E., Kvistad, M., Marshall, J., Pfeifer, L., Rau, L., Sagebiel, J., Soto, D., Tarpey, J., Weir, J., & Winiarski, B. (2019). Economic valuation of street-level urban greening: A case study from an evolving mixed-use area in Berlin. *Land Use Policy*, 89(October), 104237. <u>https://doi.org/10.1016/j.landusepol.2019.104237</u>
- Islam, T. (2014). Household level innovation diffusion model of photo-voltaic (PV) solar cells from stated preference data. *Energy Policy*, 65, 340–350. https://doi.org/10.1016/j.enpol.2013.10.004
- Knapp, L., O'Shaughnessy, E., Heeter, J., Mills, S., & DeCicco, J. M. (2020). Will consumers really pay for green electricity? Comparing stated and revealed preferences for residential programs in the United States. *Energy Research and Social Science*, 65, 0–26. https://doi.org/10.1016/j.erss.2020.101457
- Liu, X., O'Rear, E. G., Tyner, W. E., & Pekny, J. F. (2014). Purchasing vs. leasing: A benefit-cost analysis of residential solar PV panel use in California. *Renewable Energy*. https://doi.org/10.1016/j.renene.2014.01.026
- Mamkhezri, J., Thacher, J. A., & Chermak, J. M. (2020). Consumer preferences for solar energy: A choice experiment study. *Energy Journal*, 41(5), 157–184. https://doi.org/10.5547/01956574.41.5.JMAM
- Motz, A. (2021). Consumer acceptance of the energy transition in Switzerland: The role of attitudes explained through a hybrid discrete choice model. *Energy Policy*, *151*, 112152. https://doi.org/10.1016/j.enpol.2021.112152

- O'Shaughnessy, E., Heeter, J., & Burd, R. (2021). Status and Trends in the US Voluntary Green Power Market (2020 Data). *NREL*, *October*. http://www.nrel.gov/docs/fy16osti/65252.pdf
- O'Shaughnessy, E., Heeter, J., Gattaciecca, J., Sauer, J., Trumbull, K., & Chen, E. (2019). Empowered Communities: The Rise of Community Choice Aggregation in the United States. *Energy Policy*. https://www.sciencedirect.com/science/article/abs/pii/S0301421519304434
- Ozaki, R. (2011). Adopting sustainable innovation: What makes consumers sign up to green electricity? *Business Strategy and the Environment*, 20(1), 1–17. https://doi.org/10.1002/bse.650
- Pichert, D., & Katsikopoulos, K. V. (2008). Green defaults: Information presentation and pro-environmental behaviour. *Journal of Environmental Psychology*, 28(1), 63–73. https://doi.org/10.1016/j.jenvp.2007.09.004
- Sagebiel, J., Müller, J. R., & Rommel, J. (2014). Are consumers willing to pay more for electricity from cooperatives? Results from an online Choice Experiment in Germany. *Energy Research and Social Science*, 2(52385), 90–101. <u>https://doi.org/10.1016/j.erss.2014.04.003</u>
- Schulte, E., Scheller, F., Pasut, W., & Bruckner, T. (2021). Product traits, decisionmakers, and household low-carbon technology adoptions: moving beyond single empirical studies. *Energy Research and Social Science*.
- Schulte, E., Scheller, F., Sloot, D., & Bruckner, T. (2022). A meta-analysis of residential PV adoption: the important role of perceived benefits, intentions and antecedents in solar energy acceptance. *Energy Research and Social Science*, 84. https://doi.org/10.1016/j.erss.2021.102339
- Sergi, B., Davis, A., & Azevedo, I. (2018). The effect of providing climate and health information on support for alternative electricity portfolios. *Environmental Research Letters*, 13(2). https://doi.org/10.1088/1748-9326/aa9fab
- Shaughnessy, E. O., Heeter, J., Gattaciecca, J., Trumbull, K., Chen, E., Shaughnessy, E. O., Heeter, J., Gattaciecca, J., Sauer, J., Trumbull, K., & Chen, E. (2019).
 Community Choice Aggregation: Challenges, Opportunities, and Impacts on Renewable Energy Markets Community Choice Aggregation: Challenges, Opportunities, and Impacts on Renewable Energy Markets. *National Renewable EnergyLaboratory (NREL), February*, 1–56.

III. FORECASTING RESIDENTIAL SOLAR UPTAKE IN THE ERA OF UTILITY-SCALE RENEWABLE GENERATION: AN AGENT-BASED ANALYSIS

Ankit Agarwal¹, Casey Canfield¹, and Mahelet Fikru²

¹Engineering Management and Systems Engineering, Missouri University of Science and Technology, Rolla, MO 65409

²Department of Economics, Missouri University of Science and Technology, Rolla, MO 65409

ABSTRACT

Predicting residential solar PV adoption is of paramount importance for various stakeholders. Engineering managers stand to benefit as it aids in planning future grid infrastructure, while policymakers can devise economic incentives that catalyze investment and job growth in the renewables sector. Though past predictive efforts have centered around tax incentives, net-metering schemes, and time-of-use tariffs, the influence of streamlined procurement options like utility-scale renewables and Community Choice Aggregations (CCAs) remains unexplored. This research employs an empirically-grounded Agent-Based Model (ABM) to forecast residential PV adoption in environments with both CCA and non-CCA electric utilities. The model is informed by initializing agents using data from a discrete-choice experiment and is tested under two distinct scenarios: presence and absence of CCAs. The model's predictive potency is further validated using case studies from a sample of suburban California households and a pro-residential solar community in San Diego under CCA service. Through sensitivity analysis, the study unveils that alongside the change in annual electricity costs and

procurement effort, the duration of PV procurement emerges as a critical determinant for PV adoption. Such simulations are instrumental for engineering managers to anticipate future renewable generation sources. Moreover, the findings underscore the necessity for policymakers to sustain financial incentives and prioritize efforts to expedite the PV procurement process, emphasizing its potential to significantly boost adoption rates.

Keywords: Agent-based model, Small-world network, PV Diffusion

1. INTRODUCTION

1.1. BACKGROUND

In recent years, solar photovoltaic (PV) systems have witnessed an exponential rise in popularity, especially in residential settings. States such as California, Texas and Florida set quarterly records for installing residential PV in 2022 (Wood Mackenzie & SEIA, 2022). The U.S. solar installations in 2023, combined for utility-scale and residential, is projected to be 32 gigawatts (GW) and is expected to grow to 375 GW by 2028 (SEIA, 2023). As a result, there is growing interest in being able to predict residential behind-the-meter PV adoption. From grid infrastructure to economic stimuli, and environmental initiatives, these predictions serve as foundational insights shaping our collective sustainable future.

Firstly, it facilitates enhancement of grid infrastructure and stability. Historically, the energy grid was conceived for centralized energy production. However, with a surge in localized energy sources, the dynamics are transformed. Increased solar integration can lead to potential grid congestion and voltage irregularities if not strategically managed. By forecasting residential solar PV adoption, utility providers can judiciously evaluate the grid's capacity to accommodate distributed energy inputs and subsequently modify and upgrade the infrastructure. This proactive approach ensures grid stability and reliability for consumers (Denholm et al., 2016).

Secondly, the integration of solar PV systems in households represents a direct countermeasure against the over-reliance on fossil fuels. From an environmental perspective, every solar panel installed is a step towards diminishing greenhouse gas emissions. Predictive analytics can offer insights into potential environmental impacts based on adoption rates, aiding scientists and environmentalists in quantifying the benefits and strategizing further interventions. These predictions can also be pivotal in gauging the progress towards global environmental commitments, such as the Paris Agreement (Creutzig et al, 2017).

Lastly, the renewable energy sector, especially solar PV, is a burgeoning space for investors and businesses. Forecasting adoption trends can provide an understanding of market dynamics and potential economic opportunities. For investors, predictability translates to minimized risk. Hence, a clear foresight into solar PV adoption can catalyze increased investments in research, solar technology manufacturing, and development sectors. This influx of investments can invigorate the economy and drive technological advancements, fostering a positive feedback loop that further facilitates solar adoption (Azhgaliyeva et al., 2023).

The growth of residential photovoltaic (PV) systems may positively or negatively interact with the growth of utility-scale renewables in the future. Notably, residential

consumers are progressively leveraging the benefits of renewable power offered by utilities. Utility companies are consistently enhancing their renewable generation capacities in alignment with carbon emission targets set forth by federal and state authorities. Forecasts suggest that renewable sources could contribute to over 50% of the U.S. electricity grid by 2050. This utility-level transformation is bolstered by the emergence of community-owned entities in the wholesale electricity market, notably the Community Choice Aggregation (CCA) model. CCA is a model that allows communities to take control of their electricity sourcing. Rather than relying solely on investor-owned utilities, which might prioritize profits over sustainability, communities can opt for greener electricity sources (O'Shaughnessy et al., 2019). The popularity of CCA is growing because it offers potential cost savings, local control over energy choices, and a chance to significantly boost the proportion of renewable energy in the community's mix. As communities shift towards greener energy through CCAs, traditional utilities are also compelled to modify their portfolios. Predicting residential solar PV adoption becomes crucial here. If a significant number of households adopt solar PV, it can influence the amount of power a CCA needs to source. For utilities, understanding these numbers helps in negotiating power purchase agreements and ensuring grid reliability. While CCAs often have ambitious renewable energy goals, understanding the potential rate of PV adoption can help these entities fine-tune their targets. If residential PV adoption is projected to be high, a CCA might opt for a more aggressive renewable portfolio standard. Furthermore, the financial models underpinning CCAs rely on understanding both supply (from renewable projects) and demand (from consumers). Predicting PV adoption can significantly influence these models. If many households produce their own

electricity, this might impact the CCA's pricing structures and its long-term financial feasibility.

Prior research in this field has focused on understanding residential PV adoption patterns in various scenarios, such as: 1) changes in feed-in-tariffs (Baur & Uriona, 2018), 2) time-of-use electricity pricing schemes , 3) The financial dynamics of green pricing programs and community solar (Mittal et al., 2019). Our research adds to this literature by examining how traditional utilities and CCAs contribute to providing renewable power. While earlier studies did rely on empirical data for predictive modeling, they mostly used data limited to psychometric measures and sociodemographic factors. This study's approach enhances this by using an agent-based model informed by consumer preference data from a discrete-choice experiment (DCE). The data highlights consumers' preferences for various renewable procurement options, considering factors like cost, renewable content, effort, and duration, both within and outside the CCA framework. These considerations allow for a comprehensive comparison between utility-scale electricity and grid-tied PV systems. Using the datainformed ABM, we address the following questions:

- 1. How does a high utility-scale renewable content affect solar PV adoption?
- What role do the attributes of PV adoption play in consumer decision-making? How does the CCA framework impact these trends?

In subsequent sections, we summarize the literature, including modeling of PV adoption and the integration of DCE with ABM. This is followed by an in-depth description of the model's setup and execution. We validate our model using two test

cases, followed by a sensitivity analysis. The concluding sections discuss the implications of our findings and potential avenues for future improvements.

1.2. LITERATURE REVIEW

This section presents a review of prior modeling and simulation methodologies employed for forecasting residential PV adoption. Subsequently, we summarize earlier endeavors to inform ABM using DCE outcomes.

1.2.1. Modeling PV Adoption. Over the last decade, the modeling approaches for PV adoption have varied from spatial analysis (Busic-Sontic & Fuerst, 2018), systems dynamics models (Candas et al, 2019), diffusion models (Boumaiza et al., 2018) and ABMs (Rai & Henry, 2016). Out of all modeling approaches, ABMs have gained prominence because of their ability to capture the social and behavioral dynamics of PV adoption. ABMs are computational models where individual entities (agents) with defined behaviors interact within an environment. Agents follow rules, make decisions, and can adapt over time. These models are used to simulate complex systems and emergent phenomena. In recent years, the use of ABMs has gained traction due to their ability to capture complex interactions within systems, making them especially useful for studying the diffusion of technologies like PV. Policy analyses benefit from ABMs as they provide insights into how different policy measures might impact the adoption and spread of these technologies in various scenarios. Though employed in nearly a quarter of futuristic studies, their prominence is even more pronounced in dissemination rate predictions, accounting for over half of such studies. This highlights the confidence

researchers have in the capability of ABMs to offer reliable predictions in the realm of PV adoption (Alipour et al., 2021).

In the realm of predicting PV adoption using ABMs, there have been two major advancements: 1) grounding the models in real-world data and 2) introducing relevant contexts. Incorporating empirical data helps in depicting varied characteristics and behaviors of agents. Typically, these traits cover socio-demographic details, beliefs about PV, and aspects like property location and size. When agents make decisions, they often weigh factors such as net present value (NPV), payback time (Mittal et al., 2019; Rai & Robinson, 2015), and expected revenue (Wang et al., 2018). These empirical data-driven models open the door for researchers to explore how various policies impact PV adoption. For instance, in the Middle East, where tax breaks and feed-in-tariffs aren't prevalent, lower electricity prices might boost PV adoption (Mohandes et al., 2018). In rural China, many homeowners hesitate to go for PV installations due to misinformation. Research suggests that offering free insurance for possible installation damages and providing expert guidance could enhance PV adoption via positive word of mouth(Wang et al., 2018). A study focusing on California's subsidy program revealed that having a bigger budget had minimal impact on PV adoption. Instead, providing free PV to select households sped up its diffusion more effectively than subsidies (Zhang et al., 2016). Another intriguing model used data from Iowa to simulate a community where every entity, from households to businesses, either adopted PV or engaged in green pricing programs. This was a pioneering effort to weave in alternative green energy sources into the PV adoption narrative. However, it fell short in validation since it couldn't compare its results to any existing green energy market, and overlooked the importance of the

electricity supply's renewable mix. To sum up, while multiple contexts have been explored in studying PV adoption, the majority still revolve directly around PV itself.

This study fills a critical gap by examining an external factor's impact on PV adoption (Schulte et al., 2022). Many homeowners keen on using renewable energy face a choice: either install PV systems or continue relying on their utility company, assuming the company generates a significant portion of its electricity from renewable sources. For those who might be hesitant or unable to get PV systems, sourcing green energy from their utility could be a practical alternative. Notably, obtaining renewable energy from the utility spares homeowners the effort and costs linked to setting up PV systems. This situation underscores the importance of comparing PV with green energy supplied by utilities. It's essential to factor in the effort involved in procuring renewable energy when modeling agent decision-making. Data that reflects consumer preferences, especially regarding effort and time considerations in choosing renewable energy sources, can be instrumental in achieving this.

1.2.2. Agent Social Network. One of the fundamental aspects of ABMs is the network structure which determines how agents are connected to one another. The network topology can significantly influence the diffusion of information, behaviors, or diseases within the system. Three commonly considered network topologies in the realm of ABMs are small-world, scale-free, and random networks. Each of these has distinct characteristics and implications for diffusion processes. Small-world networks are characterized by high clustering and short average path lengths. Imagine a network where most nodes are connected to their nearest neighbors, like a lattice (Kleinberg, 2000). However, a few long-range connections are randomly introduced, linking nodes that

would otherwise be far apart. The "six degrees of separation" phenomenon, where any two people in the world are, on average, separated by six or fewer acquaintances, can be thought of as a real-world representation of a small-world network (Watts & Strogatz, 1998). For diffusion in ABMs, the presence of these long-range connections means that information or diseases can jump across large parts of the network quickly. This makes the diffusion process more efficient as compared to regular lattices. This is the most commonly used agent network structure used for modeling PV diffusion (Alipour et al., 2021; Mittal et al., 2019; Rai & Robinson, 2015). Scale-free networks are networks where the node degree distribution follows a power-law, meaning that there are a few nodes (hubs) with very high degrees and many nodes with a low degree. This topology arises naturally in many real-world networks like the internet, citation networks, and some social networks (Barabási, 2009). The hubs play a crucial role in the diffusion process in scale-free networks. If a new piece of information or a contagious disease hit one of these hubs early on, the diffusion can be incredibly rapid, given the extensive connections of the hub. However, this also means that targeting these hubs can be an effective strategy for interventions, whether that's disseminating information or curtailing the spread of a disease. Previous studies have used scale-free graphs to model innovative technology diffusion (Araghi et al., 2014; Kiesling et al., 2012). In a random network, connections between nodes are made randomly. The Erdős–Rényi model is a classic example where each possible edge between two nodes is formed with a certain probability (Gómez-Gardeñes & Moreno, 2006). Random networks lack the clustered structure of small-world networks and the hub-dominated structure of scale-free networks. For diffusion processes, this means that there isn't any predictability based on

the structure itself. Diffusion can be quite efficient if the average node degree is high because the chances of any given node being connected to a large portion of the rest of the network increase. However, without the presence of hubs or clustered communities, the diffusion patterns may lack the extremes observed in small-world and scale-free networks. When modeling diffusion in agent-based models, it's essential to consider the underlying network topology. Small-world networks offer shortcuts across the network through their long-range connections are highly optimized in terms of clustering as well as path lengths. On the other hand, scale-free networks rely excessively on hubs for diffusion which is often not indicative in technology diffusion scenario and random networks provide a more unpredictable, homogeneous connectivity pattern. Therefore, small-world networks are an ideal choice of network which can positively influence the outcomes of the diffusion process.

1.2.3. ABM-DCE Integration. Utilizing a Discrete Choice Experiment (DCE) to inform an Agent-Based Model (ABM) offers several distinct advantages. Central among these is the provision of an empirical underpinning for the model, anchoring agent behaviors to the real-world preferences and choices of individuals, thereby amplifying the external validity of the simulation (Manski, 2000). DCEs elucidate the nuanced trade-offs individuals navigate when selecting among diverse options characterized by multiple attributes. Integrating these insights into an ABM allows for a more faithful representation of intricate decision-making dynamics.

In a previous study, the complex decision associated with car purchasing was adeptly modeled using an ABM (Zang et al., 2011). This research employed the ABM framework to examine determinants influencing the proliferation of eco-innovations, with a focus on Alternative Fuel Vehicles (AFVs). The method captured the intricate interplay among pivotal stakeholders in the automotive domain, such as manufacturers, consumers, and regulatory bodies. The model's credibility was bolstered by grounding it in empirical evidence, incorporating DCE outcomes from over 7,000 respondents to mirror diverse consumer inclinations and integrating data on manufacturers' cost structures. The researchers discerned that their model precisely mirrored consumer reactions to alterations in automotive design attributes, underscoring the efficacy of ABMs informed by DCE datasets in delineating attribute-specific sensitivities. This investigation provides salient insights into harnessing ABMs to discern factors modulating AFV uptake, a knowledge potentially translatable to other eco-innovative contexts.

A paramount feature of ABM-DCE integration is the ability to capture individuallevel variance in preferences, manifesting the heterogeneity inherent within the agent cohort, an essential element for simulating emergent phenomena (Train, 2009). A case in point is research grounded in DCE data sourced from Swiss round-wood sellers (Holm et al., 2016). Agents' predispositions towards favorable wood selling prices were modulated by part-worth utilities derived via a Latent Class Analysis (LCA) and a Hierarchical Bayes (HB) model. While the LCA technique segregated agents into three discrete categories, the HB model allocated individual-specific part-worths. Comparing both methodologies revealed the superior suitability of HB in the agent-based paradigm, given its capacity to endow each agent with individualized, empirically validated decisionmaking paradigms.

Another merit lies in parameter calibration. The DCE outcomes furnish datainformed directives, obviating arbitrary decision-making. This empirically anchored approach augments scenario analysis robustness. ABMs, with their foundational roots in real-world inclinations, can simulate a plethora of scenarios. One illustrative study probed the amalgamation of DCE outcomes across eight European nations with an ABM to decipher adoption trajectories for smart thermostats (Chappin et al., 2022). Initialized using mixed logit model outcomes, the research appraised the ramifications of varied subsidy magnitudes extended to households and also assessed zero-subsidy scenarios. The simulations advanced the proposition that tailored subsidies for low-income households could engender equitable diffusion across all demographic segments. This research underscored the utility of DCEs in encapsulating the heterogeneity of consumer predilections for eco-innovations under diverse policy landscapes. In summation, anchoring agent choices in observed behaviors through DCEs can potentiate the ABM's predictive capabilities, especially in environments resonating with the original DCE context.

In the integration of ABM-DCE, potential challenges may arise. DCE captures preferences at a specific temporal snapshot, which might not remain constant. Within the dynamic systems modeled by ABMs, the preferences of agents could evolve, causing potential discrepancies between DCE results and long-term behaviors. For the purposes of this research, the context remains unchanged as agents make decisions. Additionally, there is no pronounced fluctuation in the renewable energy market that necessitates consideration. While DCE offers statistical validity, it may not encompass all behavioral factors that impact decision-making in real-world scenarios. For instance, agents could be swayed by emotions, prior experiences, or psychological elements not encapsulated in DCE. In this research, for the sake of model simplicity, agents are perceived as rational consumers, deriving a quantifiable benefit from PV adoption. It's worth noting that, to the researchers' knowledge, there haven't been studies linking irrationalities to PV adoption. In practice, agents might face a wider or altered choice spectrum, resulting in potential variances between modeled and actual behaviors. In this study, two hypothetical scenarios were employed to ascertain preferences, one representing a situation where the electricity provider adhered to the Renewable Portfolio Standard (RPS) and another where it exceeded the RPS (in the CCA context). Subsequent sections elaborate on how DCE results from these scenarios were utilized to initialize agents.

2. METHOD

2.1. MODEL OVERVIEW

In this study, an Agent-Based Model (ABM) is utilized to forecast the proportion of households in a suburban residential community that opt to adopt solar PV, taking into account the attributes of their local electricity supply. The behavior of the agents is influenced by their inherent characteristics, the actions of neighboring agents, and the features of the available renewable energy options. The simulation models the spread of information about solar PV throughout the agents' social network and the agents' decision-making process, which encompasses an attribute-based comparison between the utility derived from PV adoption and electricity procured from the grid. The model operates over 24 time steps, with each step representing a month, thereby representing a two-year market trend. This model has been implemented using the Python Mesa package version 0.9.0 (Masad & Kazil, 2015). All relevant input data, code, and output files are accessible in the provided <u>GitHub repository</u>.

2.2. AGENT INITIALIZATION

In a discrete choice experiment conducted in 2022, a nationally representative sample of participants was sourced from an online panel (refer Chapter 2). These participants were presented with renewable energy procurement options, delineated by five attributes: Renewable Content, PV Installation, Change in Annual Electricity Costs, Procurement Effort, and Procurement Duration. The sample was representative of the U.S. demographic in terms of age, race and gender and predominantly consisted of liberal-leaning, Democrat-leaning, college-educated suburban homeowners with high environmental concern.

Decision Variable	Non-CCA DCE part- worths M(SD)	CCA DCE part-worths M(SD)			
Renewable Content	10 (17)	15 (11)			
Annual Change in	-44 (19)	-39(15)			
Electricity Cost					
Procurement Effort (Low)	15 (18)	10 (13)			
Procurement Effort	4 (12)	-0.5 (13)			
(Medium)					
Procurement Effort (High)	-19 (20)	-9.5 (18)			
Procurement Duration	-10 (10)	-12 (12)			
PV Installation	5 (37)	5 (23)			

Table 1: Part-worth utilities to initialize agents

Participants were randomly allotted to one of two hypothetical scenarios. In one scenario, the electricity supply was portrayed as aligning with the existing RPS, while the other indicated an electricity supply exceeding the RPS in a CCA context (Agarwal et al., 2023). The collected data were then modeled using a Hierarchical Bayes (HB) approach, requiring 10,000 iterations to achieve convergence. Subsequent results informed the calculation of the attributes' part-worths. Individual estimates were presumed to follow a normal distribution, with their means and standard deviations employed for agent initialization (refer to Table 1).

Every agent possesses a distinctive attribute: the anticipated savings in annual electricity costs, expressed as a percentage. This information was derived from a previous survey involving 1,176 PV adopters in California, who disclosed their monthly electricity bills both prior to and post solar installation during summer and winter months (Sigrin et al., 2017). The average monthly bill was computed by separately determining the mean of bills in winter and summer, both with and without solar. Subsequently, the total electricity cost over a span of 25 years was calculated, assuming an inflation rate of 3% (EIA). The differential in electricity costs with and without PV over these 25 years was aggregated, discounted at a 5% rate, and then expressed as a percentage. The resulting annual savings percentages were normally distributed within the sample, M = 62%, SD =31%. Opting for this percentage-based approach over upfront costs was deemed more appropriate due to the variability among customers concerning their chosen system's generation capacity, technology, and the sunlight their property receives for offsetting electricity costs. Moreover, not every customer bears the entire cost of PV installation upfront, many choose financing or leasing options. Hence, using the percentage of

savings offers a more effective means for agents to compare electricity costs with and without PV when making decisions.

2.3. MODEL ENVIRONMENT INITIALIZATION

The model emulates a suburban residential community in California representative of an area highly driven to diminish its carbon footprint. This community comprises environmentally conscious inhabitants who are serviced by the same electricity provider. The renewable component in their electricity supply is denoted as *REN* which is assumed to derive from utility-scale sources like solar, wind, biomass, geothermal, and hydroelectric (carbon-neutral) facilities and it varies from 0 to 100%.

The renewable procurement options (both PV and from the electricity company) introduced upon initializing the model are characterized by several attributes, including Procurement Effort (*PE*), Procurement Duration (*PD*), and Change in Annual Electricity Cost (*CEC*). *PE* captures the effort-related expenses of renewable procurement. This includes tasks like identifying a suitable PV installer, researching the most appropriate system for the household, the modality of communication with the service provider (be it phone, online, or in-person), and the frequency of such interactions. For the model, *PE* can take three possible levels – Low, Medium, High as presented to participants in the DCE. *PD* quantifies the number of days required to finalize the procurement and it varies from 0 to 120 days. This can encompass steps like obtaining a quote, securing approvals from municipal offices or homeowners associations, the actual installation process, and the time required by the electricity company to address service requests. *CEC* represents the percentage deviation in electricity expenses compared to the prevailing costs.

Additionally, the model's environmental initialization is contingent upon the activation of the CCA context. Within the CCA context, it is assumed that *REN* surpasses the state's RPS, prompting an alternate distribution assignment for the renewable procurement attributes in agents (CCA DCE Group).

The agents' social network is structured as a 30 x 30 warped lattice, replicating a Kleinberg small-world network (Kleinberg, 2000). In this configuration, agents establish links with their immediate neighbors. Additionally, 30% of these agents create links with two other agents, ensuring optimal clustering and diffusion path lengths. This design aims to accurately mirror the densely interconnected suburban neighborhoods prevalent in the U.S., while also accommodating a few external links that represent connections elsewhere in the community.

2.4. SIMULATION

The flow of the ABM is explained by Figure 1. At the onset, 5% of the agents are randomly chosen to be existing adopters of solar PV. This sets the initial conditions for PV adoption in the simulated environment. PV adopters are the only agents that can motivate their link neighbors to have positive intentions to adopt PV. As the simulation progresses with each step incrementing, existing PV adopters exert an influence within their social circles, motivating their peers to consider PV adoption. Every agent then calculates two utility values: one derived from adopting PV (*Utility*_{PV}) and the other from continuing with their existing electricity supply (*Utility*_{Electricity}). *Utility*_{PV} is calculated as the sum of products of part worth utilities of DCE attributes assigned to the agent and the attributes of the PV installation (see Equation 1). In this case, PV = 1

represents a scenario where the renewable procurement option involves PV installation. This calculation is triggered only when i^{th} agent adopts PV and influences j^{th} agent to enter the PV market ($I_{ij} = 1$).

$$Utility_{PV} = I_{ij}(\beta_1 REN + \beta_2 CEC + \beta_3 PE_{low} + \beta_4 PE_{medium} + \beta_5 PE_{high} + \beta_5 PD + \beta_6 PV)$$
(1)

Similarly, for electricity supply $Utility_{Electricity}$ is calculated as the sum of products with the same part worth utilities with electricity supply attributes. In this model, the *CEC* is set at zero, taking the electricity supply's kWh rate as the benchmark cost. The Procurement Duration (*PD*) is designated as 3 days, which corresponds to the anticipated duration for establishing a new residential connection or addressing service inquiries. Notably, a value of *PV* =0 delineates a scenario wherein the renewable procurement exclusively relies on utility-scale renewable generation facilities.

The decision to adopt PV is based on a direct comparison of $Utility_{Electricity}$ and $Utility_{PV}$. If the $Utility_{PV}$ exceeds $Utility_{Electricity}$, the agent decides to adopt PV. The new adopters then motivate their respective link neighbors to enter the PV market and do the same comparison themselves. This process runs in iterative cycles, progressing one time step in each cycle, representing one month in the real world. The model executes for 24 time steps which represents a two-year time period at which point the simulation concludes. At the end of each iteration (or month), agents either choose to adopt PV or continue without adoption based on their utility calculations.



Figure 1: Model Flowchart

$$Utility_{Electricity} = \beta_1 REN + \beta_2 CEC + \beta_3 Effort_{low} + \beta_5 Duration$$
(2)

After the model stops executing, the percentage of PV adopters is calculated as shown in Equation 3.

$$Adoption \% = \frac{PV Adopters}{No. of agents}$$
(3)

Each simulation run is evaluated by the percentage of PV adopters. To get a distribution of results and construct a confidence interval, the simulation is repeated 1000 times.

3. RESULTS

In this section, the ABM's predictive capabilities are validated using two test cases, 1) A representative sample of California households, and 2) A suburban community located in San Diego. Following this validation, a comprehensive sensitivity analysis is presented to facilitate discussion on the model's dynamics.

3.1. PREDICTING PV ADOPTION FOR CALIFORNIA HOUSEHOLDS

Within the state of California, there are approximately 1.5 million small-scale solar PV systems, each with a capacity under 10 kW (Forrester et al., 2022). Drawing from the U.S. Census data, 55% of the 14.5 million residences in California are owneroccupied (U.S. Census, 2021). Therefore, approximately 17% of these homeowner properties are equipped with rooftop PV installations, representing the state's solar PV adoption rate. Even in regions with robust PV markets, the required effort to procure PV remains high. Potential adopters must navigate through comprehensive research, solicit quotes, vet references, and ensure the chosen contractor possesses the requisite licenses and certifications. Additionally, they must arrange site surveys and consultations with solar installation specialists. The procurement duration in California can be extended, given the mandatory permit acquisitions from local governing bodies. This often involves meticulous application procedures and strict adherence to local building regulations and zoning stipulations. Transitioning to solar also necessitates an interconnection to the electrical grid, a process requiring local utility company approval. This entails a combination of administrative paperwork, technical evaluations, and meticulous

inspections, potentially extending the process by 90 days or more (O'Shaughnessy et al., 2020).



Figure 2: PV adoption percentage distribution for 1000 simulations for a sample of California households.

At present, 80% of California's residential consumers live outside CCA service territories (S&P Global, 2023) and rely on investor-owned utilities, rural electric cooperatives, or municipal utilities. These specific regional conditions have been replicated in the ABM by initializing parameters: REN at 33%, CEC at 61%, PE categorized as high, PD set to 90 days, and CCA denoted as 0. The resultant data from 1000 simulation iterations have been depicted in a histogram, as visualized in Figure 2. The simulation outputs, with a mean (M) of 16% and a standard deviation (SD) of 2%, were observed to follow a normal distribution. Notably, the actual PV adoption Percentage in California, or the "true mean," falls within the 95% confidence interval of the model's predicted outcomes.

3.2. PREDICTING PV ADOPTION FOR PRO-SOLAR COMMUNITY.

San Diego holds the distinction of possessing the highest proportion of solar adopters across the United States. Within its myriad of suburbs, the LaCosta Ridge community emerges prominently, recognized nationwide for its unparalleled adoption rate of solar-powered residences. Within this gated community of 16,500 houses, 30% have installed small-scale solar PV systems (Cape Analytics, 2021). A variety of factors may account for this: the community has high-quality competing several installers, the local administrative bodies, including municipal offices and the homeowners association, proactively support solar installations (Cape Analytics, 2021). As a result, there are expedited approval mechanisms, reducing procurement effort and duration, and regular informational seminars, increasing diffusion of information about solar adoption to residents. Presently, the community's energy requirements are provided by the Clean Energy Alliance CCA, which sources half of its electricity from renewable sources. To recreate the unique environmental conditions inherent to the LaCosta Ridge community in the model, specific parameters were employed: REN was set at 50%, average CEC at 62%, PE was defined as low, PD was set at 60 days, and CCA was assigned a value of 1. After initializing these settings, the model underwent 1,000 iterations, revealing outputs that are normally distributed. The actual adoption rate (30%) is within the 95% confidence interval of the anticipated model outputs as shown in Figure 3.



Figure 3: Distribution of PV adoption over 1000 runs for a sample of households in LaCosta Ridge Community, Carlsbad CA

3.3. SENSITIVITY ANALYSIS

To ensure the model's robustness, we conducted a sensitivity analysis. This method helps discern the degree to which each input parameter affects the model's output. This is achieved by isolating each parameter and testing its extremes, essentially its best and worst values, while holding all other parameters steady. In the worst case scenario, agents are least inclined to adopt PV. This could be due to factors like a grid already rich in renewables, minimal savings from electricity, or high time and effort required for procurement. Conversely, in the best case scenario, agents are most inclined to adopt PV. This could be a result of a grid with limited renewables, significant electricity savings, or streamlined procurement processes. Table 1 and 2 enumerate the baseline, best, and worst-case values for each parameter, as well as their sensitivity both

with and without CCA contexts. To derive meaningful results, each parameter setting was run a thousand times, capturing the average output. Sensitivity is determined by the ratio of the difference between the worst and best case outputs relative to the difference in corresponding input values. Utilizing the baseline input parameters, an average PV adoption percentage of 13% was observed in the CCA context, with a marginally higher (15%) observed in the non-CCA context. As shown in Fig. 4, the diffusion and decisionmaking of agents take at least 10 time steps to stabilize, and the output is calculated at t= 24. In the "Renewable Content" parameter, the delineated worst-case scenario, with a value of 0%, simulates a situation where electricity is derived entirely from conventional fuel sources. On the other hand, the best-case scenario, at 100%, indicates a situation where electricity is sourced purely from renewable methods. The output remained consistent despite variations in Renewable Content across both contexts. Interestingly, higher PV adoption rates were noted in the non-CCA context across all Renewable Content levels. This observation contrasts with initial expectations; based on DCE results, the CCA group exhibited a heightened sensitivity to Renewable Content. However, it's plausible that the influence of other attributes, notably the heightened sensitivity to changes in Annual Electricity Cost and Procurement Duration, overshadowed agents' decisions. This pattern infers that within traditional utility frameworks, consumers might exhibit a greater propensity for individual PV purchases, whereas in a CCA framework, a reduced consumer inclination for adoption might prevail.



Figure 4: Relationship between simulation steps and the model output for baseline inputs

For the Change in Annual Electricity Cost parameter, the worst-case value, set at 0%, mirrors a situation wherein average monetary returns from PV are negligible, while a value of 100% indicates that agents can achieve full reimbursement of electricity costs. It was ascertained that, excluding the CCA context, PV adoption dropped to 7% in worst-case scenario and peaked at 23% in best-case scenario. Within the CCA context, these values were recorded at 7% and 19%, respectively. As depicted in Figure 5(b), PV adoption exhibits a non-linear relation with Change in Annual Electricity Cost, with pronounced decrements evident at values of 80% and 20%. As expected from lower sensitivity values in CCA context, a lower PV adoption was observed for similar Change in Annual Electricity Cost values within the CCA purview giving relatively lesser importance to the cost-associated attribute and higher importance to procurement duration and renewable content during decision-making processes. Furthermore, it was

observed that at higher Change in Annual Electricity Cost values, forecast variability is pronounced as opposed to lower Change in Annual Electricity Cost values, complicating the prediction of PV adoption during periods of heightened financial returns.

In relation to the Procurement Duration parameter, the worst-case value, set at 120 days, encapsulates a situation where elongated approval and construction timelines hinder PV adoption. In stark contrast, a value of 0 days signifies immediate, same-day PV installation feasibility. Excluding the CCA context, observed PV adoption percentages were 10% and 70% for the worst and best-case scenarios, respectively. Within the CCA context, these values were recorded at 10% and 75%. Figure 5(c) elucidates that PV adoption undergoes a non-linear decline as Procurement Duration extends from 0 to 60 days. Notably, the output of the model has the highest sensitivity to this parameter especially when the value goes lower than 60. Moreover, in contexts with minimized procurement durations, forecast variability intensifies, suggesting that expedited procurement timelines render PV adoption predictions increasingly challenging.

Variable	Baseline	Worst Case			Best Case			Sensitivity
		Input	Output	Change	Input	Output	Change	
			(%)	(%)		(%)	(%)	
REN (%)	33	100	15	0	0	15	0	0
CEC (%)	-62	0	7	-53	-100	23	53	0.16
PD (days)	90	120	10	-33	0	70	336	0.50
PE	Medium	High	10	-33	Low	17	13	-
Adoption	15							

Table 2: Sensitivity of input variables without CCA context

Considering the Procurement Effort parameter, the designated worst-case scenario, labeled "High," depicts a situation where consumers confront limited installation agency choices, coupled with an information deficit and protracted PV adoption processes. Contrastingly, the "Low" scenario reflects ease in locating proficient installation agencies, comprehensive information accessibility, and abbreviated time commitments for PV adoption. Excluding the CCA context, observed PV adoption percentages were 10% and 17% for the worst and best-case scenarios, respectively, with values of 10% and 14% recorded within the CCA framework. As indicated in Figure 5(d), PV adoption reduces as Procurement Effort increases from low to high. Within the CCA context, heightened PV adoption percentages materialize in worst-case scenarios, possibly attributable to DCE respondents within the CCA context exhibiting reduced sensitivity to extensive procurement endeavors. Additionally, in best-case scenarios, the variability in forecasted results is accentuated, indicating that PV adoption predictions become increasingly intricate when procurement processes are streamlined.

Baseline	Worst Case			Best Case			Sensitivity
	Input	Output	Change	Input	Output	Change	
	-	(%)	(%)	-	(%)	(%)	
33	100	13	0	0	13	0	0
-62	0	7	-46	100	19	46	0.16
90	120	10	-23	0	75	476	0.54
Medium	High	10	-23	Low	14	8	-
13							
	Baseline 33 -62 90 Medium 13	Baseline Input 33 100 -62 0 90 120 Medium High 13 13	Baseline Worst Ca Input Output (%) 33 33 100 13 -62 0 7 90 120 10 Medium High 10 13 - -	Baseline Worst Case Input Output Change (%) (%) (%) 33 100 13 0 -62 0 7 -46 90 120 10 -23 Medium High 10 -23 13 13 13 13	Baseline Worst Case Input Output Change Input (%) (%) (%) 33 100 13 0 0 -62 0 7 -46 100 90 120 10 -23 0 Medium High 10 -23 Low 13 0 -46 100 -23 10	Baseline Worst Case Best Case Input Output Change Input Output (%) (%) (%) (%) 33 100 13 0 0 13 -62 0 7 -46 100 19 90 120 10 -23 0 75 Medium High 10 -23 Low 14 13 13 10 -23 14 14	Baseline Worst Case Best Case Input Output Change Input Output Change (%) (%) (%) (%) (%) Change 33 100 13 0 0 13 0 -62 0 7 -46 100 19 46 90 120 10 -23 0 75 476 Medium High 10 -23 Low 14 8 13 13 13 14 8 13 13 14 14 14

Table 3: Sensitivity of input variables with CCA context



Figure 5:Relationship between PV Adoption vs. a) Renewable content, b) Average Change in Annual Electricity Cost, c) Procurement Effort, and d) Procurement Duration

4. CONCLUSION

This study focuses on creating an ABM using previously captured individual preferences for renewable energy procurement options to predict PV adoption. These preferences are initialized based on the part-worth utilities obtained from a DCE. The model can be set up with DCE estimates, both with and without considering the Community Choice Aggregation (CCA) context. In this model, agents decide between installing their own PV system versus getting renewable energy from the electricity grid. Their choices hinge on factors like the amount of renewable content in the grid, anticipated changes in electricity costs, and the time and effort needed for procurement. To validate the model, two scenarios were tested. In the first scenario, the environment for PV procurement in California was simulated. The model's predicted percentage of PV adopters closely matched the real figures, falling within the 95% confidence interval. Over a two-year span, the model's adoption trend mirrored findings from a past study on 2,000 California households (Zhang et al., 2016). In that study, between 2009 and 2011, PV adopters rose from 5% to 15% with almost 1.5 percentage points rise quarterly. For the second scenario, we simulated PV adoption in the LaCosta Ridge community in the San Diego metro area. The conditions where the time and effort required for procurement were minimal were replicated. Again, the model's predictions closely matched actual figures, with the real average lying within the 95% confidence interval.

Then, we conducted a sensitivity analysis to determine the impact of various attributes on PV adoption. While the amount of renewable content did not affect adoption rates, the model exhibited highest sensitivity to procurement duration followed by the annual change in electricity cost and the procurement effort. In the analysis, all three sensitive parameters demonstrated a decline when transitioning from best-case to worst-case scenarios. Interestingly, this decline was non-linear for both procurement duration and the annual change in electricity cost. The sensitivity to procurement duration surpassed the results from a prior discrete-choice experiment (DCE) that incorporated project time duration as an attribute in gauging preferences related to PV installers (Bao et al., 2020). A possible explanation for this could be that the previous study assessed PV installation as a standalone factor, rather than contrasting its duration against utility

options. The change in annual electricity cost parameter was the second most sensitive variable. The model reacted more sensitively to this parameter than anticipated based on prior findings, such as Wolske et al.'s (2018) insights into the effects of potential savings on PV adoption attitudes. This heightened sensitivity was consistent both within and outside the CCA context. This trend aligns with a previous ABM (Zhang et al., 2016), which indicated that increasing the PV incentive budget by up to eight times led to 10% higher PV adoption. This finding highlights the necessity of continuing the financial incentives that contribute to the attractiveness of PV as a money-saving tool and therefore higher adoption. The data also suggests that simplifying the PV purchasing process, expediting installation approvals, and reducing homeowner involvement might spur greater demand. However, one must approach this with caution as the variability in predictions was more pronounced in the best-case scenarios. The significant influence of effort and duration, as discussed, is a novel finding in PV adoption studies, indicating a need for more in-depth research on these attributes.

Utilizing DCE estimates as a foundation for the model has markedly improved its predictive accuracy. However, for it to be an instrumental tool in policymaking, additional modifications are imperative. Initially, the model operates under the assumption that all homes within a specific region are exposed to sufficient sunlight, thereby ensuring optimal energy generation. This assumption could be misleading. By integrating GIS data, the model can better reflect the diverse and sometimes challenging conditions homeowners encounter when contemplating PV adoption. Furthermore, the methodology employed to gauge the influence of renewable content might benefit from reassessment. The renewable content measure might be intertwined with other attributes
associated with the utility company. For instance, the company's transparency regarding renewable energy sources, billing practices, service quality, and customercentricity could all play roles. If a utility company performs poorly in these areas, the allure of renewable content alone may be insufficient to sway consumers towards PV. Additionally, utility-scale renewable production can be derived from a variety of sources, including solar, wind, biomass, and geothermal energy. Prior research indicates that certain energy sources might be favored over others. As such, utility-scale production using less favored sources might not resonate as positively with consumers. (Herbes & Ramme, 2014; Motz, 2021). Future studies might focus on enhancing the clarity and efficacy of communications regarding renewable content and utility supply. Additionally, it would be beneficial to develop more refined methods for capturing consumers' perceptions of electricity supplies with high renewable content. This could clarify if a higher renewable content in the grid makes renewables seem more mainstream, boosting PV demand, or if respondents feel there's no need for individual PV purchases when the grid is already sustainable. Given that this model represents an initial step towards comparing PV and greener electricity supply based on attributes, there's ample opportunity to refine and adapt it for broader applications.

The ascension of renewables in the electricity supply matrix is not just a trend, it is a testament to the evolving energy priorities of this age. These priorities stem from increasing concerns about climate change which is the driving factor behind accelerated renewable adoption at both the utility-scale and residential levels. Studying this increase is essential to gauge the collective progress towards a sustainable future, and its ripple effects on residential solar PV adoption are both direct and profound. As renewables

shape the broader energy narrative, they concurrently influence individual choices, driving a more sustainable, decentralized, and empowered energy consumer base. This ABM highlights the pivotal role played by incentives and ease of procurement in accelerating solar PV adoption among homeowners. Financial incentives, such as tax credits, rebates, and feed-in tariffs, directly reduce the cost of installation, making solar energy more affordable and appealing. Beyond monetary incentives, other mechanisms like net metering, where users can sell excess electricity back to the grid, and public recognition programs for solar adopters further incentivize the transition. Collectively, these incentives not only make solar adoption economically attractive but also promote a cultural shift towards sustainable energy solutions. Anticipating the growth trajectory of residential solar installations enables governments to draft holistic, forward-looking policies. Easing the procurement process for solar PV can greatly amplify its adoption among residential consumers. A streamlined and simplified process reduces the perceived complexity and administrative burdens often associated with transitioning to solar. When homeowners find it straightforward to understand, select, and install solar PV systems, they are more likely to take the initiative. Additionally, an uncomplicated procurement process can shorten the time from decision-making to installation, resulting in quicker returns on investment. Ultimately, by simplifying the acquisition journey, not only does it increase solar PV uptake, but it also reinforces consumer trust and satisfaction, leading to positive word-of-mouth and broader community engagement in sustainable energy solutions.

As solar PV gains popularity among residential consumers, electric utility companies and CCAs face an evolving energy landscape that necessitates a re-evaluation of their business models. The decentralization of power generation, epitomized by individual households producing their own electricity, challenges traditional utility revenue structures based on centralized generation and transmission. This shift can lead to reduced demand from the grid, potentially eroding utilities' revenue streams. For CCAs, which offer alternative energy sourcing to communities, the proliferation of residential solar might demand a recalibration of their energy portfolios and contracts. Both entities must also grapple with grid management complexities introduced by intermittent solar energy and the need for enhanced infrastructure like energy storage. Predicting these changes and proactively adapting business models will ensure that utilities and CCAs remain viable and relevant in a solar-dominated future.

REFERENCES

- Abreu, J., Wingartz, N., & Hardy, N. (2019). New trends in solar: A comparative study assessing the attitudes towards the adoption of rooftop PV. *Energy Policy*, 128, 347– 363. https://doi.org/10.1016/j.enpol.2018.12.038
- Agarwal, A., Canfield, C., & Fikru, M. G. (2023). Role of Greener Default options on Consumer Preferences for Renewable Energy Procurement (under review). *Renewable EnergyRenewable Energy*.
- Ajzen, I. (1991). The Theory of Planned Behavior. ORGANIZATIONAL BEHAVIOR AND HUMAN DECISION PROCESSES, 50(1), 179–211. https://doi.org/10.47985/dcidj.475
- Alipour, M., Salim, H., Stewart, R. A., & Sahin, O. (2021). Residential solar photovoltaic adoption behaviour: End-to-end review of theories, methods and approaches. *Renewable Energy*, 170, 471–486. https://doi.org/10.1016/j.renene.2021.01.128
- Araghi, Y., Bollinger, L., & Lee, E. P. (2014). Informing agent based models with discrete choice analysis. *Social Simulation Conference*. http://ddd.uab.cat/pub/poncom/2014/128005/ssc14_a2014a30iENG.pdf

- Azhgaliyeva, D., Beirne, J., & Mishra, R. (2023). What matters for private investment in renewable energy? *Climate Policy*, *23*(1), 71–87. https://doi.org/10.1080/14693062.2022.2069664
- Bao, Q., Sinitskaya, E., Gomez, K. J., MacDonald, E. F., & Yang, M. C. (2020). A human-centered design approach to evaluating factors in residential solar PV adoption: A survey of homeowners in California and Massachusetts. *Renewable Energy*, 151, 503–513. https://doi.org/10.1016/j.renene.2019.11.047
- Barabási, A. L. (2009). Scale-free networks: A decade and beyond. *Science*, *325*(5939), 412–413. https://doi.org/10.1126/science.1173299
- Borchers, A. M., Duke, J. M., & Parsons, G. R. (2007). Does willingness to pay for green energy differ by source? *Energy Policy*, *35*(6), 3327–3334. https://doi.org/10.1016/j.enpol.2006.12.009
- Boumaiza, A., Abbar, S., Mohandes, N., & Sanfilippo, A. (2018). Modeling the impact of innovation diffusion on solar PV adoption in city neighborhoods. *International Journal of Renewable Energy Research*, 8(3), 1749–1762. https://doi.org/10.20508/ijrer.v8i3.7999.g7484
- Busic-Sontic, A., & Fuerst, F. (2018). Does your personality shape your reaction to your neighbours' behaviour? A spatial study of the diffusion of solar panels. *Energy and Buildings*, 158, 1275–1285. https://doi.org/10.1016/j.enbuild.2017.11.009
- Cape Analytics. (2021). *These maps show the cities with the most solar in the U.S.* Panasonic. https://www.fastcompany.com/90423202/these-maps-show-the-citieswith-the-most-solar-in-the-u-s
- Cape Light Compact. (2023). C a p e L i g h t C o m p a c t A n n o u n c e s N e w, L o w e r P r i c i n g f o r P o w e r S u p p l y. 1–6. https://www.capelightcompact.org/10655-2/
- Chappin, E. J. L., Schleich, J., Guetlein, M. C., Faure, C., & Bouwmans, I. (2022). Linking of a multi-country discrete choice experiment and an agent-based model to simulate the diffusion of smart thermostats. *Technological Forecasting and Social Change*, 180(January), 121682. https://doi.org/10.1016/j.techfore.2022.121682
- Chen, M. F., & Tung, P. J. (2014). Developing an extended Theory of Planned Behavior model to predict consumers' intention to visit green hotels. *International Journal of Hospitality Management*, 36, 221–230. https://doi.org/10.1016/j.ijhm.2013.09.006
- Dagher, L., Bird, L., & Heeter, J. (2017). Residential green power demand in the United States. *Renewable Energy*, 114, 1062–1068. https://doi.org/10.1016/j.renene.2017.07.111

- Danne, M., Meier-Sauthoff, S., & Musshoff, O. (2021). Analyzing German consumers' willingness to pay for green electricity tariff attributes: a discrete choice experiment. *Energy, Sustainability and Society, 11*(1), 1–16. https://doi.org/10.1186/s13705-021
- Denholm, P., Clark, K., & O'Connell, M. (2016). Emerging Issues and Challenges in Integrating High Levels of Solar into the Electrical Generation and Transmission System. *NREL*, *May*, 68. https://www.nrel.gov/docs/fy16osti/65800.pdf
- EIA. (2023). Renewable generation surpassed coal and nuclear in the U.S. electric power sector in 2022. U.S. Energy Information Administration. https://www.eia.gov/todayinenergy/detail.php?id=55960
- EPA. (2022). *How Do CCAs Work ? When Was CCA-Enabling Legislation Passed in Various. Figure 1*, 1–7. https://www.epa.gov/green-power-markets/community-choice-aggregation#four
- Eyal, P., Rothschild, D., Evernden, Z., Gordon, A., & Damer, E. (2021). Data Quality of Platforms and Panels for Online Behavioral Research Data Quality of Platforms and Panels for Online Behavioral Research. *Behavior Research Methods*, *August*, 1–46.
- Fikru, M. G., & Canfield, C. (2022). Demand for renewable energy via green electricity versus solar installation in Community Choice Aggregation. *Renewable Energy*, 186, 769–779. https://doi.org/10.1016/j.renene.2022.01.008
- Forbes. (2020). Renewable Energy Prices Hit Record Lows: How Can Utilities Benefit From Unstoppable Solar And Wind? https://www.forbes.com/sites/energyinnovation/2020/01/21/renewable-energyprices-hit-record-lows-how-can-utilities-benefit-from-unstoppable-solar-andwind/?sh=7b2ac9782c84
- Forrester, S., Barbose, G. L., O'Shaughnessy, E., Darghouth, N. R., & Crespo Montañés, C. (2022). Residential Solar-Adopter Income and Demographic Trends: November 2022 Update. *Lawrence Berkeley National Laboratory*, 34158. https://emp.lbl.gov/publications/residential-solar-adopter-income-1
- Freedman, J. L., & Fraser, S. C. (2017). Compliance without pressure: The foot-in-thedoor technique. Social Psychology in Natural Settings: A Reader in Field Experimentation, 4(2), 217–232. https://doi.org/10.4324/9781315129747
- Fruth, E., Kvistad, M., Marshall, J., Pfeifer, L., Rau, L., Sagebiel, J., Soto, D., Tarpey, J., Weir, J., & Winiarski, B. (2019a). Economic valuation of street-level urban greening: A case study from an evolving mixed-use area in Berlin. *Land Use Policy*, 89(August), 104237. https://doi.org/10.1016/j.landusepol.2019.104237

- Fruth, E., Kvistad, M., Marshall, J., Pfeifer, L., Rau, L., Sagebiel, J., Soto, D., Tarpey, J., Weir, J., & Winiarski, B. (2019b). Economic valuation of street-level urban greening: A case study from an evolving mixed-use area in Berlin. *Land Use Policy*, 89(October), 104237. https://doi.org/10.1016/j.landusepol.2019.104237
- Funkhouser, E., Blackburn, G., Magee, C., & Rai, V. (2015). Business model innovations for deploying distributed generation: The emerging landscape of community solar in the U.S. *Energy Research and Social Science*, 10, 90–101. https://doi.org/10.1016/j.erss.2015.07.004
- Gómez-Gardeñes, J., & Moreno, Y. (2006). From scale-free to Erdos-Rényi networks. *Physical Review E - Statistical, Nonlinear, and Soft Matter Physics*, 73(5), 1–7. https://doi.org/10.1103/PhysRevE.73.056124
- Gracia, A., Barreiro-Hurlé, J., & López-Galán, B. (2014). Are Local and Organic Claims Complements or Substitutes? A Consumer Preferences Study for Eggs. *Journal of Agricultural Economics*, 65(1), 49–67. https://doi.org/10.1111/1477-9552.12036
- Hartmann, P., & Apaolaza-Ibáñez, V. (2012). Consumer attitude and purchase intention toward green energy brands: The roles of psychological benefits and environmental concern. *Journal of Business Research*, 65(9), 1254–1263. https://doi.org/10.1016/j.jbusres.2011.11.001
- Herbes, C., & Ramme, I. (2014). Online marketing of green electricity in Germany—A content analysis of providers' websites. *Energy Policy*. http://dx.doi.org/10.1016/j.enpol.2013.10.083
- Hess, D. J. (2019). Coalitions, framing, and the politics of energy transitions: Local democracy and community choice in California. *Energy Research and Social Science*, 50(December 2018), 38–50. https://doi.org/10.1016/j.erss.2018.11.013
- Hobman, E. V., & Frederiks, E. R. (2014). Barriers to green electricity subscription in Australia: "love the environment, love renewable energy … but why should i pay more?" *Energy Research and Social Science*, 3(C), 78–88. https://doi.org/10.1016/j.erss.2014.07.009
- Horne, C., Kennedy, E., & Familia, T. (2021). Rooftop solar in the United States: Exploring trust, utility perceptions, and adoption among California homeowners. *Energy Research & Social Science*. https://doi.org/10.1016/j.erss.2021.102308
- Hsu, D. (2022). Straight out of Cape Cod: The origin of community choice aggregation and its spread to other states. *Energy Research and Social Science*, 86(May 2021), 102393. https://doi.org/10.1016/j.erss.2021.102393

- Huang, C., & Shen, R. (2020). Does city or state make a difference? The effects of policy framing on public attitude toward a solar energy program. *Journal of Behavioral Public Administration*, 3(2), 1–21. https://doi.org/10.30636/jbpa.32.126
- IRENA. (2023). Global renewables capacity grew by 10 %. Reuters.
- Islam, T. (2014). Household level innovation diffusion model of photo-voltaic (PV) solar cells from stated preference data. *Energy Policy*, 65, 340–350. https://doi.org/10.1016/j.enpol.2013.10.004
- Kennedy, B. (2019). *More U.S. homeowners say they are considering home solar panels*. Pew Research. https://www.pewresearch.org/fact-tank/2019/12/17/more-u-shomeowners-say-they-are-considering-home-solar-panels/
- Kiesling, E., Günther, M., Stummer, C., & Wakolbinger, L. M. (2012). Agent-based simulation of innovation diffusion: A review. *Central European Journal of Operations Research*, 20(2), 183–230. https://doi.org/10.1007/s10100-011-0210-y
- Kjær, T. (2005). A Review of the Discrete Choice Experiment With Emphasis on its Application in Healthcare. *Health Economic Papers*, *1*, 1–139.
- Kleinberg, J. (2000). The small-world phenomenon: An algorithmic perspective. *Proceedings of the Annual ACM Symposium on Theory of Computing*, 163–170. https://doi.org/10.1145/335305.335325
- Knapp, L., O'Shaughnessy, E., Heeter, J., Mills, S., & DeCicco, J. M. (2020). Will consumers really pay for green electricity? Comparing stated and revealed preferences for residential programs in the United States. *Energy Research and Social Science*, 65, 0–26. https://doi.org/10.1016/j.erss.2020.101457
- Litvine, D., & Wüstenhagen, R. (2011). Helping "light green" consumers walk the talk: Results of a behavioural intervention survey in the Swiss electricity market. *Ecological Economics*, 70(3), 462–474. https://doi.org/10.1016/j.ecolecon.2010.10.005
- Liu, X., O'Rear, E. G., Tyner, W. E., & Pekny, J. F. (2014). Purchasing vs. leasing: A benefit-cost analysis of residential solar PV panel use in California. *Renewable Energy*. https://doi.org/10.1016/j.renene.2014.01.026
- Mamkhezri, J., Thacher, J. A., & Chermak, J. M. (2020). Consumer preferences for solar energy: A choice experiment study. *Energy Journal*, 41(5), 157–184. https://doi.org/10.5547/01956574.41.5.JMAM

- Masad, D., & Kazil, J. (2015). Mesa: An Agent-Based Modeling Framework. *Proceedings of the 14th Python in Science Conference*, *Scipy*, 51–58. https://doi.org/10.25080/majora-7b98e3ed-009
- McFadden, D. (1973). *Conditional logit analysis of qualitative choice behavior*. https://doi.org/10.1080/07373937.2014.997882
- Michaud, G. (2018). Deploying solar energy with community choice aggregation: A carbon fee model. *Electricity Journal*, *31*(10), 32–38. https://doi.org/10.1016/j.tej.2018.11.003
- Mittal, A., Krejci, C. C., Dorneich, M. C., & Fickes, D. (2019). An agent-based approach to modeling zero energy communities. *Solar Energy*, 191, 193–204. https://doi.org/10.1016/j.solener.2019.08.040
- Mohandes, N., Sanfilippo, A., & Fakhri, M. Al. (2018). Modeling residential adoption of solar energy in the Arabian Gulf Region. *Renewable Energy, september*, 2–5.
- Momsen, K., & Thomas, S. (2014). From intention to action: Can nudges help consumers to choose renewable energy? *Energy Policy*. https://doi.org/10.1016/j.enpol.2014.07.008
- Motz, A. (2021). Consumer acceptance of the energy transition in Switzerland: The role of attitudes explained through a hybrid discrete choice model. *Energy Policy*, 151, 112152. https://doi.org/10.1016/j.enpol.2021.112152
- NREL. (2021). Documenting a Decade of Cost Declines for PV Systems. https://www.nrel.gov/news/program/2021/documenting-a-decade-of-cost-declines-for-pv-systems.html
- O'Shaughnessy, E., Barbose, G., & Wiser, R. (2020). Patience is a virtue: A data-driven analysis of rooftop solar PV permitting timelines in the United States. *Energy Policy*, *144*. https://doi.org/10.1016/j.enpol.2020.111615
- O'Shaughnessy, E., Heeter, J., & Burd, R. (2021). Status and Trends in the US Voluntary Green Power Market (2020 Data). *NREL*, *October*. http://www.nrel.gov/docs/fy16osti/65252.pdf
- O'Shaughnessy, E., Heeter, J., Gattaciecca, J., Sauer, J., Trumbull, K., & Chen, E. (2019). Empowered Communities: The Rise of Community Choice Aggregation in the United States. *Energy Policy*. https://www.sciencedirect.com/science/article/abs/pii/S0301421519304434

- Ozaki, R. (2011). Adopting sustainable innovation: What makes consumers sign up to green electricity? *Business Strategy and the Environment*, 20(1), 1–17. https://doi.org/10.1002/bse.650
- Pichert, D., & Katsikopoulos, K. V. (2008). Green defaults: Information presentation and pro-environmental behaviour. *Journal of Environmental Psychology*, 28(1), 63–73. https://doi.org/10.1016/j.jenvp.2007.09.004
- Rai, V., & Beck, A. L. (2015). Public perceptions and information gaps in solar energy in Texas. *Environmental Research Letters*, 10(7). https://doi.org/10.1088/1748-9326/10/7/074011
- Rai, V., & Henry, A. D. (2016). Agent-based modelling of consumer energy choices. *Nature Climate Change*, 6(6), 556–562. https://doi.org/10.1038/nclimate2967
- Rai, V., & Robinson, S. A. (2013). Effective information channels for reducing costs of environmentally- friendly technologies: Evidence from residential PV markets. *Environmental Research Letters*, 8(1). https://doi.org/10.1088/1748-9326/8/1/014044
- Rai, V., & Robinson, S. A. (2015). Agent-based modeling of energy technology adoption: Empirical integration of social, behavioral, economic, and environmental factors. *Environmental Modelling and Software*, 70(March), 163–177. https://doi.org/10.1016/j.envsoft.2015.04.014
- S&P Global. (2023). California CCA membership surpasses 200 communities , 28 % of utility load. 1–6.
- Sagebiel, J., Müller, J. R., & Rommel, J. (2014). Are consumers willing to pay more for electricity from cooperatives? Results from an online Choice Experiment in Germany. *Energy Research and Social Science*, 2(52385), 90–101. https://doi.org/10.1016/j.erss.2014.04.003
- Schelly, C. (2014). Residential solar electricity adoption: What motivates, and what matters? A case study of early adopters. *Energy Research and Social Science*. http://dx.doi.org/10.1016/j.erss.2014.01.001
- Schulte, E., Scheller, F., Pasut, W., & Bruckner, T. (2021). Product traits, decisionmakers, and household low-carbon technology adoptions: moving beyond single empirical studies. *Energy Research and Social Science*.
- Schulte, E., Scheller, F., Sloot, D., & Bruckner, T. (2022). A meta-analysis of residential PV adoption: the important role of perceived benefits, intentions and antecedents in solar energy acceptance. *Energy Research and Social Science*, 84. https://doi.org/10.1016/j.erss.2021.102339

- SEIA. (2023). Solar Installations in 2023 Expected to Exceed 30 GW for the First Time in History / SEIA. 10–11.
- Sergi, B., Davis, A., & Azevedo, I. (2018). The effect of providing climate and health information on support for alternative electricity portfolios. *Environmental Research Letters*, *13*(2). https://doi.org/10.1088/1748-9326/aa9fab
- Shaughnessy, E. O., Heeter, J., Gattaciecca, J., Trumbull, K., Chen, E., Shaughnessy, E. O., Heeter, J., Gattaciecca, J., Sauer, J., Trumbull, K., & Chen, E. (2019).
 Community Choice Aggregation: Challenges, Opportunities, and Impacts on Renewable Energy Markets Community Choice Aggregation: Challenges, Opportunities, and Impacts on Renewable Energy Markets. *National Renewable EnergyLaboratory (NREL), February*, 1–56.
- Sigrin, B., Dietz, T., Henry Adam, Ingle, A., Lutzenhiser, L., Moezzi, M., Spielman, S., Stern, P., Todd, A., Tong, J., & Wolske, K. (2017). Understanding the Evolution of Customer Motivations and Adoption Barriers in Residential Solar Markets: Survey Data. National Renewable Energy Laboratory. *National Renewable Energy Laboratory*, 10–12.
- Sigrin, B., Pless, J., & Drury, E. (2015). Diffusion into new markets: Evolving customer segments in the solar photovoltaics market. *Environmental Research Letters*, 10(8). https://doi.org/10.1088/1748-9326/10/8/084001
- Souchet, L., & Girandola, F. (2013). Double foot-in-the-door, social representations, and environment: Application for energy savings. *Journal of Applied Social Psychology*, *43*(2), 306–315. https://doi.org/10.1111/j.1559-1816.2012.01000.x
- Stern, P. C., Dietz, T., Abel, T., Guagnano, G. A., & Kalof, L. (1999). A value-beliefnorm theory of support for social movements: The case of environmentalism. *Human Ecology Review*, 6(2), 81–97.
- SVCE. (2023). Silicon Valley Clean Energy Residential Generation Rates and Generation Service Cost Comparison Silicon Valley Clean Energy Residential Generation Rates and Generation Service Cost Comparison. 7–10. https://svcleanenergy.org/wp-content/uploads/Residential-Rate-Update-05.01.2023-_formatted.pdf
- Troiano, S., Marangon, F., Tempesta, T., & Vecchiato, D. (2016). Organic vs local claims: Substitutes or complements for wine consumers? A marketing analysis with a discrete choice experiment. *New Medit*, *15*(2), 14–21.
- U.S. DOE EIA. (2021). Renewables became the second-most prevalent U.S. electricity source in 2020. *Today In Energy*, 2021–2022. https://www.eia.gov/todayinenergy/detail.php?id=48896

- Wang, G., Zhang, Q., Li, Y., & Li, H. (2018). Policy simulation for promoting residential PV considering anecdotal information exchanges based on social network modelling. *Applied Energy*, 223(March), 1–10. https://doi.org/10.1016/j.apenergy.2018.04.028
- Watts, D. J., & Strogatz, S. H. (1998). Collective dynamics of "small-world" networks. *Conservation Biology*, 32(2), 287–293. https://doi.org/10.1111/cobi.13031
- Weaver, A. (2017). The Social Acceptance of Community Solar: A Portland Case Study. *ProQuest Dissertations and Theses*, 175. http://193.60.48.5/docview/1964910246?accountid=15997%0Ahttp://resolver.ebsco host.com/openurl?ctx_ver=Z39.88-2004&ctx_enc=info:ofi/enc:UTF-8&rfr_id=info:sid/ProQuest+Dissertations+%26+Theses+A%26I&rft_val_fmt=info: ofi/fmt:kev:mtx:dissertation&rft.genre=di
- Wei, J., Zhao, X., Liu, Y., & Xi, Y. (2021). Measuring purchase intention towards green power certificate in a developing nation: Applying and extending the theory of planned behavior. *Resources, Conservation & Recycling.* https://doi.org/10.1016/j.resconrec.2020.105363
- Wilson, P. (2020). Four Types of Scandals Utility Companies Get Into With Money From Your Electric Bills. *ProPublica*, 1–7. https://www.propublica.org/article/four-types-of-scandals-utility-companies-get-into-with-money-from-your-electric-bills
- Wolske, K. S., Stern, P. C., & Dietz, T. (2017). Explaining interest in adopting residential solar photovoltaic systems in the United States: Toward an integration of behavioral theories. *Energy Research and Social Science*, 25, 134–151. https://doi.org/10.1016/j.erss.2016.12.023
- Wolske, K. S., Todd, A., Rossol, M., James, M., & Sigrin, B. (2018). Accelerating demand for residential solar photovoltaics: Can simple framing strategies increase consumer interest? *Global Environmental Change Journal*, 53. https://doi.org/10.1016/j.gloenvcha.2018.08.005
- Wood Mackenzie, & SEIA. (2022). U.S. SOLAR MARKET INSIGHT Executive Summary. GTM Research and SEIA, December, 5. http://www.seia.org/sites/default/files/k7bZk7JSHC2016Q2SMI.pdf
- Zang, T., Genseler, S., & Garcia, R. (2011). J of Product Innov Manag 2011 Zhang -A Study of the Diffusion of Alternative Fuel Vehicles An Agent-Based Modeling.pdf. *Journal of Product Innovation Management*, 28, 152–168.

- Zarwi, F. El, Vij, A., & Walker, J. L. (2017). A Discrete Choice Framework for Modeling and Forecasting The Adoption and Diffusion of New Transportation Services Feras El Zarwi (corresponding author) Department of Civil and Environmental Engineering University of California at Berkeley 116 McLaughli. *Transportation Research Part C: Emerging Technologies*, 1–32. https://doi.org/10.1016/j.trc.2017.03.004
- Zhang, H., Vorobeychik, Y., Letchford, J., & Lakkaraju, K. (2016). Data-driven agentbased modeling, with application to rooftop solar adoption. *Autonomous Agents and Multi-Agent Systems*, 30(6), 1023–1049. https://doi.org/10.1007/s10458-016-9326-8

IV. GO BIG OR GO HOME: HOW UTILITY-SCALE RENEWABLES AND COMMUNITY CHOICE AGGREGATION MIGHT ECLIPSE RESIDENTIAL SOLAR PV

Ankit Agarwal¹, Casey Canfield¹, and Mahelet Fikru²

¹Engineering Management and Systems Engineering, Missouri University of Science and Technology, Rolla, MO 65409

²Department of Economics, Missouri University of Science and Technology, Rolla, MO 65409

ABSTRACT

Installation of solar photovoltaic (PV) systems is often a good investment, both from financial and environmental perspectives, for homeowners. Recently, centralized renewable energy generation has grown in the United States, becoming increasingly accessible to residential consumers via business models such as green pricing and Community Choice Aggregation (CCA). CCAs are community-owned entities that facilitate the transformation of the local electricity retail landscape, offering consumers economical renewable sourcing and equitable billing procedures as well as bolstering the local economy. CCA consumers may perceive residential PV investments differently, given the improved economic and environmental context. This study evaluates the impact of messages about high renewable content from different senders on consumers' PV adoption intentions and perceptions. Through a 2 x 4 factorial design, consumers were shown messages detailing four levels of renewable content, both within and outside a CCA framework. The messages were anticipated to cause a shift in their interest towards individual PV installations, intention to engage local installation agencies, and overarching perceptions of PV. Multiple linear regression models were constructed with interest and intention serving as the dependent variables, fit against promotional content and other salient adoption determinants. The outcomes reveal a noteworthy inverse relationship between high renewable content and the interest in PV adoption. Intriguingly, perceptions about PV remained unaltered by CCA-driven promotional content. This research introduces a novel context for evaluation of PV by residential consumers, bearing significant repercussions for the renewable energy sector. Keywords – Community Choice Aggregation, Residential Solar PV, Marketing Messages, PV Adoption, Context

1. INTRODUCTION

Most households install solar photovoltaics (PV) with the intention of long-term energy cost savings (i.e., financial reasons) and/or distancing themselves from fossil fuels (i.e., environmental reasons). However, barriers such as high initial investments, technical limitations, and information barriers in certain regions hinder the adoption of solar PV systems, despite the interest expressed by homeowners. Despite these barriers, residential solar PV generation capacity is projected to increase by at least 30% in the next five years (Wood Mackenzie & SEIA, 2022). However, residential PV installations make up barely 20% of generation capacity. The rest of the PV generation capacity comes from utility-scale and community solar projects, which are projected to grow by 70% and 40% over the next five years (Wood Mackenzie & SEIA, 2022). It is unclear how this rapid expansion of utility-scale renewables will influence residential solar PV adoption, especially in the context of novel business models.

Due to federal and state policies, renewable generation capacity in the US is set to expand through 2030 (U.S. DOE EIA, 2021). This expansion is partially driven by community-based efforts to increase renewable procurement. Policy entrepreneurs have been actively working to empower communities by restructuring retail electricity markets, challenging the dominance of investor-owned utilities (IOUs), and introducing community-owned electricity services known as Community Choice Aggregation (CCA) (Hsu, 2022). Originating in Massachusetts in 1999, CCAs have expanded to ten states thus far with seven more states expected to introduce legislation (EPA, 2022). When allowed via state legislation, CCAs enable local organizations, often non-profits collaborating with municipalities, to procure electricity for a specific territory. These entities are not classified or regulated as electric utilities but are instead recognized as "electric service providers." The primary objective of these entities is to aggregate the demand within a city or community, negotiate lower rates from utilities, and often prioritize purchasing power from large-scale renewable generation projects. In certain cases, CCAs have even promoted local renewable generation systems, typically smaller than 1 MW, to enhance local grid stability and minimize transmission losses (Michaud, 2018). As of 2022, CCAs are serving approximately 4.7 million customers, with projected expansion to reach 11-18 million customers within the next decade.

Today, more than 50% of residential customer participation in green electricity sales occurs through CCAs (O'Shaughnessy et al., 2021). This is largely attributed to the opt-out design, where customers are automatically enrolled in renewable energy

procurement unless they remove themselves from the CCA and secure electricity directly from the incumbent provider (Momsen & Thomas, 2014; Pichert & Katsikopoulos, 2008). Most customers do not remove themselves and CCAs have high customer retention rates of 85-95% (Michaud, 2018; O'Shaughnessy et al., 2019, 2021). In legislative processes, CCAs in coalition with consumer groups have supported fairness in pricing, reduced greenhouse gases, and local autonomy (Hess, 2019). CCAs such as Silicon Valley Clean Energy in California offer 100% clean, carbon-free electricity by default to all customers with the option to upgrade to 100% wind and solar supply. Apart from reducing their customers' environmental impact, their rates for were lower than Pacific Gas and Electric, the IOU in the region, in 2023 (SVCE, 2023). Similarly in Massachusetts, Cape Light Compact (CLC) announced a 32% decrease in tariffs while maintaining nearly 60% renewables in their standard supply (Cape Light Compact, 2023).

Given that CCAs are a newer market model compared to traditional utilities, it is unclear whether and how consumers' procurement preferences and behavior respond to the context of CCAs. For example, having more renewable energy in the electricity mix with competitive prices may influence consumers' perception of the financial and nonfinancial costs of installing solar PV. Residential solar PV installations require adequate sunlight, adherence to specific building codes, and considerable time and financial investment for renovation and installation. For residents who are disinclined to bear the upfront costs of individual solar panel procurement, solve technical challenges, or engage in the bureaucratic processes of installation, the CCA model allows them to reap the benefits of renewable generation with little effort. Moreover, CCAs are established

through democratic processes, with local officials elected to prioritize consumers' interests above all else. When the CLC was awarded its initial power supply contract, it dedicated resources to programs benefiting businesses, government agencies, and lowincome households, emphasizing energy efficiency development. The Northeast Ohio Public Energy Council (NOPEC) supported local projects in communities by advocating for the elimination of exit fees, competitive pricing, and low-interest loan programs for local projects (Hsu, 2022). Overall, CCAs have demonstrated a commendable track record of reinvesting benefits into communities and serving customers. Conversely, IOUs have gained notoriety for imposing inflated rates on customers that allegedly do not align with the true cost of services. They consistently raise tariffs to maximize profits for their shareholders and bypass pro-consumer policies (Wilson, 2020). Such practices erode consumer trust in utilities, compelling them to adopt solar PV as a safeguard against escalating costs and unscrupulous IOU practices. Introducing CCAs into the context of solar PV adoption may potentially reduce the demand for solar PV, as consumers may feel better protected by the pro-consumer policies and practices of CCAs, thereby fostering trust in the energy sector.

Previous research has highlighted the importance of including the traits of decisionmaker, decision object and the context of the decision when explaining intentions to adopt low carbon technology such as solar PV (Schulte et al., 2021). The intention to adopt solar PV is explained through financial and environmental benefits, subjective norms, and technical and non-technical considerations. It is likely that the influence of these belief constructs may be moderated by different contexts such as net-metering policies, financing options, and diffusion stage in the region (Schulte et al., 2022). While

these contextual considerations are explicitly about PV itself, external factors such as CCA-sourced cheap renewable energy may also alter how these belief constructs affect intention and interest for PV. This study measures the impact of introducing a CCA program that provides electricity from cleaner sources at competitive rates on the perceived benefits, behavioral control, interest and intention to adopt PV systems. Our contribution is to operationalize contextual considerations in PV adoption using messages about a CCA's impact on household energy costs and carbon emissions. Providing greener electricity at a lower price changes the context, which may influence perception and therefore adoption of solar PV. We hypothesize that higher levels of renewable content provided to households by default through a community-owned entity will be associated with lower intentions to adopt PV, diminished perceived benefits of PV, and heightened sensitivity to barriers in PV adoption. This study has implications for the marketing of renewable energy procurement options, design of business models for CCAs, and long-term planning for consumer demand for renewable energy.

2. LITERATURE REVIEW

2.1. ROLE OF CONTEXT ON PV ADOPTION

Prior literature manipulated context via marketing messages to influence consumer interest in solar PV (Huang & Shen, 2020; Wolske et al., 2018). In one study, while no significant impacts for gain/loss and temporal frames were observed, advertisements highlighting detailed financial returns tended to increase appeal as the level of yearly benefits increased. Conversely, ads that provided a simple explanation of

benefits resulted in significantly higher skepticism. These findings suggest that solely focusing on financial benefits and break-even points does not significantly influence consumer intentions (Wolske et al., 2018). In another study conducted in the United States, the combination of spatial construal frames (city government vs. state government) and economic vs. environmental benefit messages were used to gauge the impact on willingness to pay and policy support for PV systems. The results suggest that willingness to pay for PV was higher when a policy framed as environmentally beneficial was implemented by the city government. On the other hand, policies framed as economically beneficial received greater support when implemented by the state government. This study suggests that the perceived effectiveness of city governments in delivering environmentally friendly policies may be higher (Huang & Shen, 2020). CCA programs are often implemented by city governments to meet the communities emission reduction goals, and may be an important context in PV adoption. Notably, both studies measured interest and willingness to pay for individual PV adoption in the absence of other renewable generation options.

Utilities often incorporate residential solar, alongside their own generation capacity, to fulfill the RPS requirements. Additionally, government agencies provide incentives for PV adoption funded by taxpayers. A study in New Mexico measured preferences across different individuals with respect to PV and higher renewable content in the grid (Mamkhezri et al., 2020). The study examined participants' willingness to pay, reflected in higher monthly bills, for rooftop PV incentives and the installation costs of utility-scale solar to meet RPS goals. The findings suggested that participants were reluctant to financially support residential rooftop PV installations when the RPS demanded over 62% of grid electricity generation to come from renewable sources. The added RPS requirement was preferred to be fulfilled from utility-scale installations and diminished willingness to pay for rooftop PV incentivizing policies. The reduced interest for rooftop PV friendly policies implies that participants would be less interested in acquiring the technology for their own household. It is possible that if consumers are already paying for the administrative costs of CCA development and utility-scale renewable generation facilities through taxes and tariffs, they may be unwilling to adopt rooftop PV individually.

Hypothesis 1: For messages where Renewable Content is higher, there is lower Interest and Intention to adopt PV.

Hypothesis 2: The effect of higher Renewable Content in lowering the Interest and Intention to adopt PV is stronger in the CCA Context.

2.2. MODERATING EFFECTS OF CONTEXT ON PV ADOPTION

Solar PV adoption has garnered significant attention in social science literature during the past two decades. Various behavioral frameworks, including the value-beliefnorm theory (VBN), diffusion of innovation theory (DOI), and theory of planned behavior (TPB), have been employed in experimental studies and simulation-based approaches to offer valuable insights into the characteristics of PV adopters, PV considerers, and non-adopters (Alipour et al., 2021; Rai & Beck, 2015; Rai & Robinson, 2015; Wolske et al., 2017). According to VBN theory, individuals' pro-environmental behaviors are influenced by the interplay between their personal values, beliefs about the environment, and social norms. When individuals have pro-environmental values, hold

beliefs that support environmental protection, and perceive social norms that endorse sustainable behaviors, they are more likely to engage in actions that benefit the environment (Stern et al., 1999). The DOI theory explains how new ideas, products, or technologies spread and are adopted by individuals or groups within a society (Islam, 2014)(Rogers, 2003). It describes the process by which innovations are communicated over time and the factors that influence their adoption. The theory identifies several factors that influence the rate and extent of adoption as well as categorize individuals or groups based on their readiness to adopt an innovation. Some of the belief constructs from TPB overlap with those of DOI. TPB is a psychological framework that explains and predicts human behavior based on three key factors: attitudes, subjective norms, and perceived behavioral control. Attitudes refer to an individual's positive or negative evaluations of a particular behavior. Subjective norms represent the perceived social pressure or influence from important others in an individual's social environment. Perceived behavioral control refers to an individual's perception of the ease or difficulty of performing the behavior. This theory is commonly used to explain pro-environment behavior (Abreu et al., 2019; Chen & Tung, 2014; Litvine & Wüstenhagen, 2011; Wei et al., 2021). Attempts to develop integrated frameworks and meta-analysis have found that the inclusion of perceived benefits, environmental concern, Novelty Seeking, subjective norms, and perceived behavioral control (hard and soft barriers) play a significant role in explaining the intention to adopt PV at the residential level (Schulte et al., 2022; Wolske et al., 2017). To enhance the explanatory power of these frameworks, inclusion of context was first recommended during the developmental phase of TPB (Ajzen, 1991) as well as more recent studies (Schulte et al., 2021, 2022). The context could either be specific to

PV, such as net-metering policies or diffusion stage, or it can be external, such as expansion of large-scale renewable generation. These contexts could alter the effects of consumers' beliefs when evaluating the decision object, residential solar PV. Here, we focus on how the context influences perceived benefits, soft barriers, and trust.

Perceived benefits contribute to the formation of positive attitudes toward solar PV systems. In TPB, attitudes are considered a key determinant of intention and subsequent behavior. When individuals perceive significant benefits associated with adopting solar PV, such as cost savings, environmental sustainability, or energy independence, it enhances their overall attitude toward using this technology. Positive attitudes, in turn, increase the likelihood of intending to install solar PV systems and actually following through with the behavior. The benefits of PV have been included in behavioral models to explain the attitude towards adoption behavior and were found to have significant positive effect (Horne et al., 2021; Rai & Beck, 2015). CCAs are also known to offer similar advantages to consumers, although, the savings from PV can be higher if the net-metering policies are favorable. A previous study found that consumers who already owned PV systems declined green tariff subscriptions, stating that they were already contributing to reducing carbon emissions and were unwilling to pay extra for the service (Hobman & Frederiks, 2014). Given that CCAs are providing carbon-free electricity at no extra cost or sometimes at a lower cost, it may be possible that a reverse effect could exist in adoption decisions. If CCAs can meet consumers' needs for cost savings and emission reductions, it remains uncertain whether they would still be interested in adopting PV systems. Therefore, we hypothesize that:

Hypothesis 3: For messages where Renewable Content is higher, the positive effect of Perceived Benefits on Intention and Interest is lower.

The upfront costs and installation efforts associated with PV systems often deter homeowners from adopting this technology. Previous research studies have consistently identified these barriers and highlighted the perceived riskiness of PV as a significant obstacle to its widespread adoption (Rai & Beck, 2015; Schulte et al., 2021; Wolske et al., 2017). Specifically, the main concern lies in the uncertainty of achieving a return on investment after making a substantial upfront payment for installation. Moreover, consumers are hesitant to undertake the extensive efforts involved in securing financing, identifying a suitable installation agency, and ensuring compliance with relevant building codes. Consequently, homeowners expect a reasonable level of certainty regarding the returns on their investment. The emergence of CCAs offers a potential solution to mitigate the risks associated with PV installation. CCAs enable community-level renewable energy procurement, eliminating the need for individual households to bear upfront costs or administrative burdens. By pooling resources and coordinating collective efforts, CCAs provide an alternative avenue for accessing renewable energy. Thus, we propose the following hypothesis:

Hypothesis 4: For messages where Renewable Content is higher, the negative effect of soft barriers on Intention and Interest is higher.

Another recent study measured consumers' perceptions of IOUs in terms of trust, to explain interest in PV adoption (Horne et al., 2021). This study revealed how strained relationships between utilities and customers in California led to higher consumer interest in PV adoption. In contrast, CCAs exhibit higher customer retention rates and enjoy a more favorable perception due to their focus on local control, sustainability, and cost savings rather than maximizing shareholder profit (Hess, 2019). It is possible that a community-owned entity would reduce consumer interest in PV due to high trust. We thus developed the following hypotheses:

Hypothesis 5: For higher Trust, the negative effect of CCA Context on Interest and Intention to adopt PV is higher.

Hypothesis 6: For higher Trust, the negative effect of Renewable Content on Interest and Intention to adopt PV is higher.

2.3. ADDITIONAL FACTORS TO PREDICT PV ADOPTION

Adoption of solar PV is also influenced by novelty seeking, hard technical barriers, environmental concern, and subjective norms – the effect of which may be influenced by context. PV systems are often preferred by consumers who are drawn to the novelty of a product (Wolske et al., 2017; Wolske et al., 2018). For example, urban respondents tend to have a higher preference for rooftop PV rather than utility-scale generation (Mamkhezri et al., 2020). This was attributed in part to urban respondents' higher likelihood to need to have innovative technologies around them for emissions reductions. Despite CCAs offering similar emission reductions and potential financial savings, they may lack the innovativeness that PV offers to consumers.

Hard technical barriers are deterrents which are typically beyond the consumers control such as the solar irradiation in their region, inclination and direction of roofs, and shade around their properties (Rai & Robinson, 2013; Schulte et al., 2022). These factors are already accounted for as contextual considerations for PV adoption as they are external influences which are beyond the decision subject and object (Schulte et al., 2021).

Higher environmental concern is often attributed to consumers likelihood to combine solar PV with utility-scale green electricity options (Borchers et al., 2007; Hartmann & Apaolaza-Ibáñez, 2012). Despite having a CCA in the region, consumers who are looking to make a direct impact on emissions reduction may be more willing to adopt PV.

Consumers' decisions regarding the adoption of PV systems are also influenced by the information they receive from their peers (Rai & Robinson, 2013; Sigrin et al., 2015). When consumers observe their peers actively participating in the PV market, it can significantly impact their own inclination to engage in PV adoption. The degree to which peer behavior influences an individual's decision-making process is closely tied to the stage of PV diffusion within a community. In regions where a substantial number of individuals have already adopted PV systems, such as California and New Jersey, consumers may already hold a favorable perception of the product regardless of the context.

3. METHOD

3.1. DESIGN

In a 2 x 4 experimental design, we manipulated the CCA Context (present, not present) and the renewable content in the electricity supply (no information, 30%, 60%, 100%). Both factors were presented in a single marketing message, followed by an

advertisement for PV. The CCA Context encompassed two levels: CCA present or not present. The CCA present condition described the replacement of their existing utility with a newly established community-owned entity. The marketing message emphasized that the CCA is community-owned and has competitive rates. In contrast, groups without the CCA Context were instructed to consider the marketing message as originating from their existing utility. The second factor, Renewable Content, comprised four levels: no information, 30%, 60%, and 100%. These levels corresponded to prevailing standards set by CCAs across various regions in the United States. The no information level withheld information about Renewable Content from the message to serve as a control condition. In the CCA Context, the no information group was exclusively informed about the community-owned and competitive rates aspects, while in groups without the CCA Context, participants received no information about their utility and were directly exposed to the PV ad. This design enabled independent assessment of the effects attributable to Renewable Content and the CCA Context, while also providing a baseline for comparison with other groups. Moreover, the groups exposed to the CCA Context along with information about renewable content enabled us to evaluate the combined effects of both factors on participants' interest and intention to adopt PV technology.

Subsequently, participants were informed about the opportunity to install solar PV systems through a local company. The provided advertisement indicated that the company could provide installation, maintenance services, troubleshooting support, and financing options. The dependent variables were the intention to contact the solar installation company and the overall interest in PV adoption for their household.

3.2. SAMPLE

We recruited adult homeowners and residents of single family homes in the United States who represent a diverse range of demographic characteristics via Prolific (Eyal et al., 2021). Our sample consisted of individuals residing in states where CCAs are currently operational (CA, IL, OH, VA, MD, NJ, NY, NH, MA, RI), states where legislation for CCAs is in progress (AZ, CO, MI, CT), and states where CCAs are being monitored by the Environmental Protection Agency (EPA) for potential implementation (WA, OR, NM). By limiting our sample to the 17 states where CCAs have been or are likely to be implemented, participants are more likely to be familiar with the concept of CCAs and state policies that support the adoption of PV systems. Otherwise, these states vary in terms of political alignment, demographic characteristics, and solar irradiance levels (Horne et al., 2021; Wolske et al., 2017, 2018). Based on a power analysis to detect a small effect, we recruited 1200 participants (approximately 150 per condition).

3.3. MEASURES

Dependent Variables: Previous studies on consumers' evaluation of PV have used both interest and intention as an outcome variables (Horne et al., 2021; Rai & Beck, 2015). Intention is a more proximal construct compared to interest. Intention refers to a person's immediate plans or willingness to perform a particular behavior, in this case calling the solar installation company for a quote. Meanwhile, interest represents a general liking or attraction towards an activity or topic, in this case installing solar on the participant's home. Intention aligns with the action-oriented aspect of behavior (Ajzen, 1991). It signifies an individual's commitment to carry out a specific behavior in the near future. In

contrast, interest may be more exploratory or reflective of general preferences without a firm commitment to take action. However, interest can still be a valuable predictor in certain contexts or when combined with other variables. For example, interest may be more influential when predicting behaviors that are not directly under an individual's control or when considering long-term commitment to a behavior. Additionally, interest can shape the formation of beliefs and attitudes that contribute to the development of intention. Therefore, while intention is generally considered a stronger predictor, both interest and intention can provide valuable insights into understanding and predicting behavior within the framework of TPB. The measures for interest and intention are reported in Table 1.

Independent Variables: As reported in Table 1, we included CCA Context, Renewable Content, Perceived Benefits, Soft Barriers, Trust, Environmental Concern, Consumer Novelty Seeking, Consumer Independent Judgment Making, Subjective Norm, Technical Barriers. To measure Perceived Benefits, participants were asked whether they agree or disagree if PV adoption would reduce their household's environmental impact and emissions, increase their home's resale value and monetary savings . Soft barriers such as hassles of installing PV, affordability, and uncertainty of receiving significant returns are measured using four items, consistent with (Rai & Beck, 2015; Wolske et al., 2017). To measure Environmental Concern, a 7-item scale was adopted from the previous study (Horne et al., 2021). To measure Novelty Seeking, we replicated the 3-item scale for Consumer Novelty Seeking combined with a 3-item measure of Consumer Independent Judgment Making (reversed), as utilized in the integrated behavioral study (Wolske et al., 2017). To measure subjective norms, we employed the 3-item scale, which encompasses both descriptive and injunctive norms (Wolske et al., 2017). To measure influence of Technical barriers of PV adoption were measure using statements on home suitability and solar irradiation in the region, consistent with (Wolske et al., 2017). The measurement of trust is evaluated using a 5-point scale comprising two items that focus on consumers' trust in Illumin's claims on the postcard and regarding their commitment to acting in the best interests of customers. All dependent and independent variable measures are available in Table 1. To enhance the robustness of the study, attention and manipulation check questions were incorporated at each stage of the treatment.

Participants solely exposed to the CCA Context, without renewable content, did not encounter question 2, while those exposed solely to the PV ad were excluded from the preceding questions. The correct answer for these questions depended on the assigned condition. In addition, following exposure to the PV advertisement, participants were asked: "Which of the following services are provided by SunSpark? Please select all that apply. A) Installation, B) Maintenance, C) Troubleshooting, D) Financing."

Variable	Measures	
Dependent Variables		
Intention	I intend to call/email SunSpark to get a quote	
Interest	I am interested in getting solar panels for my home	
Independent Variables		
CCA Context	Dummy Variable (0, 1)	
Renewable Content	Categorical Variable (no information, 30%, 60%, 100%)	
	Solar panels can reduce my household's environmental impact	
Perceived Benefits	Solar panels can reduce carbon emissions for my residence	
	Solar panels can save money for my household in the long run	
	Solar panels improve the resale value of my home	

 Table 1: Dependent and Independent Variables. All Likert scale questions were measured using a 7-point scale.

Soft Barriers	Solar panels would not provide the level of benefits I would be
	Expecting
	Installing solar panels is a nassie
	I can't afford solar on my family budget
Trust	Solar panels are still very expensive, even with government incentives
	I trust that my electricity provider would always act in my best interest
	I trust the communications I receive from my electricity provider
	I care about conserving nature
Environmental Concern	It is important to me to take care of the environment in my local
	community
	It is important to me to protect the environment for people around the
	world
	It is important to me to protect the environment for future generations
	I am worried about climate change
	I am worried about the impacts of climate change in my community
Consumer Novelty Seeking	I am worried about the impacts of climate change around the world
	I continuously look for new experiences from new products
	I continuously look for new products and brands
	I like to visit places where I'm exposed to information about new
	products and brands
Consumer Independent Judgement Making	Before I buy a new product or service, I often ask acquaintances about
	their experiences with that product or service (reversed)
	Before buying a new brand, I usually ask someone who has experience
	with the brand for advice. (reversed)
	When considering a new product/service, I usually trust the opinions of
	friends who have used the product/service. (reversed)
Subjective Norms	Most people who are important to me would support me if I decided to
	go solar
	People who are important to me would be in favor of installing solar
	panels
	My family members would be opposed to getting solar panels.
	(reversed)
Technical Barriers	It's not sunny enough in my area for solar panels to work well
	At my home, there's no place to put solar panels that would get enough
	sunlight

Table 1: Dependent and Independent Variables. All Likert scale questions were measured using a 7-point scale. (cont.)

In addition, we measured individual differences including their current electricity bill cost, homeownership status (to confirm eligibility as homeowners), presence of solar panels on their property (applicable only to homeowners who confirmed ownership), previous exposure to PV advertisements, state of residence, age, political affiliation, ideological leanings, educational background, income, race, and gender.

3.4. STIMULI

The experimental design encompassed eight groups, with four groups situated within the CCA Context. Participants in these groups were exposed to a scenario where their local government replaced the incumbent Investor-Owned Utility (IOU) with a CCA known as Illumin Community Energy. Participants were informed that the newly adopted CCA would provide clean and carbon-free electricity at no additional cost, with automatic enrollment and the option to opt-out if desired. Emphasizing the renewable nature of the electricity supply, a postcard from the CCA highlighted varying levels of renewable content (30%, 60%, and 100%), sourced from solar, wind, hydropower, and biomass generation (see Figure 1). In one of the four CCA groups, referred to as the control group, participants received the scenario without specific information about the renewable content and sources. Meanwhile, groups without the CCA Context were presented with postcards providing details about upgraded renewable content in their supply, with no additional fees (with one group receiving no information). Subsequently, all participants were exposed to an advertisement from a local solar installer agency (see Figure 2).

This advertisement conveyed messages related to the viability of solar energy adoption for homeowners, taking into account factors such as solar irradiance and associated costs, including available financing options



Figure 1: Six groups were informed about renewable content through postcards out of which only three included a CCA context. Another group was given a CCA context without the inclusion of renewable content in the postcard



Figure 2: PV ad received after electricity provider's messages.

. Additionally, the advertisement alluded to potential monetary savings achievable through PV installation, without providing a specific amount. Contact information of the solar installer was provided to facilitate further engagement. The fifth and final group, served as the control for the solar advertisement, received no information about the CCA and solely viewed an advertisement promoting solar PV.

3.5. PROCEDURE

Prior to participation, informed consent was obtained from each participant. They were then randomly assigned to one of eight experimental conditions. To verify participants' engagement with the information provided, attention check questions were included. Subsequently, participants were shown an advertisement from a fictitious local solar installation agency named SunSpark. Participants were encouraged to contact SunSpark for a free quote. Following exposure to the advertisement, participants were asked a series of questions regarding their perception of the installation company. They were then shown both images once again and prompted to answer questions pertaining to their intention to install photovoltaic (PV) systems in their homes, their level of environmental concern, and their beliefs regarding solar PV installation. Furthermore, participants were asked to provide their opinions about Illumin, aiming to gauge their reaction to the different framings presented. Lastly, participants were asked to provide demographic information.

3.6. ANALYSIS

To ensure the reliability of the belief constructs, which were measured using multiple Likert scale questions, confirmatory factor analysis was conducted to assess the internal consistency of the items. Following the calculation of weighted means, the obtained values were utilized as index variables, following the approach employed by Rai & Beck (2015).

The data were fitted using a regression model (Equation 1). The dependent variables, *Interest* and *Intention*, are continuous. β_p captured the direct effect of

Renewable Content RC_a , where *a* and *p* represent each level of renewable content respectively (30%, 60%, 100%) and no info level is set as baseline. β_1 captured the direct effect of CCA Context. β_q captured the q^{th} interaction effect of CCA Context with the a^{th} level of Renewable Content. β_2 captured the direct effect of Perceived Benefits (PB). β_r captured the r^{th} interaction effect of Perceived Benefits with the a^{th} level of Renewable Content. β_3 captured the direct effect of Soft Barriers (SB). β_q captured the q^{th} interaction effect of each a^{th} level of Renewable Content with Soft Barriers. β_4 captured the direct effect of Trust. β_5 captured the interaction effect of Trust with CCA Context. β_t captured the t^{th} interaction of Trust with the a^{th} level of Renewable Content. β_x captured the vector of variables A_x including Novelty Seeking, Subjective Norms, Technical Barriers, Environmental Concern, and demographic variables. Some of the demographic variables are represented as dummy variables for e.g., College Education, Political Affiliation, Ideology, Gender, Race, Low Income, while others will be continuous variables such as Age, Electricity Bills, Attention Scores.

$$Interest \mid Intention = \beta_0 + \beta_p RC_a + \beta_1 CCA + \beta_q RC_a * CCA + \beta_2 PB + \beta_r RC_a *$$
$$PB + \beta_3 SB + \beta_s RC_a * SB + \beta_4 TC + \beta_5 CCA * TC + \beta_t RC_a * TC +$$
$$\beta_x A_x$$
(1)

Hypothesis 1 was tested by observing β_p which is expected to have a negative sign to confirm the negative effect of Renewable Content on the dependent variables. Hypothesis 2 was tested by observing β_q which is expected to have a negative sign to confirm that interaction of higher Renewable Content and CCA Context on dependent variables. Hypothesis 3 was tested by observing β_r which is expected to have a significant positive sign, with a lower effect size for each r representing higher Renewable Content. Hypothesis 4 was tested by observing β_s which is expected to have a significant negative sign, with a lower effect size for each s representing higher Renewable Content. Hypothesis 5 was tested by observing β_5 which is expected to have a negative sign to confirm that for higher levels of Trust, CCA Context has a stronger negative effect on Intention and Interest. Hypothesis 5 was tested by observing β_t which is expected to have a negative sign to confirm that for higher levels of Trust, higher Renewable Content has a stronger negative effect on Intention and Interest.

4. RESULTS AND DISCUSSION

4.1. SAMPLE

The survey received 1200 responses on Prolific. To ensure the integrity of the analysis, we excluded participants who reported residence zip codes outside the designated 17 states where recruitment was permitted (N = 31). Nearly 10% of respondents reported having solar PV installed at their residence which was high compared to 4% of homeowners all across the United States. This is because California, New Jersey, Arizona and New York are some of the largest residential PV markets PV ownership was not significantly different across experimental conditions, F(7, 1039) = 0.63, p > .05. These respondents were removed from subsequent analysis to limit the sample to solar considerers and non-adopters (N = 130). Homeownership was reported by 75% of the respondents and was not significantly different across experimental

conditions. Non-homeowners were not removed from the sample they reported living in a single family home which was owned by their home.

The remaining responses (N = 1039) were included in descriptive analysis and model fitting. The majority of responses came from California (N = 270). Percentage distribution of participants by state is available in Table A.1 in Appendix. As shown in Table 2, the participants were roughly equally distributed in each of the eight experimental conditions. The average age reported in the sample (M = 41, SD = 14), is close to the U.S. median age (38.9 years) and was not significantly different across the experimental conditions, F(7, 1011) = 0.42, p > .05. The sample has a higher percentage of males and also higher than the U.S. gender ratio (49% males), this could be due to higher homeownership rates among males. The gender ratio was not significantly different across the experimental conditions, F(7, 1039) = 0.82, p > .05. The racial distribution of the group was similar to the U.S. (76% White) with up to 75% white respondents, not significantly different across experimental conditions F(7, 1039) = 0.63, p > .05. Regarding income, the reported average income range in the sample fell within the $\frac{575}{-100}$ bracket, consistent with the U.S. median income of homeowners which is nearly \$78k. The reported income was not significantly different across experimental conditions, F(7, 1008) = 0.61, p > .05. The majority of respondents were reportedly college educated which is higher than U.S. (39%), identified with liberal ideologies (56%), and were democrat leaning (50%). College education F(7, 1037) = 0.43, p > .05, liberal ideology F(7, 1039) = 0.80, p > .05, and democrat support F(7, 1039) = 0.53, p > .05.05 were not significantly different across experimental groups.
Variable	Current Utility				CCA Context				
	Renewable Content			Renewable Content					
	30%	60%	100%	CCA	30%	60%	100%	No	Sample
				only				Message	
Age	41	41	41	40	41	40	41	41	41
0	(14)	(15)	(15)	(14)	(14)	(15)	(13)	(14)	(14)
Gender			(-)				(-)		
Female	47%	46%	46%	40%	44%	48%	42%	53%	46%
Male	49%	52%	50%	56%	54%	50%	54%	46%	51%
Non-	4%	2%	4%	4%	2%	2%	6%	1%	3%
Conforming/	-170	270	-170	70	270	270	070	170	570
Missing									
wiissing									
White	71%	79%	74%	71%	71%	75%	69%	72%	73%
,,,,,,,,,,,,,,,,,,,,,,,,,,,,,,,,,,,,,,,	, 1,0	.,,,,	, ,,,,	, 1,0	, 1,0	1070	0,70		1010
Income									
<\$50k	28%	27%	34%	28%	30%	30%	26%	27%	24%
\$50k - 100k	38%	39%	36%	38%	36%	37%	38%	35%	39%
>\$100k	34%	34%	30%	34%	34%	33%	36%	38%	34%
> \$100M	5170	5170	2070	5170	5170	5570	2070	2070	5170
College	63%	66%	62%	63%	60%	57%	61%	61%	61%
Educated									
Liberal	52%	51%	58%	53%	60%	55%	53%	58%	56%
Politics									
Democrats	47%	51%	50%	48%	49%	49%	50%	56%	50%
Republicans	18%	21%	22%	15%	21%	21%	17%	18%	20%
Independent	26%	23%	21%	28%	24%	24%	28%	21%	25%
		,		, _					
Attentiveness	62%	65%	56%	55%	57%	51%	55%	82%	-
Average	166	173	172	172	183	172	172	177	173
Electricity	(99)	(100)	(87)	(99)	(107)	(96)	(99)	(105)	(98)
Bill	()					()	()		()
Homeowners	72%	76%	75%	75%	72%	72%	75%	74%	75%
CCA	11%	14%	8%	11%	13%	10%	11%	7%	11%
Awareness	/-	, .		/•			/•	.,.	,-
110000000055									
PV owners	7%	9%	9%	9%	11%	10%	9%	13%	10%
	. , .	2 / 0		- / •	/ 0	/0	- / 0		/0
Received PV	64%	67%	63%	59%	60%	59%	59%	64%	63%
ads									

Table 2:Demographical characteristics of the sample (N = 1039). Unlike other characteristics expressed as percentages, Age and Average Electricity bills are expressed in terms of mean and standard deviation.

Overall, the sample is representative to the US in terms of age, racial distribution, and conforms with homeowners in terms of income, education, and gender distribution. The electricity bills reported by the sample (M = 173, SD = 98) is higher than the national average (U.S. average residential bill = \$120, EPA 2021) and is not significantly different across experimental conditions, F(7, 822) = 0.63, p > .05. CCA awareness was reported by 11% of respondents and was not significantly different across experimental conditions, F(7, 822) = 0.63, p > .05. CCA awareness was reported by 11% of respondents and was not significantly different across experimental conditions, F(7, 1039) = 0.31, p > .05. This indicates that the majority of respondents have limited or no opinions on CCA's role in the local electricity supply. PV ads were reported to have been received by 63% of the respondents. This indicates that participants had sufficient awareness of the opportunities to install PV in their neighborhood.

The respondents who answered all attention check questions correctly were marked as attentive using a binary variable and was significantly different across experimental groups, F(7, 1039) = 5.35, p < .01. Fewer respondents in groups exposed to renewable content information answered all questions correctly compared to groups with only CCA context or no message. This discrepancy can be attributed to the additional questions with multiple correct answers about renewable content and sources provided to these groups which required higher information retention.

4.2. DESCRIPTIVE FINDINGS

Confirmatory factor analysis (CFA) was performed on Likert measures for each construct. This analysis employed Cronbach's alpha to evaluate the consistency and reliability of the Likert-scale items applied to gauge unseen independent variables. A higher alpha value indicates greater shared variance among the items, suggesting they likely capture a similar concept. The means and standard deviation of each latent variable is reported in Table 3. While a majority of the respondents were interested in getting solar PV, they did not plan on installing them on their property in the immediate future. The sample had a left-skewed distribution for Interest in getting solar PV for their residence (M = 5.1, SD = 1.8) but the means are not significantly different across experimental groups, F(7, 822) = 1.83, p > .05. In comparison, the Intention to call solar installer for a quote was lower and was uniformly distributed across the sample (M = 4.2, SD = 1.8). Intention was significantly different across experimental conditions with significantly higher means reported in the 100% renewable group without CCA context than the same with CCA context, F(7, 1025) = 2.27, p < .05.

The means for Perceived Benefits suggested that most respondents in all groups believed that there are financial and environmental benefits of PV installations, and their beliefs were unaltered by messages. Perceived Benefits (Cronbach's α = 0.83) of solar PV was high (M = 5.6, SD = 1.0) with a left-skewed distribution but the differences in means were not significant across conditions, F(7, 1039) = 1.23, p > .05. Soft Barriers (α = 0.67) had normally distributed means with high standard deviation suggesting a diverse range of beliefs about the risks and affordability of PV installation. Soft Barriers of PV installation was normally distributed with means located near the midpoint of the scale (M = 4.1, SD = 1.2) and not significantly different across experimental conditions, F(7,1033) = 0.44, p > .05. The obtained means for Trust (α = 0.85) suggested that respondents were unsure about receiving electricity service from a hypothetical community-owned provider. There was a significant decrease in means from the non-CCA to the CCA groups, , F(7, 1037) = 2.59, p < .05. The means were normally distributed across the sample with the mean value closer to the middle of the scale (M = 4.2, SD = 1.5).



Figure 3: Distribution of Interest and Intention across the sample

The majority of the respondents were environmentally conscious and were aware of the consequences of climate change. Environmental Concern (α = 0.94) was extremely left-skewed in the sample and was high in all experimental conditions (M = 5.8, SD =1.2) without significantly different means, F(7, 1036) = 0.38, p > .05. The majority of respondents reported themselves to be interested in new products and brands. Consumer Novelty Seeking (α = 0.87) was on the higher side for the entire sample (M = 4.9, SD =1.3) with slightly left-skewed distribution but no significant differences in means were observed across experimental groups, F(7, 1034) = 0.89, p > .05. This indicates that the majority of the consumers identified as innovators or early adopters. Consumer Independent Judgement Making (α = 0.83) had a right-skewed distribution with means lower than midpoint (M = 2.5, SD = 1.1) and no significant difference across experimental groups, F(7, 1038) = 1.48, p > .05. This further confirms that the majority of the respondents were open to trying new products and brands without consulting their peers first. Subjective Norms (α = 0.81) had a left-skewed distribution (M = 5.4, SD = 1.2) and no significantly different means across experimental groups, F(7, 1033) = 1.91, p > .05. This indicates that the majority of the respondents believed that the decision to install PV would be welcomed by their family and peers. Technical Barriers (α = 0.83) were reported to be low across the sample with a right-skewed distribution (M = 2.8, SD = 1.6) and no significant differences across experimental conditions, F(7, 1023) = 1.38, p > .05. This indicates that the majority of the respondents lived in an area with abundant sunshine for solar power generation. On average, respondents expressed a high interest in acquiring solar panels for their homes, though the immediate intentions to engage with a PV installer vary widely. The sample means suggest that respondents are convinced of the benefits conferred by PV, are inclined towards innovative technologies, and are keenly aware of peer influence in their adoption decisions, with a pronounced commitment to environmental preservation.

On average, respondents display neutrality regarding the challenges to PV adoption and their trust in utility companies. They exhibit limited concerns about the technical viability of installing PV on their properties and demonstrate lesser dependence on peers for information concerning new brands and products. The descriptive statistics and F-tests conducted suggest that the beliefs of respondents are uniform across all experimental conditions and are seemingly unaltered by the messages received about CCA and renewable content. The only exception being trust in utility which seems to be higher for non-CCA contexts. This suggests that respondents may feel more confident about existing entities rather than put faith in a new and hypothetically introduced organization. The factor loadings of each items on psycho-social variable were

calculated using confirmatory factor analysis (Table A.3 in Appendix).

	Current Utility			CCA Context					
Variable	30%	60%	100%	CCA	30%	60%	100%	No	Sample
				only				Message	
Interest	4.8	5.0	4.8	5.1	4.8	5.2	5.3	5.2	5.1
	(1.9)	(1.8)	(1.8)	(1.7)	(1.9)	(1.7)	(1.5)	(1.7)	(1.8)
Intention	4.0	4.2	3.9	4.3	4.2	4.4	4.5	4.1	4.2
	(1.7)	(1.9)	(1.8)	(1.1)	(1.9)	(1.8)	(1.8)	(1.7)	(1.8)
D 1 1									
Perceived	5.4	5.7	5.7	5.5	5.4	5.7	5.7	5.7	5.6
Benefits	(1.0)	(1.1)	(1.0)	(1.2)	(1.1)	(1.2)	(1.0)	(0.9)	(1.0)
Soft Barriers	13	12	12	12	11	<i>A</i> 1	3.0	4.0	<i>A</i> 1
soji burners	(1 1)	(1.2)	(1.2)	(1.5)	(1.2)	(1.2)	(1 1)	(1 1)	(1 2)
Trust	(1.1)	(1.2)	(1.2)	(1.5)	(1.2)	(1.2)	(1.1)	(1.1)	(1.2)
11431	(1.5)	(1.4)	(1.6)	(1.2)	(1.5)	(1 A)	(1.6)	(1.5)	(1.5)
	(1.3)	(1.4)	(1.0)	(1.2)	(1.3)	(1.4)	(1.0)	(1.3)	(1.3)
Environmental	5.8	5.8	5.7	5.8	5.8	5.9	5.7	5.8	5.8
Concern	(1.2)	(1.3)	(1.2)	(1.2)	(1.2)	(1.3)	(1.2)	(1.2)	(1.2)
	、	`			、	、		~ /	~ /
Consumer	4.8	5.0	4.9	4.9	4.9	5.0	4.8	4.9	4.9
Novelty	(1.3)	(1.3)	(1.4)	(1.3)	(1.4)	(1.3)	(1.4)	(1.3)	(1.3)
Seeking						. ,	. ,		. ,
Consumer	2.4	2.5	2.7	2.3	2.6	2.6	2.6	2.6	2.5
Independent	(1.1)	(1.1)	(1.2)	(1.0)	(1.2)	(1.1)	(1.2)	(1.1)	(1.1)
Judgement									
Making									
				5.0	- 1				
Subjective	5.4	5.4	5.4	5.3	5.1	5.6	5.5	5.5	5.4
Norm	(1.2)	(1.3)	(1.2)	(1.2)	(1.3)	(1.2)	(1.0)	(1.2)	(1.2)
Technical	28	29	28	28	3.0	26	27	25	28
Barriers	(1.6)	(1.6)	(1.5)	(1.7)	(1.6)	(1.4)	(1.7)	(1.5)	(1.6)

Table 3: Descriptive statistics of latent variables

4.3. REGRESSION RESULTS

In this section, the evidence for the study's hypotheses was examined and discussed using results from multiple linear regression models. Three models were developed using stepwise addition of variables for each dependent variable, Interest and Intention. In these models, the CCA context was included in the regression as a dummy-coded variable (1 = CCA context given, 0 = No Context). Renewable Content was included as a factor variable where no information on renewable content was set as a baseline for comparison with 30%, 60% and 100% levels. All psycho-social and sociodemographic variables used in model fitting underwent standardization to mitigate distribution skewness and enable comparability across magnitudes. (See Tables 4 and 5).

In Model 1, the dependent variable Interest was explained through the main effects of five independent variables: Renewable Content, CCA context, Perceived Benefits, Soft Barriers, and Trust, $R^2 = .45$, F(7, 1025) = 121.7, p < .001. Model 4 has the same effects used to explain the Intention variable, $R^2 = .33$, F(7, 1017) = 73, p < .001. Expanding on this foundation, Model 2 incorporated additional psycho-social variables, namely Subjective Norms, Environmental Concern, Consumer Novelty Seeking, Consumer Independent Judgment Making, and Technical Barriers to explain Interest, R^2 = .46, F(25, 981) = 36.1, p < .001. Furthermore, Model 2 introduced five interaction effects – CCA context with Renewable Content, Renewable Content with Perceived Benefits, Renewable Content with Soft Barriers, and 5) Trust with Renewable Content. These interaction effects would provide evidence for the influence of hypotheses 2 - 5respectively. Model 5 has the same effects used to explain the Intention variable, $R^2 = .33$ F(25, 972) = 20.6, p < .001. Model 3, an extension of the prior models, included sociodemographic variables such as income level, education level, age, in addition to binary variables representing homeownership and attentiveness to explain Interest, $R^2 =$.47, F(30, 920) = 36.1, p < .001. Model 6 uses the same variables to explain the influence on Intention, $R^2 = .34$, F(30, 911) = 17.3, p < .001. The regression results yielded weak support for hypothesis 1, but no conclusive evidence for the remaining hypotheses.

Our regression analyses suggest that increase in utility-scale renewable procurement may lead to a significant decline in interest among consumers regarding individual solar PV adoption. In evaluating hypothesis 1, Renewable Content had a significant negative influence on Interest. However, the same effect was not observed for Intention. Notably, there was a significant decrease in Interest as the Renewable Content increased from 30% to 60% (β = -0.23, p < .05). This was followed by a similar increase in negative influence from 60% to 100% (β = -0.24, p < .05). However, the negative impact achieved statistical significance only for the 60% and 100% renewable levels in Model 1. In Model 2, with the introduction of interaction effects and the inclusion of various psycho-social variables, the previously significant effect no longer remained across any of the renewable content levels. This could be due to the presence of more dominant predictors in the model. However, in Model 3, the negative influence of 100% renewable content on Interest was statistically significant (β = -0.23, p < .05), whereas the impact from other Renewable Content levels did not attain significance. These results suggest that renewable content is more likely to reduce Interest when the electricity supply is 100% renewable, while controlling for other substantial psycho-social and demographic characteristics of the respondents. These results are consistent with earlier studies revealing reduced support for taxpayer-funded renewable energy initiatives when

the RPS exceeds 60% (Mamkhezri et al., 2020). Collectively, there is a weak indication that interest in residential PV decreases as renewable content in the grid increases. This findings may vary by individual as some may be more sensitive to the messages from utility/CCA. These findings are new to PV adoption literature and if confirmed by multiple studies in the future, may have implications on residential PV industry as utilities expand their centralized renewable generation infrastructure.

Contrary to expectations, the effect on interest in adopting PV remains statistically insignificant even when a high proportion of renewable energy is supplied through CCA entities. The statistical models also did not yield any significant impact of a high renewable content within the CCA context on the intention to adopt PV technology. In evaluating hypothesis 2, it was observed that the combined influence of messages pertaining to Renewable Content and CCA context yielded no effect. Notably, this effect failed to achieve statistical significance across all three levels. In both Models 2 and 3, neither Interest nor Intention displayed significant effects attributable to the combined effects of these two variables. Although in Model 1, the CCA context did exhibit a statistically significant positive impact on Intention ($\beta = 0.20$, p < .001); however, this effect lost significance upon the inclusion of other dominant psycho-social and demographic characteristics. Therefore, there is no conclusive evidence suggesting that a community-owned entity providing electricity services in the area might augment respondents' tendency to take action towards individually procuring PV, in the presence of other peer effects and demographic characteristics. This suggests that customers may exhibit a relative indifference to the ownership structure of the utility company when actively seeking to enhance the proportion of renewable energy in their energy portfolios.

A previous study suggested that utility-sponsored community solar (USCS) initiatives strike an optimal balance by furnishing customers with locally generated clean energy, ensuring revenue stability, and promoting high customer engagement without necessitating substantial cost premiums (Funkhouser et al., 2015). This can be facilitated by improving the regulatory oversight on RPS compliance while also incentivizing utilities to actively engage in building new centralized generation infrastructure.

Contrary to our initial hypotheses, our investigation revealed that beliefs regarding the financial and environmental advantages associated with adopting PV technology remained unaffected by the contextual factors of CCA and the level of renewable content in the energy supply. In evaluating hypothesis 3, it is noteworthy that Perceived Benefits yielded a significant positive impact on both Interest (β = 0.42, p < .001) and Intention (β = 0.30, p < .001), aligning with findings from previous studies on PV adoption (Horne et al., 2021; Wolske et al., 2017). When Renewable Content was introduced as an interaction term with Perceived Benefits, the resulting effect on both Interest and Intention was non-significant. Consequently, it may be inferred that respondents' inclination toward PV and their intent to engage with installation services are predominantly steered by their perceptions of PV's benefits. It appears that, even in the presence of a higher proportion of renewable energy in the supply, consumers continue to be primarily driven by the compelling economic incentives and the potential return on investment that render PV adoption a financially prudent choice. This finding suggests that, regardless of whether more stringent RPS are enforced or CCAs opt to procure an increased share of electricity from centralized renewable sources, as long as policies continue to provide substantial financial incentives, PV adoption is likely to

remain an attractive investment option. A significant majority of respondents within our sample indicated prior exposure to solar PV advertisements, and they also reside in regions where PV adoption is relatively commonplace. This suggests that they possess a heightened awareness of the implications and advantages associated with PV adoption.

The experimental manipulations involving variations in renewable content and the presence of a Community Choice Aggregation (CCA) context yielded no significant impact on the relationship between perceived barriers and PV adoption. In evaluating hypothesis 4, Soft Barriers exerted a significant negative influence on both Interest (β = - 0.16, p < .01) and Intention (β = -0.28, p < .001) (Rai & Beck, 2015; Wolske et al., 2017). However, when the interaction variables of Renewable Content and Perceived Benefits were introduced, they did not yield significant impacts on either Interest or Intention. This suggests that while respondents' beliefs regarding the challenges and affordability of PV installation do negatively influence their PV adoption behavior, information

Variables	Model 1	Model 2	Model 3	
	$\beta(S.E)$	β (S.E)	β (S.E)	
Intercept	5.2*** (0.09)	0.06 (0.06)	0.21* (0.09)	
<i>RC30</i>	-0.15 (0.12)	-0.11 (0.09)	-0.16 (0.1)	
RC60	-0.23* (0.12)	-0.09 (0.09)	-0.14 (0.1)	
RC100	-0.24* (0.12)	-0.17 (0.09)	-0.23* (0.1)	
CCA	0.10 (0.08)	0.03 (0.095)	-0.01 (0.06)	
Perceived Benefits	0.96*** (0.05)	0.47*** (0.05)	0.42*** (0.06)	
Trust	0.04 (0.33)	0.01 (0.05)	-0.01 (0.06)	
Soft Barriers	-0.41*** (0.05)	-0.15** (0.05)	-0.16** (0.06)	
Subjective Norm		0.18*** (0.03)	0.21* (0.03)	
Environmental		0.01 (0.03)	0.01 (0.03)	
Concern				
Consumer Novelty		0.05 (0.03)	0.05 (0.03)	
Seeking				

Table 4: OLS Regression results with Interest as dependent variable

<i>C</i>		0.01 (0.02)	0.00(0.02)
Consumer		-0.01 (0.03)	0.00 (0.05)
Independent			
Judgement Making			
Technical Barriers		-0.02 (0.03)	-0.02 (0.03)
CCA * 30%		0.044 (0.13)	0.08 (0.14)
Renewable			
CCA * 60%		-0.036 (0.13)	-0.02 (0.14)
Renewable			
CCA * 100%		0.131 (0.13)	0.16 (0.14)
Renewable			
Perceived Benefits *		-0.108 (0.07)	-0.09 (0.07)
30% Renewable			
Perceived Benefits *		0.013 (0.07)	0.03 (0.08)
60% Renewable			
Perceived Benefits *		-0.044 (0.07)	-0.03 (0.08)
100% Renewable			
Soft Barriers* 30%		-0.048 (0.1)	-0.04 (0.08)
Renewable			
Soft Barriers* 60%		-0.097 (0.1)	-0.08 (0.08)
Renewable			
Soft Barriers* 100%		-0.016 (0.1)	0.01 (0.08)
Renewable			
Trust * CCA		-0.049 (0.05)	-0.03 (0.05)
Trust * 30%		0.130 (0.1)	0.13 (0.07)
Renewable		× ,	~ /
Trust * 60%		-0.020 (0.1)	0.00(0.07)
Renewable			
Trust * 100%		0.021(0.1)	0.04(0.07)
Renewable			
Income			-0.02(0.02)
Education			-0.02(0.03)
			-0.08*** (0.03)
1180			0.00 (0.05)
Attention			-0.09(0.05)
Home Owner			-0.07(0.05)
			-0.07 (0.00)
AIC	3491	2247	1776
N	1033	1007	965
Adi R-Squared	0.45	0.46	0 47
my. n-squarea	0.75	0.70	0.77

Table 4: OLS Regression results with Interest as dependent variable (cont.)

concerning the renewable content in utility supply exerts no measurable influence on this relationship. Beliefs pertaining to uncertainties surrounding financial returns,

affordability despite economic incentives, and associated effort-related costs exhibited

consistent effects on PV adoption behavior, irrespective of exposure to messaging regarding increased renewable content. This implies that the factors hindering consumer interest in adopting PV technology remain steadfast, even in scenarios characterized by the implementation of more stringent RPS or voluntary efforts by CCAs to procure a higher proportion of renewable energy. These efforts are likely to remain relevant and necessary, even in an environment where utility-scale renewable generation becomes increasingly prevalent.

In this study, it is notable that our sample exhibited a high level of trust in their respective utility companies, and our analytical models even suggest a positive effect of trust on the intention to adopt PV technology. In evaluating hypotheses 5 and 6, Trust exhibits no statistically significant impact on Interest in PV adoption. However, Trust does exert a significant positive influence on the Intention (β = 0.12, p < .001) to engage with installation agencies.

Contrary to previous research findings (Horne et al., 2021), Trust in the utility company manifests as a positively influential factor on the intention to adopt PV. Notably, interactions between Trust and CCA context, as well as interactions between Renewable Content and Trust, do not yield statistically significant effects on either Interest or Intention. This suggests that respondents' trust in the utility company furthers their inclination towards PV. Furthermore, this relationship between PV adoption behavior and trust in utility companies is not significantly influenced when the utility is community-owned and procures a high percentage of electricity from renewable sources. This contrasts with a previous study focused on California IOU customers, where the survey primarily captured responses from dissatisfied customers (Horne et al., 2021). The broader geographical representation and diversity of utility customers in our study may account for this discrepancy in the observed effects of trust on PV adoption intentions compared to prior research.

Regarding the remaining variables, in alignment with prior research, Subjective Norms, Consumer Novelty Seeking, income, and age demonstrated significant associations with Intention. Among these variables, Subjective Norms had a significant positive influence on both Interest (β = 0.21, p < .05) and Intention (β = 0.12, p < .001) towards PV. Hence, the model confirms that PV adoption behavior increases in the presence of familial and peer support as found in previous studies (Rai & Beck, 2015; Wolske et al., 2017). Consumer Novelty Seeking was found to have a non-significant relationship with Interest but significant positive relationship with Intention (β = 0.06, p < .05) to adopt PV. This confirms previous findings on innovators and early adopters perception of PV as a novel technology (Wolske et al., 2018). Age of respondents had a significant negative influence on Intention which confirms previous findings about younger respondents exhibiting a higher likelihood of responding to PV ads (Wolske et al., 2018). Unlike previous studies we found that individuals who are younger, possess lower income, identify as innovators or early adopters, and enjoy support from their peers are more inclined to initiate contact with solar installation agencies for a quote (β = -0.09, p < .001). In contrast to earlier investigations, this study did not find a significant positive relation between PV adoption behavior and Environmental Concern. This divergence might be attributed to the fact that the entire sample expressed notable concern for the environment and an acute awareness of climate change, irrespective of their expressed interest or intention to adopt PV.

Variables	Model 4	Model 5	Model 6	
Intercept	-0.10 (0.06)	-0.10 (0.08)	-0.02 (0.1)	
RC30	0.00 (0.07)	0.04 (0.1)	0.05 (0.65)	
RC60	-0.02 (0.07)	0.01 (0.1)	0.00 (0.11)	
RC100	-0.05 (0.07)	-0.09 (0.11)	-0.12 (0.11)	
CCA	0.20*** (0.05)	0.18 (0.06)	0.18 (0.11)	
Perceived Benefits	0.33*** (0.03)	0.34*** (0.06)	0.30*** (0.06)	
Trust	0.16*** (0.03)	0.13* (0.06)	0.12* (0.11)	
Soft Barriers	-0.27*** (0.03)	-0.25*** (0.06)	-0.28*** (0.04)	
Subjective Norm		0.10** (0.03)	0.12*** (0.04)	
Environmental		-0.03 (0.03)	-0.03 (0.03)	
Consumer Novelty		0.05* (0.03)	0.06* (0.03)	
Consumer		-0.03 (0.03)	-0.03 (0.03)	
Technical Barriers		0.02 (0.03)	0.01 (0.03)	
CCA * 30%		-0.04 (0.15)	-0.07 (0.15)	
CCA * 60%		-0.03 (0.15)	-0.07 (0.15)	
CCA * 100%		0.14 (0.15)	0.15 ((0.15)	
Perceived Benefits *		-0.12 (0.08)	-0.10 (0.08)	
Perceived Benefits *		-0.05 (0.08)	-0.05 (0.08)	
Perceived Benefits *		-0.08 (0.08)	-0.04 (0.09)	
Soft Barriers* 30%		-0.03 (0.08)	-0.01 (0.09)	
Soft Barriers* 60%		-0.04 (0.08)	-0.02 (0.08)	
Soft Barriers* 100%		0.04 (0.09)	0.09 (0.09)	
Trust * CCA		0.00 (0.05)	0.00 (0.05)	
Trust * 30%		0.04 (0.08)	0.05 (0.08)	
Trust * 60%		0.03 (0.08)	0.03 (0.08)	
Trust * 100%		0.03 (0.08)	0.06 (0.08)	
Income			-0.09*** (0.03)	
Education			0.04 (0.03)	
Age			-0.06* (0.03)	
Attention			-0.02 (0.06)	
Home Owner			-0.06 (0.07)	
AIC	2476	2424	1866	
N	1025	998	942	
Adj. R-Squared	0.32	0.33	0.34	

Table 5:OLS Regression Results with Intention as dependent variable

Consumer Independent Judgment Making and Technical Barriers did not have a significant effect on Interest or Intention regarding PV adoption. Furthermore, homeownership status and respondents' attentiveness exhibited no significant relationships with either Interest or Intention.

5. CONCLUSIONS

In previous research, investigations into factors influencing photovoltaic (PV) adoption behavior have primarily centered on concepts involving gain-loss frames and varying levels of construal regarding expected return on investment (Wolske et al., 2018). While some studies have explored the relationship between RPS and residential PV adoption, their focus has been primarily confined to predicting the emergence of community solar programs (Funkhouser et al., 2015). In this research, we implemented a systematic experimental methodology encompassing diverse renewable content levels. Furthermore, control groups were incorporated, both associated with and independent of the CCA framework. While geographical, economic, and sociological contexts are crucial determinants in PV adoption, this investigation elucidates an alternative avenue for renewable energy procurement beyond PV. The trend of community or investor-owned utilities furnishing a significant proportion of renewable resources for residential consumers is on the rise in the U.S. Nonetheless, there is a discernible gap in academic literature regarding the dissemination of information to homeowners about these largescale renewable initiatives and their reaction to such information. To investigate the influence of increased renewable content and the presence of a CCA context on PV

adoption, this study drew its sample from states where CCAs are currently active (CA, IL, OH, VA, MD, NJ, NY, NH, MA, RI) or slated for introduction (AZ, CO, MI, CT, WA, OR, NM). While this sample selection strategy enriches our understanding of prospective PV markets in these 17 states, it is important to acknowledge a potential limitation stemming from limited awareness of CCA activities among respondents. Only 11% of participants in our sample reported awareness of CCAs operating within their localities. Given that CCAs are operational in only 10 of the 17 states included in our study, it is plausible that the majority of respondents lack comprehensive information about the impact of CCAs on their communities. Even within CCA states, the billing process continues to be administered by privately owned utilities in the respondents' areas, despite occasional outreach efforts by CCAs through mailers. This operational arrangement further contributes to the limited awareness of CCAs. Furthermore, assessing the degree of public knowledge about new CCA legislation in the remaining seven states from which we recruited participants remains challenging. Presently, CCAs have not achieved the same level of popularity as solar PV as a means of renewable energy procurement for households. It is likely that the conditioning from CCA and renewable content messages were not comprehended as expected which may have led to weaker manipulation. To mitigate these awareness-related challenges, we recommend that future research endeavors adopt a sample composition characterized by a balanced representation of CCA customers who actively engage in community-level discussions regarding renewable procurement, alongside non-CCA customers. This approach is likely to provide a more comprehensive understanding of the dynamics at play in the context of PV adoption and community-level renewable procurement.

In the context of this study, the differences in economic policies incentivizing the adoption of PV technology and overall benefits to consumers across all 17 states were not controlled for. This assumption was adopted to aid the simplification of the design, analysis, and interpretation of our experiments. Nevertheless, it is crucial to acknowledge the potential influence of varying incentive levels among states on the impact of the CCA context and renewable content on PV adoption behavior. For instance, the payback period for residential solar installations differs significantly between states like California and Arizona compared to states such as Maryland, New Jersey, and New York. This disparity is primarily attributable to the variance in solar irradiation levels, with California and Arizona benefiting from higher levels of irradiation, resulting in more favorable payback periods. Additionally, these states offer more substantial net-metering rebates and statelevel incentives. Furthermore, within the context of some CCAs, customers opting for green tariff subscriptions are eligible for higher net-metering rebates in California. In contrast, in states like Massachusetts, net-metering rebates remain fixed regardless of choices related to utility-scale renewable procurement. These are some of the several instances which prove that operationalizing context is highly complex, and the method chosen for operationalization may affect the likelihood of measuring an observable effect. It is plausible that customers residing in states where the payback period is extended may be more profoundly influenced by the CCA context and higher renewable content. Therefore, we recommend that future efforts on this subject consider employing a blocked experimental design that incorporates varying levels of financial benefits as a confounding factor. This approach will enhance the robustness of analyses and provide a

more nuanced understanding of how economic incentives interact with CCA and renewable content to influence PV adoption behavior.

In the final aspect of our study, we introduced experimental manipulations to participants in the form of postcards originating from hypothetical companies. It is plausible that the Community Choice Aggregation (CCA) introduced to participants may not have resonated significantly with them, primarily due to their unfamiliarity with the hypothetical company. Moreover, participants may have encountered difficulty in placing trust in a community-owned utility entity about which they possessed minimal information. This challenge was compounded by the fact that many participants were unaware of the possibility of restructuring within the electricity market, potentially resulting in an underestimation of the influence of the CCA context and higher renewable content on our observed outcomes. Similarly, this scenario applies to the hypothetical solar PV company introduced in our study. The presence of an unfamiliar PV company may have induced hesitancy among respondents in deciding whether to engage with this entity, potentially impacting the measurement of their intention to do so. In reality, respondents may be cognizant of other reputable solar installation agencies in their local communities, having received advertisements from them and gained insights into their work quality through interactions with neighbors and peers. This may have led to an underestimation of the interest and intention for PV adoption. Therefore, we recommend that future investigations explore individual preferences in the context of companies with established reputations within the community. Such an approach will likely yield a more accurate understanding of how CCA-related renewable procurement influences individuals' inclinations to collaborate with solar installation agencies.

REFERENCES

- Abreu, J., Wingartz, N., & Hardy, N. (2019). New trends in solar: A comparative study assessing the attitudes towards the adoption of rooftop PV. *Energy Policy*, 128, 347– 363. https://doi.org/10.1016/j.enpol.2018.12.038
- Agarwal, A., Canfield, C., & Fikru, M. G. (2023). Role of Greener Default options on Consumer Preferences for Renewable Energy Procurement (under review). *Renewable EnergyRenewable Energy*.
- Ajzen, I. (1991). The Theory of Planned Behavior. ORGANIZATIONAL BEHAVIOR AND HUMAN DECISION PROCESSES, 50(1), 179–211. https://doi.org/10.47985/dcidj.475
- Alipour, M., Salim, H., Stewart, R. A., & Sahin, O. (2021). Residential solar photovoltaic adoption behaviour: End-to-end review of theories, methods and approaches. *Renewable Energy*, 170, 471–486. https://doi.org/10.1016/j.renene.2021.01.128
- Araghi, Y., Bollinger, L., & Lee, E. P. (2014). Informing agent based models with discrete choice analysis. *Social Simulation Conference*. http://ddd.uab.cat/pub/poncom/2014/128005/ssc14_a2014a30iENG.pdf
- Azhgaliyeva, D., Beirne, J., & Mishra, R. (2023). What matters for private investment in renewable energy? *Climate Policy*, 23(1), 71–87. https://doi.org/10.1080/14693062.2022.2069664
- Bao, Q., Sinitskaya, E., Gomez, K. J., MacDonald, E. F., & Yang, M. C. (2020). A human-centered design approach to evaluating factors in residential solar PV adoption: A survey of homeowners in California and Massachusetts. *Renewable Energy*, 151, 503–513. https://doi.org/10.1016/j.renene.2019.11.047
- Barabási, A. L. (2009). Scale-free networks: A decade and beyond. *Science*, *325*(5939), 412–413. https://doi.org/10.1126/science.1173299
- Borchers, A. M., Duke, J. M., & Parsons, G. R. (2007). Does willingness to pay for green energy differ by source? *Energy Policy*, 35(6), 3327–3334. https://doi.org/10.1016/j.enpol.2006.12.009
- Boumaiza, A., Abbar, S., Mohandes, N., & Sanfilippo, A. (2018). Modeling the impact of innovation diffusion on solar PV adoption in city neighborhoods. *International Journal of Renewable Energy Research*, 8(3), 1749–1762. https://doi.org/10.20508/ijrer.v8i3.7999.g7484

- Busic-Sontic, A., & Fuerst, F. (2018). Does your personality shape your reaction to your neighbours' behaviour? A spatial study of the diffusion of solar panels. *Energy* and Buildings, 158, 1275–1285. https://doi.org/10.1016/j.enbuild.2017.11.009
- Cape Analytics. (2021). *These maps show the cities with the most solar in the U.S.* Panasonic. https://www.fastcompany.com/90423202/these-maps-show-the-citieswith-the-most-solar-in-the-u-s
- Cape Light Compact. (2023). C a p e L i g h t C o m p a c t A n n o u n c e s N e w, L o w e r P r i c i n g f o r P o w e r S u p p l y. 1–6. https://www.capelightcompact.org/10655-2/
- Chappin, E. J. L., Schleich, J., Guetlein, M. C., Faure, C., & Bouwmans, I. (2022). Linking of a multi-country discrete choice experiment and an agent-based model to simulate the diffusion of smart thermostats. *Technological Forecasting and Social Change*, 180(January), 121682. https://doi.org/10.1016/j.techfore.2022.121682
- Chen, M. F., & Tung, P. J. (2014). Developing an extended Theory of Planned Behavior model to predict consumers' intention to visit green hotels. *International Journal of Hospitality Management*, 36, 221–230. https://doi.org/10.1016/j.ijhm.2013.09.006
- Dagher, L., Bird, L., & Heeter, J. (2017). Residential green power demand in the United States. *Renewable Energy*, 114, 1062–1068. https://doi.org/10.1016/j.renene.2017.07.111
- Danne, M., Meier-Sauthoff, S., & Musshoff, O. (2021). Analyzing German consumers' willingness to pay for green electricity tariff attributes: a discrete choice experiment. *Energy, Sustainability and Society*, 11(1), 1–16. https://doi.org/10.1186/s13705-021-00291-8
- Denholm, P., Clark, K., & O'Connell, M. (2016). Emerging Issues and Challenges in Integrating High Levels of Solar into the Electrical Generation and Transmission System. NREL, May, 68. https://www.nrel.gov/docs/fy16osti/65800.pdf
- EIA. (2023). Renewable generation surpassed coal and nuclear in the U.S. electric power sector in 2022. U.S. Energy Information Administration. https://www.eia.gov/todayinenergy/detail.php?id=55960
- EPA. (2022). *How Do CCAs Work ? When Was CCA-Enabling Legislation Passed in Various. Figure 1*, 1–7. https://www.epa.gov/green-power-markets/community-choice-aggregation#four
- Eyal, P., Rothschild, D., Evernden, Z., Gordon, A., & Damer, E. (2021). Data Quality of Platforms and Panels for Online Behavioral Research Data Quality of Platforms and Panels for Online Behavioral Research. *Behavior Research Methods*, *August*, 1–46.

- Fikru, M. G., & Canfield, C. (2022). Demand for renewable energy via green electricity versus solar installation in Community Choice Aggregation. *Renewable Energy*, 186, 769–779. https://doi.org/10.1016/j.renene.2022.01.008
- Forbes. (2020). Renewable Energy Prices Hit Record Lows: How Can Utilities Benefit From Unstoppable Solar And Wind? https://www.forbes.com/sites/energyinnovation/2020/01/21/renewable-energyprices-hit-record-lows-how-can-utilities-benefit-from-unstoppable-solar-andwind/?sh=7b2ac9782c84
- Forrester, S., Barbose, G. L., O'Shaughnessy, E., Darghouth, N. R., & Crespo Montañés, C. (2022). Residential Solar-Adopter Income and Demographic Trends: November 2022 Update. *Lawrence Berkeley National Laboratory*, 34158. https://emp.lbl.gov/publications/residential-solar-adopter-income-1
- Freedman, J. L., & Fraser, S. C. (2017). Compliance without pressure: The foot-in-thedoor technique. Social Psychology in Natural Settings: A Reader in Field Experimentation, 4(2), 217–232. https://doi.org/10.4324/9781315129747
- Fruth, E., Kvistad, M., Marshall, J., Pfeifer, L., Rau, L., Sagebiel, J., Soto, D., Tarpey, J., Weir, J., & Winiarski, B. (2019a). Economic valuation of street-level urban greening: A case study from an evolving mixed-use area in Berlin. *Land Use Policy*, 89(August), 104237. https://doi.org/10.1016/j.landusepol.2019.104237
- Fruth, E., Kvistad, M., Marshall, J., Pfeifer, L., Rau, L., Sagebiel, J., Soto, D., Tarpey, J., Weir, J., & Winiarski, B. (2019b). Economic valuation of street-level urban greening: A case study from an evolving mixed-use area in Berlin. *Land Use Policy*, 89(October), 104237. https://doi.org/10.1016/j.landusepol.2019.104237
- Funkhouser, E., Blackburn, G., Magee, C., & Rai, V. (2015). Business model innovations for deploying distributed generation: The emerging landscape of community solar in the U.S. *Energy Research and Social Science*, 10, 90–101. https://doi.org/10.1016/j.erss.2015.07.004
- Gómez-Gardeñes, J., & Moreno, Y. (2006). From scale-free to Erdos-Rényi networks. *Physical Review E - Statistical, Nonlinear, and Soft Matter Physics*, 73(5), 1–7. https://doi.org/10.1103/PhysRevE.73.056124
- Gracia, A., Barreiro-Hurlé, J., & López-Galán, B. (2014). Are Local and Organic Claims Complements or Substitutes? A Consumer Preferences Study for Eggs. *Journal of Agricultural Economics*, 65(1), 49–67. https://doi.org/10.1111/1477-9552.12036
- Hartmann, P., & Apaolaza-Ibáñez, V. (2012). Consumer attitude and purchase intention toward green energy brands: The roles of psychological benefits and environmental concern. *Journal of Business Research*, 65(9), 1254–1263. https://doi.org/10.1016/j.jbusres.2011.11.001

- Herbes, C., & Ramme, I. (2014). Online marketing of green electricity in Germany— A content analysis of providers' websites. *Energy Policy*. http://dx.doi.org/10.1016/j.enpol.2013.10.083
- Hess, D. J. (2019). Coalitions, framing, and the politics of energy transitions: Local democracy and community choice in California. *Energy Research and Social Science*, 50(December 2018), 38–50. https://doi.org/10.1016/j.erss.2018.11.013
- Hobman, E. V., & Frederiks, E. R. (2014). Barriers to green electricity subscription in Australia: "love the environment, love renewable energy … but why should i pay more?" *Energy Research and Social Science*, 3(C), 78–88. https://doi.org/10.1016/j.erss.2014.07.009
- Horne, C., Kennedy, E., & Familia, T. (2021). Rooftop solar in the United States: Exploring trust, utility perceptions, and adoption among California homeowners. *Energy Research & Social Science*. https://doi.org/10.1016/j.erss.2021.102308
- Hsu, D. (2022). Straight out of Cape Cod: The origin of community choice aggregation and its spread to other states. *Energy Research and Social Science*, 86(May 2021), 102393. https://doi.org/10.1016/j.erss.2021.102393
- Huang, C., & Shen, R. (2020). Does city or state make a difference? The effects of policy framing on public attitude toward a solar energy program. *Journal of Behavioral Public Administration*, 3(2), 1–21. https://doi.org/10.30636/jbpa.32.126
- IRENA. (2023). Global renewables capacity grew by 10 %. Reuters.
- Islam, T. (2014). Household level innovation diffusion model of photo-voltaic (PV) solar cells from stated preference data. *Energy Policy*, 65, 340–350. https://doi.org/10.1016/j.enpol.2013.10.004
- Kennedy, B. (2019). *More U.S. homeowners say they are considering home solar panels*. Pew Research. https://www.pewresearch.org/fact-tank/2019/12/17/more-u-shomeowners-say-they-are-considering-home-solar-panels/
- Kiesling, E., Günther, M., Stummer, C., & Wakolbinger, L. M. (2012). Agent-based simulation of innovation diffusion: A review. *Central European Journal of Operations Research*, 20(2), 183–230. https://doi.org/10.1007/s10100-011-0210-y
- Kjær, T. (2005). A Review of the Discrete Choice Experiment With Emphasis on its Application in Healthcare. *Health Economic Papers*, *1*, 1–139.
- Kleinberg, J. (2000). The small-world phenomenon: An algorithmic perspective. *Proceedings of the Annual ACM Symposium on Theory of Computing*, 163–170. https://doi.org/10.1145/335305.335325

- Knapp, L., O'Shaughnessy, E., Heeter, J., Mills, S., & DeCicco, J. M. (2020). Will consumers really pay for green electricity? Comparing stated and revealed preferences for residential programs in the United States. *Energy Research and Social Science*, 65, 0–26. https://doi.org/10.1016/j.erss.2020.101457
- Litvine, D., & Wüstenhagen, R. (2011). Helping "light green" consumers walk the talk: Results of a behavioural intervention survey in the Swiss electricity market. *Ecological Economics*, 70(3), 462–474. https://doi.org/10.1016/j.ecolecon.2010.10.005
- Liu, X., O'Rear, E. G., Tyner, W. E., & Pekny, J. F. (2014). Purchasing vs. leasing: A benefit-cost analysis of residential solar PV panel use in California. *Renewable Energy*. https://doi.org/10.1016/j.renene.2014.01.026
- Mamkhezri, J., Thacher, J. A., & Chermak, J. M. (2020). Consumer preferences for solar energy: A choice experiment study. *Energy Journal*, 41(5), 157–184. https://doi.org/10.5547/01956574.41.5.JMAM
- Masad, D., & Kazil, J. (2015). Mesa: An Agent-Based Modeling Framework. *Proceedings of the 14th Python in Science Conference*, *Scipy*, 51–58. https://doi.org/10.25080/majora-7b98e3ed-009
- McFadden, D. (1973). Conditional logit analysis of qualitative choice behavior. https://doi.org/10.1080/07373937.2014.997882
- Michaud, G. (2018). Deploying solar energy with community choice aggregation: A carbon fee model. *Electricity Journal*, 31(10), 32–38. https://doi.org/10.1016/j.tej.2018.11.003
- Mittal, A., Krejci, C. C., Dorneich, M. C., & Fickes, D. (2019). An agent-based approach to modeling zero energy communities. *Solar Energy*, 191, 193–204. https://doi.org/10.1016/j.solener.2019.08.040
- Mohandes, N., Sanfilippo, A., & Fakhri, M. Al. (2018). Modeling residential adoption of solar energy in the Arabian Gulf Region. *Renewable Energy, september*, 2–5.
- Momsen, K., & Thomas, S. (2014). From intention to action: Can nudges help consumers to choose renewable energy? *Energy Policy*. https://doi.org/10.1016/j.enpol.2014.07.008
- Motz, A. (2021). Consumer acceptance of the energy transition in Switzerland: The role of attitudes explained through a hybrid discrete choice model. *Energy Policy*, *151*, 112152. https://doi.org/10.1016/j.enpol.2021.112152

- NREL. (2021). Documenting a Decade of Cost Declines for PV Systems. https://www.nrel.gov/news/program/2021/documenting-a-decade-of-cost-declinesfor-pv-systems.html
- O'Shaughnessy, E., Barbose, G., & Wiser, R. (2020). Patience is a virtue: A data-driven analysis of rooftop solar PV permitting timelines in the United States. *Energy Policy*, *144*. https://doi.org/10.1016/j.enpol.2020.111615
- O'Shaughnessy, E., Heeter, J., & Burd, R. (2021). Status and Trends in the US Voluntary Green Power Market (2020 Data). *NREL*, *October*. http://www.nrel.gov/docs/fy16osti/65252.pdf
- O'Shaughnessy, E., Heeter, J., Gattaciecca, J., Sauer, J., Trumbull, K., & Chen, E. (2019). Empowered Communities: The Rise of Community Choice Aggregation in the United States. *Energy Policy*. https://www.sciencedirect.com/science/article/abs/pii/S0301421519304434
- Ozaki, R. (2011). Adopting sustainable innovation: What makes consumers sign up to green electricity? *Business Strategy and the Environment*, 20(1), 1–17. https://doi.org/10.1002/bse.650
- Pichert, D., & Katsikopoulos, K. V. (2008). Green defaults: Information presentation and pro-environmental behaviour. *Journal of Environmental Psychology*, 28(1), 63–73. https://doi.org/10.1016/j.jenvp.2007.09.004
- Rai, V., & Beck, A. L. (2015). Public perceptions and information gaps in solar energy in Texas. *Environmental Research Letters*, 10(7). https://doi.org/10.1088/1748-9326/10/7/074011
- Rai, V., & Henry, A. D. (2016). Agent-based modelling of consumer energy choices. *Nature Climate Change*, 6(6), 556–562. https://doi.org/10.1038/nclimate2967
- Rai, V., & Robinson, S. A. (2013). Effective information channels for reducing costs of environmentally- friendly technologies: Evidence from residential PV markets. *Environmental Research Letters*, 8(1). https://doi.org/10.1088/1748-9326/8/1/014044
- Rai, V., & Robinson, S. A. (2015). Agent-based modeling of energy technology adoption: Empirical integration of social, behavioral, economic, and environmental factors. *Environmental Modelling and Software*, 70(March), 163–177. https://doi.org/10.1016/j.envsoft.2015.04.014
- S&P Global. (2023). California CCA membership surpasses 200 communities , 28 % of utility load. 1–6.

- Sagebiel, J., Müller, J. R., & Rommel, J. (2014). Are consumers willing to pay more for electricity from cooperatives? Results from an online Choice Experiment in Germany. *Energy Research and Social Science*, 2(52385), 90–101. https://doi.org/10.1016/j.erss.2014.04.003
- Schelly, C. (2014). Residential solar electricity adoption: What motivates, and what matters? A case study of early adopters. *Energy Research and Social Science*. http://dx.doi.org/10.1016/j.erss.2014.01.001
- Schulte, E., Scheller, F., Pasut, W., & Bruckner, T. (2021). Product traits, decisionmakers, and household low-carbon technology adoptions: moving beyond single empirical studies. *Energy Research and Social Science*.
- Schulte, E., Scheller, F., Sloot, D., & Bruckner, T. (2022). A meta-analysis of residential PV adoption: the important role of perceived benefits, intentions and antecedents in solar energy acceptance. *Energy Research and Social Science*, 84. https://doi.org/10.1016/j.erss.2021.102339
- SEIA. (2023). Solar Installations in 2023 Expected to Exceed 30 GW for the First Time in History / SEIA. 10–11.
- Sergi, B., Davis, A., & Azevedo, I. (2018). The effect of providing climate and health information on support for alternative electricity portfolios. *Environmental Research Letters*, *13*(2). https://doi.org/10.1088/1748-9326/aa9fab
- Shaughnessy, E. O., Heeter, J., Gattaciecca, J., Trumbull, K., Chen, E., Shaughnessy, E. O., Heeter, J., Gattaciecca, J., Sauer, J., Trumbull, K., & Chen, E. (2019).
 Community Choice Aggregation: Challenges, Opportunities, and Impacts on Renewable Energy Markets Community Choice Aggregation: Challenges, Opportunities, and Impacts on Renewable Energy Markets. *National Renewable EnergyLaboratory (NREL), February*, 1–56.
- Sigrin, B., Dietz, T., Henry Adam, Ingle, A., Lutzenhiser, L., Moezzi, M., Spielman, S., Stern, P., Todd, A., Tong, J., & Wolske, K. (2017). Understanding the Evolution of Customer Motivations and Adoption Barriers in Residential Solar Markets: Survey Data. National Renewable Energy Laboratory. *National Renewable Energy Laboratory*, 10–12.
- Sigrin, B., Pless, J., & Drury, E. (2015). Diffusion into new markets: Evolving customer segments in the solar photovoltaics market. *Environmental Research Letters*, 10(8). https://doi.org/10.1088/1748-9326/10/8/084001
- Souchet, L., & Girandola, F. (2013). Double foot-in-the-door, social representations, and environment: Application for energy savings. *Journal of Applied Social Psychology*, 43(2), 306–315. https://doi.org/10.1111/j.1559-1816.2012.01000.x

- Stern, P. C., Dietz, T., Abel, T., Guagnano, G. A., & Kalof, L. (1999). A value-beliefnorm theory of support for social movements: The case of environmentalism. *Human Ecology Review*, 6(2), 81–97.
- SVCE. (2023). Silicon Valley Clean Energy Residential Generation Rates and Generation Service Cost Comparison Silicon Valley Clean Energy Residential Generation Rates and Generation Service Cost Comparison. 7–10. https://svcleanenergy.org/wp-content/uploads/Residential-Rate-Update-05.01.2023-_formatted.pdf
- Troiano, S., Marangon, F., Tempesta, T., & Vecchiato, D. (2016). Organic vs local claims: Substitutes or complements for wine consumers? A marketing analysis with a discrete choice experiment. *New Medit*, *15*(2), 14–21.
- U.S. DOE EIA. (2021). Renewables became the second-most prevalent U.S. electricity source in 2020. *Today In Energy*, 2021–2022. https://www.eia.gov/todayinenergy/detail.php?id=48896
- Wang, G., Zhang, Q., Li, Y., & Li, H. (2018). Policy simulation for promoting residential PV considering anecdotal information exchanges based on social network modelling. *Applied Energy*, 223(March), 1–10. https://doi.org/10.1016/j.apenergy.2018.04.028
- Watts, D. J., & Strogatz, S. H. (1998). Collective dynamics of "small-world" networks. *Conservation Biology*, 32(2), 287–293. https://doi.org/10.1111/cobi.13031
- Weaver, A. (2017). The Social Acceptance of Community Solar: A Portland Case Study. *ProQuest Dissertations and Theses*, 175. http://193.60.48.5/docview/1964910246?accountid=15997%0Ahttp://resolver.ebsco host.com/openurl?ctx_ver=Z39.88-2004&ctx_enc=info:ofi/enc:UTF-8&rfr_id=info:sid/ProQuest+Dissertations+%26+Theses+A%26I&rft_val_fmt=info: ofi/fmt:kev:mtx:dissertation&rft.genre=di
- Wei, J., Zhao, X., Liu, Y., & Xi, Y. (2021). Measuring purchase intention towards green power certificate in a developing nation: Applying and extending the theory of planned behavior. *Resources, Conservation & Recycling*. https://doi.org/10.1016/j.resconrec.2020.105363
- Wilson, P. (2020). Four Types of Scandals Utility Companies Get Into With Money From Your Electric Bills. *ProPublica*, 1–7. https://www.propublica.org/article/four-typesof-scandals-utility-companies-get-into-with-money-from-your-electric-bills
- Wolske, K. S., Stern, P. C., & Dietz, T. (2017). Explaining interest in adopting residential solar photovoltaic systems in the United States: Toward an integration of behavioral theories. *Energy Research and Social Science*, 25, 134–151. https://doi.org/10.1016/j.erss.2016.12.023

- Wolske, K. S., Todd, A., Rossol, M., James, M., & Sigrin, B. (2018). Accelerating demand for residential solar photovoltaics: Can simple framing strategies increase consumer interest? *Global Environmental Change Journal*, 53. https://doi.org/10.1016/j.gloenvcha.2018.08.005
- Wood Mackenzie, & SEIA. (2022). U.S. SOLAR MARKET INSIGHT Executive Summary. GTM Research and SEIA, December, 5. http://www.seia.org/sites/default/files/k7bZk7JSHC2016Q2SMI.pdf
- Zang, T., Genseler, S., & Garcia, R. (2011). J of Product Innov Manag 2011 Zhang -A Study of the Diffusion of Alternative Fuel Vehicles An Agent-Based Modeling.pdf. *Journal of Product Innovation Management*, 28, 152–168.
- Zarwi, F. El, Vij, A., & Walker, J. L. (2017). A Discrete Choice Framework for Modeling and Forecasting The Adoption and Diffusion of New Transportation Services Feras El Zarwi (corresponding author) Department of Civil and Environmental Engineering University of California at Berkeley 116 McLaughli. *Transportation Research Part C: Emerging Technologies*, 1–32. https://doi.org/10.1016/j.trc.2017.03.004
- Zhang, H., Vorobeychik, Y., Letchford, J., & Lakkaraju, K. (2016). Data-driven agentbased modeling, with application to rooftop solar adoption. *Autonomous Agents and Multi-Agent Systems*, 30(6), 1023–1049. https://doi.org/10.1007/s10458-016-9326-8

SECTION

2. CONCLUSIONS AND FUTURE WORK

To address the pressing need to counteract the detrimental impacts of climate change, it's pivotal that residential consumers seamlessly transition to renewable energy sources for their homes. As multiple options emerge in the market, it's imperative to analyze them within a framework where they function as alternatives to one another. Considering the prevailing reluctance among retail electricity consumers to actively seek renewable energy, increasing the renewable content at a utility scale, particularly when sourced from a CCA, can enhance household adoption rates.

The first study sought to determine the impact of specific attributes on consumers' electricity procurement decisions and their willingness to pay. It revealed significant economic influences on these decisions, with negative effects observed due to Monthly Expense and positive effects from Monetary Benefits, supporting the notion that financial considerations drive the adoption of low-carbon technologies. Notably, consumers exhibited a marked preference and readiness to pay for electricity with a higher renewable content. This inclination, especially towards centralized and combined procurement methods over solar PV, can be linked to the sample's demographic, predominantly consisting of younger, more educated, and liberal individuals. Contrary to prior research, the study found that the effort associated with the setup of these sources negatively affected choice, suggesting that aversion to high-effort sources might be counteracted with substantial incentives. Furthermore, providing information about

potential carbon savings notably enhances consumer preference for greener energy mixes, implying a proactive strategy for increasing renewable content in grids. However, the study faced limitations, especially in its choice experiment design, which merged centralized and distributed sources, and its sample's skewed representation. Future research should focus on diversifying samples, segregating attributes for clearer interpretation, and presenting monetary benefits quantitatively for more precise understanding and willingness to pay evaluations. Overall, the study's insights offer a roadmap for strategizing renewable energy uptake while also pinpointing areas for further investigation.

The second study has significant implications for the dynamics of electricity retail markets, especially in scenarios where providers furnish multiple procurement avenues. One such competition exists between CCAs and IOUs in residential supply. Notably, the success of CCAs in amplifying renewable procurement at the municipal level is attributed in part to the opt-out model and the consequential influence of default options. Evidence from this study suggests that when presented with a greener default, consumers are more inclined to select competitively priced green electricity, especially when juxtaposed with options that are either pricier or less renewable. For energy organizations aiming to optimize their market strategies, these insights can prove invaluable. They can refine their green electricity product offerings and marketing campaigns in light of these findings. The efficacy of the CCA opt-out structure in enhancing sales of voluntary renewable energy is evident. However, if the default option only marginally exceeds the state RPS, then augmentative efforts are requisite to champion green premium programs. A potential strategy is to target price-sensitive consumers by sculpting marketing narratives that draw

parallels between 100% renewable products and default offerings from incumbent utilities, which might boost sales of premium alternatives.

Nevertheless, the study's findings are not without constraints. The sample predominantly consisted of participants with a liberal, environmentally-aware bent, and a democratic inclination. This composition, albeit congruent with the typical profile of green electricity consumers, diverges from broader U.S. demographics, casting a shadow over the generalizability of the results. Additionally, the study did not factor in the role of social norms in shaping procurement choices, given the inconsistent evidence concerning their impact on the uptake of green tariffs offered by IOUs and CCAs, and the more pronounced visibility advantage of solar PV in norm-driven adoption scenarios. A critical aspect to contemplate is the potential disparity between expressed preferences and realworld actions. The study relied on a stated preference methodology, which could potentially yield exaggerated preference estimates that might not mirror actual consumer behavior. This discrepancy, often termed the value-action gap in renewable energy literature, underscores the chasm between consumers' environmental inclinations and their practical actions, implying that the active pursuit of greener electricity might be more muted in reality than indicated here.

The third study was centered around the development of an ABM using preexisting individual preferences for renewable energy procurement choices to forecast PV adoption rates. These inclinations were initialized based on part-worth utilities derived from a DCE. This model was designed to incorporate DCE estimates in two contexts: with and without the influence of CCA. In the model, agents were faced with a decision: either to install their own PV system or to source renewable energy directly from the electricity grid. Their decisions were influenced by variables such as the percentage of renewable content available in the grid, forecasted shifts in electricity prices, and the time and effort associated with procurement. To evaluate the model's accuracy, two specific scenarios were simulated. The initial scenario replicated the environment for PV procurement in California. The subsequent scenario simulated was rooted in the LaCosta Ridge community situated in the San Diego metropolitan area, mirroring conditions where procurement-related time and effort were minimized. Subsequently, a sensitivity analysis was conducted to assess the impact of various parameters on PV adoption rates. The gathered data emphasized the need for continuing monetary policies that incentivize PV adoption, simplifying the PV purchase process, expediting the installation procedure, and reducing homeowner involvement to potentially stimulate greater adoption rates. However, the potential variability in predictions, especially in optimal conditions, warranted a cautious approach.

Using DCE estimates as a foundational element has notably amplified the model's predictive accuracy. But for this model to truly inform policy decisions, several improvements are necessary. Currently, it assumes consistent sunlight exposure for all households in a given region, potentially offering a skewed perspective. By integrating GIS data, this model can provide a more accurate representation of the diverse conditions homeowners might face when contemplating PV adoption. Additionally, the metrics used to measure the influence of renewable content might need to be revisited. Multiple factors associated with utility companies, such as transparency, billing practices, and service quality, can all influence the perceived value of renewable content. Understanding and incorporating these nuances can offer a more holistic view of consumer decision-making

in relation to PV adoption. The current surge in renewable adoption in the electricity sector reflects a broader shift towards sustainable energy priorities. This study's ABM illuminates the critical role of financial incentives and ease of procurement in catalyzing PV adoption among homeowners. The results also underscore the potential challenges and opportunities for utilities and CCAs in an evolving energy landscape, highlighting the need for adaptability and proactive strategizing.

The fourth study highlights the limitations of prior research into photovoltaic (PV) adoption which has mainly focused on gain-loss frames and the expected return on investment (Wolske et al., 2018). While some studies probed the link between Renewable Portfolio Standards (RPS) and residential PV adoption, they predominantly targeted the advent of community solar programs (Funkhouser et al., 2015). In the research in question, a comprehensive experimental method addressing varied renewable content levels was implemented, integrating control groups tied with and distinct from the Community Choice Aggregation (CCA) structure. Although geographical, economic, and sociological contexts play pivotal roles in PV adoption, this study offered an alternative lens into renewable energy procurement.

Interestingly, there's a burgeoning trend in the U.S. where community or investorowned utilities provide sizable renewable resources to residential customers. Yet, there seems to be a gap in academic literature about effectively informing homeowners about these expansive renewable projects and gauging their subsequent reactions. To understand the impact of escalated renewable content and a CCA backdrop on PV adoption, a sample was drawn from states where CCAs are either operational or poised for launch. A noteworthy aspect of the sampling methodology was the limited cognizance

among respondents about CCA initiatives in their regions—only 11% indicated awareness, even though CCAs are functional in 10 out of the 17 sampled states. One evident reason for this limited awareness is that even in CCA states, billing predominantly remains under the purview of private utilities, with CCAs occasionally reaching out through mailers. There's a palpable discrepancy between the experimental conditioning using CCA and renewable content messages and the actual comprehension by participants in this study. Furthermore, while certain economic assumptions across the 17 states were made to streamline the design and analysis in the study, it's vital to consider the potential influence of diverse state incentives on PV adoption. Factors such as solar irradiation variances and state-specific rebates and incentives play a crucial role. States like California and Arizona, due to higher solar irradiation, have more favorable payback periods and offer substantial net-metering rebates. The intricacy of these factors underscores that a more comprehensive methodology might be necessary for a precise understanding. Lastly, the study used experimental postcards from hypothetical companies as a mode of manipulation. This might have diluted the resonance of the introduced Community Choice Aggregation (CCA) due to participants' unfamiliarity with these fictitious entities. The same holds for the hypothetical solar PV company presented, potentially influencing the measurement of their intent to engage. In real-world scenarios, respondents might be more receptive to renowned solar installation firms in their vicinity. It's suggested that subsequent studies might benefit from employing familiar, reputable community companies to understand the true influence of CCA-led renewable procurement on PV adoption inclinations.

In conclusion, this dissertation emphasizes the significance of contextualizing household renewable energy adoption within the framework of CCA. The primary products evaluated herein are residential PV and green electricity. It is recommended that subsequent research endeavors develop novel frameworks to compare utility-scale options, incorporating attributes not examined in this dissertation. As the CCA model is a recent introduction to the wholesale electricity markets, its impact on consumer preferences for renewable procurement remains largely uncharted in empirical data. Future research could concentrate on innovative methodologies to assess the influence of CCAs and their provision of high renewable content.

APPENDIX

There were no significant differences in the sample for the two experimental groups (see Table 1). The sample reflects the U.S. population in terms of gender (U.S. national average = 50.5% female), age (U.S. national average = 39 years old), and race (U.S. national average = 75.8% White). There is no statistically significant difference in the annual income, F(1, 587) = 1.2, p > 0.05. The median income in both groups was in the \$50,000-75,000 range, consistent with the U.S. national income distribution (U.S. median income = \$67,541). In addition, most participants had received a college degree or higher. Most of the participants were Moderate to Very Liberal Democrats. Most participants were homeowners and lived in single-family homes. Overall, participants had high attention, correctly answering each of the three attention check questions (see Table 1). The differences in attention scores achieved by the two groups are significantly different, F(1, 603) = 10.9, p < 0.01.

Most participants were aware of renewable energy options and had made energy efficiency investments. This suggests that the sample reflects the type of consumers who would be inclined to consider procuring renewable energy when choosing an electricity package. The median monthly electricity bill was \$120 (SD = \$88), with no significant differences between groups, F(1,486) = 1.05, p > 0.05. Most (53%) participants were aware of solar PV installation options in their area and a small percent (3%) had it installed. Awareness of green electricity options in their area was lower overall (23%),
Measure	Levels	15% Renewable	30% Renewable
Homeowners	Yes	60%	55%
	No	40%	44%
Home Type	Single Family	66%	68%
	Apartment	25%	21%
	Townhouse	6%	6%
	Other	1%	4%
Awareness solar	Yes	55%	51%
	No	18%	17%
	Already installed	2.6%	5%
	Don't know	23%	26%
A	Vac	270/	200/
Awareness green	res	27%	20%
		1/%	24%
	Already subscribed	0% 490/	8%
	Don't know	48%	47%
Energy Efficient	Efficient lighting	52%	57%
	Efficient appliances	48%	48%
	Efficient furnace,	37%	35%
	Added Insulation	24%	24%
	Efficient windows	23%	23%
	Weatherized/air-	17%	21%
	Sealed/Insulated	10%	10%
	Others	1%	2%
	None	31%	24%
Low Carbon	Heat Pump	14%	18%
2011 00000	Hybrid Vehicle	7%	7%
	Electric Vehicle	3%	2%
	Solar Water Heater	2%	3%
	None	73%	70%
Average monthly		Mean - \$147	Mean - \$149
electricity bill		S.D. – \$94.7	S.D. – \$88.9

but a higher percent of participants (7%) had already subscribed to it. In both groups, most (18%) participants had invested in at least two energy efficient technologies, with efficient appliances and lighting being the most common. Most (71%) participants did not own any low-carbon products, but a small percent reported owning heat pumps (16%), hybrid vehicles (7%), and electric vehicles (2%). For environmental benefits (Cronbach alpha = 0.94), participants reported high awareness in both groups (M = 4.16, SD = 0.92). Additional details broken out by experimental group are in Table A1.

Likert Scale Measures	15% default	30% default
	Std. Ldg./	Std. Ldg./
	Mean (SD)	Mean (SD)
Environmental Benefits	(Cronbach α	(Cronbach α
	= 0.94)	= 0.94)
Renewable energy helps slow down climate change	0.91	0.89
If more households get electricity from renewable	0.92	0.94
sources, environmental quality will improve		
Having electricity from renewable sources would be a	0.93	0.91
good way to reduce my environmental impact		
Environmental Benefits Score	4.14 (0.94)	4.20 (0.90)
Trust		
I trust that my utility company always acts in my best	2.4 (1.1)	2.4 (1.1)
interest		
I trust that the green electricity provided by my utility	3.2 (0.9)	3.4 (0.93)
is from renewable sources		

Table A.2. Respondent beliefs

Variables	Standardized factor loading
Perceived Benefits ($\alpha = 0.83$)	10000008
Solar panels can reduce my household's environmental impact - PB1	0.822
Solar panels can reduce carbon emissions for my residence - PB2	0.817
Solar panels can save money for my household in the long run - PB3	0.771
Solar panels improve the resale value of my home - PB4	0.597
Soft Barriers ($\alpha = 0.67$)	
Solar panels would not provide the level of benefits I would be expecting – SB1	0.776
Installing solar panels is a hassle – SB2	0.554
I can't afford solar on my family budget – SB3	0.383
Solar panels are still very expensive, even with government incentives – SB4	0.404
Trust ($\boldsymbol{\alpha} = 0.85$)	
I trust that my electricity provider would always act in my best interest – T1	0.914
I trust the communications I receive from my electricity provider – T2	0.819
Environmental Concern ($\alpha = 0.94$)	
I care about conserving nature – EC1	0.685
It is important to me to take care of the environment in my local community – EC2	0.704
It is important to me to protect the environment for people around the world – EC3	0.786
It is important to me to protect the environment for future generations $-EC4$	0.750
Lam worried about climate change – EC5	0.936
I am worried about the impacts of climate change in my community $- FC6$	0.904
I am worried about the impacts of climate change in my community $-$ ECO I am worried about the impacts of climate change around the world $-$ EC7	0.944
Consumer Novelty Seeking ($\alpha = 0.87$)	
I continuously look for new experiences from new products – CNS1	0.908
I continuously look for new products and brands – CNS2	0.910
I like to visit places where I'm exposed to information about new products and brands – CNS3	0.692
Consumer Independent Independent Making (a - 0.83)	
Before I buy a new product or service, I often ask acquaintances about their $\frac{1}{2}$	0.862
Before buying a new brand, I usually ask someone who has experience with the brand for advice (reversed) - CIIM2	0.869
When considering a new product/service, I usually trust the opinions of friends who have used the product/service, (reversed) – CIJM3	0.631

Table A.3: Confirmatory Factor Analysis results from Chapter 4

Table A.S. Commutatory Factor Analysis results from Chapter 4 (cont.)Subjective Norm ($\alpha = 0.81$)Nost people who are important to me would support me if I decided to go0.825solar – SN1People who are important to me would be in favor of installing solar panels –0.882SN2My family members would be opposed to getting solar panels. (reversed) –0.629SN3

BIBLIOGRAPHY

- Abreu, J., Wingartz, N., & Hardy, N. (2019). New trends in solar: A comparative study assessing the attitudes towards the adoption of rooftop PV. *Energy Policy*, 128, 347– 363. https://doi.org/10.1016/j.enpol.2018.12.038
- Borchers, A. M., Duke, J. M., & Parsons, G. R. (2007). Does willingness to pay for green energy differ by source? *Energy Policy*, 35(6), 3327–3334. https://doi.org/10.1016/j.enpol.2006.12.009
- Boumaiza, A., Abbar, S., Mohandes, N., & Sanfilippo, A. (2018). Modeling the impact of innovation diffusion on solar PV adoption in city neighborhoods. *International Journal of Renewable Energy Research*, 8(3), 1749–1762. https://doi.org/10.20508/ijrer.v8i3.7999.g7484
- Busic-Sontic, A., & Fuerst, F. (2018). Does your personality shape your reaction to your neighbours' behaviour? A spatial study of the diffusion of solar panels. *Energy and Buildings*, *158*, 1275–1285. https://doi.org/10.1016/j.enbuild.2017.11.009
- Cape Analytics. (2021). *These maps show the cities with the most solar in the U.S.* Panasonic. https://www.fastcompany.com/90423202/these-maps-show-the-citieswith-the-most-solar-in-the-u-s
- Cape Light Compact. (2023). C a p e L i g h t C o m p a c t A n n o u n c e s N e w, L o w e r P r i c i n g f o r P o w e r S u p p l y. 1–6. https://www.capelightcompact.org/10655-2/
- Chappin, E. J. L., Schleich, J., Guetlein, M. C., Faure, C., & Bouwmans, I. (2022). Linking of a multi-country discrete choice experiment and an agent-based model to simulate the diffusion of smart thermostats. *Technological Forecasting and Social Change*, 180(January), 121682. https://doi.org/10.1016/j.techfore.2022.121682
- Chen, M. F., & Tung, P. J. (2014). Developing an extended Theory of Planned Behavior model to predict consumers' intention to visit green hotels. *International Journal of Hospitality Management*, 36, 221–230. https://doi.org/10.1016/j.ijhm.2013.09.006
- Dagher, L., Bird, L., & Heeter, J. (2017). Residential green power demand in the United States. *Renewable Energy*, *114*, 1062–1068. https://doi.org/10.1016/j.renene.2017.07.111
- Danne, M., Meier-Sauthoff, S., & Musshoff, O. (2021). Analyzing German consumers' willingness to pay for green electricity tariff attributes: a discrete choice experiment. *Energy, Sustainability and Society*, 11(1), 1–16. https://doi.org/10.1186/s13705-021-00291-8

- Denholm, P., Clark, K., & O'Connell, M. (2016). Emerging Issues and Challenges in Integrating High Levels of Solar into the Electrical Generation and Transmission System. NREL, May, 68. https://www.nrel.gov/docs/fy16osti/65800.pdf
- EIA. (2023). Renewable generation surpassed coal and nuclear in the U.S. electric power sector in 2022. U.S. Energy Information Administration. https://www.eia.gov/todayinenergy/detail.php?id=55960
- EPA. (2022). *How Do CCAs Work ? When Was CCA-Enabling Legislation Passed in Various. Figure 1*, 1–7. https://www.epa.gov/green-power-markets/community-choice-aggregation#four
- Eyal, P., Rothschild, D., Evernden, Z., Gordon, A., & Damer, E. (2021). Data Quality of Platforms and Panels for Online Behavioral Research Data Quality of Platforms and Panels for Online Behavioral Research. *Behavior Research Methods, August*, 1–46.
- Fikru, M. G., & Canfield, C. (2022). Demand for renewable energy via green electricity versus solar installation in Community Choice Aggregation. *Renewable Energy*, 186, 769–779. https://doi.org/10.1016/j.renene.2022.01.008
- Forbes. (2020). Renewable Energy Prices Hit Record Lows: How Can Utilities Benefit From Unstoppable Solar And Wind? https://www.forbes.com/sites/energyinnovation/2020/01/21/renewable-energyprices-hit-record-lows-how-can-utilities-benefit-from-unstoppable-solar-andwind/?sh=7b2ac9782c84 89(October), 104237. https://doi.org/10.1016/j.landusepol.2019.104237
- Funkhouser, E., Blackburn, G., Magee, C., & Rai, V. (2015). Business model innovations for deploying distributed generation: The emerging landscape of community solar in the U.S. *Energy Research and Social Science*, 10, 90–101. https://doi.org/10.1016/j.erss.2015.07.004
- Horne, C., Kennedy, E., & Familia, T. (2021). Rooftop solar in the United States: Exploring trust, utility perceptions, and adoption among California homeowners. *Energy Research & Social Science*. https://doi.org/10.1016/j.erss.2021.102308
- Hsu, D. (2022). Straight out of Cape Cod: The origin of community choice aggregation and its spread to other states. *Energy Research and Social Science*, 86(May 2021), 102393. https://doi.org/10.1016/j.erss.2021.102393
- Huang, C., & Shen, R. (2020). Does city or state make a difference? The effects of policy framing on public attitude toward a solar energy program. *Journal of Behavioral Public Administration*, 3(2), 1–21. https://doi.org/10.30636/jbpa.32.126

IRENA. (2023). Global renewables capacity grew by 10 %. Reuters.

Islam, T. (2014). Household level innovation diffusion model of photo-voltaic (PV) solar

- Kleinberg, J. (2000). The small-world phenomenon: An algorithmic perspective. *Proceedings of the Annual ACM Symposium on Theory of Computing*, 163–170. https://doi.org/10.1145/335305.335325
- Knapp, L., O'Shaughnessy, E., Heeter, J., Mills, S., & DeCicco, J. M. (2020). Will consumers really pay for green electricity? Comparing stated and revealed preferences for residential programs in the United States. *Energy Research and Social Science*, 65, 0–26. https://doi.org/10.1016/j.erss.2020.101457
- Litvine, D., & Wüstenhagen, R. (2011). Helping "light green" consumers walk the talk: Results of a behavioural intervention survey in the Swiss electricity market. *Ecological Economics*, 70(3), 462–474. https://doi.org/10.1016/j.ecolecon.2010.10.005
- Mohandes, N., Sanfilippo, A., & Fakhri, M. Al. (2018). Modeling residential adoption of solar energy in the Arabian Gulf Region. *Renewable Energy*, september, 2–5.
- Momsen, K., & Thomas, S. (2014). From intention to action: Can nudges help consumers to choose renewable energy? *Energy Policy*. https://doi.org/10.1016/j.enpol.2014.07.008
- Motz, A. (2021). Consumer acceptance of the energy transition in Switzerland: The role of attitudes explained through a hybrid discrete choice model. *Energy Policy*, *151*, 112152. https://doi.org/10.1016/j.enpol.2021.112152
- NREL. (2021). Documenting a Decade of Cost Declines for PV Systems. https://www.nrel.gov/news/program/2021/documenting-a-decade-of-cost-declines-for-pv-systems.html
- O'Shaughnessy, E., Barbose, G., & Wiser, R. (2020). Patience is a virtue: A data-driven analysis of rooftop solar PV permitting timelines in the United States. *Energy Policy*, *144*. https://doi.org/10.1016/j.enpol.2020.111615
- O'Shaughnessy, E., Heeter, J., & Burd, R. (2021). Status and Trends in the US Voluntary Green Power Market (2020 Data). *NREL*, *October*. http://www.nrel.gov/docs/fy16osti/65252.pdf
- O'Shaughnessy, E., Heeter, J., Gattaciecca, J., Sauer, J., Trumbull, K., & Chen, E. (2019). Empowered Communities: The Rise of Community Choice Aggregation in the United States. *Energy Policy*. https://www.sciencedirect.com/science/article/abs/pii/S0301421519304434
- S&P Global. (2023). California CCA membership surpasses 200 communities , 28 % of utility load. 1–6.

- Sagebiel, J., Müller, J. R., & Rommel, J. (2014). Are consumers willing to pay more for electricity from cooperatives? Results from an online Choice Experiment in Germany. *Energy Research and Social Science*, 2(52385), 90–101. https://doi.org/10.1016/j.erss.2014.04.003
- Schelly, C. (2014). Residential solar electricity adoption: What motivates, and what matters? A case study of early adopters. *Energy Research and Social Science*. http://dx.doi.org/10.1016/j.erss.2014.01.001
- Schulte, E., Scheller, F., Pasut, W., & Bruckner, T. (2021). Product traits, decisionmakers, and household low-carbon technology adoptions: moving beyond single empirical studies. *Energy Research and Social Science*.
- Schulte, E., Scheller, F., Sloot, D., & Bruckner, T. (2022). A meta-analysis of residential PV adoption: the important role of perceived benefits, intentions and antecedents in solar energy acceptance. *Energy Research and Social Science*, 84. https://doi.org/10.1016/j.erss.2021.102339
- SEIA. (2023). Solar Installations in 2023 Expected to Exceed 30 GW for the First Time in History / SEIA. 10–11.
- Sergi, B., Davis, A., & Azevedo, I. (2018). The effect of providing climate and health information on support for alternative electricity portfolios. *Environmental Research Letters*, 13(2). https://doi.org/10.1088/1748-9326/aa9fab
- Shaughnessy, E. O., Heeter, J., Gattaciecca, J., Trumbull, K., Chen, E., Shaughnessy, E. O., Heeter, J., Gattaciecca, J., Sauer, J., Trumbull, K., & Chen, E. (2019).
 Community Choice Aggregation: Challenges, Opportunities, and Impacts on Renewable Energy Markets Community Choice Aggregation: Challenges, Opportunities, and Impacts on Renewable Energy Markets. *National Renewable EnergyLaboratory (NREL), February*, 1–56.
- Sigrin, B., Dietz, T., Henry Adam, Ingle, A., Lutzenhiser, L., Moezzi, M., Spielman, S., Stern, P., Todd, A., Tong, J., & Wolske, K. (2017). Understanding the Evolution of Customer Motivations and Adoption Barriers in Residential Solar Markets: Survey Data. National Renewable Energy Laboratory. *National Renewable Energy Laboratory*, 10–12.
- Sigrin, B., Pless, J., & Drury, E. (2015). Diffusion into new markets: Evolving customer segments in the solar photovoltaics market. *Environmental Research Letters*, 10(8). https://doi.org/10.1088/1748-9326/10/8/084001
- Souchet, L., & Girandola, F. (2013). Double foot-in-the-door, social representations, and environment: Application for energy savings. *Journal of Applied Social Psychology*, *43*(2), 306–315. https://doi.org/10.1111/j.1559-1816.2012.01000.x

- Stern, P. C., Dietz, T., Abel, T., Guagnano, G. A., & Kalof, L. (1999). A value-beliefnorm theory of support for social movements: The case of environmentalism. *Human Ecology Review*, 6(2), 81–97.
- SVCE. (2023). Silicon Valley Clean Energy Residential Generation Rates and Generation Service Cost Comparison Silicon Valley Clean Energy Residential Generation Rates and Generation Service Cost Comparison. 7–10. https://svcleanenergy.org/wp-content/uploads/Residential-Rate-Update-05.01.2023-_formatted.pdf
- Troiano, S., Marangon, F., Tempesta, T., & Vecchiato, D. (2016). Organic vs local claims: Substitutes or complements for wine consumers? A marketing analysis with a discrete choice experiment. *New Medit*, *15*(2), 14–21.
- U.S. DOE EIA. (2021). Renewables became the second-most prevalent U.S. electricity source in 2020. *Today In Energy*, 2021–2022. https://www.eia.gov/todayinenergy/detail.php?id=48896
- Wang, G., Zhang, Q., Li, Y., & Li, H. (2018). Policy simulation for promoting residential PV considering anecdotal information exchanges based on social network modelling. *Applied Energy*, 223(March), 1–10. https://doi.org/10.1016/j.apenergy.2018.04.028
- Watts, D. J., & Strogatz, S. H. (1998). Collective dynamics of "small-world" networks. *Conservation Biology*, 32(2), 287–293. https://doi.org/10.1111/cobi.13031
- Weaver, A. (2017). The Social Acceptance of Community Solar: A Portland Case Study. *ProQuest Dissertations and Theses*, 175. http://193.60.48.5/docview/1964910246?accountid=15997%0Ahttp://resolver.ebsco host.com/openurl?ctx_ver=Z39.88-2004&ctx_enc=info:ofi/enc:UTF-8&rfr_id=info:sid/ProQuest+Dissertations+%26+Theses+A%26I&rft_val_fmt=info: ofi/fmt:kev:mtx:dissertation&rft.genre=di
- Wei, J., Zhao, X., Liu, Y., & Xi, Y. (2021). Measuring purchase intention towards green power certificate in a developing nation: Applying and extending the theory of planned behavior. *Resources, Conservation & Recycling*. https://doi.org/10.1016/j.resconrec.2020.105363
- Wilson, P. (2020). Four Types of Scandals Utility Companies Get Into With Money From Your Electric Bills. *ProPublica*, 1–7. https://www.propublica.org/article/four-types-of-scandals-utility-companies-get-into-with-money-from-your-electric-bills
- Wolske, K. S., Stern, P. C., & Dietz, T. (2017). Explaining interest in adopting residential solar photovoltaic systems in the United States: Toward an integration of behavioral theories. *Energy Research and Social Science*, 25, 134–151. https://doi.org/10.1016/j.erss.2016.12.023

- Wolske, K. S., Todd, A., Rossol, M., James, M., & Sigrin, B. (2018). Accelerating demand for residential solar photovoltaics: Can simple framing strategies increase consumer interest? *Global Environmental Change Journal*, 53. https://doi.org/10.1016/j.gloenvcha.2018.08.005
- Wood Mackenzie, & SEIA. (2022). U.S. SOLAR MARKET INSIGHT Executive Summary. GTM Research and SEIA, December, 5. http://www.seia.org/sites/default/files/k7bZk7JSHC2016Q2SMI.pdf
- Zang, T., Genseler, S., & Garcia, R. (2011). J of Product Innov Manag 2011 Zhang -A Study of the Diffusion of Alternative Fuel Vehicles An Agent-Based Modeling.pdf. *Journal of Product Innovation Management*, 28, 152–168.
- Zarwi, F. El, Vij, A., & Walker, J. L. (2017). A Discrete Choice Framework for Modeling and Forecasting The Adoption and Diffusion of New Transportation Services Feras El Zarwi (corresponding author) Department of Civil and Environmental Engineering University of California at Berkeley 116 McLaughli. *Transportation Research Part C: Emerging Technologies*, 1–32. https://doi.org/10.1016/j.trc.2017.03.004
- Zhang, H., Vorobeychik, Y., Letchford, J., & Lakkaraju, K. (2016). Data-driven agentbased modeling, with application to rooftop solar adoption. *Autonomous Agents and Multi-Agent Systems*, 30(6), 1023–1049. https://doi.org/10.1007/s10458-016-9326-8

VITA

Ankit Agarwal was born in Kuleisila village in the state of Odisha, India. He received a Bachelor of Technology in Electronics and Telecommunication Engineering from the Biju Patnaik University of Technology in June 2016 and a Master of Science in Engineering Management from Missouri University of Science and Technology in May 2021. He worked for TATA Consultancy Services from 2016 to 2019 as a Systems Engineer before joining the Engineering Management and Systems Engineering Department at Missouri S&T as a graduate student. During his Ph.D. studies, he was a Research Assistant and also served on the Tau Beta Pi Executive Committee. He received a Doctor of Philosophy in Engineering Management from Missouri S&T in December 2023.