

An Engineering and Behavioral Sciences Approach to Understand and Inform Energy Efficiency and Renewable Energy Decision-Making

Submitted in partial fulfillment of the requirements for

the degree of

Doctor of Philosophy

in

Engineering & Public Policy

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August, 2018

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Acknowledgements

It takes a village to raise a child, and perhaps to graduate a PhD. I am honored to acknowledge the many mentors, friends, and family who unequivocally had a hand in my academic and personal growth over the past four years.

First, thank you to my advisor and chair, Gabrielle Wong-Parodi. I am truly inspired by your curiosity, research prowess, and incredible capacity for teaching. But you are more than just an amazing research advisor to me – you are an unparalleled role model and confidante.

Next, I am lucky to thank my other co-advisors and committee members: Inês Azevedo, Alex Davis, Mitchell Small, and Naïm Darghouth. Thank you for all of your guidance on how to approach (and define!) interesting research questions, direction on how to be a better TA, and gentle criticism that allowed me to both laugh at myself and improve.

My work here was funded by the Department of Engineering and Public Policy and the National Science Foundation's Graduate Research Fellowship Program Grant No. DGE1252522. Additional funding was provided by the Skoll Foundation, the Simon Seed Initiative and the Innovations in Engineering and Education Program, and the Emerson and Elizabeth Pugh Fellowship in Engineering and Public Policy. I would not be submitting this dissertation without this generous support. Thank you.

I would be remiss to not attribute the original pursuit of my graduate research to Dr. Kevin Hallinan at the University of Dayton. I am forever grateful that you helped focus my energy as a young engineering student and demonstrated how interdisciplinary research could be harnessed to do some good in a community.

I am also thankful for researchers at national labs, professors at other universities, and research groups that provided me data and insight. Namely, I would like to acknowledge Dr. Benjamin Sigrin and Meghan Mooney from the National Renewable Energy Laboratory for providing LIDAR data for Chapter 4 and enjoyable discussions on how best to estimate roof space. Additionally, I am indebted to Dr. Evelina Trutnevyte for hosting me at her lab at ETH Zürich, which sparked many collaborations and lasting friendships. I am also thankful for the guidance from Dr. Christopher Payne from Lawrence Berkeley National Laboratory who allowed me to visit Berkeley Lab for a most memorable summer. Thank you to Dr. Baruch Fischhoff and everyone in the Behavior, Decision, and Policy Group for their helpful feedback and for sharing their compelling research. Lastly, I would like to thank Dr. Susan Finger for helping me craft my NSF materials – much of the aforementioned would not have happened without the fellowship.

I am also grateful for the support of the Engineering and Public Policy Staff. Thank you for always lending an ear and for answering all of my questions. Special thanks to Adam Loucks for being so kind and putting on some lovely choir concerts that brightened my semesters.

To my friends in the program who only let me slip into a controlled insanity – thank you. Rather than embark on a list of names, I'll describe some moments that I won't soon forget: 19-701 reading group meetings, working late nights on homework, all of the help I received during my shoulder surgery recovery (especially getting rides to school, the big Rosie the Riveter poster of me, and that reclining chair in my bedroom), potluck dinners on Beeler, some crying on shoulders, spirited dancing, bike rides to concerts and ice cream parlors, all of the Alpine hiking, my surprise birthday party in Hamburg, all of your beautiful weddings (and the associated road trips), secret handshakes, long distance Skype calls, coffee breaks, the 2017 Women's March, all the surprise knickknacks/cards/books/treats that were left on my desk throughout the years, Risk Buffalo, swimming/yoga/lifting/tennis, taco lunches, my first ski trip, Qualee – my dino baby, This is Us marathons, roommate dinners, and every single person who made me smile and laugh. "For in the dew of little things the heart finds its morning and is refreshed." – Khalil Gibran.

I also literally wouldn't be here today without my chosen family in Chicago – Tanya, Kevin, and Allison – who physically moved me to Pittsburgh, provided sanctuary "back home" when I needed it most, and visited me to make sure I hadn't lost my spirit. Thank you. The same can be said for my college roommates – Amy, Katy, Courtney, Eileen, Renee, Mere, and Corinne – who will forever be a source of giggling and pure joy in my life.

Lastly, thank you to my loving parents, Leo and Terry, and sister, Kelly. In ways that only family can, you were there to celebrate the mini victories with me and to encourage me when things weren't going my way. You can still call me Peepers, Porkchop, or Seester... but please put a "Dr." in front of it ;)

Abstract

In 2017, approximately 62% of electricity generated in the United States (U.S.) came from coal and natural gas sources, while only 8% came from wind and solar energy sources. This heavily fossil fuel dependent generation mix contributes to approximately 30% of total U.S. greenhouse gas emissions. Energy efficiency (EE) and renewable energy (RE) are two ways to reduce the carbon footprint of our electricity sector. This dissertation addresses the decision-making behavior of actors in and across the commercial, residential and educational sectors on the adoption of EE and RE technologies in the U.S. This work characterizes the barriers and motivations to adoption as well as the associated health and environmental benefits from offsetting electricity generated by fossil fuel power plants.

In Chapter 2, I employ an interview study to explore the behavioral and social factors in commercial building energy efficiency investment decision-making and to clarify the distinction between influences related to Economics/Technology and Psychology/Context. I find heterogeneity among interviewed experts and owners/managers regarding the value of corporate social responsibility (CSR). I also find that the relationship between owners/managers and their building engineering team heavily influences decision-making. Finally, the interviews reveal potentially promising new concepts related to psychological and social influences in the EE investment decision domain.

Chapter 3 focuses on the residential sector and details findings from two studies evaluating the effect of a clean energy campaign on civic engagement (e.g. signing a petition) among parents already taking advocacy actions (i.e. advocacy sample) and those who aren't (i.e. public sample). Among our public sample, I find that participants who believe the campaign to be credible and comprehensible are more likely to take action than those who discredit the campaign or do not understand its message. Additionally, I find parents who have children under the age of 18 negatively adjust their attitudes towards fossil fuels after being presented with health information.

Finally, in Chapter 4, I focus on the educational sector and employ a benefit-cost analysis (BCA) to determine which states in the U.S. will benefit most from installing solar photovoltaic (PV) on their educational facilities and which PV projects are financially feasible. I find that solar PV in U.S. educational institutions can provide 100 TWh of electricity services annually, meeting 75% of these buildings current electricity consumption. The provision of electricity services from rooftop solar PV on educational institutions can reduce environmental, health and climate change damages by roughly \$4 billion per year.

Discussed in Chapter 5 are this work's contribution to the literature and the policy implications regarding the adoption of EE and RE among various actors revealed in Chapters 2 through 4. For instance, findings from Chapter 2 suggest that policy makers should consider non-economic factors related to EE adoption, such as the relationship between owners and building engineers. In Chapter 3, I learn that campaigns can inspire civic engagement among residential consumers if campaign materials are perceived credible and advocacy actions seem effective. In Chapter 4, results detail which regions in the U.S. stand to benefit the most from installing PV on their educational buildings and provides a baseline analysis for efficient incentive design.

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Glossary of Acronyms

AASHE	Association for the Advancement of Sustainability in Higher Education
ANOVA	Analysis of Variance
AP2	2 nd version of the Air Pollution Emission Experiments and Policy analysis model
CBA	Cost-Benefit Analysis
CBECS	Commercial Building Energy Consumption Survey
CDC	Centers for Disease Control and Prevention
CEO	Chief Executive Officer
CO ₂	Carbon Dioxide
CSR	Corporate Social Responsibility
DOE	Department of Energy
DSM	Digital Surface Model
EASIUR	Estimating Air Pollution Social Impact Using Regression Model
EE	Energy Efficiency
EIA	Energy Information Agency
EPA	Environmental Protection Agency
FEMA	Federal Emergency Management Agency
GHG	Greenhouse Gas
GIS	Geographical Information System
GW	Gigawatt
HVAC	Heating, Ventilation, and Air Conditioning
ITC	Investment Tax Credit
kW	Kilowatt
kWh	Kilowatt-hour
LBNL	Lawrence Berkeley National Lab
LIDAR	Light Detection and Ranging
LMP	Locational Marginal Pricing
MADD	Mothers Against Drunk Driving
NCES	National Center for Education Statistics
NO _x	generic term for Nitrogen Oxides
NREL	National Renewable Energy Laboratory
PM _{2.5}	atmospheric Particulate Matter with a diameter less than 2.5 micrometers
PV	Photovoltaic
REC	Renewable Energy Credit
SI	Supplementary Information
SO ₂	Sulfur Dioxide
STARS	Sustainability Tracking, Assessment, and Rating System
TMY3	Typical Meteorological Year (Version 3)
TWh	Terawatt-hour
UCOP	University of California Office of the President
U.N.	United Nations
U.S.	United States

1. Introduction

“An innumerable host of actions and attitudes, comprising perhaps the bulk of all land relations, is determined by the land-users’ tastes and predilections, rather than by his purse.”

– Aldo Leopold, *The Land Ethic*

“She generally gave herself very good advice, (though she very seldom followed it).”

– Lewis Carroll, *Alice’s Adventures in Wonderland*

It is difficult to ignore the omnipresent negative effects associated with the release of greenhouse gasses (GHGs) and criteria air pollutants from burning fossil fuels in the United States (U.S.). These harmful effects manifest as positive climate forcing – a change in Earth’s energy balance that promotes a warming effect – which has increased by 37% between 1990 and 2015 due to anthropogenic GHG emissions [1]. Additionally, GHG emissions directly contribute to changes in air quality (e.g. increases in ozone, changes in particulate matter, and changes in allergens and asthma triggers), extreme weather events, vector borne diseases, and water and food safety [2], resulting in annual health costs amounting to roughly 4% of the national gross domestic product (GDP) [3]. Environmental and health risks are particularly acute for at-risk populations such as asthmatics, the elderly, and those living near a coast [4]–[8].

In 2016, the electricity sector contributed 28% of all GHG emissions in the U.S. that made it, along with the transportation sector, the top source of domestic emissions [9]. According to the U.S. Energy Information Administration (EIA) [10], this trend is likely to continue into the foreseeable future and might expand under low oil price and high economic growth scenarios. A strong dependence on fossil fuels explains the link between electricity generation and GHG emissions – today more than 60% of electricity generated in the U.S. comes from fossil fuel sources, while only 2% comes from solar photovoltaic (PV) and 6% comes from wind [11]. On balance, there are two approaches to reduce electricity sector emissions: reduce consumption (i.e. increase energy efficiency) or change the portfolio (i.e. adopt more renewable energy).

Fully realizing these approaches requires multiple actors at various scales to take action to increase the share of energy efficiency (EE) and renewable energy (RE) throughout the U.S. Traditionally, economic incentives have been used as the main tool to promoting this change across actors and actions. Moreover, a sectoral incentive approach is often taken where, for

instance, programs are designed only for actors in the residential sector (e.g. residents reducing energy consumption in the home through the use of in-home energy displays), rather than recognizing that actors can act across sectors (e.g. residents petitioning a local utility to invest in clean energy)[12], [13]. This top-down approach does not exploit all of the political and technological actions that are available to these actors wishing to reduce their fossil fuel electricity demand, and it does not motivate the discovery of new actions. This thesis employs a bottom-up decision and engineering science approach to explore the behavioral, regulatory, and technical factors that inspire actors to effect change of their own energy behavior and that of their energy providers.

1.1 Decision-making

The research described in this thesis contributes to literature in judgement and decision-making (JDM) related to EE and RE technology adoption and investments. In general, decision-making is studied at the individual [14] and group levels [15] – where group decision-making is also organized into large group (e.g. mob) behavior [16], intergroup relations [17], special types of groups (e.g. therapy groups), team groups [18], and small groups [15]. Decision-making is thought to be influenced by cognition (e.g. how decision-makers attend to provided information and seek additional information) [14], [19], [20], the decision environment (e.g., task, content, and context) [21]–[24], and the decision-maker's internal state (e.g., beliefs, values, goals, and prior experience) [25]–[27]. Moreover, individual differences that are shown to particularly matter include gender [28], age [29], personality types relating to proneness to risky behavior [30] and susceptibility to framing [31], and cognitive traits/styles (e.g. numeracy) [32]. Indeed, JDM is complex and is difficult to map onto mathematical models since humans apply a wide variety of processing modes and strategies to available choices based on internal and external constraints [14]. For instance, attention accounts for a larger proportion of response when the decision-maker is explicitly provided all information in numeric or graphic form [33].

Alternatively, memory and learning are important in decisions drawn from experience, where information about outcome types and likelihood is acquired from trial and error sampling of options over time [34]. Similarly, affective processes are important in dynamic decisions under uncertainty and analytic evaluations play an important role in static uncertain decisions [35].

This thesis explores ways to elicit a decision-maker's values and motives regarding EE and RE

technologies as well as characterize the decision context to allow for behaviorally realistic interventions that promote adoption.

1.1.1 Individual energy decision-making

Psychological models of decision-making, such as the Theory of Planned Behavior (TPB) [36], help explain how individual actors might be motivated to adopt EE and RE. Within the framework of TPB, beliefs about such things as self-efficacy, subjective norms, and/or the behavior in question determine intention to act and consequent behavior [36]. Additionally, within this framework, it is also shown that contextual forces and personal capabilities/habits contribute to the effect that attitudes have on behaviors [37]. Therefore, the TPB framework suggests that one should focus on understanding attitudes and measuring intentions in order to understand the likelihood of action and/or behavior change. Still, some policies aim to promote desired behaviors by simply increasing information dissemination and closing the Value-Action Gap that persists when members of society experience cognitive dissonance (e.g. espousing pro-environmental values but not acting in accordance with them) [38]. However, this particular theory of behavior change, coined the Information Deficit Model (IDM), fails to address why some science communications increase polarization and result in non-activity [39], [40].

Therefore, when employing IDM methods for promoting adoption and/or behavior change, how information is framed could play a critical role in communication efficacy. Framing involves selectively emphasizing certain dimensions of an issue over the others, which implies (inadvertently or not) a specific diagnosis as well as prescription for action [41], [42]. In this way, framing provides an opportunity to leverage the Theory of Motivated Reasoning, which suggests that partisan audiences are motivated to interpret and process information in a biased manner that reinforces their predispositions [43], [44]. Yet, in all of these decision-making frameworks, the “audience” is comprised of individual actors and the mechanisms within each theory are complicated when the audience is comprised of two or more actors working together.

1.1.2 Organizational energy decision-making

Models for EE and RE investments in organizations (e.g. commercial buildings), tend to fall into two categories: (1) capital investment theory (CIT) models and (2) organizational behavior science (OBS) theories.

Tenets of CIT maintain that investment decisions are based on capital budgeting tools, such as payback period, net present value, and internal rate of return [45]–[47]. Within this framework, sometimes investments are dismissed if hidden/transaction costs and high levels of risk lower their profitability below the firm’s cost of capital [45]. In fact, sometimes commercial building investment decision-makers will artificially increase the required rate of return for EE and RE investments due to these perceived hidden costs and risks, forcing EE and RE investments to perform better than the cost of capital [48], [49] or other investments aimed at increasing production capacity [45]. Yet, CIT fails to address the strategic nature of energy investments often comprised of several steps, does not explain the differences in behavior between similar firms operating in the same industry, and omits the hidden benefits of EE and RE investments which are often quantifiable [50]–[53].

Researchers in organizational behavior sciences address some of the gaps in the CIT literature by asserting that certain organizational factors play an important role in EE and RE investment decisions, thus weakening the weight of financial factors underscored in the CIT literature [51]. Significantly, OBS identifies the following factors that influence EE and RE investments: power relationships [49]; managers’ interests and mindsets towards energy [54]; organizational energy culture [49], [55]; and characteristics of the investment itself and its link to core business [56]–[59]. The link to an organization’s core business is found to be especially important in a study by Weber [59], who confirms his hypothesis that “barriers to energy efficiency in organizations may result from...a trade-off with non-energy-specific goals,” with robust, longitudinal results from empirical research related to decisions and energy consumption in 100 Swiss office buildings between 1986 and 1996. Finally, it is usually the case that these trade-offs in EE and RE decision-making are often made by one (e.g. building manager) or a few individuals (e.g. sustainability management team) within a larger organization [58]. Individual factors of these energy leaders, such as their internal sustainability motivations and technical savvy, influence the adoption of EE and RE [60]. Therefore, this thesis explores the motivations and barriers of individual actors and their abilities to act across sectors.

1.2 Potential for reducing the end use and changing the mix

The literature surrounding the technical potential and financial feasibility of EE and RE tends to take a sectoral approach (e.g., electricity sector, commercial sector, residential sector, etc.). For instance, Pacala and Socolow’s theory of “Stabilization Wedges” [61] urges the adoption and

scaling up of existing technologies in five main categories as a means to stabilize atmospheric CO₂ levels at 500 ppm by the year 2054: (1) energy efficiency and conservation, (2) fuel shifting, (3) CO₂ capture and storage, (4) nuclear fission, and (5) forests and agricultural soils. Relevant here is their treatment of energy efficiency improvements as primarily manifesting in the transportation sector (e.g. electric vehicles and mass transit innovation), building sector (e.g. cutting carbon emissions by 25% from buildings and efficient appliances), and the electricity sector (e.g. improving efficiency of baseload coal plants from 40% to 60%)[61]. The “Unlocking Energy Efficiency in the U.S. Economy” report by McKinsey [62] suggests that energy efficiency can yield gross energy savings worth more than \$1.2 trillion, with an estimated reduction in end-use energy consumption in 2020 by 9.1 quadrillion BTUs (Quads), or 23% of projected demand, offsetting 1.1 gigatons of GHGs each year. In their report, they suggest pathways to these savings that reduce industrial sector energy consumption by 18% and commercial and residential sectors energy consumption by 29% and 28%, respectively [62]. As for renewable energy potential, the U.S. Energy Information Administration (EIA) suggests that electricity-scale solar and wind will reach 1.1 and 2.6 Quads, respectively, or 10% and 23% of total U.S. generation, by 2019 in their short-term energy outlook [63]. Sector- and technology-specific studies estimate that PV systems installed on small, medium, and large buildings in the U.S. can generate 1,400 TWh of electricity [64] and estimate that the residential sector alone can provide 419 TWh from rooftop solar PV [65]. However, these technical potential studies make little or no assumptions about adoption behavior and/or narrowly define rational actors as investors who operate within a set of goals and constraints consistent with the CIT framework [66] – yielding technical potential results that may not be behaviorally realistic.

Even diffusion models of certain technologies like rooftop PV that do consider behavioral inputs (e.g. agent-based models) tend to focus on adoption one sector at a time given various price signals and top-down regulation, neglecting the bottom-up role that individual actors can take to have an influence across sectors [67]. For instance, much of the residential sector literature addresses effective interventions for energy-efficient appliance adoption [68]–[71]; residential peer effects in diffusion rates [72], [73]; and rebound effects within the household [74], [75] – little is known about the preferences of actors within these households to influence their electricity providers or engage with their state legislators to set renewable portfolio standards. Additionally, the potential footprint of some actors are completely overlooked in these

sectoral technical potential studies. Such is the case of educational institutions, which are often classified as commercial buildings in PV technical potential papers, despite the fact that educational institutions comprise 11% of total U.S. building electricity consumption and 14% of building floorspace [76]. Siloing actors into large sectors obscures the granularity in knowing what is possible from specific actors and discounts the nuance of the various options available to these actors to promote the adoption of EE and RE – and ultimately their power to reduce GHG emissions from electricity generation. This thesis explores how less well-examined actors may influence the electricity sector directly by adopting their own energy efficiency and renewable energy technologies or influencing the adoption of these technologies by utilities.

1.3 Thesis organization

This thesis includes findings from three studies I conducted with an overarching aim to expand on actor-specific barriers and motivations to EE and RE. In Chapter 2, I employ an interview study to explore the behavioral and social factors in commercial building investment decision-making and to clarify the distinction between actors serving as decision-makers and actors serving as decision-influencers. Chapter 3 details findings from two studies evaluating the effect of a clean energy campaign on civic engagement among parent actors in the residential sector who are already taking advocacy actions (i.e. advocacy sample) and who aren't yet (i.e. public sample). In Chapter 4, I consider actors in educational institutions, which also include building managers and parents. Here, I employ a benefit-cost analysis (BCA) to determine which states in the U.S. will gain the most social benefits from installing solar PV on their educational facilities and which PV projects are financially feasible. Finally, Chapter 5 summarizes all of these studies and discusses their contributions to the JDM literature as well as their implications for some existing and potential interventions to inspire actors to adopt energy efficiency and renewable energy.

2. The role of psychology and social influences in energy efficiency adoption

Abstract

Current energy efficiency policy and incentive programs tend to target economic motivations, which may misalign with other potentially important motivations arising from situational factors, individual differences, and social context. Thus, in this research, we review areas of work that have focused on psychological and social influences to energy efficiency adoption in commercial buildings. We then conduct an empirical scoping study interviewing 10 commercial building owners/managers (decision-makers) and 10 experts/consultants (decision-influencers) regarding perceived motives and barriers to energy efficient investments, decision-maker attributes, and the social context of the decision. Potential factors that emerge from the interviews, which are not yet extensively discussed in the energy efficiency literature, include owners/managers' resistance to change and the influence of investment funding origins on the decision. Our results also suggest potential heterogeneity in energy efficiency decision-making philosophies between the two groups. Interviewed owners/managers prioritize corporate social responsibility (CSR) and prefer internal consulting (e.g. building engineers). Conversely, experts/consultants do not emphasize CSR and are more concerned with external policies. These findings suggest that accounting for the decision-maker and the social context in which decisions are made could enhance the design of commercial sector energy efficiency programs.

2.1 Introduction

Commercial buildings account for approximately 20% of total energy consumption in the United States and the Department of Energy (DOE) reports that savings of 3% each year for commercial buildings is achievable [77], [78]. In recent years the U.S. federal government has expressed interest in capturing these savings, by implementing national initiatives such as the Better Buildings Initiative in 2011 aimed to make commercial buildings 20% more efficient over the next ten years. To date, only 4% of commercial building square feet has been committed to this challenge, saving on average 2% each year [78], [79]. One possible explanation for this may be ineffective policy and incentive programs [12]. These programs often assume commercial building owners are solely motivated by economic factors rather than situational factors, individual differences, and social context [80]–[82]. Ignoring psychological and social factors may reduce a program's effectiveness. For instance, public opposition to wind farms for aesthetic or environmental reasons can delay or terminate wind energy development [83], unfamiliar energy savings information (e.g. kWh units) can confuse potential adopters [84], and stakeholder preferences can derail transition pathways to cost-optimal energy portfolios [85]. To aid in our examination of the various factors that may influence energy efficient (EE) investment decisions, we develop an influence diagram. This diagram (shown in Figure 1) summarizes the

four main areas of literature explaining EE investment decisions made by a single decision-maker: (1) Economics, (2) Technology, (3) Psychology, and (4) Context.

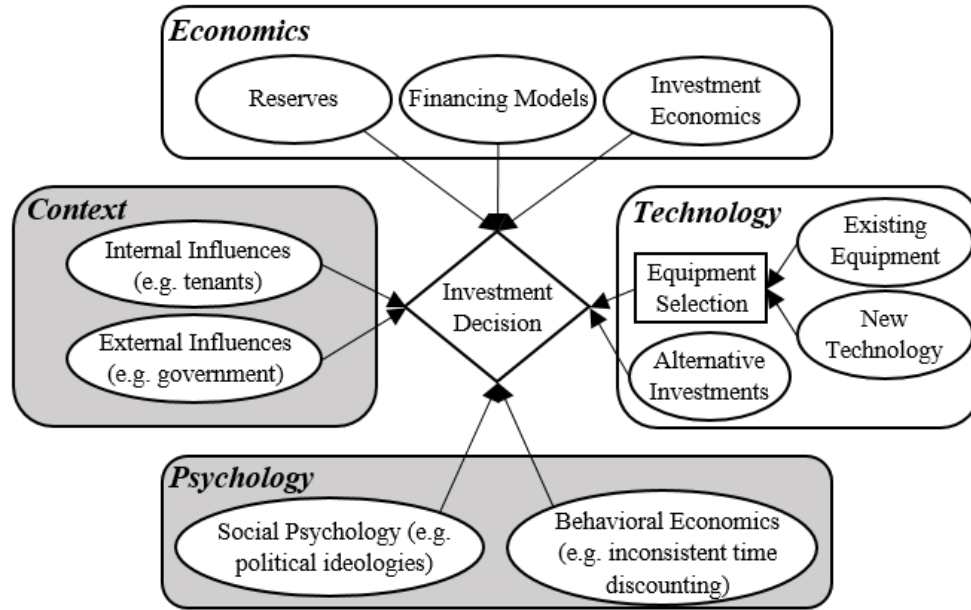


Figure 1. The four main components of an individual EE investment decision profile used to scope Ch. 2 interviews: (1) Economics, (2) Technology, (3) Psychology, and (4) Context.

To illustrate how this diagram might characterize EE decision-making, consider a commercial building owner who is interested in installing a new lighting control. The owners' decision-making is subject to Economics (e.g. what sort of financing is available to me?), Technology (e.g. what are the new technologies available to me?), Psychology (e.g. how much do I value having a small capital investment today over the potential savings of a larger capital investment over time), and Context (e.g. will my tenants like having new lighting controls?). While much is known about influences related to Economics and Technology, less is known about how Psychology and Context contribute to EE investment decisions in large commercial buildings. Thus, our empirical scoping study focuses on Psychology and Context and expands on previous work in this space by drawing three distinctions: (1) our focus is on the commercial rather than residential building sector, (2) we look beyond the normative, expert opinions by also interviewing owners/managers (decision-makers), and (3) interview findings suggested existence of heuristic decision-making that has not yet been explored in the commercial EE literature. In the next sections we examine what is known about the four main components of EE decision-making and where our study diverges from the existing literature.

2.1.1 Economic and technology influences

First, we consider those factors related to Economics and Technology (Table 1). Economic influences can be both internal (e.g. capital constraints) and external (e.g. fuel prices) and are those related to project budgeting and the benefiting parties. For instance, limited or nonexistent reserves and conflicting budget priorities between owners and engineers may dissuade decision-makers from considering EE investments [49], [86]. Split incentives are also a significant deterrent in non-owner occupied commercial buildings – energy savings will bypass the owner if tenants pay the utility bills and thus reduce the owner’s incentive to invest in EE [86].

Table 1. Economic and Technological influences to energy efficiency adoption.

Economic Influences	References
Capital constraints	[49], [86], [87]
Principal-agent relationships	[49]
Split incentives	[49], [86]
Hidden costs	[49], [86]
Fuel prices	[88], [89]
Incentive programs	[12], [90]
Technological Influences	References
Knowledge of technology	[91]
Low prioritization	[91]
Available EE technologies	[12], [92]
Renewable energy options	[12], [92]

Other Economic influences include hidden costs (e.g. inferior performance of a new technology or overhead costs of energy management), fuel prices (e.g. high fuel prices tend to increase demand for EE whereas low fuel prices lower demand – see Appendix A.1 for more information), and available incentive programs (e.g. direct rebates and on-bill financing) [12], [86], [88], [90].

Technology options influence decision-making at a number of stages, as the owner must first acknowledge the current state of existing building systems before addressing the accessibility of new technologies. As such, cities vary in their conservation efforts as demonstrated by differing adoption rates of EE markers such as Energy Star¹ and organized 2030

¹ Energy Star is an award assigned to high-performing buildings whose energy consumption is benchmarked on Portfolio Manager; both Energy Star and Portfolio Manager are maintained by the U.S. Environmental Protection Agency (Colaizzi 2015).

Districts.² Explanations for this heterogeneity in commitment to building energy efficiency include availability of technologies and installers across the U.S. as well as existing building conditions in the real estate market [12], [93]. However, increasing the stock of EE technologies alone is insufficient; information presented in personalized and specific terms can influence EE decision-making [46], [94], [95] (see Sections 1.1.1 and 2.1.2 for more on the Information Deficit Model). An EE investment decision-maker with technical knowledge of the project can more readily understand how the equipment will operate in their specific energy management program and visualize how the technology will contribute to their building's primary function [91], [96]. Thus, knowledge should increase technology accessibility in the EE market and also reduce uncertainty of investment benefits [97].

Although the commercial building EE literature is currently advanced on topics related to Economics and Technology, influences related to Psychology and Context are less explored. The next section highlights non-economic factors related to EE investment decisions as they are presently characterized in the literature and suggests areas for further research.

2.1.2 Psychological and contextual influences

Influences related to Psychology and Context (Table 2) include the decision-maker's own set of individual differences and decision-making heuristics as well as social influences that could occur within the building (e.g. tenants) or from outside the building (e.g. other buildings).

Psychological influences are shown to be substantial forces in similar areas of pro-environmental behavior such as recycling, taking action towards pollution control, and implementing residential energy efficiency. In the recycling literature, we find that certain relevant attitudes (e.g. environmental concern) are more predictive of recycling if it requires a high degree of effort, which can be influenced by situational factors such as prompts, normative influence, and feedback [98]. In addition to attitudes and situational factors influencing pro-environmental behavior, there also exist theoretical models that connect pollution mitigation behavior to moral norms against human and environmental harm [99]. Moreover, studies in the residential sector find that non-price incentives (e.g. health and environmental benefits) increase participation rates in energy savings programs more effectively than messaging that focuses on

² There exist 10 separate 2030 Districts, spanning Seattle to Stamford, with building owners committed to 50% reduction in energy use, water consumption, and transportation emissions by 2030 (2030 Districts 2015).

economic benefits; effect is enhanced in participants who claim having pro-environmental attitudes [68], [70], [71].

Explanations for pro-environmental behavior that extend beyond neo-classical economic theory, which characterize the residential sector, may also apply to commercial EE investment decision-making. For instance, a decision-maker with pro-environmental beliefs may willingly invest in EE, reducing the significance of economics (should they be unfavorable) in their decision [100]. Furthermore, decision-making heuristics, such as bounded rationality, can stifle EE investment action due to the investor's potentially limited knowledge of or search capacity for technologies/incentives, their misunderstanding of the EE technology functionality, or simply their lack of time for making a decision [101]. Another heuristic, time discounting on investments, tends to discourage decision-makers from EE investments due to their aversion for paying up-front costs (including an implied opportunity cost) for delayed cost savings [100]. Time discounting may also be influenced by the availability of cost savings information and its corresponding certainty [69]. Empirical evidence suggests that owners have relatively high implicit discount rates compared to the market discount rates, ranging from 25% to over 100% [102]–[104]. These high discount rates could suggest that commercial EE decision-makers perceive higher uncertainty in returns on EE investments than other types of investments [94], [97], [100]. Alternatively, a high implicit discount rate could suggest investors are simply looking for short payback periods (e.g. 3 years) for energy efficiency projects; corresponding to high internal rate of return (IRR) values. As many EE investments fail to achieve rapid payback and a high IRR, some investors will find them unattractive, especially when considered in addition to other, necessary investments with low profitability [105]. However, many energy efficiency investors do not even compute the IRR or compare them to the weighted average cost of capital (WACC), which would more often yield a positive investment decision if they agreed that projects with profitability higher than the WACC would increase overall profitability [105]. Ultimately, it is difficult to attribute inaction on investments to single metrics, like discount rates, due to the complex set of decision factors, potential conflicting goals of the decision-maker(s), and the lack of conformity on investment capital practices in this domain that often fly in the face of finance theory prescriptions [51]. It does seem that trepidation towards EE investments might be reduced if there exist some element of Corporate Social Responsibility (CSR) motivated from within the decision-maker [106]. CSR could also provide external motivation to

a building owner who is considering EE by increasing competition in the commercial building community, which informs the decision-maker's Context of internal and external influences (Figure 1).

Table 2. Psychological and Contextual influences to energy efficiency adoption.

Psychological Influences	References
Attitudes towards energy efficiency	[100]
Heuristic decision-making	[101], [107]
Time discounting	[42], [102], [103]
Uncertainty & perceived risk	[94], [97], [100]
Corporate social responsibility	[106]
Contextual Influences	References
Organizational structure	[49], [51]
Societal Norms	[49], [108]
Community Characteristics	[72], [109], [110]
Corporate social responsibility	[106]
Stakeholders (e.g. tenants)	[111]
Sustainable legislation	[92], [93]
Building codes	[100], [112]
Real estate market	[93], [111]

Several studies have focused on how Context influences residential energy efficiency adoption. Often social network analyses related to energy efficiency focus on residential consumers' responses to monitoring and reporting of electricity consumption, either privately or on a public benchmarking website [68], [72], [73], [113], [114]. For instance, in a randomized field study of 600,000 U.S. households, Allcott [115] found a 2% reduction in energy consumption after OPOWER provided Home Energy Reports. Furthermore, Peschiera and Taylor [116] demonstrated an inverse relationship between residential energy consumption and the number of comparable peers. Economic sociologists also posit that residential consumer action is embedded in social relations and that community forums or neighborly competition may inspire EE investment decisions and increase technology diffusion [82], [108]. Therefore, it seems plausible that these social influences could also infiltrate commercial building EE investment decisions. Yet, these direct social influences might be harder to trace due to the complexity of the stakeholder structure and decision process within the commercial sector [51].

Another source of external influence on the decision context includes the informational materials available to the decision-makers. Indeed, some energy efficiency policies aim to

promote desired behaviors and investments by simply increasing information dissemination and closing the Value-Action Gap that persists when members of society espouse pro-environmental values but do not act in accordance with them [38]. However, this theory of behavior change, coined the Information Deficit Model, fails to address why some incentive program communications may result in non-activity or worse, increased resistance to invest [39]. In fact, information conduits are just as important as the energy information. Lutzenhiser et al. [117] found in a series of expert interviews that energy efficiency decision-makers have varying levels of skill and expertise in different professional domains and decisions contexts, “all of which affect their ability to access, process, and act on energy information.” Additionally, in an interview study of organizations who participated in an energy audit program, Goitein [118] found that lack of information was one of the least likely barriers to energy efficiency to be listed (cited less often only by “not having a good contractor”). As such, these complex dimensions of information diffusion and decision-making are little understood in the context of commercial building energy efficiency investments.

Aside from external social influences (e.g. commercial owner peers and energy efficiency campaigns), Context for a commercial building owner could also include organizational/internal influences, legislation, and the real estate market. Organizational influences are those related to the composition of the building ownership/management structure as well as the mission of the organization. In fact, in the commercial building sector, one should likely reject the unitary rational actor model in favor of an organizational decision-making perspective that incorporates power dynamics, as organizations are often comprised of a collection of actors with individual objectives that could be in conflict [118]–[120]. For instance, a dedicated EE coordinator in a management team may identify opportunities more effectively than a building engineer who is primarily concerned with keeping the building systems in good condition and pleasing the tenants [51]. Indeed, Stern et al. [121], identifies addressing and improving in-house energy expertise, empowering building operators, and using information technologies such as social media throughout the organizations as opportunities for reducing commercial energy consumption. Building stakeholders, such as tenants, influence decisions by requesting reductions in energy costs and improvements in air quality [111]. Building energy codes, such as those established by the American Society of Heating, Refrigeration and Air-Conditioning (ASHRAE) or the International Energy Conservation Code (IECC) mandate inclusion of EE

technologies and practices in new construction designs [112], [117]. However, energy codes and other EE legislation may be futile if there exist information gaps [84], rebound effects [74], [75], or capital constraints that undermine compliance with energy legislation [100]. Therefore, policy makers should bridge the normative component of commercial building EE policy with the descriptive component in order to design behaviorally realistic prescriptions that yield energy savings at a level comparable to other successful nationwide initiatives such as the CAFÉ standards or appliance efficiency standards [90], [122].

The existing commercial building EE literature currently addresses several important influences; however, it may omit additional behavioral and social factors addressed in other domains that may be pertinent here. This study aims to identify those additional factors and clarify the distinction between influences related to Economics/Technology and Psychology/Context. The next section entails the development and implementation of an interview protocol designed to explore EE investment decisions, followed by an explanation of the analysis methods (Section 2.3) employed in this study. Section 2.4 outlines the results of the cognitive interviews, Section 2.5 provides a discussion of implications of these results relating to EE policy, and Section 2.6 concludes with suggestions for future work.

2.2 Materials and methods

It is difficult to reach commercial building owners/managers due to their limited time and often limited resources (e.g. building staff). This may be one reason why many energy efficiency studies that employ a behavioral sciences approach tend to focus on the much more accessible residential sector. Therefore, we ascertained that it was best to first employ an interview study to explore what factors might be prevalent in the commercial building population before developing and implementing a survey. Since we obtained a smaller, non-representative sample we do not make statistical claims of these findings. However, our interviews did allow us to explore the various factors that decision-makers intuit are important as well as to compare these factors to those already identified in the literature.

2.2.1 Interview protocol

The interview protocol was informed by the Mental Models approach, which is a systematic method for determining knowledge gaps between experts and laypeople in order to design effective risk communications [123]. The Mental Models approach primarily involves three

steps: (1) normative research, (2) descriptive research, and (3) prescriptive research [123]. Normative research includes a review of the literature and consultation with experts to identify the key information that needs to be communicated to the public (expert model). Next, descriptive research is performed through interviews and surveys with laypeople to determine their knowledge, values, and beliefs about the information experts deem important and how they actually make decisions (lay model). Finally, through a systematic comparison of expert and lay models of decision-making, prescriptive research identifies gaps in knowledge or differences in perception and values to be addressed through a risk communication. These risk communications avoid pitfalls resulting from the presumption that a researcher knows in advance the full set of potentially relevant beliefs, knowledge, and values, as well as the terms in which they are intuitively expressed. Historically, these communication materials aided the public in making informed judgments about risks associated with such topics as health and climate change [124], [125]. In our study, we adapted this approach to identify potentially important factors influencing EE decision-making between owners/managers and experts. Comparing these two groups is particularly useful for determining existing knowledge differences regarding the Psychological (perhaps unrecognizable in consulting meetings) and Contextual (potentially effective information conduits) influences.

In our interviews we were particularly interested in Psychology and Context, as we found this to be less examined in the commercial EE investment decision literature. Therefore, our reported findings reflect this focus. Furthermore, since the commercial EE literature regarding the Psychology of commercial EE invests is relatively limited, our protocol was less informed in this area and discussions were more organic. The protocol was designed to encourage interviewees to openly discuss their perspectives on large commercial building energy efficiency. We developed two different versions of the interview protocol, one for EE experts (see Appendix A.2) and one for building owners/managers (see Appendix A.3). The overall structure and content of the protocols were similar and are briefly summarized in the paragraphs below (see Appendix A.4 for further details). The protocol was pilot tested in April 2015 for comprehensiveness by two energy efficiency consultants from Chicago and two scholars of behavioral decision sciences from Carnegie Mellon University in Pittsburgh.

The first part of the interview started with open-ended questions. The first set of discussion topics considered market gaps or energy policies in Pittsburgh and included questions

such as the following: “Can you describe what, if any, areas of the market have had less penetration in regard to energy efficiency?” The second set of topics allowed the interviewees to openly describe what they think might motivate or prevent EE investments and included questions such as: “What do you believe motivates building owners/managers to pursue energy efficiency?” Finally, the third set of open-ended questions allowed participants to discuss the extent to which building owner/manager investment decisions are motivated by social influences: “Can you tell me more about how opportunities to invest in your building came to your attention?”

The second part of the interview involved three ranking exercises. Participants were asked to rank 17 motivations and 20 barriers to EE investments in order of descending importance, where 1 = most important and 17 (or 20) = least important. They were asked to add any seemingly missing concepts and tied rankings were also permitted. Additionally, owners/managers performed the same ranking exercise for a set of 24 social influences. The items contained in each of the three sets were informed by the literature [12], [56], [86], [92], [93], [100], discussions during the pilot tests, and additions provided by the interviewees (see Appendix A.5). Finally, interviewees answered demographic questions, reported on their interview experience, and noted any topics missing from the protocol.

2.2.2 Recruitment and participants

Our sample included building experts and owners/managers of large commercial buildings having an area of $\geq 50,000$ ft² in Pittsburgh. We interviewed a total of 20 participants – one group of ten experts and one group of ten owners/managers. Plateauing concept saturation curves for each group (see Appendix A.6) confirmed sufficient sample sizes [123].

We collaborated with Pittsburgh’s Green Building Alliance (GBA) to recruit much of our non-representative sample and employed snowball sampling methods to recruit the remainder [126]. Snowball sampling involves participants listing any social connections they believe might be interested in participating in an interview. Seven experts and nine owners/managers were affiliated with the GBA’s Pittsburgh 2030 Districts. We recruited from both of Pittsburgh’s 2030 Districts – Downtown and Oakland – which comprises 70% of the real estate square footage in Pittsburgh. We assumed expert involvement in the 2030 Districts did not drastically bias their EE knowledge. We did not make the same assumption for owners/managers. However, we defined “energy efficient” as a combination of varying levels of commitment and internal/external

competition (see Appendix A.7). In Pittsburgh, for instance, an owner/manager might compete in the Green Workplace Challenge, which involves a high level of *commitment* and *external competition*; together, these two attributes of energy efficiency programs can lead to high actual achieved energy savings in the building [127]. Irrespective of EE labeling, the intention of this study was to elicit a set of concepts related to the behavioral and social influence impacts to EE investment decisions. We do not make claims regarding the prevalence of these concepts in the population of owners/managers in Pittsburgh or elsewhere.

Of the total 20 participants, 60% were male. Most participants were between the ages of 25 and 54 (70%), and the remainder were over 54 (30%). The majority of owners/managers had pursued Energy Star and LEED (70%); this group included representation from Class A commercial office buildings, hospital campuses, and university campuses. Experts included those from EE consulting, academia, real estate, and policy. Each interview took approximately one hour to complete, was audio-recorded, and participants were compensated with a \$50 Amazon gift card for their time. Appendix A.8 provides additional demographic information.

2.3 Analyses

2.3.1 Coding

All interviews were transcribed either directly by the lead author or split into five-minute audio files and processed by transcribers recruited through Amazon Mechanical Turk.³ The lead author checked all Mechanical Turk transcription file for errors before compiling each interview. Using NVivo,⁴ the lead author performed an open-coding procedure, which is an inductive and iterative approach for comparing responses of the two groups [128]. While coding open-ended responses, the lead author assigned each common or new concept in the interviews to one or multiple codes (short labels that summarizes the content). The lead author developed a master code by performing a first-round assessment of the ten expert interviews. Next, the lead author consulted with the second author on coding scheme, made refinements, and performed a second iteration of coding on the expert interviews. The lead author used this refined master code to assess the ten owner/manager interviews and additional codes were created for any new findings. Finally, the lead author recoded the expert interviews with the new codes. A second coder independently

³ Mechanical Turk is an online forum where “workers” are compensated for assisting in research, such as participating in an experiment or transcriptions. Web link: <https://www.mturk.com/mturk/welcome>

⁴ NVivo is a qualitative data analysis software by QSR International. Web link: <http://www.qsrinternational.com/>

coded the interviews and a final assessment resulted in a Cohen's Kappa coefficient of 73% agreement. The Cohen's Kappa coefficient is a measure of inter-rater reliability, which considers the pairwise agreement between the coding schemes of two coders while taking into account the amount of agreement that could be expected to occur through chance [129]. The major code groups are summarized in Table 3 and a full list of sub-codes under these categories can be found in Appendix A.9.

Table 3. Major code groups.

Code Group	Description of Excerpts
EE Definition	Interviewee definition of energy efficiency
Metering	Utility measurement type (e.g. sub-metering)
Work Experience	Interviewee work experience
Relationship with Building Engineer	Relationship betw. building engineers and owners/managers
Investment Decision Process	How EE investment decisions are made
Organization Details	How experts describe their organization
Reason for Repeated Business	Explanations for why a client/consultant relationship is lasting
EE Climate	Perception of Pittsburgh's building EE climate
Market Gaps	Perception of lagging building sectors
Market Gap Solutions	Suggestions for closing the gap
Energy Star Designation	Perception of Energy Star
Energy Star Target Goals	Suggested improvements to Energy Star
LEED Certification	Perception of LEED
LEED Target Goals	Suggested improvements to LEED
Mandatory Energy Benchmarking	Perception of mandatory energy benchmarking in Pittsburgh
Mandatory Energy Auditing	Perception of mandatory energy auditing in Pittsburgh
Perception of EE Public Subsidies	Perception of EE public subsidies
Motivations	Perception of EE motivations
Barriers	Perception of EE barriers
Social Influences	Perception of EE social influences
Pro. Societies – Purposes	Perception of the role of professional societies
Pro. Societies – Level of involvement	Level of involvement in professional societies
Building Technologies	Aspirational/difficult technologies to implement

We calculated frequency of mentions for single sub-codes for each participant and compared the overall frequencies between the two groups. For instance, we compared the number of mentions for the sub-code titled EEClowpriority (“energy efficiency is a low priority in Pittsburgh”) between experts and owners/managers to gain an understanding of how these two groups perceive the EE climate in Pittsburgh. Additionally, we developed pairings for the sub-codes and calculated frequencies of mention to determine which interactions occurred most often. As an example, we looked at a combination of the sub-code titled ESTARpositive (“Energy Star mentioned positively”) with a sub-code such as RBEpositive (“owner/manager has

positive relationship with building engineer”). Finally, we studied the number of participants mentioning each sub-code or sub-code pairing to gain an understanding of the potential difference in prevalence of certain concepts between the two groups.

2.3.2 Ranking data

Ranking results were explored first by frequency and secondly incorporating their ordinal component. To compare the number of listings between experts and owners/managers, we developed dot plots representing the number of unique listings in each category. Since only the owners/managers ranked social influences, it was unnecessary to perform comparative analyses. Next, ranking plots and simple descriptive statistics helped to further characterize the ordinal component of the barriers, motivations, and social influences rankings. Finally, the ranking data was supported by some key findings from the open-ended discussion portion of the interviews.

2.4 Results

2.4.1 Coding results

Our analyses revealed 95 unique responses from ten experts and ten owners/managers in Pittsburgh. Overall, participants most frequently discussed financing & budgeting for EE investments, organization & jurisdiction of decisions, and economic barriers Table 4. This interview study was designed to be exploratory research aimed at uncovering important factors to commercial building EE investment decision-making and potential policy interventions that could be informed by the decision-making behavior.

Table 4. This table depicts the three most frequently discussed topics among the interviews with all participants (n = 20). These subcodes represent unique items that fall under broader topic categories. For instance, IDP represents the Investment Decision Process code and BAR represents the Barriers code.

Subcode	Description	No. of Mentions	% of Participants (No. of Participants)
IDPfinancing& budget	What the decision-maker targets in incentives, financing, and budget of EE investment decisions	63	70% (14)
IDPorganization	Chain of command and jurisdiction in EE investment decisions	53	85% (17)
BAReconomic-not.split.inc.	Economic or financial barriers to EE investment decision unrelated to split incentives	48	75% (15)

In this paper, we further analyze the subcodes in the context of (1) Investment Decision Process and (2) Potential Public Policy Interventions. The Investment Decision Process category includes budget details as well as technical information required to make EE decisions. This category comprises 268 mentions and 100% of the participants discussed it at some capacity during their interview. The Potential Public Policy category includes discussions regarding mandatory energy benchmarking, mandatory energy auditing, and public subsidies. Combined, participants mentioned topics in this category 92 times and 100% of the participants discussed this topic category at some capacity during their interview. In the last section of coding results, we discuss some potentially emerging topics in the field of EE investment decision-making.

Discussions of Investment Decision Process

A large portion of the open-ended interview protocol was aimed at characterizing the EE Investment Decision Process simplified in Figure 1. The dual protocols allowed for comparison of the cognitive model of the Investment Decision Process between experts and owners/managers. Figure 2 illustrates the total number of mentions by each group throughout the interview, categorized by each component.

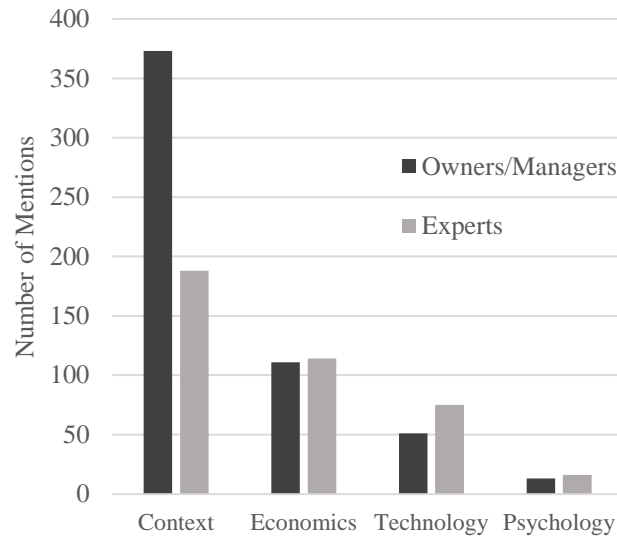


Figure 2. Comparison of number of mentions regarding the four components to EE investment decision-making: (1) Context, (2) Economics, (3) Technology, and (4) Psychology. Each bar represents the total number of mentions throughout the open-ended interview section.

Appendix A.10 includes a full description of what subcodes are in each component of the Investment Decision Process; Context includes 37 subcodes, Economics includes 6 subcodes, Technology includes 4 subcodes, and Psychology includes 4 subcodes. In this figure, the number of mentions in each of the EE investment decision components has a similar decreasing pattern for both groups of participants. However, owners/managers tended to discuss the contextual influences to the decision-making process more than experts. Table 5 includes combined and simplified subcodes to illustrate the most commonly discussed topics between the two groups.

Table 5. Frequency of mention table depicting interview discussions surrounding the Investment Decision Process. Numbers in parenthesis represent total number of participants in each group that mentioned the concepts during their interview.

Investment Decision Process	Number of Mentions (Number of Participants)	
	Expert	Owner/Manager
<i>Context</i>		
Organization (chain of command, jurisdiction)	26 (9)	27 (8)
Goals & strategy (investment strategies)	8 (4)	31 (7)
Investment consultant	0 (0)	32 (10)
Barriers related to organizational & social influences	43 (9)	24 (8)
Motivations related to organizational & social influences	60 (9)	47 (10)
Social influences mentioned during interview	47 (7)	123 (10)
Discussion of building staff	6 (4)	98 (10)
<i>Economics</i>		
Investment financing and budgeting	18 (4)	45 (10)
Desired economics of investment	20 (8)	25 (9)
Barriers related to economics	53 (8)	24 (7)
Motivations related to economics	23 (7)	17 (6)
<i>Technology</i>		
Investment information (technical details of equipment)	19 (8)	17 (7)
Decision-maker pilot tests the equipment	0 (0)	9 (4)
Barriers related to building systems	38 (8)	16 (7)
Motivations related to building systems	18 (6)	9 (5)
<i>Psychology</i>		
Fear of change	13 (4)	4 (3)
Mental accounting	1 (1)	0 (0)
Agenda setting	1 (1)	3(2)
Rewarding work	1 (1)	6 (4)

Owners/managers discussed their investment financing strategies and desired project economics more frequently than experts. There was much disparity in the various budgeting strategies described for EE investments; participants mentioned rotating funds, energy service contracts, and combined budgets (e.g. utility and EE projects). Budget responsibilities also varied across owners/managers; some managers had authority to implement projects not exceeding \$50,000 in capital expenses, while other managers needed owner approval for every purchase. Despite the differences in budgeting practices, most experts and owners/managers

tended to agree that decision-makers focus on simple economic indicators, such as simple payback period,⁵ which varied depending on the building type.

“This is a generalization, but certain federal governments are looking for upwards of a 15-yr payback, higher education looks for upwards of a 10-yr payback, healthcare looks for 5- to 6-yr payback, commercial office building owners are looking for somewhere between 3- and 5-yr paybacks, and industrial sector is looking for less than a 3-yr payback.” (Participant EE2)

Aside from economics, owners/managers also frequently mentioned investment goals and strategies as a large part of their EE Investment Decision Process (31 mentions, 70% of owners/managers).

“We try to be strategic about our investments – we do multiple analyses to find the different building energy hogs across our portfolio. We have what we call the good, the bad, and the ugly. The good buildings don’t need much investment, just operational tweaks. The bad and ugly might need more retrofits.” (Participant OM2)

In fact, the goals sometimes involved non-economic attributes of an investment such as maintaining innovative competitiveness in the building sector.

“It’s more of the innovation behind those projects and trying to be the company that’s setting the first step into some of that new work.” (Participant OM2)

Whereas the experts tended to think owners/managers’ goals more often centered on economics.

“And they usually show interest in one specific thing. Like they’ll latch onto, ‘Oh, I want to save money on my energy bills,’ or they’ll latch onto, ‘Oh, you’ll do my utility analysis for me.’” (Participant EE 5)

Additionally, owners/managers discussed their processes for investigating opportunities, which often involved consultants assessing their systems and performing pilot tests before implementing a technology throughout their building portfolio. The Investment Consultant subcode included the number of times owners/managers discussed this process and their stance on reaching out to a consultant for advice. Owners/managers that did work with consultants found them through trusted networks.

⁵ Simple payback period is the period of time required to recoup the funds spent on an investment; for an EE investment, this would be the amount of time required to recoup the funds from the annual energy savings.

“We invite people to bid based on their qualifications and experience – both experience with use and others. Then once you have been invited to bid, you are sort of pre-qualified for the project. We get five or six people that we believe are a good fit for the project.” (Participant OM4)

It seemed that without that experience or trust in place, owners/managers might avoid consultants.

“My experience with consulting groups is that just because you can come in and say that changing a setpoint is going to make a difference, you still need to sit down and talk with my building engineers – because maybe they already tried and it doesn’t work.” (Participant OM1)

Discussions of potential public policy interventions

The next most frequently discussed topics involved potential EE policy interventions (Table 6) such as mandatory energy benchmarking, energy audits, and public subsidies.

Table 6. Total mentions regarding EE policy interventions.

Public Policy Interventions	No. of Mentions (No. of Participants)	
	Expert	Owner/Manager
<i>Mandatory Energy Benchmarking</i>		
Positive	15 (9)	8 (6)
Negative	2 (1)	8 (5)
Methodology	4 (3)	2 (1)
<i>Mandatory Energy Auditing</i>		
Positive	6 (6)	3 (3)
Negative	6 (4)	8 (6)
Methodology	4 (3)	2 (2)
<i>Public Subsidies</i>		
Positive	9 (6)	3 (3)
Negative	1 (1)	2 (2)
Methodology	4 (4)	5 (4)

Owners/managers were fairly neutral about energy benchmarking, but preferred if it was disaggregated by buildings types so that inherently large consumers (e.g. hospitals) were not penalized. Experts and owners/managers agreed that mandatory energy auditing resulted in funding issues – both for the audits as well as the recommendations outlined in the audits.

“It’s an unfunded mandate. In some cases you can measure it [energy efficiency] or you can do it, but you don’t have the money to do both.” (Participant OM4)

Furthermore, experts believed mandating energy audits would not lead to action if the owners/managers were uninterested in energy efficiency.

“I think it’s beneficial when people do it voluntarily, because then they’re more bought into it. If they don’t like it or don’t want it, they’re probably not going to implement the solutions anyway.” (Participant EE7)

Although experts felt positively about public subsidies, owners/managers were sometimes uncertain of their eligibility or did not understand program requirements (e.g. monitoring and verification).

“They watch you so much and if you don’t do it right then you have to pay them back. So there are strings attached. I like small governments.” (Participant OM6)

Supporting this finding, experts who spoke positively of public subsidies also mentioned information as a major barrier to EE investments (50% of the experts mentioned both concepts) and participants thought it was important to have organizations dedicated to summarizing all funding opportunities and technologies available to the decision-makers.

“You need organizations to hand it to managers on a silver platter, ‘Look, this is what you could be doing, we will give you all the information you need to do it.’ ...I mean probably 75% of our projects are paid [with incentives]. Once again, I don’t think there’s enough companies out there to pass along the information.” (Participant OM5)

Other studies also illustrate information gaps, such as a misunderstanding of the most effective investments for conserving energy (Attari et al. 2010) and more classical market failures (e.g. inadequate provision of incentive information) leading to low adoption rates of EE technologies and utilization of public incentives (Jaffe and Stavins 1994; Swim et al. 2014).

Potential emerging topics

A few concepts arose in the interviews that are, to our knowledge, not currently or heavily considered in the building EE literature. These items were coded as Fear of Change (17 mentions, 35% of participants), Mental Accounting (1 mention, 5% of participants), Agenda Setting (4 mentions, 15% of participants), and Rewarding Work (7 mentions, 25% of participants). Fear of Change was described differently by various participants, but included barriers related to technical knowledge and reluctance to implement a new system.

“The facilities people aren’t working all the time... so if an Energy Manager came in, they would require more work and that would result in a Fear of Change. And the [facilities] people don’t always choose the projects, but they are certainly instrumental in the savings over time.” (Participant EE7)

One expert explained that owners/managers spend money differently in their homes than they do on their buildings – this was coded as Mental Accounting.

“It’s this mentality that it’s somebody else’s money that makes it easier to do things. The downside of that is it makes it very easy to pollute... it makes it easy to do any kind of abuse when it’s not affecting them.” (Participant EE9)

Agenda Setting was used to code any discussion of how the financial institutes or funding sources dictate spending in the building (e.g. requiring CSR).

“This is a more recent trend that we’ve found... buildings that are backed by some kind of fund are often constrained... investors definitely want to see that their money is being spent on ecological activities.” (Participant EE9)

Finally, some owners/managers believed their engineering team pursued EE goals because it was rewarding work – we coded these discussions as Rewarding.

“I think it pushes the team that works here...it kind of works when you feel good about what you do - Energy Star really makes you come to work and push yourself.” (Participant OM5)

These emerging concepts may warrant additional follow-up studies of large commercial building owner/managers.

2.4.2 Ranking results

In this section, we explore the results of the ranking exercises performed on barriers, motivations, and social influences. As shown in Figure 3, experts tended to list more barriers than owners/managers; however, both groups agreed upon economic barriers such as Capital (capital constraints), Uncertainty (uncertainty of savings), Investment Horizon (investment will not pay off in the time horizon of building ownership), and Time Discounting (savings are not immediate).

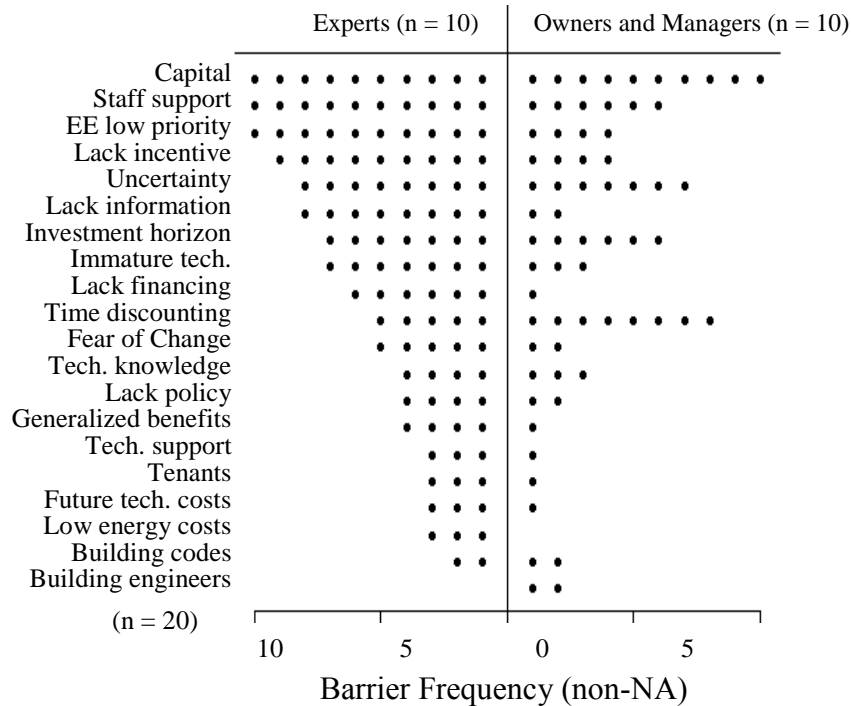


Figure 3. Dot plot comparing number of barrier listings between experts and owners/managers.

From our interviews, we find a stark difference in the number of listings between experts and owners/managers for EE Low Priority and Lack Information (information regarding technologies, incentives, or available funding); it seems that experts may perceive these as strong barriers to EE investment decision-making. Indeed, during the open-ended discussions, experts expressed the belief that EE was a low priority among owners and managers.

“I can tell you that after you develop a building and you have a management company managing it, all they’re worried about is keeping the building occupied. The whole issue of making a building energy efficient is outside of the skillset of most managers... if there is cash flowing and their buildings are filling up, maybe that is sufficient.” (Participant EE1)

However, owners and managers did not readily admit to not prioritizing energy efficiency as illustrated in the ranking results depicted in Figure 3 and open-ended interview results (EE low priority: 15 mentions by 7 experts compared to 3 mentions by 3 owners/managers).

“If two projects had the same return on investment, and one of them was an energy project and one was a non-energy project, you would value the energy project higher.” (Participant OM4)

An econometric study by Schleich (2009) demonstrated organizations underestimating internal priority setting as a barrier to EE investments; however, our finding may suggest a difference in perception of prioritization between experts and owners/managers.

To compare expert and owner/manager rankings of these barriers, we developed side-by-side boxplots (Figure 4). Average ranking for the set is 3.7 with a standard deviation of 2.4 and a maximum ranking of 13 (1 = highest importance, 13 = lowest importance). See Appendix A.11 for the full set of barrier boxplots. Generally, both groups agreed that economic barriers (Capital, Time Discounting, and Staffing) have relative importance in EE investment decision-making; however, owners/manager rankings suggest that uncertainty of savings is a larger deterrent for EE investments than experts may currently assume.

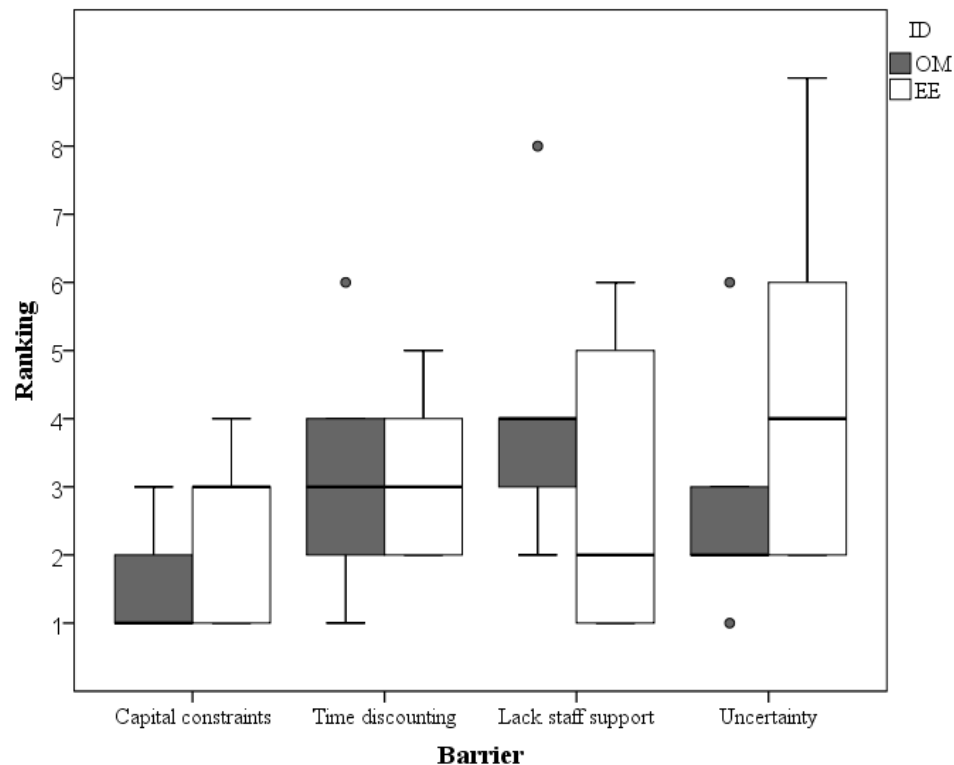


Figure 4. Side-by-side boxplots depicting differences in selected barrier rankings between experts and owners/managers. Lower rankings indicate higher importance (1 = highest importance and 9 = lowest importance).

From the open-ended discussions, we also find that economics are the most often discussed barrier to EE investment decisions (34 mentions by 8 experts and 14 mentions by 7 owners/managers). Economic barriers are coded as those barriers mentioned in the interviews that relate to topics such as lack of capital reserves and debt aversion.

“Medium sized manufacturers. They probably represent the biggest sector in Pittsburgh’s economy. They operate on such a margin that they don’t have the personnel to devote to [energy efficiency] – they’re worried about making payroll and getting product out the door.” (Participant EE10)

Some of the most common code-pairings for economic barriers include discussion of building technologies the participants deemed aspirational (13 pairings), discussion of professional societies providing insight (13 pairing), and lack of information available to decision-makers regarding available technologies and funding opportunities (12 pairings).

Next, we compare motive listings and rankings between the two groups. In a dot plot of motives (Figure 5), we do not see quite the discrepancy in the total number of listings between each group. However, we do find that owners/managers tend to list motives related to CSR (Occupant Comfort, Social Responsibility, and Industry Leaders) more often than experts.

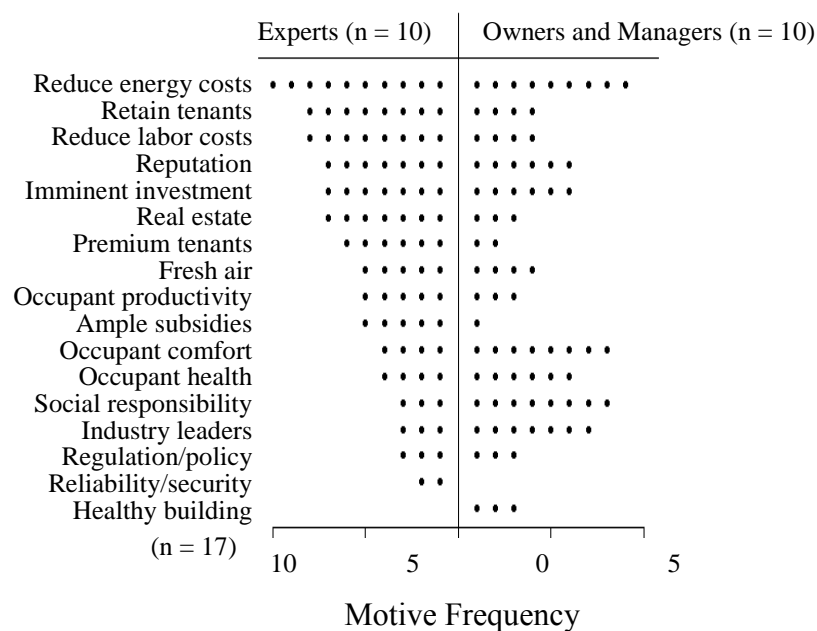


Figure 5. Dot plot comparing number of motive listings between experts and owners/managers.

Average ranking for the motive set is 4.2 with a standard deviation of 2.9 and a maximum ranking of 14 (see Appendix A.12 for the full set of motive boxplots). Both groups listed Reduce Energy Costs with the highest frequency and, similarly, ranked this with the highest relative importance (Figure 6). Ranking results depicted in the boxplots also illustrate the potential discrepancy in expert and owner/manager opinion of motives associated with CSR (i.e., Occupant comfort, Industry leaders, and Social responsibility).

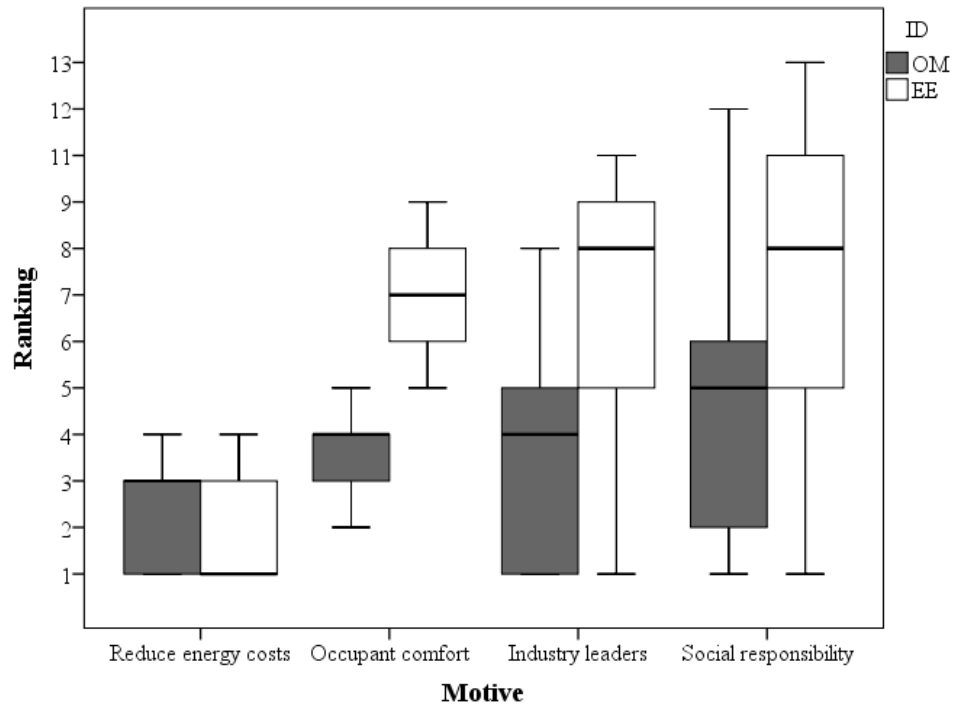


Figure 6. Side-by-side boxplots depicting differences in selected motive rankings between experts and owners/managers. Lower rankings indicate higher importance (1 = highest importance and 13 = lowest importance).

However, during the open-ended discussions, we found that both experts and owners/managers tended to discuss motivations related to CSR such as mission and leadership (26 mentions by 7 experts and 14 mentions by 5 owners/managers).

“It goes back to motivation. This stuff isn’t a technology issue, it’s a value issue.”

(Participant EE6)

“I think the people can change when there is a change from the top. If management says, ‘We’re going to do this – we now want to focus on sustainability, it’s important to our business,’ then the team will get on board.” (Participant EE8)

Often, participants who described motivations related to CSR also discussed the benefits of Energy Star (11 code pairings), LEED certification (10 code pairings), and mandatory energy benchmarking (10 code pairings).

Only the ten owners/managers were asked to list their perceived social influences to building EE investments (Figure 7). Internal influences, such as Building Engineers, Tenants, and Employees were often listed as influential sources in EE investment decision-making.

Conversely, owners/managers avoided listing sources representing a certain technology or product such as Renewable Energy Companies and Controls Contractors.

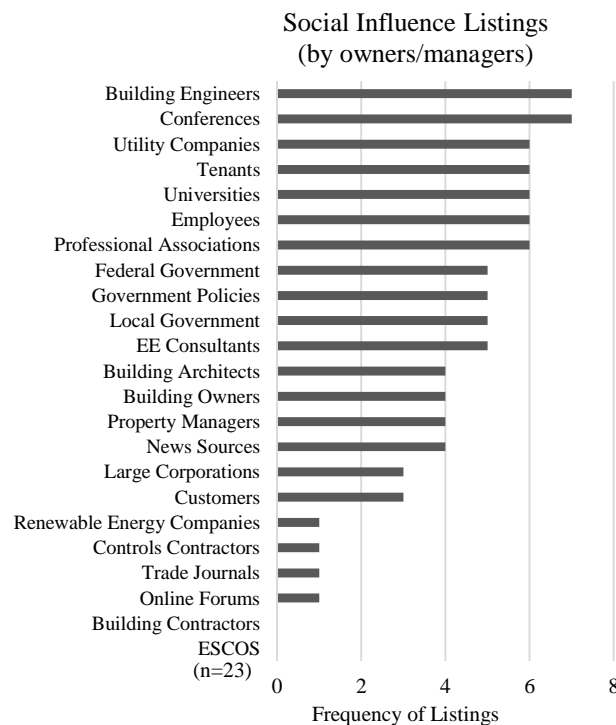


Figure 7. Bar chart representing the number of times each social influence type is listed by the 10 owners/managers interviewed in this study. The maximum number of listings is eight (Building Engineers and Conferences) and the minimum is zero (Building Contractors and ESCOs).

Next, we compared the social influence rankings with boxplots; average ranking for the social influence set was 4.8 with a standard deviation of 3.3 and a maximum ranking of 16 (see Appendix A.13 for the full set of boxplots). Selected boxplots may suggest that owners/managers may value information received from utility companies and the government similar to how they value information from internal sources, such as their building staff (Figure 8).

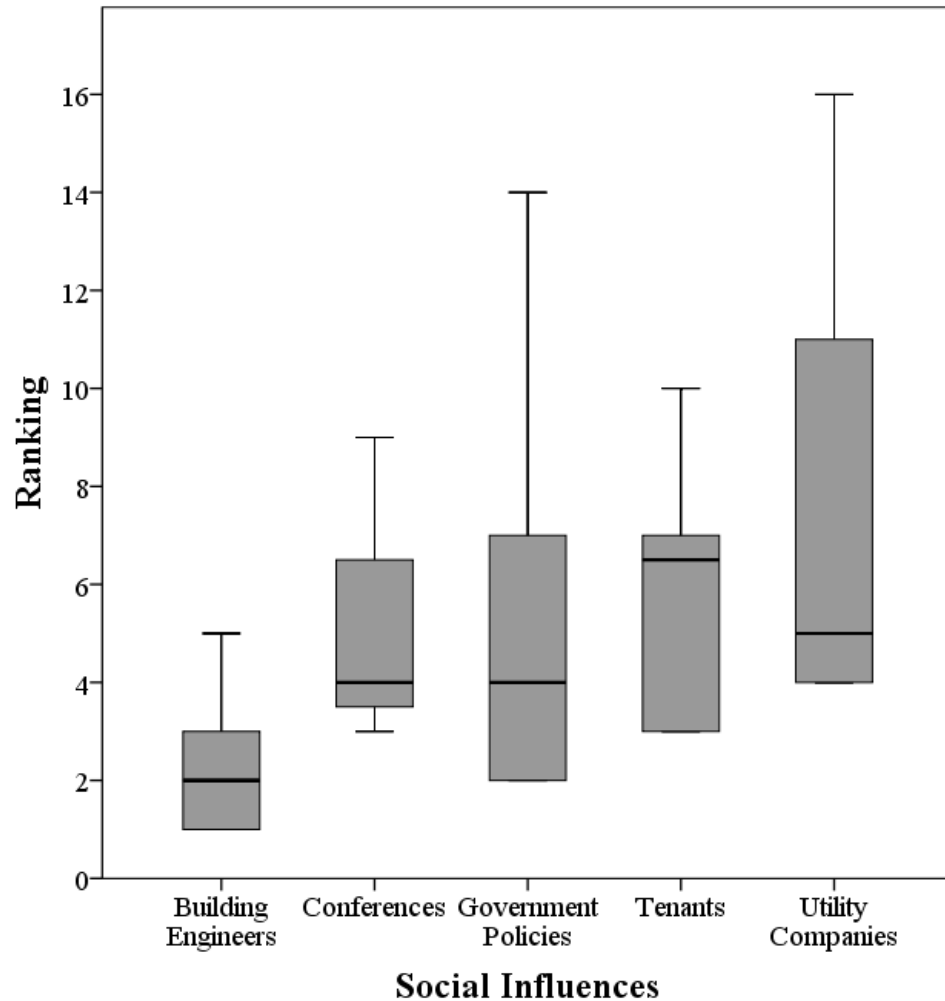


Figure 8. Boxplots depicting owner/manager rankings of selected social influences to EE investment decision-making. Lower rankings indicate higher importance (1 = highest importance and 16 = lowest importance).

2.5 Discussion

A few thematic patterns emerge from the interview data. Some of these ideas map onto the influence diagram (Figure 1) explained in the Introduction, while other ideas are promising concepts not yet heavily studied in the EE literature: (1) heterogeneity among experts and owners/managers regarding value of CSR, (2) differing approaches to the Investment Decision Process between experts and owners/managers, (3) owners/managers trust in various information sources, and (4) emerging behavioral concepts related to EE investment decision-making.

2.5.1 Heterogeneity among experts and owners/managers regarding value of CSR

During the open-ended questions, both groups often discussed the compelling role of Corporate Social Responsibility in EE investment decision-making. However, when asked to rank motivation cards, experts found others to have greater relative importance. Experts only listed Social Responsibility and Being Industry Leaders six times with average rankings of 8 (recall, 1 = most important and 13 = least important), while owners/managers ranked these items 15 times with average rankings of 4.5. These findings suggest that it may be beneficial for experts to illustrate CSR benefits to EE investments when communicating with owners/managers of large commercial buildings. Furthermore, benchmarking policy may be attractive to owners/managers who are inclined to reduce energy consumption in an attempt to signal CSR, which as a result may minimize the issue of split incentives between owners and tenants [121]. One might consider the following hypothesis: When two investments have similar economics, owners/managers of commercial buildings are more likely to pick the one with CSR benefits.

2.5.2 Differing approaches to the Investment Decision Process between groups

As shown in Table 5, experts and owners/managers differed greatly in their approach to the Investment Decision Process. The most distinct differences occurred in their discussions of goals and strategy and the role of an investment consultant in decision-making. The number of mentions of “Goals & Strategy” is nearly four times higher for owners/managers as it is for the experts. Specifically, it seems that owners/managers are focused on meeting company goals such as improving occupant comfort or maintaining innovative competitiveness, which was often highlighted in their open-ended responses as well as their motivation rating frequencies shown in Figure 5. In this instance, it seems that experts tend to overlook the strategic logic potentially in place with owners/managers’ decision-making, instead focusing on the economic barriers to energy efficiency investments. The experts’ emphasis on economic barriers is shown by how they mentioned Economic Barriers in open-ended questions (Table 5) two times, the benefits of Public Subsidies to investments (Table 6) three times, and Lack Financing six times more than did owners/managers. One possible explanation for this difference is owners/managers may evaluate how energy efficiency equipment helps them achieve overarching core business goals and not just economic goals. Indeed, Dutton et al. [130] found that organizational context influences the dimensions of an issue that are most salient to the decision-maker. Future study

should further examine these contextual factors and how they might influence owner/manager decision-making.

2.5.3 *Owners/managers trust in various information sources*

During the ranking exercises, it was apparent that owners/managers valued input from internal sources such as their building engineers and tenants. Conversely, they did not tend to list social influences affiliated with certain technologies, such as controls contractors. When asked to explain their ranking rationale, many owners/managers admitted feeling pressured by vendors or energy service contractors.

“Sometimes I don’t trust [ESCOs], because they push their product. I usually go for people that are running the same thing you’re running, they’re trying to do the same thing you’re doing.” (Participant OM6)

Similarly, some owners/managers discredited EE consultants, because they believed the consultants’ goals (making a profit) ultimately misaligned with their goals (save energy). Most owners/managers expressed trust in their building engineering team, who often interfaces with the controls contractors, ESCOs, and vendors.

“My guys are really good. They like learning about this stuff [energy efficiency], so they went to school for it. I’m confident in their abilities.” (Participant OM1)

Therefore, a bad relationship between engineers and contractors may result in a bad relationship between the owners and contractors. Indeed, Beamish et al. [131], identify trust networks among owners/managers and contractors as a means to minimize risk aversion related to the adoption of new energy efficient technologies, providing a mechanism for demystifying innovative products/practices. To mitigate reliance on contractors, perhaps offering training services for building engineers may be an alternate and effective way to increase EE. These findings inspire hypotheses such as the following: Owners/managers of commercial buildings trust information regarding EE investments more when they come from their building engineering team than if they come from external consultants.

2.5.4 *Emerging behavioral concepts related to EE investment decision-making*

Several concepts arose from the interviews between experts and owners/managers that are not yet considered or heavily discussed in the EE investment decision literature. These concepts were coded as Fear of Change, Mental Accounting, Agenda Setting, and Rewarding (Table 7):

Table 7. Emerging concepts in EE decision-making.

Code	Concept	References
Fear of Change	Resistance to change	[132]
	Aversion to technology	[133]
Mental Accounting	Mental accounting	[134]
Agenda Setting	R&D agenda setting	[135]
Rewarding	Social demand characteristics	[136]
	Team collaboration & job satisfaction	[137]

For instance, Fear of Change might be defined as resistance to change, which is explained through routine seeking, emotional reaction to imposed change, cognitive rigidity, and short-term focus [132]. Fear of Change has minimal mention in previous building EE studies involving focus groups for commercial building performance [138], open-ended interviews in multi-family residential buildings [139], [140], and surveys regarding new construction and technology diffusion [141]. Conversely, a manager's high technology adoption rate might be explained by their self-perceived lack of responsibility for the funding. As such, Mental Accounting suggests that funding origins impact spending patterns [134]. Furthermore, financial institutes mandating sustainable investments seems to resemble R&D Agenda Setting [135]. Finally, social demand characteristics, team collaboration, and job satisfaction are topics heavily studied in Organizational Behavioral Sciences that may explain why pursuing energy efficiency can influence the performance of building engineers [136], [137]. Each of these emerging concepts warrants its own hypothesis – one example might be: Owners/managers of commercial buildings are deterred from making an EE investment if their engineering staff is reluctant to install the new technology.

2.6 Conclusion

This paper discusses the findings from open-ended interviews with ten experts and ten owners/managers in Pittsburgh. This research characterizes potential non-economic factors associated with EE investment decisions made in large commercial buildings. Specifically, the authors are interested in exploring the social influences and behavioral decision profiles of EE investment decision-makers.

Findings from this scoping study identify several policy implications. First, policy makers and incentive program designers should focus on delivering economic incentives as well

as social and behavioral incentives. Secondly, policy makers should carefully consider their methods for conveying program information. When considering potential information conduits, it is important to consider the dynamics of the building engineering team as well as the owner/manager's current perceptions of various social influences. For instance, owners/managers may perceive the government and/or NGOs as neutral sources capable of delivering unbiased, trustworthy information regarding building EE investments.

Additional research is necessary to determine the potential efficacy of these suggested policy implications on a population of owners/managers. For instance, a follow-up detailed survey study of large commercial building owners could characterize the prevalence of these identified thematic patterns. A similar survey study among experts could allow for systematic comparisons between groups (i.e. Experts and Owners/Managers) as well as within groups (i.e. types of experts ranging from academics to energy efficiency consultants). Findings from this interview study also suggest that social influences do play a role in decision-making; therefore, one might perform a social network analysis of owners/managers to characterize how concepts identified in this study propagate through a network. In sum, our work aims to target late adopters by cataloging the distinctions and ranges of energy efficient building manager attributes as well as deepening the understanding of identified barriers through employment of a social network perspective. Integrating behavioral and social drivers with economic factors in energy efficiency policy may be the necessary catalyst for yielding substantial savings in support of U.S. national efforts, such as the Better Buildings Initiative.

3. Framing clean energy campaigns to promote civic engagement among parents

Abstract

Civic engagement is one important way citizens can influence the rate of the decarbonization in the electricity sector. However, motivating engagement can be challenging even if people are affected and interested in participating. Here we employed a randomized controlled trial to assess the effect clean energy campaigns emphasizing cost savings, health, climate, or health and climate, or no additional information at all (control) on civic engagement behaviors (signing a petition or making a phone call) among parents. We targeted parents as they have been shown to be powerful agents of political and business practice change in other contexts, and hence could play an important role in the decarbonization of the energy sector. In Study 1 we recruited $n=292$ parents already engaged in climate advocacy; in Study 2, we recruited a representative sample of $n=1,254$ parents drawn from the general public. Both studies were conducted in Michigan, Florida, and California, as these states have sizable advocacy group membership, divergent energy profiles, and strategic importance to the climate movement. In both studies, we find the odds of taking action are reduced by over 90% when participants are asked to make a phone call and leave a voicemail message, versus signing an online petition. Among the parents already engaged in advocacy, we observe a ceiling effect regarding attitudes towards clean energy and find the cost campaign produces unintended consequences. Among our public sample, we find that participants who believe the campaign to be credible and comprehensible are more likely to take action than those who discredit the campaign or do not understand its message. Additionally, we find parents who have children under the age of 18 negatively adjust their attitudes towards fossil fuels after being presented with health information. Ultimately, we find that campaign messages can influence energy attitudes and parents are willing to take action on the topic if the advocacy action seems like an effective approach.

3.1 Introduction

Approximately two-thirds of the electricity generated in the United States (U.S.) comes from fossil fuels, with negative externalities occurring at every point of the supply chain. Water and air pollution emanate from extraction processes; air pollution and spills can arise from fuel transportation; and, finally, environment and public health impacts result from burning fossil fuels and hazardous waste [142]–[150]. At-risk populations such as families with children, asthmatics, and those living in flood-prone regions are particularly vulnerable [5]–[8], [68]. However, without clear signals, utilities have little incentive to use cleaner energy sources to mitigate these ill effects [151]. Civic engagement – voting, demonstrating, signing petitions, and fundraising – is one way that people can signal their dissatisfaction with fossil fuels [152]–[155], and is increasingly vital as negative externalities are more widely understood and as environmental regulatory bodies are weakened through proposed budget cuts [156]–[158]. The

challenge, however, is learning how to leverage this concern and transform it into action on clean energy issues.

Parents are a potential compelling target audience for clean energy campaigns. Parenthood has been described as either a hindrance to political activism, because parents are so busy, or a reason to participate [159]. However, there is a strong reason to believe that parents can be powerful agents of change. Examples of parent movements abound, including the immensely successful Mothers Against Drunk Driving (MADD) founded by Candy Lightner [160]; Shannon Watts' Moms Demand Action for Gun Sense in America [161]; and more recently MomsRising, which campaigns for initiatives such as maternity/paternity leave as well as health care for all [162]. Other seminal examples of parent initiatives include Lois Gibbs' establishment of the Love Canal Homeowner's Association that lobbied successfully for the remediation of hazardous chemical waste in Niagara Falls, New York [163] and Mary Brune's *Making our Milk Safe* initiative, which demanded that retailers stop selling baby products made with polyvinyl chloride [164]. Finally, there also exists the EcoMom Alliance, a nonprofit empowering women through education to help create an "environmentally, socially and economically sustainable future" [165] and numerous school cafeteria food initiatives such as Farm to School [166] or Parents for Healthy Schools [167]. Drawing on these examples, there is reason to believe that parents wishing to protect their children from environmental threats, such as buried toxic waste and water pollution, may be highly motivated activists [168], [169]. Additionally, we focus on parents since the majority (85%) of women in the U.S. between the ages of 18 and 44 have had at least one child [170] and, hence, our findings could potentially generalize to a large segment of society. Therefore, our research objective is to investigate the extent to which health and environmental arguments influence parents' attitudes towards and motivation to take civic action on clean energy.

To achieve our research objective, parents in Florida, California and Michigan are exposed to a real clean energy campaign. They are then randomly assigned to learn more about cost savings, health, climate, health + climate impacts related to fossil fuel consumption, or to learn nothing more (control). Finally, they are randomly asked to either sign a petition or leave a voice message to urge their local utility to increase its share of clean energy and encourage energy efficiency, with the signed petitions and voice messages being batched and sent to utility company CEOs. Established audience segmentation analyses suggest that messaging which

assumes a diverse population as homogenous will fall flat or potentially result in unintended “boomerang effects”; therefore, it is important to identify sources of diverse perspectives [70], [171], [172].⁶ Hence, we perform two studies where we evaluate the effect of a clean energy campaign among (Study 1) those parents who are already actively engaged on climate change and (Study 2) those who are not. We hypothesize:

H1: Compared to cost savings or no information, exposure to health, climate, or the combination of health and climate information will result in less favorable attitudes by parents towards fossil fuels and more favorable attitudes towards clean energy.

H2: Compared to cost savings or no information, exposure to health, climate, or the combination of health and climate information will result in higher intention and action rates by parents.

H3: Those parents who accept climate change, see the campaigns as more credible, and believe taking action is effective will express higher civic engagement intent and higher action rates.

3.2 Study 1 – Advocacy Parents Sample

3.2.1 Method

Sampling and participants

We recruited from the membership lists of two advocacy organizations, Climate Parents (climateparents.org) and Moms Clean Air Force (momscleanairforce.org), targeting parents and grandparents concerned about climate change. Participants completed a web-based study in exchange for being entered to win 1 of 4 solar gift bundles, valued at \$200 each. The target population consisted of adults (age 18 years or older) who were or had ever been parents, aunts or uncles. We targeted members who were customers of select utilities residing in Michigan (Consumers Energy and DTE Energy), Florida (Florida Power and Light and Duke Energy), and California (Southern California Edison). We selected these utility districts and states based on advocacy group membership, divergent energy profiles, and strategic importance to the climate movement [173]–[176].⁷ Between September 13, 2016 and November 7, 2016, the advocacy groups invited 51,774 of their members by email to participate in a survey. Email reminders were sent out five times between September and November 2016. A total of 364 responded, with

⁶ See Appendix B.1 for more details on background, framing, and theoretical models of decision-making.

⁷ See Appendix B.2 for justification of utility selection and associated electricity generation portfolios.

292 completing the study for a completion rate of 0.6%.^{8,9} According to self-reports, the participants' average age was 58 (SD = 15.4), 53% were female (n = 153), 79% were White or Caucasian (n = 229), 55% had at least a bachelor's degree (n = 162), and 45% had a household annual income of \$40k or greater (n = 133). In terms of party affiliation, 47% identified as Democrats (n = 136), 29% identified as Independents or Undecided (n = 84), 3% identified as Republicans (n = 10), and 21% preferred not to answer (n = 62). Most participants answered that they were parents (62%, n = 182), and of these 45% were also grandparents (n = 82) and 84% were also aunts or uncles (n = 153). Of those who reported being aunts or uncles, 63 out of 182 participants reported not having children of their own. A number of participants reported having at least one child under the age of 18 living at home (43 out of 182; 24%), and of these 21% had at least one child age 5 or under (n = 9). Only 5% (n = 15) of participants in Study 1 were not involved in other community service activities, 46% were involved in 1-3 other activities (n = 134), and 49% were involved in more than 3 activities (n = 143).

Experimental protocol

Figure 9 summarizes the study design; the full survey can be found in Appendix B.7. In this study, participants were randomly assigned to one of ten *conditions*, with clean energy campaign and advocacy action as fully crossed factors. The five types of Campaign¹⁰ were:

- i. **Control.** Participants read a neutral, informative message about the role of electricity utilities in generating and distributing electricity.
- ii. **Cost.** Identical to the control but with additional information about potential reductions in future electricity bills if utilities switched to renewables or were more efficient.
- iii. **Health.** Identical to the control but with additional information about negative health impacts associated with burning fossil fuels.
- iv. **Climate.** Identical to the control but with additional information about negative climate impacts associated with burning fossil fuels.
- v. **Health + Climate.** Identical to the control but with additional information about negative health and climate impacts associated with burning fossil fuels.

⁸ An a priori power analysis using G*Power [237] indicated a total sample of 196 for a medium effect size ($\eta^2 = 0.25$) with 80% power, for ANOVA (fixed effects, main effects, and interactions) with alpha at 0.05.

⁹ See Appendix B.3 for email templates and Appendix Tables B3-B5 for a summary of the Study 1 sample.

¹⁰ See Appendix B.6 for campaign materials.

After reading the campaign, participants were informed that this was a real campaign albeit within a study. They then were asked to urge their utility to invest in clean energy and energy efficiency by either signing a petition or leaving a voice message:

- i. **Petition.** If they chose to sign the petition, they were taken to a page to fill out their participant code, first name, last name, and zip code (See Appendix Figures B8 and B10).
- ii. **Message.** If they chose to leave a voice message, they were taken to a page where they were given a phone number for the researchers' Google voice mail account, name of the utility CEO, and a sample script. They were asked to also include their participant code and name in their voice message (See Appendix Figures B9 and B11).

Campaign materials, selected advocacy actions, and survey questions were developed in collaboration with Moms Clean Air Force and Climate Parents. Campaign materials and survey questions were pre-tested for affect, readability, and comprehension in a series of in-person interviews ($n = 5$) and online pilot tests ($n = 172$). Additional explanation of framing selection is provided in Appendix B.1. In addition to exposing participants to various clean energy campaigns and measuring advocacy intentions and actions, we also collected data on key variables that were relevant to the campaign materials (e.g. agreement with utilities using various energy sources) and measured individual differences (e.g. climate change acceptance). These variables are explained in the next section. The Institutional Review Board of Carnegie Mellon University approved all procedures. All participants provided informed consent.

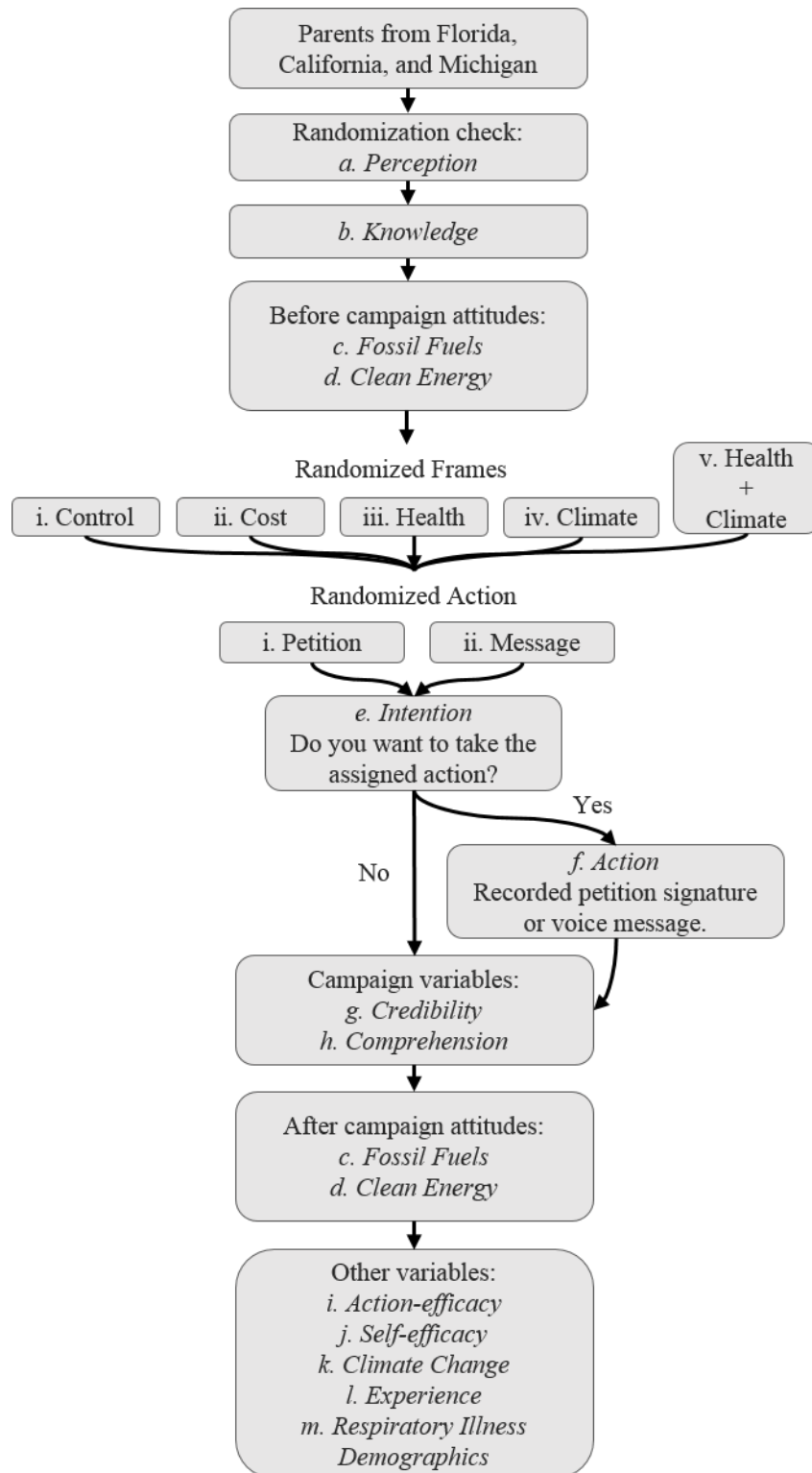


Figure 9. Schematic of the Chapter 3 study design.

Variables

For a further description of the included variables and coding methodology, please see Appendix B.8.

- a. **Perception.** Participants indicated their perception of their utility's electricity portfolio by answering the following question: "What percentage of the electricity that you use in your home do you think comes from fossil fuels (i.e., natural gas, oil, and/or coal)?" the responses were recorded on a sliding scale from 0% to 100%.
- b. **Knowledge.** Given a participant's perception of the fossil fuel percentage of their utility's portfolio, we calculated knowledge as an absolute difference from their response and the actual percentage published on their respective utility's websites.¹¹
- c. **Fossil fuel attitudes.** Participants indicated their fossil fuel attitudes with their agreement to the following statement (1 = strongly disagree, 5 = strongly agree): "My utility should use fossil fuels to make electricity," before and after being exposed to their condition.
- d. **Clean energy attitudes.** Participants' attitudes towards clean energy were measured by taking the mean of their agreement with the following two statements (1 = strongly disagree, 5 = strongly agree) before and after the conditions: "My utility should use wind, sun, and other renewable energy sources to make electricity," and "My utility should use energy efficiency to reduce the amount of electricity needed." (Before: Cronbach's α = 0.33; After: Cronbach's α = 0.62).
- e. **Intention.** Participants indicated their intention to take action¹² by either selecting, "Sign the petition"/"Leave a message" or "No thanks".
- f. **Action.** Participants who took action were assigned a 1, and those who didn't take action were assigned a 0.
- g. **Credibility.** Participants indicated their perception of campaign credibility by answering the following question (1 = definitely no, 5 = definitely yes): "Was the clean energy information just presented to you credible?"
- h. **Comprehension.** Participants' comprehension was measured by their responses to two questions (1 = definitely false, 5 = definitely true): (1) "My utility can only provide

¹¹ See Appendix Tables B1 and B2 for utility portfolios.

¹² See Appendix Figures B8-B11 for an example of the Intention and Action Screens.

electricity generated from fossil fuels” [correct answer = definitely false] and (2) “My utility can choose to invest in energy efficiency” [correct answer = definitely true].

- i. **Action-efficacy.** Participants indicated action efficacy beliefs by indicating their agreement (1 = strongly disagree, 5 = strongly agree) with either “Signing an online petition is an effective way to change my utility’s practices” or “Joining others who have already made a phone call to my utility is an effective way to change my utility’s practices.”
- j. **Self-efficacy.** Participants’ self-efficacy was assessed by taking the mean of their agreement with two statements from Schwarzer and Jerusalem’s General Self-Efficacy Scale [177] (1 = strongly disagree, 5 = strongly agree): (1) “I am often able to overcome barriers” and (2) “I generally accomplish what I set out to do” (Cronbach’s $\alpha = 0.76$) [178].
- k. **Climate change.** Participants’ climate change acceptance was assessed by taking the mean of their agreement with four statements from Leiserowitz et al.’s Global Warming’s Six Americas survey [179] (1 = definitely no to 5 = definitely yes): (1) “Do you think that climate change is happening?” (2) “Do you think that climate change is mostly caused by humans?” (3) “Do you think that climate change will harm future generations?” and (4) “Are you worried about climate change?” (Cronbach’s $\alpha = 0.75$) [178].
- l. **Experience.** Participants indicated their experience of extreme events by checking any of the following: coastal/inland flooding, drought, severe weather, wildfires, other, and prefer not to answer.
- m. **Respiratory Illness.** Participants answered, “Have YOU been diagnosed by a doctor or other qualified medical professional with asthma, chronic bronchitis, COPD, or other lung disease?”

Analytic strategy

Statistical analyses were conducted using Stata 14.2. We performed a Pearson’s chi-squared test to confirm balanced experimental conditions. To ensure successful randomization, we performed a 2-way Analysis of Variance (ANOVA) with Campaign x Action on Perception. We conducted separate linear regressions, considering Campaign and Action on change of attitude (after campaign – before campaign) for Fossil Fuels (Model 1) and Clean Energy (Model 2). In these regressions, we controlled for Knowledge, Credibility, Comprehension, Experience, Respiratory

Illness and demographics. We conducted separate logistic regressions using a hierarchical variable-entry strategy to analyze correlates of our dependent variables, Intention and Action, in theoretically relevant blocks.¹³

3.2.2 Results

Table 8 provides summary statistics for our dependent variables across the experimental conditions in Study 1.

Balance and randomization check

A chi-square test of independence found no significant difference in the number of participants assigned to each condition, $\chi^2(4, N = 292) = 1.11, p = 0.893$, indicating a balanced experimental design. A 2-way ANOVA also found no significant interaction between Campaign and Action on Perception, $F(4, 292) = 1.65, p = 0.161$, suggesting successful randomization.¹⁴

Attitudes

Figure 10 depicts the effects of Campaign on overall attitudes towards fossil fuels. As shown in Table 9 (Model 1) and Figure 10, cost information resulted in fossil fuels being viewed more favorably than neutral information (control) or climate information [approached significance].

Figure 11 depicts the effects of Campaign on overall attitudes towards renewable energy. While we observed no significant main effects from campaign on clean energy attitudes, it is important to note that views across all conditions were high before ($M = 4.92, SD = 0.27$) and after ($M = 4.91, SD = 0.31$), indicating the strong environmental orientation of our sample (Figure 11).

Unplanned post hoc analyses found those shown health information saw fossil fuels more negatively than those shown cost information (Contrast = $-0.71, SE = 0.22, p = 0.002$).¹⁵

Intention

Cost information resulted in lower intent to take action than neutral information (control) (Table 10, Model 5a and Appendix Figure B18). We found those asked to make a phone call were much less likely (99%) to intend to do so than those asked to sign a petition (Models 3a-5a). Greater climate change acceptance was associated with higher levels of intent to take action when controlling for demographics and when not (Model 5a and 4a, respectively). Additionally, the odds of intention to make a phone call or sign a petition were 2 times greater among those who

¹³ See Appendix B.8 for regression block details.

¹⁴ See Appendix B6 and B7 for additional balance and randomization check results for Study 1.

¹⁵ See Appendix Tables B8 and B9 for additional post-hoc analysis results for Study 1.

expressed stronger belief in the efficacy of the action than those less convinced, when not controlling for demographics (Model 4a). Finally, we found the odds of intention were 1.5 times higher among those who reported higher self-efficacy than those who reported low self-efficacy, when controlling for demographics (Model 5a). No other significant predictors or interactions were observed.

Action

Figure 12 depicts the effects of Campaign on action rates. Cost information resulted in lower action rates than neutral information (control) (Table 10, Model 5b and Figure 12), controlling for demographic variables. We also found those asked to make a phone call were much less likely (99% less likely) to do so than those asked to sign a petition (Models 3b-5b). We also found those who reported greater climate change acceptance and stronger beliefs in the effectiveness of the requested action were significantly more likely to take action when and when not controlling for demographics (Model 5b and 4b, respectively). No other significant predictors or interactions were observed. See Appendix B.13 for more details about differences across states.

Table 8. Ch.3, Study 1 summary statistics of dependent variables across experimental conditions.

Campaign	Action	Average change in fossil fuel attitude			Average change in clean energy attitude			Count of intentions		Count of actions	
		n ^a	Mean	SD	n	Mean	SD	n	Made Intention ^b	n	Took Action ^c
Control	Petition	30	-0.10	0.96	30	0.08	0.42	33	33	33	32
Cost	Petition	38	0.31	1.16	38	0.01	0.25	40	40	40	37
Health	Petition	36	0.11	1.14	36	-0.10	0.49	37	34	37	33
Climate	Petition	32	-0.15	0.51	33	-0.05	0.20	34	34	34	32
Health + Climate	Petition	31	0.00	0.89	31	0.03	0.48	34	33	34	31
Control	Voice Message	21	0.10	0.70	22	-0.02	0.11	31	10	31	5
Cost	Voice Message	27	-0.07	0.92	27	0.04	0.19	29	9	29	6
Health	Voice Message	31	-0.06	0.36	33	-0.03	0.21	35	9	35	7
Climate	Voice Message	25	-0.12	0.60	25	-0.02	0.27	29	5	29	4
Health + Climate	Voice Message	29	-0.31	0.85	29	-0.09	0.30	34	11	34	3

^a Participants were not required to answer every question in the online survey. Therefore, we observe some small differences in the n values for different dependent variables within each condition.

^b “Made Intention” means participants indicated their intention to take action.

^c “Took Action” means participants took their assigned advocacy actions.

Table 9. Ch. 3, Study 1 (advocacy) linear regression predicting changes^a in attitudes towards fossil fuels and clean energy^b.

Variables	Model 1 (Fossil Fuels) (n = 284)			Model 2 (Clean Energy) (n = 286)		
	B(95% CI)	SE	t	B(95% CI)	SE	t
Campaign (Ref = Control)						
Cost	0.50 (0.02, 0.98)*	0.24	2.05	-0.03 (-0.22, 0.17)	0.10	-0.27
Health	-0.21 (-0.69, 0.28)	0.24	-0.85	-0.01 (-0.20, 0.19)	0.10	-0.08
Climate	0.07 (-0.48, 0.62)	0.28	0.24	-0.03 (-0.25, 0.20)	0.11	-0.23
Health + Climate	0.06 (-0.46, 0.58)	0.26	0.24	0.05 (-0.16, 0.26)	0.11	0.46
Action (Ref = Petition)						
Voice Message	-0.10 (-0.40, 0.21)	0.15	-0.64	-0.16 (-0.28, -0.04)*	0.06	-2.48
Knowledge	0.00 (-0.01, 0.00)	0.00	-1.06	0.00 (-0.01, 0.00)	0.00	-1.06
Credibility	-0.25 (-0.50, 0.01)	0.13	-1.91	0.06 (-0.04, 0.17)	0.05	1.19
Comprehension	-0.04 (-0.43, 0.35)	0.20	-0.20	-0.06 (-0.21, 0.10)	0.08	-0.71
Constant	2.01 (0.35, 3.68)*	0.84	2.40	-0.20 (-0.87, 0.47)	0.34	-0.59
R ²	0.16			0.12		

*** $p < .001$, ** $p < .01$, * $p < .05$

^a Here changes in attitudes were calculated by subtracting attitudinal responses after participants viewed the campaigns and were asked to take an action from their original responses.

^b Demographics controlled for in Model 1 and Model 2 include Age, Income, Number of Children, Experience with climate change-related weather, and whether or not the participant suffers from respiratory illness

Table 10. Ch. 3, Study 1 (advocacy) logistic regression predicting intention and action^a.

Variable	Intentions									Actions								
	Model 3a (n = 287)			Model 4a (n = 284)			Model 5a (n = 123)			Model 3b (n = 287)			Model 4b (n = 284)			Model 5b (n = 123)		
	B	SE	OR(<i>e</i> ^B)	B	SE	OR(<i>e</i> ^B)	B	SE	OR(<i>e</i> ^B)	B	SE	OR(<i>e</i> ^B)	B	SE	OR(<i>e</i> ^B)	B	SE	OR(<i>e</i> ^B)
Campaign (Ref. = Control)																		
Cost	0.06	0.61	1.06	-0.34	0.66	0.71	-3.05*	1.49	0.05	-0.11	0.67	0.90	-0.69	0.70	0.50	-3.12*	1.49	0.04
Health	-0.17	0.61	0.84	0.05	0.65	1.05	-2.18	1.32	0.11	0.22	0.66	1.25	0.42	0.69	1.52	-1.37	1.20	0.25
Climate	-0.32	0.64	0.73	-0.45	0.68	0.64	-2.22	1.48	0.11	-0.07	0.68	0.93	-0.29	0.72	0.75	-0.30	1.28	0.74
Health + Climate	0.09	0.60	1.09	0.06	0.64	1.06	-0.53	1.33	0.59	-0.42	0.69	0.66	-0.59	0.71	0.55	-1.51	1.38	0.22
Action (Ref. = Petition)																		
Voice Message	-5.03***	0.65	0.01	-5.24***	0.72	0.01	-7.43***	1.59	0.00	-4.88***	0.51	0.01	-5.25***	0.59	0.01	-6.44***	1.20	0.00
Knowledge	0.00	0.01	1.00	0.00	0.01	1.00	0.02	0.02	1.02	0.01	0.01	1.01	0.01	0.01	1.01	0.01	0.02	1.01
Credibility	0.61	0.34	1.84	0.41	0.35	1.51	1.14	0.63	3.13	0.83*	0.34	2.29	0.64	0.35	1.90	0.78	0.58	2.18
Comprehension	0.31	0.42	1.36	0.46	0.43	1.58	-1.82	1.03	0.16	-0.04	0.40	0.96	0.10	0.42	1.11	-1.27	0.83	0.28
Action-Efficacy				0.69**	0.21	1.99	0.53	0.43	1.70				0.82***	0.23	2.27	1.09*	0.47	2.97
Self-Efficacy				0.14	0.29	1.15	1.49*	0.74	4.44				-0.26	0.33	0.77	-0.05	0.62	0.95
Climate Change				1.46*	0.72	4.31	2.85**	1.09	17.29				1.78*	0.69	5.93	2.45*	1.11	11.59
Demographics ^c	No			No			Yes			No			No			Yes		
Constant	0.59	1.92	1.80	-8.54*	3.68	0.00	-16.79*	6.51	0.00	-1.18	1.91	0.31	-10.73**	3.65	0.00	-14.92*	6.65	0.00
R ^{2d}	0.50			0.55			0.66			0.56			0.60			0.65		

****p*<.001, ***p*<.01, **p*<.05

^a We chose not to include Climate x Action interaction term in these regression models.

^b A significant odds ratio with a value below 1 indicates that the specified independent variable reduces the odds of a participant stating an intention to act (i.e. Intention = 1). An odds ratio greater than 1 indicates an increase in these odds. Therefore, we can subtract 1 from the ratio and multiply by 100 to determine the percent change in the odds of intending to take an action. The same can be done for the observed action regressions.

^c Demographics controlled for in this regression include Age, Income, Number of Children, Experience with climate change-related weather, and whether or not the participant suffers from Respiratory illness.

^d These represent pseudo R² values for logistic regressions.

3.2.3 Discussion

Overall, our participants who are members of climate advocacy groups held very positive views about clean energy and additional information about impacts did little to shift those views. We did not find support for H1 and H2. In support of H3, other factors seemingly increased action rates, including whether the participant saw the action as being able to make a difference in their utility's practices and if they accepted climate change. Finally, on balance, people found it easier to sign a petition than make a phone call. See Appendix B.14 for additional Study 1 discussion. Whether these findings hold among parents who don't prioritize climate change or other environmental issues is an empirical question, which we investigate in Study 2.

3.3 Study 2 – Public Parents Sample

3.3.1 Method

Sampling and participants

Respondents were drawn from the GfK KnowledgePanel, which uses address-based random sampling methods to recruit individuals in U.S. households. Data were weighted to account for probability of selection and any differences in the demographics of our sample compared to U.S. Census benchmarks. Panelists completed Web-based surveys in return for compensation or free Internet. The target population consisted of adults (age 18 or older) who were or had ever been parents and are customers of the same utilities targeted in Study 1. Between September 23, 2016 and October 3, 2016, GfK invited 1,890 people to participate, with 1,254 completing the study for a completion rate of 66%.^{16,17} According to self-reports, the participants' average age was 51 (SD = 15), 54% were female (n = 683), 53% were White or Caucasian (n = 670), 26% had at least a bachelor's degree (n = 324), and 69% had a household annual income of \$40k or greater (n = 873). In terms of party affiliation, 45% identified as Democrats (n = 557), 2% identified as Independents or Undecided (n = 27), and 53% identified as Republicans (n = 670). All participants in Study 2 answered that they were parents, and of these 48% were also grandparents (n = 605) and 74% were also aunts or uncles (n = 924). Some participants reported having at least one child under the age of 18 living at home (363 out of 1,254; 30%), and of these 35% had

¹⁶ An a priori power analysis using G*Power [237] indicated a total sample of 1,199 for a small effect size ($\eta^2 = 0.10$) with 80% power, for ANOVA (fixed effects, main effects, and interactions) with alpha at 0.05.

¹⁷ See Appendix B.15 for a description of GfK's sampling method and Appendix Table B11 for a summary of the Study 2 sample.

at least one child age 5 or under ($n = 127$). In Study 2, 16% of participants were not involved in other community service activities ($n = 229$), 64% were involved in 1-3 other activities ($n = 794$), and 20% were involved in more than 3 activities ($n = 201$).

Experimental protocol

Study 2 followed the same exact experimental protocol as that described in Study 1 (Figure 9).

Variables

For Clean Energy Attitudes, we found a Cronbach's α of 0.78 and 0.79 for before and after presentation of the campaign, respectively. We found a Cronbach's α of 0.77 and 0.92 for Self-efficacy and Climate Change, respectively [178].

Analytic strategy

We performed the same exact set of analyses for Study 2 as we did for Study 1, with the inclusion of sampling weights to retain demographic representativeness.¹⁸ To investigate how different parent segments reacted to the clean energy campaigns, we performed analyses on two group distinctions within this sample: (1) grandparents / non-grandparents and (2) parents with children under 18 years old / parents without children under 18 years old. We ran the same change of attitude regressions for Fossil Fuels and Clean Energy as well as logistic regressions for Intention and Action, controlling for demographics. All results are included in Appendix B.23.

3.3.2 Results

Table 11 provides summary statistics for our dependent variables across the experimental conditions in Study 2.

Balance and randomization check

Similar to Study 1, a chi-square test of independence indicated a balanced experimental design [$\chi^2(4, N = 1254) = 1.80, p = 0.773$] and a 2-way ANOVA with Campaign x Action on Perception suggested successful randomization [$F(4, 1247) = 0.95, p = 0.433$].¹⁹

¹⁸ See Appendix B19 for unweighted results.

¹⁹ See Appendix Tables B14 and B15 for additional balance and randomization check results for Study 1.

Attitudes

Health information resulted in significantly less favorable attitudes towards clean energy (Table 12, Model 7), seemingly driven by parents in Florida.²⁰ Unplanned post hoc analyses found those presented with the health impacts viewed clean energy (Contrast = -0.34, SE = 0.12, $p = 0.005$) and fossil fuels (Contrast = -0.41, SE = 0.167, $p = 0.009$) less favorable than those presented with the cost benefits of utilities switching to renewables and increasing efficiency. However, coupling health with climate information resulted in more favorable views towards clean energy than those shown health information alone (Contrast = 0.29, SE = 0.12, $p = 0.017$).²¹

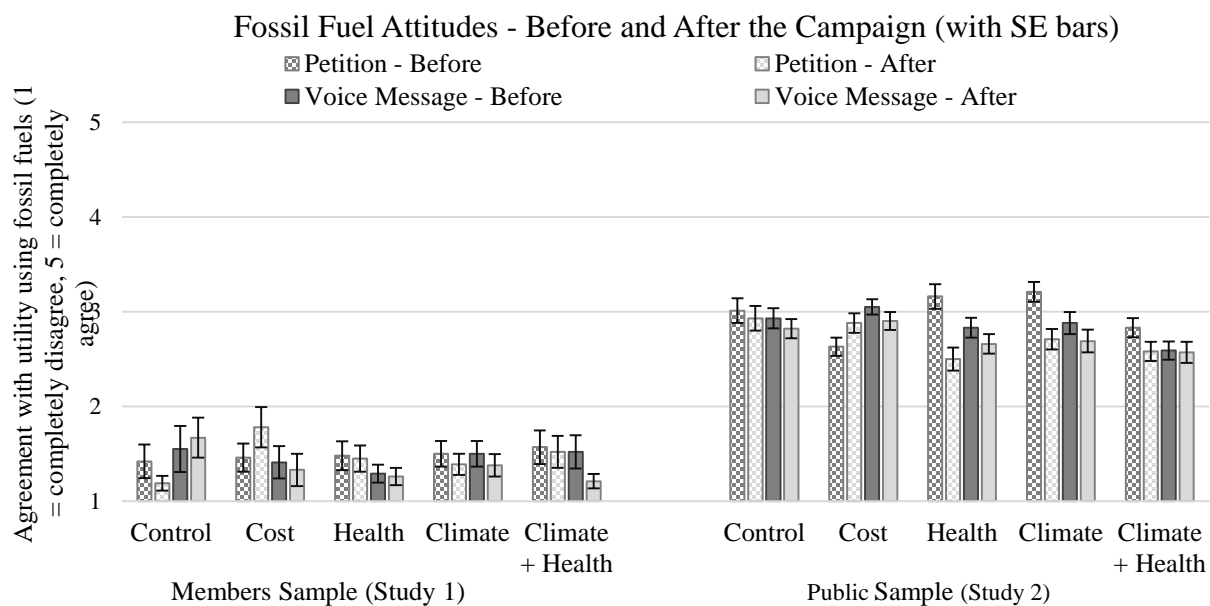


Figure 10. The effects of Campaign (Control, Cost, Health, Climate, and Health + Climate) on overall attitudes towards fossil fuels (before – after) in the advocacy sample (Ch.3, Study 1) and the general public sample (Ch. 3, Study 2).

²⁰ Looking at state differences, we found that in Florida showing the health information increased negative views of both clean energy (before = 4.32, after = 3.95) and fossil fuels (before = 3.04, after = 2.51). In Michigan, however, views on clean energy remained virtually unchanged (before = 4.48, after = 4.45) but did become less favorable for fossil fuels (before = 3.05, after = 2.63).

²¹ See Appendix Tables B16 and B17 for additional post-hoc analysis results for Study 2.

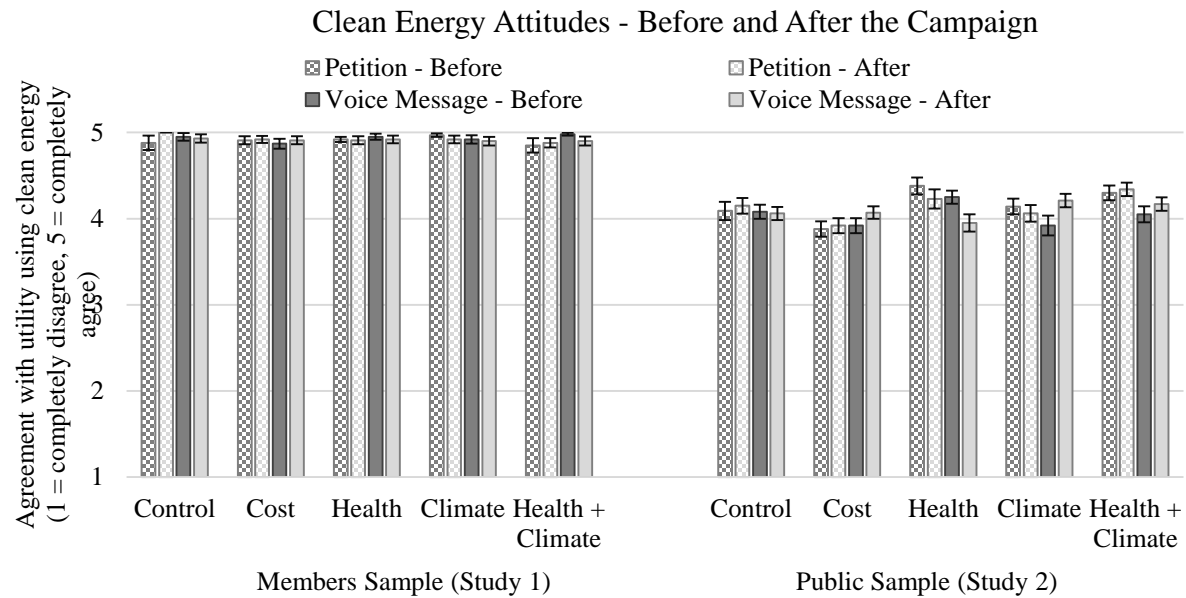


Figure 11. The effects of Campaign (Control, Cost, Health, Climate, and Health + Climate) on overall attitudes (before – after) towards renewable energy in the advocacy sample (Ch. 3, Study 1) and the general public sample (Ch. 3, Study 2).

Table 11. Ch. 3, Study 2 summary statistics of dependent variables across experimental conditions.

Campaign	Action	Average change in fossil fuel attitude			Average change in clean energy attitude			Count of intentions		Count of actions	
		n ^a	Mean	SD	n	Mean	SD	n	Made Intention ^b	n	Took Action ^c
Control	Petition	110	-0.12	0.66	111	0.04	0.79	112	45	112	43
Cost	Petition	125	0.01	1.01	126	0.08	0.77	127	53	127	53
Health	Petition	116	-0.31	1.18	119	-0.08	0.84	120	51	120	50
Climate	Petition	113	-0.33	1.25	115	-0.07	0.85	118	61	118	56
Health + Climate	Petition	125	-0.22	1.06	126	0.06	0.86	129	58	129	56
Control	Voice Message	125	-0.05	0.97	127	-0.01	0.89	132	13	132	5
Cost	Voice Message	122	-0.23	1.00	126	0.17	0.83	126	11	126	5
Health	Voice Message	134	-0.13	1.21	138	-0.05	0.98	140	15	140	5
Climate	Voice Message	119	-0.11	1.10	120	0.00	0.84	120	15	120	3
Health + Climate	Voice Message	127	-0.13	0.99	128	0.09	0.83	130	14	130	2

^a Participants were not required to answer every question in the online survey. Therefore, we observe some small differences in the n values for different dependent variables within each condition.

^b “Made Intention” means participants indicated their intention to take action.

^c “Took Action” means participants took their assigned advocacy actions.

Table 12. Ch. 3, Study 2 (general public) linear regression predicting changes^a in attitudes towards fossil fuels and clean energy^b.

Variables	Model 6 (Fossil Fuels) (n = 1205)			Model 7 (Clean Energy) (n = 1222)		
	B(95% CI)	SE	t	B(95% CI)	SE	t
Campaign (Ref = Control)						
Cost	0.16 (-0.10, 0.41)	0.13	1.18	0.09 (-0.16, 0.34)	0.13	0.71
Health	-0.26 (-0.53, 0.01)	0.14	-1.88	-0.25 (-0.48, -0.01)*	0.12	-2.06
Climate	-0.17 (-0.52, 0.18)	0.18	-0.97	0.14 (-0.17, 0.44)	0.16	0.90
Health + Climate	-0.04 (-0.32, 0.25)	0.15	-0.26	0.04 (-0.20, 0.28)	0.12	0.34
Action (Ref = Petition)						
Voice Message	0.09 (-0.13, 0.31)	0.11	0.81	0.04 (-0.13, 0.22)	0.09	0.51
Knowledge	0.00 (0.00, 0.01)	0.00	0.47	0.00 (0.00, 0.00)	0.00	-0.16
Credibility	-0.11 (-0.21, -0.01)*	0.05	-2.10	0.07 (-0.01, 0.14)	0.04	1.69
Comprehension	-0.10 (-0.23, 0.03)	0.07	-1.50	0.15 (0.05, 0.26)**	0.05	2.79
Constant	0.74 (0.00, 1.47)*	0.37	0.05	-0.65 (-1.25, -0.06)*	0.30	-2.17
R ²	0.07			0.06		

*** $p < .001$, ** $p < .01$, * $p < .05$

^a Here changes in attitudes were calculated by subtracting attitudinal responses after participants viewed the campaigns and were asked to take an action from their original responses.

^b Demographics controlled for in Model 6 and Model 7 include Age, Income, Number of Children, Experience with climate change-related weather, and whether or not the participant suffers from respiratory illness.

Intention

A main effect was observed for intention with those asked to make a phone call being much less likely (~90%) to intend to do so than those asked to sign a petition (Table 13, Models 8a-10a).

We also found the odds of intending to take action were 2 times higher among those who believed the campaign to be credible than those who didn't believe it to be credible (Model 8a). Those who accepted climate change and expressed a stronger belief in the efficacy of the action were more likely to intend to take action when and when not controlling for demographics (Model 9a and 10a, respectively). No significant other main effects or interactions were observed.

Action

A main effect was observed for action with those asked to make a phone call being much less likely (~90%) to do so than those asked to sign a petition (Table 13, Models 8b-10b). No other significant main effects or interactions were observed. We also found those who believed the campaign to be more credible, expressed stronger beliefs in the efficacy of the action, and

accepted climate change were more likely to take action when and when not controlling for demographics (Model 9b and 10b, respectively). No other significant predictors were observed. See Appendix B.22 for more details about state differences.

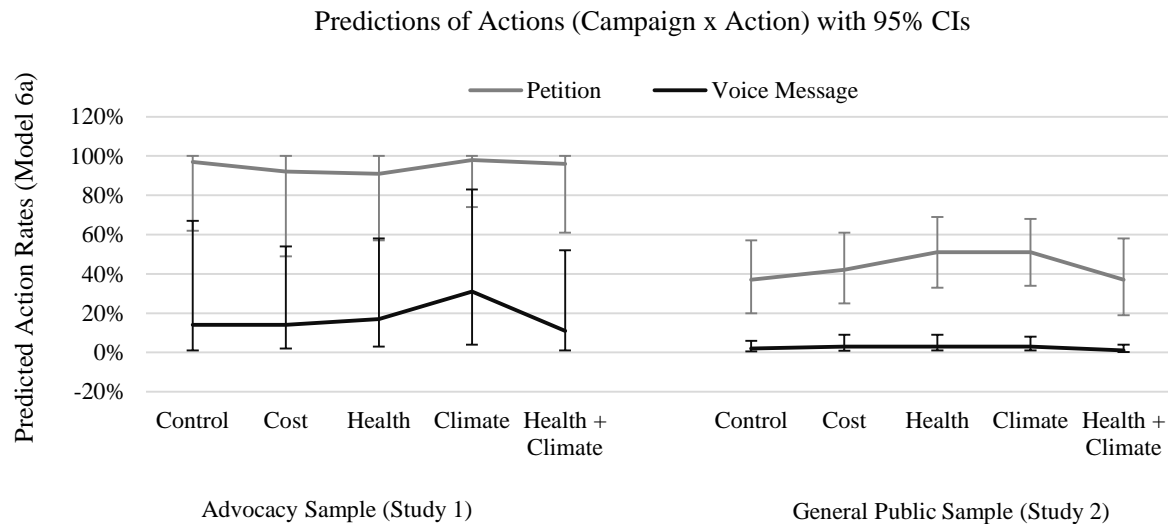


Figure 12. The effects of Campaign (Control, Cost, Health, Climate, and Health + Climate) on action rates in the advocacy sample (Ch. 3, Study 1) and the general public sample (Ch. 3, Study 2). This chart illustrates the predicted action rates with 95% confidence intervals from Models 5b and 10b.

Table 13. Ch. 3, Study 2 (general public) logistic regression predicting intention and action^a.

Variable	Intentions									Actions								
	Model 8a (n = 1237)			Model 9a (n = 1200)			Model 10a (n = 1168)			Model 8b (n = 1237)			Model 9b (n = 1200)			Model 10b (n = 1168)		
	B	SE	OR(<i>e^B</i>)	B	SE	OR(<i>e^B</i>)	B	SE	OR(<i>e^B</i>)	B	SE	OR(<i>e^B</i>)	B	SE	OR(<i>e^B</i>)	B	SE	OR(<i>e^B</i>)
Campaign (Ref. = Control)																		
Cost	-0.34	0.35	0.71	-0.14	0.39	0.87	-0.18	0.40	0.84	0.09	0.42	1.09	0.46	0.47	1.58	0.42	0.48	1.52
Health	0.17	0.35	1.19	-0.03	0.38	0.97	0.12	0.39	1.13	0.53	0.40	1.70	0.45	0.44	1.57	0.60	0.46	1.82
Climate	0.31	0.36	1.36	0.47	0.37	1.60	0.52	0.36	1.68	0.24	0.37	1.27	0.49	0.41	1.63	0.50	0.42	1.65
Health + Climate	0.02	0.41	1.02	-0.10	0.45	0.90	-0.15	0.47	0.86	-0.22	0.44	0.80	-0.36	0.47	0.70	-0.46	0.50	0.63
Action (Ref. = Petition)																		
Voice Message	-2.19***	0.27	0.11	-2.42***	0.32	0.09	-2.66***	0.33	0.07	-3.55***	0.33	0.03	-4.07***	0.39	0.02	-4.37***	0.41	0.01
Knowledge	0.00	0.01	1.00	0.00	0.01	1.00	0.001	0.01	1.00	0.01	0.01	1.01	0.01	0.01	1.01	0.01	0.01	1.01
Credibility	0.77***	0.15	2.16	0.38*	0.17	1.46	0.44*	0.18	1.55	0.92***	0.14	2.51	0.58***	0.15	1.79	0.63***	0.16	1.88
Comprehension	0.26	0.17	1.30	0.28	0.19	1.32	0.25	0.20	1.28	0.22	0.19	1.25	0.35	0.20	1.42	0.36	0.22	1.43
Action-Efficacy				0.69***	0.13	1.99	0.75***	0.12	2.12				0.82***	0.14	2.27	0.87***	0.14	2.39
Self-Efficacy				-0.10	0.18	0.90	-0.18	0.18	0.84				-0.30	0.20	0.74	-0.37	0.21	0.69
Climate Change				0.49***	0.13	1.63	0.49**	0.15	1.63				0.42**	0.13	1.52	0.38**	0.14	1.46
Demographics ^c	No			No			Yes			No			No			Yes		
Constant	-3.43***	0.70	0.03	-5.85***	1.09	0.00	-5.17***	1.23	0.01	-4.5***	0.80	0.01	-6.77***	1.31	0.00	-6.21***	1.55	0.00
R ^{2d}	0.23			0.32			0.37			0.35			0.44			0.47		

*** $p < .001$, ** $p < .01$, * $p < .05$

^a We chose not to include Climate x Action interaction term in these regression models.

^b A significant odds ratio with a value below 1 indicates that the specified independent variable reduces the odds of a participant stating an intention to act (i.e. Intention = 1). An odds ratio greater than 1 indicates an increase in these odds. Therefore, we can subtract 1 from the ratio and multiply by 100 to determine the percent change in the odds of intending to take an action. The same can be done for the observed action regressions.

^c Demographics controlled for in this regression include Age, Income, Number of Children, Experience with climate change-related weather, and whether or not the participant suffers from Respiratory illness.

^d These represent pseudo R² values for logistic regressions.

Segmentation analysis

Parents who aren't grandparents. Parents who are not also grandparents presented with health information reported significantly less favorable attitudes towards fossil fuels ($B = -0.43$, $p = 0.029$) than those presented with neutral information. Moreover, for these parents, stronger reported self-efficacy was associated with less action taking ($B = -0.60$, $p = 0.30$). We did observe, however, similarities between parents who are and who are not also grandparents with those being asked to make a phone call being much less likely to intend to or to actually do so than sign a petition. We also found that across all parents, greater perceived campaign credibility, action efficacy, and belief in climate change was associated with greater intention and action. No other significant effects were observed ($p > .05$).

Having a child under the age of 18 at home. Parents who have children under the age of 18 years old presented with health information reported significantly less favorable attitudes towards fossil fuels ($B = -0.51$, $p = 0.044$) than those presented with neutral information. Moreover, for these parents, greater message comprehension was predictive of greater action ($B = 0.69$, $p = 0.024$). We also observed similarities between parents who have children under the age of 18 and those who don't with those being asked to make a phone call being much less likely to do intend to or to actually do so than sign a petition. We also found that across all parents, greater perceived campaign credibility, action efficacy, and belief in climate change was associated with greater intention and action. No other significant effects were observed ($p > .05$).

3.3.3 Discussion

Overall, our participants recruited from the general public held relatively neutral opinions on energy sources. Here, among those shown health information, we found more negative attitudes towards clean energy than the control group as well as more negative attitudes towards both fossil fuels and clean energy than the cost group (in partial support of H1). We did not find support for H2; we found the campaigns had no effect on intention or action rates. In support of H3, we found climate change acceptance and beliefs about campaign credibility among the participants to be more predictive of intention and action than the campaign materials. Our segmentation analysis demonstrated that parents should be treated as a heterogeneous group.

3.4 General discussion

Attitudes. On the whole, parents who are members of the advocacy groups, Climate Parents and Moms Clean Air Force, held negative views towards fossil fuels and positive views towards

clean energy (Study 1). Alternatively, parents recruited from the general population were more ambivalent (Study 2). When compared to neutral information (control), cost information had little effect on general public parents' attitudes. However, we were surprised to find that advocacy group parents reported more favorable views of their utilities using fossil fuels after being presented information describing the potential for reduced electricity bills when utilities switched to cleaner energy sources. This could suggest a boomerang effect, supported by Self-Perception Theory, which posits that clean energy campaigns heralding monetary benefits, an extrinsic motivation, may not work well with self-defined intrinsically motivated environmentalists [70], [180].

Surprisingly, we also found general public parents expressed less favorable attitudes towards their utilities using clean energy when shown health information compared to when they were presented with neutral or cost information with those in Florida seemingly driving this effect. However, when health was coupled with climate information, attitudes towards clean energy improved among general public parents. According to the Centers for Disease Control and Prevention (CDC) National Asthma Control Program, Florida had asthma rates lower than the national average in 2011,²² but has experienced the highest number of flood insurance claims since 1978 among our three targeted states of Florida, Michigan and California (and 3rd in the nation) [181], [182]. Thus, one possible explanation is that Florida parents are more concerned about the climate and sea level rise, due the availability heuristic, rather than the health implications of burning fossil fuels [183], [184]. We also found that younger parents (e.g. those parents who were not also grandparents and/or who have children under the age of 18 years old) reported significantly less favorable attitudes towards fossil fuels when shown health information, compared to the control. This could also be due to the availability heuristic or the issue of co-benefits [185]; some parents will respond well to information that has direct relevance for themselves and their family (i.e. health) compared to information often perceived as abstract (i.e. climate change).

Intentions and behaviors. Few differences were observed between advocacy and general public parents with behavioral intent and action. On balance, people expressed greater intent and action rates when asked to sign a petition versus leaving a voice message. Previous research also

²² Lifetime asthma rates among adults in Florida were 10.2% in 2011 compared to the national average of 13.3% and child current asthma prevalence was 8.3% compared with the national average of 9%.

suggests that as the level of perceived or actual effort required increases,²³ the level of civic engagement decreases [186]. Self- and action-efficacy enhances this effect; participants who perceive having agency in a matter should express more persistent efforts, manifested in our study by higher action rates [187], [188]. This also echoes the common finding in public health that messages both conveying the risk and providing a plausible solution enhance pro-health behaviors [189]. We also found that greater acceptance of climate change, perceiving the information as credible, and seeing the proposed action as effective were associated with enhanced behavioral intention and action rates. Risk communications research suggests that trust in the source and the information itself determine whether people pay attention and perhaps more importantly in this context, take action [190], [191].

Another difference is that advocacy parents tended to have higher action rates across all campaign types whereas general public parents tended only to be responsive when exposed to cost, health or climate information (as shown in Figure 12). This suggests potentially two phenomena. First, advocacy parents may be less susceptible to the influence of messaging due to their existing dedication to advocacy action. Moreover, factors such as social influences and peer behavior, recent news headlines, and familiarity with petitions may play a larger role than do the messages for the advocacy parents. The second is that public parents can be influenced by messages. Our findings suggest that these parents are responding differently to different messages largely due to their individual differences (e.g. climate change acceptance); recognizing these differences is essential for more impactful targeting of the general population. This general conclusion is also supported by findings in our brief segmentation analysis presented in Section 3.3.2. and other widely accepted segmentation analyses regarding climate change acceptance and messaging [171], [179].

3.5 Conclusion

We found promising results in our study of how clean energy campaign framing moves parents to take civic action and urge their utilities to provide clean energy. Parents, regardless of their involvement in climate advocacy groups, are open to changing their perception of energy sources

²³ In attempt to reduce the varying levels of perceived effort to complete these actions (e.g. increased embarrassment from expressing personal qualms with fossil fuels in a voice message, increased amount of time required to make a phone call, and general ignorance regarding contacting utilities), we provided the participants with a suggested script that included the utility's contact information. We also specified that they would be recording a message that we would deliver later, assuring them that they wouldn't be speaking with a live person.

when presented with relevant information. However, unintended consequences can occur with people expressing seemingly contradictory viewpoints and inaction. We also found that beliefs about action-efficacy, climate change, and information credibility matters. Hence, sensitivity to the heterogeneity that exists among parents in terms of knowledge, values, and culture is paramount when developing and executing a campaign – this point is underscored by our segmentation analysis, which illustrated differences among younger and older parents. Future study could examine how parents are influenced by campaigns delivered by a host of messengers and mediums (e.g. campaigns delivered directly by electric utilities or government agencies) to take a broader set of clean energy actions (e.g. installing their own on-site generation or switching utilities).²⁴ Ultimately, we find that campaigns can influence energy attitudes and parents are willing to take action on the topic if the advocacy action seems like an effective approach.

²⁴ See Appendix B.26 for additional discussion of study limitations and suggestions for future study.

4. Solar PV as a mitigation strategy for the U.S. education sector

Abstract

Solar PV will be an important strategy to decarbonize the energy sector in the United States, and to reduce the health, environmental, and climate change damages associated with the production of electricity from fossil fuel sources. While the potential for solar PV in the residential and commercial sectors has been widely studied, the potential in educational buildings is largely unknown. Educational institutions account for 11% of total U.S. building electricity consumption and 14% of building floorspace. These buildings also contribute to approximately 4% of total U.S. CO₂ emissions, thus playing a potentially important role in climate mitigation strategies. We estimate the electricity use for 132,592 educational institutions across the U.S. and estimate electricity generation, greenhouse gas and health damaging air emissions reductions, and private and social costs and benefits that would result from adopting rooftop solar PV. We find that solar PV in U.S. educational institutions could provide 100 TWh of electricity services annually, meeting 75% of these buildings' current electricity consumption. We estimate the highest generation potential in Texas, California, and Florida with K-12 Public educational institutions comprising the bulk of that generation. The provision of electricity services from rooftop solar PV on educational institutions could reduce health, environmental, and climate change damages by roughly \$4 billion per year (assuming a social cost of carbon of \$40/ton and value of statistical life of \$10M in 2018 USD). This analysis suggests that some states, like Texas, could increase their school PV incentives to match the high social benefits they realize from these systems. Other states, such as California, are currently over-incentivizing school PV systems as the value of these incentives is higher than the health, environmental, and climate change benefits they provide.

4.1 Introduction

Solar photovoltaic (PV) capacity has grown at an unprecedented rate over the last few years in the United States (U.S.). Despite that increase, more than 60% of the electricity generated in the U.S. comes from fossil fuel sources, compared to only about 2% that is now provided by solar PV [145]. In 2015, electricity generation accounted for 30% of all U.S. greenhouse gas (GHG) emissions [145], contributing to annual health costs amounting to roughly 4% of the national gross domestic product (GDP) [146]. Health effects arise mostly due to secondary formation of particulate matter < 2.5 microns wide (PM_{2.5}) from sulfur dioxide (SO₂) emissions, with negative impacts in particular for at-risk populations such as asthmatics, the elderly, and low-income families [3]–[6], [8], [192].

The technical potential and costs/benefits of installing solar PV in the residential and commercial sectors have been quantified in detail in the literature. Gagnon et al. [64] estimate that PV systems installed on small, medium, and large buildings in the U.S. can generate 1,400

TWh of electricity; Denholm and Margolis [65] estimate the residential sector alone can provide 419 TWh from rooftop solar PV. Recently, a study by Vaishnav et al. [193] estimates annual state-level health and environmental benefits for residential and commercial systems to be on the range of \$50/kW-yr. Previous studies demonstrate that residential solar PV has been mostly adopted by high-income households, benefitting from publicly-funded incentives [193], [194]. As for non-residential adoption, an economic analysis of historical project costs by Barbose et al. [195] demonstrates that installed prices are higher for tax exempt customer sites than for for-profit commercial sites. Despite these currently discouraging installation costs, educational institutions, like industrial facilities, often have large, flat roofs that might allow for greater economies of scale. Additionally, their low summer electricity consumption profiles and locations in residential communities could make them decent candidates for community solar projects [196]. The decreasing installation costs of solar PV may also make these projects potentially economical [197].

However, to date, little attention has been devoted regarding the use of solar PV in the education sector. Educational institutions account for 11% of total U.S. building electricity consumption and 14% of building floorspace [76]. They contribute to approximately 4% of total U.S. carbon dioxide (CO₂) emissions, making them a decent target for climate mitigation strategies [198]. Many institutions, especially in higher education, have already set goals to reduce energy consumption and GHG emissions. According to the Bloomberg Philanthropies' America's Pledge Report, in 2016, 587 U.S. universities with a total enrollment of 5.2 million students (25% of the U.S. college and university student population), had voluntarily adopted GHG targets [199]. To date, 335 colleges and/or universities have GHG emissions inventories and 78 have defined climate action plans [200].

In this paper, we focus on estimating the potential electricity generation, emissions reductions, and private and social net-benefits of installing rooftop solar PV on educational institutions throughout the U.S. We consider public and private K-12 as well as higher education institutions [201], [202].

The rest of this paper is organized as follows. First, we explain our data and methods. Next, we present our results, which include regionally specific estimates of electricity generation from rooftop PV, avoided electricity consumption from the grid, emissions reductions, and the private and social costs and benefits. We also include a sensitivity analysis regarding inputs such

as discount factor, system size, and the value of excess generation. Finally, we conclude and provide policy recommendations.

4.2 Data and methods

We estimate the electricity generation, CO₂, SO₂, PM_{2.5} and nitrogen oxide (NO_x) emissions reductions, and private and social net-benefits of installing solar PV on each K-12 and higher education public and private institution across the United States. We assume systems are installed today and use recent system installation costs as detailed below. We assume a system lifetime of 20 years and use alternative discount rates of 2% and 7% per year when computing the private and social net-benefits. We provide our results in terms of annual electricity generation, reduced emissions, and net-benefits.

We use the following modeling strategy, as shown in Figure 13: (1) we estimate the available PV rooftop area for each U.S. educational institution, (2) we estimate the hourly electricity output of the panels given the local irradiation for that site, (3) we estimate the hourly electricity demand of each institution, (4) we calculate the amount of electricity that can be saved annually from using the panels instead of acquiring the electricity from the grid by subtracting hourly demand from hourly PV generation, (5) we determine the value of electricity generated by the panels (i.e. electricity cost savings and excess generation sales), (6) we quantify the emissions of criteria air pollutants and GHGs avoided by the PV systems, and (7) we monetize the avoided health, environmental, and climate change (HE&CC) damages associated with the avoided emissions using two reduced form air quality models. In Table 14, we summarize the different data sources that are used in our analysis. In the Appendix C.1, we provide a table of model assumptions and our treatment of uncertainty.

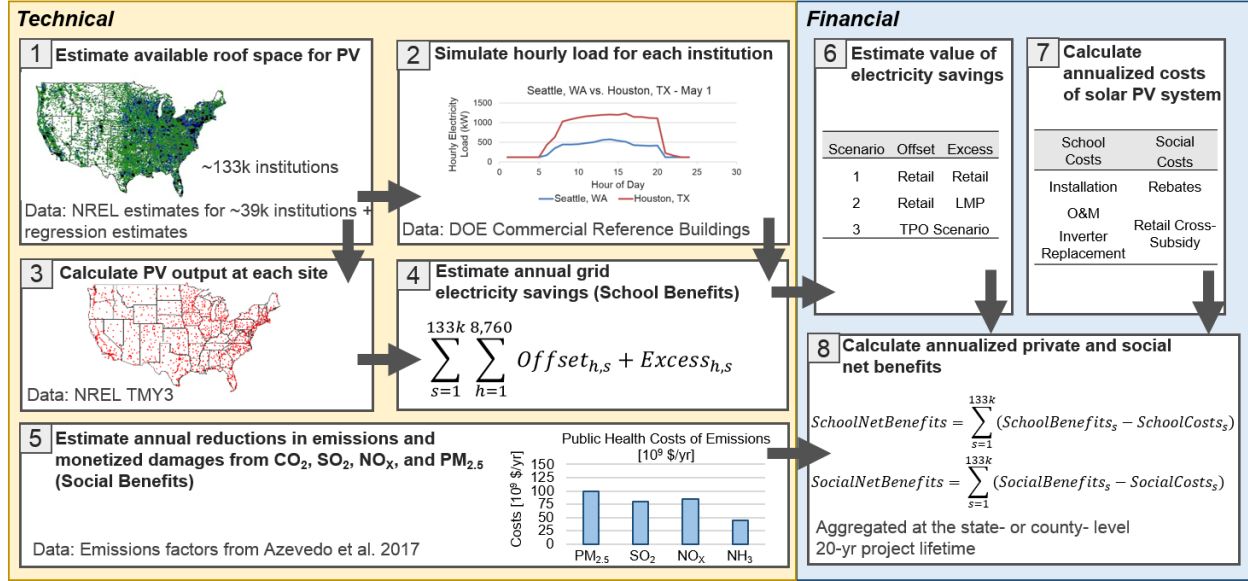


Figure 13. Framework used in Ch. 4: (1) we estimate the available PV rooftop area for each U.S. educational institution, (2) we estimate the hourly electricity output of the panels given the local irradiation for that site, (3) we estimate the hourly electricity demand of each institution, (4) we calculate the amount of electricity that can be saved annually from using the panels instead of acquiring the electricity from the grid by subtracting hourly demand from hourly PV generation, (5) we determine the value of electricity generated by the panels, (6) we quantify the emissions of criteria air pollutants and greenhouse gases avoided by the PV systems, and (7) we monetize the avoided health, environmental, and climate change damages associated with the avoided emissions using two reduced form air quality models.

Table 14. Inputs and data sources used in Ch. 4 analysis.

Variable	Source	Reference
Institution location and counts		
Higher education (N = 7,084 institutions)	Integrated Postsecondary Education Data System	[203]
K-12 public schools (N = 99,772 institutions)	Common Core of Data	[204]
K-12 private schools (N = 25,736 institutions)	Private School Universe Survey	[205]
Solar irradiance data	NREL TMY3 Data	[206]
Building load profiles	DOE Commercial Reference Buildings	[207]
Solar PV system costs	LBNL Tracking the Sun 10	[197]
Rebates	LBNL Tracking the Sun 10	[197]
Electricity rates		
Retail rates	EIA 2016 Commercial Rates	[208]
Locational marginal price	ISO/RTO portals	[209]
Available roof space	NREL LIDAR data	[64]
Health & environmental damages	EASIUR Model, AP2 Model	[210][211]

Available PV roof space

We construct a database of 132,592 educational institutions' building counts and location (see Figure 14) using three National Center for Education Statistics (NCES) datasets: the Integrated Postsecondary Education Data System – 2014/2015 (for higher education institutions), the Common Core of Data – 2014/2015 (for K-12 public institutions), and the Private School Universe Survey – 2013/2014 (for K-12 private institutions) [203]–[205].

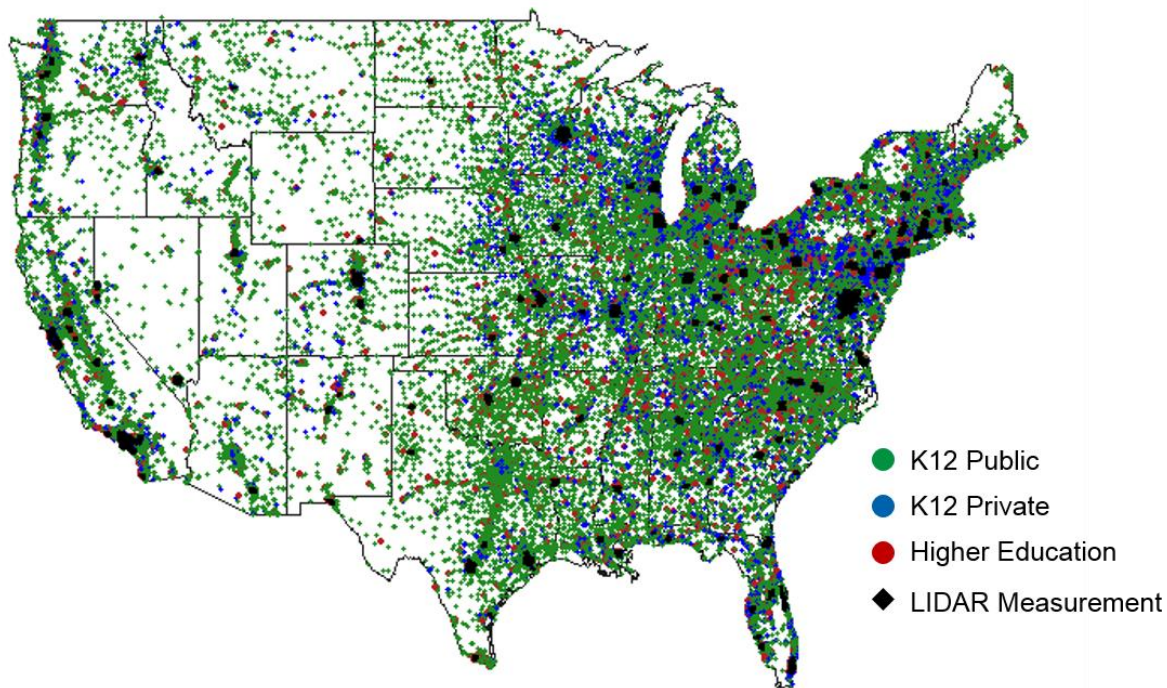


Figure 14. Map of U.S. educational institutions in our datasets: K-12 public institutions are shown in green, K-12 private institutions are shown in blue, and higher education institutions are shown in red. Institutions for which we have direct NREL LIDAR data on available rooftop space are marked with a black diamond. Data on institution location comes from NCES datasets (Integrated Postsecondary Education Data System – 2014/2015; Common Core of Data – 2014/2015; and Private School Universe Survey – 2013/2014).

The Integrated Postsecondary Education Data System is a mandatory survey of postsecondary institutions that receive federal funding under Title IX (including degree- and non-degree granting); this dataset also includes non-federal funded schools, but that percentage is unknown [203], [212]. The Common Core of Data [204] and Private School Universe Survey [205] are both considered to include the entire population of public and private K-12 schools,

respectively, which NCES uses for sampling frames. These datasets do not include rooftop space, and thus we have established a strategy to estimate such areas. We use National Renewable Energy Laboratory (NREL) light detection and ranging (LIDAR) estimates of available rooftop space for 16,000 institutions that are included in NREL's dataset (which account for 12% of all educational institutions in the NCES dataset). Although a total of 39,000 institutions are linked by NREL to LIDAR data, only 16,000 of these institutions are linked to open-street mapping (OSM) polygons. To characterize suitable rooftop space for solar PV on buildings in the U.S., NREL uses LIDAR data provided by the Department of Homeland Security (DHS) in combination with Geographic Information System (GIS) methods and statistical modeling [64]. First, NREL runs a shading simulation on the digital surface model for each city provided in the DHS dataset. Next, they classify roof orientation using the LIDAR dataset to determine the tilt and azimuth of each 1m^2 space. Finally, they use NREL's System Advisor Model (SAM) to determine generation profiles of each site, defining a suitability threshold for each of the 128 cities in the dataset. NREL links as many institutions as they can with OSM polygon data, which allows them to consider entire campuses that are associated with the institution address. If multiple institutions are co-located in an OSM polygon, NREL's method is to proportionally distribute the roof space using the reported institution populations (taken from NCES). In Appendix C.2 we provide a detailed explanation of their estimation procedure, and for more details the reader can refer to Gagnon et al. [64]. The advantage of using these estimates is that they are readily available and reasonably measure²⁵ rooftop area [64], [213].

In order to estimate the rooftop areas for the remaining institutions that are in the NCES dataset, but not in NREL's rooftop estimates, we start by fitting simple linear regression models for each institution type to explain the observed NREL LIDAR rooftop estimates as a function of several institution- and county-level variables. We then use the results from that regression to predict the available PV rooftop area for the remaining institutions in our dataset. While more sophisticated regressions could be envisioned, we balanced the modeling parsimony and insight that could be provided and concluded that selecting a simple model would be preferable.

²⁵ NREL's best-case performance validation method involved training their model on 3,312 ZIP codes with 90% or greater LIDAR coverage, predicting results for these ZIP codes, and analyzing the difference between the predictions and actual values – they found their model under-predicts the true value and thus available rooftop space estimates are conservative (total error for all ZIP codes is 21.9 m^2 or 2.6% relative error) [64].

Appendix C.3 provides additional information on the data and results from our estimation procedure.

Estimating solar PV hourly generation at each institution

We use NREL’s TMY3 data, which provides hourly solar irradiance for 936 locations across the contiguous U.S. We assign each educational institution to the geographically closest location for which we have solar irradiance data. We then use the method outlined in Lorenzo [214], which is also used in Vaishnav et al. [193], to estimate hourly power output for the systems installed at each institution. We assume the PV panels will cover 100% of the suitable roof space and then relax this assumption in our sensitivity analysis.

Estimating hourly load profiles for each institution

We use the typical hourly load profiles for “secondary schools” compiled by the U.S. Department of Energy (DOE) for each of the TMY3 locations [207]. These reference building load profiles are specific to 16 different climate zones across the U.S. The DOE characterizes the secondary school reference buildings as having an average floor area of 210,887 ft² and two stories. Assuming the floor area divides evenly among stories, this equates to a roof area of approximately 100,000 ft². The 95th percentile of the OSM-linked rooftop area data is 90,000 ft² and the 95th percentile of the regression estimated rooftop area across all educational institutions is 77,000 ft² (see Appendix C.2 for more details of rooftop area summary statistics). We scale the building load profile linearly using the building roof space for each institution, assuming the ratio between the net-power and peak load remains the same across building sizes. See Appendix C.4 for a detailed description of how we estimate net-power and load scaling.

Electricity cost savings, net-metering, and third-party ownership

First, we calculate the electricity savings from using the PV power instead of grid electricity by computing the difference between hourly solar PV generation and hourly load. We assume that if load exceeds hourly generation in that hour, the remaining power is bought from the grid (again, see Appendix C.4 for a description of net-power estimation). Electricity cost savings are determined by multiplying the difference between solar hourly production and load by a volumetric electricity price (\$/kWh), which we assume to be the state-average 2016 commercial retail rate (henceforth referred to as the “retail rate”).²⁶

²⁶ In this analysis, we do not use time-of-use (TOU) rates due to their highly specialized, utility-specific structure (e.g. utilities often design them to be revenue-neutral).

We also estimate demand cost savings. We do so as follows: (1) the demand charge accounts for 20% of the average rates for educational institutions and (2) rooftop solar PV can provide average monthly demand savings of 20%. Ultimately, we adjust the retail rate as follows to account for the demand cost savings and appropriately reduce the volumetric rate:

$$\text{Commercial.Rate}_{\text{State}} = \text{Avg.Rate}_{\text{State}} * .8 + \text{Avg.Rate}_{\text{State}} * .20 * .20 \quad (1)$$

The *Avg.Rate* represents the state-average 2016 commercial retail rate. Therefore, the first part of the *Commercial.Rate* approximates the variable rate observed for each state and the second part approximates the demand savings for each state. These assumptions are informed by a demand rate analysis following a method outlined in Darghouth et al. [215], where we simulate secondary school DOE reference building loads in 15 cities across the U.S. using NREL’s System Advisor Model (SAM) [216] (see Appendix C.5 for more details). In the sensitivity analysis, we vary the demand charge rates and fractional savings.

Finally, we characterize net-metering and third-party ownership (TPO) scenarios. Net-metering policies vary widely across the U.S., although it is established in most states at some capacity (see Appendix C.6 for a table of net-metering policies currently outlined in the DSIRE database) [217]. Therefore, in this analysis we assume net-metering is available to educational institutions across the U.S. We consider two scenarios as bounding cases for valuing the excess electricity generated by the PV systems: (1) retail rates and (2) locational marginal prices (LMPs). Valuing excess generation with the retail rate closely approximates net-metering policies in effect today (e.g. customers are allowed to roll over monthly applied power credits over a 12-month period); this scenario is the “best case” scenario from the institution’s perspective. However, if net-metering policies are financed by spreading costs over the entire rate base, there is a transfer of resources from those who do not install PV to those who do install these systems [193]. We estimate this cross-subsidy as the difference between the retail and LMPs for that institution, and we consider it a social cost in this scenario. The “worst case” net-metering scenario experienced by institutions would be when excess generation is valued at the LMP;²⁷ this scenario is sensible since small, distributed power sources may be valued by using an avoided cost calculation or considering costs associated with distribution.

²⁷ Following Vaishnav et al. [193], we download hourly LMP data for year 2015 for representative aggregate pricing nodes in each state from the IST/RTO data portals. Generation nodes reported by neighboring ISOs are used for states not in an electricity market. See Horner [209] Section 4.3.2. and Table 4.4. for additional information.

The TPO scenario is characterized as the difference between the regular annual electricity consumption costs to the educational institutions (without PV) and the costs of electricity if schools purchased electricity at a TPO-defined rate. This TPO-defined rate is assumed to be less than the retail rate. Here, annual electricity costs to the school at the TPO-defined rate are estimated as the annualized cost of owning the PV systems, assuming commercial owners can take advantage of the Federal Investment Tax Credit (ITC) and that excess generation is valued at the LMP. Table 15 describes each of the three benefit-cost analysis (BCA) scenarios for valuing electricity cost savings and excess generation sales that we consider in this study.

Table 15. Three BCA scenarios for valuing electricity savings and excess generation considered in Ch. 4.

Scenario	Value of offset consumption ^a	Value of excess generation
Net-metering at LMPs	State-average 2016 commercial retail rate	LMP
Net-metering at retail rates	State-average 2016 commercial retail rate	State-average 2016 commercial retail rate
Third-party ownership	School purchases electricity from the TPO at a rate reduced from the State-average 2016 commercial retail rate. We estimate the rate by amortizing the cost of the system for a 20-yr lifetime.	

^a Each scenario also includes an estimate for the demand savings, using the described methodology.

Installed price of system

We use Lawrence Berkeley National Laboratory’s (LBNL) Tracking the Sun X (TTS10) data on recently observed solar PV system prices in 2015 and in 2016. Since a previous study by Barbose et al. [195] finds that tax-exempt sites have higher average installation costs than for-profit commercial sites, we limit our LBNL dataset consideration to only school, government and non-profit sites to derive an estimate for project installation cost. There are approximately 1,046 projects out of the roughly 800,000 projects meeting these criteria in the LBNL TTS10 database (see Appendix C.7 for more details). These projects represent 11 states in the U.S., with the top three most represented being California, Maine, and Arizona [197]. The mean project cost from these observations is approximately \$3,800/kW. We use this mean value to estimate project costs for all systems in our combined educational institution dataset, varying this assumption in our sensitivity analysis. We also include annual operations and maintenance

(O&M) costs of \$15/kW-yr and inverter replacement costs of \$120/kW at year ten [218]. We assume O&M and inverter replacement costs are constant across the U.S. We do not include the decommissioning cost of the system at the end of its useful life in our analysis.

PV system rebates

We include rebates when estimating the upfront project costs. We use the state-average rebates (\$/kW) observed in the LBNL TTS10 database for school, government, and non-profit installations on recently observed projects in 2015 and in 2016 [197]. The rebate values identified range from \$100/kW to \$1,700/kW. Since the Federal ITC only applies to residential, commercial, industrial, investor-owned utility, cooperative utilities, and agricultural PV projects, these are not included in our non-TPO BCA scenarios; however, we do assume third parties can take advantage of the ITC [219], [220]. In Appendix C.6, we provide a table of available state-level rebates assumed in our analysis as well as a table of rebates currently outlined in the DSIRE database.

Valuing health, environmental, and climate change benefits

We estimate marginal avoided damages from reducing emissions of CO₂, SO₂, NO_x, and PM_{2.5} that arise from using the electricity generated by the solar PV systems instead of grid electricity. First, we estimate the avoided marginal emissions damages in each Emissions & Generation Resource Integrated Database (eGrid) subregion characterized by the Environmental Protection Agency (EPA) using the time of day, by season emissions factors posted in the Center for Climate and Energy Decision Making “Electricity Marginal Factors Estimates” website by Azevedo et al. [221]. These estimates are produced by our research group using an approach similar to the one described in Siler-Evans et al. [222], [223] and used in the literature to assess the emissions and damages consequences from renewables, energy efficiency, and storage [69], [112], [193], [224]–[227]. Marginal damages reported on this website are marginal emissions reductions that are translated to damage reductions using two integrated air quality models: AP2 and EASIUR [210], [223], [228]. These models estimate the dispersion of pollutants and the resulting concentration in all U.S. counties and then rely on dose-response functions to estimate physical impacts. Finally, these models monetize the impacts by using estimates for such inputs as the value of statistical life (which is assumed to be \$10M in 2018 USD with a relative risk of 1.06 for concentration-response relation) and the value of lost commodities [228]. For the climate change benefits, Azevedo et al. [221] multiply the CO₂ emissions outputs from AP2 and

EASIUR by the social cost of carbon, which they assume to be \$40/ton CO₂ following EPA's Social Cost of Carbon for Regulatory Impact Analysis [211], [229]. For our analysis, we use the marginal emissions damage factors by eGRID sub-regions for the year 2016 reported in Azevedo et al. [221]. We multiply time of day marginal emissions damage factors by the hourly electricity generation from the solar system for each institution to estimate the hourly damages avoided, and then compute the total marginal damages for year 2016.

Private and social net-benefits

We estimate the annualized benefits and costs to the educational institutions and society separately. Costs to educational institutions include PV system capital costs, annual O&M costs, and an inverter replacement at year 10, minus any available rebates (which will effectively reduce the capital cost). The annual benefit to the educational institution is comprised of the cost savings from electricity that does not need to be purchased from the grid, as well as the value of excess electricity that the institution can now sell back to the grid. As previously described, the TPO option is characterized as the difference between the regular annual electricity consumption costs to the educational institutions (without PV) at the retail rate and annual electricity consumption costs at a lower TPO-defined rate.

Social costs include any rebates made available to the educational institutions, which tax payers need to support. Costs also include the Federal ITC in the TPO scenario as well as the cross-subsidy in the aforementioned net-metering scenario where institutions sell excess generation at the retail rate. The social benefits are the monetized annual benefits associated with the reduction in CO₂, SO₂, NO_x, and PM_{2.5} emissions.

The following simplified equations depict how we calculate net-benefits for each educational institution, considering the three BCA scenarios for valuing electricity savings and excess generation described in Table 15.

Net-metering scenario, with excess generation from the PV system valued at the LMP:

$$School.NB.LMP = -[Installation - Rebate] + [(Offset \times Retail) + (Excess \times LMP)] - O\&M - Inv. \quad (2)$$

$$Social.NB.LMP = -Rebate + [(Offset + Excess) \times Marginal\ Damages] \quad (3)$$

Net-metering scenario, with excess generation from the PV system valued at the retail rate:

$$School.NB.Retail = -[Installation - Rebate] + [(Offset + Excess) \times Retail] - O\&M - Inv. \quad (4)$$

$$Social.NB.Retail = -Rebate - [Offset \times (Retail - LMP)] + [(Offset + Excess) \times Marginal\ Damages] \quad (5)$$

Third-party ownership scenario:

$$\text{School.NB.TPO} = \text{Annual Electricity Cost @ Retail} - \text{Annual Electricity Cost @ TPO.rate} \quad (6)$$

$$\text{Annual Electricity Cost @ TPO.rate} = \text{Annualized}\{-[\text{Installation} - \text{Rebate} - \text{ITC}] + [(\text{Offset} \times \text{Retail}) + (\text{Excess} \times \text{LMP})] - \text{O\&M} - \text{Inv.}\} \quad (7)$$

$$\text{Social.NB.TPO} = -[\text{Rebate} + \text{ITC}] + [(\text{Offset} + \text{Excess}) \times \text{Marginal Damages}] \quad (8)$$

In these equations, *School.NB.LMP* and *Social.NB.LMP* represent the school and social net-benefits, respectively, when excess generation from the PV system is valued at the LMP rate. *School.NB.Retail* and *Social.NB.Retail* represent the school and social net-benefits, respectively, when excess generation from the PV system is valued at the retail rate. *School.NB.TPO* and *Social.NB.TPO* represent the school and social net-benefits, respectively, when the PV systems are owned and operated by third-party owners and schools purchase electricity from the third-party owners. Note, in order to systematically estimate a TPO rate that is lower than the current retail rate for each state, we ultimately assume that the third parties are compensated by the schools at a rate that breaks even over the lifetime costs of the systems. Therefore, in order to estimate conservative cost savings for the schools (e.g. TPOs could design rates that yield better economics for them as well as for the schools), net-benefits are estimated to be zero for TPOs in this analysis. *Installation* represents the total installation cost for each educational institution, *Rebate* represents the state-average rebates (\$/kW) observed in the LBNL TTS10 database, *Offset* represents the hourly solar PV generation consumed by the educational building, *Excess* represents the difference between hourly solar PV generation and hourly load when the PV generation exceed the load, *Retail* represents the state-level average 2016 commercial retail rate, *LMP* represents the hourly locational marginal price, *O&M* represents the annual operations and maintenance costs, *Inv.* is the annualized cost of the inverter replacement, *ITC* represents the 30% Federal Investment Tax Credit, and *Marginal Damages* represented the monetized health, environmental, and climate change damages associated with hourly offset emissions. Although not captured in these simplified equations, we take the present value of annual school benefits (i.e. electricity cost savings and excess generation sales) and annual school costs (i.e. O&M and inverter) for each year the system is in operation. Similarly, we take the present value of annual social benefits (i.e. avoided damages) and annual social costs (i.e. retail cross-subsidy) for each year the system is in operation. Therefore, we arrive at a net-benefit from the perspective of schools and society for each educational institution, assuming a project lifetime of 20 years. In

this paper, we present annualized net-benefits using alternate discount rates of 2% and 7%. We also report values by dividing the school and social annualized benefits and costs by the system capacity to arrive at per-kilowatt estimates of annual benefits and costs. When reporting aggregated results, we sum the annualized benefits and costs of all the systems in the unit of aggregation (e.g. a state) and divide by the sum of the total system capacity within the unit. See Appendix C.8 for a detailed description of BCA equations used in this analysis.

Sensitivity analysis

We perform parametric sensitivity analyses on seven key inputs in our analysis: (1) project installation costs, (2) discount factor, (3) available rebates, (4) system size, (5) project lifetime, (6) social cost of carbon, and (7) annual emissions/damages levels. We also consider the best- and worst-case scenarios for demand charge costs and fractional savings for the educational institutions. We vary each of these inputs separately and report varying outcomes in a spider plot and tables. Reference Appendix C.9 on limitations and future study, including discussion of our geographic scope and focus on PV deployment rather than production and disposal.

4.3 Results

Total PV technical potential and avoided emissions on U.S. educational institutions

We estimate a total available rooftop space of 0.4 billion m² for all U.S. educational institutions. This results in a total installed generation potential of 64 GW or 100 TWh of annual electricity generation, serving 75 million students and teachers in the associated educational institutions and meeting 75% of their current electricity consumption from the grid [76]. The electricity output generated by solar PV at educational institutions thus corresponds to roughly 3% of total U.S. electricity consumption [230]. As a comparison, Gagnon et al. [64] find the total available rooftop space for all commercial and residential buildings to be approximately 8 billion m², resulting in a total technical potential of 1.1 TW of installed capacity or 1,400 TWh of annual energy generation. These values are understandably larger since educational institutions constitute 14% of commercial floorspace, suggesting the available rooftop PV space for educational institutions should be a similar fraction of space [231].

Avoided emissions associated with solar PV on all U.S. educational facilities amounts to approximately 60M metric tons of CO₂ per year, 7K metric tons of PM_{2.5} per year, 45K metric tons of NO_x per year, and 45K metric tons of SO₂ per year. As previously mentioned, the U.S. education sector is estimated to be responsible for 4% of total U.S. CO₂ emissions [198], which

equates to roughly 211 million metric tons/yr [9]. Therefore, this paper estimates that solar PV could reduce the education sector carbon footprint by 28%.

Varying PV technical potential and avoided emissions across the U.S.

In Figure 15 we illustrate our estimates of the potential PV generation in different states. When reporting aggregated results, we sum the annualized estimated generation of all the systems in the state and divide by the sum of the total system peak capacity within that state. In terms of absolute generation potential, we find that Texas, California, and Florida (with K-12 Public educational institutions comprising the bulk of that generation) have the largest technical potential. We estimate that 11% of the institutions do not have suitable roof space for solar PV based on NREL's LIDAR and GIS modeling and our own linear regression modeling. See Appendix C.11 for state- and county-level generation maps.

In Figure 15 we also illustrate our estimates of total offset CO₂, PM_{2.5}, NO_x, and SO₂ emissions in each state from the solar PV systems installed on K-12 public, K-12 private, and higher education institutions. We separate the CO₂ emissions plot from the other criteria air pollutants, because the total offset metric tons are in different orders of magnitude. We find that the top five states generating electricity from solar PV on schools (Texas, California, Florida, North Carolina, and Illinois) are not the exact same top five states that offset CO₂ emissions (Texas, California, Florida, Illinois, and Ohio) nor are they the same top five states that offset PM_{2.5}, NO_x, and SO₂ emissions (Texas, Illinois, Ohio, Indiana, and Pennsylvania).

Private net-benefits of U.S. school PV to educational institutions

We estimate net-benefits from PV systems to educational institutions under three scenarios: (1) net-metering with excess generation valued at the LMP, (2) net-metering with excess generation valued at the retail rate, and (3) third-party ownership. In Figure 16, we show annualized private net-benefits for educational institutions for the different scenarios explored (using a 7% discount rate). When reporting aggregated results, we sum the annualized net-benefits of all the systems in the state and divide by the sum of the total system peak capacity within that state. We find that there is no private case to adopt solar unless it is third-party owned and operated. Even in states such as California, with large rebates and high PV generation potential, these investments do not break-even. In Table 16, we show that even when a lower discount rate is assumed (2%) the scenarios that do not involve a third-party do not pass the private benefit-cost analysis. In Appendix C.12 we provide histograms of annualized school benefits (offset electricity cost savings + excess generation sales) and costs (installation – rebate + O&M + inverter) to educational institutions across the U.S. and in each state, organized by institution type.

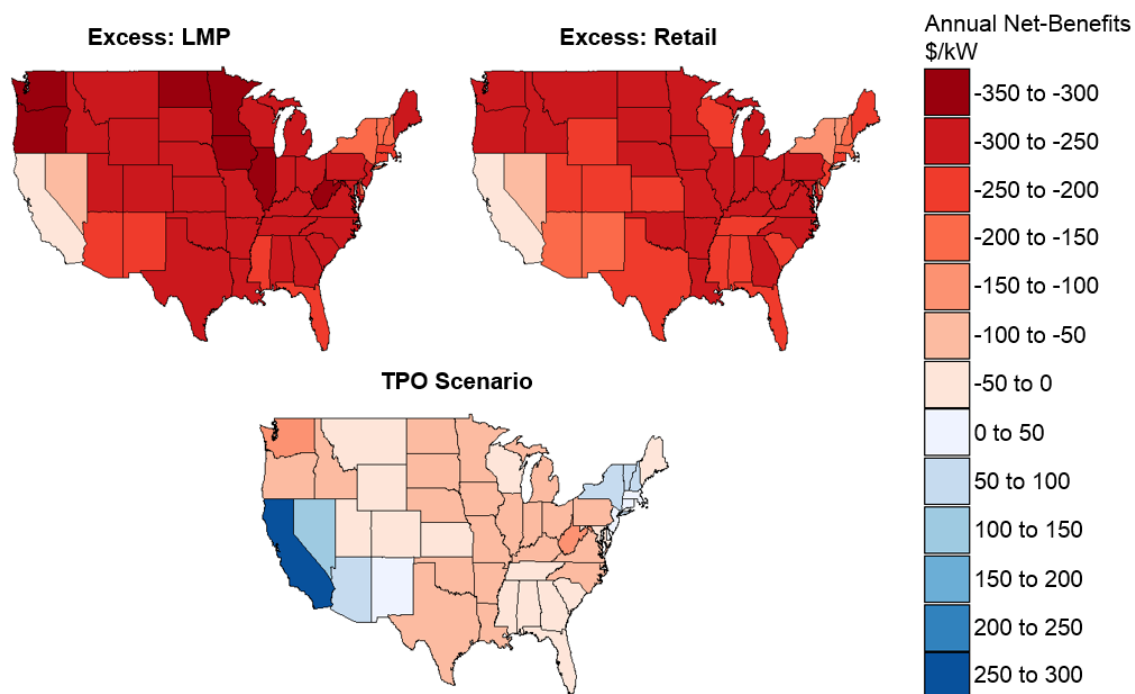


Figure 16. Annualized private net-benefits (\$) by peak kW for three scenarios: selling excess generation at the LMP (left), selling excess generation at the retail rate (right), and third-party ownership (bottom), assuming a 7% discount rate. When reporting aggregated results, we sum the annualized net-benefits of all the systems in the state and divide by the sum of the total system peak capacity within that state. In Appendix C.12 we show the distribution of these results across all institutions in our dataset.

Table 16. Annualized educational institutions net-benefits and social net-benefits (assuming a 20 year project lifetime) in each of the three electricity value scenarios.

Scenario	Discount Rate	School Net-Benefits (\$B/yr)	Society Net-Benefits (\$B/yr)
Net-metering at LMPs	7%	-16	3.1
	2%	-8.5	3.5
Net-metering at retail rates	7%	-15	1.3
	2%	-6.9	2.3
Third-party ownership	7%	-1	-3.6
	2%	4	-0.8

Social net-benefits of U.S. school PV to the public

In Figure 17, we provide the annualized net-benefits to society under the same three scenarios reported for the schools (again, using a 7% discount rate). When reporting aggregated results, we sum the annualized net-benefits of all the systems in the state and divide by the sum of the total system peak capacity within that state. We find that in most of the U.S., the HE&CC benefits provided by the installation of solar PV at U.S. educational institutions exceeds the subsidies/incentives that are provided when the business model is that the educational institutions install and own the systems (with the exceptions of California, New York, Delaware, New Hampshire, Nevada, and Vermont - which have relatively high rebate levels). Midwestern states like Wisconsin and Ohio have the highest aggregated social net-benefits, under current policies and grid generation portfolios. However, under a third-party operated model, the costs of the subsidies/incentives exceed the societal benefits, since third-party operators will have access to an additional subsidy/incentive: the Federal ITC. In Appendix C.12 we provide histograms of annualized social benefits (offset HE&CC damages) and costs (rebate + cross-subsidies) to the public across the U.S. and in each state, organized by institution type.

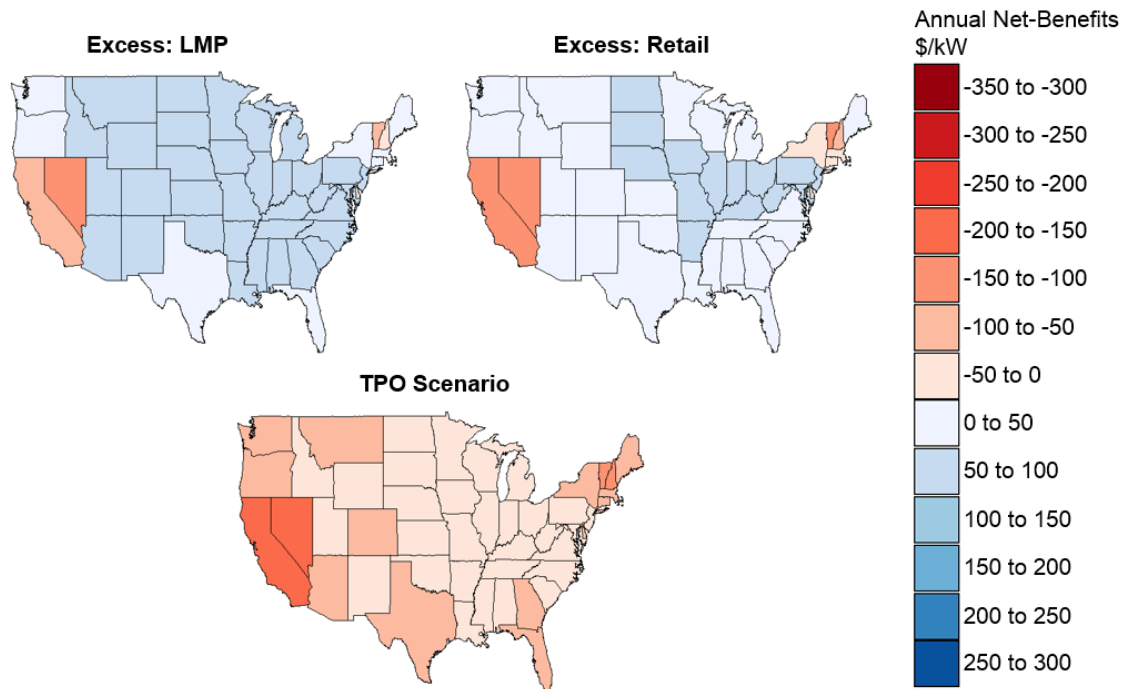


Figure 17. Annualized social net-benefits (\$) by peak kW for three scenarios: selling excess generation at the LMP (left), selling excess generation at the retail rate (right), and third-party ownership (bottom), assuming a 7% discount rate. When reporting aggregated results, we sum the annualized net-benefits of all the systems in the state and divide by the sum of the total system peak capacity within that state. In Appendix C.12 we show the distribution of these results across all institutions in our dataset.

Overall, the provision of electricity services from rooftop solar PV on educational institutions is estimated to create annualized HE&CC benefits on the order of \$4 billion per year. In Figure 18 we present the highest-ranking states in terms of avoided HE&CC damages and compare those monetized benefits with the social costs for incentivizing the adoption of such PV systems. See Appendix C.12 for these results depicted on an average per school basis. We find that the HE&CC benefits provided by these systems would generally exceed the level of the incentives – with the exception of California and New York, where the rebates exceed the health, environmental, and climate change benefits provided by these PV systems. For instance, we estimate that California would need to value carbon at \$160/ton CO₂ to make the current PV incentive for educational institutions pay off (compared to the roughly \$40/ton CO₂ that we used in the rest of this paper). It is worth noting that it is not difficult to find literature arguing that CO₂ emissions should be valued at more than \$160/ton [232]–[234]. Alternatively, California would need to provide incentives of \$350/kW to meet carbon offsets currently valued at \$40/ton CO₂ (compared to the current average incentive value of \$1400/kW in the LBNL TTS10 dataset

[197]). Other states could substantially increase their rebates to match the HE&CC benefits that solar PV at educational institutions could provide. For example, Pennsylvania could have a rebate of up to \$958/kW, which would break even with the societal benefits provided from solar PV at educational institutions. Even if we assumed Pennsylvania valued the reduction in carbon emissions at \$0/ton CO₂, it would still make sense in terms of the health and environmental benefits provided from reducing criteria air pollutant emissions from the main electric grid by providing a rebate to solar PV at educational institutions of up to \$590/kW. See Appendix C.13 for state-by-state analysis on this topic.



Figure 18. Avoided damages from CO₂, SO₂, NO_x and direct PM_{2.5} emissions when compared to the rebates and cross-subsidy paid by public when excess generation is valued at the retail rate for the 10 states with the largest health, environmental, and climate change avoided damages. All values are reported in millions of dollars. In this plot we used the EASIUR model to monetize the emissions damages avoided.

Sensitivity analysis

We perform parametric sensitivity analyses on seven key inputs in our analysis: (1) project installation costs, (2) discount factor, (3) available rebates, (4) system size, (5) project lifetime, (6) social cost of carbon, and (7) annual emissions/damages levels. We also consider the best- and worst-case scenarios for demand charge costs and fractional savings for the educational institutions. We vary each of these inputs separately and report varying outcomes in a spider plot and tables. In all baseline scenarios, we assume excess generation is sold back at the LMP (see

Appendix C.14 for sensitivity analysis results assuming excess generation is sold back at the retail rate).

Figure 19 depicts the parametric sensitivity analysis for the first six aforementioned key inputs. We parametrically adjust the baseline values listed in Table 17 from -50% to +50%, using 10% increments.

Table 17. Baseline values for parametric sensitivity analysis.

Variable	Baseline Value
Installation Cost	LBNL average: \$3,800/kW
Discount Rate	7%
PV Rebate	LBNL average: \$780/kW
Project Size	Each school's system size (ft ²)
Project Lifetime	20 years
Social Cost of Carbon	\$40/ton CO ₂

Values depicted in Figure 19 are the median private and social annualized net-benefits from the full distribution across all educational institutions (see Appendix C.14 for separate CDFs of net-benefits for each sensitivity input). We find that median educational institution net-benefits become positive when the average available rebate is \$2,700/kW (or 3.5 times the current average available rebate of \$780/kW) and is available for all institutions. We also find that private net-benefits are overall most sensitive to installation cost and discount rate. Finally, it seems that the costs of rebates to society may outweigh the benefits if project sizes grow at the same rate as rebate increases.

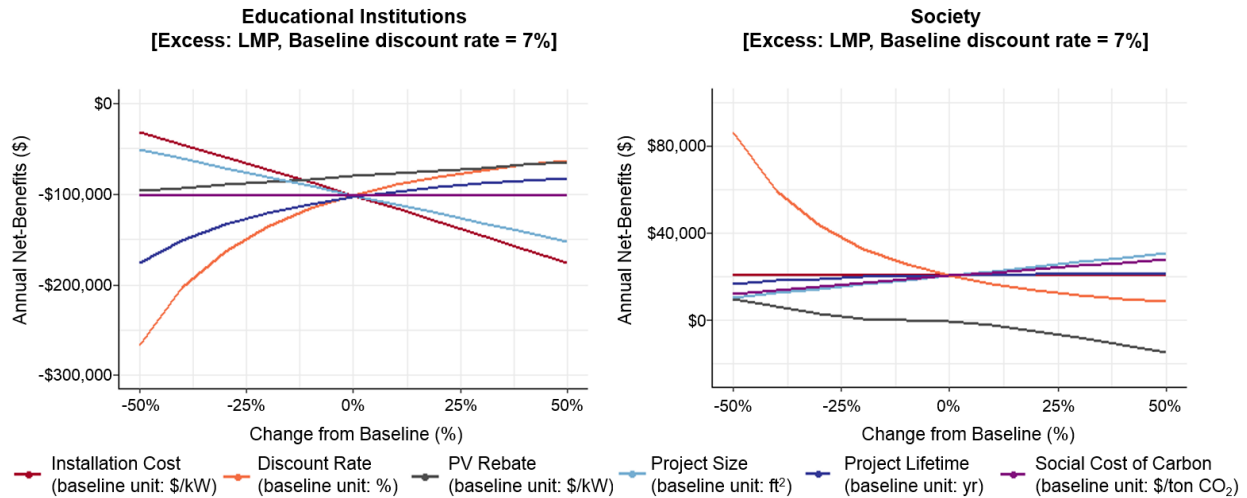


Figure 19. Parametric sensitivity analysis for six key inputs, varying each input from -50% to +50% of the baseline values, holding all other values constant. These plots depict the median private (left) and social (right) annualized net-benefits from the full distribution across all educational institutions (see Appendix C.14 for separate CDFs of net-benefits for each sensitivity input). For simplification, when adjusting the PV Rebate value, an average was assumed across all states (i.e. the entire TTS10 dataset), which resulted in annualized private and social net-benefits that do not match the median value that is observed in the true baseline scenario (where observed state-level PV rebates vary).

Table 18 depicts the parametric sensitivity analysis for annual emissions levels/avoided damages. Here, we consider annually increasing and decreasing avoided damages ranging from -5% to 5% of the baseline assumption (i.e. constant avoided damages). We find that even if the avoided damages decreased each year by 5% (from external factors decarbonizing the electricity grid) our median net-benefits to society would still be positive.

Table 18. Results of parametric sensitivity analysis of rate of annual avoided damages to social net-benefits.

Percent Annual Change	Social Net-Benefits			
	Min	Max	Median	Mean
-5%	-\$4,000,000	\$1,700,000	\$12,000	\$14,000
-2.5%	-\$3,800,000	\$2,000,000	\$16,000	\$18,000
0%	-\$3,500,000	\$2,400,000	\$20,000	\$23,000
2.5%	-\$3,200,000	\$2,900,000	\$26,000	\$30,000
5%	-\$2,700,000	\$3,500,000	\$32,000	\$39,000

Table 19 depicts the scenario analysis for changes in demand rates and savings. We use the 25th and 75th percentile “Fraction of Average Rate for Demand Charge” and “Estimated

Demand Savings from PV” values taken from our demand rate analysis that we conducted for 15 reference educational institutions across the US (Appendix C.5). We construct a best-case scenario, in terms of overall cost savings to educational institutions, by matching the 25th percentile demand charge fraction with the 75th percentile demand savings value. The worst-case scenario is then the opposite combination. We find that median net-benefits to educational institutions are only marginally different between the best-case and worst-case scenarios.

Table 19. Results of scenario analysis of demand charge costs and fractional savings to school net-benefits.

Scenario	Fraction of Average Rate for Demand Charge	Estimated Demand Savings from PV	School Net-Benefits			
			Min	Max	Median	Mean
Best-case	15% (25th percentile)	18% (75th percentile)	-\$11,000,000	\$50,000	-\$99,000	-\$120,000
Worst-case	41% (75th percentile)	6% (25th percentile)	-\$13,000,000	\$0	-\$120,000	-\$150,000

4.4 Conclusion and policy implications

In this paper, we estimate the potential electricity generation, emissions reductions, and private and social net-benefits of installing rooftop solar PV on educational institutions throughout the U.S. We estimate a total installed generation potential of 64 GW or 100 TWh of annual electricity generation, serving 75 million students and teachers in the associated educational institutions and meeting 75% of their current electricity consumption from the grid [76]. We find regional heterogeneity in the private and social benefits of solar PV, similar to the findings from a study by Siler-Evans et al. (2013). We find energy output to be highest in the Southwest and lowest in New England. Furthermore, we find solar PV to have the highest health, environmental, and climate change benefits in regions where it is offsetting carbon-intensive and high-polluting technologies such as coal-fired power plants in the Midwest. California, Texas, and Florida have the highest technical potential for educational institution PV electricity generation. Similarly, these states have some of the highest estimated social benefits under current grid generation portfolios (whereas Midwestern states like Wisconsin and Ohio have the highest aggregated social net-benefits, under current policies and grid generation portfolios).

TPOs are the most economically viable option for educational institutions

Ultimately, we find that at the level of rebates observed in the LBNL dataset and current electricity rates, it is not economically viable for educational institutions to purchase these systems outright in any state. However, a TPO scenario that allows for educational institutions to divert the capital and annual costs of owning a system is estimated to be economically viable in some parts of the country. It is assumed that the TPO would offer educational institutions a contract electricity rate that is derived from the lifetime cost of the system to the TPO (including an ITC) and that is less than the current annual cost of electricity for the educational institutions.

Internalizing health and environmental benefits increase value of solar

Alternatively, this analysis suggests that if environmental, health, and climate change externalities were to be internalized such that educational institutions would be rewarded for reducing emissions, then it would be feasible for institutions to purchase the systems outright. Electricity prices that reflect the cost of emissions is one way to internalize this benefit from PV systems. Alternatively, utilities and government agencies could increase rebates. Results depicted in Figure 15 suggest that policy makers might focus on incentivizing the adoption of solar PV on K-12 Public, higher education, and K-12 private institutions (in descending order), if the goal is to maximize PV generation. We also find that in current rebate conditions, K-12 public institutions present the highest annualized net-benefits to society and higher education institutions present the lowest annualized net-benefits to society in non-TPO scenarios. Results from our sensitivity analysis suggest that median educational institution net-benefits become positive when the average available rebate is \$2,700/kW (or 3.5 times the current average available rebate of \$780/kW) and is available for all institutions.

Heterogeneity in PV incentive efficiency

Finally, this analysis suggests that some states such as New York, Wisconsin, Texas, and Maine do not currently offer rebates at the level they are observing social benefits. Furthermore, some states such as California, Nevada, Vermont, and Delaware, might be currently offering PV rebates to educational institutions at rates that would exceed total HE&CC benefits if all institutions installed rooftop PV. For instance, it is estimated that California would need to value carbon at \$160/ton CO₂ to make the current PV incentive for educational institutions pay off (compared to the roughly \$40/ton CO₂ reported in the EPA's Social Cost of Carbon for

Regulatory Impact Analysis [229] and used in this paper). See Appendix C.13 for state-by-state analysis on this topic.

Solar PV will be an important strategy to decarbonize the energy sector in the United States, and to reduce the health, environmental, and climate change damages associated with the production of electricity from fossil fuel sources. While the potential for solar PV in the residential and commercial sectors has been widely studied, the potential in educational buildings is largely unknown. Our analysis identifies which regions in the U.S. stand to gain the most HE&CC benefits from solar PV on educational institutions. Moreover, our work provides a baseline analysis for efficient school PV incentive design. Our findings suggest that solar PV on educational institutions can serve an important role in U.S. emissions mitigation strategies if attractive economic options are made available to them.

5. Discussion

Realizing the full potential of energy efficiency (EE) and renewable energy (RE) adoption in reducing electricity sector greenhouse gas (GHG) emissions requires that multiple actors at various scales take action. Restricting the actions to those that are specific to “their sector” – such as homeowners acting only in the residential sector – limits the range of new and innovative possibilities for enhancing the adoption of EE and RE. The aim of this thesis is to go beyond such a disjointed approach, to employ bottom-up decision and engineering science approaches to explore the behavioral, regulatory, and technical factors that inspire actors across sectors to effect change in energy behavior. This thesis contributes to the decision-making literature on EE and RE investments across a range of actors, provides insights for how to consider the behavioral viability of technical potential analyses, and yields concrete suggestions for policy makers aiming to encourage actors to change their own energy behavior or that of their energy providers.

5.1 Understanding and informing EE and RE decisions

This thesis employs a hybrid engineering and behavioral sciences approach to characterizing EE and RE decisions to inform behaviorally realistic interventions. First, I use behavioral sciences (e.g. expert elicitation and a survey) to contextualize actors’ preferences towards EE and RE adoption. Next, I employ engineering and economic models to assess the technical potential and financial feasibility of such technologies. Chapters 2 through 4 allow me to develop this hybrid model and build upon each other in the types of actors and actions that I consider.

Chapter 2 employs expert elicitation to reveal motives and barriers to EE that are not yet heavily discussed in the literature, and to identify differences in the perceptions of decision-making among the actual decision-makers (i.e. building owners/managers) and decision-influencers (i.e. energy efficiency experts). Potential factors that emerge from the interviews, which are not yet extensively discussed in the energy efficiency literature, include owners/managers’ resistance to change and the influence of investment funding origins on the decision. Results also suggest potential heterogeneity in energy efficiency decision-making philosophies between the two groups. Interviewed owners/managers prioritize corporate social responsibility (CSR) and prefer internal consulting (e.g. building engineers). Conversely, experts/consultants do not emphasize CSR and are more concerned with external policies.

Results from this study yield intervention opportunities specific to these actors that promote EE adoption, directly reducing demand on the electricity sector.

Building on Chapter 2, I next focus on understanding and designing interventions to motivate actors from the public to indirectly influence the electricity sector. In Chapter 3, I employ a randomized controlled field trial of clean energy campaigns to study how campaigns can influence parents' energy attitudes and willingness to engage with their utilities on the topic. I study two groups: parents already involved in climate advocacy groups (e.g. Study 1, Advocacy Sample) and those who are not involved in advocacy groups and who represent the general public (e.g. Study 2, Public Sample). In both studies, I find the odds of taking action are reduced by over 90% when participants are asked to make a phone call and leave a voicemail message, versus signing an online petition. Among the parents already engaged in advocacy, I observe a ceiling effect regarding attitudes towards clean energy and find the cost campaign produces unintended consequences (i.e. advocacy parents reported more favorable attitudes towards fossil fuels after being presented cost information). Among the public sample, I find that participants who believe the campaign to be credible and comprehensible are more likely to take action than those who discredit the campaign or do not understand its message. Additionally, I find parents who have children under the age of 18 reduce their support of fossil fuels after being presented with health information. Ultimately, I find that parents are interested in taking action to influence their utilities to adopt clean energy technologies to preserve their children's health and safety.

Finally, building on Chapter 2 and 3, I turn my attention to understanding what is the actual technical potential for educational facilities to adopt RE technologies, which is necessitated by the support of two actors already considered (e.g. building owners/managers and parents/public) to directly (e.g. invest in solar PV) and indirectly (e.g. support with incentives) affect the electricity sector. Here, I employ a benefit cost analysis (BCA) to analyze the economic feasibility of PV adoption and to provide insight for incentive programs that target schools. In Chapter 4, I find that solar PV in U.S. educational institutions could provide 100 TWh of electricity services annually, meeting 75% of these buildings current electricity needs. I estimate the highest generation potential in Texas, California, and Florida with K-12 Public educational institutions comprising the bulk of that generation. The provision of electricity services from rooftop solar PV on educational institutions could reduce environmental, health and climate change damages by roughly \$4 billion per year.

The hybrid engineering and decision sciences approach employed in this thesis yields actor- and action-specific results regarding the technical potential and behavioral viability of specific technologies, and also contributes to the decision-making literature in this field.

5.2 Contributions to the decision environment and decision-maker literature

As previously described in this thesis, decision-making is thought to be influenced by cognition, the decision environment, and the decision-maker's internal state. Chapters 2 through 4 detail exploratory and empirical studies that contribute to the literature surrounding the decision environment (e.g., management organization, information, and economics) and the decision-maker's internal state (e.g. attitudes and values).

The organizational behavior science (OBS) literature suggests that EE and RE investments made in an organization or by a building management team are influenced by power relationships [49], organizational energy culture [49], [55], and characteristics of the investment that align (or misalign) with the core business of the organization [56]–[59]. Furthermore, it is shown that EE and RE decision-making is often handled by one or a few individuals within a larger organizations and, therefore, the differences and relationships between these decision-makers and decision-influencers (e.g. EE experts and vendors) are particularly important to understand [58]. In Chapter 2, I found experts and owners/managers differed greatly in their approach to the investment decision process. The most distinct differences occurred in their discussions of goals and strategy and the role of an investment consultant in decision-making. Specifically, it seems that owners/managers are focused on meeting company goals such as improving occupant comfort or maintaining innovative competitiveness, which was often highlighted in their open-ended responses as well as their motivation rating frequencies. In this instance, it seems that experts tend to overlook the strategic logic potentially in place with owners/managers' decision-making, instead focusing on the economic barriers to energy efficiency investments. Although Chapter 2 highlights some differences between decision-makers and influencers, it is also underscores the importance in understanding the relationships between the two and demonstrates how information conduits can influence EE adoption. During the ranking exercises, it was apparent that owners/managers valued input from internal sources such as their building engineers and tenants. Conversely, they did not tend to list social influences affiliated with certain technologies, such as controls contractors. Therefore, a bad relationship between engineers and contractors may result in a bad relationship between the

owners and contractors. Indeed, Beamish et al. [131] identify trust networks among owners/managers and contractors as a means to minimize risk aversion related to the adoption of new energy efficient technologies, providing a mechanism for demystifying innovative products/practices. I also find that specific information and information sources influence the public's decision to engage with their electric utilities.

Chapter 3 of this thesis experiments with various clean energy campaign framing designed to improve attitudes towards clean energy and promote civic engagement among parents. The campaigns include a control frame with neutral information about electricity generation; a cost frame that suggests introducing more clean energy into a portfolio will lower costs to the consumer in the long-run; and health, environment, and health + environment frames that each promote associated benefits from adopting EE and RE technologies in electricity plants. Studies find that framing, selectively emphasizing certain dimensions of an issue over others [41], [235], can promote pro-environmental behaviors such as buying more energy efficient technologies and practicing curbside recycling [42], [98]. Research suggests that framing should target people's unique social, psychological, and cultural makeup [171], [180], [236], otherwise messaging may backfire. Indeed, I find in Chapter 3 that advocacy group parents reported more favorable views of their utilities using fossil fuels after being presented information describing the potential for reduced electricity bills when utilities switched to cleaner energy sources. This could suggest a *boomerang effect*, supported by Self-Perception Theory, which posits that clean energy campaigns heralding monetary benefits, an extrinsic motivation, may not work well with self-defined intrinsically motivated environmentalists [70], [180]. Additionally, risk communications research suggests that trust in the source and the information itself determine whether people pay attention, and perhaps more importantly in this context, take action [190], [191]. In Chapter 3, I find that parents are more likely to take action if they report greater acceptance of climate change, perceive the campaign information as credible, and see the proposed action as an effective one to take.

In Chapter 4, I explore the "effectiveness" of a particular RE technology for a specific set of actors: rooftop PV on educational facilities, which are installed by decision-makers on campus with or without incentives that are supported by the public. To date, 335 colleges and/or universities have GHG emissions inventories and 78 have defined climate action plans.[200] Chapter 4 contributes to the limited literature that currently addresses rooftop PV as a viable

option for educational facilities to meet their own sustainability goals and contribute to a reduction in electricity sector GHG emissions. I find regional heterogeneity in the private and social benefits of solar PV, similar to the findings from a study by Siler-Evans et al. [223]. I find energy output to be highest in the Southwest and lowest in New England. Furthermore, I find solar PV to have the highest health and environmental benefits in regions where it is offsetting carbon-intensive and high-polluting technologies such as coal-fired power plants in the Midwest. California, Texas, and Florida are estimated to have the highest technical potential for educational institution PV electricity generation. Similarly, these states have some of the highest estimated social benefits under current grid generation portfolios (whereas Midwestern states like Wisconsin and Ohio have the highest aggregated social net-benefits, under current policies and grid generation portfolios). Despite the promising potential for rooftop PV systems on schools to offset harmful emissions across the U.S., I ultimately find that the current level of rebates and the current electricity rates, make purchasing these systems outright economically inviable. Rather, I conclude that a third-party ownership scenario that allows for educational institutions to divert the capital and annual costs of owning a system is a better option.

This thesis also contributes to the literature surrounding the internal state of the decision-maker – specifically, how a single decision-maker or a group of decision-makers value EE and RE technologies. Within the Theory of Planned Behavior (TPB) framework, beliefs about subjective norms and intrinsic motivations can influence intention to act and consequent behavior [36], [37]. Therefore, the TPB framework suggests that one should focus on understanding attitudes and measuring intentions in order to understand the likelihood of action and/or behavior change. Chapter 2 explored the intrinsic motivations of commercial building management teams and Chapter 3 explored how different framing can evoke different construal levels of parents in the public.

In Chapter 2, open-ended questions posed to decision-makers (e.g. building owners/managers) and decision-influencers (e.g. EE experts) exposed the compelling role of CSR in EE investment decision-making. However, when asked to rank motivation cards, experts found others to have greater relative importance. Experts only listed Social Responsibility and Being Industry Leaders six times with average rankings of 8 (recall, 1 = most important and 13 = least important), while owners/ managers ranked these items 15 times with average rankings of 4.5. These findings suggest that it may be beneficial for experts to first acknowledge and

characterize CSR benefits of EE investments, and then communicate these results with owners/managers of large commercial buildings. I also find, in Chapter 3, that non-economic factors matter to parents aiming to protect their children by urging their utilities to adopt clean energy.

In Chapter 3, I learn that messaging about health and climate effects of clean energy have varying effects on the public depending on local climate change experiences and characteristics of the family. For instance, I find general public parents express less favorable attitudes towards their utilities using clean energy when shown health information compared to when they were presented with neutral or cost information, with those in Florida seemingly driving this effect. However, when health was coupled with climate information, attitudes towards clean energy improved among general public parents. According to the Centers for Disease Control and Prevention National Asthma Control Program, Florida had asthma rates lower than the national average in 2011, but has experienced the highest number of flood insurance claims since 1978 among our three targeted states of Florida, Michigan and California (and 3rd in the nation) [181], [182]. Thus, one possible explanation is that Florida parents are more concerned about the climate and sea level rise, due the availability heuristic, rather than the health implications of burning fossil fuels [183], [184]. We also found that younger parents (e.g. those parents who were not also grandparents and/or who have children under the age of 18 years old) reported significantly less favorable attitudes towards fossil fuels when shown health information, compared to the control. This could also be due to the availability heuristic or the issue of co-benefits [185], suggesting that some parents will respond well to information that has direct relevance for themselves and their family (i.e. health) compared to information often perceived as abstract (i.e. climate change).

5.3 Policy implications and future study

Each chapter has policy implications regarding how to promote the proliferation of energy efficiency and renewable energy among a host of actors in the United States.

Findings from Chapter 2 yield recommendations for policy that can influence actors in the commercial building sector, such as building owners/managers and building energy efficiency experts. However, additional research is necessary for determining the potential efficacy of such policies on the population of large commercial building owners and managers – since Chapter 2 was conducted on a small, non-representative sample. First, policy makers and

incentive program designers might focus on delivering economic incentives as well as social and behavioral incentives to inspire commercial building energy efficiency adoption. Secondly, policy makers should carefully consider their methods for conveying commercial building program information. When considering potential information conduits, it is important to consider the dynamics of the building engineering team as well as the owner/manager's current perceptions of various social influences. For instance, owners/managers may perceive the government and/or non-governmental organizations as neutral sources capable of delivering unbiased, trustworthy information regarding building EE investments. Findings from this interview study also suggest that social influences do play a role in decision-making; therefore, one might perform a social network analysis of owners/managers to characterize how concepts identified in this study propagate through a network. Integrating behavioral and social drivers with economic factors in energy efficiency policy may be the necessary catalyst for yielding substantial savings in support of U.S. national efforts, such as the Better Buildings Initiative.

Chapter 3 yields promising results of how clean energy campaign framing moves parent actors in the residential sector to take civic action and urge their utilities to provide clean energy. Parents, regardless of their involvement in climate advocacy groups, are open to changing their perception of energy sources when presented with relevant information. However, among the parents already engaged in advocacy, there is a ceiling effect regarding attitudes towards clean energy as well as unintended consequences associated with the cost campaign. Among the public sample, participants who believe the campaign to be credible and comprehensible are more likely to take action than those who discredit the campaign or do not understand its message. Finally, parents who have children under the age of 18 negatively adjust their attitudes towards fossil fuels after being presented with health information. Hence, sensitivity to the heterogeneity that exists among parents in terms of knowledge, values, and culture is paramount when developing and executing a campaign. Future study could examine how parents are influenced by campaigns delivered by a host of messengers and mediums to take a broader set of clean energy actions. For instance, one could use the health campaigns developed in Chapter 3 and design a similar randomized controlled trial (RCT) to study how reported campaign credibility, action efficacy, and observed behavior vary over a multitude of *messengers* who are the stated authors of the campaign materials, such as government agencies, non-profits, schools, and utilities.

Chapter 4 provides valuable insights to educational institutions, PV installers, and regulators about the future of PV adoption in the U.S. education sector. Two ways to make PV economically viable for actors in educational institutions are to (1) espouse the third-party ownership model or (2) internalize monetized health and environmental benefits associated with PV systems. Incentives and/or rebates are one option for internalizing these benefits and results from my sensitivity analysis suggest that median educational institution net-benefits become positive when the average available rebate is 3.5x greater than the current value of \$780/kW (or when it becomes \$2,700/kW). However, results suggest that PV incentive program designers should be aware of regional heterogeneity in incentive efficiency. We find that some states such as New York, Wisconsin, Texas, and Maine do not currently offer rebates at the level they are observing social benefits. Whereas, some states such as California, Nevada, Vermont, and Delaware, might be currently offering PV rebates to educational institutions at rates that would exceed total health and environmental benefits if all institutions installed rooftop PV. Future studies could elicit the investment decision-making behaviors of actors in educational institutions, eliciting their treatment of quantifiable health and environmental benefits associated with rooftop PV. Additionally, it would be beneficial to understand how social influences such as parental concerns of the environment, building management hierarchies, campus visibility projects, affect decisions to install on-site generation at schools. These insights could further inform incentive program design and shed a light on the behaviorally realistic technical potential of PV adoption among educational institutions.

While obvious actors in the electricity sector, such as power companies and public utilities commissions, play a large role in reducing GHG emissions, less well-studied actors can be empowered to adopt their own energy generation and energy efficiency strategies. Therefore, I recommend a hybrid engineering and decision sciences approach be applied to address overarching questions regarding the decision-making of less well-studied actors, such as the following:

- What is the public's perception of low-carbon options available to their electricity providers? How do they perceive the levelized cost of electricity from various sources and how do they characterize the social benefits from reduced pollution and CO₂ emissions? How do these perceptions compare to estimated costs and benefits from regionally specific normative models and what information gaps exist?

- What do actors value when considering their own distributed generation choices or demand-side management strategies? How do actors decide between alternative distributed generation technologies that allow them to trade-off installation costs, monthly energy costs, and regional emissions levels? Can hypothetical choices regarding EE and RE technologies be accurately understood using discrete choice surveys and randomized controlled trials and do results map onto actual market behavior?
- When performing a standard benefit-cost analysis of a specific technology, what inputs are not easily quantified and how much could they influence adoption viability? Additionally, what are the advantages and disadvantages of incentivizing a specific technology (e.g. rooftop PV) compared to non-specific/non-technology policies (e.g. energy benchmarking) in regards to cost effectiveness, ease of adoption, and estimated GHG reductions?

Conceivably, a hybrid engineering and decision sciences approach is applicable in any field where the perception or behavior of individual actors enhances or thwarts the adoption and performance of specific technologies and is not yet well understood.

5.4 Conclusion

This thesis offers a hybrid approach for studying the options available to actors at various scales for reducing electricity sector GHG emissions by adopting energy efficiency and renewable energy technologies. The three studies contained in this thesis provide insight to actor-specific motivations and barriers to adoption, highlight the technical potential and financial feasibility of specific adoption strategies, and yield a nuanced understanding of adoption behavior for policy makers wishing to look beyond the typical, top-down financial incentive approach. Ultimately, this thesis aims to help bridge the gap between characterizing the innumerable host of actors and actions necessary for reducing GHG emissions and inspiring those actors to take action.

Bibliography

- [1] U.S. EPA (United States Environmental Protection Agency), “Climate Change Indicators: Greenhouse Gases,” 2017. [Online]. Available: <https://www.epa.gov/climate-indicators/greenhouse-gases>.
- [2] U.S. EPA (United States Environmental Protection Agency), “Climate Impacts on Human Health,” 2017. [Online]. Available: https://19january2017snapshot.epa.gov/climate-impacts/climate-impacts-human-health_.html.
- [3] B. Machol and S. Rizk, “Economic value of U.S. fossil fuel electricity health impacts,” *Environ. Int.*, vol. 52, pp. 75–80, 2012.
- [4] C. A. Pope III and D. W. Dockery, “Health Effects of Fine Particulate Air Pollution : Lines that Connect,” *J. Air Waste Manage. Assoc.*, vol. 56, no. 6, pp. 709–742, 2006.
- [5] E. Severnini, “Impacts of nuclear plant shutdown on coal-fired power generation and infant health in the Tennessee Valley in the 1980s,” *Nat. Energy*, vol. 2, 2017.
- [6] M. Crowell, J. Westcott, S. Phelps, T. Mahoney, K. Coulton, and D. Bellomo, “Estimating the United States Population at Risk from Coastal Flood-Related Hazards,” in *Coastal Hazards*, Springer, 2013, pp. 151–183.
- [7] T. R. Karl, J. M. Melillo, and T. C. Peterson, “Global Climate Change Impacts in the United States,” 2009.
- [8] U.S. EPA (United States Environmental Protection Agency), “Endangerment and Cause or Contribute Findings for Greenhouse Gases Under Section 202(a) of the Clean Air Act: Atribute of Observed Climate Change,” Washington, D.C., 2009.
- [9] U.S. EPA (United States Environmental Protection Agency), “Inventory of U.S. Greenhouse Gas Emissions and Sinks,” 2018.
- [10] U.S. EIA (United States Energy Information Administration), “Annual Energy Outlook 2018,” Washington, D.C., 2018.
- [11] U.S. EIA (United States Energy Information Administration), “Electricity Data Browser,” 2018. [Online]. Available: <https://www.eia.gov/electricity/data/browser/#/topic/0?agg=2>.
- [12] K. Gillingham *et al.*, “Energy Efficiency Economics and Policy,” *Annu. Rev. Resour. Econ.*, vol. 1, pp. 597–620, 2009.
- [13] K. Gillingham, R. G. Newell, and W. A. Pizer, “Modeling endogenous technological change for climate policy analysis,” *Energy Econ.*, vol. 30, no. 6, pp. 2734–2753, 2008.
- [14] E. U. Weber and E. J. Johnson, “Mindful Judgment and Decision Making,” *Annu. Rev. Psychol.*, vol. 60, no. 1, pp. 53–85, 2009.
- [15] N. L. Kerr and R. S. Tindale, “Group Performance and Decision Making,” *Annu. Rev. Psychol.*, vol. 55, no. 1, pp. 623–655, 2004.

- [16] M. H. Bond and P. B. Smith, "Cross-cultural social and organizational psychology," *Annu. Rev. Psychol.*, vol. 47, pp. 205–235, 1996.
- [17] M. Hewstone, M. Rubin, and H. Willis, "Intergroup Bias," *Annu. Rev. Psychol.*, vol. 53, no. 1, pp. 575–604, 2002.
- [18] M. M. Chemers, "Leadership research and theory: A functional integration," *Gr. Dyn. Theory, Res. Pract.*, vol. 4, no. 1, pp. 27–43, 2000.
- [19] J. R. Busemeyer and A. Diederich, "Survey of decision field theory," *Math. Soc. Sci.*, vol. 43, no. 3, pp. 345–370, 2002.
- [20] J. C. Stout, J. R. Busemeyer, and A. Lin, "Cognitive modeling analysis of decision-making processes in cocaine abusers," *Psychomonic Bull. Rev.*, vol. 11, no. 4, pp. 742–747, 2004.
- [21] E. Elwin, P. Juslin, H. Olsson, and T. Enkvist, "Constructivist coding: Learning from selective feedback," *Psychol. Sci.*, vol. 18, no. 2, pp. 105–110, 2007.
- [22] Y. Trope and N. Liberman, "Temporal construal," *Psychological Rev.*, vol. 110, no. 3, pp. 403–421, 2003.
- [23] A. Tversky and D. Kahneman, "Advances in Prospect Theory: Cumulative Representation of Uncertainty," *J. Risk Uncertain.*, vol. 5, no. 4, pp. 297–323, 1992.
- [24] C. González-Vallejo, A. A. Reid, and J. Schiltz, "Context effects: The proportional difference model and the reflection of preference," *J. Exp. Psychol. Learn. Mem. Cogn.*, vol. 29, no. 5, pp. 942–953, 2003.
- [25] D. Albarracín and S. Shavitt, "Attitudes and Attitude Change," *Annu. Rev. Psychol.*, vol. 69, pp. 299–327, 2018.
- [26] O. Bartra, J. T. McGuire, and J. W. Kable, "The valuation system: A coordinate-based meta-analysis of BOLD fMRI experiments examining neural correlates of subjective value," *Neuroimage*, vol. 76, pp. 412–427, 2013.
- [27] M. Fishbein and I. Ajzen, "Chapter 3 - Attitudes and Their Determinants," in *Predicting and Changing Behavior - The Reasoned Action Approach*, New York: Taylor and Francis Group, LLC, 2010.
- [28] A. Schwartz and M. Hasnain, "Risk perception and risk attitude in informed consent," *Risk, Decis. Policy*, vol. 7, no. 2, pp. 121–130, 2002.
- [29] N. A. Jianakoplos and A. Bernasek, "Financial Risk Taking by Age and Birth Cohort," *South. Econ. J.*, vol. 72, no. 4, p. 981, 2006.
- [30] N. Nicholson, E. Soane, M. Fenton-O'Creevy, and P. Willman, "Personality and domain-specific risk taking," *J. Risk Res.*, vol. 8, no. 2, pp. 157–176, 2005.
- [31] I. P. Levin, G. J. Gaeth, J. Schreiber, and M. Lauriola, "A new look at framing effects: Distribution of effect sizes, individual differences, and independence of types of effects," *Organ. Behav. Hum. Decis. Process.*, vol. 88, no. 1, pp. 411–429, 2002.

- [32] E. Peters, D. Västfjäll, P. Slovic, C. K. Mertz, K. Mazzocco, and S. Dickert, “Numeracy and Decision Making Numeracy,” *Psychol. Sci.*, vol. 17, no. 5, pp. 407–413, 2013.
- [33] I. Erev, I. Glozman, and R. Hertwig, “What impacts the impact of rare events,” *J. Risk Uncertain.*, vol. 36, no. 2, pp. 153–177, 2008.
- [34] R. Hertwig, G. Barron, E. U. Weber, and I. Erev, “Decision From Experience and the Effect of Rare Events in Risky Choice,” *Am. Psychol. Soc.*, vol. 15, no. 8, pp. 534–539, 2012.
- [35] B. Figner, R. J. Mackinlay, F. Wilkening, and E. U. Weber, “Affective and deliberative processes in risky choice: Age differences in risk taking in the Columbia Card Task,” *J. Exp. Psychol. Learn. Mem. Cogn.*, vol. 35, no. 3, pp. 709–730, 2009.
- [36] I. Ajzen, “The theory of planned behavior,” *Organizational Behav. Hum. Decis. Process.*, vol. 50, pp. 179–211, 1991.
- [37] P. C. Stern, “Toward a Coherent Theory of Environmentally Significant Behavior,” *J. Soc. Issues*, vol. 56, no. 3, pp. 407–424, 2000.
- [38] E. Shove, “Beyond the ABC: Climate change policy and theories of social change,” *Environ. Plan. A*, vol. 42, no. 6, pp. 1273–1285, 2010.
- [39] P. Sturgis and N. Allum, “Science in Society: Re-Evaluating the Deficit Model of Public Attitudes,” *Public Underst. Sci.*, vol. 13, no. 1, pp. 55–74, 2004.
- [40] P. S. Hart and E. C. Nisbet, “Boomerang Effects in Science Communication: How Motivated Reasoning and Identity Cues Amplify Opinion Polarization About Climate Mitigation Policies,” *Communic. Res.*, vol. 39, no. 6, pp. 701–723, 2012.
- [41] M. C. Nisbet, “Communicating Climate Change: Why Frames Matter for Public Engagement,” *Environ. Sci. Policy Sustain. Dev.*, vol. 51, no. 2, pp. 12–23, 2009.
- [42] J. Min, I. L. Azevedo, J. Michalek, and W. B. de Bruin, “Labeling energy cost on light bulbs lowers implicit discount rates,” *Ecol. Econ.*, vol. 97, pp. 42–50, 2014.
- [43] Z. Kunda, “The case for motivated reasoning,” *Psychol. Bull.*, vol. 108, no. 3, pp. 480–498, 1990.
- [44] C. S. Taber and M. Lodge, “Motivated Skepticism in the Evaluation of Political Beliefs,” *Am. J. Pol. Sci.*, vol. 50, no. 3, pp. 755–769, 2006.
- [45] S. T. Anderson and R. G. Newell, “Information programs for technology adoption: The case of energy-efficiency audits,” *Resour. Energy Econ.*, vol. 26, pp. 27–50, 2004.
- [46] A. B. Jaffe and R. N. Stavins, “The energy-efficiency gap What does it mean?,” *Energy Policy*, vol. 22, no. 10, pp. 804–810, 1994.
- [47] R. J. Sutherland, “Market Barriers to Energy-Efficiency Investments,” *Energy J.*, vol. 12, no. 3, pp. 15–34, 1991.
- [48] S. J. Decanio, “Barriers within firms to energy- efficient investments,” *Energy Policy*, pp. 906–914, 1993.

- [49] S. Sorrell *et al.*, “Reducing barriers to energy efficiency in public and private organisations,” 2000.
- [50] D. Meadows, “Leverage Points - Places to Intervene in a System,” 1999.
- [51] C. Cooremans, “Make it strategic! Financial investment logic is not enough,” *Energy Effic.*, vol. 4, no. 4, pp. 473–492, 2011.
- [52] M. Jakob, “Marginal costs and co-benefits of energy efficiency investments. The case of the Swiss residential sector,” *Energy Policy*, vol. 34, no. 2 SPEC. ISS., pp. 172–187, 2006.
- [53] E. Mills *et al.*, “The business case for energy management in high-tech industries,” *Energy Effic.*, vol. 1, pp. 5–20, 2008.
- [54] P. C. Stern, “What psychology knows about energy conservation,” *Am. Psychol.*, vol. 47, no. 10, pp. 1224–1232, 1992.
- [55] M. Togeby, T. P. Kraemer, L. Gjesse, J. Klok, C. Clases, and F. Prose, “Why do some companies have success with energy efficiency?,” *Proc. ACEEE Summer Study Energy Effic. Ind.*, pp. 311–322, 1997.
- [56] H. L. F. De Groot, E. T. Verhoef, and P. Nijkamp, “Energy saving by firms: Decision-making, barriers and policies,” *Energy Econ.*, vol. 23, no. 6, pp. 717–740, 2001.
- [57] P. Sandberg and M. Söderström, “Industrial energy efficiency: The need for investment decision support from a manager perspective,” *Energy Policy*, vol. 31, pp. 1623–1634, 2003.
- [58] L. Weber, “Energy-relevant decisions in organisations within office buildings,” 2000.
- [59] L. Weber, “Some reflections on barriers to the efficient use of energy,” *Energy Policy*, vol. 25, no. 10, pp. 833–835, 1997.
- [60] J. Rigby, “When Rhetoric Meets Reality - Implementing Policies Based On Market Failure : Some Observations From The Development And Delivery Of The UK ’ s Energy Efficiency Best Practice Programme,” *Policy Res. Eng. Sci. Technol.*, vol. 02-10, 2002.
- [61] R. Socolow and S. Pacala, “Stabilization Wedges: Solving the Climate Problem for the Next 50 Years with Current Technologies,” *Science (80-.)*, vol. 305, no. 5686, pp. 968–972, 2004.
- [62] H. C. Granade, J. Creyts, A. Derkach, P. Farese, S. Nyquist, and K. Ostrowski, “Unlocking Energy Efficiency in the U . S . Economy,” 2009.
- [63] U.S. EIA (United States Energy Information Agency), “Short-Term Energy Outlook (STEO),” 2018.
- [64] P. Gagnon, R. Margolis, J. Melius, C. Phillips, and R. Elmore, “Rooftop Solar Photovoltaic Technical Potential in the United States: A Detailed Assessment,” no. January, p. 82, 2016.
- [65] P. Denholm and R. Margolis, “Supply Curves for Rooftop Solar PV-Generated Electricity

- for the United States,” *Natl. Renew. Energy Lab.*, pp. 1–23, 2008.
- [66] P. E. Tetlock and B. A. Mellers, “The Great Rationality Debate,” *Psychol. Sci.*, vol. 13, no. 1, pp. 94–99, 2002.
 - [67] I. Azevedo *et al.*, “Characterizing Utility Customer Preferences for Technologies and Services - A Review of Methods and their Applications,” 2017.
 - [68] O. I. Asensio and M. A. Delmas, “Nonprice incentives and energy conservation,” *Proc. Natl. Acad. Sci. U. S. A.*, vol. 112, no. 6, pp. E510–E515, 2015.
 - [69] J. Min, I. L. Azevedo, and P. Hakkarainen, “Assessing regional differences in lighting heat replacement effects in residential buildings across the United States,” *Appl. Energy*, vol. 141, pp. 12–18, 2015.
 - [70] J. W. Bolderdijk, L. Steg, E. S. Geller, P. K. Lehman, and T. Postmes, “Comparing the effectiveness of monetary versus moral motives in environmental campaigning,” *Nat. Clim. Chang.*, vol. 3, no. 4, pp. 413–416, 2013.
 - [71] D. Schwartz, W. Bruine de Bruin, B. Fischhoff, and L. Lave, “Advertising energy saving programs: The potential environmental cost of emphasizing monetary savings,” *J. Exp. Psychol. Appl.*, vol. 21, no. 2, pp. 158–66, 2015.
 - [72] G. Peschiera, J. E. Taylor, and J. A. Siegel, “Response-relapse patterns of building occupant electricity consumption following exposure to personal, contextualized and occupant peer network utilization data,” *Energy Build.*, vol. 42, no. 8, pp. 1329–1336, 2010.
 - [73] R. K. Jain, R. Gulbinas, J. E. Taylor, and P. J. Culligan, “Can social influence drive energy savings? Detecting the impact of social influence on the energy consumption behavior of networked users exposed to normative eco-feedback,” *Energy Build.*, vol. 66, pp. 119–127, 2013.
 - [74] B. A. Thomas and I. L. Azevedo, “Estimating direct and indirect rebound effects for U.S. households with input-output analysis Part 1: Theoretical framework,” *Ecol. Econ.*, vol. 86, no. x, pp. 199–210, 2013.
 - [75] S. Sorrell, J. Dimitropoulos, and M. Sommerville, “Empirical estimates of the direct rebound effect: A review,” *Energy Policy*, vol. 37, no. 4, pp. 1356–1371, 2009.
 - [76] U.S. EIA, “2012 CBECS Survey Data,” 2012.
 - [77] S. Bin, “Greening Work Styles: Analysis of Energy Behavior Programs in the Workplace,” *Am. Counc. an Energy-Efficient Econ.*, vol. B121, no. January, pp. 1–46, 2012.
 - [78] U.S. DOE, “Better Buildings Challenge: Winter 2016 Progress Update,” 2016.
 - [79] EIA, “Commercial Buildings Energy Consumption Survey,” *Energy Information Agency*, 2015. [Online]. Available: <http://www.eia.gov/consumption/commercial/reports/2012/buildstock/index.cfm>.
 - [80] P. Ludwig and M. Isaacson, “Addressing climate change by retrofitting Chicago’s

- buildings: The whole home energy savers experience,” in *ACEEE Summer Study on Energy Efficiency in Buildings*, 2010, pp. 15–20.
- [81] E. U. Weber and P. C. Stern, “Public understanding of climate change in the United States,” *Am. Psychol.*, vol. 66, no. 4, pp. 315–328, 2011.
 - [82] M. Granovetter, “Economic action and social structure: the problem of embeddedness,” *Am. J. Sociol.*, vol. 91, no. 3, pp. 481–510, 1985.
 - [83] M. J. Pasqualetti, “Opposing Wind Energy Landscapes: A Search for Common Cause,” *Ann. Assoc. Am. Geogr.*, vol. 101, no. 4, pp. 907–917, 2011.
 - [84] S. Z. Attari, M. L. DeKay, C. I. Davidson, and W. Bruine de Bruin, “Public perceptions of energy consumption and savings,” *Proc. Natl. Acad. Sci.*, vol. 107, no. 37, pp. 16054–16059, 2010.
 - [85] E. Trutnevyte and N. Strachan, “Nearly perfect and poles apart : investment strategies into the UK power system until 2050,” *Pap. Int. Energy Work. 2013, 19-21 June 2013, Paris*, pp. 1–11, 2013.
 - [86] J. Schleich, “Barriers to energy efficiency: A comparison across the German commercial and services sector,” *Ecol. Econ.*, vol. 68, no. 7, pp. 2150–2159, 2009.
 - [87] M. Ross, “Capital budgeting practices of twelve large manufacturers,” *Financ. Manag.*, pp. 15–22, 1986.
 - [88] C. A. Dahl, “A Survey of Energy Demand Elasticities in Support of the Development of the NEMS,” *Munich Pers. RePEc Arch.*, 1993.
 - [89] D. R. Bohi and M. B. Zimmerman, “An update on econometric studies of energy demand behavior,” *Annu. Rev. Energy*, vol. 9, no. 1, pp. 105–154, 1984.
 - [90] H. Geller, P. Harrington, A. H. Rosenfeld, S. Tanishima, and F. Unander, “Policies for increasing energy efficiency: Thirty years of experience in OECD countries,” *Energy Policy*, vol. 34, no. 5, pp. 556–573, 2006.
 - [91] P. Du, L. Q. Zheng, B. C. Xie, and A. Mahalingam, “Barriers to the adoption of energy-saving technologies in the building sector: A survey study of Jing-jin-tang, China,” *Energy Policy*, vol. 75, pp. 206–216, 2014.
 - [92] J. Stephenson, B. Barton, G. Carrington, D. Gnoth, R. Lawson, and P. Thorsnes, “Energy cultures: A framework for understanding energy behaviours,” *Energy Policy*, vol. 38, no. 10, pp. 6120–6129, 2010.
 - [93] N. Kok, M. McGraw, and J. M. Quigley, “The diffusion of energy efficiency in building,” *Am. Econ. Rev.*, vol. 101, no. 3, pp. 77–82, 2011.
 - [94] R. B. . A. H. S. Howarth, “Discount Rates and Energy Efficiency,” vol. 13, no. July, pp. 101–109, 1995.
 - [95] P. C. Stern, “What psychology knows about energy conservation,” *Am. Psychol.*, vol. 47, no. 10, pp. 1224–1232, 1992.

- [96] P. Morgenstern, R. Raslan, and G. Huebner, "Applicability, potential and limitations of staff-centred energy conservation initiatives in English hospitals," *Energy Effic.*, vol. 9, no. 1, pp. 27–48, 2016.
- [97] M. Farsi, "Risk aversion and willingness to pay for energy efficient systems in rental apartments," *Energy Policy*, vol. 38, no. 6, pp. 3078–3088, 2010.
- [98] P. W. Schultz, "Changing Behavior With Normative Feedback Interventions : A Field Experiment on Curbside Recycling," *Basic Appl. Soc. Psychology*, vol. 21, no. 1, pp. 25–36, 1999.
- [99] P. C. Stern, T. Dietz, and J. S. Black, "Support for Environmental Protection - the Role of Moral Norms," *Popul. Environ.*, vol. 8, no. 3–4, pp. 204–222, 1986.
- [100] E. Hirst and M. Brown, "Closing the efficiency gap: barriers to the efficient use of energy," *Resour. Conserv. Recycl.*, vol. 3, no. 4, pp. 267–281, 1990.
- [101] A. Tversky and D. Kahneman, "Judgment under Uncertainty: Heuristics and Biases," *Util. Probab. Hum. Decis. Mak.*, vol. 185, no. 4157, pp. 141–162, 1975.
- [102] A. Sanstad, M. Hanemann, and M. Aufhammer, "End-Use Energy Efficiency in a 'Post-Carbon' California Economy," *Manag. Greenh. gas Emiss. Calif.*, 2006.
- [103] K. Train, "Discount rates in consumers' energy-related decisions: A review of the literature," *Energy*, vol. 10, no. 12, pp. 1243–1253, 1985.
- [104] H. Ruderman, M. D. Levine, and J. E. McMahon, "The Behavior of the Market for Energy Efficiency in Residential Appliances Including Heating and Cooling Equipment," *Energy J.*, vol. 8, no. 1, pp. 101–124, 1987.
- [105] F. Venmans, "Triggers and barriers to energy efficiency measures in the ceramic, cement and lime sectors," *J. Clean. Prod.*, vol. 69, pp. 133–142, 2014.
- [106] C. Corbett and S. Muthulingam, "Adoption of voluntary environmental standards: The role of intrinsic benefits in the diffusion of the LEED green building standards," *Work. Pap. Univ. Calif. Los Angeles, Anderson Sch. Manag.*, pp. 1–32, 2007.
- [107] C. Wilson and H. Dowlatabadi, "Models of Decision Making and Residential Energy Use," *Annu. Rev. Environ. Resour.*, vol. 32, no. 1, pp. 169–203, 2007.
- [108] B. Bollinger and K. Gillingham, "Peer Effects in the Diffusion of Solar Photovoltaic Panels," *Mark. Sci.*, vol. 31, no. 6, pp. 900–912, 2012.
- [109] D. McKenzie-Mohr, *Fostering sustainable behavior: An introduction to community-based social marketing*. New society publishers, 2011.
- [110] D. Noll, C. Dawes, and V. Rai, "Solar community organizations and active peer effects in the adoption of residential PV," *Energy Policy*, vol. 67, pp. 330–343, 2014.
- [111] P. Eichholtz, N. Kok, and J. M. Quigley, "American Economic Association Doing Well by Doing Good ? Green Office Buildings Doing Well by Doing Good ? Green Office Buildings," *Am. Econ. Rev.*, vol. 100, no. 5, pp. 2492–2509, 2010.

- [112] N. Gilbraith, I. L. Azevedo, and P. Jaramillo, “Evaluating the benefits of commercial building energy codes and improving federal incentives for code adoption,” *Environ. Sci. Technol.*, vol. 48, no. 24, pp. 14121–14130, 2014.
- [113] I. Ayres, S. Raseman, and A. Shih, “Evidence from Two Large Field Experiments that Peer Comparison Feedback Can Reduce Residential Energy Usage,” *J. Law, Econ. Organ.*, vol. 29, no. 5, pp. 992–1022, 2013.
- [114] C. Fischer, “Feedback on household electricity consumption: A tool for saving energy?,” *Energy Effic.*, vol. 1, no. 1, pp. 79–104, 2008.
- [115] H. Allcott, “Social norms and energy conservation,” *J. Public Econ.*, vol. 95, no. 9–10, pp. 1082–1095, 2011.
- [116] G. Peschiera and J. E. Taylor, “The impact of peer network position on electricity consumption in building occupant networks utilizing energy feedback systems,” *Energy Build.*, vol. 49, pp. 584–590, 2012.
- [117] L. Lutzenhiser, K. Janda, R. Kunkle, and C. Payne, “Understanding the response of commercial and institutional organizations to the California energy crisis,” 2002.
- [118] B. Goitein, “Organizational decision-making and energy conservation investments,” *Eval. Program Plann.*, vol. 12, no. 2, pp. 143–151, 1989.
- [119] K. B. Janda, “Building communities and social potential: Between and beyond organizations and individuals in commercial properties,” *Energy Policy*, vol. 67, pp. 48–55, 2014.
- [120] J. Pfeffer, “Decisions and Implementation,” in *Managing with Power: Politics and Influence in Organizations*, Boston, MA: Harvard Business School Press, 1992, pp. 3–31.
- [121] P. C. Stern, K. B. Janda, M. A. Brown, L. Steg, E. L. Vine, and L. Lutzenhiser, “Opportunities and insights for reducing fossil fuel consumption by households and organizations,” *Nat. Energy*, vol. 1, 2016.
- [122] M. Taylor, A. Spurlock, and H.-C. Yang, “Confronting Regulatory Cost and Quality Expectations: An Exploration of Technical Change in Minimum Efficiency Performance Standards,” no. 1000576, pp. 1–5, 2015.
- [123] M. G. Morgan, B. Fischhoff, A. Bostram, and C. J. Arman, *Risk Communication: A Mental Models Approach*. Cambridge University Press, 2002.
- [124] J. S. Downs, W. B. de Bruin, and B. Fischhoff, “Parents’ vaccination comprehension and decisions,” *Vaccine*, vol. 26, no. 12, pp. 1595–1607, 2008.
- [125] A. Bostrom, M. Morgan, and B. Fischhoff..., “What do people know about global climate change? 1. Mental models,” *Risk Anal.*, vol. 14, no. 6, 1994.
- [126] B. L. Berg, *Qualitative Research Methods for the Social Sciences*, 5th Editio. Pearson Education, Inc., 2004.
- [127] Pittsburgh Green Workplace Challenge, “2014-2015 Competition Guidebook Version 06.20.2015,” 2014.

- [128] A. L. Strauss, *Qualitative Analysis for Social Scientists*. New York: Cambridge University Press, 1987.
- [129] J. Cohen, "A Coefficient of Agreement for Nominal Scales," *Educ. Psychol. Meas.*, no. 1, pp. 37–46, 1960.
- [130] E. Dutton, J. Walton, and E. Abrahamson, "Business Administration, University," no. July, 1989.
- [131] T. Beamish, R. Kunkle, and N. W. Biggart, "Why innovation happens: Structured actors and emergent outcomes in the commercial buildings sector," *Proc. ACEEE Summer Study Energy Effic. Build.*, vol. 8, 2000.
- [132] S. Oreg, "Resistance to change: Developing an individual differences measure.," *J. Appl. Psychol.*, vol. 88, no. 4, pp. 680–693, 2003.
- [133] M. Craske, U. Wittchen, M. Stein, G. Andrews, and R. Lebeu, "Severity Measure for Specific Phobia– Adult," *Am. Psychiatr. Assoc.*, 2013.
- [134] R. Thaler, "Mental_accounting_and_consumer.PDF," *Mark. Sci.*, vol. 4, no. 3, pp. 199–214, 1985.
- [135] S. Frickel *et al.*, "Movement and Civil Society Challenges Undone Science : Charting Social Setting to Research Agenda Abstract," *Sci. Technol. Hum. Values*, vol. 35, no. 4, pp. 444–473, 2010.
- [136] M. T. Orne, "On the social psychology of the psychological experiment: With particular reference to demand characteristics and their implications," *Am. Psychol.*, vol. 17, no. 11, pp. 776–783, 1962.
- [137] A. H. Rosenstein, "Nurse-Physician Relationships: Impact on Nurse Satisfaction and Retention," *Am. J. Nurs.*, vol. 102, no. 6, pp. 26–34, 2002.
- [138] S. Hall, D. Sparks, C. Hargroves, C. Desha, and P. Newman, "The development of a simple multi-nodal tool to identify performance issues in existing commercial buildings," 2013.
- [139] Å. L. Hauge, J. Thomsen, and E. Löfström, "How to get residents/owners in housing cooperatives to agree on sustainable renovation," *Energy Effic.*, vol. 6, no. 2, pp. 315–328, 2013.
- [140] J. A. Vogel, P. Lundqvist, P. Blomkvist, and J. Arias, "Problem areas related to energy efficiency implementation in Swedish multifamily buildings," *Energy Effic.*, vol. 9, no. 1, pp. 109–127, 2016.
- [141] J. A. Gambatese and M. Hallowell, "Factors that influence the development and diffusion of technical innovations in the construction industry," *Constr. Manag. Econ.*, vol. 29, no. 5, pp. 507–517, 2011.
- [142] U.S. EPA, "Abandoned Mine Drainage," *Environmental Protection Agency*, 2015. [Online]. Available: <https://www.epa.gov/nps/abandoned-mine-drainage>. [Accessed: 01-Jan-2017].

- [143] P. R. Epstein *et al.*, “Full cost accounting for the life cycle of coal,” *Ann. N. Y. Acad. Sci.*, vol. 1219, no. 1, pp. 73–98, 2011.
- [144] O. Edenhofer *et al.*, *IPCC, 2011: Summary for Policymakers. In: IPCC Special Report on Renewable Energy Sources and Climate Change Mitigation*. 2011.
- [145] U.S. EIA, “Electric Power Monthly,” *Energy Information Agency*, 2016. [Online]. Available: http://www.eia.gov/electricity/monthly/epm_table_grapher.cfm?t=epmt_1_01_a.
- [146] U.S. EPA, “Inventory of U.S. Greenhouse Gas Emissions and Sinks: 1990-2015,” *Environmental Protection Agency*, 2017. [Online]. Available: https://www.epa.gov/sites/production/files/2017-02/documents/2017_complete_report.pdf.
- [147] G. Holland and C. L. Bruyère, “Recent intense hurricane response to global climate change,” *Clim. Dyn.*, vol. 42, no. 3–4, pp. 617–627, 2014.
- [148] R. E. Kopp *et al.*, “Probabilistic 21st and 22nd century sea-level projections at a global network of tide-gauge sites,” *Earth’s Futur.*, vol. 2, no. 8, pp. 383–406, 2014.
- [149] T. Stocker *et al.*, “Climate Change 2013: The Physical Science Basis. Contribution of Working Group I to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change,” Cambridge, United Kingdom and New York, NY, 2013.
- [150] A. Grinsted, J. C. Moore, and S. Jevrejeva, “Projected Atlantic hurricane surge threat from rising temperatures,” *Proc. Natl. Acad. Sci. U. S. A.*, vol. 110, no. 14, pp. 5369–73, 2013.
- [151] A. Noguee, S. Clemmer, B. Paulos, and B. Haddad, “Powerful Solutions 7 Ways to Switch America to Renewable Electricity,” *Union Concerned Sci.*, no. January, 1999.
- [152] M. X. D. Carpin, F. L. Cook, and L. R. Jacobs, “Public Deliberation, Discursive Participation, And Citizen Engagement: A Review of the Empirical Literature,” *Annu. Rev. Polit. Sci.*, vol. 7, pp. 315–344, 2004.
- [153] S. Keeter, C. Zukin, M. Adolina, and K. Jenkins, “The civic and political health of the nation: A generational portrait,” 2002.
- [154] G. Burke, C. Finn, and A. Murphy, “Community Choice Aggregation: the Viability of Ab 117 and Its Role in California’s Energy Markets,” *2005 Eur. Microw. Conf.*, pp. xiii–xlv, 2005.
- [155] S. Littlechild, “Municipal aggregation and retail competition in the Ohio energy sector,” *J. Regul. Econ.*, vol. 34, pp. 164–194, 2008.
- [156] S. M. Hoffman, “Community Energy: A Social Architecture for an Alternative Energy Future,” *Bull. Sci. Technol. Soc.*, vol. 25, no. 5, pp. 387–401, 2005.
- [157] G. Thrush and C. Davenport, “Donald Trump Budget Slashes Funds for E.P.A. and State Department,” *The New York Times*, 15-Mar-2017.
- [158] C. Davenport, “Trump Budget Would Cut E.P.A. Science Programs and Slash Cleanups,” *The New York Times*, 19-May-2017.

- [159] R. E. Klatch, "The contradictory effects of work and family on political activism," *Qual. Sociol.*, vol. 23, no. 4, pp. 505–519, 2000.
- [160] J. C. Fell and R. B. Voas, "Mothers Against Drunk Driving (MADD): the first 25 years.," *Traffic Inj. Prev.*, vol. 7, no. 3, pp. 195–212, 2006.
- [161] R. Berman, "The Split Between the States Over Guns," *The Atlantic*, 31-Dec-2015.
- [162] R. Berkman, "Nonprofits Get More From Social Media with Metrics," *MIT Sloan Manag. Rev.*, vol. 55, no. 1, p. 1, 2013.
- [163] K. Hess, "Motherhood as a Unifying Theme in Social Movements : Symbolic Essentialism , Environmental Justice , and the Movement Against Bisphenol A in Maine," *Honor. Coll.*, vol. 55, 2012.
- [164] G. Dicum, "Fed up with breast-milk contamination, mothers form a national activist group," *Grist*, 07-Nov-2006.
- [165] S. C. Logsdon-Conradsen and S. L. Allred, "Motherhood and environmental activism: A developmental framework.," *Ecopsychology*, vol. 2, no. 3, pp. 141–146, 2010.
- [166] Tides Center, "National Farm to School Network," 2017. [Online]. Available: <http://www.farmtoschool.org/>. [Accessed: 04-Jun-2017].
- [167] Centers for Disease Control and Prevention, "Parents for Healthy Schools: A Guide for Getting Parents Involved from K-12," *US Dept. Heal. Hum. Serv.*, no. November, 2015.
- [168] L. Hamilton, "Concern about Toxic Wastes: Three Demographic Preditors," *Sociol. Perspect.*, vol. 28, no. 4, pp. 463–486, 1985.
- [169] L. Hamilton, "Who cares about water pollution? Opinions in a small-town crisis," *Sociol. Inq.*, vol. 55, no. 2, pp. 170–181, 1985.
- [170] G. Livingston, "Childlessness," *Pew Research Center*, 2015. [Online]. Available: <http://www.pewsocialtrends.org/2015/05/07/childlessness/>.
- [171] C. Roser-Renouf, N. Stenhouse, J. Rolfe-Redding, E. Maibach, and A. Leiserowitz, "Engaging Diverse Audiences with Climate Change: Message Strategies for Global Warming's Six Americas," *SSRN*, 2014.
- [172] E. Maibach, C. Roser-Renouf, and A. Leiserowitz, "Global Warming's Six Americas 2009: An Audience Segmentation Analysis," 2009.
- [173] U.S. Census Bureau, "2011-2015 American Community Survey 5-Year Estimates," *U.S. Census Bureau*, 2016. [Online]. Available: <https://factfinder.census.gov/faces/tableservices/jsf/pages/productview.xhtml?src=CF>. [Accessed: 12-Dec-2016].
- [174] U.S. EIA, "Table CT1. Energy Consumption Estimates for Major Energy Sources in Physical Units, 1960-2014, Michigan," *Energy Information Agency*, 2016. [Online]. Available: https://www.eia.gov/state/seds/data.php?incfile=%2Fstate%2Fseds%2Fsep_use%2Ftotal%2Fuse_tot_MIa.html&%3Bsid=MI. [Accessed: 29-Dec-2016].

- [175] A. Proudlove, B. Lips, D. Sarkisian, and A. Shrestha, "The 50 States of Solar Report: 2016 Annual Review and Q4 Update," 2016.
- [176] CEC, "California Energy Commission," *Ca.gov*, 2017. [Online]. Available: <http://www.energy.ca.gov/>. [Accessed: 29-Dec-2016].
- [177] R. Schwarzer and M. Jerusalem, "Generalized Self-Efficacy Scale," *Anxiety. Stress. Coping*, vol. 12, pp. 329–345, 2010.
- [178] M. Tavakol and R. Dennick, "Making sense of Cronbach's alpha," *Int. J. Med. Educ.*, vol. 2, pp. 53–55, 2011.
- [179] A. Leiserowitz, E. Maibach, and C. Roser-Renouf, "Global Warming's 'Six Americas,'" 2009.
- [180] D. J. Bem, "Self-perception: An alternative interpretation of cognitive dissonance phenomena.," *Psychol. Rev.*, vol. 74, no. 3, pp. 183–200, 1967.
- [181] CDC, "Asthma in Florida," 2008.
- [182] FEMA, "Claim Information by State (1978 - Current Month)," *U.S. Department of Homeland Security Federal Emergency Management Agency*, 2017. [Online]. Available: <https://bsa.nfipstat.fema.gov/reports/1040.htm>. [Accessed: 05-Mar-2017].
- [183] a. Spence, W. Poortinga, C. Butler, and N. F. Pidgeon, "Perceptions of climate change and willingness to save energy related to flood experience [Letter]," *Nat. Clim. Chang.*, vol. 1, no. 4, pp. 46–49, 2011.
- [184] C. Keller, M. Siegrist, and H. Gutscher, "The role of the affect and availability heuristics in risk communication," *Risk Anal.*, vol. 26, no. 3, pp. 631–639, 2006.
- [185] IEA, "Capturing the Multiple Benefits of Energy Efficiency Capturing the Multiple Benefits of Energy Efficiency," 2014.
- [186] H. L. Berry, B. Rodgers, and K. B. G. Dear, "Preliminary development and validation of an Australian community participation questionnaire: Types of participation and associations with distress in a coastal community," *Soc. Sci. Med.*, vol. 64, no. 8, pp. 1719–1737, 2007.
- [187] A. Bandura, "Human agency in social cognitive theory," *Am. Psychol.*, vol. 44, no. 9, pp. 1175–84, 1989.
- [188] J. J. Mondak, M. V. Hibbing, D. Canache, M. A. Seligson, and M. R. Anderson, "Personality and Civic Engagement: An Integrative Framework for the Study of Trait Effects on Political Behavior," *Am. Polit. Sci. Rev.*, vol. 104, no. 1, pp. 85–110, 2010.
- [189] K. Witte and M. Allen, "A Meta-Analysis of Fear Appeals : Implications for Effective Public Health Campaigns," vol. 27, no. October, pp. 591–615, 2000.
- [190] A. J. Fessenden-raden, J. M. Fitchen, J. S. Heath, J. Fessenden-raden, J. M. Fitchen, and J. S. Heath, "Providing Risk Information in Communities : Factors Influencing What Is Heard and Accepted Stable URL : <http://www.jstor.org/stable/689388> REFERENCES Linked references are available on JSTOR for this article : Providing Risk Infonnation in

- Communities : F,” vol. 12, no. 3, 2016.
- [191] P. Slovic, “Trust, emotion, sex, politics, and science: Surveying the risk-assessment battlefield (Reprinted from *Environment, ethics, and behavior*, pg 277-313, 1997),” *Risk Anal.*, vol. 19, no. 4, pp. 689–701, 1999.
 - [192] T. R. Karl, J. M. Melillo, and T. C. Peterson, “Global climate change impacts in the United States,” 2009.
 - [193] P. Vaishnav, N. Horner, and I. Azevedo, “Was it worthwhile? Where have the benefits of rooftop solar photovoltaic generation exceeded the cost?,” *Environ. Res. Lett.*, vol. 12, 2017.
 - [194] M. Moezzi, A. Ingle, L. Lutzenhiser, and B. Sigrin, “A Non-Modeling Exploration of Residential Solar Photovoltaic (PV) Adoption and Non-Adoption,” *Natl. Renew. Energy Lab.*, 2017.
 - [195] G. Barbose, N. Darghouth, and S. Weaver, “Tracking the Sun VI An Historical Summary of the Installed Price Tracking the Sun VI An Historical Summary of the Installed Price of,” *SunShot - U.S. Dep. Energy*, no. September, p. 70, 2014.
 - [196] “Aggregating Higher Education Demand for Renewables: A Primer,” *Assoc. Adv. Sustain. High. Educ.*, 2018.
 - [197] G. Barbose, N. Darghouth, D. Millstein, K. LaCommare, N. Disanti, and R. Widiss, “Tracking the Sun 10 The Installed Price of Residential and Non-Residential Photovoltaic Systems in the United States,” 2017.
 - [198] D&R International Ltd., “2011 Buildings Energy Data Book,” Silver Springs, MD, 2012.
 - [199] Bloomberg Philanthropies, “America’s Pledge Phase 1 Report: States, Cities, and Businesses in the United States Are Stepping Up on Climate Action,” 2017.
 - [200] The Association for the Advancement of Sustainability in Higher Education, “The Sustainability Tracking, Assessment & Rating System,” 2017. [Online]. Available: https://stars.aashe.org/institutions/data-displays/2.0/content/?institution__ms_institution__country=United+States&reporting_field=6092.
 - [201] A. L. Higgs and V. M. McMillan, “Teaching through modeling: Four schools’ experiences in sustainability education,” *J. Environ. Educ.*, vol. 28, no. 1, pp. 39–53, 2006.
 - [202] J. Karliner, “The little green schoolhouse: Thinking big about ecological sustainability, children’s environmental health, and K-12 education in the USA,” 2005.
 - [203] NCES, “Integrated Postsecondary Education Data System,” *National Center for Education Statistics*, 2015. [Online]. Available: <https://nces.ed.gov/ipeds/Home/UseTheData>.
 - [204] NCES, “Common Core of Data,” *National Center for Education Statistics*, 2015. [Online]. Available: <https://nces.ed.gov/ccd/pubschuniv.asp>.
 - [205] NCES, “Private School Universe Survey,” *National Center for Education Statistics*, 2015.

- [Online]. Available: <https://nces.ed.gov/surveys/pss/tableswhi.asp>.
- [206] M. Sengupta, A. Habte, P. Gotseff, A. Weekley, and A. Lopez, “A Physics-Based GOES Satellite Product for Use in NREL ’ s National Solar Radiation Database,” *Solar*, no. July, 2014.
- [207] U.S. DOE, “Commercial Reference Buildings,” *Department of Energy*, 2017. [Online]. Available: <https://energy.gov/eere/buildings/commercial-reference-buildings%0A>.
- [208] OpenEI, “Utility Rate Database,” *Open EI*, 2017. [Online]. Available: http://en.openei.org/wiki/Utility_Rate_Database.
- [209] N. Horner, “Powering the Information Age: Metrics, Social Cost Optimization Strategies, and Indirect Effects Related to Data Center Energy Use,” Carnegie Mellon Univeristy, 2016.
- [210] N. Z. Muller, *Towards the Measurement of Net Economic Welfare: Air Pollution Damage in the US National Accounts – 2002, 2005, 2008.*, no. September. 2014.
- [211] J. Heo, P. J. Adams, and H. O. Gao, “Public Health Costs of Primary PM_{2.5} and Inorganic PM_{2.5} Precursor Emissions in the United States,” *Environ. Sci. Technol.*, vol. 50, no. 11, pp. 6061–6070, 2016.
- [212] A. Shehabi, M. Ganeshalingam, L. Demates, P. Mathew, and D. Sartor, “Characterizing the Laboratory Market,” 2017.
- [213] J. Melius, R. Margolis, and S. Ong, “Estimating Rooftop Suitability for PV : A Review of Methods , Patents , and Validation Techniques Estimating Rooftop Suitability for PV : A Review of Methods , Patents , and Validation Techniques,” no. December, 2013.
- [214] E. Lorenzo, “Chapter 20: Energy Collected and Delivered by PV Modules,” in *Handbook of Photovoltaic Science and Engineering*,; A. Luque and S. Hegedus, Eds. John Wiley & Sons, Ltd., 2003, pp. 905–970.
- [215] N. Darghouth, G. Barbose, A. Mills, R. Wiser, P. Gagnon, and L. Bird, “Exploring Demand Charge Savings from Commercial Solar,” 2017.
- [216] N. Blair *et al.*, “System Advisor Model , SAM 2014.1.14: General Description,” 2014.
- [217] NC Clean Energy Technology Center, “Database of State Incentives for Renewables & Energy Efficiency (DSIRE): LADWP - Net Metering,” 2017. [Online]. Available: <http://programs.dsireusa.org/system/program/detail/4855>.
- [218] C. Davidson *et al.*, “Nationwide Analysis of U . S . Commercial Building Solar Photovoltaic (PV) Breakeven Conditions Nationwide Analysis of U . S . Commercial Building Solar Photovoltaic (PV) Breakeven Conditions,” no. October, 2015.
- [219] U.S. DOE, “Business Energy Investment Tax Credit (ITC),” *DSIRE*, 2017. [Online]. Available: <http://programs.dsireusa.org/system/program/detail/658>.
- [220] U.S. DOE, “Residential Renewable Energy Tax Credit,” *DSIRE*, 2017. [Online]. Available: <http://programs.dsireusa.org/system/program/detail/1235>.

- [221] I. L. Azevedo, N. Horner, K. Siler-evans, and P. Vaishnav, “Electricity Marginal Factors Estimates,” *Center for Climate and Energy Decision Making*, 2017. [Online]. Available: <https://cedm.shinyapps.io/MarginalFactors/>.
- [222] K. Siler-Evans, I. L. Azevedo, and M. G. Morgan, “Marginal Emissions Factors for the U.S. Electricity System,” *Environ. Sci. Technol.*, vol. 46, no. 9, pp. 4742–4748, 2012.
- [223] K. Siler-evans, I. Azevedo, M. G. Morgan, and J. Apt, “Regional variations in the health , environmental , and climate bene fi ts of wind and solar generation,” *Proc. Natl. Acad. Sci.*, vol. 110, no. 29, pp. 11768–11773, 2013.
- [224] M.-A. Tamayao, J. J. Michalek, C. Hendrickson, and I. L. Azevedo, “Regional Variability and Uncertainty of Electric Vehicle Life Cycle CO2 Emissions across the United States,” *Environ. Sci. Technol.*, vol. 49, no. 14, pp. 8844–8855, 2015.
- [225] T. Yuksel, M.-A. Tamayao, C. Hendrickson, I. L. Azevedo, and J. J. Michalek, “Effect of regional grid mix, driving patterns and climate on the comparative carbon footprint of gasoline and plug-in electric vehicles in the United States,” *Environ. Res. Lett.*, vol. 11, no. 4, 2016.
- [226] E. Hittinger and I. L. Azevedo, “Bulk Energy Storage Increases United States Electricity System Emissions,” *Environ. Sci. Technol.*, vol. 49, no. 5, pp. 3203–3210, 2015.
- [227] E. Hittinger and I. M. L. Azevedo, “Estimating the quantity of wind and solar required to displace storage-induced emissions,” *Environ. Sci. Technol.*, vol. 51, pp. 12988–12997, 2017.
- [228] J. Heo, P. J. Adams, and H. O. Gao, “Reduced-form modeling of public health impacts of inorganic PM2.5 and precursor emissions,” *Atmos. Environ.*, vol. 137, pp. 80–89, 2016.
- [229] Interagency Working Group on Social Cost of Greenhouse Gases, “Technical Update of the Social Cost of Carbon for Regulatory Impact Analysis Under Executive Order 12866,” 2016.
- [230] U.S. EIA, “Electric Power Annual 2016,” Washington, D.C., 2017.
- [231] U.S. EIA, “Commercial Building Energy Consumption Survey,” *U.S. Energy Information Agency*, 2012. [Online]. Available: <http://www.eia.gov/consumptions/commercial/data/2012/#b12>.
- [232] W. Nordhaus, “Estimates of the Social Cost of Carbon: Background and Results from the RICE-2011 Model,” 2011.
- [233] F. Ackerman and E. A. Stanton, “Climate Risks and Social Costs: Revising the Social Cost of Carbon,” *Econ. Open-Access, Open-Assessment E-Journal*, vol. 6, pp. 0–26, 2012.
- [234] U.S. EPA (United States Environmental Protection Agency), “EPA Fact Sheet - Social Cost of Carbon,” 2016.
- [235] T. Myers, M. Nisbet, E. Maibach, and A. Leiserowitz, “A public health frame arouses hopeful emotions about climate change A Letter,” *Clim. Change*, vol. 113, pp. 1105–1112, 2012.

- [236] M. C. Nisbet and D. A. Scheufele, "What's next for science communication? promising directions and lingering distractions," *Am. J. Bot.*, vol. 96, no. 10, pp. 1767–1778, 2009.
- [237] F. Faul, E. Erdfelder, A. Buchner, and A.-G. Lang, "Statistical power analyses using G*Power 3.1: tests for correlation and regression analyses.," *Behav. Res. Methods*, vol. 41, no. 4, pp. 1149–60, 2009.

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Appendix A.1: Estimated energy own-price elasticities

Table A1. Estimated energy own-price elasticities for the commercial sector – absolute values are shown; all values are negative.

Energy	Short-term		Long-term	
	Range	References	Range	References
Electricity	0 - 0.46	[1]	0.24 - 1.36	[1], [2]
Natural Gas	0.14 - 0.29	[1], [2]	0.40 - 1.38	[2], [3]
Fuel Oil	0.13 - 0.49	[1], [2]	0.39 - 3.5	[2]

Consider the electricity elasticities in Table A1, which was adopted from Gillingham et al. [4]; for each unit increase in electricity prices, electricity demand decreases from 0 to .46% in the short-term and .24% to nearly 1.40% in the long-term. Increases in prices also tend to increase EE technology adoption and innovation in upstream development processes [5], [6].

References

- [1] C. A. Dahl, “A Survey of Energy Demand Elasticities in Support of the Development of the NEMS,” *Munich Pers. RePEc Arch.*, 1993.
- [2] S. H. Wade, “Price Responsiveness in the AEO2003 NEMS Residential and Commercial Buildings Sector Models,” Washington, D.C., 2003.
- [3] D. R. Bohi and M. B. Zimmerman, “An update on econometric studies of energy demand behavior,” *Annu. Rev. Energy*, vol. 9, no. 1, pp. 105–154, 1984.
- [4] K. Gillingham, R. G. Newell, and K. Palmer, “Energy Efficiency Economics and Policy,” *Annu. Rev. Resour. Econ.*, vol. 1, no. 1, pp. 597–620, 2009.
- [5] R. G. Newell, A. B. Jaffe, and R. N. Stavins, “Chapter 5: The Induced Innovation Hypothesis and Energy-Saving Technological Change,” in *Technological Change and the Environment*, 2003, pp. 461–516.

Appendix A.2: Expert interview protocol

I. COMPANY AND SERVICES (10 MIN)

Our research focuses on the motivations and barriers for pursuing building energy efficiency. We are interested in identifying social catalysts that influence building owners to make energy efficient investments in their building.

If at any point during the interview you would like me to repeat a question, please do not hesitate to ask. Also, if you would prefer not to answer a question just ask that we skip it.

1. First, I would like you to start by telling me a little bit about your business. Can you describe your typical clients and projects?
2. How might you describe your role in promoting building energy efficiency and sustainability?
3. Which building employees do you often work with to implement energy efficiency (i.e. building owners, facility managers, building engineers, etc.)? Can you describe those interactions and how responsibilities seem to be delegated?
4. Can you tell me about the quality of communications with your clients? What factors and/or conditions lead to strong communication conduits and what factors and/or conditions weaken communication conduits?
5. Do you have any recurring clients? Can you explain why they might keep coming to you?

II. ENERGY EFFICIENCY CLIMATE (10 MIN)

Next, I'd like to ask you to talk about how you perceive the building energy efficiency and sustainability climate in Pittsburgh.

6. What are the types of owners in today's building energy efficiency climate?
7. How might you identify a building owner who prioritizes energy efficiency?
8. How do you perceive building owners/managers financing their energy efficiency investments?

[SPECTRUM OF CLIENTS]

9. How might you describe a low/medium/high energy efficient building owner?
10. How might you describe a low/medium/high energy efficient building?

[MARKET GAPS]

11. Can you describe what areas of the market have had less penetration in regards to energy efficiency? Can you speculate as to why this might be?
12. How do you think you can close this gap? Is this within your control? If not, what is required to close this gap?

[ENERGY STAR AND LEED]

13. Next, I would like to discuss Energy Star and LEED. What impacts do you believe these designations have on building performance?
14. Do you think these designations or rating systems should be targeting anything specific in building performance?

[POLICY INTERVENTIONS]

15. What is your position on mandatory energy benchmarking in Pittsburgh?
16. What is your position on mandatory energy audits in Pittsburgh commercial buildings?
17. Do you think public subsidies for energy efficiency are effective?

III. MEASURES (10 MIN)

Next, I would like to discuss some energy efficiency measures that you believe can or should be implemented in large buildings in Pittsburgh.

18. Can you describe a typical energy efficiency measure or sustainable technology that you believe all buildings should have at a minimum?
19. How about an aspirational energy efficient technology or measure that buildings should aim to achieve or implement?
20. Can you describe a technology or measure that you've noticed most building owners have issue with?

IV. MOTIVATIONS AND BARRIERS (10 MIN)

At this point, I would like to discuss what you consider to be the biggest motivations and barriers to energy efficiency investments in the building sector.

[MOTIVATIONS]

21. Could you start by explaining what you think might motivate building owners to pursue energy efficiency? Are these the same reasons they might pursue LEED or Energy Star? Do you think reasons may differ between the two and can you expand on this?
22. Here are a few common reasons people pursue building energy efficiency and sustainability. Let's add the motivation you mentioned in the previous question to the blank flashcards. Now, please select the relevant flashcards that represent the motivations you see in the market.

[Motivations will be on flash cards and subjects will select the cards they find relevant. Have them write additional motivations on blank cards.]

23. Can you explain how these motives might have changed over time?

[BARRIERS]

24. Could you explain what you think building owners might perceive as barriers for pursuing energy efficiency?

[Draw a blank, follow-up question...]

- Can you describe any common barriers you experience with your clients regarding the adoption of energy efficiency investments?

25. Here are a few common barriers to pursuing building energy efficiency and sustainability. Let's add the barrier you mentioned in the previous question to the blank flashcards. Now, please select the relevant flashcards that represent the barriers you see in the market.

[Barriers will be on flash cards and subjects will select the cards they find relevant. Have them write additional motivations on blank cards.]

26. Can you explain how these barriers might have changed over time?
27. Could you describe Fear of Change?
28. Where there any issues related to social influences, motivations or barriers that we did not cover and you would like to discuss now?

V. PROFESSIONAL SOCIETIES (5 MIN)

At this time, we would like to discuss the professional associations in which you participate.

29. Are you currently a part of any professional associations (e.g., USGBC, ASHRAE, GBA, etc.)? Could you tell me about these professional associations?

30. If so, how would you rate your level of commitment/activity on a scale from 1 to 5? (1 being very active, 5 being very inactive). 1 2 3 4 5
31. What do you gain from membership?

VI. PERSONAL QUESTIONS (10 MIN)

The final set of questions asks about you. I assure you again that your responses to all of these questions will be held confidential so that no one will be able to know these personal answers about you or any of the questions you have answered. If you would like to skip any of these questions, please let me know.

32. What is your age?
33. What is your occupation?
34. What is your highest level of educational attainment?
35. How was it to participate in the interview?
36. Do you have any questions for me?
37. Can you think of any other energy experts or building owners/managers who might be interested in participating in this research?

Those are all the questions that I had. Thank you. Turn off recorder: Would you prefer to receive a \$50 money order or a \$50 amazon.com gift certificate. If you choose the gift certificate, a code will be emailed to you that will be redeemable on Amazon.com.

[If gift certificate,] May I please have your email address so that we can email you the gift code? This will take about 3 days.

[If money order,] May I please have your complete mailing address so that we can mail you the \$50.00 compensation? This will take about 5-7 days. *[Ask for the correct spelling of their name and address. Read it back to them]* If you have any further thoughts that you think may be helpful to the project, or if you know Pittsburgh large-building (>50,000 ft²) owners who would be interested in participating in this research please do not hesitate to contact us at nhanus@andrew.cmu.edu or 937-269-9675.

Again, you've been very helpful to our research. Thank you for your time.

Appendix A.3: Owner/manager interview protocol

I. BUILDING DATA (5 MIN)

Our research focuses on the motivations and barriers for pursuing building energy efficiency investments. It is important that we characterize the differences in building types and occupants, as that will heavily influence how building energy efficiency is pursued.

If at any point during the interview you would like me to repeat a question, please do not hesitate to ask. Also, if you would prefer not to answer a question, you can ask that we skip it.

During this interview, I would like you to consider your largest building.

1. How did you acquire your building?
2. How long have you owned this building?
3. How would you describe the state of your mechanical systems? (e.g. does anything need repair or replacement?)
4. Do you have any unique requirements for occupants?
5. Do you have a facility manager, building engineer, or dedicated BAS/HVAC contractor?
[Have them elaborate on their team. How many people? What types?]
6. Please describe the tasks assigned to each of these employees.
7. *[For each of the listed building team members]*

On a scale from 1 to 5, how much would you say you trust this person?

1 (Strongly Distrust)

2

3

4

5 (Strongly Trust)

[Response to potential follow-up question: "What do you mean by trust?"]

- How much do you trust their opinion in an investment?
- How much do you trust their ability to perform assigned tasks?

8. On a scale from 1 to 5, how competent do you think they are at their jobs?
1 (Very Competent)
2
3
4
5 (Very Incompetent)
9. On a scale from 1 to 5, how would you rate your relationship with them?
1 (Very Strong)
2
3
4
5 (Weak Relationship)

II. GENERAL ENERGY EFFICIENCY (10 MIN)

Next, I'd like to ask you to talk about energy efficiency (EE) investments. Can you start by telling me about what you think energy efficiency is?

Draw a blank (try in order):

10. Have you ever heard of energy efficiency? [can you tell me what you've heard?]
11. [if they say no] Let's see if I can help you out. Energy efficiency means the building uses less energy but has the same energy services.
12. [if they give an inaccurate definition] For this interview, the way we define energy efficiency is that the building uses less energy but has the same energy services.
13. Do you think your building is energy efficient?
14. Can you please list the buildings and/or companies (if any) that you perceive as highly energy efficient? (If they provide answers, ask them to expand on each of them and provide reasoning)

[ENERGY STAR AND LEED]

15. Next, I would like to discuss Energy Star and LEED. What impacts do you believe these designations have on building performance?
16. Do you think these designations or rating systems should be targeting anything specific in building performance?
17. Are you targeting any other energy or sustainability goals (e.g. Pittsburgh 2030 District)?
18. Why do you pursue these goals?
19. Did anyone or any organization introduce you to Energy Star, LEED, or Pittsburgh 2030 District?

[POLICY INTERVENTIONS]

20. What is your position on mandatory energy benchmarking in Pittsburgh?
21. What is your position on mandatory energy audits in Pittsburgh commercial buildings?
22. Do you think public subsidies for energy efficiency are effective?

**III. ENERGY EFFICIENCY INVESTMENT HISTORY AND POTENTIAL STRATEGIES
(10 MIN)**

[HISTORIC]

1. How do you define a major EE investment?
2. Can you begin by explaining your level of involvement in making energy efficiency investments? Are there certain cost thresholds that influence your involvement?
3. Can you tell me about the process involved with making EE investments?
4. Who is involved?
5. Did you target or utilize any incentives?
6. Any consulting?
7. *[This should be phrased according to the building type listed at the beginning of the interview.]* Can you tell me more about interactions with tenants or occupants you've had with respect to investments in your building?

[FUTURE PLANS]

8. Next, I would like to discuss your current and future energy efficiency plans.
 - a. Are you currently considering energy efficiency investments for today or the future?
 - b. Can you tell me about your company's strategy or plan for making these investments?
 - c. Will you handle future energy efficiency investments differently than past energy efficiency investments? If so how and why?

- d. Will you seek consulting? If so, from who?
 - e. Will you target any incentives? If so, which ones?
9. Do these investment plans relate to any other investment/upgrade plans for your building?
Can you tell me more? (e.g. you need to build-out certain floors and are considering demand control ventilation in those areas)
 10. Where there any issues related to EE investments or strategies that we did not cover and you would like to discuss now?

[ENERGY EFFICIENCY ASPIRATIONS]

11. Are there any technologies or measures you think your building should have (or has) at a minimum?
12. Are there any technologies or measures that you believe are aspirational for your building?
13. Are they any technologies or measures that you have had issue with implementing?

IV. INVESTMENT MOTIVATORS AND BARRIERS (10 MIN)

[RANKING EXERCISES]

Next, what I'd like to ask you to do is to talk about who or what influences you to make these investments decisions. In considering the investments we just talked about, please try to recall how these investments came to be.

[SOCIAL INFLUENCES]

14. Can you tell me more about how opportunities to invest in your building came to your attention?

[If they list people or types of people, add their names to the blank cards. If they don't list people, document those methods.]

15. Let's discuss who and what you perceive as influential when you consider EE investments. Please feel free to add any groups not mentioned in this list. *[Groups will be on flash cards and subjects will select the cards they find relevant. Have them write additional groups on blank cards.]*
16. Of the categories that you selected, please rank them in order of priority (e.g. place the categories you deem most important at the top of the pile).

[Following questions are aimed at characterizing relationship of owner with their selected influential groups.]

17. Please describe each actors type of influence (e.g., are they educational, competitive, etc.).
18. Can you describe how you met them or began a consulting relationship with them?
19. Can you describe your current relationship with them?
20. Rank these people by how much you trust their opinion. *[Have them place the cards in descending order of trust; allow them to place side-by-side.]*

[MOTIVATIONS]

21. Now let's discuss your motivations for pursuing EE. Here are a few common reasons people pursue building energy efficiency and sustainability. Please feel free to add any motivations that are not mentioned in this list. *[Motivations will be on flash cards and subjects will select the cards they find relevant. Have them write additional motivations on blank cards.]*

22. Can you explain how these motives might have changed over time?

[BARRIERS]

23. Next, let's discuss some barriers to pursuing energy efficiency. In other words, do you ever experience any hardships when making these investment decisions? Here are a few common barriers to pursuing building energy efficiency and sustainability. Please feel free to add any barriers that are not mentioned in this list. *[Barriers will be on flash cards and subjects will select the cards they find relevant. Have them write additional motivations on blank cards.]*

24. Have them elaborate on "Fear of Change" if they select this one.

- a. Is there a specific technology they are concerned about?
- b. How do you think it fails?
- c. How often do you think it fails?
- d. What do you think happens as a result of the failure?

25. Can you explain how these barriers might have changed over time?

26. Were there any investment opportunities that you believe that you missed? When did they occur?

27. Where there any issues related to social influences, motivations or barriers that we did not cover and you would like to discuss now?

V. PROFESSIONAL SOCIETIES & VOLUNTARY ENERGY EFFICIENCY CERTIFICATIONS (10 MIN)

At this time, we would like to discuss what associations or certifications you are pursuing and the reasons behind these decisions.

1. Are you currently involved in any professional societies aimed at promoting energy efficiency and sustainability (e.g., USGBC, ASHRAE, BOMA, etc.)?
2. If so, how would you rate your level of commitment/activity on a scale from 1 to 5? (1 being very inactive, 5 being very active). 1 2 3 4 5
3. What do you gain from membership?
4. Do you require your facility managers/building engineers to be active in any of these professional societies?
5. Do you require your facility managers/building engineers to have any certifications?
6. Please list any voluntary building energy efficiency ratings/certifications you have achieved (e.g., Energy Star, LEED, 2030 District?)
7. Why do you participate in the 2030 District/Energy Star/LEED/Better Buildings Challenge?
8. Is there a person or organization who introduced you to these organizations?
9. If so, please explain why you pursued these certifications.
10. Can you think of any benefits gained from achieving these certifications?
11. If you are not pursuing these ratings/certifications, do you mind explaining your reasoning?
12. Where there any issues related to Professional Societies or Voluntary EE certifications that we did not cover and you would like to discuss now?

VI. PERSONAL QUESTIONS (10 MIN)

The final set of questions asks about you. I assure you again that your responses to all of these questions will be held confidential so that no one will be able to know these personal answers about you or any of the questions you have answered. If you would like to skip any of these questions, please let me know.

- [1] What is your age?
- [2] What is your highest level of educational attainment?
- [3] What is approximately your gross income from the building? What about net?
- [4] How was it to participate in the interview?
- [5] Do you have any questions for me?
- [6] Can you think of any other energy experts or building owners/managers who might be interested in participating in this research?

Those are all the questions that I had. Thank you. Turn off recorder: Would you prefer to receive a \$50 money order or a \$50 amazon.com gift certificate. If you choose the gift certificate, a code will be emailed to you that will be redeemable on Amazon.com.

[If gift certificate,] May I please have your email address so that we can email you the gift code? This will take about 3 days.

[If money order,] May I please have your complete mailing address so that we can mail you the \$50.00 compensation? This will take about 5-7 days. *[Ask for the correct spelling of their name and address.*

Read it back to them] If you have any further thoughts that you think may be helpful to the project, or if you know Pittsburgh large-building (>50,000 ft²) owners who would be interested in participating in this research please do not hesitate to contact us at nhanus@andrew.cmu.edu or 937-269-9675.

Again, you've been very helpful to our research. Thank you for your time.

[If they haven't completed the Building Specs form prior to interview, ask them to complete after interview.]

Appendix A.4: Interview protocol outline

A. Interviewee perception of energy efficiency climate in Pittsburgh, PA

In this section of the protocol, interviewees were asked open-ended questions about their views on the building energy efficiency climate in Pittsburgh, PA. In addition, they were asked about various energy efficiency designations and policies that may or may not already exist in Pittsburgh. Questions in this section included the following:

- Can you describe what, if any, areas of the market have had less penetration in regard to energy efficiency? Can you speculate why this might be?
- What impacts, if any, do you believe Energy Star or LEED designations have on a building's performance?
- What is your position on mandatory energy benchmarking?
- Do you think public subsidies for energy efficiency are effective?

B. Interviewee perception of motivations and barriers to energy efficiency

This section involved card-ranking exercises of barriers and motivations related to energy efficiency investments. These cards involved brief descriptions of barriers and motivations found in the literature, such as "capital constraints" or "increase real estate value." Interviewees were asked to pick the cards they believed were most relevant to investment decisions and then rank them in descending order of importance. Barriers and motivations could have tied rankings and interviewees were prompted to write down any omitted concepts they believed were important. Interviewees often provided explanations for their rankings, although this was not required. In total, interviews ranked 20 barriers and 17 motivations.

1. Interviewee perception of social influence to energy efficiency

Finally, these interview protocols allowed participants to discuss the extent to which their investment decisions are motivated by social influences. In the Owner/Manager Interview Protocol, subjects performed a similar card-ranking exercise of 24 categories of people such as "tenants" and "local government" depicting their level of influence these categories. Furthermore, both protocols involved having the participants list the professional societies in which they participate as well as their level of activity in these societies (rankings from 1 = low level of activity to 5 = high level of activity). In addition, participants were asked to explain why they participated in the various professional societies. Other interview questions that characterized owners/managers perceptiveness to social influence included the following:

- Can you tell me more about how opportunities to invest in your building came to your attention?
- Can you please list buildings and/or companies (if any) that you perceive as highly energy efficient?

Appendix A.5: Ranking sets

Table A2. Ranking card items.

Motivations (17 items)	Barriers (20 items)	Social Influences (24 items)
Reduce energy costs and save money	Capital constraints (High initial investment and internal constraints on budget)	Conferences
Improve occupant health	Uncertainty of energy savings associated with new technology (and Uncertainty of value creation)	Building Engineers
Improve occupant productivity	Not enough technical support	Professional Associations
Reputation	Low tenant engagement	Employees
Improve occupant comfort	Other investments are a higher priority than energy efficiency	Universities
Aging equipment / Imminent investment	Energy costs are not sufficiently important	Tenants
Reduce labor and maintenance costs	Energy efficiency investments are in the disinterest of the building engineers	Utility Companies
Retain tenants longer	Lack of access to information on costs and benefits of using energy-saving technologies	Energy Efficiency Consultants
Increase real estate value	Do not currently have resources, in the form of staff support, available at the time	Local Government
Attract premium tenants	Lack of financial institutions and external funding opportunities	Government Policies
Demonstrate social responsibility	Investment will not pay off in the time horizon of building ownership	Federal Government
Be industry leaders in sustainability and energy efficiency	Time discounting (Savings are not immediate)	News Sources
Ample investment subsidies	Reluctance to install a new technology because you are unsure how to properly use it	Property Managers
Sufficient regulation and policy	Consider new technologies too immature at this point	Building Owners

Table A2. Ranking card items. (cont.)

Motivations (17 items)	Barriers (20 items)	Social Influences (24 items)
Reliability and Security	Technology will become cheaper in the future	Building Architects
Fresh air	Lack of regulation and policy	Customers
Maintain a healthy building	Building codes are too stringent	Large Corporations
	Insufficient incentives and/or rebates (and Better to wait for subsidies)	Online Forums
	Fear of change	Trade Journals
	Benefits are not often specialized for each customer	Controls Contractors
		Renewable Energy Companies
		ESCOS
		Building Contractors

Appendix A.6: Saturation curves

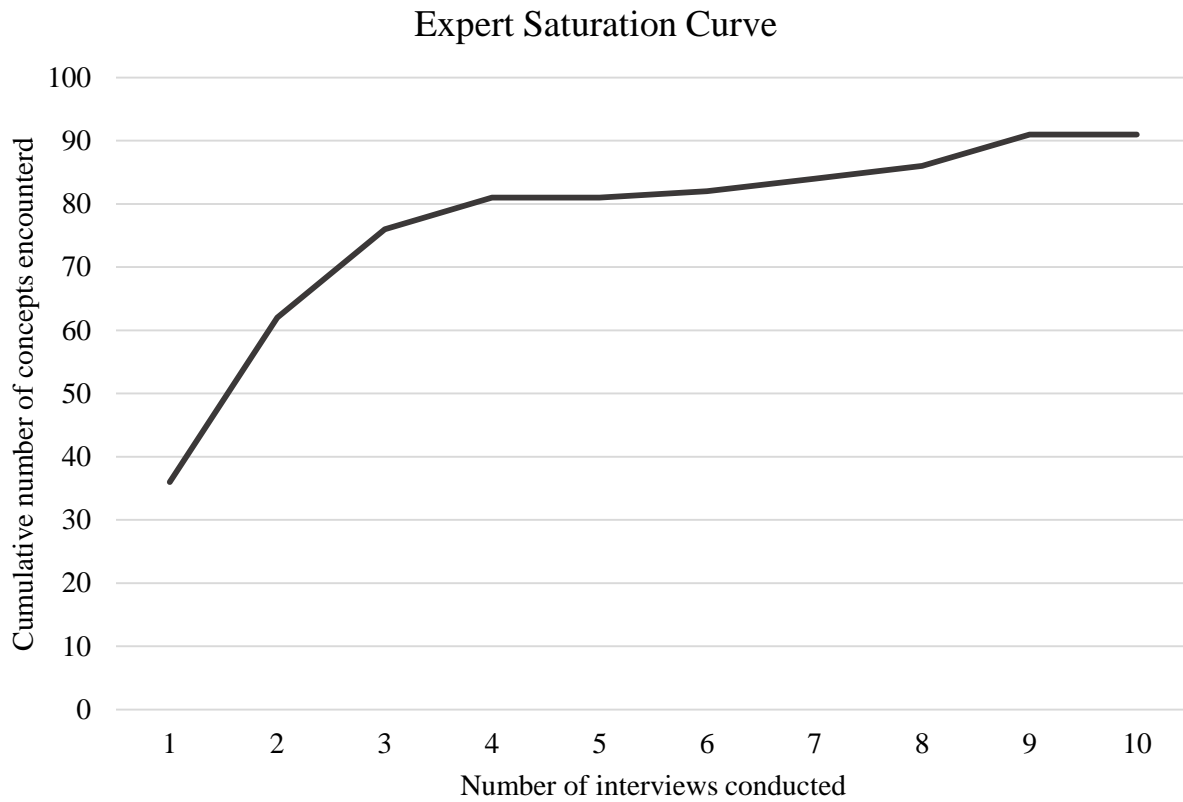


Figure A1. Expert saturation curve depicting new concepts plateauing at the 9th interview. A saturation curve depicts the number of new concepts encountered in mental models interviews. These curves for interviews on commercial building energy efficiency are conducted with populations having potentially similar beliefs.



Figure A2. Owner/manager saturation curve depicting new concepts plateauing at the 8th interview. A saturation curve depicts the number of new concepts encountered in mental models interviews. These curves for interviews on commercial building energy efficiency are conducted with populations having potentially similar beliefs.

Appendix A.7: Indicators of building energy efficiency

	Internal Competition	External Competition
High Commitment (required, frequent benchmarking; third-party reporting)	Energy Star LEED	Green Workplace Challenge
Low Commitment (voluntary, infrequent benchmarking; self-reporting)	Internal benchmarking Design to LEED standards	2030 District 2020 Challenge ASHE Stars

Figure A3. Energy efficiency matrix.

Appendix A.8: Interview participant data

Table A3. Interview participant demographics.

Order	Label	Interview Length (HH:MM:SS)	Organization Data		Demographic Data		
			Company/Building	Energy Star/LEED	Gender	Age	Level of Education
1	EE1	1:00:00	Development & Real Estate Management	N/A	Female	35	College Degree
2	OM1	1:00:00	Class A Commercial Building	Energy Star & LEED	Male	40	College Degree
3	EE2	1:00:00	Energy Efficiency Consultants	N/A	Male	50	Graduate Degree (MBA)
4	OM2	1:00:00	Class A Commercial Building	Energy Star & LEED	Female	28	College Degree
5	EE3	1:05:00	Energy Efficiency Consultants (NGO)	N/A	Female	36	College Degree
6	OM3	0:45:00	University	Energy Star & LEED	Male	55	College Degree
7	OM4	0:45:00	University	Energy Star & LEED	Male	52	Graduate Degree (PhD)
8	EE4	1:00:00	Development & Real Estate Management	N/A	Female	28	Graduate Degree (Master's)
9	EE5	0:45:00	Development & Real Estate Management	N/A	Female	28	College Degree
10	EE6	1:45:00	Academic	N/A	Female	70	Graduate Degree (PhD)
11	EE7	1:05:00	Energy Efficiency Consultant (ESCO)	N/A	Female	59	Graduate Degree (Master's)
12	EE8	1:10:00	Policy	N/A	Male	36	Graduate Degree (MBA)
13	OM5	1:10:00	Class A Commercial Building	Energy Star & LEED	Male	36	Technical School
14	EE9	1:30:00	Energy Efficiency Consultants	N/A	Male	48	College Degree
15	OM6	1:30:00	Biology Lab	None	Male	58	Marine Corps

Table A3. Interview participant demographics. (cont.)

Order	Label	Interview Length (HH:MM:SS)	Organization Data		Demographic Data		
			Company/Building	Energy Star/LEED	Gender	Age	Level of Education
16	OM7	1:45:00	Hospital	Energy Star	Male	57	College Degree
17	OM8	0:50:00	Class A Commercial Building	Energy Star & LEED	Female	43	Graduate Degree (Master's)
18	OM9	0:45:00	Class A Commercial Building	Energy Star & LEED	Male	50	High School Degree
19	OM10	0:45:00	Class A Commercial Building	None	Male	63	College Degree
20	EE10	1:10:00	Energy Efficiency Consultants	N/A	Male	45	Graduate Degree (PhD)

Appendix A.9: Master code

Table A4. Master codebook.

Code Name	Code	Subcode	Subcode Description
MO Self-perception of EE	MSPE	MSPEavg	owner/manager believes they are average
	MSPE	MSPEhigh	owner/manager believes they are energy efficient
	MSPE	MSPElow	owner manager believes they are inefficient
EE Definition	DEE	DEEbenchmarking	benchmarking, EUIs, save energy
	DEE	DEEcontrols	building controls or systems operations
	DEE	DEEenergystar	meet energy star is energy efficient
	DEE	DEElead	operating a building to meet LEED is energy efficient
	DEE	DEEsavemoney&energy	saves money on utilities or maintenance
	DEE	DEEoccupant	occupant comfort, productivity, stakeholder happiness
	DEE	DEErenewable	defines energy efficiency as renewable energy
	DEE	DEEsustainable&environment	energy efficiency is being sustainable or environmentally friendly
	DEE	DEEwater	people bring up water when discussing energy efficiency
Metering	UM	UMagg	building has aggregated utilities
	UM	UMsub	building has sub-metered utilities
Work Experience	EXP	EXPacad	academic
	EXP	EXParch	architect
	EXP	EXPconsultant	energy engineer, mechanical engineer, civil engineer, energy consultant
	EXP	EXPdev	developer
	EXP	EXPom	owner/manager
Investment Decision Process	IDP	IDPconsultant	owner/manager mentions they reach out to consultants
	IDP	IDPeconomics	desired economics
	IDP	IDPfinancing&budget	What the decision maker targets in incentives, financing, and budget of EE investment decisions
	IDP	IDPgoals&strategy	goals, investment is made to make or meet goals
	IDP	IDPinformation	information, specifics of what is required to make the decision
	IDP	IDPnoconsultant	owner/manager is adamant about not using consultants when considering EE investments
	IDP	IDPorganization	Chain of command and jurisdiction in EE investment decisions
	IDP	IDPpilot	pilot-testing is important to an investment decision

Table A4. Master codebook. (cont.)

Code Name	Code	Subcode	Subcode Description
Building Data	BD	BDage	age of building
	BD	BDcode	the building code or energy code the building complies with
	BD	BDcom	commercial building
	BD	Bdenergystar	building is energy star certified
	BD	BDleed	building is leed certified
	BD	BDlength	how long owner/manager has been with building
	BD	BDnegsystems	negative state of systems
	BD	BDnotunique	building does not have unique operating requirements
	BD	BDportfolio	owner/manager discusses how he/she is in charge of multiple buildings
	BD	BDpossystems	positive state of systems
	BD	BDunique	building has unique operating requirements
Building Staff	BS	BSenergyculturehi	the owners/managers/engineers are interested in building energy efficiency
	BS	BSenergyculturelow	the owners/managers/engineers are NOT interested in building energy efficiency
	BS	BSfocus	focus of the building operators
	BS	BSorganization	discussion of how the the building staff is organized
	BS	BSrelationshipavg	relationship with engineers and building staff isn't good or bad
	BS	BSrelationshipphi	owner/manager expresses a positive relationship with the building engineers
	BS	BStechnicalskills	building staff has technical skills required for ee
EE Investments	EEI	EEIfuture	the building plans to make EE investments in the future
	EEI	EEIhistoric	the building has made EE investments in the past
	EEI	EEInofuture	the building does not plan to make EE investments in the future
Organization Details	OD	ODcollab	company collaborations
	OD	ODhistory	company history
	OD	ODmission	company goals/mission/sector focus
	OD	ODsuccess	elements/examples of successful projects
Repeated Business	RRB	RRBmultistage	clients have long-term goals/foot in the door/multi-stage projects
	RRB	RRBportfolio	client has large portfolio
	RRB	RRBtrust&success	clients trust their work/past successes

Table A4. Master codebook. (cont.)

Code Name	Code	Subcode	Subcode Description
Energy Efficiency Climate	EEC	EECbuildingstock	existing building stock
	EEC	EECfinancing&rebates	existing financing, rebates, and incentive opportunities available
	EEC	EEClagging	Pittsburgh is lagging other cities
	EEC	EEClégislation&politics	existing legislation/policy/regulations/codes
	EEC	EEClowpriority	energy efficiency is a low priority
	EEC	EECnocomment	no comment/doesn't know
	EEC	EEContheverge	on the verge/in progress/ a change is on the way
	EEC	EECprogressive	Pittsburgh is progressive/a role model/very energy efficient
Market Gaps	MG	MGcom	commercial
	MG	MGnewconstruction	new construction
	MG	MGpublic	public
	MG	MGresidential	residential
Market Gap Solutions	MGS	MGSfinancial	financial - incentives, subsidies, financing, resources
	MGS	MGSinformation	information - education, discussion, peer groups
	MGS	MGSregulation	regulation - building codes, mandatory energy audits, mandatory benchmarking
	MGS	MGtechnology	technologies - specific mention of technology solutions to close gaps
Energy Star Designation	ESTAR	ESTARnegative	negative description of Energy Star
	ESTAR	ESTARpositive	Energy Star benefits
Energy Star Target Goals	ESTG	ESTGairquality&comfort	air quality, fresh air, occupant comfort
	ESTG	ESTGbehavior&controls	occupant behavior and controls
	ESTG	ESTGnone	interviewee doesn't thinking energy star should be targeting anything
	ESTG	ESTGsubmetering	technologies LEED should target
	ESTG	ESTGunknown	unknown/interviewee doesn't have a response
LEED Certification	LEED	LEEDnegative	negative description of LEED
	LEED	LEEDpositive	LEED benefits to building or owner

Table A4. Master codebook. (cont.)

Code Name	Code	Subcode	Subcode Description
LEED Target Goals	LTG	LTGairquality&comfort	air quality, fresh air, occupant comfort
	LTG	LTGbehavior&controls	occupant behavior and controls
	LTG	LTGmarketgap	sectors and market gaps
	LTG	LTGnone	interviewee doesn't think LEED should be targeting anything
	LTG	LTGunknown	unknown/interviewee doesn't have a response
Mandatory Energy Benchmarking	MEB	MEBmethod	subject provides explanation for how it might be implemented
	MEB	MEBneg	negative reaction to MEA
	MEB	MEBpos	positive reaction to MEA
Mandatory Energy Auditing	MEA	MEAmethod	subject provides explanation for how it might be implemented
	MEA	MEAneg	negative reaction to MEA
	MEA	MEApos	positive reaction to MEA
Perception of EE Public Subsidies	PS	PSpos	positive perception of public subsidies
	PS	PSneg	negative perception of public subsidies
	PS	PSmethod	subject discusses methods for implementing public subsidies
Motivations	MOT	MOTagendasetting	agenda setting; people may feel compelled to pursue EE if their financial
	MOT	MOTimminent	institution requests/requires it
	MOT	MOTmentalacct	imminent technology replacement
	MOT	MOTmission&leadership	mental accounting; where money comes from plays a role
	MOT	MOTnot	mission/signal to other buildings/leadership/reputation/competition
	MOT	MOTrealestate	explicitly listed as not a motivation
	MOT	MOTrewarding	increase real estate value
	MOT	MOTsavemoney	people feel saving energy to be rewarding work
	MOT	MOTsecurity	save money / bottom line
	MOT	MOTstakeholders	energy security / reliability
	MOT	MOTSustain&environment	occupant health, comfort, productivity, stakeholders
			energy efficiency is a way to help environment and/or be sustainable

Table A4. Master codebook. (cont.)

Code Name	Code	Subcode	Subcode Description
Barriers	BAR	BAReconomic - not split inc.	economic or financial barriers to EE investment decision (besides split incentive)
	BAR	BARfearofchange	fear of change defined or discussed
	BAR	BARinformation	confusing/don't know where to start/benefits are not specified for owners
	BAR	BARlegislation&code	barriers related to building or city codes, legislation, regulation
	BAR	BARlowpriority	low priority
	BAR	BARnot	explicitly listed as not a barrier
	BAR	BARoldsystems	the building is old and inherently inefficient
	BAR	BARsplitincentive	split incentive issue
	BAR	BARstakeholders	low tenant/stakeholder engagement
	BAR	BARtechnicalsupport	building doesn't have skillset required for energy efficient technologies
	BAR	BARuncertainty	uncertainty of savings or technology operation
Social Influences	SI	SIacademia	universities, professors, or graduate students
	SI	SIbuildingengineer	building engineers
	SI	SIconsultants	consultants
	SI	SIgeo	other cities, states, regions, or countries
	SI	SIgovt	government
	SI	SIinternet	internet resources
	SI	SInone	interviewee says there isn't any other role models they can think of
	SI	SInot	explicitly listed as not a social influence
	SI	SIpeers	peer organizations, role model companies/organizations, competition
	SI	SIprofessionalsocieties	professional societies, conferences
	SI	SIpublications	owner/manager references publications
	SI	SIstakeholders	tenants, employees, students, faculty, or board members
	SI	SIutilities	utility companies

Table A4. Master codebook. (cont.)

Code Name	Code	Subcode	Subcode Description
Pro. Societies - names	PSN	PSNaap	american association of planners
	PSN	PSNaass	american association for the advancement of science (aaas)
	PSN	PSNaee	association of energy engineers
	PSN	PSNaess	association for the environmental studies and sciences (aess)
	PSN	PSNaia	american institute of architects
	PSN	PSNapa	association of plant administrators
	PSN	PSNappa	educational facilities mgmt
	PSN	PSNasbc	american sustainable building council (asbc)
	PSL	PSNasce	american society of civil engineers
	PSN	PSNasee	american society of engineering education
	PSN	PSNaashe	associoation for the advancement of sustainability in higher education
	PSN	PSNashrae	member of ashrae
	PSN	PSNboma	BOMA
	PSN	PSNbpi	building performance institute
	PSN	PSNcoaa	construction owners association of america
	PSN	PSNcommittee	interviewee sits on various city committees
	PSN	PSNcos	champions of sustainability
	PSN	PSNees	environmental education society
	PSN	PSNenergyfoundation	the energy foundation
	PSN	PSNgba	green building alliance
	PSN	PSNhpn	Housing Partnership Network
	PSN	PSNifma	international facility mgmt association
	PSN	PSNnaiop	national association of industrial properties
	PSN	PSNnaruc	national association of regulated utility commissioners (naruc)
	PSN	PSNosha	OSHA
	PSN	PSNpahma	professional affordable housing managers association
	PSN	PSNpdp	pittsburgh downtown partnership
	PSN	PSNrelay	Relay Network
	PSN	PSNscup	society for college and urban planning
	PSN	PSNusgbc	US green building council

Table A4. Master codebook. (cont.)

Code Name	Code	Subcode	Subcode Description
Pro. Societies - purposes	PSP	PSPinsight	insight, peer sharing, education
	PSP	PSPlobbying	lobbying, policy development
	PSP	PSPnetwork	networking and finding clients
Pro. Societies - involvement	PSI	PSIavg	medium engagement, ranking 3
	PSI	PSIhigh	high engagement, ranking 4-5 (if 5 is high) and 1-2 (if 1 is high)
	PSI	PSIlow	low engagement, ranking 1-2 (if 5 is high) and 4-5 (if 1 is high)
Building Technologies	BT	BTasp	aspirational building technologies
	BT	BTdifficult	technologies that subject thinks owners/managers have difficulty installing
	BT	BTminimum	technologies that subject thinks building should have in place at minimum
Demographic Data	DD	DDage	age of the participant
	DD	DDeducation	highest level of educational attainment
	DD	DDinterview	interview experience; points out interview gaps; discussion of interview process
	DD	DDtitle	interviewee's official title
New Contact	NC		interviewee mentions another contact

Appendix A.10: Investment decision process subcode organization

Table A5. Investment decision process subcodes.

Context	Economics	Technology	Psychology
IDPorganization	IDPeconomics	IDPinformation	Fear of Change
IDPgoals&strategy	IDPfinancing&budget	IDPpilot	Mental Accounting
IDPconsultant	BAReconomic - not split incentive	BARoldsystems	MOTAgendaSetting
IDPnoconsultant	BARuncertainty	MOTimminent	MOTRewarding
BARlowpriority	BARsplitincentive		
BARtechnicalsupport	MOTsavemoney		
BARstakeholders			
BARlegislation&code			
MOTmission&leadership			
MOTstakeholders			
MOTrealestate			
MOTsecurity			
MOTSustain&environment			
Sistakeholders			
Siprofessionalsocieties			
Sipeers			
SIgovt			
SIacademia			
Siconsultants			
Sinternet			
Slutilities			
SIbuildingengineer			
SIgeo			
SInone			

Table A5. Investment decision process subcodes.

Context	Economics	Technology	Psychology
SIpublications			
BSenergyculturehi			
BSorganization			
BSrelationship			
BSfocus			
BStechnicalskills			
BSrelationshipavg			
PPSNetworking			
PPSInsight			
PPSLobbying			
ProfHigh			
ProfLow			
ProfAverage			

Appendix A.11: Barrier boxplots

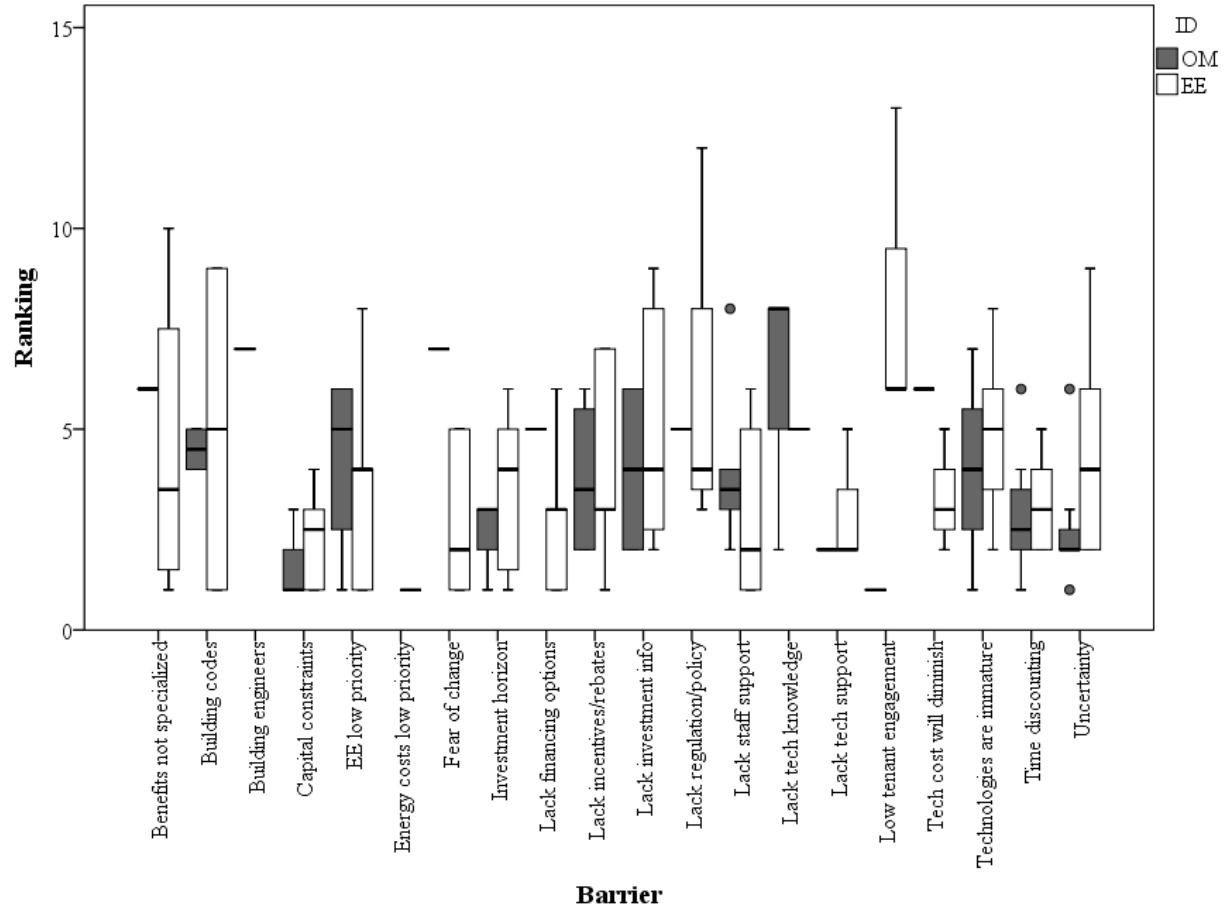


Figure A4. Barrier boxplots.

Appendix A.12: Motive boxplots

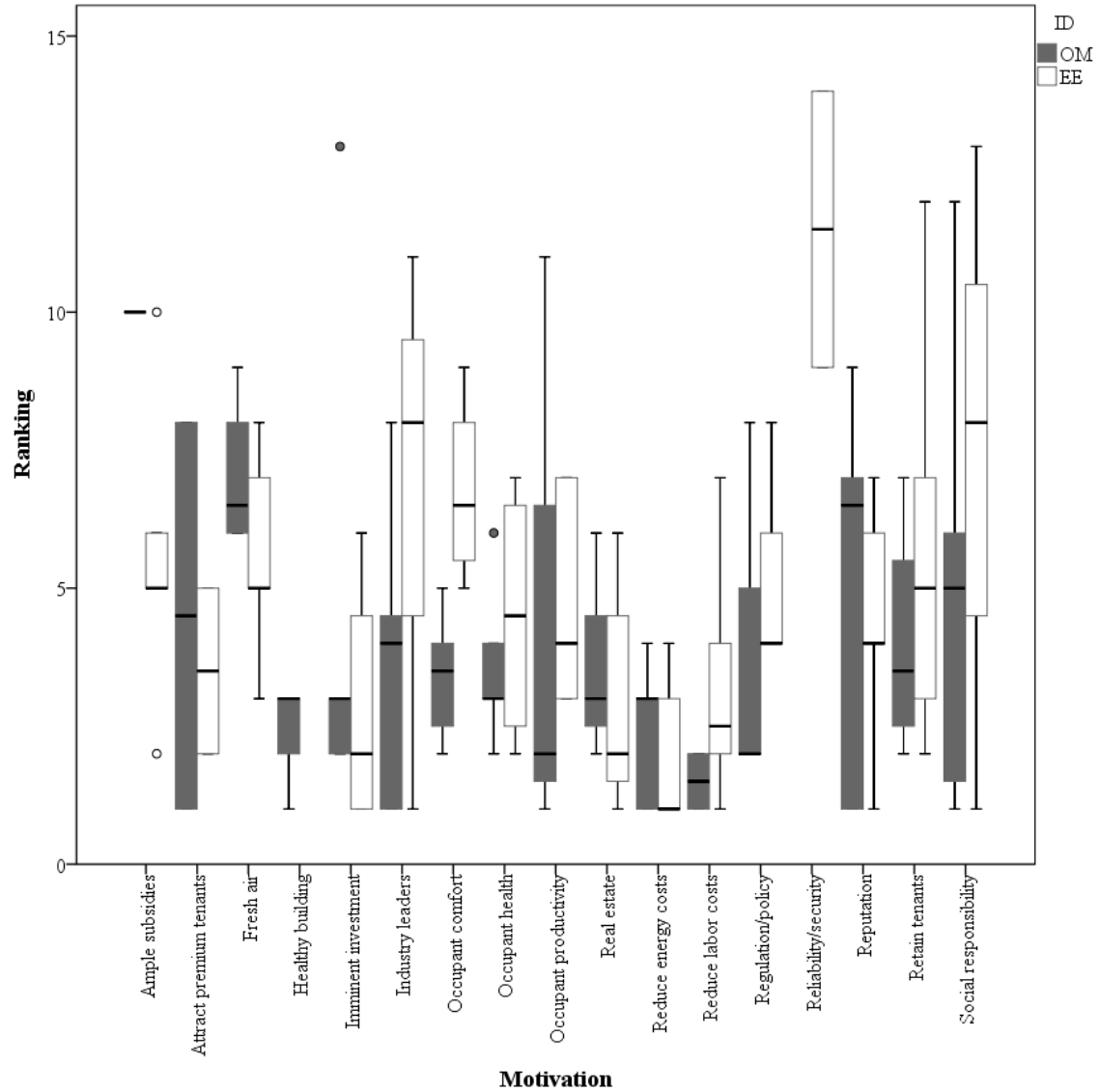


Figure A5. Motivation boxplots.

Appendix A.13: Social influence boxplots

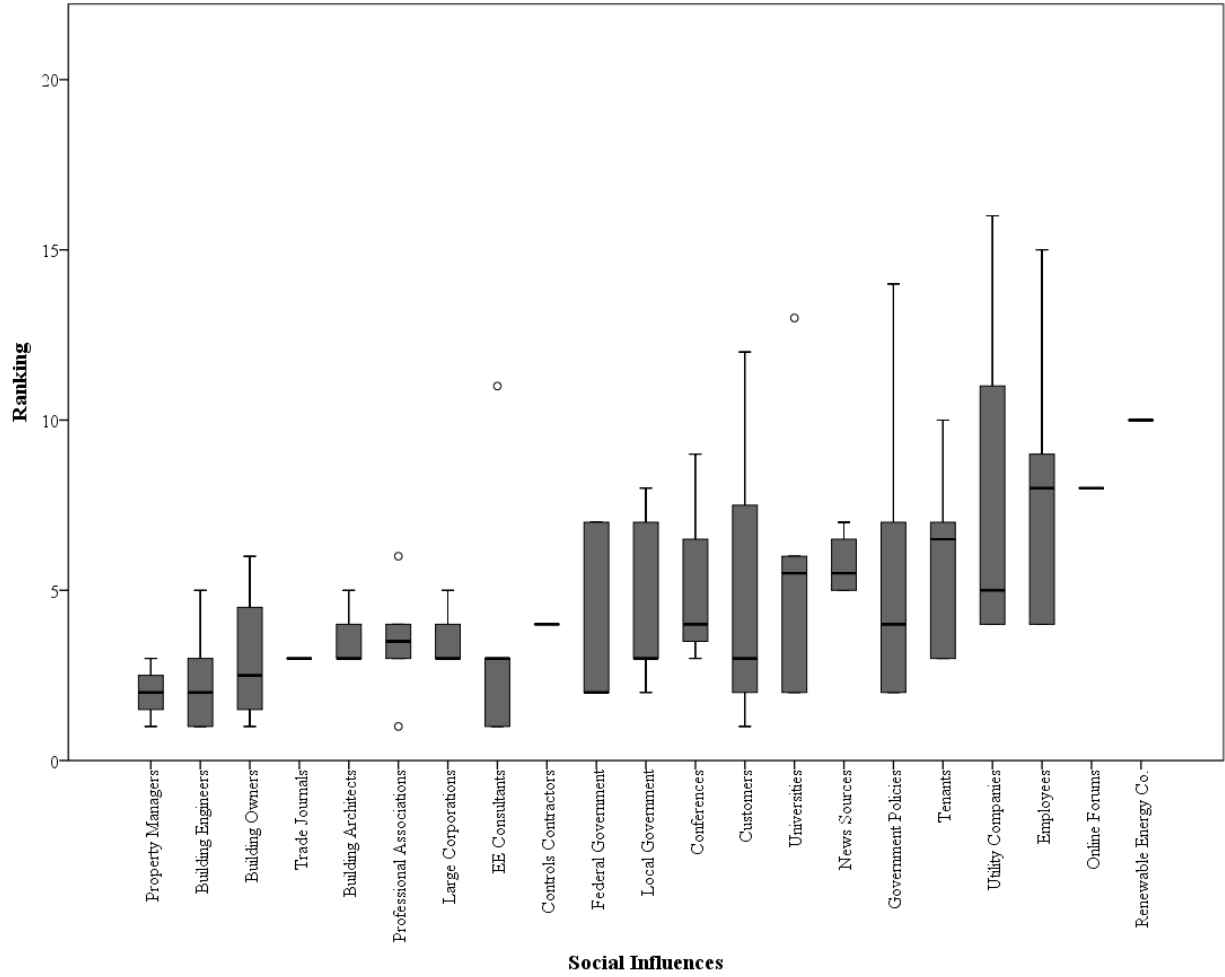


Figure A6. Social influence boxplots.

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Appendix B.1: Background and theoretical models

One way to signal dissatisfaction with fossil fuels is through direct or indirect forms of civic engagement [1-4] such as voting, demonstrations, signing petitions, and fundraising.

Increasingly, clean energy is perceived as an important policy goal among the general public and is a growing movement. However, not everyone expresses their views about energy through civic engagement because they have low expectations for change and/or energy is seen as an issue of less importance compared to others such as health care [5]. Perceptions about the value and effectiveness of civic engagement on energy issues may be changing as negative externalities associated with the current energy system are more widely understood and as environmental regulatory bodies such as the Environmental Protection Agency are weakened through proposed budget cuts [6-8]. The challenge, however, is learning how to leverage this concern and transform it into action on clean energy issues.

Studies find that framing, selectively emphasizing certain dimensions of an issue over others [9], [10] can promote pro-environmental behaviors such as buying more energy efficient technologies and practicing curbside recycling [11], [12]. Research suggests that framing should target people's unique social, psychological, and cultural makeup [13-15], otherwise messaging may backfire. For example, appealing to the potential monetary savings of an energy efficiency program can be a powerful way to engage audiences [16-21], yet doing so can have unintended consequences ("boomerang effect") [22]. Schwartz et al. [23] found among those who saw themselves as environmentalists, emphasizing monetary benefits reduced their willingness to participate in the programs. Thus, targeted energy and climate campaigns sensitive to the knowledge and values of the intended audience increases the chances of success [24].

One potential target audience for clean energy campaigns is parents. Parenthood has been described as either a hindrance to political activism, because parents are so busy, or a reason to participate [25]. However, there is a strong reason to believe that parents can be powerful agents of change. Examples of parent movements abound, including the immensely successful Mothers Against Drunk Driving (MADD) founded by Candy Lightner [26]; Shannon Watts' Moms Demand Action for Gun Sense in America [27]; and more recently MomsRising, who campaign for initiatives such as maternity/paternity leave as well as health care for all [28]. Other seminal examples of parent initiatives include Lois Gibbs' establishment of the Love Canal Homeowner's Association that lobbied successfully for the remediation of hazardous chemical

waste in Niagara Falls, New York [29] and Mary Brune's *Making our Milk Safe* initiative, which demanded that retailers stop selling baby products made with polyvinyl chloride [30]. Finally, there also exists the EcoMom Alliance, a nonprofit empowering women through education to help create an "environmentally, socially and economically sustainable future" [31] and numerous school cafeteria food initiatives such as Farm to School [32] or Parents for Healthy Schools [33]. Drawing on these examples, there is reason to believe that parents wishing to protect their children from environmental threats, such as buried toxic waste and water pollution, are more likely to be proactive environmentalists [34], [35]. Understanding how to harness natural parental concern about their children's health and future to motivate civic engagement on clean energy is an empirical question and one that we seek to address in this paper.

To understand how parents might be motivated to urge their utilities to increase clean energy generation, we turn to psychological models of decision-making such as the theory of planned behavior (TPB) [36]. Within the framework of TPB, beliefs about such things as self-efficacy, subjective norms, and/or the behavior in question determine intention to act and consequent behavior [36]. TPB has been used to predict environmental behavior in the past [37] – in a recent meta-analysis, Bamberg and Möser [38] demonstrate that behavioral intentions are predictive of pro-environmental actions (e.g. explaining 27% of variance) and that personal moral norms are predictive of intentions (e.g. explaining 52% of variance). Additionally, in a review of the literature, Stern [39] highlights that contextual forces and personal capabilities/habits contribute to the effect that attitudes have on behaviors. With regards to civic engagement, it is shown that opinion intensity is a central driver of participation on policy issues and is predictive of whether or not a citizen calls or writes to their elected official, participates in public demonstration, or joins an advocacy group [40], [41]. Therefore, the TPB framework suggests that one should focus on understanding attitudes and measuring intentions in order to understand the likelihood of civic engagement uptake.

Still, some policies aim to promote desired behaviors by simply increasing information dissemination and closing the Value-Action Gap that persists when members of society espouse pro-environmental values but do not act in accordance with them [42]. However, this theory of behavior change, coined the Information Deficit Model, fails to address why some science communications increase polarization and result in non-activity or worse, increased anti-environmental attitudes [43], [44]. As such, these complex dimensions of civic engagement are

little understood in the context of electricity consumers' preferences and personal actions towards increasing clean energy generation. In our study, we expose parent electricity customers to various forms of clean energy campaign framing and assess their shifts in attitudes and consequential behavioral intentions and actions.

Framing involves selectively emphasizing certain dimensions of an issue over the others, which implies (inadvertently or not) a specific diagnosis as well as prescription for action [9], [10]. It is difficult to avoid framing within science communication, as a clear goal of such communication is to increase understanding across audiences by emphasizing certain technical details over others [14]. In addition to improving comprehension of technical details, social scientists have also shown that the way an issue is framed has important consequences in consumer judgement tasks [45], [46]. It can be particularly influential when the targeted audience is predisposed to a certain topic or has close psychological distance to the message [14], [47]. Media framing around climate change has ranged from a *Social Progress* frame (e.g. means of improving quality of life or solving problems) to a *Pandora's Box* frame (e.g. a need for action in face of possible catastrophe and out-of-control consequences); these media frames tend to have polarizing results with Republicans and Democrats [9]. Therefore, Nisbet suggests developing and utilizing new frames that could have relevant narratives for nontraditional audiences, such as focusing on local public health implications of climate change [9]. In developing these atypical frames, there is an opportunity to leverage the theory of motivated reasoning which suggest that partisan audiences (e.g. parents with young children) are motivated to interpret and process information in a biased manner that reinforces their predispositions [48], [49]. Even more, one could identify trusted information sources within these partisan audiences (i.e. advocacy groups) to deliver the clean energy campaigns as it is shown that trusted messengers can reinforce framing effects [50]. In conclusion, we find that framing can have stronger effects on those who have personal interest in the topic or trust in the messenger.

We experiment with various clean energy campaign framing designed to improve attitudes towards clean energy and promote civic engagement among parents. We include a cost frame that suggests introducing more clean energy into a portfolio will lower costs to the consumer in the long-run. We believe this campaign might appeal to consumers who are interested in optimizing private benefits [51], [52]; however, we also expect this campaign to crowd out intrinsic motivations of environmentalists and discourage action [53], [54]. We also

include a health frame, as it is shown that promoting the health benefits associated with clean energy is motivating for at-risk consumers such as urban communities, families with children, or consumers with asthmatics in the home [52]. Our climate frame depicts the negative environment- and climate-related weather impacts that can result from increased CO₂ emissions from the burning of fossil fuels. We believe this frame might appeal most to environmentalists wishing to signal altruistic values [53], but might also result in a boomerang effect among participants with more conservative values [44]. Finally, we include a health + climate campaign that combines the information provided in the health campaign with the information provided in the climate campaign. Aside from framing, other individual differences are expected to inspire or discourage pro-environmental behavior. For instance, Lorenzoni et al. demonstrate that feelings of hope and efficacy are strongly correlated with a willingness to engage in pro-environmental behaviors [55]. In contrast, Norgaard [56] finds that feelings of hopelessness and inefficacy related to climate change are linked with a tendency to rationalize inaction. Here we assess the generalizability of these clean energy campaigns on influencing parents' attitudes towards clean energy and engaging them in taking advocacy action to increase their utilities' clean energy portfolios.

References

- [1] M. X. D. Carpini, F. L. Cook, and L. R. Jacobs, "Public Deliberation, Discursive Participation, And Citizen Engagement: A Review of the Empirical Literature," *Annu. Rev. Polit. Sci.*, vol. 7, pp. 315–344, 2004.
- [2] S. Keeter, C. Zukin, M. Adolina, and K. Jenkins, "The civic and political health of the nation: A generational portrait," 2002.
- [3] G. Burke, C. Finn, and A. Murphy, "Community Choice Aggregation: the Viability of Ab 117 and Its Role in California'S Energy Markets," 2005 *Eur. Microw. Conf.*, pp. xiii–xlv, 2005.
- [4] S. Littlechild, "Municipal aggregation and retail competition in the Ohio energy sector," *J. Regul. Econ.*, vol. 34, pp. 164–194, 2008.
- [5] J. C. Rogers, E. A. Simmons, I. Convery, and A. Weatherall, "Public perceptions of opportunities for community-based renewable energy projects," *Energy Policy*, vol. 36, no. 11, pp. 4217–4226, 2008.
- [6] S. M. Hoffman, "Community Energy: A Social Architecture for an Alternative Energy Future," *Bull. Sci. Technol. Soc.*, vol. 25, no. 5, pp. 387–401, 2005.
- [7] G. Thrush and C. Davenport, "Donald Trump Budget Slashes Funds for E.P.A. and State Department," *The New York Times*, 15-Mar-2017.

- [8] C. Davenport, "Trump Budget Would Cut E.P.A. Science Programs and Slash Cleanups," *The New York Times*, 19-May-2017.
- [9] M. C. Nisbet, "Communicating Climate Change: Why Frames Matter for Public Engagement," *Environ. Sci. Policy Sustain. Dev.*, vol. 51, no. 2, pp. 12–23, 2009.
- [10] T. Myers, M. Nisbet, E. Maibach, and A. Leiserowitz, "A public health frame arouses hopeful emotions about climate change A Letter," *Clim. Change*, vol. 113, pp. 1105–1112, 2012.
- [11] J. Min, I. L. Azevedo, J. Michalek, and W. B. de Bruin, "Labeling energy cost on light bulbs lowers implicit discount rates," *Ecol. Econ.*, vol. 97, pp. 42–50, 2014.
- [12] P. W. Schultz, "Changing Behavior With Normative Feedback Interventions : A Field Experiment on Curbside Recycling," *Basic Appl. Soc. Psychology*, vol. 21, no. 1, pp. 25–36, 1999.
- [13] D. J. Bem, "Self-perception: An alternative interpretation of cognitive dissonance phenomena.," *Psychol. Rev.*, vol. 74, no. 3, pp. 183–200, 1967.
- [14] M. C. Nisbet and D. A. Scheufele, "What's next for science communication? promising directions and lingering distractions," *Am. J. Bot.*, vol. 96, no. 10, pp. 1767–1778, 2009.
- [15] C. Roser-Renouf, N. Stenhouse, J. Rolfe-Redding, E. Maibach, and A. Leiserowitz, "Engaging Diverse Audiences with Climate Change: Message Strategies for Global Warming's Six Americas," *SSRN*, 2014.
- [16] A. Star, M. Isaacson, D. Haeg, L. Kotewa, and CNT Energy, "The Dynamic Pricing Mousetrap: Why Isn't the World Beating Down Our Door?," in *2010 ACEEE Summer Study on Energy Efficiency in Buildings*, 2010, pp. 257–268.
- [17] AdCouncil, "U.S. Department of Energy and Ad Council Launch Consumer Education Campaign: Save Money By Saving Energy," 2011.
- [18] L. Evans, G. R. Maio, A. Corner, C. J. Hodgetts, S. Ahmed, and U. Hahn, "Self-interest and pro-environmental behaviour," *Nat. Clim. Chang.*, vol. 3, no. 2, pp. 122–125, 2012.
- [19] J. G. Holmes, D. T. Miller, and M. J. Lerner, "Committing altruism under the cloak of self-interest: The exchange fiction," *J. Exp. Soc. Psychol.*, vol. 38, no. 2, pp. 144–151, 2002.
- [20] J. Thøgersen, "Green Shopping: For Selfish Reasons or the Common Good?," *Am. Behav. Sci.*, vol. 55, no. 8, pp. 1052–1076, 2011.
- [21] D. J. Penn, "The Evolutionary Roots of Our Environmental Problems: Toward a Darwinian Ecology," *Q. Rev. Biol.*, vol. 78, no. 3, pp. 275–301, 2003.
- [22] J. W. Bolderdijk, L. Steg, E. S. Geller, P. K. Lehman, and T. Postmes, "Comparing the effectiveness of monetary versus moral motives in environmental campaigning," *Nat. Clim. Chang.*, vol. 3, no. 4, pp. 413–416, 2013.

- [23] D. Schwartz, W. Bruine de Bruin, B. Fischhoff, and L. Lave, "Advertising energy saving programs: The potential environmental cost of emphasizing monetary savings.," *J. Exp. Psychol. Appl.*, vol. 21, no. 2, pp. 158–66, 2015.
- [24] T. Ming Lee, E. M. Markowitz, P. D. Howe, C.-Y. Ko, and A. A. Leiserowitz, "Predictors of public climate change awareness and risk perception around the world," *Nat. Clim. Chang.*, vol. 5, no. November, pp. 1014–1019, 2015.
- [25] R. E. Klatch, "The contradictory effects of work and family on political activism," *Qual. Sociol.*, vol. 23, no. 4, pp. 505–519, 2000.
- [26] J. C. Fell and R. B. Voas, "Mothers Against Drunk Driving (MADD): the first 25 years.," *Traffic Inj. Prev.*, vol. 7, no. 3, pp. 195–212, 2006.
- [27] R. Berman, "The Split Between the States Over Guns," *The Atlantic*, 31-Dec-2015.
- [28] R. Berkman, "Nonprofits Get More From Social Media with Metrics," *MIT Sloan Manag. Rev.*, vol. 55, no. 1, p. 1, 2013.
- [29] K. Hess, "Motherhood as a Unifying Theme in Social Movements : Symbolic Essentialism , Environmental Justice , and the Movement Against Bisphenol A in Maine," *Honor. Coll.*, vol. 55, 2012.
- [30] G. Dicum, "Fed up with breast-milk contamination, mothers form a national activist group," *Grist*, 07-Nov-2006.
- [31] S. C. Logsdon-Conradsen and S. L. Allred, "Motherhood and environmental activism: A developmental framework.," *Ecopsychology*, vol. 2, no. 3, pp. 141–146, 2010.
- [32] Tides Center, "National Farm to School Network," 2017. [Online]. Available: <http://www.farmtoschool.org/>. [Accessed: 04-Jun-2017].
- [33] Centers for Disease Control and Prevention, "Parents for Healthy Schools: A Guide for Getting Parents Involved from K-12," *US Dept. Heal. Hum. Serv.*, no. November, 2015.
- [34] L. Hamilton, "Concern about Toxic Wastes: Three Demographic Preditors," *Sociol. Perspect.*, vol. 28, no. 4, pp. 463–486, 1985.
- [35] L. Hamilton, "Who cares about water pollution? Opinions in a small-town crisis," *Sociol. Inq.*, vol. 55, no. 2, pp. 170–181, 1985.
- [36] I. Ajzen, "The theory of planned behavior," *Orgnizational Behav. Hum. Decis. Process.*, vol. 50, pp. 179–211, 1991.
- [37] J. M. Hines, H. R. Hungerford, and A. N. Tomera, "Analysis and Synthesis of Research on Responsible Environmental Behavior: A Meta-Analysis," *J. Environ. Educ.*, vol. 18, no. 2, pp. 1–8, 1987.

- [38] S. Bamberg and G. Möser, "Twenty years after Hines, Hungerford, and Tomera: A new meta-analysis of psycho-social determinants of pro-environmental behaviour," *J. Environ. Psychol.*, vol. 27, no. 1, pp. 14–25, 2007.
- [39] P. C. Stern, "Toward a Coherent Theory of Environmentally Significant Behavior," *J. Soc. Issues*, vol. 56, no. 3, pp. 407–424, 2000.
- [40] S. Verba, K. L. Schlozman, and H. E. Brady, *Voice and equality: Civic voluntarism in American politics*. Harvard University Press, 1995.
- [41] K. Goidel and M. C. Nisbet, "Exploring the Roots of Public Participation in the Controversy Over Embryonic Stem Cell Research and Cloning," *Polit. Behav.*, vol. 28, no. 2, pp. 175–192, 2006.
- [42] E. Shove, "Beyond the ABC: Climate change policy and theories of social change," *Environ. Plan. A*, vol. 42, no. 6, pp. 1273–1285, 2010.
- [43] P. Sturgis and N. Allum, "Science in Society: Re-Evaluating the Deficit Model of Public Attitudes," *Public Underst. Sci.*, vol. 13, no. 1, pp. 55–74, 2004.
- [44] P. S. Hart and E. C. Nisbet, "Boomerang Effects in Science Communication: How Motivated Reasoning and Identity Cues Amplify Opinion Polarization About Climate Mitigation Policies," *Communic. Res.*, vol. 39, no. 6, pp. 701–723, 2012.
- [45] I. P. Levin, R. D. Johnson, C. P. Russo, and P. J. Deldin, "Framing effects in judgment tasks with varying amounts of information," *Organ. Behav. Hum. Decis. Process.*, vol. 36, no. 3, pp. 362–377, 1985.
- [46] D. Kahneman, "Maps of bounded rationality: a perspective on intuitive judgment and choice," *Sveriges Riksbank Prize Econ. Sci. Mem. Alfred Nobel*, no. December, pp. 449–489, 2002.
- [47] D. Scheufele, "Framing as a theory of media effects," *J. Commun.*, vol. 49, no. 1, pp. 103–122, 1999.
- [48] Z. Kunda, "The case for motivated reasoning," *Psychol. Bull.*, vol. 108, no. 3, pp. 480–498, 1990.
- [49] C. S. Taber and M. Lodge, "Motivated Skepticism in the Evaluation of Political Beliefs," *Am. J. Pol. Sci.*, vol. 50, no. 3, pp. 755–769, 2006.
- [50] M. C. Nisbet and J. E. Kotcher, "A Two-Step Flow of Influence?: Opinion-Leader Campaigns on Climate Change," *Sci. Commun.*, vol. 30, no. 3, pp. 328–354, 2009.
- [51] R. Thaler and C. Sunstein, *Nudge: Improving Decisions About Health, Wealth, and Happiness*. New Haven & London: Yale University Press, 2008.
- [52] J. M. Hines, H. R. Hungerford, and A. N. Tomera, "Analysis and Synthesis of Research on Responsible Pro-environmental Behaviour: a Meta Analysis," *J. Environ. Educ.*, vol. 18, pp. 1–8, 1986.

- [53] D. Ariely, A. Bracha, and S. Meier, “Doing good or doing well? Image motivation and monetary incentives in behaving prosocially,” *Am. Econ. Rev.*, vol. 99, no. 1, pp. 544–555, 2009.
- [54] U. Gneezy, S. Meier, and P. Rey-Biel, “When and Why Incentives (Don’t) Work to Modify Behavior,” *J. Econ. Perspect.*, vol. 25, no. 4, pp. 191–210, 2011.
- [55] I. Lorenzoni, S. Nicholson-Cole, and L. Whitmarsh, “Barriers perceived to engaging with climate change among the UK public and their policy implications,” *Glob. Environ. Chang.*, vol. 17, no. 3–4, pp. 445–459, 2007.
- [56] K. M. Norgaard, *Living in denial. Climate change, emotions, and everyday life*. Cambridge, Massachusetts: The MIT Press, 2011.

Appendix B.2: Electricity generation portfolios, by state and utility

We targeted members who were customers of select utilities residing in Michigan (Consumers Energy and DTE Energy), Florida (Florida Power and Light and Duke Energy), and California (Southern California Edison). We selected these utility districts and states based on advocacy group membership, divergent energy profiles, and strategic importance to the climate movement [1-4]. According to the 2015 American Community Survey, Michigan, Florida, and California were estimated to have total populations of 9.9 million, 19.6 million, and 38.4 million, respectively [1]. Michigan has historically been highly dependent on coal for electricity generation [2]; Florida has a high potential for solar energy, but the public utility commission (PUC) has blocked distributed generation solar programs [3]; and California has consistently shown strong support for renewable energy, energy efficiency, and carbon reduction goals [3], [4].

Table B1. Electricity generation portfolios across states, as of September 2016.

% of Electricity Generation	Michigan	Florida	California
Coal-Fired	37%	19%	-
Natural Gas-Fired	24%	68%	53%
Nuclear	32%	11%	9%
Hydroelectric	1%	-	13%
Other Renewables	6%	2%	25%

Table B2. Electricity generation portfolios across utilities.

% of Electricity Generation	Consumers Energy ¹	DTE Energy ²	Florida Power and Light ³	Duke Energy ⁴	Southern California Edison ⁶
Coal-Fired	46%	74%	5%	36%	-
Natural Gas-Fired	23%	4%	70%	29%	27%
Nuclear	21%	17%	17%	34%	6%
Hydroelectric	2%	0.2%	-	-	3%
Renewables	8%	5%	0.1%	1% ⁵	24%
Purchased Power and Misc.	-	-	7.9%		40%

¹April 2015 - March 2016; https://www.consumersenergy.com/uploadedFiles/CEWEB/OUR_ENVIRONMENT/Electric-Sources.pdf

²January 2013 - December 2013;

<https://www2.dteenergy.com/wps/portal/dte/aboutus/environment/details/Generation%20and%20Emissions/Fuel%20Mix>

³June 2012 - May 201; <https://www.fpl.com/clean-energy/plant-projects.html>

⁴January 2015 - December 2015; <http://sustainabilityreport.duke-energy.com/pdfs/15-duke-sr-at-a-glance.pdf>

⁵Includes hydroelectric and solar.

⁶January 2014 - December 2014; [http://www.energy.ca.gov/pcl/labels/2014_labels/all_labels/Southern_California_Edison_\(SCE\).pdf](http://www.energy.ca.gov/pcl/labels/2014_labels/all_labels/Southern_California_Edison_(SCE).pdf)

References

- [1] U.S. Census Bureau, “2011-2015 American Community Survey 5-Year Estimates,” *U.S. Census Bureau*, 2016. [Online]. Available: <https://factfinder.census.gov/faces/tableservices/jsf/pages/productview.xhtml?src=CF>. [Accessed: 12-Dec-2016].
- [2] U.S. EIA, “Table CT1. Energy Consumption Estimates for Major Energy Sources in Physical Units, 1960-2014, Michigan,” *Energy Information Agency*, 2016. [Online]. Available: https://www.eia.gov/state/seds/data.php?incfile=%2Fstate%2Fseds%2Fsep_us_e%2Ftotal%2Fuse_tot_MIa.html&%3Bsid=MI. [Accessed: 29-Dec-2016].
- [3] A. Proudlove, B. Lips, D. Sarkisian, and A. Shrestha, “The 50 States of Solar Report: 2016 Annual Review and Q4 Update,” 2016.
- [4] CEC, “California Energy Commission,” *Ca.gov*, 2017. [Online]. Available: <http://www.energy.ca.gov/>. [Accessed: 29-Dec-2016].

Appendix B.3: Advocacy group survey send-out emails

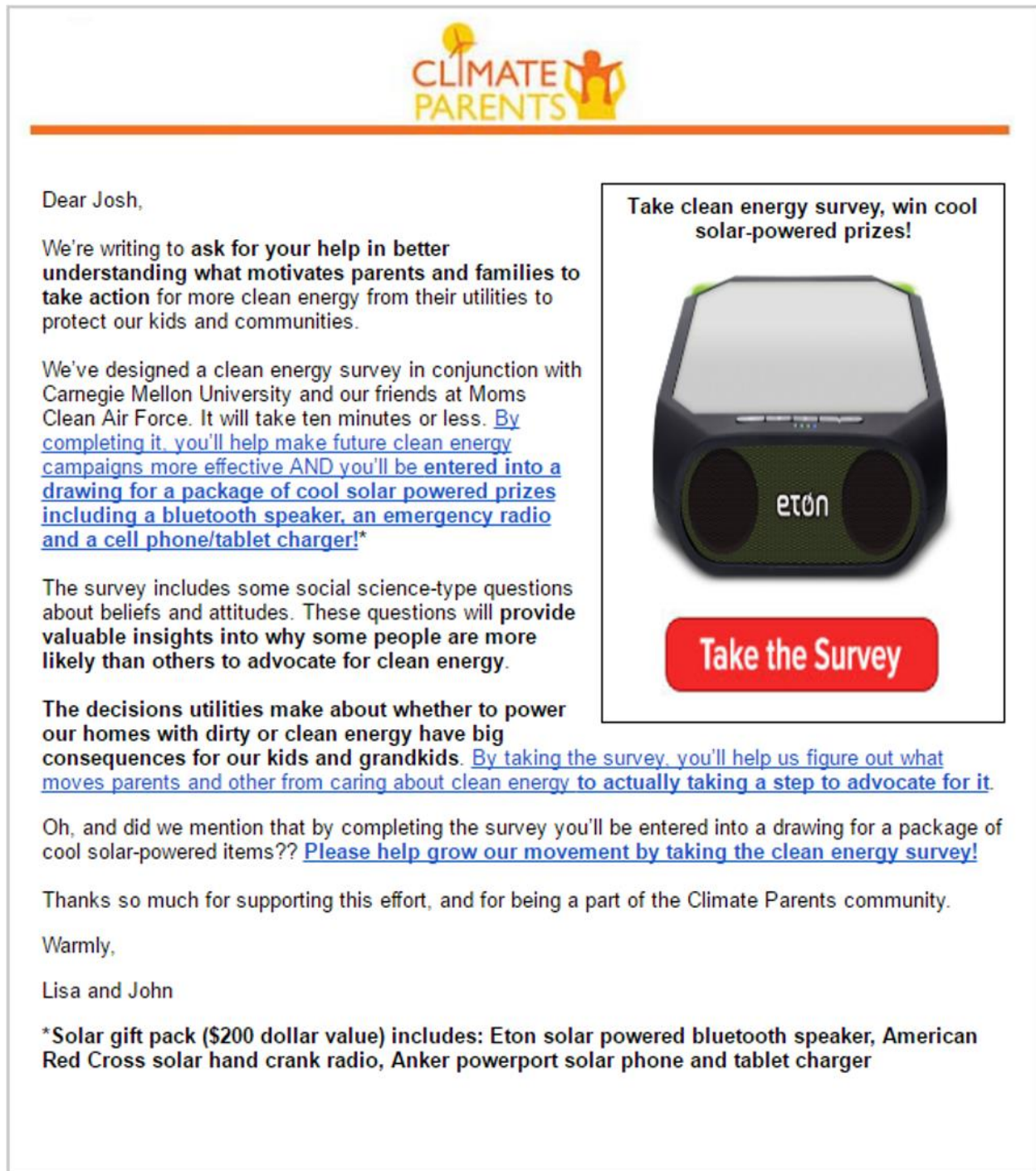


Figure B1. Sample recruitment email from Climate Parents.



Dear Keith,

As a member of Moms Clean Air Force, I know you care about clean air, and about your family. But how can we convince others like you—moms, dads, and grandparents—to speak up for their children, for their families, and for clean air? What does it take to motivate parents to demand action on clean energy?

That's why I'm asking for your help. I am looking for Moms Clean Air Force supporters in your area to take a 10 minute survey about clean energy. Can you take a few minutes to share your opinions?

[By completing this survey, you'll help inform how we, and others fighting pollution, communicate so that we have the best chance to ensure clean air and clean energy for generations to come.](#)

Even better, when you complete the survey you'll automatically be entered for the chance to win a solar gift basket worth \$200 that includes a solar emergency radio, speaker, and charger.

What's this all about? To help further our future campaigns, Moms Clean Air Force is collaborating with Carnegie Mellon University researchers and our partner Climate Parents to find out more about how to motivate parents to demand clean energy from their electric utilities. **This research will help our organizations – and other advocacy groups, large and small, all over the country – mobilize parents more effectively to create a safe and healthy future for our kids.**

Your response is important to us. [By taking the survey, you will be helping us learn more about how to motivate parents to take action on air pollution – and laying the groundwork for a clean energy future.](#)

[Remember, if you take the survey, we will enter you into a drawing to win one of four solar gift kits valued at \\$200.](#)

Thanks in advance for considering participating in this important research project.

For clean air,



Molly Rauch
Public Health Policy Director, Moms Clean Air Force

Figure B2. Sample recruitment email from Moms Clean Air Force

Appendix B.4: Advocacy group survey email rates

Table B3. Climate Parents email rates.

Date	Email subject line	Number of emails sent	Open rate	Click rate
9/21/2016	We need YOUR input to grow the clean energy movement	94	30%	1%
9/22/2016	Take clean energy survey, win solar speaker & charger!	157	27%	6%
9/22/2016	Take clean energy survey to help get more people involved	162	31%	5%
9/24/2016	Take clean energy survey, win solar speaker & charger	3,641	25%	6%
9/30/2016	Take clean energy survey, win solar speaker & charger	4,052	25%	6%
10/5/2016	DEADLINE SOON: Take survey, win solar prizes!	213	15%	2%
10/5/2016	RE: Take clean energy survey, win solar speaker & charger!	252	29%	2%
10/8/2016	RE: Take clean energy survey, win solar speaker & charger	2,747	11%	2%
11/3/2016	Take clean energy survey, win solar speaker & charger	4,241	25%	7%

Table B4. Moms Clean Air Force email rates.

Date	Email subject line	Number of emails sent	Open rate	Click rate
9/20/2016	Don't Miss This	16,016	4%	0.05%
9/20/2016	Share Your Opinions on Clean Energy	16,011	3%	0.04%
9/20/2016	Did You Have a Chance to See This?	16,007	3%	0.04%

Appendix B.5: Advocacy group member recruitment, by state

Ultimately, we recruited 66 participants from Michigan, 129 from Florida, and 97 from California.

Table B5. Summary of “members” sample, Study 1.

Advocacy Group	Michigan	Florida	California	Total
Climate Parents	55	90	82	227
Moms Clean Air Force	11	39	15	65
Total	66	129	97	292

Appendix B.6: California campaign materials



The electricity that powers our homes comes from **electric utility companies**. Utilities can be owned by the public (such as a city or region) or by private investors. Utilities either produce their own electricity from power plants, or they buy it from other power producers. They also send electricity to our homes, businesses, and industries.

Utilities make choices about the sources of energy that they'll use to generate the electricity they sell.

- They can decide whether to provide customers with **fossil fuel, nuclear or renewable energy**.
- They also decide how much to invest in **energy efficiency**.

Southern California Edison needs to hear that its customers want it to **invest more in clean energy and energy efficiency**.

Figure B3. California control campaign.



The electricity that powers our homes comes from **electric utility companies**. Utilities can be owned by the public (such as a city or region) or by private investors. Utilities either produce their own electricity from power plants, or they buy it from other power producers. They also send electricity to our homes, businesses, and industries.

Utilities make choices about the sources of energy that they'll use to generate the electricity they sell.

- They can decide whether to provide customers with **fossil fuel, nuclear or renewable energy**.
- They also decide how much to invest in **energy efficiency**.

There is an important link between the kind of energy that powers our homes and our **monthly energy bills**.

- More than half of the energy produced by Southern California Edison comes from burning natural gas, a fossil fuel.¹
- The cost of wind and solar energy has dropped over the past decade. Experts predict that costs will continue to fall.²
- Over the long term, renewable energy can cut energy costs. Replacing power plants that are costly to operate -- due to fuel prices -- with power plants that use free fuel (sun, wind, water, and heat from the earth's crust) can reduce costs.
- The world's nations are trying to reduce carbon pollution. That's why investing in carbon-free clean energy is a forward-thinking, smart choice that could keep costs down over the next few decades.
- Energy demand is on the rise, and improving energy efficiency is the cheapest way to meet growing energy demand.

Southern California Edison needs to hear that its customers want it to **invest more in clean energy and energy efficiency, to keep prices down for consumers**.

1. Southern California Edison: http://energyalmanac.ca.gov/electricity/electricity_resource_mix_pie_charts/

2. <http://reneweconomy.com.au/2015/solar-grid-parity-world-2017>

Figure B4. California cost campaign.



The electricity that powers our homes comes from **electric utility companies**. Utilities can be owned by the public (such as a city or region) or by private investors. Utilities either produce their own electricity from power plants, or they buy it from other power producers. They also send electricity to our homes, businesses, and industries.

Utilities make choices about the sources of energy that they'll use to generate the electricity they sell.

- They can decide whether to provide customers with **fossil fuel, nuclear or renewable energy**.
- They also decide how much to invest in **energy efficiency**.

There is an important link between the kind of energy that powers our homes and **the health of our children**.

- More than half of the energy produced by Southern California Edison comes from natural gas, a fossil fuel.¹ Burning natural gas for energy contributes to air pollution.
- The pollution that comes from burning fossil fuels makes asthma worse in some children. 9.3% of US children have asthma. Fossil fuel pollution can trigger asthma attacks.²
- We could help solve this problem by making sure that our utilities provide clean energy. This would help reduce the asthma attacks that harm our children.

Southern California Edison needs to hear that its customers want it to **invest more in clean energy and energy efficiency, to protect our children's health**.

1. Southern California Edison: http://energyalmanac.ca.gov/electricity/electricity_resource_mix_pie_charts/

2. Center for Disease Control and Prevention, <http://www.cdc.gov/nchs/fastats/asthma.htm>

Figure B5. California health campaign.



The electricity that powers our homes comes from **electric utility companies**. Utilities can be owned by the public (such as a city or region) or by private investors. Utilities either produce their own electricity from power plants, or they buy it from other power producers. They also send electricity to our homes, businesses, and industries.

Utilities make choices about the sources of energy that they'll use to generate the electricity they sell.

- They can decide whether to provide customers with **fossil fuel, nuclear or renewable energy**.
- They also decide how much to invest in **energy efficiency**.

There is an important link between the kind of energy that powers our homes and **climate change**.

- More than half of the energy produced by Southern California Edison comes from natural gas, a fossil fuel.¹ Burning natural gas for energy contributes to air pollution.
- Some of the harmful impacts of climate change include sea level rise, extreme storms, droughts, and wildfires.²
- We could help address this problem by making sure that our utilities provide clean energy. This would help us avoid some of the worst impacts of climate change, like the extreme storms that put our families at risk.

Southern California Edison needs to hear that its customers want it to **invest more in clean energy and energy efficiency, to protect our climate**.

1. Southern California Edison: http://energyalmanac.ca.gov/electricity/electricity_resource_mix_pie_charts/

2. National Climate Assessment, <http://nca2014.globalchange.gov/highlights/report-findings/our-changing-climate>

Figure B6. California climate campaign.



The electricity that powers our homes comes from **electric utility companies**. Utilities can be owned by the public (such as a city or region) or by private investors. Utilities either produce their own electricity from power plants, or they buy it from other power producers. They also send electricity to our homes, businesses, and industries.

Utilities make choices about the sources of energy that they'll use to generate the electricity they sell.

- They can decide whether to provide customers with **fossil fuel, nuclear or renewable energy**.
- They also decide how much to invest in **energy efficiency**.

There is an important link between the kind of energy that powers our homes and **our children's health and future**.

- More than half of the energy produced by Southern California Edison comes from natural gas, a fossil fuel.¹ Burning natural gas for energy contributes to air pollution.
- The pollution that comes from burning coal and other fossil fuels makes asthma worse in some children. 9.3% of US children have asthma. Pollution from coal and natural gas can trigger asthma attacks.²
- But dirty energy isn't just unhealthy for our kids. Dirty energy harms us by making climate change worse. Some of the harmful impacts of climate change include sea level rise, extreme storms, droughts, and wildfires.³
- We could help solve this problem by making sure that our utilities provide clean energy. This would help reduce the asthma that harms our children. And it would help us avoid some of the worst impacts of climate change, like the extreme storms that put our families at risk.

Southern California Edison needs to hear that its customers want it to **invest more in clean energy and energy efficiency, to protect our children's health and their future**.

1. Southern California Edison: http://energyalmanac.ca.gov/electricity/electricity_resource_mix_pie_charts/

2. Center for Disease Control and Prevention, <http://www.cdc.gov/nchs/fastats/asthma.htm>

3. National Climate Assessment, <http://nca2014.globalchange.gov/highlights/report-findings/our-changing-climate>

Figure B7. California health + climate campaign.

Appendix B.7: Study 1 complete survey

Since this survey is 200 pages long, please refer to this Google Drive link, which houses the final survey as Word and PDF files:

<https://drive.google.com/open?id=1LTs-zHkl2NOMH5wUths6J7n-hc-tpeEN>

Appendix B.8: Variables and regression model details

In addition to exposing participants to various clean energy campaigns and measuring advocacy intentions and actions, we also collected data on key variables that were relevant to the campaign materials (e.g. agreement with utilities using various energy sources) and measured individual differences (e.g. climate change acceptance). These variables are found to be predictive of intentions and actions in other studies [1-4]. We derived our survey questions measuring attitudes of various energy sources from normative statements of which participants rated their agreement. This method is used in other technology and energy source acceptance surveys [5], [6]; additionally, other studies demonstrate that attitudes are at least correlated and sometimes shaped by social norms and that the normative world is underpinned by the attitudes of society [7-9].

- a. **Perception.** Participants indicated their perception of their utility's electricity portfolio by answering the following question: "What percentage of the electricity that you use in your home do you think comes from fossil fuels (i.e., natural gas, oil, and/or coal)?" the responses were recorded on a sliding scale from 0% to 100%.
- b. **Knowledge.** Given a participant's perception of the fossil fuel percentage of their utility's portfolio, we calculated knowledge as an absolute difference from their response and the actual percentage published on their respective utility's websites (Table B1 and Table B2). Next, we reverse-coded knowledge. Therefore, knowledge could range from 0 = no knowledge of fossil fuel percentage in utility's portfolio to 100 = complete knowledge of fossil fuel percentage in utility's portfolio.
- c. **Fossil fuel attitudes.** Participants indicated their fossil fuel attitudes with their agreement to the following statement (1 = strongly disagree, 5 = strongly agree): "My utility should use fossil fuels to make electricity," before and after being exposed to their condition.
- d. **Clean energy attitudes.** Participants' attitudes towards clean energy were measured by taking the mean of their agreement with the following two statements (1 = strongly disagree, 5 = strongly agree): "My utility should use wind, sun, and other renewable energy sources to make electricity," and "My utility should use energy efficiency to reduce the amount of electricity needed." These measurements were taken before and after being exposed to their condition (Before: Cronbach's $\alpha = 0.33$; After: Cronbach's $\alpha = 0.62$).

- e. **Intention.** Participants indicated their intention to take action (petition/voice message) by either selecting, “Sign the petition”/“Leave a message” (coded as 1) or “No thanks” (coded as 0). See Figure B8 and Figure B9.
- f. **Action.** Participants who took action – actually signing the petition or leaving a voice message – were assigned a 1, and those who didn’t take action were assigned a 0. See Figure B10 and Figure B11.
- g. **Credibility.** Participants indicated their perception of campaign credibility by answering the following question (1 = definitely no, 5 = definitely yes): “Was the clean energy information just presented to you credible?”
- h. **Comprehension.** Participants’ comprehension was measured by their responses to two questions (1 = definitely false, 5 = definitely true): (1) “My utility can only provide electricity generated from fossil fuels” [correct answer = definitely false] and (2) “My utility can choose to invest in energy efficiency” [correct answer = definitely true]. The first question was scored as 1 (correct) for all responses less than or equal to 2, and all those greater than 2 were scored as 0 (incorrect). The second question was scored as 1 (correct) for all responses greater than or equal to 4, and all those less than 4 were scored as 0 (incorrect). Scores were then summed, where a total of 0 = low comprehension and 2 = high comprehension.
- i. **Action-efficacy.** Participants indicated action efficacy beliefs by indicating their agreement (1 = strongly disagree, 5 = strongly agree) with either “Signing an online petition is an effective way to change my utility’s practices” or “Joining others who have already made a phone call to my utility is an effective way to change my utility’s practices.”
- j. **Self-efficacy.** Participants’ self-efficacy was assessed by taking the mean of their agreement with two statements from Schwarzer and Jerusalem’s General Self-Efficacy Scale [10] (1 = strongly disagree, 5 = strongly agree): (1) “I am often able to overcome barriers” and (2) “I generally accomplish what I set out to do” (Cronbach’s $\alpha = 0.76$) [11].
- k. **Climate change.** Participants’ climate change acceptance was assessed by taking the mean of their agreement with four statements from Leiserowitz et al.’s Global Warming’s Six Americas survey [12] (1 = definitely no to 5 = definitely yes): (1) “Do you think that climate change is happening?” (2) “Do you think that climate change is mostly caused by humans?”

(3) “Do you think that climate change will harm future generations?” and (4) “Are you worried about climate change?” (Cronbach’s $\alpha = 0.75$) [11].

- l. **Experience.** Participants indicated their experience of extreme events by checking as many as applicable to them: coastal/inland flooding, drought, severe weather, wildfires, other, and prefer not to answer. Each response was coded as 1 if checked (omitting prefer not to answer) and 0 if not, the final result was summed.
- m. **Respiratory Illness.** Participants answered, “Have YOU been diagnosed by a doctor or other qualified medical professional with asthma, chronic bronchitis, COPD, or other lung disease?” with either “No” (coded as 0), “Yes” (coded as 1), or “Prefer not to answer” (coded as 2). In the final analysis, “Prefer not to answer” was treated as NA (5.5% of respiratory illness responses in Study 1 were coded as NA).

Regression Model Details

Variables were entered in theoretically relevant blocks. The first block included campaign variables – Campaign and Action, and controlled for Knowledge, Credibility and Comprehension (Model 3a, Model 3b). The second block built on the first one and also controlled for Action-efficacy, Self-efficacy, and Climate Change (Model 4a, Model 4b). The last block built on the first two and also controlled for experience and demographic variables (Model 5a, Model 5b).

References

- [1] P. C. Stern, “Toward a Coherent Theory of Environmentally Significant Behavior,” *J. Soc. Issues*, vol. 56, no. 3, pp. 407–424, 2000.
- [2] S. Bamberg and P. Schmidt, “Incentives, Morality, or Habit? Predicting Students’ Car Use for University Routes With the Models of Ajzen, Schwartz, and Triandis,” *Environ. Behav.*, vol. 35, no. 2, pp. 264–285, 2003.
- [3] S. H. Schwartz, “Normative Influences on Altruism,” *Adv. Exp. Soc. Psychol.*, vol. 10, pp. 221–279, 1977.
- [4] R. E. Dunlap, K. D. Van Liere, A. G. Mertig, and R. Emmet Jones, “New trends in measuring environmental attitudes: measuring endorsement of the new ecological paradigm: a revised NEP scale,” *J. Soc. Issues*, vol. 56, no. 3, pp. 425–442, 2000.
- [5] J. Swofford and M. Slattery, “Public attitudes of wind energy in Texas : Local communities in close proximity to wind farms and their effect on decision-making,” *Energy Policy*, vol. 38, no. 5, pp. 2508–2519, 2010.
- [6] L. Amin, H. Hashim, Z. Mahadi, M. Ibrahim, and K. Ismail, “Biotechnology for Biofuels Determinants of stakeholders’ attitudes towards biodiesel,” *Biotechnol. Biofuels*, pp. 1–17, 2017.

- [7] R. J. Vallerand, P. Deshaies, J. P. Cuerrier, and C. Mongeau, "Ajzen and Fishbein's theory of reasoned action as applied to moral behavior: A confirmatory analysis," *J. Pers. Soc. Psychol.*, vol. 62, no. 1, pp. 98–109, 1992.
- [8] R. L. Oliver and W. O. Bearden, "Crossover Effects in the Theory of Reasoned Action: A Moderating Influence Attempt," *J. Consum. Res.*, vol. 12, no. 3, pp. 324–340, 1985.
- [9] D. J. Terry and M. A. Hogg, "Group Norms and the Attitude-Behavior Relationship: A Role for Group Identification," *Personal. Soc. Psychol. Bull.*, vol. 22, no. 8, pp. 776–793, 1996.
- [10] R. Schwarzer and M. Jerusalem, "Generalized Self-Efficacy Scale," *Anxiety. Stress. Coping*, vol. 12, pp. 329–345, 2010.
- [11] M. Tavakol and R. Dennick, "Making sense of Cronbach's alpha," *Int. J. Med. Educ.*, vol. 2, pp. 53–55, 2011.
- [12] A. Leiserowitz, E. Maibach, and C. Roser-Renouf, "Global Warming's 'Six Americas,'" 2009.

Appendix B.9: Study 1 intention screens

It is important to help decision makers understand public sentiment around clean energy. Join others who have already signed an online petition to urge your utility, Southern California Edison, to invest in clean energy and energy efficiency. We will deliver all signatures to Southern California Edison's CEO, Theodore Craver.

Sign the petition

No thanks

Privacy Notice: If you choose to sign the petition, the system will record your participant code, name, and zip code. We will deliver your name and zip code to Southern California Edison's CEO. After delivering your petition signature to the CEO, we will erase any references to your name, to the connection between your participant code and your name, and to the connection between your petition signature and your responses to the survey. We will not attempt to contact you for any reason and will not give or sell your name or zip code to others.

Next

Figure B8. Study 1 petition intention screen.

It is important to help decision makers understand public sentiment around clean energy. Join others who have already urged the CEO of your utility, Southern California Edison, to invest in clean energy and energy efficiency.

You can do this by recording a voice message for the CEO in our voicemail system. We will bundle together all of the customer voice messages to Southern California Edison's CEO Theodore Craver and deliver them in one package to his office. On the next page, we provide a sample script and talking points, as well as the phone number to call to leave your voice message.

Leave a message

No thanks

Privacy Notice: If you choose to leave a message, the system will record the phone number from which you called and any identifying information that you leave. After forwarding your message to the CEO, we will erase it and any connection between it and your responses to the survey. We will not call your phone number for any reason, and will not give or sell your name or phone number to others.

Next

Figure B9. Study 1 voice message intention screen.

Appendix B.10: Study 1 action screens

Dear Southern California Edison CEO Theodore Craver,

I am a Southern California Edison customer, and I am writing to urge you to increase your investments in clean energy and energy efficiency. Thank you.

Your participant code: 6658

Enter your participant code below to sign the online petition.

Participant Code:	<input type="text"/>
First Name:	<input type="text"/>
Last Name:	<input type="text"/>
Zip Code:	<input type="text"/>

Next

Figure B10. Study 1 petition action screen.

We are collecting short voice recordings (less than 60 seconds) through our system from customers, which we will package together and deliver as voicemails to Theodore Craver, the CEO of your utility, Southern California Edison.

Here is an example of what you might say:

"Hello, my participant code is 5762 and my name is _____. I live in _____, California. I want Southern California Edison to invest more in clean energy and energy efficiency, because they are a better option than fossil fuels. Thank you."

Please call our system at (937) 210-4579 to leave your message for Southern California Edison CEO Theodore Craver. Please say your participant code 5762 before leaving your message.

Next

Figure B11. Study 1 petition action screen.

Appendix B.11: Study 1 randomization checks

Table B6. Results of 2-way ANOVA test on Perception for random assignment of experimental conditions, Study 1 – Members Sample.

Source	Sum of Squares	<i>df</i>	<i>Mean Square</i>	<i>F</i>	<i>p</i>
Campaign	1938.50	4	484.62	0.62	0.65
Action	182.21	1	182.21	0.23	0.63
Campaign x Action	5184.71	4	1296.18	1.65	0.16
Error	221138.34	282	784.18		
Total	22854.08	291			

Table B7. Results of Chi-square test for balanced assignment of experimental conditions, Study 1 – Members Sample.

Action	Campaign				
	Control	Cost	Health	Climate	Health + Climate
Petition	26 (54%)	37 (58%)	33 (51%)	32 (57%)	30 (51%)
Voice Message	22 (46%)	27 (42%)	27 (49%)	24 (43%)	29 (49%)

Note: $\chi^2 = 1.11$, $df = 4$. Numbers in parentheses indicate column percentages.

* $p < 0.05$

Appendix B.12: Study 1 post-hoc analyses on attitudes

Table B8. Simple contrasts of fossil fuel attitudes across campaigns.

Frames	Contrast	SE	F (df)	P > F
Health+Climate - Climate	-0.01	0.28	0.00 (1)	0.980
Health+Climate - Health	0.27	0.24	1.19 (1)	0.280
Health+Climate - Cost	-0.44	0.25	3.20 (1)	0.080
Climate - Cost	-0.43	0.26	2.74 (1)	0.100
Health - Cost	-0.71	0.22	10.27 (1)	0.002

Table B9. Simple contrasts of clean energy attitudes across campaigns.

Frames	Contrast	SE	F (df)	P > F
Health+Climate - Climate	0.07	0.11	0.43 (1)	0.513
Health+Climate - Health	0.06	0.10	0.32 (1)	0.570
Health+Climate - Cost	0.07	0.10	0.56 (1)	0.467
Climate - Cost	0.00	0.11	0.00 (1)	0.999
Health - Cost	0.02	0.09	0.04 (1)	0.842

Appendix B.13: Study 1 intention and action rates, by state and political party

We did not have a large enough sample size to perform statistical analyses on the members sample across states to determine if there were significant differences in frame effectiveness. However, we do report qualitative differences in Figure B12. Within the members sample, it was difficult to determine differences in Republicans and Democrats since there were very few Republicans in the sample (i.e., 47% of them identified as Democrats, 29% identified as Independents, 3% identified as Republicans, and 21% preferred not to answer the question). In Michigan, Independents tended to respond well to the Control and Climate campaigns. Democrats tended to respond best to the Cost campaign. In Florida, Independents tended to react best to the Cost campaign and Democrats tended to react best to the Health + Climate campaign. In California, Independents responded best to the Cost and Health + Cost campaigns. Democrats tended to respond best to the Control campaign. These results are further quantified in Table B10.

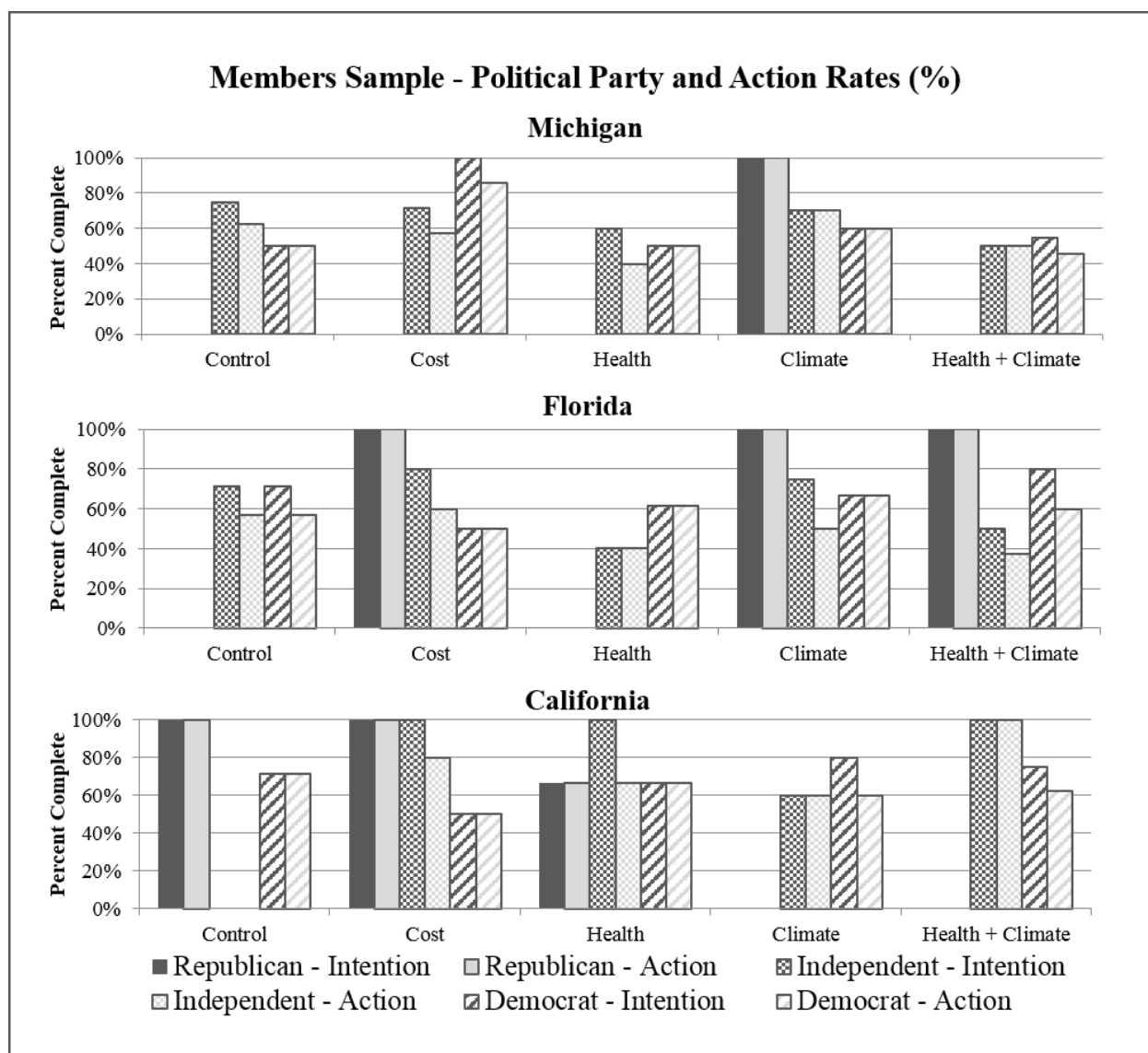


Figure B12. State-level action rates in the members sample for Michigan, Florida, and California across frames: Control, Cost, Health, Climate, and Health + Climate.

Table B10. Percentage of participants who indicated they intended to take action or completed the action across frames, states, and political affiliation, Study 1 – members sample.

		Michigan		Florida		California	
Political Party		% Intention	% Action	% Intention	% Action	% Intention	% Action
Control	Republican	0%	0%	0%	0%	100%	100%
	Independent	75%	63%	71%	57%	0%	0%
	Democrat	50%	50%	71%	57%	71%	71%
Cost	Republican	0%	0%	100%	100%	100%	100%
	Independent	71%	57%	80%	60%	100%	80%
	Democrat	100%	86%	50%	50%	50%	50%
Health	Republican	0%	0%	0%	0%	67%	67%
	Independent	60%	40%	40%	40%	100%	67%
	Democrat	50%	50%	62%	62%	67%	67%
Climate	Republican	100%	100%	100%	100%	0%	0%
	Independent	70%	70%	75%	50%	60%	60%
	Democrat	60%	60%	67%	67%	80%	60%
Health + Climate	Republican	0%	0%	100%	100%	0%	0%
	Independent	50%	600%	50%	38%	100%	100%
	Democrat	55%	45%	80%	60%	75%	63%

Appendix B.14: Study 1 discussion

Overall, our participants who are members of climate advocacy groups held very positive views about clean energy and additional information about impacts did little to shift those views. We attribute the minimal messaging impacts to ceiling and floor effects on parents' attitudes towards clean energy and fossil fuels, respectively. We did not find support for H1 and H2. We observed a potential boomerang effect among advocacy parents presented with cost information: After being shown the cost campaign, they expressed more favorable attitudes about their utilities using fossil fuels²⁸, lower intent to take action, and much lower rates of actually following through. This could be an expression of dissatisfaction with cost framing, rather than an endorsement of fossil fuels. In support of H3, other factors seemingly increased action rates, including whether the participant saw the action as being able to make a difference in their utility's practices and if they accepted climate change (e.g. individual differences). Finally, on balance, people found it easier to sign a petition than make a phone call.

²⁸ We did not include an interaction term for Campaign x Action in our model since we had no *a priori* theoretical reason to expect attitudes to differ by requested action (signing a petition or making a phone call). However, there appears to be a significant interaction with respect to those shown the cost information and asked to sign a petition for fossil fuel attitudes. We speculate that perhaps, among this particular population of advocacy parents, being asked to take action on something for perhaps distasteful reasons (saving money rather than health or environmental reasons) which they *can do* (signing a petition is a much lower bar ask than making a phone call) results in feeling more positive about a resource they initially dislike.

Appendix B.15: GfK Knowledge Panel sampling method

To fill their KnowledgePanel, GfK uses address-based sampling methods to randomly recruit participants and they provide households with access to the internet and hardware, if necessary. GfK programmed our survey on their own proprietary software and administered it to participants from their KnowledgePanel. As shown in Table B11, our internet-based experiment and survey was completed by representative public subsamples in Michigan (n = 413), Florida (n = 412), and California (n = 429); the overall number sampled for the public sample was 1,890 with a completion rate of 66%. The total number of completed surveys came to 1,254.

To encourage participation, GfK allows panelists to visit their online member page for survey taking and also sends email reminders. The panel-selection methods inform the weighting for future surveys and provide statistical control of the representativeness of the sample. Furthermore, GfK uses benchmarks from the most recent U.S. government statistics to design weights that reflect unequal selection probabilities and account for any differential nonresponse to the survey. The final weights are calculated using the method of iterative proportional fitting along the following geodemographic dimensions: gender, age (18-39, 40-49, 50-59, 60-69, 70+), race-ethnicity (Hispanic, non-Hispanic White, non-Hispanic Black, non-Hispanic other, non-Hispanic multiracial), education (less than high school, high school, some college, bachelor's degree or higher), household income (under \$25k, \$25k to < \$50k, \$50k to < \$75k, \$75k+), language proficiency (non-Hispanic, Hispanic English proficient, Hispanic bilingual, Hispanic Spanish proficient). In the final step, GfK trims any weight outliers at the extremes of the weighting distributions and scales them to the aggregate to the total sample size of all eligible respondents.

Appendix B.16: GfK Knowledge Panel recruitment, by state

Ultimately, we recruited 413 participants from Michigan, 412 from Florida, and 429 from California.

Table B11. Summary of “public” sample, Study 2.

Survey Language	Michigan	Florida	California	Total
English	411	296	336	1043
Spanish	2	116	93	211
Total	413	412	429	1254

Appendix B.17: Study 2 intention screens

QPETITION [s]

Do you want to sign this petition to be delivered to the CEO of your utility?

1. **Yes, I want to sign the petition.** Carnegie Mellon University researchers may deliver my survey ID, name, and zip code to [UTILITY]'s CEO [CEO NAME] in support of this petition.
2. **No, I do NOT want to sign the petition.** *(It's fine if you don't want to sign the petition; we still want you to complete the remainder of the survey. Thank you!)*

Privacy Notice: If you choose to sign the petition, the system will record your survey ID, name, and zip code, to Carnegie Mellon University researchers, who will deliver your name and zip code to [UTILITY]'s CEO. After delivering your petition signature to the CEO, Carnegie Mellon University researchers will erase any references to your name, to the connection between your survey ID and your name, and to the connection between your petition signature and your responses to the survey. Carnegie Mellon University will not attempt to contact you for any reason and will not give or sell your name or zip code to others.

GfK has no contract with the utility company and no responsibility for what happens after your name and zip code are delivered to the utility CEO.

Figure B13. Study 2 petition intention screen

QVM [s]

Do you want to leave a message to be delivered to the CEO of your utility?

1. **Yes, I want to leave a message.** *(Please see the next screen for the phone number to call and a sample script).*
2. **No, I do NOT want to leave a message.** *(It's fine if you don't want to leave a message; we still want you to complete the remainder of the survey. Thank you!).*

Privacy Notice: If you choose to leave a message, the system will record the phone number from which you called and any identifying information that you leave. After forwarding your message to the CEO, Carnegie Mellon University researchers will erase it and any connection between it and your responses to the survey. Carnegie Mellon University will not call your phone number for any reason, and will not give or sell your name or phone number to others.

Figure B14. Study 2 voice message intention screen

Appendix B.18: Study 2 action screens

To sign the petition, please add your name below:

Dear [UTILITY] CEO [CEO NAME],

I am a [UTILITY] customer, and I am writing to urge you to increase your investments in clean energy and energy efficiency. Thank you.

First name: [small textbox]

Last name: [small textbox]

[GFK WILL PROVIDE SURVEYID (XCMUID), STATE AND ZIP CODE IN THE DATA FILE]

Figure B15. Study 1 petition action screen

To leave a voicemail message for [UTILITY], please call this Google voicemail system at **(937) 210-4579**. Please keep your message short (less than 60 seconds). The researchers will deliver voicemails to [CEO], the CEO of your utility, [UTILITY].

Here is an example of what you might say:

"Hi, my name is _____. I live in _____, [STATE]. I want [UTILITY] to invest more in clean energy and energy efficiency because they are a better option than fossil fuels. My code is [XCMUID]. Thank you."

[PROGRAMMER NOTE: ALLOW TO CONTINUE WITH THE SURVEY IF QVM= 1 (YES) OR QVM= 1 (NO)]

Figure B16. Study 1 petition action screen

Appendix B.19: Study 2 attitude, intention, and action rates - unweighted

Table B12. Study 2 (general) linear regression predicting changes¹ in attitudes towards fossil fuels, renewable energy, and energy efficiency². Unweighted results.

Variables	Model 6 (Fossil Fuels) (n = 1205)			Model 7 (Clean Energy) (n = 1222)		
	B(95% CI)	SE	t	B(95% CI)	SE	t
Campaign (Ref = Control)						
Cost	-0.02 (-0.21, 0.18)	0.10	-0.18	0.10 (-0.05, 0.26)	0.08	1.37
Health	-0.11 (-0.30, 0.08)	0.10	-1.11	-0.09 (-0.24, 0.06)	0.08	-1.17
Climate	-0.11 (-0.31, 0.08)	0.10	-1.13	-0.04 (-0.20, 0.11)	0.08	-0.57
Health + Climate	-0.11 (-0.30, 0.08)	0.10	-1.11	0.04 (-0.11, 0.19)	0.08	0.52
Action (Ref = Petition)						
Voice Message	0.04 (-0.08, 0.17)	0.06	0.72	0.06 (-0.03, 0.16)	0.05	1.30
Knowledge	0.00 (0.00, 0.00)	0.00	-0.67	0.00 (0.00, 0.00)	0.00	-0.23
Credibility	-0.05 (-0.11, 0.02)	0.03	-1.40	0.03 (-0.02, 0.08)	0.03	1.37
Comprehension	-0.07 (-0.16, 0.01)	0.04	-1.65	0.13 (0.07, 0.20)***	0.03	3.92
Constant	0.46 (-0.03, 0.95)	0.25	1.84	-0.59 (-0.97, -0.21)**	0.19	-3.04
R ²	0.01			0.04		

*** $p < .001$, ** $p < .01$, * $p < .05$

¹ Here changes in attitudes were calculated by subtracting attitudinal responses after participants viewed the campaigns and were asked to take an action from their original responses.

² Demographics controlled for in Model 6 and Model 7 include Age, Income, Number of Children, Experience with climate change-related weather, and whether or not the participant suffers from respiratory illness.

Table B13. Study 2 (general) logistic regression predicting intention and action¹. Unweighted results.

Variable	Intentions									Actions								
	Model 8a			Model 9a			Model 10a			Model 8b			Model 9b			Model 10b		
	B	SE	OR ² (e ^B)	B	SE	OR(e ^B)	B	SE	OR(e ^B)	B	SE	OR(e ^B)	B	SE	OR(e ^B)	B	SE	OR(e ^B)
Campaign (Ref. = Control)																		
Cost	-0.08	0.24	0.92	-0.08	0.26	0.92	-0.15	0.27	0.86	0.06	0.27	1.06	0.14	0.30	1.15	0.13	0.31	1.14
Health	0.02	0.24	1.02	-0.20	0.26	0.82	-0.17	0.27	0.84	0.00	0.20	1.00	-0.23	0.30	0.79	-0.19	0.31	0.83
Climate	0.37	0.24	1.45	0.28	0.26	1.32	0.27	0.27	1.31	0.21	0.27	1.23	0.18	0.30	1.20	0.15	0.32	1.16
Health + Climate	0.05	0.24	1.05	-0.11	0.26	0.90	-0.19	0.27	0.83	-0.10	0.27	0.90	-0.27	0.30	0.76	-0.35	0.31	0.70
Action (Ref. = Petition)																		
Voice Message	-2.03	0.16	0.13	-2.28	0.18	0.10	-2.40	0.19	0.09	-3.39***	0.25	0.03	-3.83***	0.28	0.02	-3.99***	0.30	0.02
Knowledge	0.00	0.00	1.00	0.00	0.00	1.00	0.00	0.00	1.00	0.00	0.00	1.00	0.00	0.00	1.00	0.00	0.00	1.00
Credibility	0.84	0.09	2.32	0.48	0.10	1.62	0.50	0.10	1.65	1.03***	0.11	2.80	0.67***	0.11	1.95	0.72***	0.12	2.05
Comprehension	0.30	0.11	1.35	0.31	0.12	1.36	0.31	0.13	1.36	0.24	0.13	1.27	0.26	0.14	1.30	0.25	0.15	1.28
Action-Efficacy				0.65	0.08	1.92	0.69	0.08	1.99				0.78***	0.10	2.18	0.83***	0.10	2.29
Self-Efficacy				0.10	0.11	1.11	0.09	0.12	1.09				0.06	0.13	1.06	0.03	0.14	1.03
Climate Change				0.47	0.09	1.60	0.46	0.09	1.58				0.41***	0.10	1.51	0.4***	0.10	1.49
Demographics ³	No			No			Yes									Yes		
Constant	-3.60	0.47	0.03	-6.46	0.72	0.00	-5.90	0.88	0.00	-4.59***	0.56	0.01	-7.63***	0.88	0.00	-7.45***	1.04	0.00
R ²	0.23 ⁴			0.32			0.34			0.35			0.43			0.45		

*** $p < .001$, ** $p < .01$, * $p < .05$ ¹ We chose not to include Climate x Action interaction term in these regression models.² A significant odds ratio with a value below 1 indicates that the specified independent variable reduces the odds of a participant stating an intention to act (i.e. Intention = 1). An odds ratio greater than 1 indicates an increase in these odds. Therefore, we can subtract 1 from the ratio and multiply by 100 to determine the percent change in the odds of intending to take an action. The same can be done for the observed action regressions.³ Demographics controlled for in this regression include Age, Income, Number of Children, Experience with climate change-related weather, and whether or not the participant suffers from Respiratory illness.⁴ These represent pseudo R² values for logistic regressions.

Appendix B.20: Study 2 randomization checks

Table B14. Results of 2-way ANOVA test on Perception for random assignment of experimental conditions, Study 2 – Public Sample.

Source	Sum of Squares	df	Mean Square	F	p
Campaign	2589.82	4	647.45	0.76	0.55
Action	3.21	1	3.21	0.00	0.95
Campaign x Action	3241.08	4	810.27	0.95	0.43
Error	1053321.1	1,237	851.51		
Total	1059033	1,246			

Table B15. Results of Chi-square test for balanced assignment of experimental conditions, Study 2 – Public Sample.

Action	Frame				
	Control	Cost	Health	Climate	Health + Climate
Petition	112 (46%)	127 (50%)	120 (46%)	118 (50%)	129 (50%)
Voice Message	132 (54%)	126 (50%)	140 (54%)	120 (50%)	130 (50%)

Note: $\chi^2 = 1.80$, df = 4. Numbers in parentheses indicate column percentages.

* $p < 0.05$

Appendix B.21: Study 2 post-hoc analyses on attitudes

Table B16. Simple contrasts of fossil fuel attitudes across campaigns

Frames	Contrast	SE	F (df)	P > F
Health+Climate - Climate	0.14	0.20	0.47 (1)	0.490
Health+Climate - Health	0.22	0.17	1.61 (1)	0.205
Health+Climate - Cost	-0.19	0.17	1.32 (1)	0.250
Climate - Cost	-0.33	0.19	3.00 (1)	0.083
Health - Cost	-0.41	0.16	6.88 (1)	0.009

Table B17. Simple contrasts of clean energy attitudes across campaigns

Frames	Contrast	SE	F (df)	P > F
Health+Climate - Climate	-0.10	0.15	0.43 (1)	0.511
Health+Climate - Health	0.29	0.12	5.72 (1)	0.017
Health+Climate - Cost	-0.05	0.13	0.16 (1)	0.691
Climate - Cost	0.05	0.15	0.10 (1)	0.755
Health - Cost	-0.34	0.12	7.93 (1)	0.005

Appendix B.22: Study 2 intention and action rates, by state and political party

Similar to Study 1, we performed a qualitative analysis to determine if Campaign effects varied across states for the public sample. We were better able to determine differences in Campaign effects on Democrats and Republicans as there was a more even balance of the two within the sample (i.e., 45% of participants identified as Democrats, 2% identified as Independents, and 53% identified as Republicans) than there was in the members sample. Within the public parent sample, it appears that Republicans and Democrats react differently to the campaigns depending on the state in which they live. As indicated in Figure B17, Republicans tend to respond best to the Health campaign in Michigan. In Florida, Republicans tend to respond best to the Climate campaign. In California, Republicans tend to respond best to the Health + Climate campaign. In Michigan, Democrats tend to respond best to the Control campaign. In Florida, Democrats tend to respond best to the Climate campaign. In California, Democrats tend to respond best to the Health + Climate campaigns. These results are further quantified in Table B18.

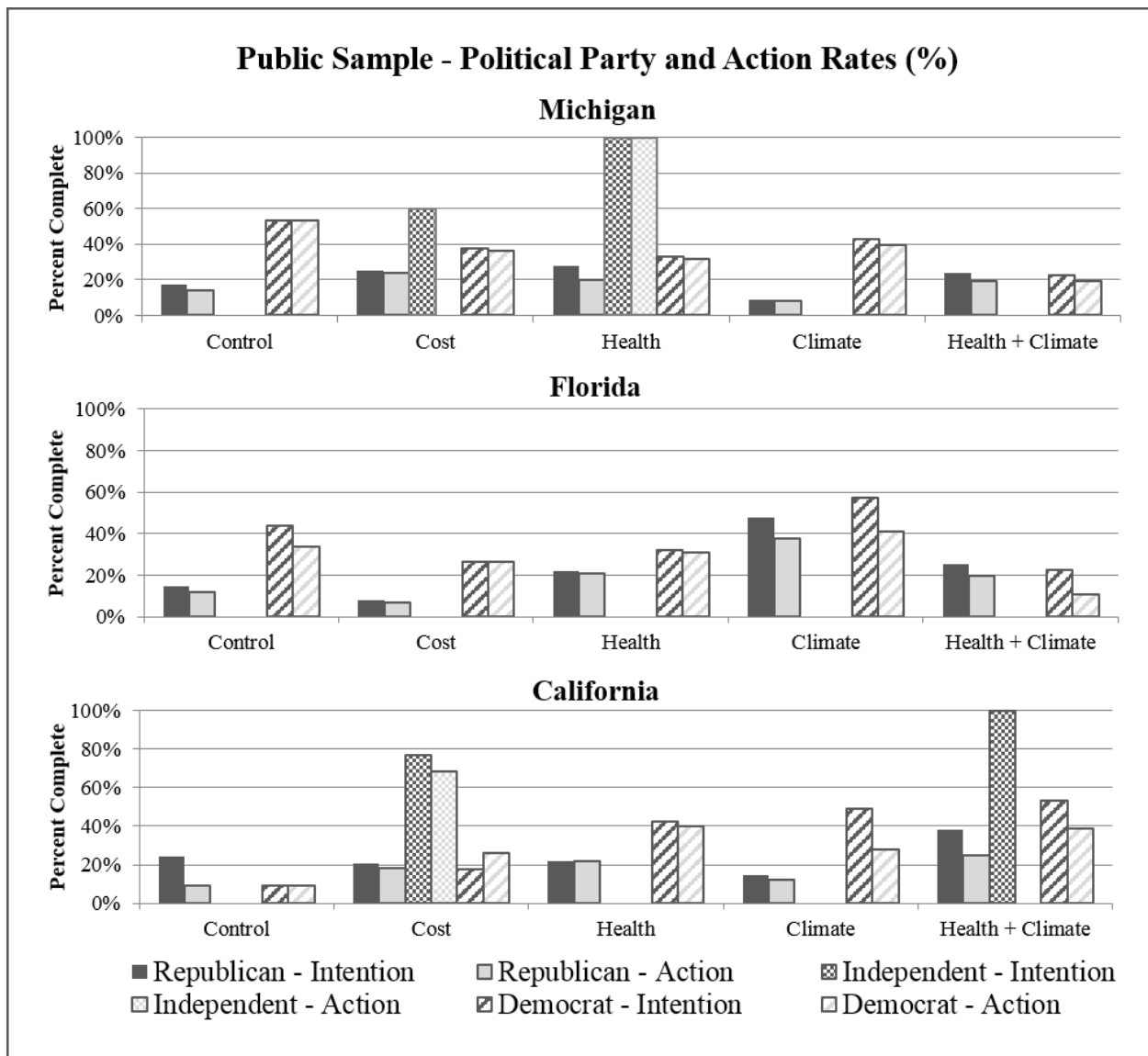


Figure B17. State-level action rates in the public sample for Michigan, Florida, and California across frames: Control, Cost, Health, Climate, and Health + Climate.

Table B18. Percentage of participants who indicated they intended to take action or completed the action across frames, states, and political affiliation. This table quantifies values depicted in the next three figures (public parent sample only).

		Michigan		Florida		California	
Political Party		% Intention	% Action	% Intention	% Action	% Intention	% Action
Control	Republican	17%	14%	15%	12%	25%	9%
	Independent	0%	0%	0%	0%	0%	0%
	Democrat	54%	54%	44%	34%	9%	9%
Cost	Republican	25%	24%	8%	7%	20%	18%
	Independent	60%	0%	0%	0%	77%	68%
	Democrat	37%	36%	27%	27%	18%	26%
Health	Republican	28%	20%	22%	21%	22%	22%
	Independent	100%	100%	0%	0%	0%	0%
	Democrat	33%	32%	32%	31%	42%	40%
Climate	Republican	9%	8%	48%	38%	15%	12%
	Independent	0%	0%	0%	0%	0%	0%
	Democrat	43%	39%	57%	41%	49%	28%
Health + Climate	Republican	24%	19%	25%	20%	38%	25%
	Independent	0%	4440%	0%	0%	100%	0%
	Democrat	23%	19%	23%	11%	53%	39%

Appendix B.23: Study 2 results for parents segments

Table B19. Energy attitudes for parents who are also grandparents and who are not also grandparents^{a,b}.

Variables	Fossil Fuels - Grandparents			Fossil Fuels - Not Grandparents			Clean Energy - Grandparents			Clean Energy - Not Grandparents		
	(n = 573)			(n = 596)			(n = 580)			(n = 606)		
	B(95% CI)	SE	t	B(95% CI)	SE	t	B(95% CI)	SE	t	B(95% CI)	SE	t
Campaign (Ref = Control)												
Cost	0.09 (-0.23, 0.41)	0.16	0.52	0.18 (-0.20, 0.55)	0.19	0.92	-0.05 (-0.38, 0.28)	0.17	-0.29	0.21 (-0.14, 0.57)	0.18	1.17
Health	-0.05 (-0.41, 0.31)	0.18	-0.26	-0.43* (-0.81, -0.04)	0.20	-2.19	-0.17 (-0.47, 0.12)	0.15	-1.17	-0.26 (-0.61, 0.08)	0.17	-1.51
Climate	0.02 (-0.31, 0.35)	0.17	0.11	-0.26 (-0.82, 0.29)	0.28	-0.92	-0.12 (-0.44, 0.19)	0.16	-0.79	0.34 (-0.11, 0.81)	0.23	1.46
Health + Climate	0.12 (-0.22, 0.25)	0.21	0.55	-0.15 (-0.54, 0.24)	0.20	-0.76	0.03 (-0.30, 0.37)	0.17	0.20	0.11 (-0.22, 0.44)	0.17	0.65
Action (Ref = Petition)												
Voice Message	0.02 (-0.22, 0.25)	0.12	0.13	0.15 (-0.17, 0.46)	0.16	0.93	-0.08 (-0.24, 0.09)	0.08	-0.94	0.10 (-0.14, 0.34)	0.12	0.81
Knowledge	0.00 (-0.01, 0.01)	0.00	-0.13	0.00 (-0.01, 0.01)	0.00	0.56	0.00 (-0.01, 0.00)	0.00	-0.49	0.00 (-0.01, 0.01)	0.00	0.11
Credibility	-0.17** (-0.30, -0.05)	0.06	-2.76	-0.05 (-0.20, 0.09)	0.08	-0.72	0.10 (-0.01, 0.20)	0.05	1.86	0.04 (-0.07, 0.15)	0.06	0.68
Comprehension	-0.26** (-0.43, -0.08)	0.09	-2.87	-0.06 (-0.24, 0.11)	0.09	-0.70	0.05 (-0.07, 0.17)	0.06	0.81	0.21** (0.06, 0.36)	0.08	2.79
Constant	1.38* (0.29, 2.46)	0.55	2.50	0.45 (-0.60, 1.51)	0.54	0.85	-0.43 (-1.29, 0.43)	0.44	-0.97	-0.71 (-1.58, 0.16)	0.44	-1.61
R ²	0.11			0.08			0.07			0.08		

***p<.001, **p<.01, *p<.05

^a Here changes in attitudes were calculated by subtracting attitudinal responses after participants viewed the campaigns and were asked to take an action from their original responses.

^b Demographics controlled for in Model 6 and Model 7 include Age, Income, Number of Children, Experience with climate change-related weather, and whether or not the participant suffers from respiratory illness.

Table B20. Energy attitudes for parents who do and do not have children under the age of 18 years old^{a,b}.

Variables	Fossil Fuels – Parents w/ children < 18yr			Fossil Fuels – Parents w/o children < 18yr			Clean Energy – Parents w/ children < 18yr			Clean Energy – Parents w/o children < 18yr	
	(n = 341)			(n = 829)			(n = 348)			(n = 838)	
	<i>B</i> (95% CI)	SE	<i>t</i>	<i>B</i> (95% CI)	SE	<i>t</i>	<i>B</i> (95% CI)	SE	<i>t</i>	<i>B</i> (95% CI)	SE
Campaign (Ref = Control)											
Cost	0.01 (-0.43, 0.46)	0.23	0.06	0.20 (-0.12, 0.52)	0.16	1.21	0.33 (-0.21, 0.87)	0.27	1.22	-0.05 (-0.28, 0.19)	0.12
Health	-0.51* (-1.01, -0.01)	0.25	-2.02	-0.12 (-0.43, 0.19)	0.16	-0.77	-0.30 (-0.79, 0.20)	0.25	-1.19	0.13 (-0.33, 0.07)	0.10
Climate	-0.26 (-0.89, 0.37)	0.32	-0.81	-0.12 (-0.41, 0.16)	0.14	-0.85	0.48 (-0.16, 1.13)	0.33	1.47	-0.09 (-0.32, 0.15)	0.12
Health + Climate	0.15 (-0.27, 0.56)	0.22	0.68	-0.18 (-0.57, 0.22)	0.20	-0.88	0.23 (-0.22, 0.69)	0.23	1.01	-0.07 (-0.30, 0.16)	0.12
Action (Ref = Petition)											
Voice Message	0.14 (-0.24, 0.52)	0.20	0.74	0.05 (-0.17, 0.28)	0.11	0.47	-0.07 (-0.41, 0.27)	0.17	-0.42	0.10 (-0.04, 0.24)	0.07
Knowledge	0.00 (-0.01, 0.01)	0.00	0.60	0.00 (-0.01, 0.01)	0.00	0.26	0.00 (-0.01, 0.01)	0.00	0.10	0.00 (0.00, 0.00)	0.00
Credibility	-0.14 (-0.32, 0.03)	0.09	-1.59	-0.07* (-0.20, 0.05)	0.07	-1.15	0.09 (-0.05, 0.24)	0.08	1.26	0.04 (-0.02, 0.18)	0.03
Comprehension	-0.05 (-0.27, 0.18)	0.11	-0.40	-0.19 (-0.33, 0.04)	0.07	-2.51	0.27* (0.07, 0.46)	0.10	2.67	0.09* (0.00, 0.18)	0.05
Constant	0.33 (-1.20, 1.86)	0.78	0.42	0.90* (0.13, 1.67)	0.39	-0.75	-1.05 (-2.30, 0.20)	0.64	-1.66	-0.35 (-0.88, 0.18)	0.27
R ²	0.10			0.08			0.12			0.03	

***p<.001, **p<.01, *p<.05

^a Here changes in attitudes were calculated by subtracting attitudinal responses after participants viewed the campaigns and were asked to take an action from their original responses.

^b Demographics controlled for in Model 6 and Model 7 include Age, Income, Number of Children, Experience with climate change-related weather, and whether or not the participant suffers from respiratory illness.

Table B21. Intentions and Actions for parents who are also grandparents and who are not also grandparents^a.

Variable	Intentions						Actions					
	Grandparents (n = 569)			Not Grandparents (n = 599)			Grandparents (n = 569)			Not Grandparents (n = 599)		
	B	SE	OR ^b (e ^B)	B	SE	OR(e ^B)	B	SE	OR(e ^B)	B	SE	OR(e ^B)
Campaign (Ref. = Control)												
Cost	-0.28	0.51	0.76	-0.11	0.55	0.90	0.51	0.73	1.67	0.46	0.63	1.58
Health	-0.07	0.63	0.93	0.35	0.53	1.42	-0.12	0.83	0.89	1.07	0.62	2.92
Climate	0.60	0.46	1.82	0.37	0.51	1.45	-0.06	0.71	0.94	0.47	0.59	1.60
Health + Climate	-0.12	0.55	0.89	-0.08	0.61	0.92	-0.21	0.71	0.81	-0.37	0.64	0.69
Action (Ref. = Petition)												
Voice Message	-3.74***	0.58	0.02	-2.42***	0.39	0.09	-6.06***	0.82	0.00	-4.08***	0.44	0.02
Knowledge	0.00	0.01	1.00	0.00	0.01	1.00	0.01	0.01	1.01	0.01	0.01	1.01
Credibility	0.84**	0.27	2.32	0.32	0.24	1.38	0.77**	0.26	2.16	0.54**	0.20	1.72
Comprehension	0.51	0.36	1.67	0.26	0.24	1.30	0.96	0.51	2.61	0.35	0.26	1.42
Action-Efficacy	1.06***	0.20	2.89	0.64***	0.16	1.90	1.50***	0.23	4.48	0.68***	0.17	1.97
Self-Efficacy	0.28	0.23	1.32	-0.33	0.24	0.72	0.36	0.30	1.43	-0.60*	0.28	0.55
Climate Change	0.50**	0.18	1.65	0.61**	0.19	1.84	0.66**	0.20	1.93	0.41*	0.18	1.51
Demographics ^c	Yes			Yes			Yes			Yes		
Constant	-13.71***	2.82	0.00	-3.49*	1.55	0.03	-17.25***	2.89	0.00	-3.22	1.66	0.04
R ^{2d}	0.52			0.34			0.61			0.44		

***p<.001, **p<.01, *p<.05

^a We chose not to include Climate x Action interaction term in these regression models.

^b A significant odds ratio with a value below 1 indicates that the specified independent variable reduces the odds of a participant stating an intention to act (i.e. Intention = 1). An odds ratio greater than 1 indicates an increase in these odds. Therefore, we can subtract 1 from the ratio and multiply by 100 to determine the percent change in the odds of intending to take an action. The same can be done for the observed action regressions.

^c Demographics controlled for in this regression include Age, Income, Number of Children, Experience with climate change-related weather, and whether or not the participant suffers from Respiratory illness.

^d These represent pseudo R² values for logistic regressions.

Table B22. Energy attitudes for parents who do and do not have children under the age of 18 years old^a.

Variable	Intentions						Actions					
	Parents w/ children < 18yr (n = 341)			Parents w/o children < 18yr (n = 827)			Parents w/ children < 18yr (n = 341)			Parents w/o children < 18 yr (n = 827)		
	B	SE	OR ^b (e ^B)	B	SE	OR(e ^B)	B	SE	OR(e ^B)	B	SE	OR(e ^B)
Campaign (Ref. = Control)												
Cost	-0.75	0.67	0.47	-0.24	0.43	0.79	0.40	0.83	1.49	0.31	0.57	1.36
Health	-0.50	0.62	0.61	0.26	0.42	1.30	0.67	0.83	1.95	0.38	0.53	1.46
Climate	-0.32	0.59	0.73	0.79	0.41	2.20	0.02	0.73	1.02	0.72	0.49	2.05
Health + Climate	-0.82	0.66	0.44	0.08	0.59	1.08	-0.32	0.83	0.73	-0.77	0.62	0.46
Action (Ref. = Petition)												
Voice Message	-3.12***	0.46	0.04	-2.43***	0.42	0.09	-4.44***	0.61	0.01	-4.21***	0.51	0.01
Knowledge	-0.01	0.01	0.99	0.01	0.01	1.01	0.00	0.01	1.00	0.02	0.01	1.02
Credibility	0.71**	0.22	2.03	0.31	0.25	1.36	0.59**	0.25	1.80	0.66**	0.20	1.93
Comprehension	0.17	0.30	1.19	0.23	0.27	1.26	0.07	0.34	1.07	0.69*	0.30	1.99
Action-Efficacy	0.87***	0.20	2.39	0.65***	0.15	1.92	0.77***	0.20	2.16	0.98***	0.19	2.66
Self-Efficacy	-0.07	0.30	0.93	-0.26	0.21	0.77	-0.31	0.33	0.73	-0.35	0.24	0.70
Climate Change	0.63*	0.26	1.88	0.39*	0.17	1.48	0.62*	0.30	1.86	0.32*	0.15	1.38
Demographics ^c	Yes			Yes			Yes			Yes		
Constant	-5.63	1.99	0.00	-4.51**	1.47	0.01	-5.88*	2.26	0.00	-7.54***	2.02	0.00
R ^{2d}	0.46			0.33			0.48			0.48		

***p<.001, **p<.01, *p<.05

^a We chose not to include Climate x Action interaction term in these regression models.

^b A significant odds ratio with a value below 1 indicates that the specified independent variable reduces the odds of a participant stating an intention to act (i.e. Intention = 1). An odds ratio greater than 1 indicates an increase in these odds. Therefore, we can subtract 1 from the ratio and multiply by 100 to determine the percent change in the odds of intending to take an action. The same can be done for the observed action regressions.

^c Demographics controlled for in this regression include Age, Income, Number of Children, Experience with climate change-related weather, and whether or not the participant suffers from Respiratory illness.

^d These represent pseudo R² values for logistic regressions.

Appendix B.24: Intention rates for advocacy and general public parents

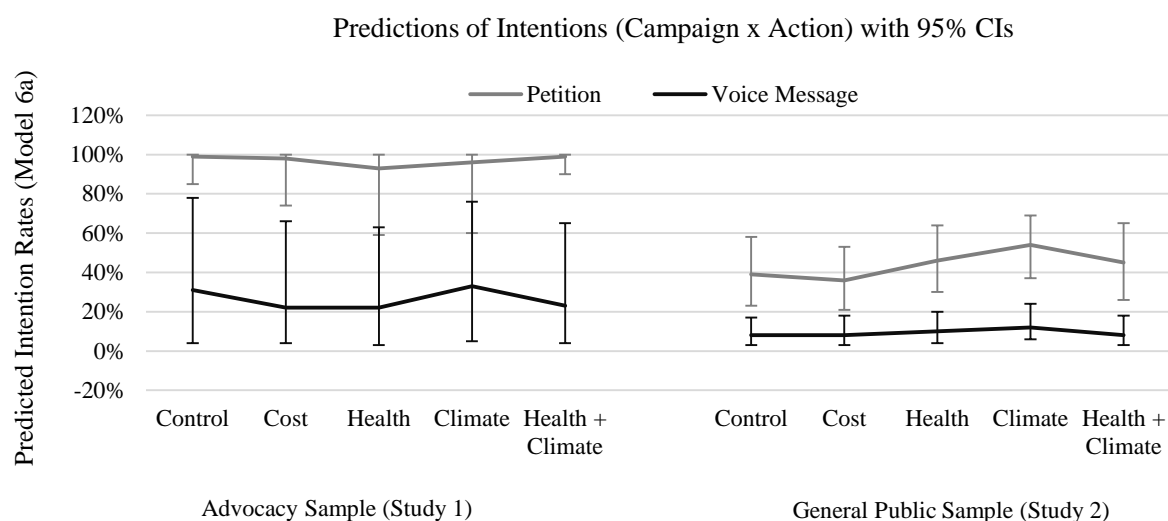


Figure B18. The effects of Campaign (Control, Cost, Health, Climate, and Health + Climate) on intention rates in the advocacy sample (Study 1) and the general public sample (Study 2). An intention to take the assigned action (petition/voice message) was measured by recording a response to a question presented directly after the assigned Campaign and Action and directly before the participant could perform the action. This chart illustrates the predicted intention rates with 95% confidence intervals from the logistic regression model that controlled for demographics and experience (Model 5a and 10a). Overall, intention rates in both studies are lower among participants assigned to the Voice Message action compared to the Petition action. In Study 1, we found a main effect of the Cost campaign on intentions; across the action types, participants who received the Cost campaign were less likely to report an intention to take an action compared to those who were assigned the control. In Study 2, we did not find any main effects for campaigns.

Appendix B.25: Study 2 discussion

Overall, our participants recruited from the general public held relatively neutral opinions on energy sources. We did not observe ceiling or floor effects among this sample regarding their attitudes. It seemed parents drawn from the public, especially those in Florida, were sensitive to health information. Here, among those shown health information, we found more negative attitudes towards clean energy than the control group as well as more negative attitudes towards both fossil fuels and clean energy than the cost group (in partial support of H1). We did not find support for H2; we found the campaigns had no effect on intention or action rates. In support of H3, we found climate change acceptance and beliefs about campaign credibility (i.e. individual differences) among the participants to be more predictive of intention and action than the campaign materials. Again, all participants found it easier to sign a petition than make a phone call. Our segmentation analysis demonstrated that younger parents shown health information (i.e. parents who are not also grandparents and who have children under the age of 18 years old) held more negative attitudes towards fossil fuels than the control or cost groups. We also found that for older parents (i.e. parents who are also grandparents and don't have children under the age of 18 years old) greater comprehension of the campaign was associated with greater action rates.

Appendix B.26: Limitations and future study

Both of our studies had a number of strengths, including (1) large, representative and differentiated samples (i.e. participants drawn from climate advocacy groups as well as the general public), (2) an experimental design with a control, and (3) campaign materials designed in collaboration with real climate advocacy groups. Still, our studies were not without their limitations.

First, we focused our attention on engaging parents in only two types of actions: signing a petition and leaving a voice message for their utility. Parents may be more willing to take other actions to promote clean energy generation or energy efficiency such as switching entirely to a new utility or installing solar PV on their roofs in order to rely less on a utility to make generation choices [1], [2]. However, since our study was designed in collaboration with climate advocacy groups, we were more interested in studying campaigns that promote actions within the purview of advocacy groups. Future study should examine how parents are influenced by campaigns to take a broader set of clean energy actions.

Second, the effects of our campaign conditions outside this experimental design may vary due to real world factors such as communication medium, the messenger, availability of competing arguments, and the nature of the prescribed actions for addressing the suggested problem [3]. As we found ask-efficacy and campaign legitimacy predictive of actions, future studies may examine the effects of similar campaigns delivered by a host of messengers (e.g., advocacy groups, utilities, local government) and mediums (e.g., email, print, Facebook). Yet, our pre-testing of the campaigns for comprehension, affect, and readability across a variety of participants within the academic community and general public (i.e. mTurk and Craigslist) enhanced the external validity of our experimental design.

Third, we observed some participation bias within the climate advocacy group parent sample (i.e. participation rate of 0.6%). These parents likely represented a subset of the advocacy population that is extremely engaged, limiting variability and making it difficult to generalize findings from this sample to all other parent members of climate advocacy groups. Indeed the most likely individuals to turn out are those who already harbor intense, well-informed opinions and who are emotionally committed to the issues at hand [4], [5]; however, they are also most likely to be the individuals in the community taking action.

Finally, we believe it would be worthwhile to compare parents with non-parents to determine if there exists heterogeneity of messaging effects and/or individual differences regarding attitudes towards various energy sources and willingness to take action on the topic. Due to the existing evidence outlined in the Introduction that parents are powerful agents of change in other domains related to children's health and safety, our study focused on differentiating effective campaigns and influential individual differences among parents.

References

- [1] M. J. Kotchen and M. R. Moore, "Private provision of environmental public goods: Household participation in green-electricity programs," *J. Environ. Econ. Manage.*, vol. 53, no. 1, pp. 1–16, 2007.
- [2] T. Krishnamurti *et al.*, "Preparing for smart grid technologies: A behavioral decision research approach to understanding consumer expectations about smart meters," *Energy Policy*, vol. 41, pp. 790–797, 2012.
- [3] T. Myers, M. Nisbet, E. Maibach, and A. Leiserowitz, "A public health frame arouses hopeful emotions about climate change A Letter," *Clim. Change*, vol. 113, pp. 1105–1112, 2012.
- [4] M. C. Nisbet and D. A. Scheufele, "What's next for science communication? promising directions and lingering distractions," *Am. J. Bot.*, vol. 96, no. 10, pp. 1767–1778, 2009.
- [5] K. Goidel and M. C. Nisbet, "Exploring the Roots of Public Participation in the Controversy Over Embryonic Stem Cell Research and Cloning," *Polit. Behav.*, vol. 28, no. 2, pp. 175–192, 2006.

Appendix C: Supplemental Information for Chapter 4

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Appendix C.1: Model assumptions

Table C1. Model assumptions and treatment of uncertainty.

Input Category	Model Input	Assumption	Treatment of Uncertainty
Available roof space	NCES datasets - building counts and locations	This is a complete list of higher education, K-12 public, and K-12 private schools in the United States.	None.
Available roof space	NREL LIDAR roof space estimates.	NREL accurately characterized higher education campuses using OSM.	Randomly selected some college campuses in the LIDAR data to compare with hand measurements taken from Google Earth.
Available roof space	NREL LIDAR roof space estimates.	NREL accurately measured available roof space for K-12 private and K-12 public schools.	Randomly selected some K-12 public and K-12 private schools in the LIDAR data to compare with hand measurements taken from Google Earth.
Available roof space	Roof space linear regression models	All three models meet the four Gauss-Markov assumptions: (1) linearity in parameters, (2) random sampling, (3) zero conditional mean of the errors, and (4) no perfect collinearity	(1) Performed cross-validation to select the model that reduced prediction error. (2) Constructed 95% confidence intervals for the predictions.
PV-generation modeling and building loads	PV system size	PV panels cover 100% of available roof space	Scenario analysis: (1) PV panels cover 100% of available space, (2) PV panels cover 50% of available roof space, and (3) PV panels produce 100% of annual electricity consumption (and spill onto non-roof surfaces, if needed).
PV-generation modeling and building loads	PV power density	Input: 150 W/m ²	None.

Table C1. Model assumptions and treatment of uncertainty. (Table continued).

Input Category	Model Input	Assumption	Treatment of Uncertainty
PV-generation modeling and building loads	"Secondary school" reference load	Electricity load scales linearly with school population.	None.
Installed price of system	Project cost taken from LBNL dataset	2015 and 2016 average project cost for non-profit, educational, and government are constant across regions.	Sample from distribution of 2015 and 2016 project costs.
PV system rebates and net-metering	DSIRE PV rebates (\$/kW)	Assume these school PV rebates are available at time of installation.	Scenario analysis: Assume no rebates are available.
PV system rebates and net-metering	Net-metering policies.	Net-metering policies vary widely across the U.S.	Scenario analysis: (1) Assume net-metering is available in every state and (2) assume net-metering is not available in any state.
Value of electricity	Value of offset consumption	Considered three scenarios: (1) Set at 2015 state-average commercial retail rates, (2) set at estimated commercial TOU rates, and (3) school purchases electricity from TPO.	Scenario analysis
Value of electricity	Value of excess generation	Considered four scenarios: (1) Set at 2015 state-average LMPs, (2) set at state-average commercial retail rates, (3) set at estimated commercial TOU rates, (4) has no value, and (5) school purchases electricity from the TPO.	Scenario analysis
Valuing health and environmental benefits	Marginal damages	Assume marginal damages from CO ₂ , SO _x , NO _x , and PM _{2.5} remain constant throughout the 20-yr project lifetime.	Assume a +/- 1% change each year throughout the 20-yr project lifetime.
Lifetime costs and benefits	Discount rates	Discount rate set at 7%	Parametric sensitivity analysis: 2%, 7%, 10%

Appendix C.2: LIDAR data and methods description

The National Renewable Energy Laboratory (NREL) uses Light Detection and Ranging (LIDAR) data in combination with GIS methods and statistical modeling to characterize suitable rooftop space for solar PV on buildings in the United States (U.S.). NREL received LIDAR data from the Department of Homeland Security (DHS) Homeland Security Infrastructure Program (HSIP) that covered 128 cities, representing approximately 23% of U.S. buildings and 40% of the U.S. population [1]. The LIDAR data was gathered between 2006 and 2014 using sensors on airplanes and in some cases, drones. LIDAR uses light in the form of a pulsed laser to measure variable distances to the Earth [2]. LIDAR instruments often consist of a laser, a scanner, and a specialized GPS receiver, which combine light pulses with other recorded data to generate 3D information about the shape of the Earth [2]. The DHS topographic LIDAR data is available exclusively to government agencies upon request. DHS provides LIDAR data in raster format at 1m^2 resolution in addition to a corresponding polygon shapefile of the building footprints. Raster data is based on the reflective surface return of LIDAR data; each pixel represents the measured height of the structure (or ground) at that location.

First, NREL ran a shading simulation on the digital surface model for each city provided in the DHS dataset. They used ArcGIS Hillshade tool to create a hillshade for every hour of daylight of four typical seasonal days: March 21, June 21, September 21, and December 21 [3]. They combined these files with records of the sun's altitude and azimuth for each location for every hour. The output of the hillshade tool is a value from 0 to 254, which approximates the amount of illumination each 1m^2 cell receives. NREL assigned an illumination threshold to each typical seasonal day: March required 60% illumination, June required 70% illumination, September required 60% illumination, and December required 50% illumination. Next, these hillshade files were converted to binary outcomes of 1 = cell is illuminated by sun or 0 = cell is in shade. These files were summed across each day as well as the year for each cell; cells that were excessively shaded were excluded for potential PV sites.

Next, NREL classified roof orientation using the LIDAR dataset to determine the tilt and azimuth (or aspect) of each 1m^2 cell. NREL defined a "flat roof" as one with less than 9.5 degrees of tilt. Next, NREL classified each cell into one of nine tilt classes: eight azimuth classes for eight cardinal directions and a class for flat planes. NREL then defined individual roof planes by determining contiguous areas of identical tilt classifications and using ArcGIS Zonal Mean

tool to create a raster of unique roof planes with single tilt values. Considered unsuitable for PV were all roof planes facing northwest through northeast and those with tilt values greater than 60 degrees. They used NREL's System Advisor Model (SAM) to determine the number of hours required to produce 80% energy generation and then assigned a threshold for each of the 128 cities in the dataset [4]. Ultimately, NREL defined building-level PV suitability as having at least one contiguous plane of a projected horizontal footprint greater than 10m² that also met shading and tilt requirements. A total area of at least 10m² provides enough area to install 1.5 kW system (assuming 15% panel efficiency), which they determine as a conservative lower bound for viable PV system sizes [5].

Finally, NREL linked their final detailed footprint dataset with our list of school addresses taken from three National Center for Education Statistics (NCES) datasets: Integrated Postsecondary Education Data System (for higher education institutions) [6], Common Core of Data (for K12 public institutions) [7], and the Private School Universe Survey (for K12 private institutions) [8] within the U.S. territory, resulting in 134,137 educational institutions. These school addresses were geocoded using Google's geocoding API. NREL linked as many school geocodes as they could with open-street mapping (OSM) data. NREL filtered OSM data for "buildings" and amenity types including: Schools, Colleges, Higher Education Campuses, and School Grounds. They removed any overlapping polygons that resulted from their multiple-criteria OSM filters. Linking the address with OSM polygons allowed them to consider entire campuses that are associated with the building address. If multiple schools were co-located in an OSM polygon, NREL proportionally distributed the roof space using the reported school populations (taken from NCES). NREL was able to link 38,761 school addresses or 29% of the combined NCES dataset. Figure C1 shows all the institutions that are listed in NCES that are considered in our analysis – the black diamonds highlight the educational institutions for which we have overall NREL LIDAR data observations.

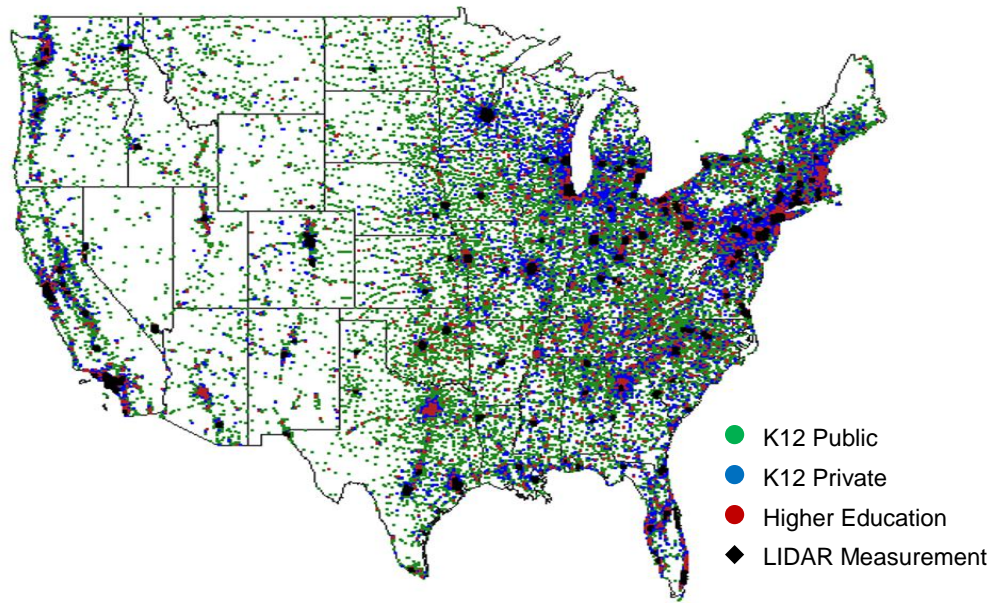


Figure C1. Map of U.S. schools in the NCES datasets: Integrated Postsecondary Education Data System (higher education), Common Core of Data (K12 public), and Private School Universe Survey (K12 private). After excluding schools with reported latitude and longitude values falling outside of the U.S. boundaries, we have combined building dataset of 134,137 schools to consider.

The NREL LIDAR estimates for the 38,760 schools yield estimates for usable roof space, total capacity, and annual generation less than values estimated by NREL for all buildings in the United States [9]. Table C2 depicts a comparison of these values.

Table C2. Comparison table of NREL solar PV estimates for our dataset vs. all US buildings.

	NREL Estimates for ~39,000 Schools	NREL Estimates for all U.S. Buildings[64]
Total PV Capacity (GW)	14	1,100
Total Annual PV Generation (Twh/yr)	20	1,400
Total Usable Space (Billion m ²)	0.1	8.1

Although a total of 38,760 schools were linked by NREL, only 16,440 of these schools were linked to OSM data. The remaining 22,321 were not linked to OSM polygons. Since these schools were unable to be linked to OSM data, the LIDAR estimates only valuate usable space for a single building rather than a campus of buildings. Therefore, these estimates are likely to be conservative, especially for higher education. Table C3 and Figures **Figure C2** **Figure C4** illustrate the downward bias of the LIDAR link estimates compared to the OSM link estimates. However, Table C4 and Figure C5 suggests that LIDAR linked schools had lower school

populations, on average, compared to OSM linked schools. This suggests that schools most likely linked with OSM data (especially K-12 schools) were more likely to have multiple buildings (e.g. high schools and middle schools were more likely linked to OSM data than elementary schools). Therefore, the downward bias of LIDAR linked schools may be somewhat justified.

Table C3. Summary statistics of NREL roof space estimates and point counts.

School Type	Overall			LIDAR Points				OSM Points			
	N (#)	Mean (SF)	Median (SF)	N (#)	N (%)	Mean (SF)	Median (SF)	N (#)	N (%)	Mean (SF)	Median (SF)
K-12 Public	26,140	25,000	13,000	13,146	50%	8,000	850	12,994	50%	39,920	29,400
K-12 Private	9,586	12,000	4,900	6,891	72%	7,300	3,000	2,695	28%	22,400	13,700
Higher Education	3,035	77,700	14,700	2,284	75%	27,500	10,600	751	25%	225,100	119,900

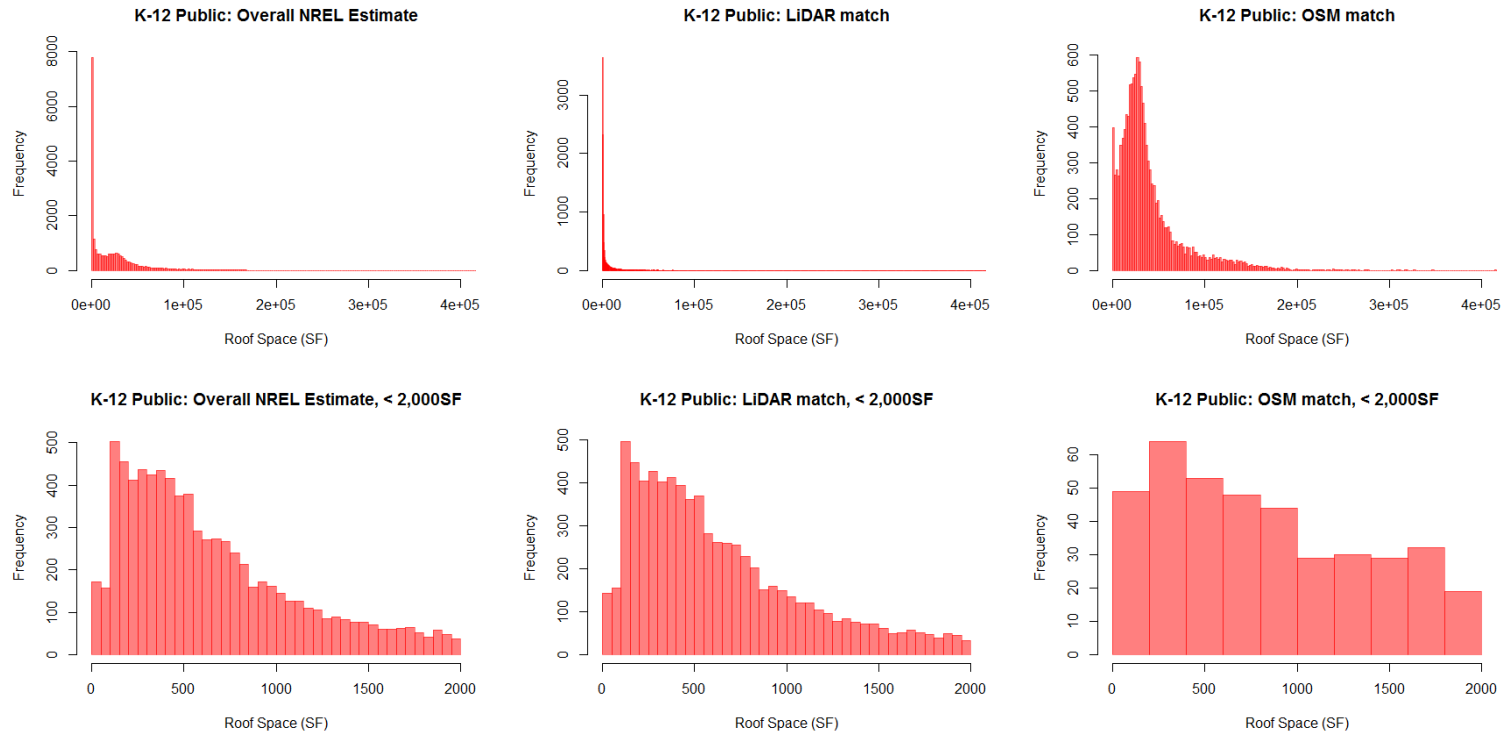


Figure C2. Histograms of roof space estimates (ft²) for K-12 public schools, organized by data type. The upper left plot depicts estimated usable space from all NREL LIDAR data; the bottom left plot depicts the lower end estimates (only 57 schools have estimated usable areas of 0ft²). The upper center plot depicts estimated usable space from LIDAR matches (i.e. single buildings); the bottom center plot depicts the lower end of these estimates. The upper right plot depicts estimated usable space from OSM matches (i.e. campuses); the bottom right plot depicts the lower end of these estimates.

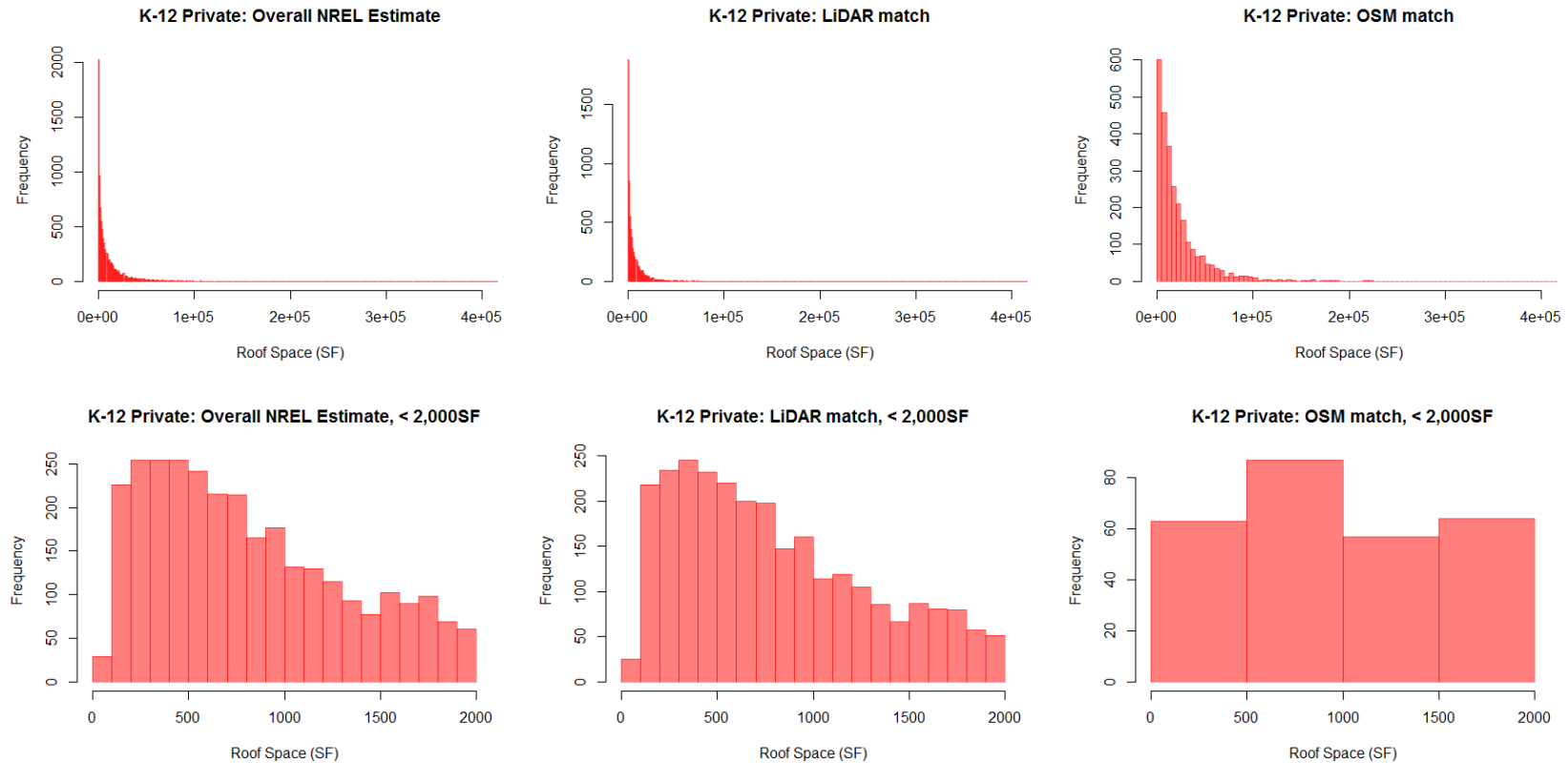


Figure C3. Histograms of roof space estimates (ft²) K-12 private schools, organized by data type. The upper left plot depicts estimated usable space from all NREL LIDAR data; the bottom left plot depicts the lower end estimates (only 11 schools have estimated usable areas of 0ft²). The upper center plot depicts estimated usable space from LIDAR matches (i.e. single buildings); the bottom center plot depicts the lower end of these estimates. The upper right plot depicts estimated usable space from OSM matches (i.e. campuses); the bottom right plot depicts the lower end of these estimates.

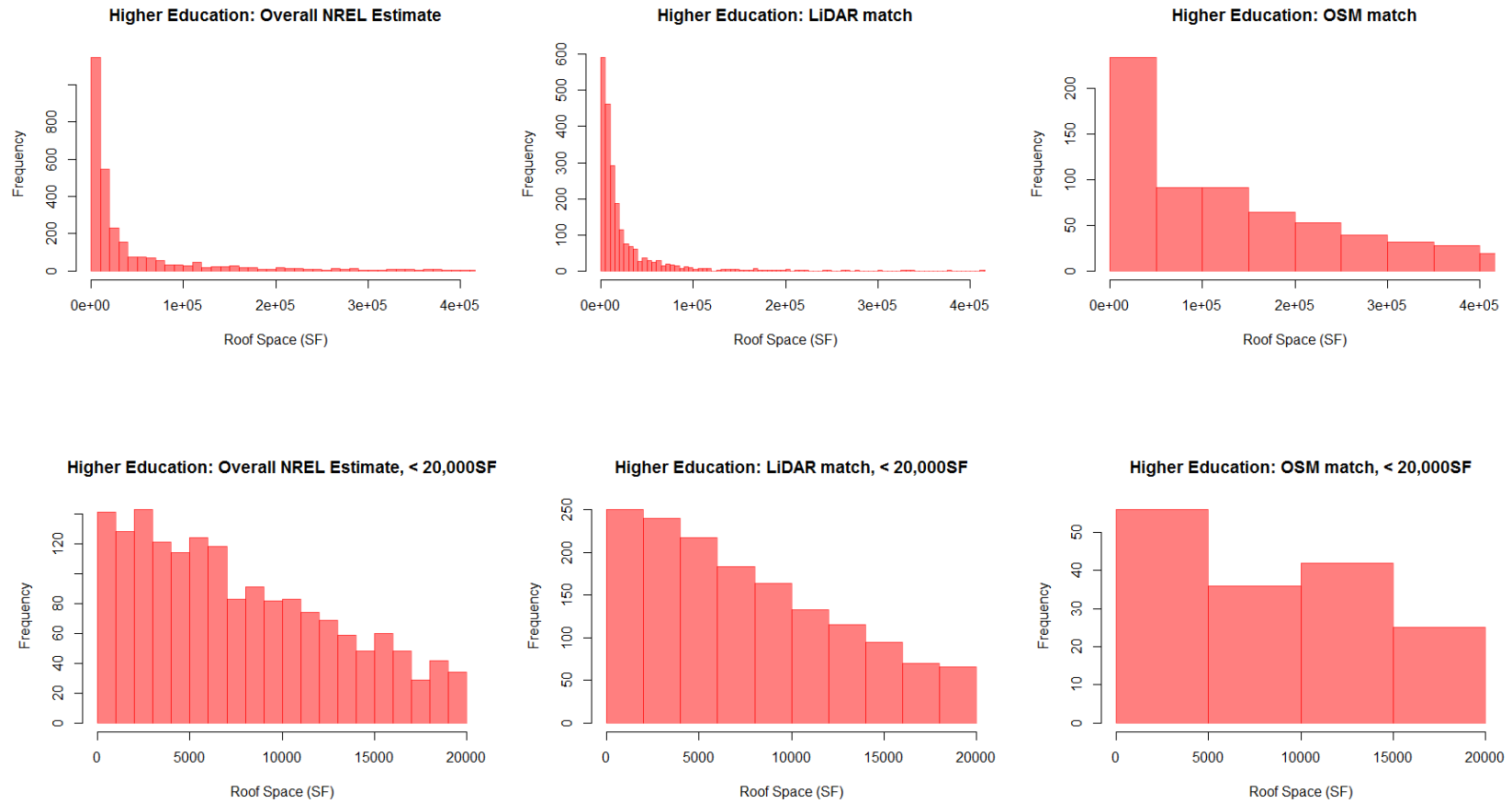


Figure C4. Histograms of roof space estimates (ft²) higher education schools, organized by data type. The upper left plot depicts estimated usable space from all NREL LiDAR data; the bottom left plot depicts the lower end estimates (only 32 schools have estimated usable areas of 0ft²). The upper center plot depicts estimated usable space from LiDAR matches (i.e. single buildings); the bottom center plot depicts the lower end of these estimates. The upper right plot depicts estimated usable space from OSM matches (i.e. campuses); the bottom right plot depicts the lower end of these estimates.

Table C4. Summary statistics of NCES school populations across different NREL LIDAR link types.

School Type	Overall			LIDAR Points				OSM Points			
	N (#)	Mean Pop.	Median Pop.	N (#)	N (%)	Mean Pop.	Median Pop.	N (#)	N (%)	Mean Pop.	Median Pop.
K-12 Public	24,723	552	470	12,164	49%	552	473	12,559	51%	706	575
K-12 Private	9,586	162	79	6,891	72%	158	78	2,695	28%	279	193
Higher Education	2,923	2,488	413	2,178	75%	884	226	745	25%	7,154	3,669

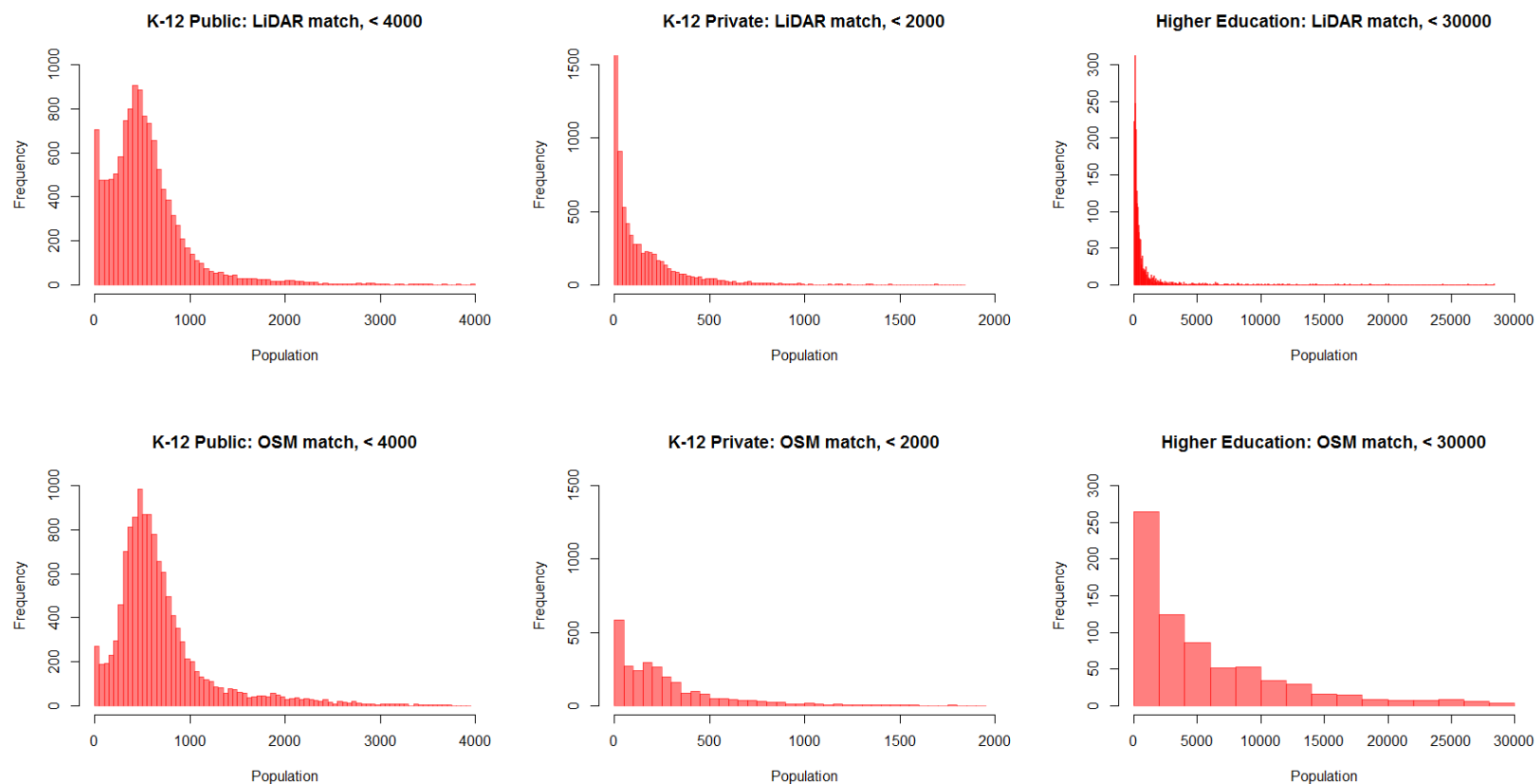


Figure C5. Histograms of school populations, organized by data type and school type. In all instances, the distributions of school populations observe a slight shift to the right for OSM data compared to the LIDAR match. There were 210 cases of schools listing population as “0” which was converted to an NA value. Therefore, none of these distributions depict a population value of 0.

References

- [1] C. Phillips, J. Melius, P. Gagnon, R. Margolis, and R. Elmore, “A Data Mining Approach to Estimating Rooftop Photovoltaic Potential in the U . S .,” pp. 1–25, 2016.
- [2] NOAA, “What is LiDAR?,” *National Ocean Service, National Oceanic and Atmospheric Administration, U.S. Department of Commerce*, 2017. [Online]. Available: <http://oceanservice.noaa.gov/facts/lidar.html>. [Accessed: 09-May-2017].
- [3] ESRI, “ArcGIS Desktop. Hillshade. 3D Analyst Toolbox.,” *Environmental Systems Research Institute*, 2016. [Online]. Available:<http://pro.arcgis.com/en/pro-app/%0Atool-reference/3d-analyst/hillshade.htm>.
- [4] “System Advisor Model.” National Renewable Energy Laboratory, 2016.
- [5] G. Barbose, N. Darghouth, and S. Weaver, “Tracking the Sun VI An Historical Summary of the Installed Price Tracking the Sun VI An Historical Summary of the Installed Price of,” *SunShot - U.S. Dep. Energy*, no. September, p. 70, 2014.
- [6] NCES, “Integrated Postsecondary Education Data System,” *National Center for Education Statistics*, 2015. [Online]. Available:<https://nces.ed.gov/ipeds/Home/UseTheData>.
- [7] NCES, “Common Core of Data,” *National Center for Education Statistics*, 2015. [Online]. Available: <https://nces.ed.gov/ccd/pubschuniv.asp>.
- [8] NCES, “Private School Universe Survey,” *National Center for Education Statistics*, 2015. [Online]. Available: <https://nces.ed.gov/surveys/pss/tableswhi.asp>.
- [9] P. Gagnon, R. Margolis, J. Melius, C. Phillips, and R. Elmore, “Rooftop Solar Photovolatic Technical Potential in the United States: A Detailed Assessment,” no. January, p. 82, 2016.

Appendix C.3: Roof space regression analysis

To estimate the available roof space for the institutions that are not present in the NREL LIDAR dataset, we perform a simple linear regression and regress school-level variables such as student counts (provided by NCES) with county-level variables such as median household income (U.S. Census), fraction living in poverty (U.S. Census), and the fraction of the population living in a rural environment (U.S. Census) onto estimated available roof space (provided by NREL).

Table C5 depicts summary statistics for all of the county- and school-level variables available to us for developing linear regression models. Figure C6 depicts the distributions of these variables that informed any transformations we make to make the data more appropriate for linear regression. Figure C7 provides scatterplots depicting the relationship between the independent variables (IV) and the dependent variable (DV) in our model: Available Roof Space. These scatterplots also inform us of any transformations that need to take place or which variables seem to be most linearly related to the DV.

Table C5. Summary statistics of model variables.

Variable	Variable Level	Type	N	Min	Max	Median	Mean
Estimated Roof Area (SF)	School – All Types	DV - continuous	35,733	0	3,348,000	9,251	25,880
Estimated Roof Area (SF)	School – K12 Public	DV - continuous	23,557	0	1,284,000	13,110	24,990
Estimated Roof Area (SF)	School – K12 Private	DV - continuous	9,241	0	738,800	4,888	11,710
Estimated Roof Area (SF)	School – Higher Ed.	DV - continuous	2,935	0	3,348,000	14,720	77,680
States	State	IV - factor	49	(Removed HI and AK; no LIDAR data for TN, SD, HI, and AK)			
Percent Rural (%)	County ¹	IV - continuous	133,784	0	100	11	24
Median Household Income (\$)	County	IV - continuous	133,769	20,580	119,100	48,040	50,740
Household Density (#/SQM ²)	County	IV - continuous	134,120	0.2	37,110	169	790
Percent Poverty (%)	County	IV - continuous	133,769	3	50	15	15.5
Population Density (#/SQM)	County	IV – continuous	134,120	0.2	69,470	415	1,832
Below 18 (#)	County	IV – continuous	133,769	71	2,501,00	80,480	237,800
18 & Above (#)	County	IV – continuous	133,769	218	7,416,000	251,800	713,600
Gov. Health ³ (TH\$ ⁴)	County	IV – continuous	133,769	0	5,677,000	29,620	306,000
No. Physicians ⁵ (#)	County	IV – continuous	133,769	0	32,060	940	3,449
Vehicles per House (rate)	County	IV – continuous	133,769	0	2.8	1.8	1.7
Gov. Highway ⁶ (TH\$)	County	IV – continuous	133,769	0	1,557,000	33,680	145,000
County Area (SQM)	County	IV – continuous	133,769	0	20,110	802	1,491
Water Area (SQM)	County	IV – continuous	133,769	0	5,425	18	113
Farm Land (Acres)	County	IV – continuous	133,769	0	6,102,000	119,300	231,600
Gov. Revenue (\$)	County	IV – continuous	133,769	0	22,400	3,152	3,409
Employment (#)	County	IV – continuous	133,769	0	5,846,000	191,400	583,800
Population (students + teachers)	School – All Types	IV - continuous	128,973	1	216,800	386	581

¹ There are 3,048 unique counties represented in this whole dataset, but not all of the census variables are available for each county. Therefore, there will be different Ns for each county-level variable depending on the U.S. Census table it was taken from.

² SQM = Square mile

³ Local government general expenditures for hospitals and health; 2002 values.

⁴ Thousands of dollars (\$).

Table C5. Summary statistics of model variables. (Table continued).

Variable	Variable Level	Type	N	Min	Max	Median	Mean
School Type	School – K12 Public	IV- factor	99,318	Alternative Education (6,006); Regular School (89,909); Special Education (1,999); Vocational Education (1,404)			
School Level (Public)	School – K12 Public	IV- factor	99,318	Primary (52,709); Middle (16,440); High (20,219); Other (6,649); Not Applicable ⁷ (3,301)			
Charter School	School – K12 Public	IV- factor	99,318	No (85,342); Yes (7,032); Not Applicable ⁸ (6,944)			
School Level (Private)	School – K12 Private	IV- factor	26,804	Elementary (17,533); Secondary (2,383); Combined (6,888)			
Religious Affiliation	School – K12 Private	IV- factor	26,804	Catholic (6,354); Other religion (11,773); Nonsectarian (8,677)			
Males	School – K12 Private	IV - continuous	26,804	0	3,319	35	76
No. Kindergarten Students	School – K12 Private	IV - continuous	26,804	0	1,800	10	15
Total Hours	School – K12 Private	IV - continuous	26,804	1	11	7	7
Percent Caucasian (%)	School – K12 Private	IV - continuous	26,804	0	100	79	67
School Level (Higher Ed.)	School – Higher Ed.	IV - factor	6,746	Assoc. Degree (3,910); Bach. Degree (837); Post Bach. Degree (1,999)			
Land Grant	School – Higher Ed.	IV - factor	6,890	Land Grant (91); Non Land Grant (6,799)			
Applications	School – Higher Ed.	IV - continuous	6,781	0	72,680	0	1,300

⁵Number of physicians in a county; 2009 values.

⁶Local government expenditures on highways.

⁷Here the “NA” is treated as a separate category, not as missing.

⁸Here the “NA” is treated as a separate category, not as missing.

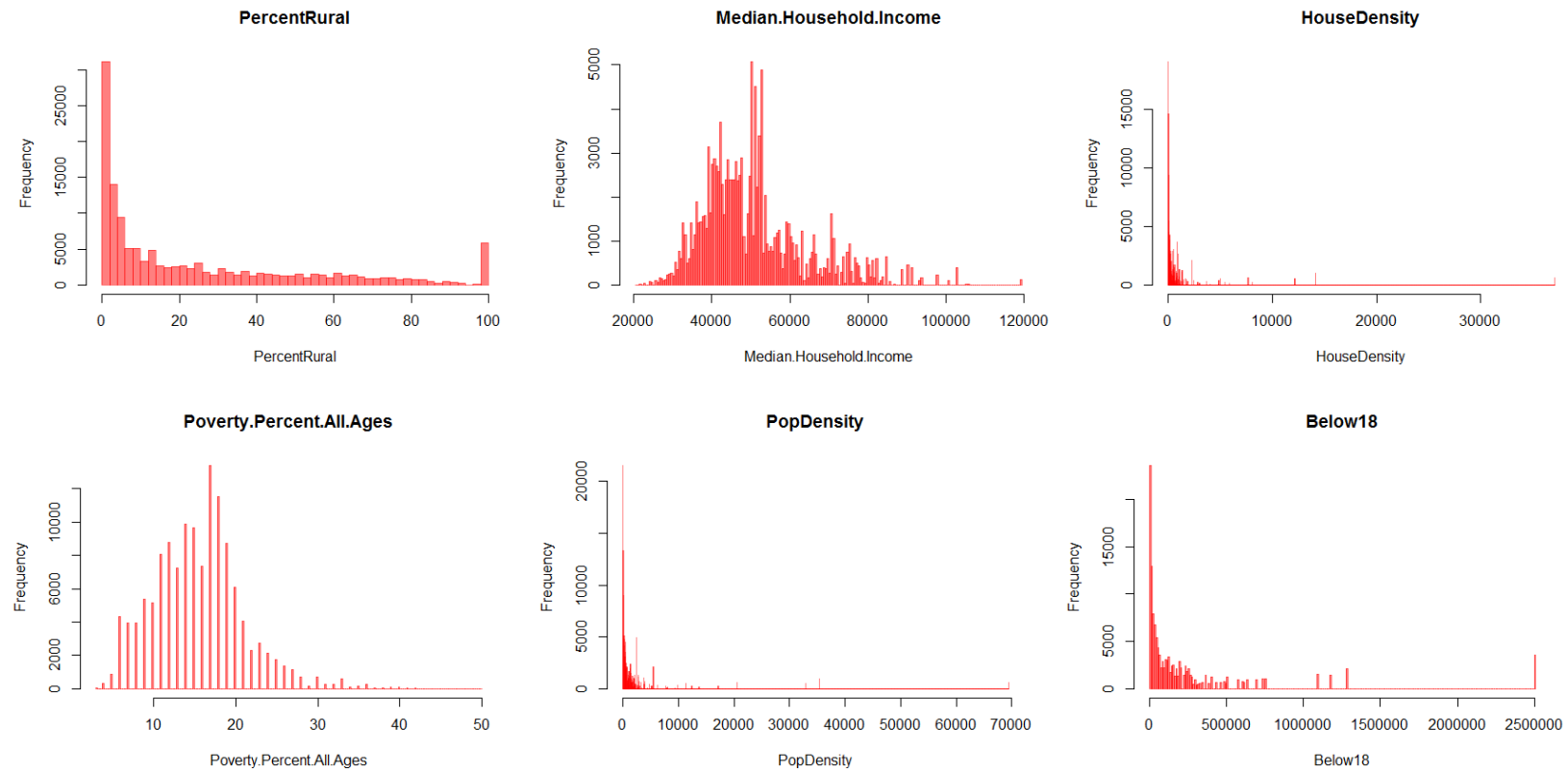


Figure C6. Distributions of variables include in the model selection.

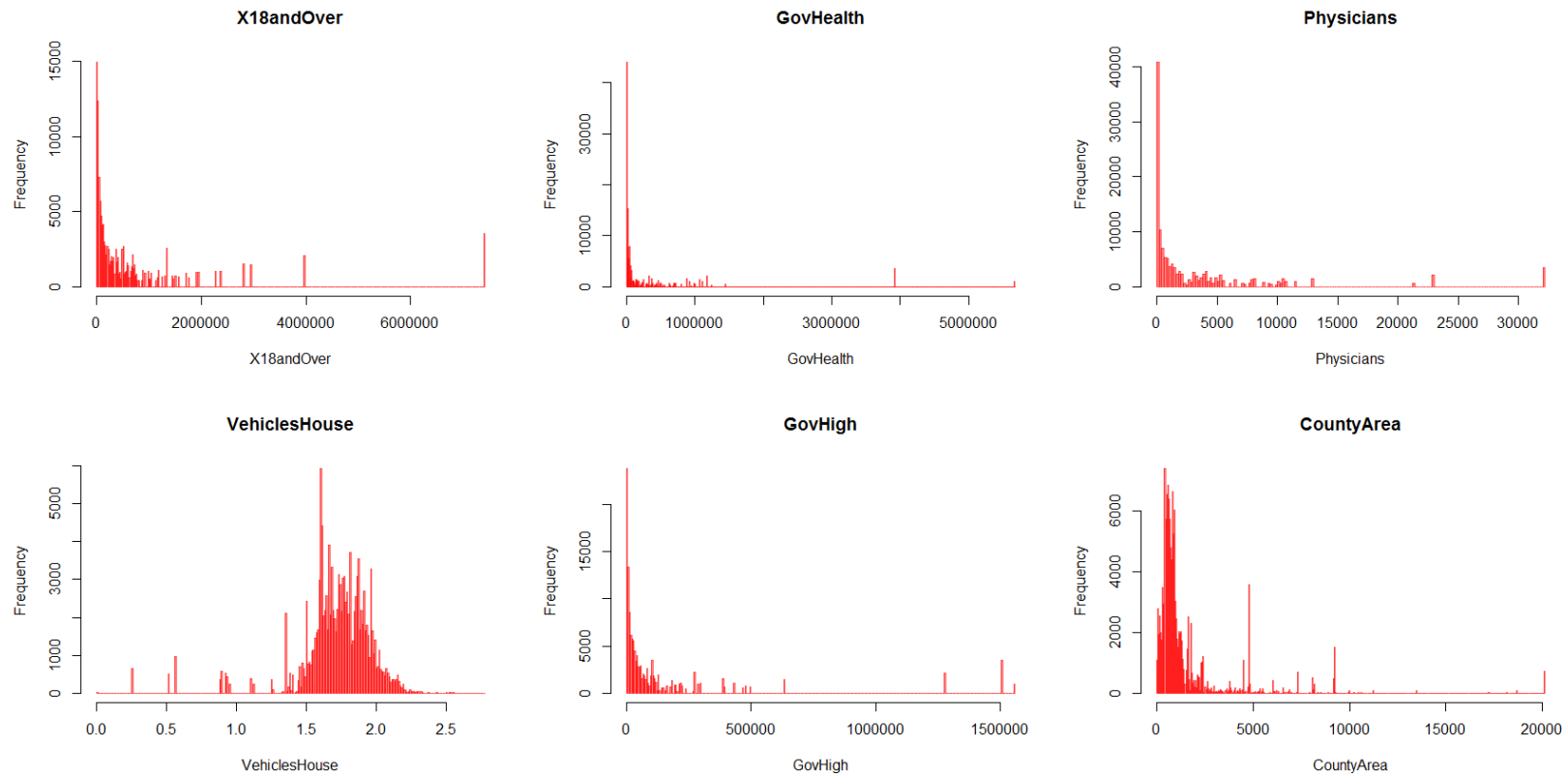


Figure C6 (Cont.). Distributions of variables include in the model selection.

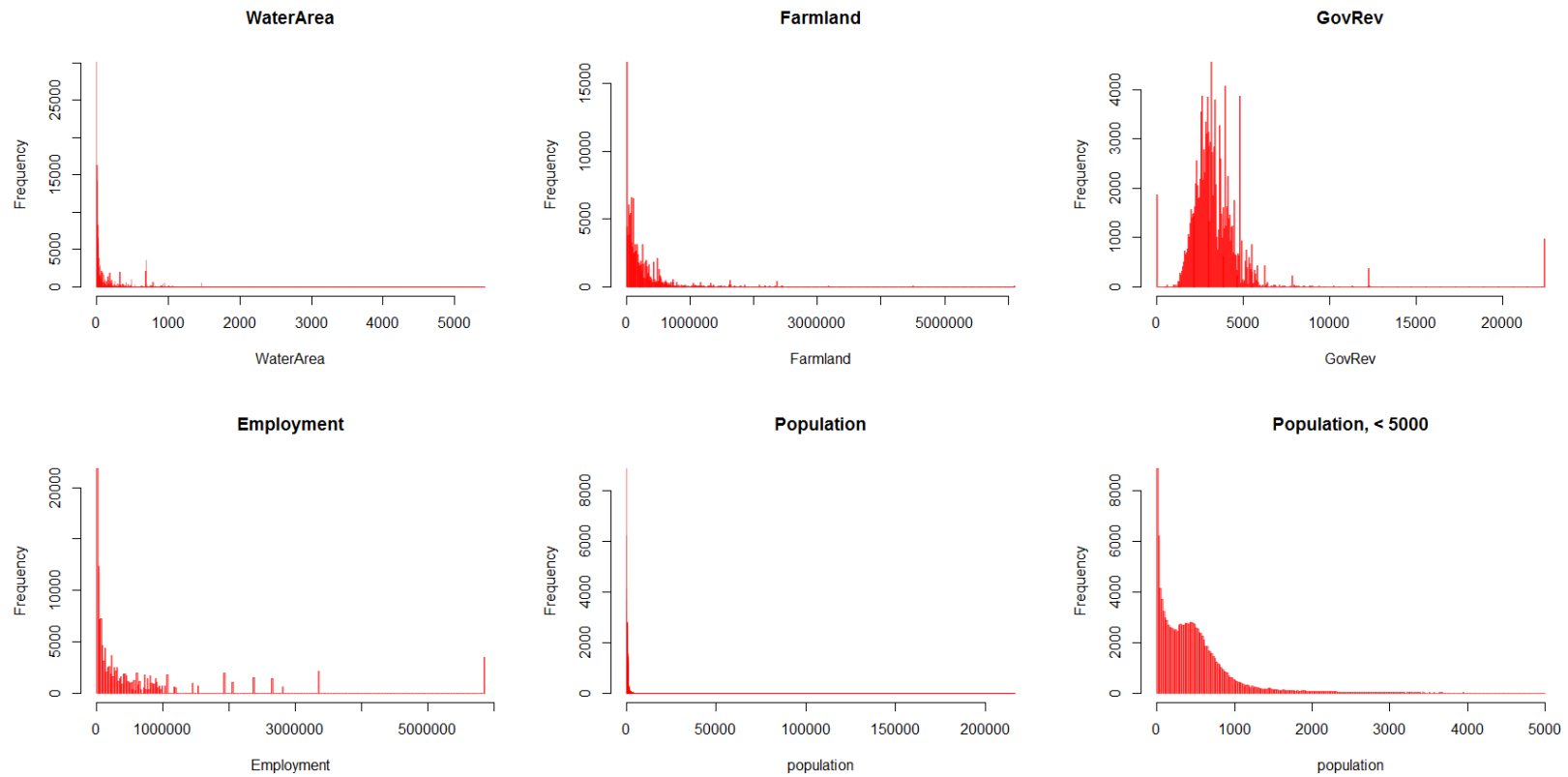


Figure C6 (Cont.). Distributions of variables include in the model selection.

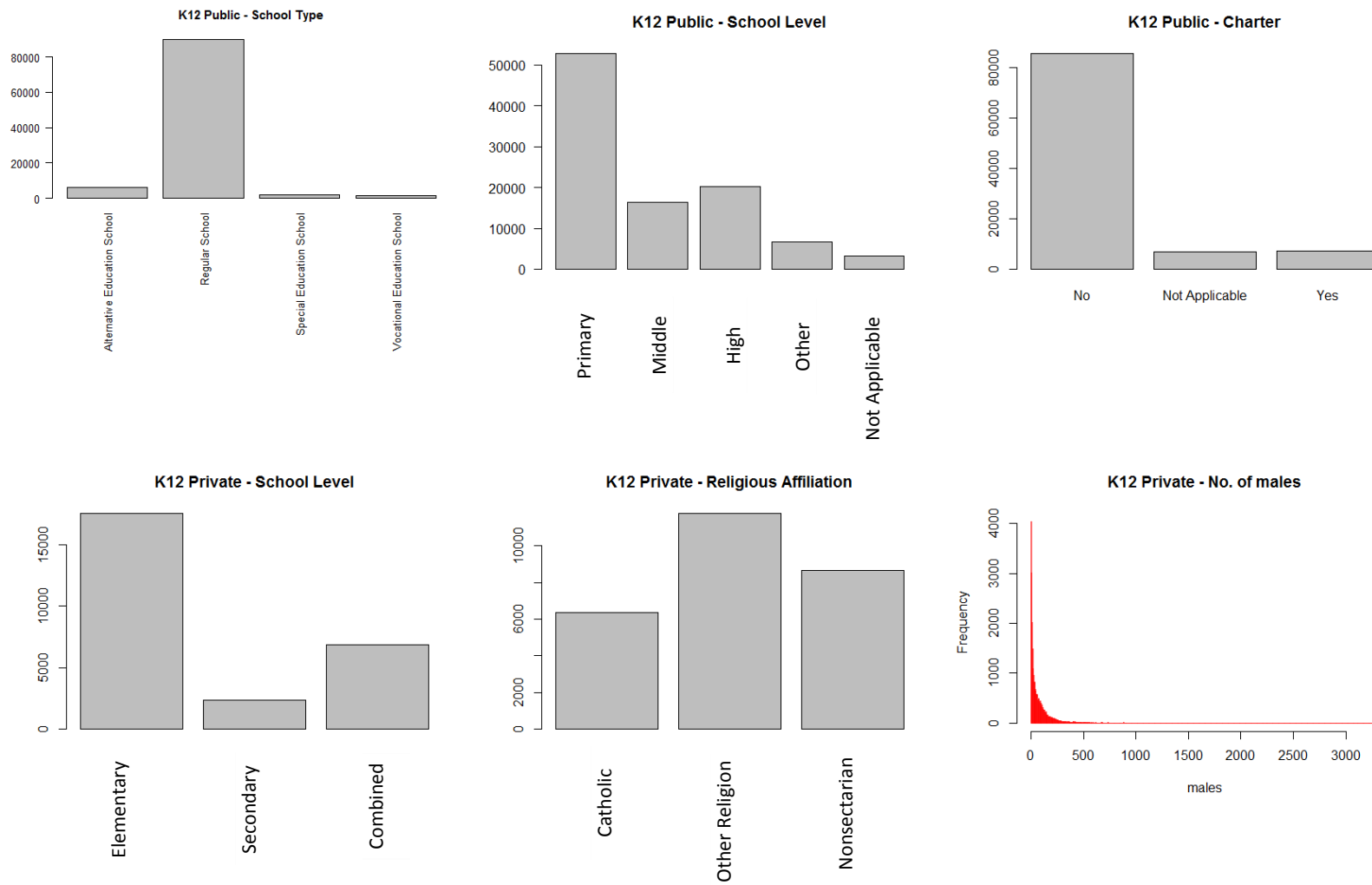


Figure C6 (Cont.). Distributions of variables include in the model selection.

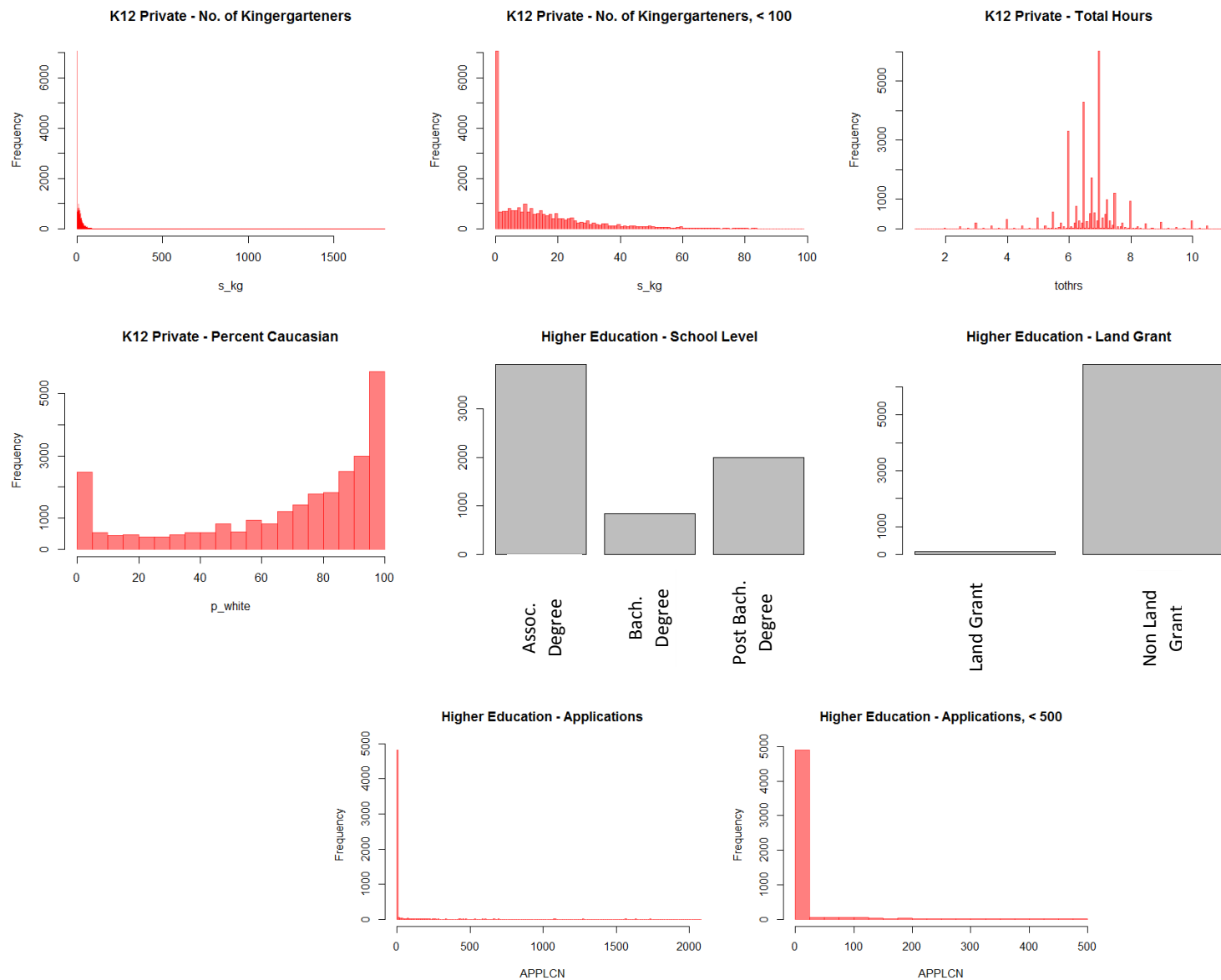


Figure C6 (Cont.). Distributions of variables include in the model selection.

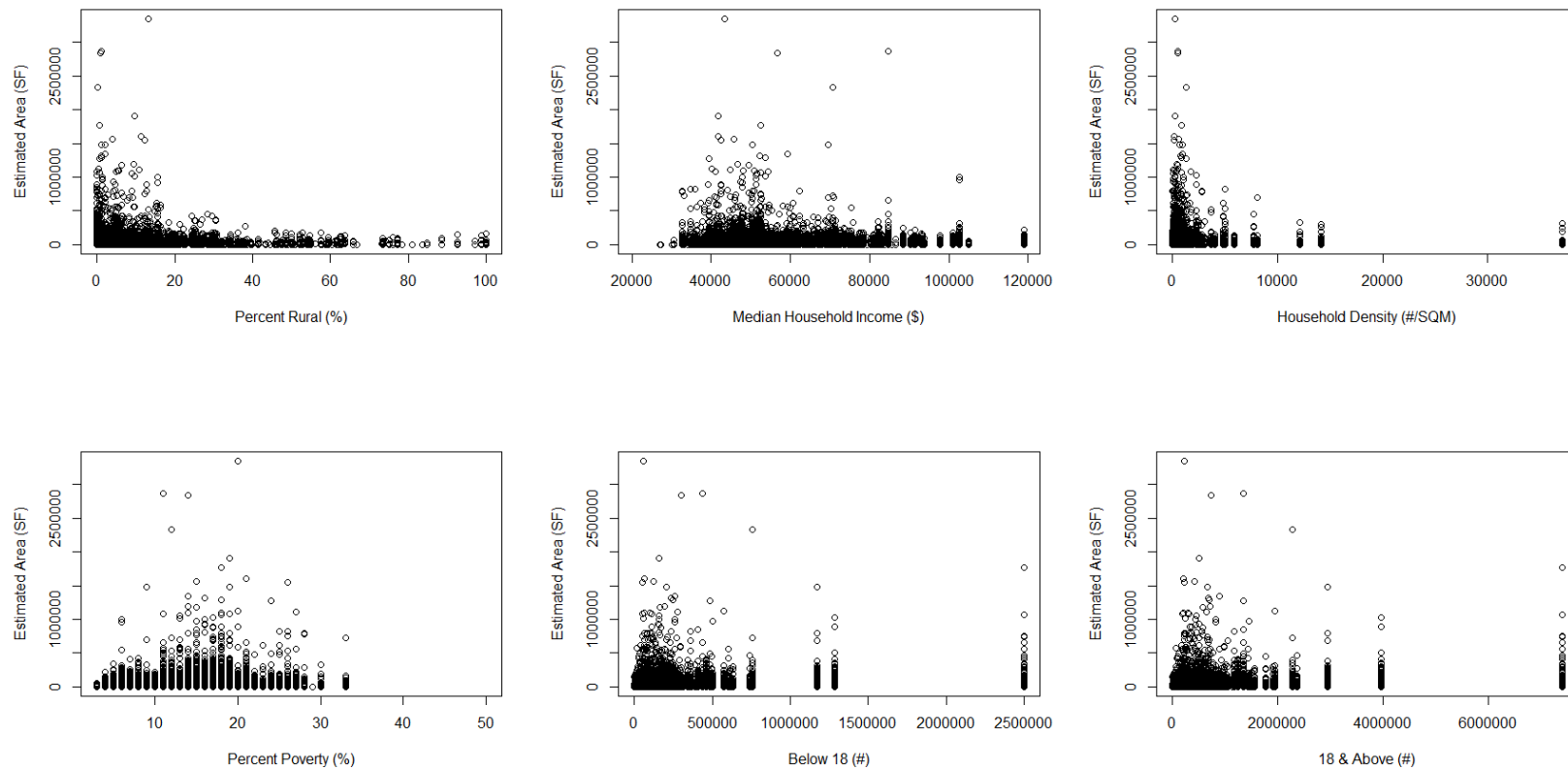


Figure C7. Scatterplots depicting the relationships between individual IVs and the dependent variable: Estimated Space.

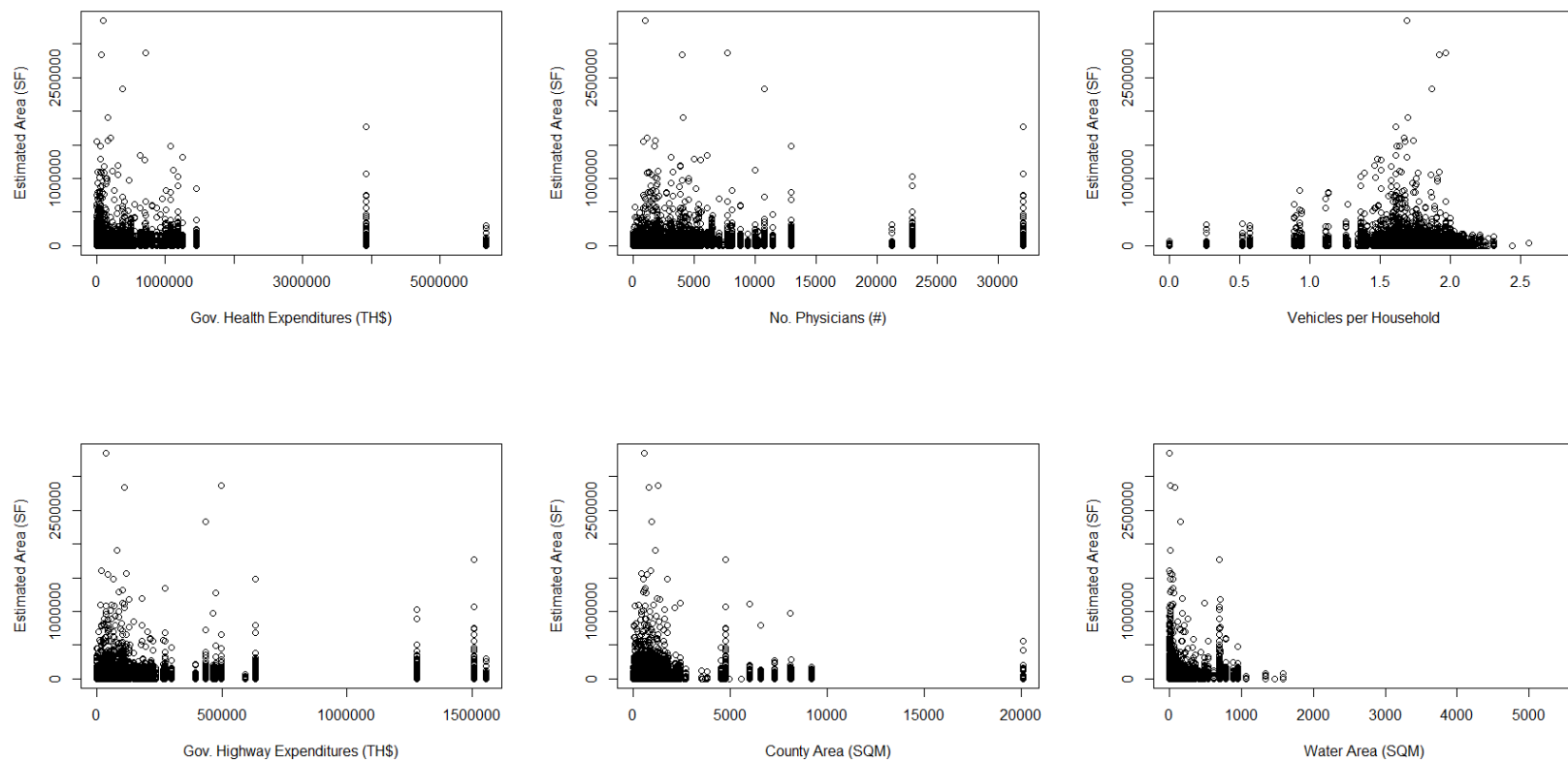


Figure C7 (Cont.). Scatterplots depicting the relationships between individual IVs and the dependent variable: Estimated Space.

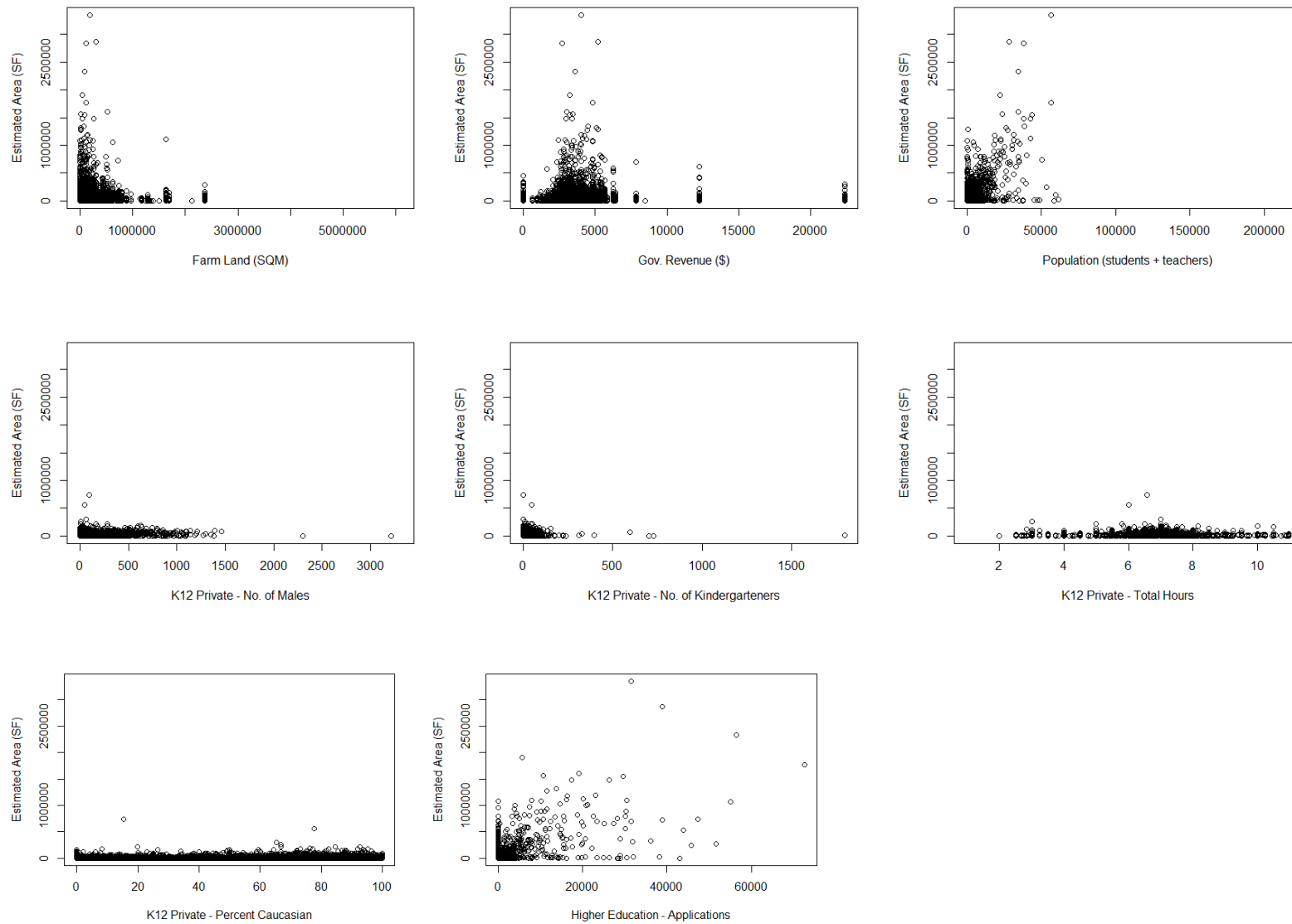


Figure C7 (Cont.). Scatterplots depicting the relationships between individual IVs and the dependent variable: Estimated Space.

Table C6 depicts Pearson correlation values for the IVs with correlations greater than 0.50.

Table C6. Correlation table between variables that have a Pearson's correlation greater than 0.50.

Variable 1	Variable 2	r
Median Household Income	Percent Poverty	-0.78
Household Density	Population Density	0.99
Below 18	18 and Over	1.00
Below 18	Government Health Expenditures	0.81
18 and Over	Government Health Expenditures	0.82
Below 18	No. of Physicians	0.95
18 and Over	No. of Physicians	0.96
Government Health Expenditures	No. of Physicians	0.77
Household Density	Vehicles per House	-0.69
Population Density	Vehicles per House	-0.73
Below 18	Government Highway Expenditures	0.90
18 and Over	Government Highway Expenditures	0.91
Government Health Expenditures	Government Highway Expenditures	0.90
No. of Physicians	Government Highway Expenditures	0.88
Government Health Expenditures	Government Revenue	0.65
Below 18	Employment	0.98
18 and Over	Employment	0.99
Government Health Expenditures	Employment	0.76
Government Health Expenditures	No. of Physicians	0.98
Government Highway Expenditures	Employment	0.88
Population (students + teachers)	No. of Males	0.90

After considering the IV distributions and correlations, we select the most parsimonious model that also has strong predictive power. In order to select the most predictive, parsimonious model, we perform K-fold cross-validation of the root mean squared error (RMSE) and progressively remove variables before selecting the model that had an acceptably low RMSE, while not requiring so many variables that we compromise on generalizability. Here, we set the K to five. When performing the cross-validation, we only consider a completely pooled model (i.e. we do not develop an intercept for each state, but rather develop a single intercept across all states). Additionally, we do not include school-level factor variables (e.g. religious affiliation), to increase the ease of the cross-validation, which randomly fits a model on a sample of 4/5 of the full list of observations and then predicts the remaining 1/5 of observations. We split the data into three groups on which to develop models and perform cross-validation: Higher Education, K-12 public schools, and K-12 private schools. Figure C8 depicts the cross-validated RMSEs with increasing numbers of variables included in the linear regression model. The red vertical lines indicate the number of continuous variables we ultimately decided to include in the model.

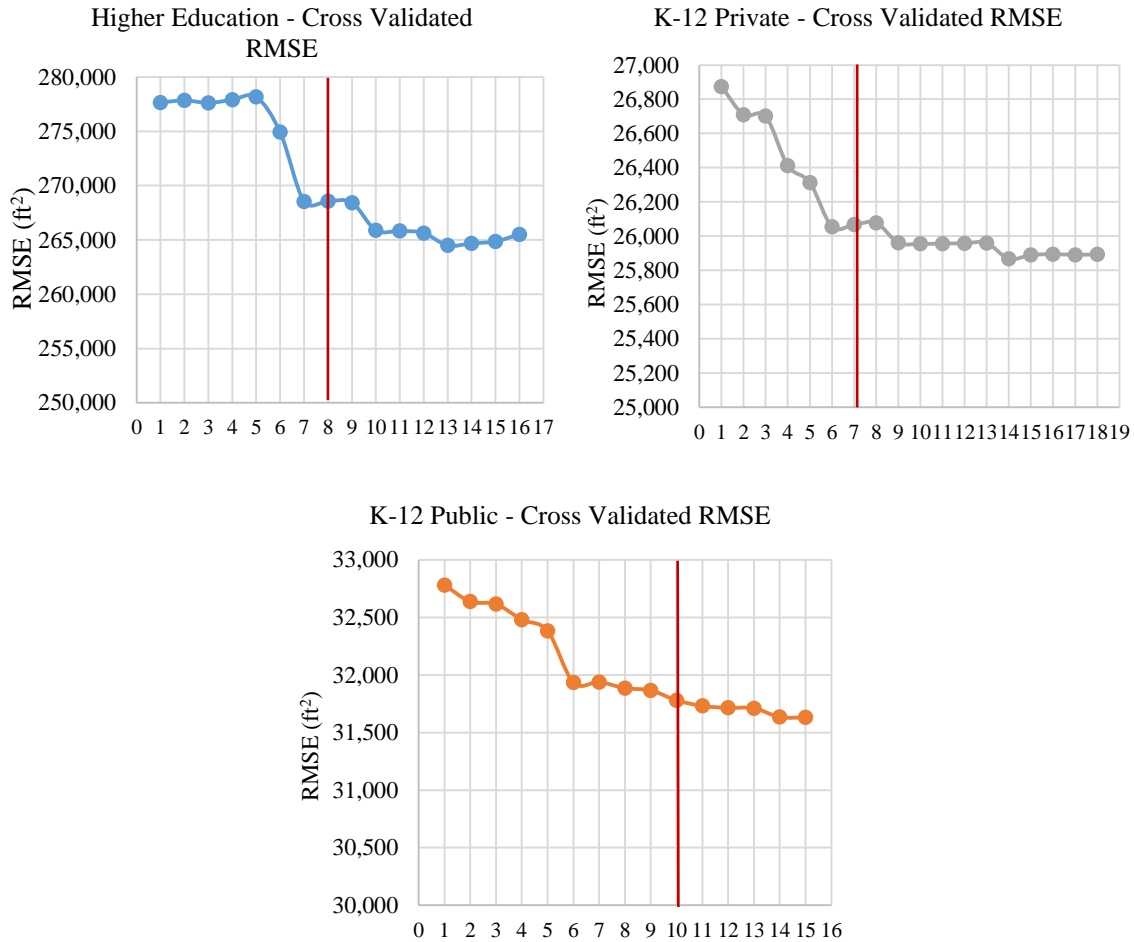


Figure C8. Cross-validated root mean squared error (RMSE) of available roof space (ft²) predictive power of the Higher Education, K-12 Private School, and K-12 Public School linear regression models. In each of these cases, we picked the most parsimonious model – meaning, we selected the number of variables that reduced the RMSE to an appropriate level. The red vertical lines indicate the number of continuous variables we ultimately decided to include in the model.

Next, we compared the predictive power of models using All LIDAR data vs. OSM-linked data; a partial pooling model vs. a no pooling model; and a very short model (e.g. only using school population) vs. the long model (e.g. model using the aforementioned number of continuous variables indicated by red lines). Table C7 depicts the key parameters we considered in model selection: Akaike information criterion (AIC), Bayesian information criterion (BIC), and deviance information criterion (DIC), and adjusted R^2 . In each case, we selected the model with the lowest AIC, BIC, and/or DIC and the highest R^2 . First, we considered models using All LIDAR data vs. OSM-linked data. We find that fitting “no pooling – short” and “no pooling – long models” models on OSM-only data resulted in higher quality models, when considering a

randomly selected 20% of the dataset. Next, we considered using a partial pooling model vs. a no pooling model. In a partially pooled model, we discount the state-level intercepts (e.g. no pooling) that do not have many observations in that state category. Essentially, partial pooling allows us to estimate an intercept for each state that shifts the observed average for that state (e.g. no pooling) toward the observed average for all observations (e.g. complete pooling), depending on the number of observations in each state category. Therefore, the larger the sample size for each state, the closer the partially pooled intercept is for that state to the no pooling intercept. Here, we find that the AIC and BIC values for the no pooling and partial pooling models with OSM-only data are comparable, when considering a randomly selected 20% of the dataset. Due to the increased ease of building no pooling models, we continue with the no pooling models. Finally, we consider using the short model compared to longer models for each school type. We find that the R² values for the no pooling models (e.g. intercept for each state) are highest when building models with more than just the school populations as the IV. We build no pooling models to predict roof space for schools located in most states and we use complete pooling models to predict roof space for schools that we did not have OSM-linked LIDAR data (Table C8).

Table C7. Predictive power of various models used in our model selection.

Model	Data	AIC	BIC	DIC	Adjusted R ²
No Pooling - Short	All LIDAR - 20%	15,200	15,400		0.34
No Pooling - Long	All LIDAR - 20%	15,100	15,300		0.35
No Pooling - Short	OSM-only - 20%	3,800	3,900		0.63
No Pooling - Long	OSM-only - 20%	3,800	3,900		0.65
Partial Pooling - Varying Int. - Short	OSM-only - 20%	3,700	3,800	3,800	
Partial Pooling - Varying Int. - Long	OSM-only - 20%	3,600	3,600	3,900	
Partial Pooling - Varying Int. & Slope - Short	OSM-only - 20%	3,700	3,800	3,800	
Partial Pooling - Varying Int. & Slope - Long	OSM-only - 20%	3,600	3,600	3,900	
No Pooling - Long - Higher Education	OSM-only - 100%	19,600	19,900		0.54
No Pooling - Long - K12 Public	OSM-only - 100%	291,300	291,700		0.76
No Pooling - Long - K12 Private	OSM-only - 100%	61,900	291,700		0.51
Complete Pooling - Long - Higher Education	OSM-only - 100%	19,600	19,600		0.31
Complete Pooling - Long - K12 Public	OSM-only - 100%	292,200	292,400		0.44
Complete Pooling - Long - K12 Private	OSM-only - 100%	62,000	62,100		0.16

Table C8. States in each school category in which we used the complete pooling model to predict available roof space.

Higher Education	K-12 Private	K-12 Public
ME	DE	SD
SD	MT	TN
TN	SD	
VT	TN	
WY		

We then take the fitted model and predict available roof space for the schools not covered in the OSM-linked LIDAR dataset, given their school-level variables such as population and associated county-level data such as median household income. In our complete pooling models, we omit the state fixed effects, but using the same IVs otherwise to predict roof space for schools in these states. Therefore, our regression model equations are defined as such:

$$\text{No Pooling Space}_i = \alpha_{j[i]} + \beta_1 X_i + \beta_2 X_i + \varepsilon_i$$

$$\text{Complete Pooling Space}_i = \alpha_i + \beta_1 X_i + \beta_2 X_i + \varepsilon_i$$

Where β_1 represents modeled coefficients for school-level variables, β_2 represents modeled coefficients for county-level variables, $\alpha_{j[i]}$ represents state fixed effects, and α_i is the complete pooling intercept. The model results are depicted in Table C9, Table C10, and Table C11. Figure C9 and Figure C10 demonstrate the estimated available roof space and corresponding electricity generated by solar PV on educational facilities in the US.

Table C9. Higher education linear regression table.

		No Pooling (N = 703)		Complete Pooling (N = 703)	
Variable Level		B	SE	B	SE
(Constant)				720K	570K
States		Factor		Factor	
Percent Rural (%)	County	-4.5K*	2.1K	-3.9K*	1.8K
Log Median Income (\$)	County	-53K	66K	-87K	49K
Log Below 18 (#)	County	-22K	19K	-6.4K	14K
Gov. Revenue (\$)	County	1.2	5.5	1.4	5.0
Log Farm Land (Acres)	County	13K*	4.4K	17K***	3.2K
Log Water Area (SQM)	County	-16K	9.9K	-6.0K	7.3K
Log Population (#)	School	68K***	7.3K	76K***	7.0K
Land Grant	School	Factor		Factor	79K
Log Applications (#)	School	20K***	3.8K	15K***	3.6K
School Level	School	Factor		Factor	
R ²		0.54		0.31	

*** $p < .001$, ** $p < .01$, * $p < .05$ **Table C10.** K-12 public schools linear regression table.

		No Pooling (N = 12,532)		Complete Pooling (N = 12,532)	
Variable Level		B	SE	B	SE
(Constant)				-43K**	13K
States		Factor		Factor	
Percent Rural (%)	County	-31	46	-260***	40
Log Median Income (\$)	County	9.0K***	1.5K	-880	1.1K
Log Below 18 (#)	County	-1.9K***	440	-4.4K***	350
Gov. Revenue (\$)	County	0.20*	0.1	-0.19*	0.10
Log Farm Land (Acres)	County	1.1K***	110	1.7K***	79
Log Water Area (SQM)	County	-11	240	-16	180
Log Population (#)	School	18K***	380	19K***	390
School Type	School	Factor		Factor	
School Level	School	Factor		Factor	
Charter School	School	Factor		Factor	
R ²		0.76		0.44	

*** $p < .001$, ** $p < .01$, * $p < .05$

Table C11. K-12 private schools linear regression table.

		No Pooling		Complete Pooling	
		(N = 2,679)		(N = 2,679)	
	Variable Level	B	SE	B	SE
(Constant)				92K**	28K
States	County	Factor		Factor	
Percent Rural (%)	County	-170	130	-340**	110
Log Median Income (\$)	County	4.6K	3.2K	-2.9K	2.4K
Log Below 18 (#)	County	-3.4K***	910	-4.9K***	700
Gov. Revenue (\$)	County	-0.17	0.16	-0.24	0.15
Log Farm Land (Acres)	County	1.2K***	250	1.2K***	160
Log Water Area (SQM)	County	-610	530	-140	390
Log Population (#)	School	3.3K***	600	3.4K***	600
Percent Caucasian (%)	School	-8.9	17	-13	16
No. Kindergarten Students (#)	School	11	31	31	31
Total Hours (#)	School	-1.3K*	560	-960	560
School Level	School	Factor		Factor	
Religious Affiliation	School	Factor		Factor	
R ²		0.51		0.16	

*** $p < .001$, ** $p < .01$, * $p < .05$

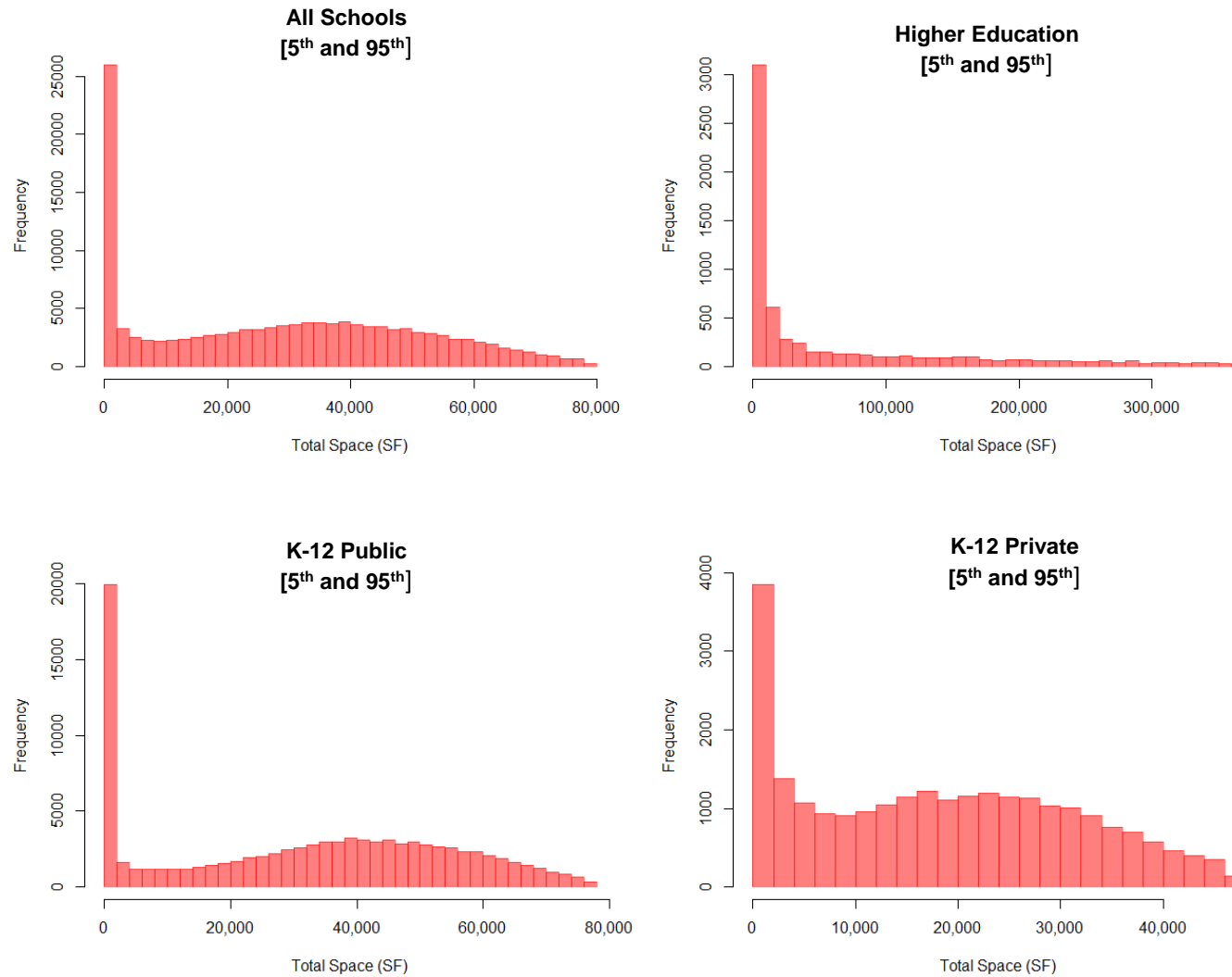


Figure C9. Histograms of available rooftop space on all schools in square feet (SF). Distributions include observed available space from the NREL data as well as estimates resulting from the linear regression models.

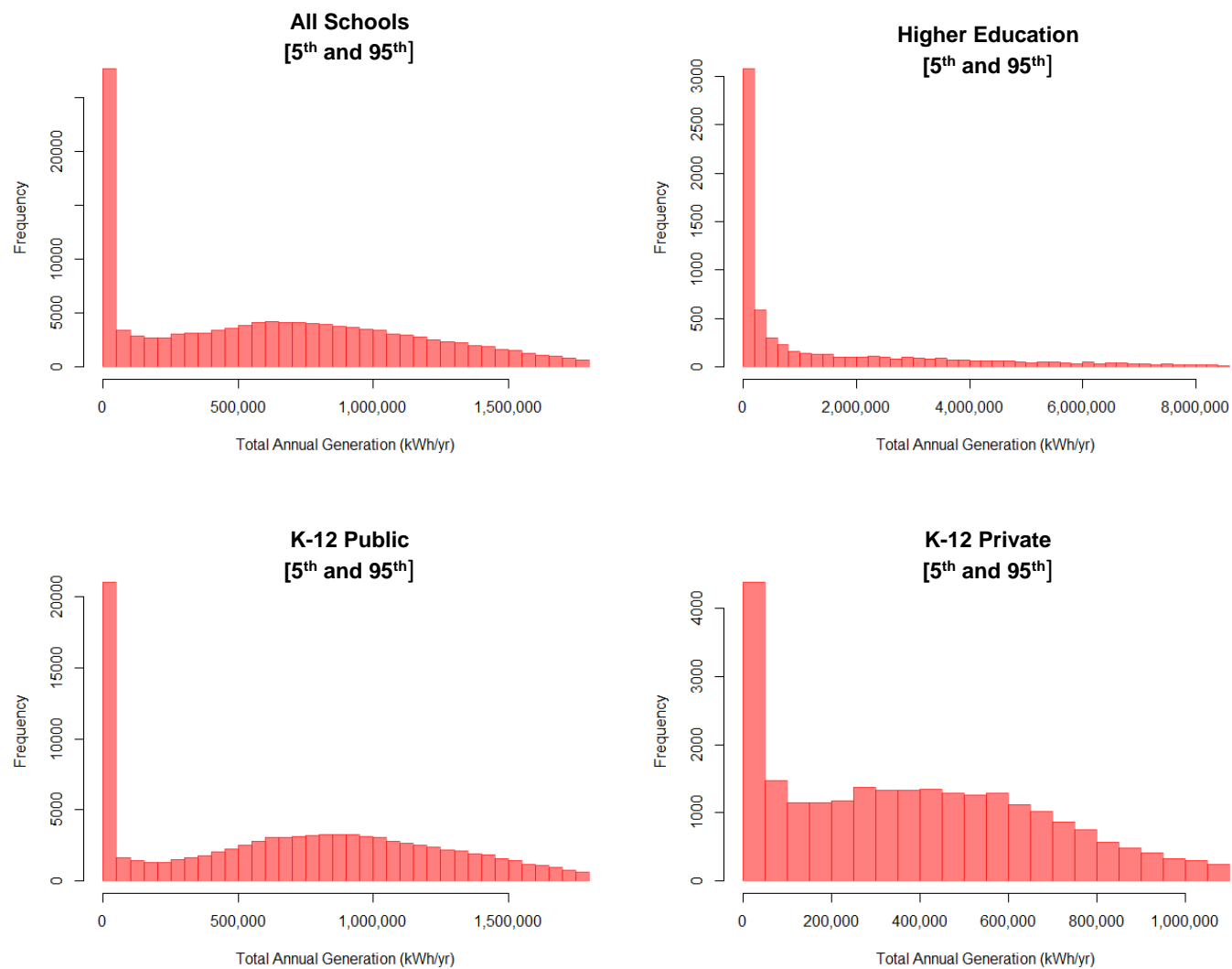


Figure C10. Histograms of estimated annual electricity generation (kWh/yr) from solar PV installed on all US educational institutions.

Appendix C.4: Load scaling & net-power

In this analysis, we assume that educational institutions consume all of the electricity that is generated by the panels and that any excess is sold back to the grid. Recall that we use the DOE “secondary school” reference buildings [1] for each of the roughly 1,000 TMY3 locations to estimate hourly building electricity consumption. The DOE characterizes the secondary school reference buildings as having an average floor area of 210,887 ft² and two stories. Assuming the floor area divides evenly among stories, this equates to a roof area of approximately 100,000 ft². The 95th percentile of the OSM-linked rooftop area data is 90,000 ft² and the 95th percentile of the regression estimated rooftop area across all educational institutions is 77,000 ft². Since these the OSM-linked and regression estimated rooftop space is smaller than the DOE reference building rooftop space, we are comfortable assuming that the ratio between excess generation and peak load remains the same between each educational institution in our dataset and their designated DOE secondary reference schools [1]. Therefore, net-power is estimated at each hour of the day in each TMY3 location as follows:

$$NetPower_{h,l} \left(\frac{MWh}{kW} \right) = \frac{\left[Power_{h,l} \left(\frac{MWh}{kW} \right) \times 80\%PeakLoad_l(kW) \right] - Load_{h,l}(MWh)}{80\%PeakLoad_l(kW)}$$

In this question, $Power_{h,l}$ is the electricity generated per kW of a solar panel installed at the specific TMY3 location (l); $80\%PeakLoad_l$ represents 80% of the peak load experienced for a reference school throughout the year at a specific TMY3 location; $Load_{h,l}$ is the electricity demand for a reference school in each hour of the year at the specific TMY3 location.

From the simulated annual building loads and PV generation, we find that the PV systems generate 21% of annual electricity consumption, on average. The following table provides some summary statistics for school electricity consumption across the dataset and the estimated PV generation:

Table C12. Annual PV generation and school electricity consumption comparison table.

	Min	Max	Mean	Median
Annual PV Generation (kWh/yr)	0	73,600,000	755,900	631,500
Annual School Electricity Consumption (kWh/yr)	0	16,400,000	158,100	135,700

References

- [1] U.S. DOE, “Commercial Reference Buildings,” *Department of Energy*, 2017. [Online]. Available: <https://energy.gov/eere/buildings/commercial-reference-buildings%0A>.

Appendix C.5: Demand charge treatment in energy cost savings estimation

Demand charges are monthly charges to a consumer that reflect their peak demand during some designated period in a billing cycle. These peak values can be measured seasonally, monthly, and/or over some other averaging interval or period window. Furthermore, demand charges can be fixed or tiered according to demand thresholds. It is important to understand how installing PV could affect demand charges for the educational sector across the United States. Following a method outlined by Darghouth et al. [1], we simulate secondary school DOE reference building loads in 15 cities using NREL's System Advisor Model (SAM) [2] as shown in Figure C11.

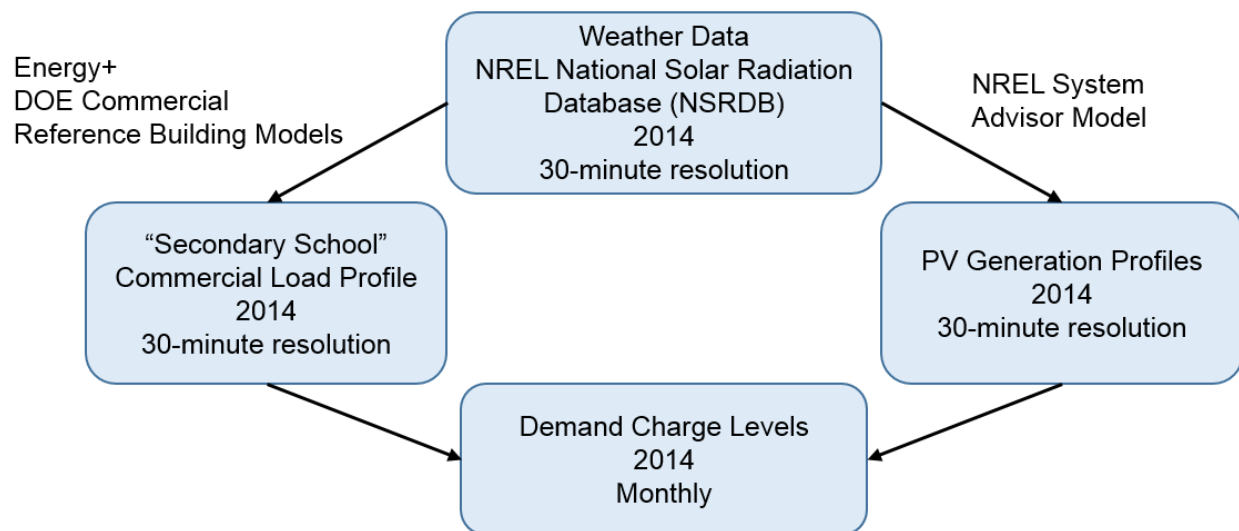


Figure C11. Demand charge analysis model

We assume the following rate structures taken from Open EI [3]:

Table C13. Open EI retail rate structures utilized in SAM simulations.

City, State	Utility	Rate
Albuquerque, NM	Public Service Co of NM	3B General Power TOU (PNM-Owned Transformer); 58b85da2682bea777c7e98de
Atlanta, GA	Georgia Power Co	Power and Light Medium, Schedule PLM-11; 58f10395682bea2739a3d696
Baltimore, MD	Baltimore Gas & Electric Co	Schedule GL General Service Large - Primary Voltage; 5977720a682bea5783cc8ad4
Boulder, CO	Public Service Co of Colorado	SG - Secondary General Service; 57196d06682bea30af85ebe4
Chicago, IL	ComEd	RDS-Medium Load Delivery Class (Primary); 5955553a682bea3b46106d77
Duluth, MN	Minnesota Power Inc	Large Light & Power - Primary voltage discount; 575b0022682bea6f019ca249
Helena, AK	Vigilante Electric Coop, Inc	Commercial; 55fc8195682bea28da64ca92
Houston, TX	CenterPoint Energy	Medium Non-Residential LSP POLR; 55fc81ba682bea28da64e630
Las Vegas, NV	Nevada Power Co	LGS-2 - Large General Service (Primary Distribution Voltage); 58a38166682bea67b4cabad0
Los Angeles, CA	Los Angeles Department of Water & Power	Primary Service (4.8 kV) CG-2€; 587e4d92682bea6da776244b
Miami, FL	Florida Power & Light Co	SDTR-2 (Option A); 58b4702a682bea017b7718a0
Minneapolis, MN	Northern States Power Co - Minnesota (South Dakota)	General Service Primary Voltage (E15); 59249bca682bea029d1c2b02
Phoenix, AZ	Arizona Public Service Co	Large General Service (E-32 L) Primary; 5890db2e682bea10e3549e8b
San Francisco, CA	Pacific Gas & Electric Co	E-19 Medium General Demand TOU (Primary); 586ec8ea682bea4eea938605
Seattle, WA	City of Seattle, Washington (Utility Company)	Schedule MDC - Medium Standard General Service: City; 58cc2eae682bea70bdc3384d

Figure C12 depicts the fraction of consumption rate comprised by demand charges before PV installation and after PV installation.

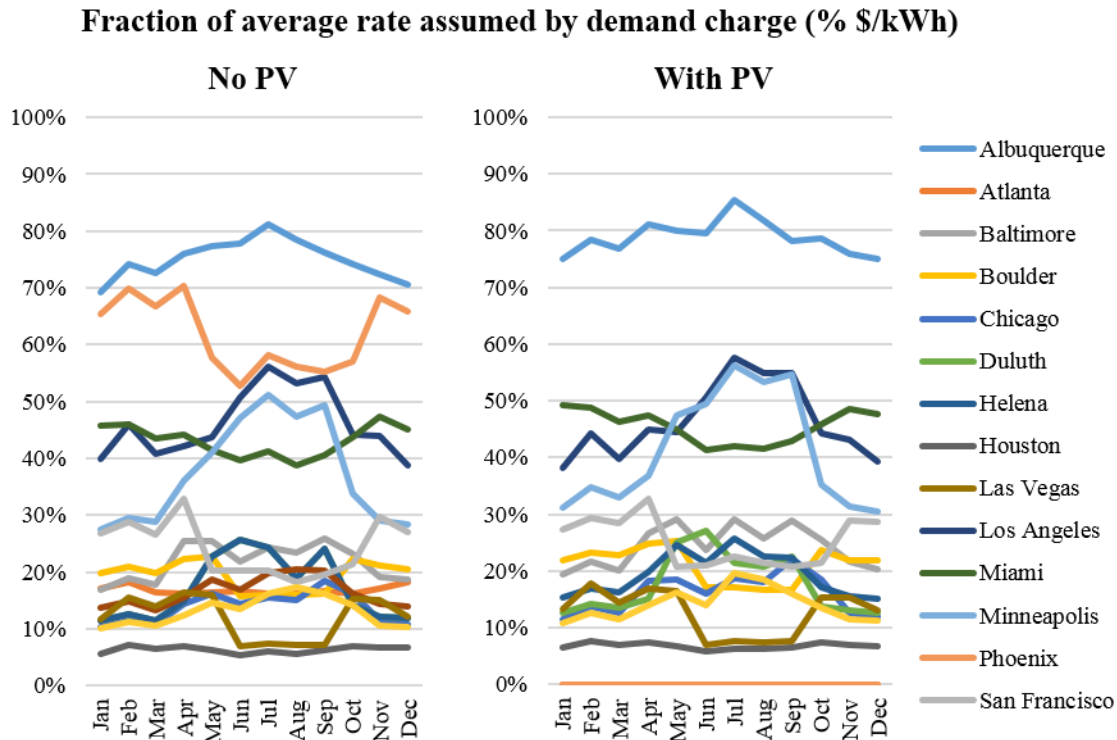


Figure C12. Fraction of total monthly consumption rate (\$/kWh) that is comprised by the demand charge. This value is calculated by dividing the monthly demand charge (\$/mo) by the total billed monthly consumption (kWh/mo).

We see a range of percentage increases and decreases across the reference schools. There does not seem to be a regional trend or overall positive or negative shift over seasons. We find that the average monthly demand charge across all reference schools accounts for 20% of the average rates and that rooftop solar PV can provide average monthly demand savings of 20%, on average. Therefore, we adjust the state-average 2016 commercial retail rate as follows to account for the demand cost savings and appropriately reduce the volumetric rate:

$$Commercial.Rate_{State} = Avg.Rate_{State} * .8 + Avg.Rate_{State} * .20 * .20$$

Here, the first part of the *Commercial.Rate* approximates the variable rate observed for each state and the second part approximates the demand savings for each state.

References

- [1] N. Darghouth, G. Barbose, A. Mills, R. Wiser, P. Gagnon, and L. Bird, "Exploring Demand Charge Savings from Commercial Solar," 2017.
- [2] N. Blair *et al.*, "System Advisor Model , SAM 2014.1.14: General Description," 2014.
- [3] OpenEI, "Utility Rate Database," *Open EI*, 2017. [Online]. Available: http://en.openei.org/wiki/Utility_Rate_Database.

Appendix C.6: PV rebates and net-metering policies, by state

This section details the state PV rebates and net-metering available to schools as currently described on the DSIRE website in January 2018 [1]. We applied the following database filters to arrive at the values depicted in Table C14:

- Eligible sector: non-residential -> public sector -> schools
- Category: Financial Incentives
- Technology: Solar PV
- Program type: Rebate Program

Due to the complex rebate structure for many of the state rebates and since some rebates are administered through single utilities rather than by the state, we elect to use the LBNL Tracking the Sun average rebates to approximate the available school rebates in each state.

Table C14. Solar PV rebates offered explicitly to schools. All details taken from DSIRE database on Jan 1, 2018.

State	Administrator	Max Size (kW)	Rebate (\$/kW)	Mean System Size in State (kW)	Start Date	Expiration Date	Website
CA	Burbank Water & Power	30	490	384	1/1/2010	12/31/2016	http://www.burbankwaterandpower.com/incentives-for-all-customers/solar-photovoltaic-power
CA	City of Palo Alto	30	1,200	384	7/1/2007	NA	http://www.cityofpaloalto.org/pvp/partners
CO	Holy Cross Energy	25	500	363	NA	NA	http://www.holycross.com/rebates/renewable-energy-rebates
DE	Delaware Department of Natural Resources and Environmental Control	50	750	670	1/26/2015	NA	http://www.dnrec.delaware.gov/energy/services/GreenEnergy/Pages/GEPDelmarva_F.aspx
DE	Delaware Department of Natural Resources and Environmental Control	Max value of \$7,500		670	1/26/2015	NA	http://www.dnrec.delaware.gov/energy/services/GreenEnergy/Pages/CoopGEP_F.aspx
DE	Delaware Department of Natural Resources and Environmental Control	Max value of \$15,000 or 33% of cost.		670	1/26/2015	NA	http://www.dnrec.delaware.gov/energy/services/GreenEnergy/Pages/DEMEC.aspx
MA	Concord Municipal Light Plant	5	625	396	NA	NA	http://www.concordma.gov/863/Renewable-Energy-Efficiency
MO	Empire District Electric Co.	25	500	445	1/1/2010	6/30/2020	http://programs.dsireusa.org/system/program/detail/5774
NH	New Hampshire Public Utilities Commission	500	550	237	11/1/2010	NA	http://www.puc.nh.gov/Sustainable%20Energy/RenewableEnergyRebates-CI.html
NV	NV Energy	25	490	399	NA	12/31/2021	http://www.Nvenergy.com/renewablegenerations
NY	New York State Energy Research and Development Authority	200	450	309	8/12/2010	12/29/2023	http://ny-sun.ny.gov/
OR	Energy Trust of Oregon	100	250	431	5/1/2003	NA	http://www.energytrust.org
OR	Eugene Water & Electric Board	25	500	431	1/25/2008	NA	http://www.eweb.org/solar
OR	Salem Electric	25	300	431	NA	NA	https://www.salemelectric.com/members/photovoltaic-program
OR	Emerald People's Utility Dist	25	500	431	NA	NA	http://www.epud.org/conservation/solarelectric.aspx
TX	CPS Energy	100	800	649	NA	NA	https://www.cpsenergy.com/en/my-home/savenow/rebates-rebate/solar-photovoltaic-rebate.html
TX	Oncor Electric Delivery	NA	539	649	NA	NA	http://www.takealoadofftexas.com/solar-pv-homes.aspx
TX	Guadalupe Valley Electric Cooperative	20	2000	649	NA	NA	http://www.maximrewards.com/gvec/default.aspx
TX	Frontier Associates and Clean Energy Associates	25	1000	649	1/1/2009	NA	http://www.txreincentives.com/apv/index.php
TX	Frontier Associates and Clean Energy Associates	25	1005	649	1/1/2009	NA	http://www.txreincentives.com/apv/index.php
TX	City of San Marcos Electric Utility	5	2500	649	1/1/2011	NA	http://www.sanmarcostx.gov/index.aspx?page=115#DistributedGenerationRebateProgram

State-level net-metering policies outlined in Table C15 were taken from the DSIRE website in January 2018 [1]. We applied the following database filters:

- Eligible sector: non-residential -> public sector -> schools
- Category: Net-metering

Due to the complex net-metering structure for many of the states and since some policies are administered through single utilities rather than by the state, we elect to use the two scenarios listed in the main text: (1) excess generation sold back at the state average commercial retail rate and (2) excess generation sold back at the state average locational marginal price.

Table C15. State-level net-metering policies available to schools. All details taken from DSIRE database on Jan 1, 2018.

State	Capacity Limit (kW)	Compensation Rate	Offered explicitly to schools?	State	Capacity Limit (kW)	Compensation Rate	Offered explicitly to schools?
AK	25	Avoided Cost	Yes	MT	50	Retail credits can expire	No
AL	NA	NA	NA	NC	1000	Retail credits can expire	Yes
AR	300	Retail	Yes	ND	100	Avoided Cost	No
AZ	Unlimited	Retail credits can expire	Yes	NE	25	Avoided Cost	Yes
CA	1000	Retail	Yes	NH	1000	Retail	Yes
CO	25	Retail	Yes	NJ	Annual gen	Retail credits can expire	Yes
CT	2000	Retail credits can expire	Yes	NM	80	Avoided Cost	Yes
DC	1000	Avoided Cost	No	NV	1000	Avoided Cost	No
DE	500	Retail	Yes	NY	2000	Retail credits can expire	Yes
FL	2000	Retail credits can expire	Yes	OH	Unlimited	Avoided Cost	No
GA	125% of demand	Avoided Cost	Yes	OK	100	NA	Yes
HI	50	Retail	No	OR	25	Retail credits can expire	Yes
IA	500	Retail	No	PA	3000	Retail credits can expire	Yes
ID	NA	NA	No	RI	10000	Avoided Cost	Yes
IL	2000	Retail credits can expire	Yes	SC	1000	Retail credits can expire	Yes
IN	1000	Retail	Yes	SD	NA	NA	NA
KS	150	Avoided Cost	Yes	TN	NA	NA	NA
KY	30	Retail	Yes	TX	NA	NA	NA
LA	300	Retail	No	UT	2000	Retail credits can expire	Yes
MA	10000	Avoided Cost	Yes	VA	1000	Retail	No
MD	2000	Retail credits can expire	Yes	VT	Unlimited	Retail credits can expire	Yes
ME	100	Retail credits can expire	Yes	WA	100	Retail credits can expire	Yes
MI	150	Avoided Cost	Yes	WI	100	Avoided Cost	No
MN	1000	Avoided Cost	Yes	WV	500	Retail	No
MO	100	Avoided Cost	Yes	WY	25	Retail credits can expire	No
MS	2000	Avoided Cost	No				

References

- [1] NC Clean Energy Technology Center, “Database of State Incentives for Renewables & Energy Efficiency (DSIRE): LADWP - Net Metering,” 2017. [Online]. Available: <http://programs.dsireusa.org/system/program/detail/4855>.

Appendix C.7: Distribution of 2015 and 2016 project costs and rebates

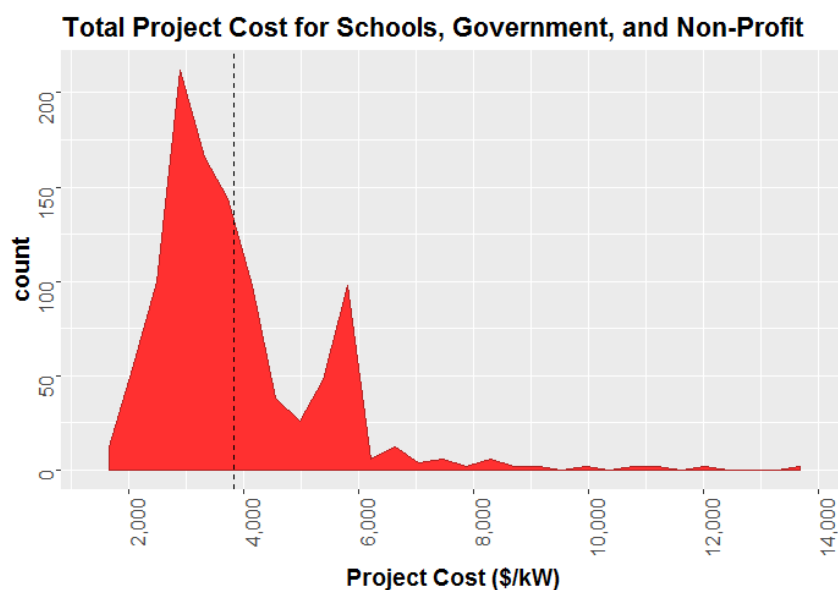


Figure C13. Distribution of LBNL Tracking the Sun PV project costs (\$/kW) for 2015 and 2016 installations on schools, government, and non-profit sites.

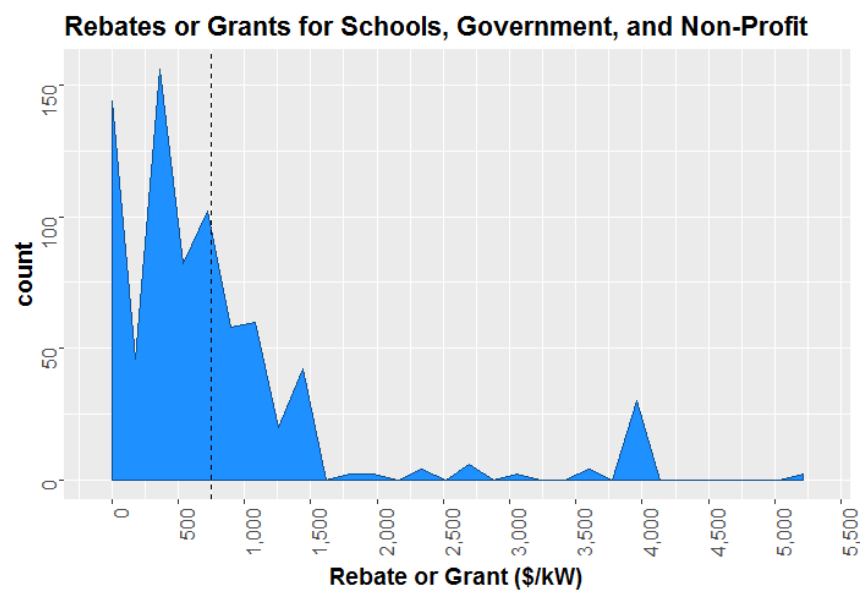


Figure C14. Distribution of LBNL Tracking the Sun PV rebates or grants (\$/kW) for 2015 and 2016 installations on schools, government, and non-profit sites.

Appendix C.8: School benefits and social costs – BCA equations

The following equations depict how we calculate net-benefits for each educational institution, considering the three scenarios for valuing electricity savings and excess generation described in Table 15 of the main text. In the *School.NB.LMP_s* and *School.NB.Retail_s* equations, we are calculating private net-benefits for each educational institution (s) if net-metering is in place and excess generation is valued at the LMP or commercial retail rates, respectively. Costs to each educational institution include the cost of installation (i_s) minus any rebates (r_s) made available to the schools as well as the cost of annual operations and maintenance (O&M) of \$15/kW-yr and inverter replacement costs (i_s) of \$120/kW at year 10. We do not include the decommissioning cost of the system at the end of its useful life in our analysis. Benefits to the schools include the hourly (h) offset electricity ($o_{s,h}$) cost savings and any excess generation ($n_{s,h}$) that is sold back to the grid. In the *Social.NB.LMP_s* and *Social.NB.Retail_s* equations, we are calculating social net-benefits for each educational institution if excess generation is valued at the LMP or commercial retail rates, respectively. Costs to society include the cost of rebates (r_s) made available to the schools as well as the cross-subsidy ($n_{s,h} \times (p_s - l_{s,h})$) if schools are compensated for the hourly excess generation at the retail rate. Benefits to society include the monetized health and environmental damages associated with hourly offset emissions ($(o_{s,h} + n_{s,h}) \times m_{s,h}$). We take the present value of annual private and social benefits and costs for each year the systems are in operation to arrive at a net-benefit from the perspective of schools and society for each educational institution, assuming a project lifetime of 20 years.

In the *School.NB.TPO_s* and *Social.NB.TPO_s* equations, we are calculating private and social net-benefits for each educational institution if schools entered in to a third-party ownership (TPO) agreement. The TPO scenario is characterized as the difference between the regular annual electricity consumption costs ($c_{s,h} \times p_s$) to the educational institutions (without PV) and the costs of electricity if schools purchased electricity at a TPO-defined rate. This TPO-defined rate is assumed to be less than the retail rate and is estimated here as the annualized cost of owning the PV systems, assuming commercial owners can take advantage of the Federal Investment Tax Credit (ITC) and that excess generation is valued at the LMP.

Net-metering scenario, excess generation valued at the LMP:

School.NB.LMP_s

$$\begin{aligned}
 &= -[i_s - r_s] - \left[\frac{inv_s}{(1+d)^{10}} + \sum_{y=2016}^{y=2036} \frac{o\&m_s}{(1+d)^{(y-2016)}} \right] \\
 &+ \sum_{y=2016}^{y=2036} \left(\left(\sum_{h=1}^{h=8760} (o_{s,h} \times p_s) + (e_{s,h} \times l_{s,h}) \right) / (1+d)^{(y-2016)} \right) \\
 \text{Social.NB.LMP}_s &= -r_s + \sum_{y=2016}^{y=2036} \left(\left(\sum_{h=1}^{h=8760} (o_{s,h} + e_{s,h}) \times m_{s,h} \right) / (1+d)^{(y-2016)} \right)
 \end{aligned}$$

Net-metering scenario, excess generation valued at the commercial retail rate:

School.NB.Retail_s

$$\begin{aligned}
 &= -[i_s - r_s] - \left[\frac{inv_s}{(1+d)^{10}} + \sum_{y=2016}^{y=2036} \frac{o\&m_s}{(1+d)^{(y-2016)}} \right] \\
 &+ \sum_{y=2016}^{y=2036} \left(\left(\sum_{h=1}^{h=8760} ((o_{s,h} + e_{s,h}) \times p_s) \right) / (1+d)^{(y-2016)} \right)
 \end{aligned}$$

Social.NB.Retail_s

$$\begin{aligned}
 &= -r_s \\
 &- \sum_{y=2016}^{y=2036} \left(\left(\sum_{h=1}^{h=8760} (e_{s,h} \times (p_s - l_{s,h})) \right) / (1+d)^{(y-2016)} \right) \\
 &+ \sum_{y=2016}^{y=2036} \left(\left(\sum_{h=1}^{h=8760} (o_{s,h} + e_{s,h}) \times m_{s,h} \right) / (1+d)^{(y-2016)} \right)
 \end{aligned}$$

Third-party ownership scenario:

School.NB.TPO_s

$$\begin{aligned}
 &= \sum_{y=2016}^{y=2036} \left(\left(\sum_{h=1}^{h=8760} (c_{s,h} \times p_s) \right) / (1+d)^{(y-2016)} \right) \\
 &\quad - \left[i_s + \frac{inv_s}{(1+d)^{10}} + \sum_{y=2016}^{y=2036} \frac{o\&m_s}{(1+d)^{(y-2016)}} - r_s - t_s \right] \\
 &\quad + \sum_{y=2016}^{y=2036} \left(\left(\sum_{h=1}^{h=8760} (o_{s,h} \times p_s) + (e_{s,h} \times l_{s,h}) \right) / (1+d)^{(y-2016)} \right)
 \end{aligned}$$

$$\text{Social.NB.TPO}_s = -[r_s + t_s] + \sum_{y=2016}^{y=2036} \frac{[\sum_{y=2016}^{y=2036} (o_{s,h} + e_{s,h}) \times m_{s,h}]}{(1+d)^{(y-2016)}}$$

In these questions, i_s is the total system s installation cost, r_s is the rebate and t_s is the 30% Federal ITC, $o_{s,h}$ is offset consumption in hour h of a typical meteorological year (y), $e_{s,h}$ is electricity sold back to the grid for a given system in a given hour, $c_{s,h}$ is the electricity consumed by each institution without PV, p_s is the state-average 2016 commercial retail rate where the system is installed, $l_{s,h}$ is the average LMP in a given hour for a given system, $m_{s,h}$ is the marginal health and environmental damage offset for a given system in a given hour, and d is the annual discount factor set at 2% and 7% for both the school and social CBAs.

Appendix C.9: Limitations and future study

Our study has a number of strengths, including (1) pulling together several vetted datasets, (2) performing a sensitivity analysis to account for uncertainty of a number of key parameters, and (3) focusing on a sector that hasn't been explored heavily in previous PV technical potential reports. Still, our work is not without its limitations. Our analysis of health and environmental benefits is considered for PV distribution only. This analysis does not include production of the PV panels or disposal of them after their useful life. As demonstrated in the supplementary information in Vaishnav et al. [1], the lifecycle emissions of greenhouse gases and other pollutants of solar PV are negligible compared to fossil fuel energy sources. This supplementary information references various studies [2-6] that find solar PV technologies emit less than 100 mg/kWh of SO₂ – compared to coal-fired generation in the U.S., which is estimated to emit 1,700 mg/kWh of SO₂ [7], [8]. Ultimately, Fthenakis [9] argues, “Replacing grid electricity with PV systems would result in an 89%–98% reduction in the emissions of greenhouse gases, criteria pollutants, heavy metals, and radioactive species.” We also assume that the vast majority of greenhouse and other pollutants from fossil fuel electricity arise from the combustion process, compared to other parts of the fossil fuel generation life cycle. We base this assumption on findings from Jaramillo et al. [10] and Burnham et al. [11].

Furthermore, our study is bounded to the United States. An international lifecycle analysis that accounts for the health and environmental benefits of installing solar PV on U.S. educational facilities may yield quite different results once taking into account mining of precious metals and/or physical transport of pollution in the atmosphere [12-14].

References

- [1] P. Vaishnav, N. Horner, and I. Azevedo, “Was it worthwhile? Where have the benefits of rooftop solar photovoltaic generation exceeded the cost?,” *Environ. Res. Lett.*, vol. 12, 2017.
- [2] E. G. Hertwich *et al.*, “Integrated life-cycle assessment of electricity-supply scenarios confirms global environmental benefit of low-carbon technologies,” *Proc. Natl. Acad. Sci.*, vol. 112, no. 20, pp. 6277–6282, 2015.
- [3] J. Sathaye *et al.*, “Renewable Energy in the Context of Sustainable Development,” *Univ. Dayt. eCommons Phys. Fac. Publ.*, p. 1076, 2011.
- [4] D. D. Hsu *et al.*, “Life Cycle Greenhouse Gas Emissions of Crystalline Silicon Photovoltaic Electricity Generation: Systematic Review and Harmonization,” *J. Ind. Ecol.*, vol. 16, no. SUPPL.1, 2012.

- [5] D. Yue, F. You, and S. B. Darling, "Domestic and overseas manufacturing scenarios of silicon-based photovoltaics: Life cycle energy and environmental comparative analysis," *Sol. Energy*, vol. 105, pp. 669–678, 2014.
- [6] V. M. Fthenakis and H. C. Kim, "Photovoltaics: Life-cycle analyses," *Sol. Energy*, vol. 85, no. 8, pp. 1609–1628, 2011.
- [7] U.S. EIA (United States Energy Information Administration), "Table 3.1.A. Net Generation by Energy Source: Total (All Sectors), 2005-2015," 2016.
- [8] [22] U.S. EIA (United States Energy Information Administration), "Table 9.1. Emissions from Energy Consumption at Conventional Power Plants and Combined-Heat-and-Power Plants," 2016.
- [9] V. Fthenakis, "Considering the total cost of electricity from sunlight and the alternatives [Point of View]," *Proc. IEEE*, vol. 103, no. 3, pp. 283–286, 2015.
- [10] P. Jaramillo, W. M. Griffin, and H. S. Matthews, "Comparative life-cycle air emissions of coal, domestic natural gas, LNG, and SNG for electricity generation," *Environ. Sci. Technol.*, vol. 41, no. 17, pp. 6290–6296, 2007.
- [11] A. Burnham, J. Han, C. E. Clark, M. Wang, J. B. Dunn, and I. Palou-Rivera, "Life-cycle greenhouse gas emissions of shale gas, natural gas, coal, and petroleum," *Environ. Sci. Technol.*, vol. 46, no. 2, pp. 619–627, 2012.
- [12] A. F. Sherwani, J. A. Usmani, and Varun, "Life cycle assessment of solar PV based electricity generation systems : A review," *Renew. Sustain. Energy Rev.*, vol. 14, pp. 540–544, 2010.
- [13] H. Zhao *et al.*, "Effects of atmospheric transport and trade on air pollution mortality in China," *Atmos. Chem. Phys.*, vol. 17, pp. 10367–10381, 2017.
- [14] Q. Zhang *et al.*, "Transboundary health impacts of transported global air pollution and international trade," *Nat. Lett.*, vol. 543, pp. 705–709, 2017.

Appendix C.10: Net-benefit results at county-level using EASIUR and AP2

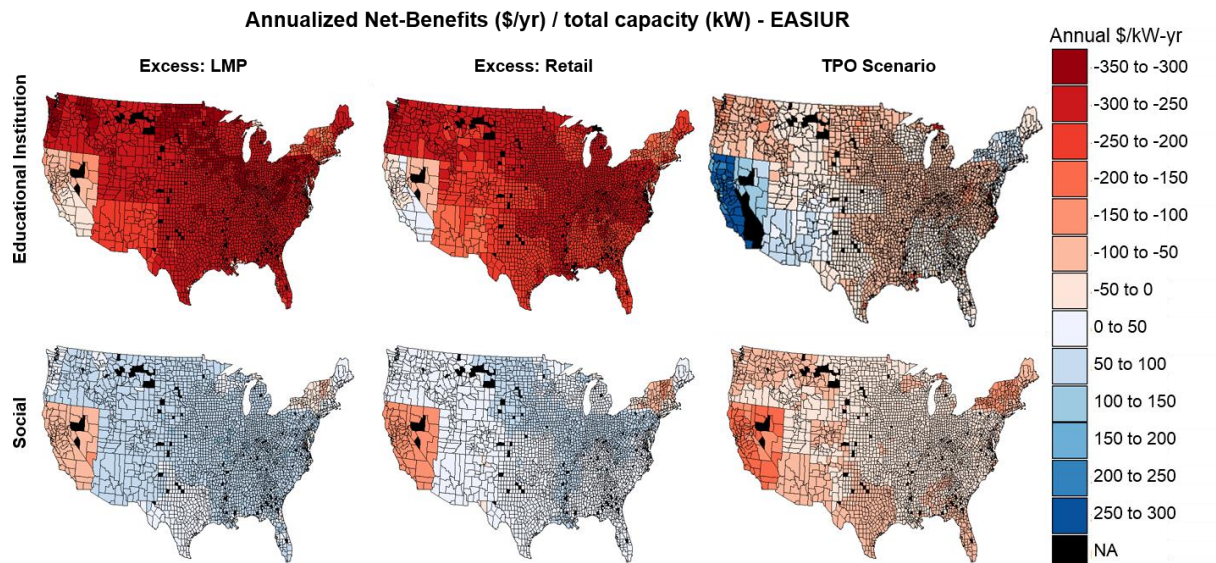


Figure C15. Annualized county-level private (top) and social (bottom) net-benefits (\$/yr) by county solar PV capacity (kW) for three scenarios: selling excess generation at the LMP (left), selling excess generation at the retail rate (middle), and third-party ownership (right). Depicted results are when using a 7% discount rate.

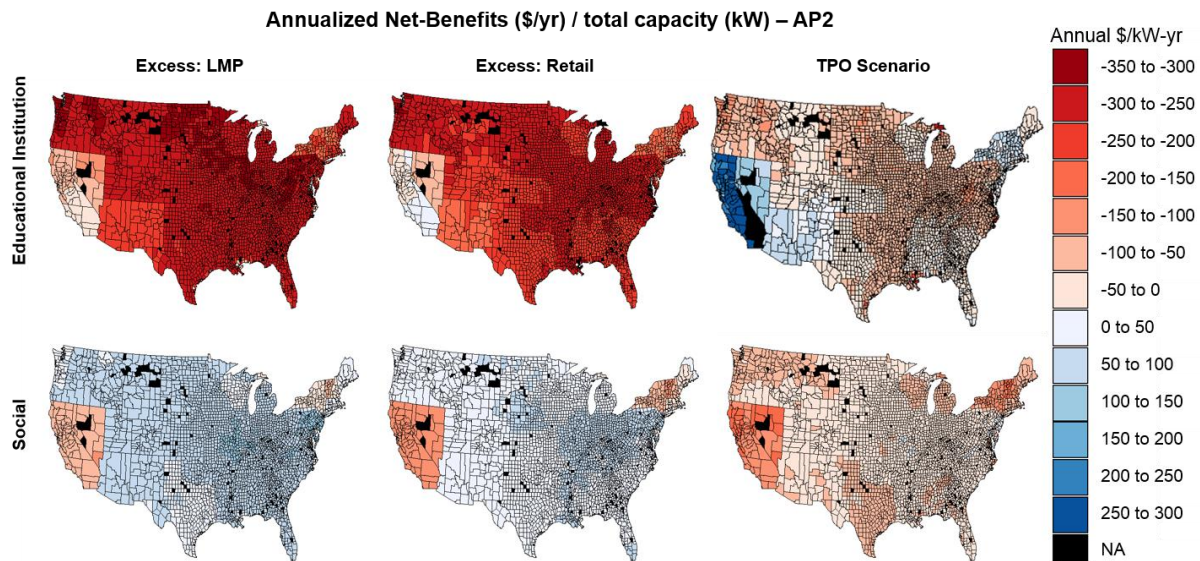


Figure C16. Annualized county-level private (top) and social (bottom) net-benefits (\$/yr) by county solar PV capacity (kW) for three scenarios: selling excess generation at the LMP (left), selling excess generation at the retail rate (middle), and third-party ownership (right). Depicted results are when using a 7% discount rate.

Appendix C.11: Magnitude of generation

In this section we provide more analysis on the generation estimated for each educational institution. First, we consider the distribution of generation across all educational institutions (Figure C17 and Figure C18). Recall that we estimate that 11% of the institutions do not have suitable roof space for solar PV; hence, there is a spike around zero.

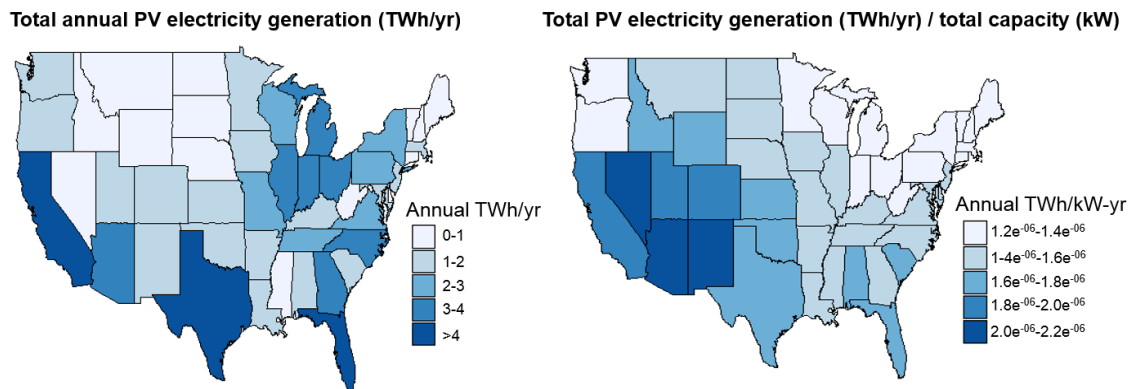


Figure C17. State maps of total solar PV generation and generation per peak kW from U.S. educational institutions. This generation includes excess generation not consumed by the educational buildings and that can be sold back to the grid.

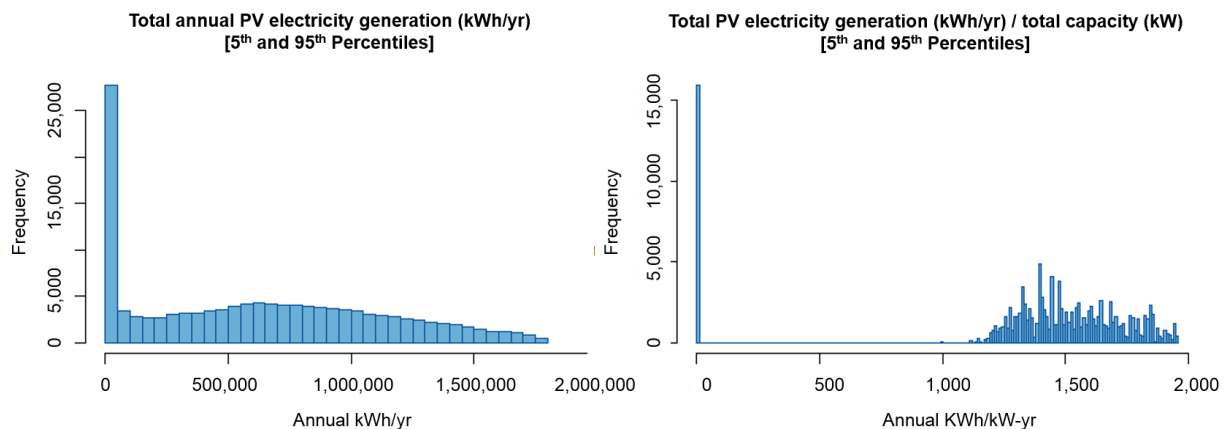


Figure C18. Histogram of potential generation from solar PV at U.S. educational institutions and respective and generation per kW.

Regional variation in technical potential is depicted in Figure C19 and Figure C20.

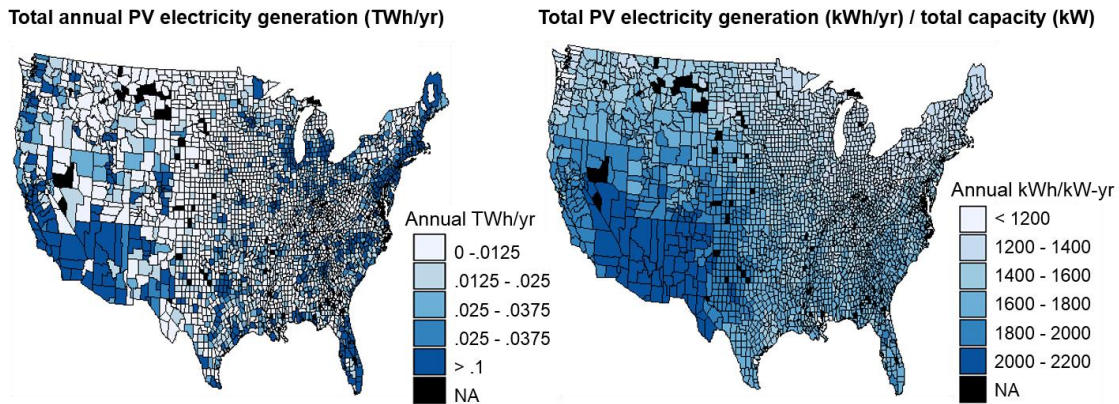


Figure C19. County maps of total solar PV generation and generation per kW at U.S. educational institutions. This generation includes excess generation not consumed by the educational buildings and that can be sold to the grid.

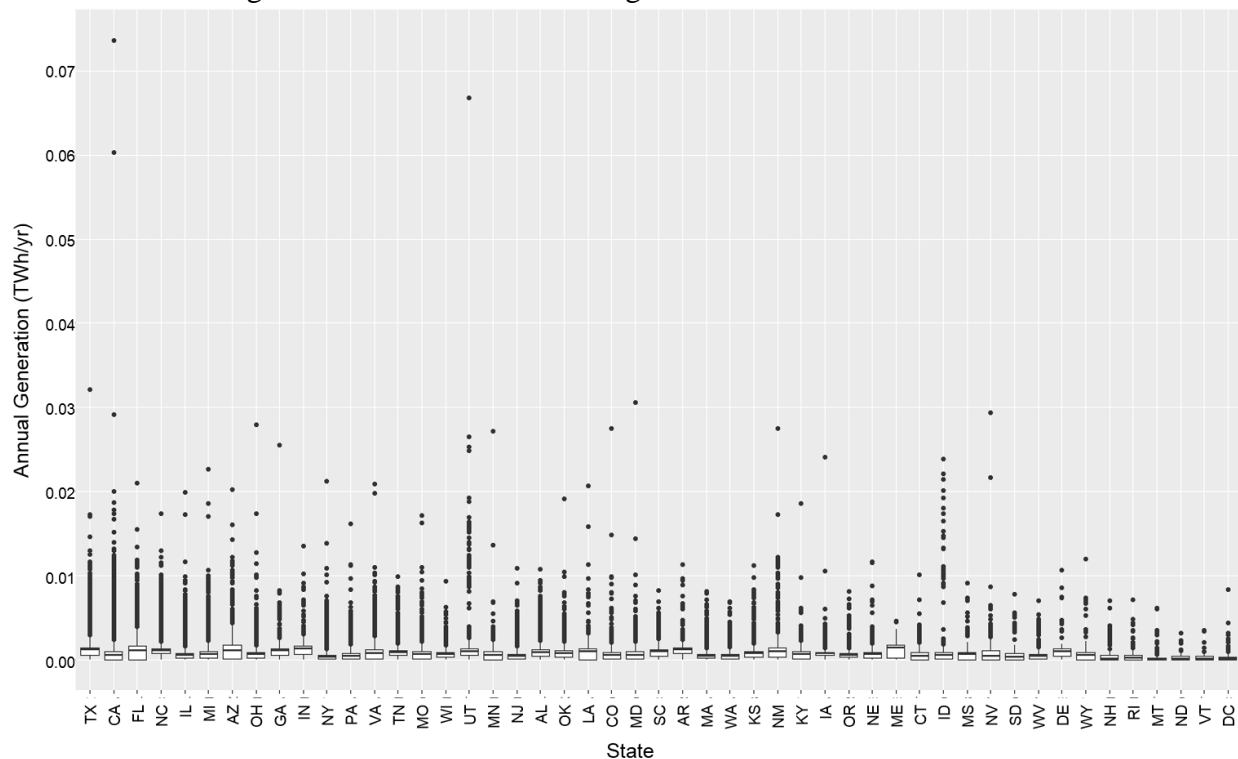


Figure C20. Boxplots of PV generation across all educational institutions in each state.

Appendix C.12: Total private and social benefits and costs school type

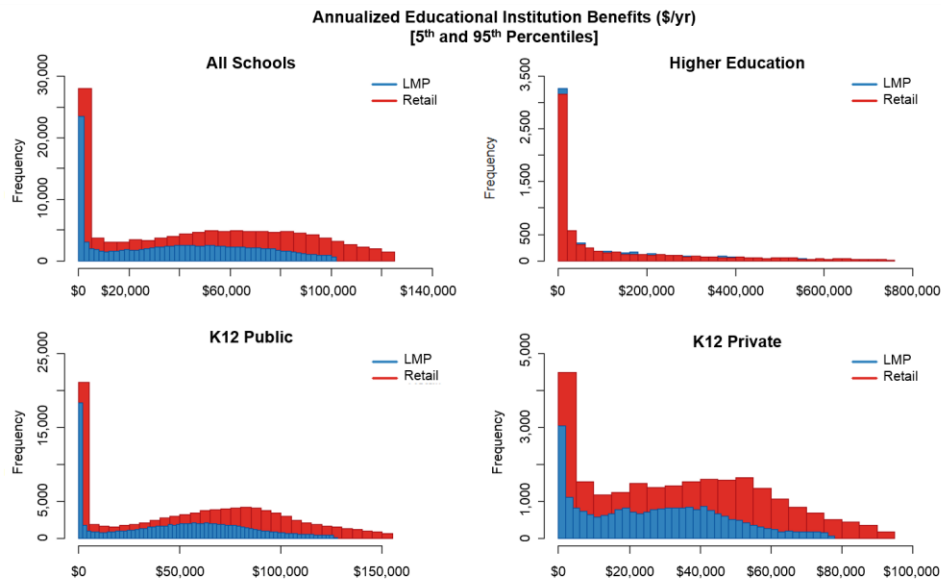


Figure C21. Annualized educational institution benefits using EASIUR (offset electricity cost savings + excess generation sales) for all institutions, higher education, K12 public, and K12 private institutions (clockwise).

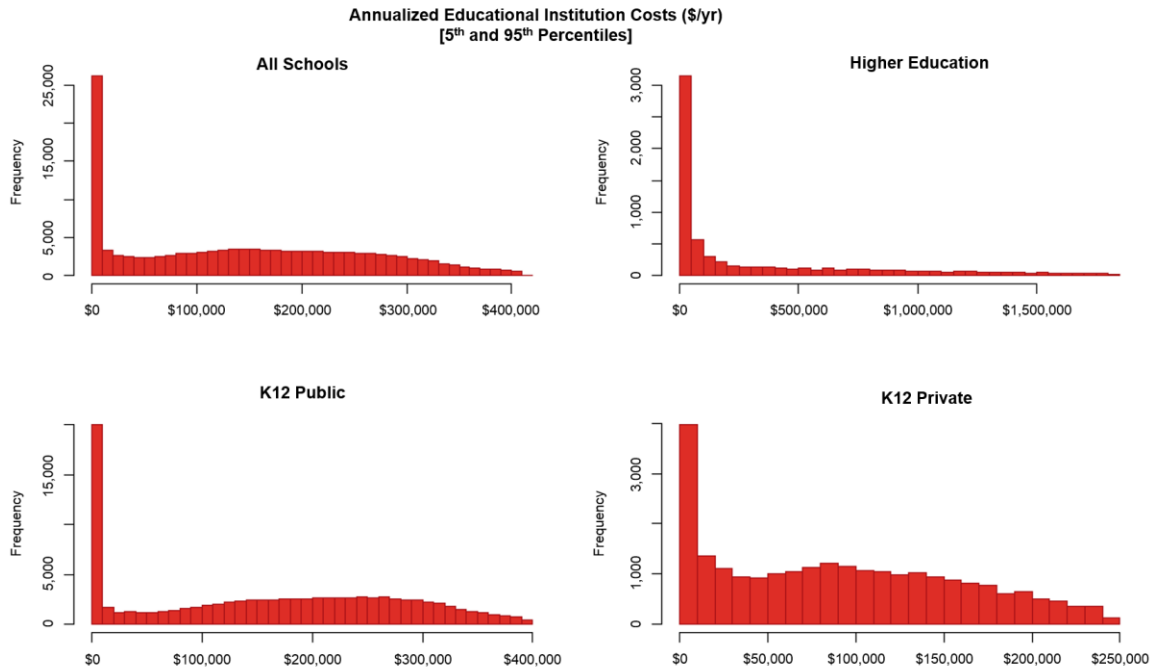


Figure C22. Annualized educational institution costs (installation – rebate + O&M + inverter) for all institutions, higher education, K12 public, and K12 private institutions (clockwise).

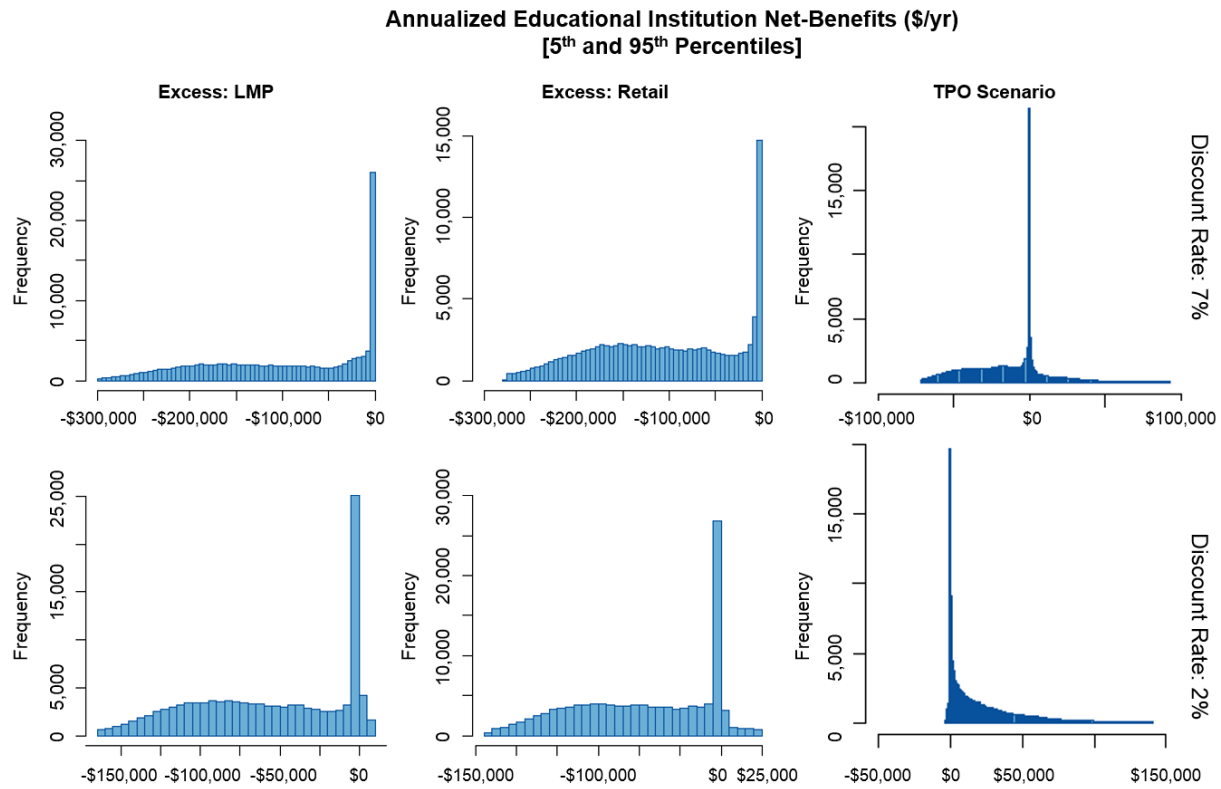


Figure C23. Annualized educational institution net-benefits over three scenarios: selling excess generation at the LMP (left), selling excess generation at the commercial rate (middle), and third-party ownership (right). All scenarios are considered using a 7% discount rate (top) and 2% discount rate (bottom).

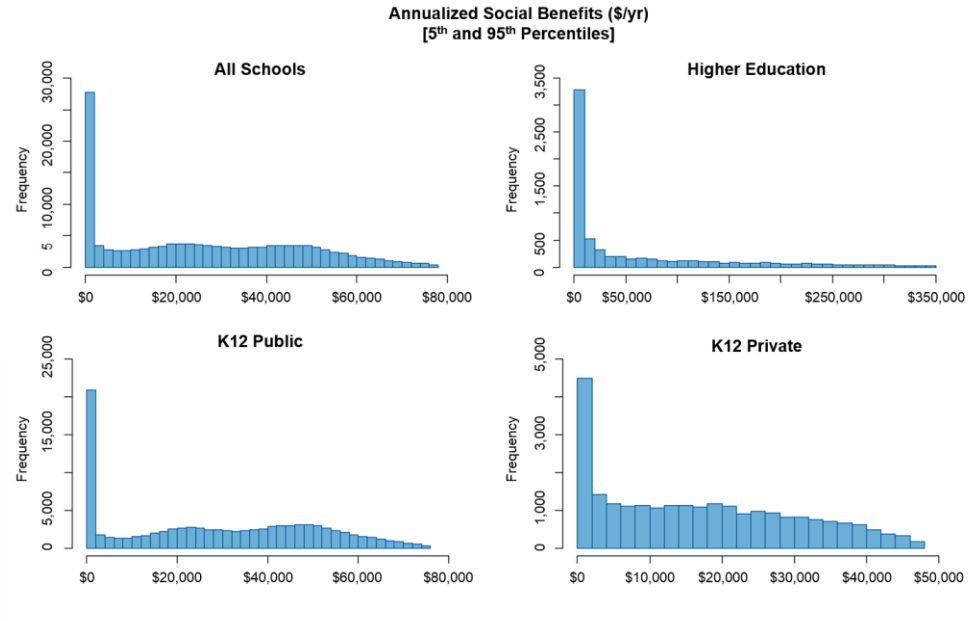


Figure C24. Annualized social benefits using EASIUR (i.e., health, environmental and climate change related benefits from reductions in SO₂, NO_x, PM_{2.5} and CO₂ emissions) for all institutions, higher education, K12 public, and K12 private institutions (clockwise).

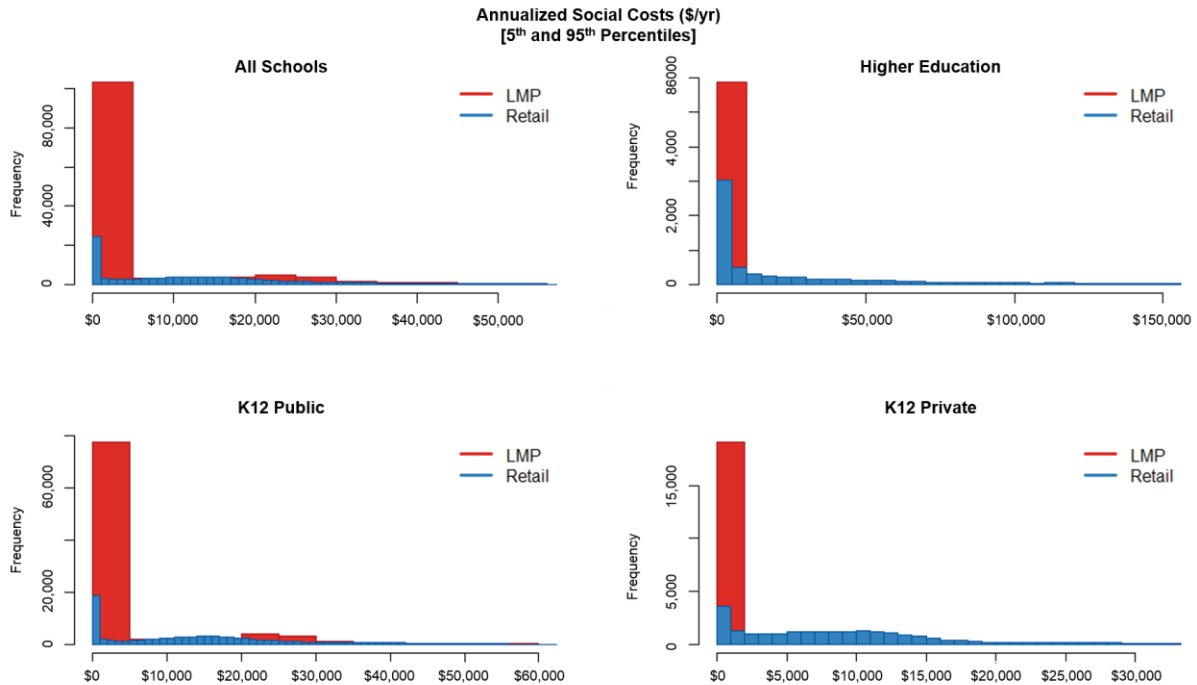


Figure C25. Annualized social costs (i.e. rebates + cross-subsidy in the retail scenario) for all institutions, higher education, K12 public, and K12 private institutions (clockwise).

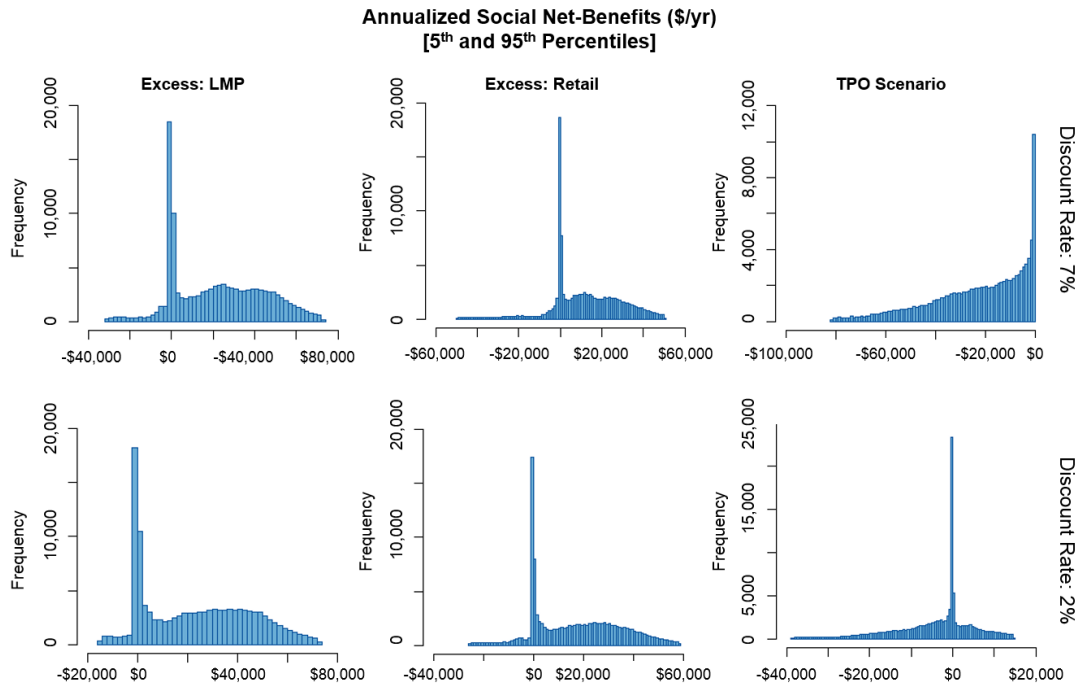


Figure C26. Annualized social net-benefits over three scenarios: selling excess generation at the LMP (left), selling excess generation at the commercial rate (middle), and third-party ownership (right). All scenarios are considered using a 7% discount rate (top) and 2% discount rate (bottom).

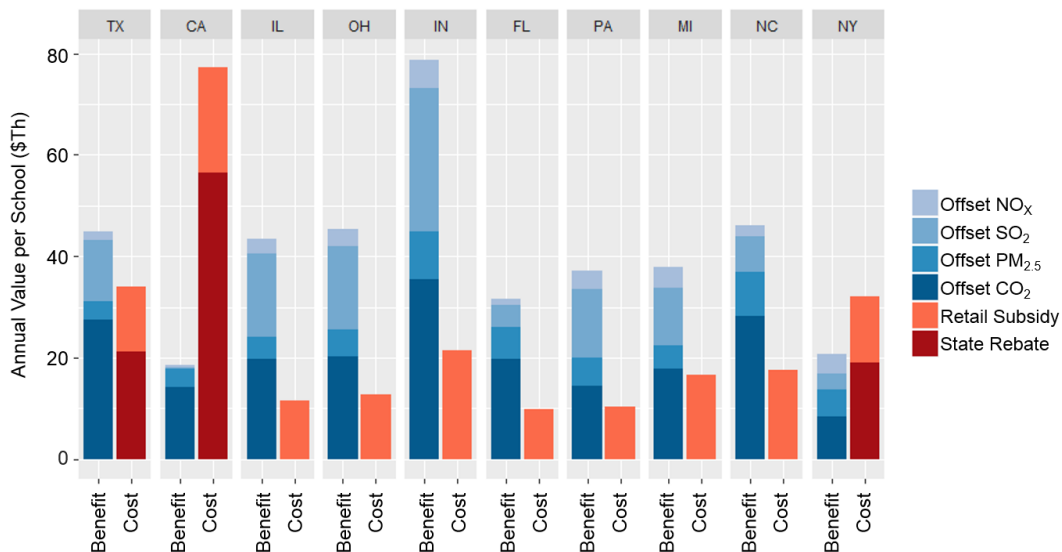


Figure C27. Average per school avoided damages from CO₂, SO₂, NO_x and direct PM_{2.5} emissions when compared to the rebates and cross-subsidy paid by public when excess generation is valued at the retail rate for the 10 states with the largest health, environmental, and climate change avoided damages. All values are reported in millions of dollars. In this plot we used the EASIUR model to monetize the emissions damages avoided. Note, avoided damages rankings are different for a per school basis compared to absolute values depicted in Figure 18.

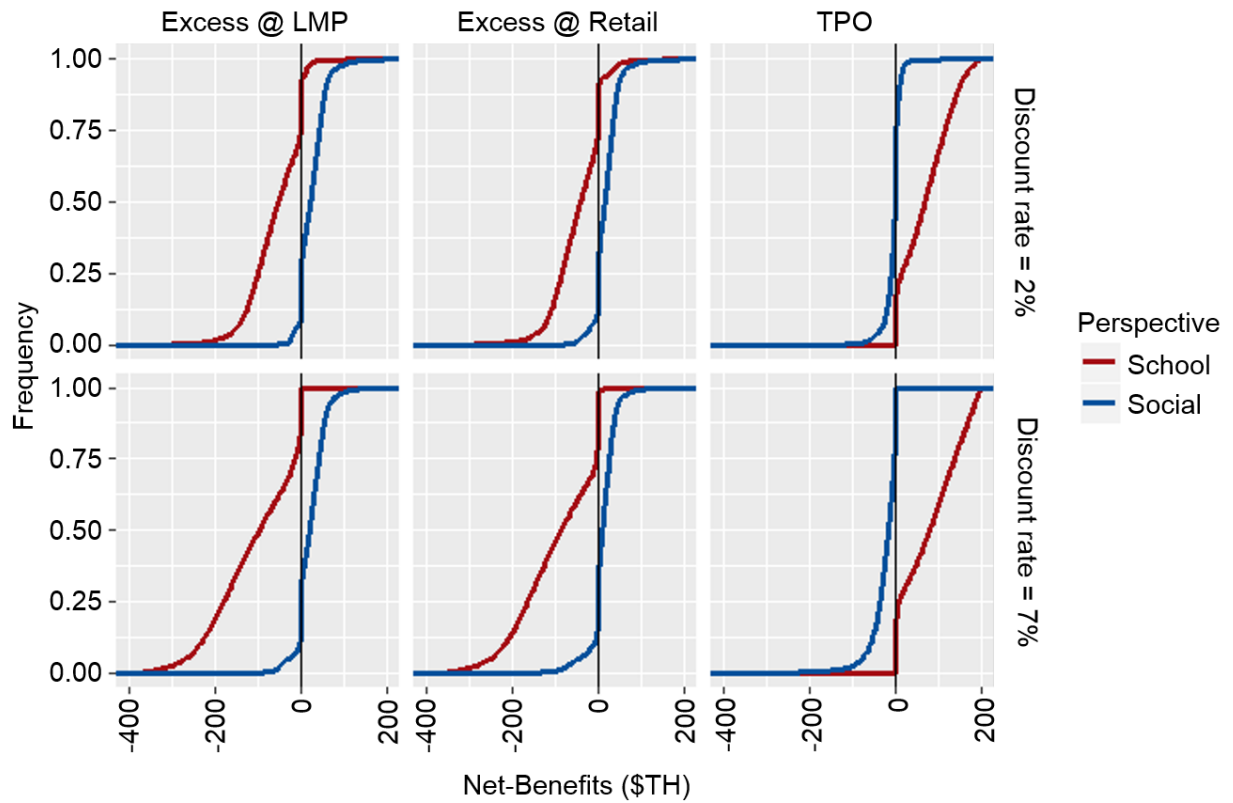


Figure C28. CDFs with limits between -400 and 200 for private and social net-benefits using the EASIUR model.

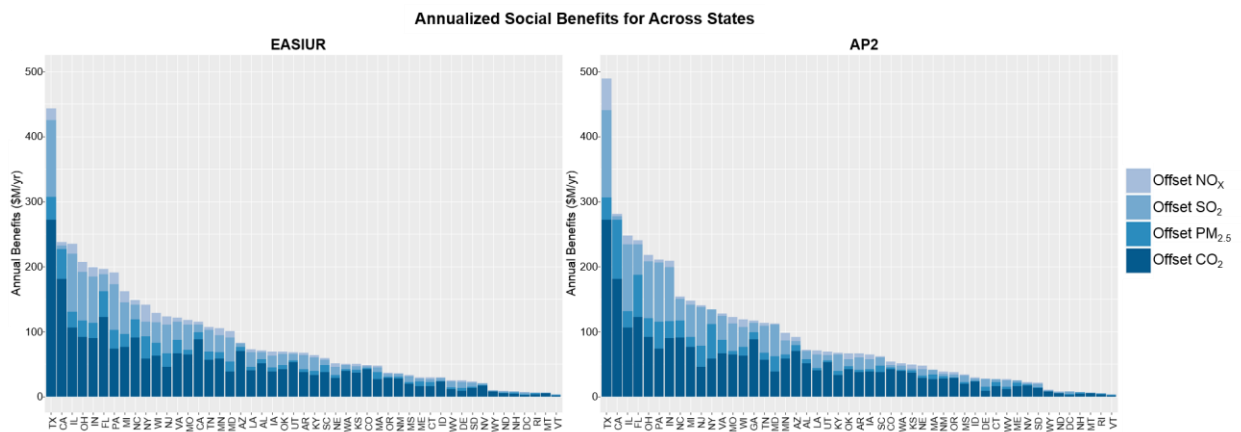


Figure C29. Comparative stacked bar chart of annual monetized social benefits (offset NO_x, SO₂, PM_{2.5}, and CO₂) across states estimated using EASIUR (left) and AP2 (right).

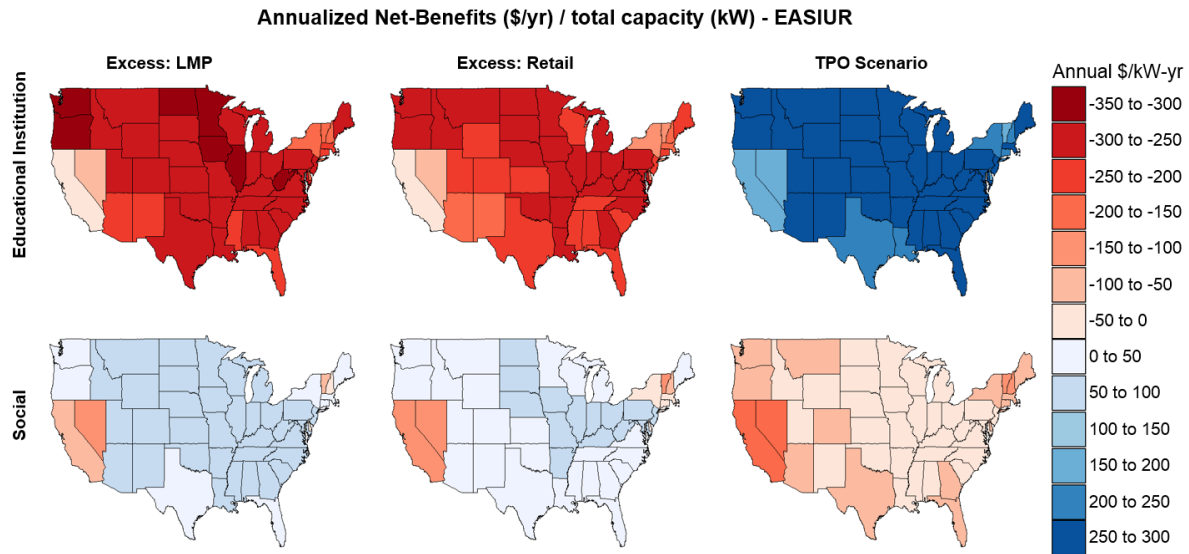


Figure C30. Annualized state-level private (top) and social (bottom) net-benefits (\$/yr) by state solar PV capacity (kW) for three scenarios: selling excess generation at the LMP (left), selling excess generation at the retail rate (middle), and third-party ownership (right). Depicted results are when using a 7% discount rate. This figure is using the EASIUR air quality model.

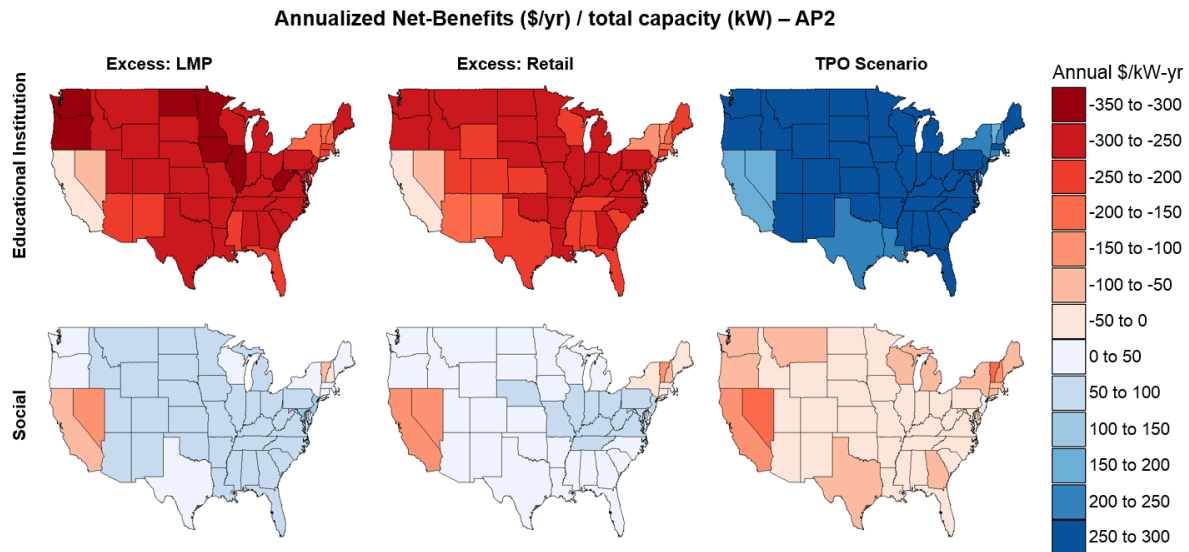


Figure C31. Annualized state-level private (top) and social (bottom) net-benefits (\$/yr) by state solar PV capacity (kW) for three scenarios: selling excess generation at the LMP (left), selling excess generation at the retail rate (middle), and third-party ownership (right). Depicted results are when using a 7% discount rate. This figure is using the AP2 air quality model.

Appendix C.13: Rebates and benefits analysis

In this section, we compare the currently state average school PV rebates observed in the LBNL TTS10 dataset with the offset damages aggregated for each state to see which rebate programs under- or over-value social benefits. First, we estimate the rebate needed to meet the observed offset CO₂, NO_x, SO₂, and PM_{2.5} damages from installing solar PV on educational institutions, aggregated for each state. We bring the annual offset damages (social benefits) to the present, assuming systems last 20 years and a discount rate of 7%:

$$Social.Benefits_s = \sum_{y=2016}^{y=2036} \left(\left(\sum_{h=1}^{h=8760} (o_{s,h} + e_{s,h}) \times m_{s,h} \right) / (1 + d)^{(y-2016)} \right)$$

Next, we aggregate these social benefits (\$) for each state. We divide the social benefits by the total estimated educational institution solar PV capacity to arrive at the estimated rebate (\$/kW):

$$Estimated.Rebate_{state} = \frac{Social.Benefits_{state}}{PV.Capacity_{state}}$$

In these equations, $o_{s,h}$ is offset consumption in hour h of a typical meteorological year (y), $e_{s,h}$ is electricity sold back to the grid for a given system in a given hour, $m_{s,h}$ is the marginal health and environmental damage offset for a given system in a given hour, and d is the discount factor set at 7% for this analysis.

Finally, we estimate the value of CO₂ for each state given the current state average school PV rebates observed in the LBNL TTS10 dataset, estimated PV capacity for each state, and the estimated social benefits. We estimate the offset CO₂ (tons) for each state using the lifetime social benefits of the systems and the current social cost of carbon of \$40/ton:

$$Offset.CO2_{state} = \frac{Social.Benefits_{state}}{\$40/tonCO2}$$

Then we divide the estimated offset CO₂ (tons) by the total estimated cost of providing rebates to educational institutions in each state:

$$Value.CO2_{state} = \frac{Offset.CO2_{state}}{LBNL.Rebate_{state} \times PV.Capacity_{state}}$$

Calculations result in the estimated rebate and value of CO₂ depicted in Table C16.

Table C16. Comparison table of current LBNL TTS10 rebates and offset damages in each state.

State	Current mean rebate taken from LBNL Tracking the Sun (\$/kW)	Estimated rebate needed to meet offset CO ₂ , NO _x , SO ₂ , and PM _{2.5} damages (\$/kW)	Current social cost of carbon (\$/ton)	Estimated value of CO ₂ given PV rebate (\$/ton)
CA	\$1,381	\$454	\$40	\$160
DE	\$1,171	\$1,076	\$40	\$118
MA	\$107	\$458	\$40	\$17
NH	\$673	\$454	\$40	\$107
NV	\$1,743	\$611	\$40	\$140
NY	\$633	\$687	\$40	\$90
TX	\$308	\$653	\$40	\$31
VT	\$1,192	\$442	\$40	\$195
WI	\$324	\$905	\$40	\$29

Appendix C.14: Further sensitivity analysis results

We perform parametric sensitivity analyses on six key inputs in our analysis: (1) project installation costs, (2) discount factor, (3) available rebates, (4) system size, (5) project lifetime, (6) and annual emissions/damages levels. We also consider the best- and worst-case scenarios for demand charge costs and fractional savings for the educational institutions. We vary each of these inputs separately and report varying outcomes in a spider plot and tables. In all baseline scenarios in this section, we assume excess generation is sold back at the retail rate.

Figure C32 depicts the parametric sensitivity analysis for the first five aforementioned key inputs. We parametrically adjust the baseline values listed in Table C17 from 0% to 500%, using 10% steps.

Table C17. Baseline values for parametric sensitivity analysis.

Variable	Baseline Value
Installation Cost	LBNL average: 3,800 \$/kW
Discount Rate	7%
PV Rebate	LBNL average: 780 \$/kW
Project Size	Each school's system size (ft ²)
Project Lifetime	20 years

Values reported in Figure C32 are the median private and social annualized net-benefits from the full distribution across all educational institutions assuming excess generation is sold back at the retail rate. We find that median educational institution net-benefits become positive when the average available rebate of 780 \$/kW is 3 times greater (or 2,340 \$/kW) and is available for all institutions. We also find that educational net-benefits are overall most sensitive to installation cost and that systems lasting less than 20 years are not economically worthwhile for educational institutions. Finally, it seems that the costs of rebates to society may outweigh the benefits if project sizes grow at the same rate as rebate increases.

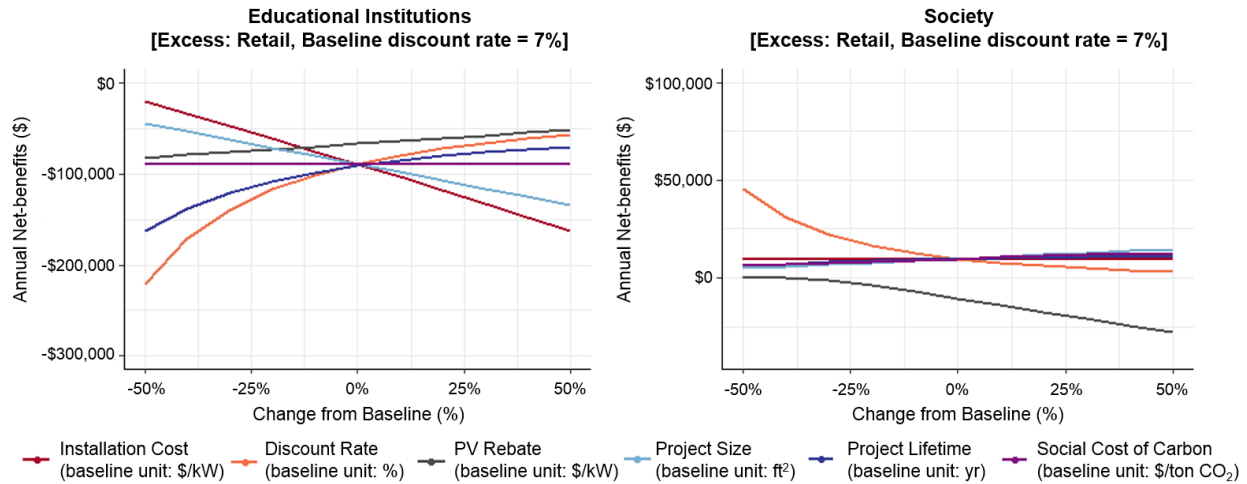


Figure C32. Parametric sensitivity analysis for six key inputs, varying each input from -50% to +50% of the baseline values, holding all other values constant. These plots depict the median private and social annualized net-benefits from the full distribution across all educational institutions (see SI Section N for separate CDFs of net-benefits for each sensitivity input).

Table C18 depicts the parametric sensitivity analysis for annual emissions levels/avoided damages. Here, we consider annually increasing and decreasing avoided damages ranging from -5% to 5% of the baseline assumption (i.e. constant avoided damages). We find that even if the avoided damages decreased each year by 5% (from external factors decarbonizing the electricity grid) and if schools can sell excess generation at the retail rate (i.e. society pays a cross-subsidy) that our median net-benefits to society would still be positive.

Table C18. Results of parametric sensitivity analysis of annual avoided damages (i.e. social benefits).

Percent Annual Change	Min	Max	Median	Mean
-5%	-\$6,100,000	\$876,000	\$2,400	\$370
-2.5%	-\$5,900,000	\$1,100,000	\$5,200	\$4,500
0%	-\$5,700,000	\$1,500,000	\$9,800	\$9,700
2.5%	-\$5,300,000	\$1,900,000	\$15,000	\$17,000
5%	-\$4,900,000	\$2,600,000	\$22,000	\$25,000

Table C19 depicts the scenario analysis for changes in demand rates and savings. We use the 25th and 75th percentile “Fraction of Average Rate for Demand Charge” and “Estimated Demand Savings from PV” values taken from our demand rate analysis that we conducted for 15 reference educational institutions across the US (Appendix C.5). We construct a best-case scenario, in terms of overall cost savings to educational institutions, by matching the 25th percentile demand charge fraction with the 75th percentile demand savings value. The worst-case

scenario is then the opposite combination. We find that median net-benefits to educational institutions are only marginally different between the best-case and worst-case scenarios. Furthermore, even when schools sell excess at the retail rate, these net-benefits are still negative.

Table C19. Results of scenario analysis of demand charge costs and fractional savings.

Scenario	Fraction of Average Rate for Demand Charge	Estimated Demand Savings from PV	Min	Max	Median	Mean
Best-case	15% (25th percentile)	18% (75th percentile)	-\$10,000,000	\$330,000	-\$87,000	-\$107,000
Worst-case	41% (75th percentile)	6% (25th percentile)	-\$13,000,000	\$0	-\$116,000	-\$142,000

Next, we created cumulative density functions at the lowest (0%), middle (250%), and highest (500%) adjustments to the baseline sensitivity parameters: (1) project installation costs, (2) discount factor, (3) available rebates, (4) system size, (5) project lifetime, (6) and annual emissions/damages levels. We vary each of these inputs separately and report varying outcomes in Figure C33 - Figure C38, demonstrating net-benefits for educational institutions (top) and society (bottom) assuming excess generation is valued at the LMP. To simplify matters, we depict the 5th and 95th percentiles. Generally, the CDFs for social net-benefits are roughly normally distributed under each sensitivity condition. However, the CDFs for schools are positively skewed, likely driven by high installation costs for the larger projects.

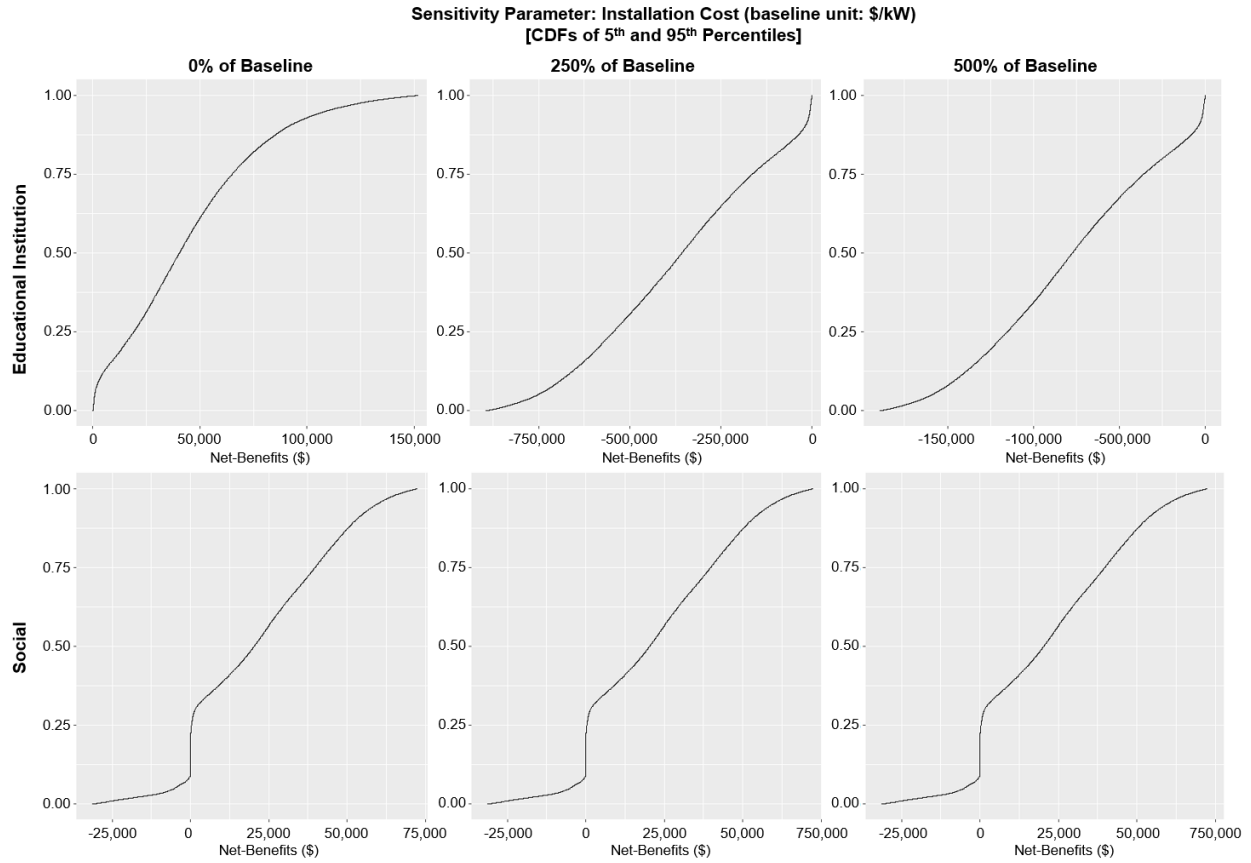


Figure C33. Cumulative density function plots of the low (0%), medium (250%), and high (500%) adjustment to the baseline Installation Cost (\$/kW) input for private (top) and social (bottom) net-benefits.

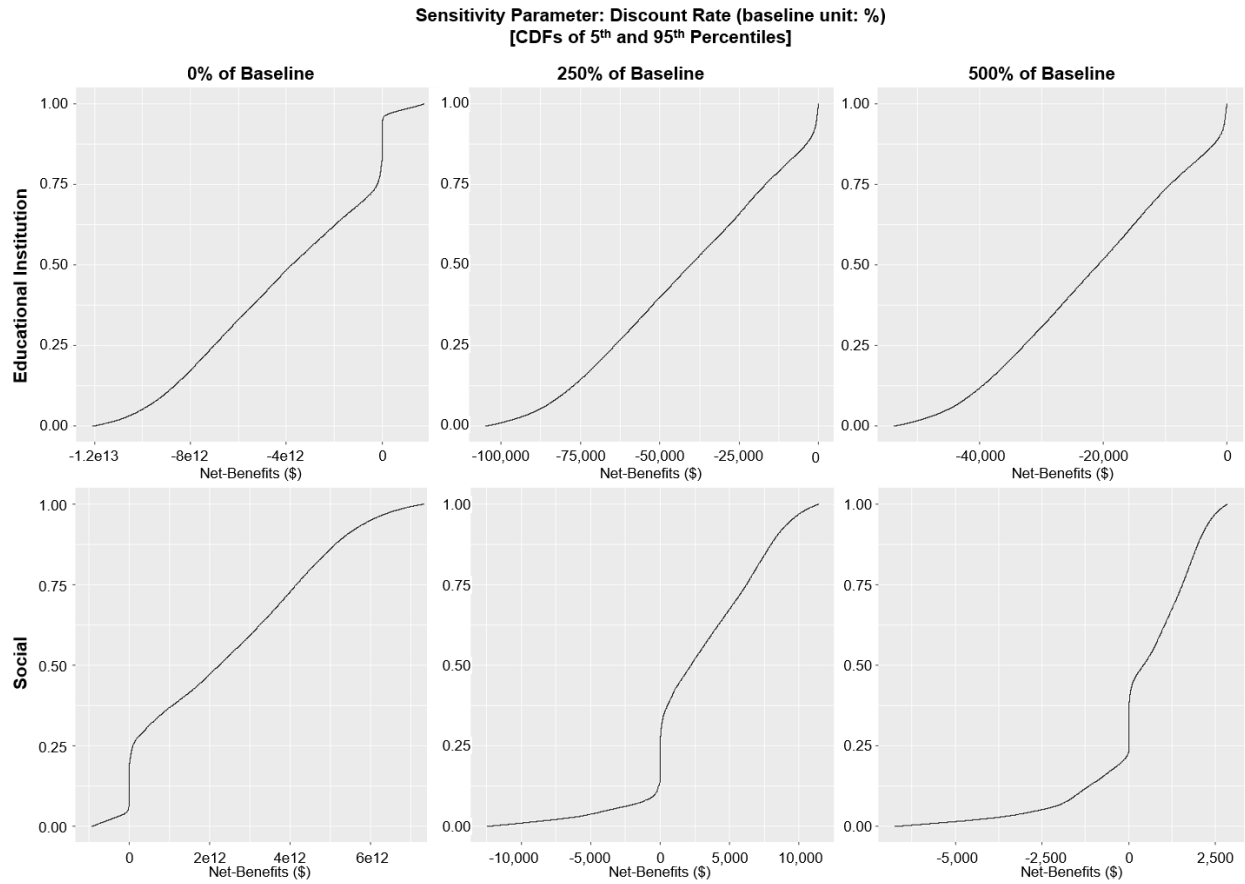


Figure C34. Cumulative density function plots of the low (0%), medium (250%), and high (500%) adjustment to the baseline Discount Rate (7%) input for private (top) and social (bottom) net-benefits.

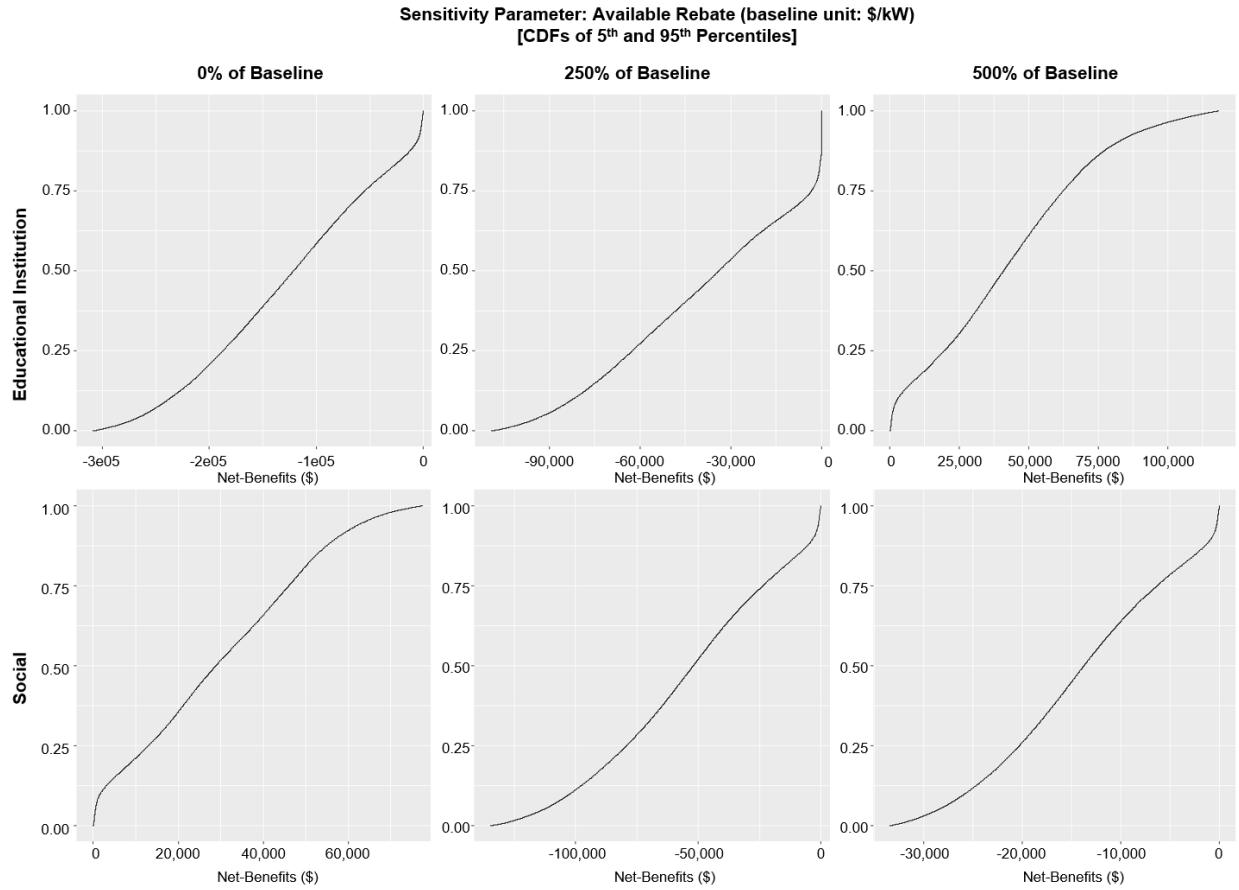


Figure C35. Cumulative density function plots of the low (0%), medium (250%), and high (500%) adjustment to the baseline Available Rebate (\$/kW) input for private (top) and social (bottom) net-benefits.

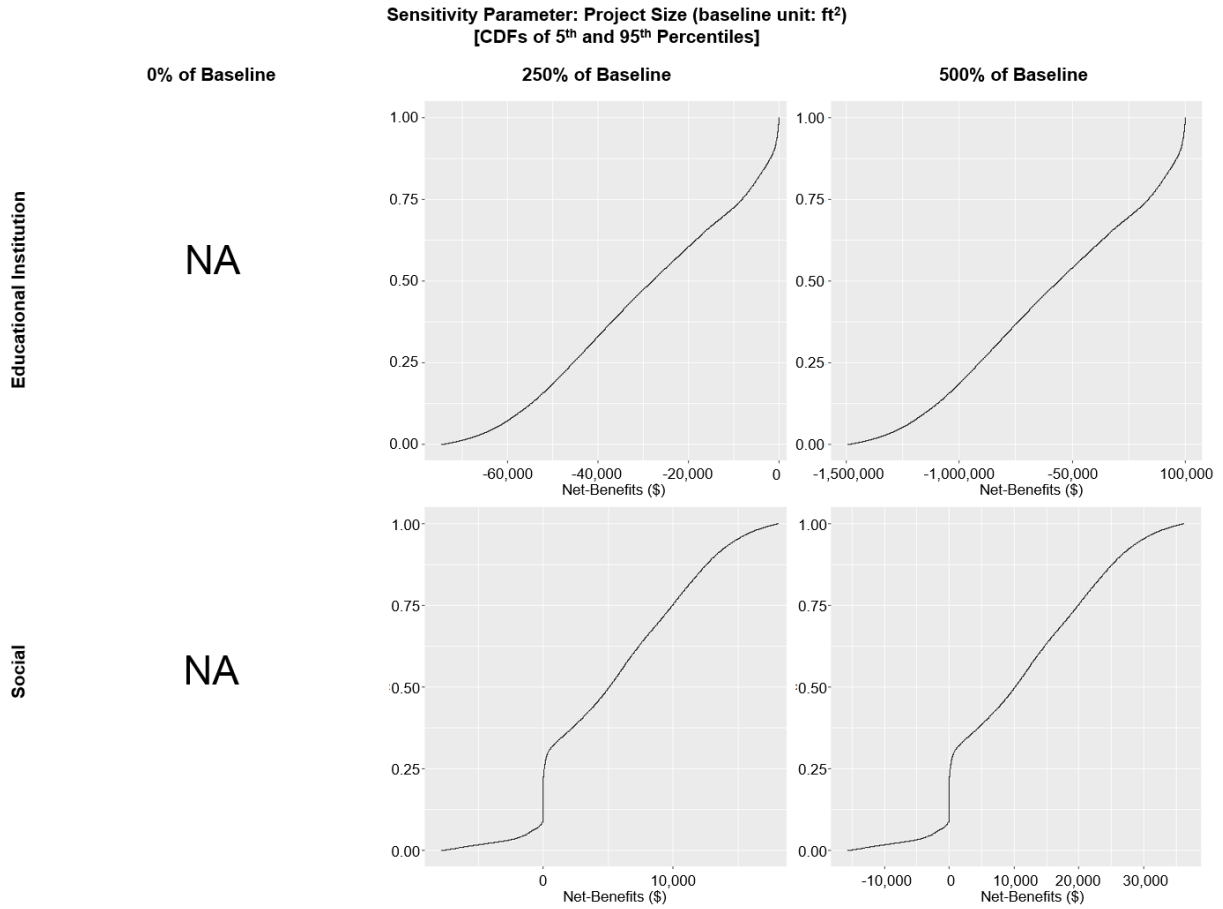


Figure C36. Cumulative density function plots of the low (0%), medium (250%), and high (500%) adjustment to the baseline Project Size (ft²) input for private (top) and social (bottom) net-benefits. At 0% of the baseline Project Size there are no private or social net-benefits.

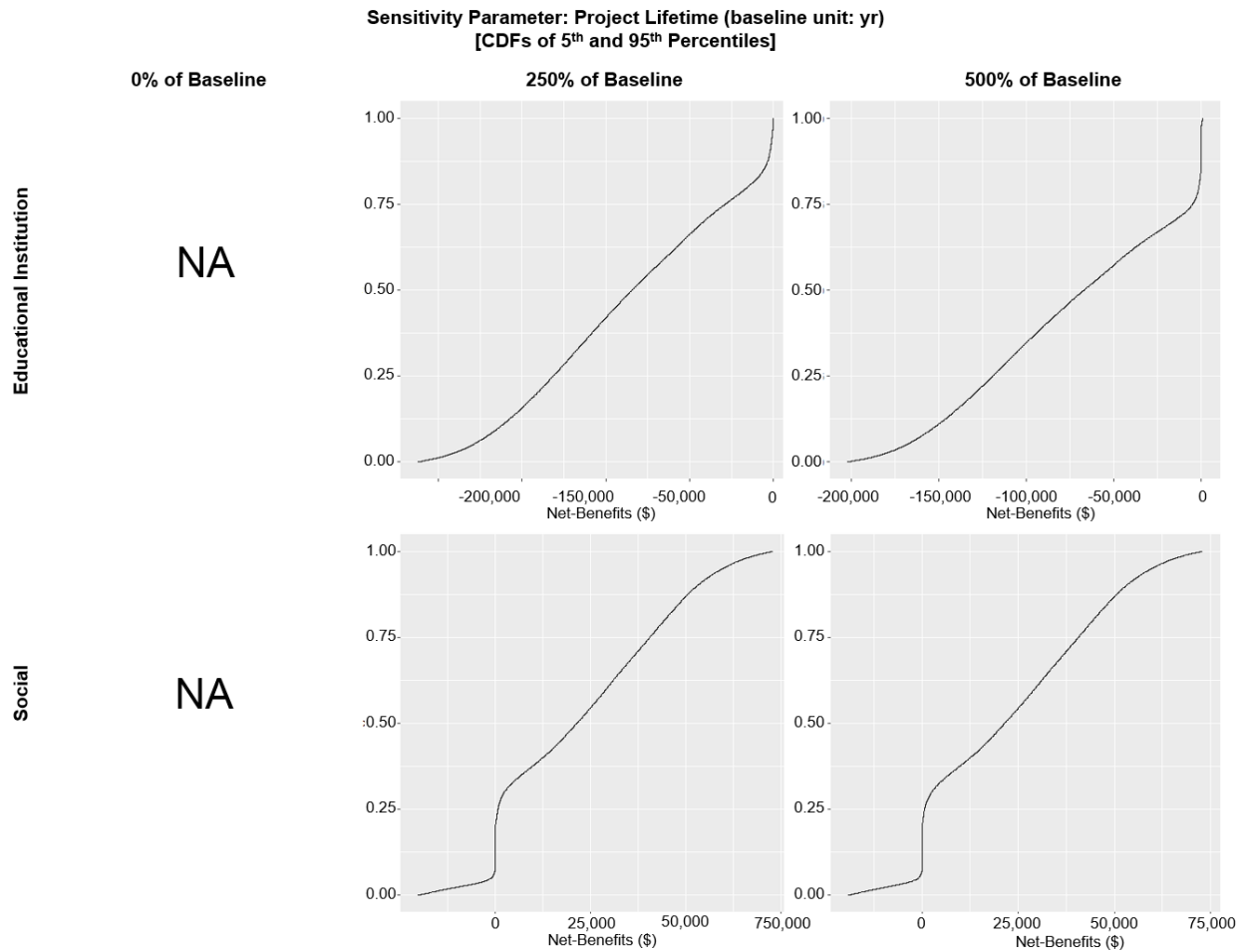


Figure C37. Cumulative density function plots of the low (0%), medium (250%), and high (500%) adjustment to the baseline Project Lifetime (yr) input for private (top) and social (bottom) net-benefits. At 0% of the baseline Project Lifetime there are no private or social net-benefits.

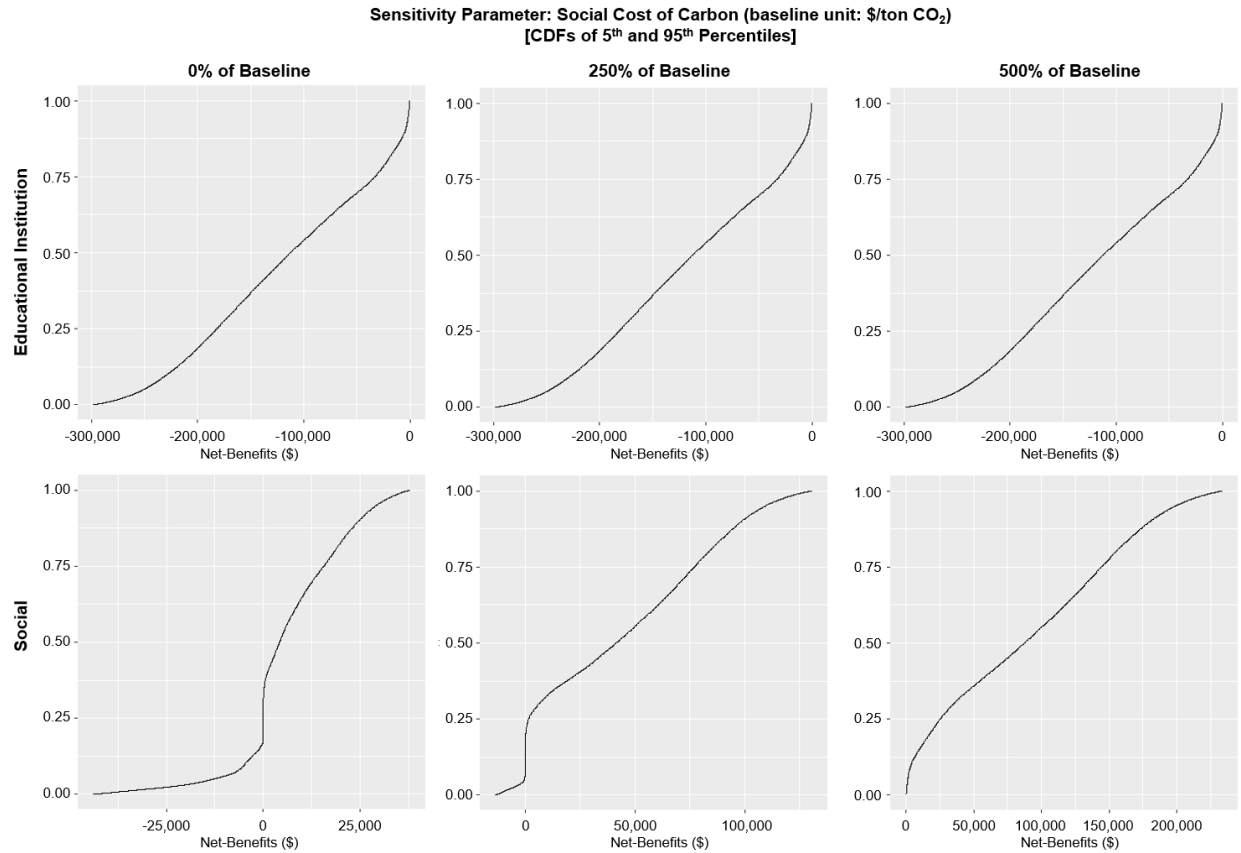


Figure C38. Cumulative density function plots of the low (0%), medium (250%), and high (500%) adjustment to the baseline Social Cost of Carbon (\$/ton CO₂) input for private (top) and social (bottom) net-benefits.