Consumer Preferences for Solar Energy: A Choice Experiment Study

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Abstract

U.S. electricity generation is moving towards renewables, not only due to renewable portfolio standards (RPS), but also due to cost competitiveness and consumer preferences. Consumer preferences may impact the type of renewable energy utilized, as well as state-determined RPS requirements. We implement a choice experiment survey to gain understanding of consumer preferences and their preference heterogeneity. We conduct the survey in New Mexico, a state with RPS and great potential for renewables, particularly in solar where it ranks third in the U.S. for that potential, as well as a poor economy that has traditionally been highly dependent on fossil fuel extraction. Focusing on the consumers of the state’s major utility, our choice experiment considers an increase in renewable energy and preference for different types of solar energy. We control for location heterogeneity (i.e., rural vs. urban), as well as exposure to solar installations. Utilizing multinomial logit and random parameter logit our results suggest respondents support an increased RPS solar requirement and they have a positive marginal willingness to pay (MWTP) for rooftop solar and smart meter installation. These values are impacted by several factors, including location and exposure to solar. We also observe a distance decay effect on respondents’ MWTP for different solar plans. For regulators considering additional RPS levels, or utilities considering solar installations, the results provide improved information on consumer preferences, heterogeneity of response, and MWTP for solar energy.

Keywords: renewable portfolio standard; solar energy; stated preference; MWTP; choice experiment survey; spatial heterogeneity

JEL: C93; Q40
1 Motivation

In 2016, the U.S. contributed approximately 15% of global carbon dioxide emissions (Boden, Andres, & Marland, 2017). The electric sector is responsible for the largest share of U.S. emissions (28%) (EPA, 2016). As such, electricity generation in the U.S. is rapidly moving away from coal-fired generation to more environmentally-friendly fossil fuels and, increasingly, towards renewables. Seventeen percent of electricity generation in the U.S. was from renewable resources in 2017\(^1\). The move toward renewables is in part due to renewable portfolio standards (RPS), which are currently required by 29 states (Barbose, 2017). RPS is responsible for approximately 50% of U.S.’s growth in renewable electricity generation and generation capacity since 2,000\(^2\). RPS policies mandate electric providers to generate a portion of their generation or sale from renewable energy (RE) within a certain time frame. RPS policies’ main goal is to reduce air pollution by using fossil fuels less, particularly within the electric sector. Subsequently, RPS also help with reducing water consumption and have impacts on state economies (Barbose et al., 2016).

RPS designs are unique to each state and mainly focus on wind and solar energy. Some RPSs have distinct goals solely for solar energy. Among the 29 states with RPS requirements, 18 states have mandated that electric providers within respective states include a minimum amount (carve-out) from solar energy. For example, New Mexico’s RPS has mandated that by 2020, 20% of energy production derive from renewables, including a 23% solar carve-out. Similarly,


\(^2\) Source: [https://www.eia.gov/energyexplained/?page=renewable_home#tab4](https://www.eia.gov/energyexplained/?page=renewable_home#tab4) (accessed 08/24/2018)
Nevada’s RPS has mandated that by 2025 25% of energy production result from renewables, with a 5% solar carve-out\(^3\).

Iowa was the first state to regulate an RPS in 1983. In the past roughly three decades since, states have considered modifying or even repealing their RPS requirements. For example, California, New York, and New Jersey\(^4\) extended their RPS to 50% by 2030 and Hawaii to 100% by 2045\(^5\); Kansas altered its mandatory RPS to a voluntary policy; West Virginia and Ohio repealed their RPS in 2015 and 2017 respectively; to name a few changes across states. As such, RPS has caught scholars’ attentions in both market and nonmarket valuation studies, prompting investigations that seek to understand how these changes within states and across states affect not only the regional economies but also people’s preferences.

Market valuation studies have demonstrated costs, benefits, and other economic and environmental impacts of RPS (e.g., Yi, 2015; Barbose et al., 2016; Wiser et al., 2016; Divounguy et al. 2017). For instance, Wiser et al. (2016) estimate that additional RE resources utilized to fulfill RPS compliance reduced 59-million metric tons of carbon dioxide-equivalent emissions, saved 27 billion consumptive water usage caused from fossil fuel, and supported 200,000 jobs in in the U.S. in 2013. However, Divounguy et al. (2017) show that under a 12.5% by 2025 RPS, Ohio would lose more than 134,000 jobs and cause a loss of $15.5 billion in GDP by 2026. On the other hand, nonmarket valuation studies, the focus of this research, usually do not specify an exclusive RPS goal to gauge respondents’ willingness to pay (WTP), but instead investigate more RE in the energy mix. Of those that do specify an RPS level, they find that respondents are willing to pay a positive premium (Mozumder et al., 2011; Nkansah & Collins,\(^6\) For more information on the RPS carve-outs, see: http://ncsolarcen-prod.s3.amazonaws.com/wp-content/uploads/2015/01/2014-Daniel-In-State-RPS-Requirements.pdf (accessed 07/23/2018)\(^7\) Source: https://www.energy.gov/savings/renewables-portfolio-standard-0 (accessed 08/24/2018)\(^8\) Source: https://www.sparklibrary.com/the-future-of-rps-policies/ (accessed 07/22/2018)
For example, Nkansah & Collins (2018) found an annual per-capita WTP of $19.25 to $26.75 for West Virginia’s repealed RPS. Similarly, Mozumder et al. (2011) found that New Mexico (NM) consumers are willing to pay $5.77/month for a 10%-RPS and $15.04/month for a 20%-RPS.

Numerous empirical studies have commonly found electricity consumers have positive WTP for the move to RE around the globe (e.g., Soon and Ahmad, 2015; Murakami et al., 2015; Möllendorff & Welsch, 2017; Shim et al., 2018). For example, Soon and Ahmad (2015) conducted a meta-analysis on thirty studies from all continents from 2000 and beyond and found a mean WTP of $7.16/month to increase electricity from RE\(^6\). Previous research has also found and linked heterogeneity in preferences for RE to several factors including, but not limited to: energy type (e.g., Borchers et al., 2007; Gracia et al., 2012; Murakami et al., 2015; Nkansah & Collins, 2018); respondents’ exposure or proximity to RE (e.g., Meyerhoff, 2013; Vecchiato and Tempesta, 2015; Kalkbrenner et al., 2017; Möllendorff & Welsch, 2017; Nkansah & Collins, 2018); respondents’ geographic location (urban/rural) (e.g., Bergmann et al., 2008; Yoo, 2011); and people’s attitudes towards the environment (e.g., Álvarez-Farizo and Hanley, 2002; Clark et al., 2003; Hansla et al., 2008; Longo et al., 2008; Strazzera et al., 2012; Yoo & Ready, 2014).

In regard to what type of RE is being valued, WTP towards wind energy tends to have inconsistent results; wherein researchers sometimes find positive WTP (e.g., Koundouri et al., 2009) and sometimes negative WTP (e.g., Groothuis et al., 2008). Scholars have linked this inconsistency in wind energy results to the “NIMBY” (not-in-my-backyard) effect, wind turbines externalities, and/or the distance decay effect (Möllendorff & Welsch, 2017; Rehdanz et al., 2017; Nkansah & Collins, 2018). The NIMBY issue implies that a proposed amenity should be

\(^6\) Among others see Sundt & Rehdanz (2015), Ma et al. (2015), and Soon and Ahmad (2015) for meta-analysis on WTP for RE.
sited outside of respondents’ neighborhood. Wind turbine externalities include but are not limited to noise, height, shadow, killing of birds and bats, etc. (Möllendorff & Welsch, 2017). Distance decay effect refers to lower WTP the farther away respondents live to a RE development, and vice versa. In contrast to studies about wind energy preferences, solar energy preferences are stable with the majority of studies demonstrating positive WTP across consumer populations (Rehdanz et al., 2017). For example, Borchers et al. (2007) found that solar energy is the most favored RE technology in comparison to wind, farm methane, biomass, and a generic “green” energy. Likewise, Gracia et al., (2012) showed that electricity generated from solar is preferred over wind and biomass as well. As acknowledged by other scholars (e.g., Yoo & Ready, 2014; Vecchiato and Tempesta, 2015; Welsch, 2016), preference toward photovoltaic solar (also known as solar farm or utility-scale solar), residential photovoltaic (also known as rooftop solar), or a combination of the two, is one of the most under-studied topics in the field of RE acceptance. To our knowledge, there is no paper that distinctly distinguishes between these two types of solar energy (solar farm and rooftop solar) within the extant literature. This paper, in part, aims to fulfill this gap in the literature by examining whether preference toward rooftop solar and solar farm varies.

In regard to consumer preferences and WTP with respect to exposure or proximity to RE, wind energy has been investigated the most (e.g., Knapp & Ladenburg, 2015; Nkansah & Collins, 2018; Gudding et al., 2018). It is also prudent to examine proximity to solar energy as it has negative externalities such as killing birds and interrupting deer migratory paths. To our knowledge there are only three peer-reviewed papers that investigate proximity to solar energy

7 They found that Delawarean consumers are willing to pay a mean premium of $19.03/month and 14.68/month for a voluntary and mandatory program of 10% solar generation respectively.
8 For an overview of the existing literature on distance to wind energy's impact on WTP, See Table 1 of either Knapp & Ladenburg, 2015 or Gudding et al., 2018.
Using a hedonic regression approach, Dastrup et al., (2012) found that rooftop solar add 3.6% to the sale price of a house in California. They relate this to financial and moral benefits to the rooftop solar owner, known as “warm glow”. Möllendorff & Welsch, (2017) measured exposure to solar farm (along with biomass and wind) effect on German consumers’ well-being (life satisfaction) and found statistically significantly negative effect when solar facility is located in neighboring postcode district and no significant effect when solar facility is located within the same postcode district of a respondent. In an attempt to explain why they found no effect within the same postcode district, the authors also refer to “warm glow” which may counterbalance solar energy’s negative externalities. Finally, using an random parameter logit model, Vecchiato and Tempesta (2015) investigated Italian consumers preferences for hypothetical policies that were distinguished by price, the source of energy (solar farm versus biomass), distance to energy facility, the size of energy facility, and the certification of the origin (only for biomass). Unlike Möllendorff & Welsch, (2017) where they sufficed with a vague “postcode”, Vecchiato and Tempesta (2015) provided a distance range at which their respondents would no longer support solar energy development. The authors found that Italians prefer solar energy over biomass and smaller plants that are located within 3 km of their place of residence. Further, the authors also found that respondents do not exhibit a statistically significant preference towards solar farm if located more than 10 km away from them. These findings are utilized to further investigate the relationship between respondents’ exposure to solar energy installation and their WTP for solar energy diffusion; wherein, we hypothesize that distance to rooftop solar and/or solar farm is associated with decreased WTP for solar energy improvement ($H_{Distance}$). This research is the first nonmarket valuation study that has included respondents’ distance to rooftop and solar farm
and its impact on their WTP simultaneously. If there is a statistically significant distance impact
on respondents’ support, then perhaps respondents’ exposure to solar energy may be a factor in
shaping their WTP. Our work incorporates actual distance to the nearest solar location, rather
than an artificially-introduced distance through the survey instrument.

Another contextual dynamic that is responsible for variations in WTP among consumer
populations arises from geographic variations shaped by residential locations. Bergmann et al.
(2008) demonstrates that there is heterogeneity in preferences for RE improvement in urban
versus rural place of residence in Scotland. They found that rural citizens support RE projects
more than their urban counterparts as majority of RE construction will occur in rural areas.
Similarly, Yoo, (2011) finds that rural residents in Pennsylvania are more supportive of solar
farm development than urban residents, though not statistically significant. Further, Brown et al.,
(2017) noted that a majority of utility-scale RE development to comprise with RPS will be
located primarily in rural areas of the U.S. (Brown et al., 2017). As such, we hypothesize that
respondents who live in rural area are distinctly more supportive of both solar farm ($H_{rural-solar}$
farm), and RPS ($H_{rural-RPS}$).

Previous research indicates that environmental attitudes captured by the New Environmental
Paradigm (NEP) scale has been strongly correlated with high levels of pro-environmental
behaviors and/or positive environmental worldview (Dunlap et al., 2000; Whitmarsh, 2009;
Whitmarsh & O’Neill, 2010; Hawcroft & Milfont, 2010; Kennedy et al., 2015). The NEP scale is
designed to capture the relationship between humans and the environment. The higher the NEP
scores the higher the commitment to the conservation of natural resources, and vice versa
(Hawcroft and Milfont, 2010). Hawcroft & Milfont (2010) reviewed more than 300 articles that
had used a version of the NEP scale and indicated that “… it is probably advisable for
researchers to continue using the NEP Scale as a standardized measure of environmental attitude. The NEP scale has been used extensively in environmental sociology, but not so much in nonmarket valuation. As noted by Faccioli et al. (2018), within stated preference valuation literature, the NEP scale has been given little attention. A majority of the peer-reviewed articles use contingent valuation technique (e.g., Aldrich et al., 2007; Meldrum, 2015; Halkos & Matsiori, 2017). To the best of our knowledge, no study to date has used the NEP scale to analyze environmental attitudes toward RE in a choice experiment setting. We fill this gap by hypothesizing \( H_{\text{NEP}} \) that higher NEP score is associated with higher support for our environmental variables, RE captured by RPS and rooftop solar, lower water usage, and smart meter implementation in a choice experiment setting.

Smart meters are electrical meters that can directly transfer electricity consumption information two ways, to both the customer and the corresponding utility company. This real-time communication will allow utility companies to dictate different time-of-use prices on electricity, which may encourage some customers to switch their use from peak hours (expensive) to low-use hours (less expensive) to save money. Further, smart meter facilitates the use of RE in the grid and prevents the need for additional power plants to accommodate peak-hour times (peaking natural gas power plants), which results in lower carbon emissions (Ida et al., 2012) and water usage. Based on the Energy Information Administration (EIA, 2017a), electric companies in the U.S. owned 70.8 million smart meter in 2016. Residential customers made up the majority of smart meter installations (88%), with half of all U.S. electricity customers own smart meter (EIA, 2017b).

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9 For further information on the NEP scale, see Hawcroft & Milfont (2010).
In the last decade, several studies have focused on the monetary estimation from the adoption of smart meter and public’s attitudes toward smart meter in Europe (e.g., Gerpott & Paukert, 2013; Kaufmann et al., 2013; Durmaz et al., 2017) and Asia (e.g., Ida, Murakami, & Tanaka, 2012; Shim et al., 2018). To our knowledge, no study has investigated the public’s perception in terms of willingness to pay or accept in the U.S. context. This study, in part, aims at targeting this gap in the literature investigating whether the public supports, opposes, or is indifferent to smart meters and estimates marginal WTP (MWTP) for various smart meters that differ in the way in which they communicate electricity consumption information to the consumer.

As discussed above, there are currently 29 states with unique RPS programs, which utilize a wide variety of designs to encourage increased use of renewable energy. However, these governing bodies still lack a clear understanding of their constituents’ preferences for the level and type of renewables used in their localities. In this research, we attempt to fill the aforementioned gaps within the literature to gain a better understanding of consumer preferences and how these may be applied for successful policy development. We conducted a choice experiment survey focusing on preferences for solar energy. The survey is conducted in NM, a state with an RPS. This is also a state with great potential for renewables, particularly in solar where it ranks third in the U.S. for that potential, as well as an economy that has traditionally been highly dependent on fossil fuel extraction. Focusing on the state’s major utility consumer base, our choice experiment considers an increase in the RPS and, specifically, preferences for different types of solar. In addition to gauging households’ WTP for RPS, we assess households’ attitudes towards smart meter in NM. Our evaluation considers the “average” consumer’s support for increasing the RPS requirement, and then heterogeneity and focuses on consumer’s
location, (i.e., rural versus urban), environmental worldview, as well as the consumer’s distance to the nearest solar location. This research extends the literature by differentiating solar energy types, employing the NEP scale in a primary research of RE valuation in a choice experiment setting, and assessing preferences on smart meter. We test the impact of the actual distance to the nearest solar location, rather than an artificially-introduced distance through the survey instrument. We find that, on average, respondents are supportive of increasing the RPS level; they are willing to pay a premium of $27/month to achieve an 80% RPS. Further, after a certain level, respondents would prefer the extra RPS to come from solar farm rather than rooftop solar. If smart meter program was to be implemented, our sample would be willing to pay $8.48/month and $9.24/month when they could access their usage and electricity price information via the internet and in-home display respectively. Additionally, rural respondents are statistically significantly more supportive of solar farm improvement than urban respondents. We observe distance decay effect only for solar farm. Lastly, we find that higher NEP score is correlated with higher support for our environmental attributes.

The rest of this paper is organized into four main sections. Section 2 presents the study area. Section 3 gives a description of the choice experiment design, the survey structure and administration, spatial heterogeneity, theory and the econometrics model, and finally the hypotheses that our paper seeks to test. In Section 4, we discuss the regression results. A discussion of results and conclusion will follow in the last section, Section 5.

2 Study Area

NM possesses substantial renewable resources, yet it lags in terms of widespread uptake of RE usage compared to other states. Nonetheless, over the past decade or so, NM has made enormous strides in developing its wind and solar power capacity. NM’s available geo-
physiological landmass is vast, which can be highly beneficial for achieving greater uptake of RE sources. The vast areas of NM with non-arable land that receives high wind and sunlight levels, is optimal for increasing RE usage. There are more than 310 days of sunshine with suitable temperature for solar power in NM (AED, 2018). Based on the sun index level developed by the National Renewable Energy Laboratory, NM is ranked 3rd amongst the states with the greatest energy potential from solar energy (NEO, 2010). NM was one of the top 10 states in solar electric capacity on a per-capita basis in both 2014 and 2015 (Weissman and Sargent, 2016) and ranked 15th in the nation in installed solar capacity in 2016 (EIA, 2018a).

NM has a poor economy, ranked 48th in the U.S. with a poverty rate of 19.8%10, which is highly dependent on energy industry. NM’s budget is volatile as it is vastly driven by oil and natural gas prices: according to the Legislative Finance Committee 2016 report, respectively, a 1-dollar and a 10-cent increase in unit prices of oil and natural gas translate into $9.5 million in general fund and $6.5 million in additional revenue for NM11. Further, NM has three active coal mines that provide two percent of the nation’s coal output. NM’s coal is either burned in its coal-fired power plants or exported to Arizona’s power plant (EIA, 2018a). Although conventional energy’s contribution to NM’s economy is remarkable, they have the highest contribution to climate change in the state. In 2015, NM’s energy industry was responsible for 50.2 million metric tons of carbon dioxide with coal being the main (40.6%) polluter, followed by oil (31.9%) and natural gas (27.5%). The potential economic impact of business-as-usual climate change to NM is considerable. Amongst other costs, increased energy-related costs alone is estimated to be

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11 Source: https://www.nmlegis.gov/Entity/LFC/Documents/Finance_Facts/finance%20facts%20oil%20and%20gas%20revenue.pdf For more information on NM’s legislations including historical NM’s general fund revenue see https://www.nmlegis.gov/ (accessed 8.23.18)
$248 million to NM in 2020 (McCALLY, 2015, p14). As such, NM has joined the move toward RE.

In March 2004, NM adopted an RPS (Senate Bill 43). Under NM’s RPS, all large electric utilities are required to produce 20% of total electricity sale in-state from renewable sources by 2020\(^{12}\). Of this 20%, at least 23% is mandated to come from solar energy: no less than 20% of solar farm and at least 3% rooftop solar\(^{13}\). In the 53\(^{rd}\) legislative session in 2017, a new bill was introduced that would require all large utilities to generate 80% of their total sales from renewables by 2040 (80% RPS by 2040) (Stewart and Small, 2017). However, this bill did not pass. Although RPS policies are designed to mitigate emissions, they also help with saving water consumed by fossil fuel generation. Any source of water (surface or groundwater) is scarce in NM\(^{14}\). Currently, the entire state is faced with some aspect of drought condition, with more than 86% of the state experiencing severe drought conditions, affecting 100% of NM’s population\(^ {15}\). Thus, water preservation that can arise from decreased utilization of fossil fuel and increased utilization of RE can be potentially useful.

There are three large electric utilities in NM: Public Service Company of New Mexico (PNM), El Paso Electric, and Xcel Energy. Of these three, PNM is NM’s largest electric utility company with more than 500,000 residential and business customers (more than 60% of the total

\(^{12}\) RPS requires NM’s rural electric cooperatives to generate 10% of total electricity sold in-state from renewable sources by 2020.

\(^{13}\) Public Regulation Commission set RE diversity targets to create a diversified RPS for NM. Based on this portfolio, utility companies are to comprise at least 30% sourcing from wind, 20% from solar, 3% from rooftop solar, and 5% from other resources (other than solar and wind) by 2020. More information about NM’s RPS can be found at: [http://programs.dsireusa.org/system/program/detail/720](http://programs.dsireusa.org/system/program/detail/720) (accessed 5.31.18).

\(^{14}\) Source: [https://www.env.nm.gov/water/](https://www.env.nm.gov/water/) (accessed 8.23.18)

\(^{15}\) As of August 21, 2018, 100% population of NM is affected by drought. Source: [https://www.drought.gov/drought/states/new-mexico](https://www.drought.gov/drought/states/new-mexico) (accessed 8.23.18)
NM consumer pool\textsuperscript{16} and serves 13 counties\textsuperscript{17} out of 33 total counties. PNM has more than 1 million solar panels (15 solar farms) and currently more than 11,000 rooftop solar installations connected to its grid (PNM, 2018). This company also has purchase power agreements with several solar facilities within NM to comply with its RPS requirements. In 2017, the RE share of PNM electricity sales was about 15\% and it is projected to meet its RPS goal of 20\% by 2020 (PNM, 2018).

PNM is considering a number of changes for the future of the company. Currently, PNM rooftop solar customers can utilize RE credits saved during spring months (high-production and low-use months) to use during the summer, when electricity is more expensive. There is a discussion of implementing a policy at PNM in the future that rooftop solar owners can only use their credits in the same month that excess electricity is generated\textsuperscript{18}. Furthermore, in 2016, PNM proposed implementing a mandatory smart meter program for its residential customers. New Mexico Public Regulation Commission (NMPRC) (2018) rejected PNM’s proposed mandatory smart meter residential program in 2018.

3 Methodology

3.1 Survey structure and administration

The survey was divided into five sections. We sought respondents’ opinions on different sources of energy in the first section. In the second section, we provided short descriptions of rooftop solar and solar farm and asked about preferences toward them. The third section was

\textsuperscript{16} In 2016, there were 762,551 households in NM. \url{https://www.census.gov/quickfacts/NM} (accessed 5.31.18).

\textsuperscript{17} Thirteen counties are: Bernalillo, Grant, Hidalgo, Lincoln, Luna, Otero, San Miguel, Sandoval, Santa Fe, Socorro, Torrance, Union, and Valencia.

\textsuperscript{18} For more information on the current and the future discussion see: \url{https://www.abqjournal.com/518250/rooftop-solar.html} (accessed 5.31.18).
dedicated to the Discrete Choice Experiment (DCE) questions. We gave an overview of the attributes involved in the proposed solar energy plan, asked relevant questions on each attribute, and provided respondents with a set of 4 choices over 3 plans. To reduce hypothetical bias, we reminded our respondents about their budget constraint before asking the DCE questions. The fourth section investigated attitudes toward RE, climate change, level of trust for authorities, and asked a shortened version of the New Environmental Paradigm (NEP) questions. The last section was dedicated to demographic questions. We tested the survey by conducting focus groups and debriefings in Summer 2017, and a pre-test to 100 PNM customers in Fall.\textsuperscript{19}

We administered a mixed-mode survey, following the Tailored Design Method (Dillman et al., 2014) to 1,300 randomly-selected consumers of the state’s largest electricity utility from 13 counties across NM. We purchased our sample from SSI.\textsuperscript{20} We sent out 5 contacts by first-class mail: a brief pre-notice letter, the survey packet a week later, a follow-up postcard a week later, a replacement survey 2 weeks later, and the final contact that contained the last survey 18 days later. We included a one-dollar bill incentive in the first survey packet (contact 2).

Excluding pre-test responses, overall, 404 responses were collected, and 211 questionnaires or invitations were returned by postal service. Assuming all survey recipients of unknown eligibility (undelivered) were not eligible to participate in the survey (AAPOR, 2016), we had a response rate of 37.1\% (404/1,089), with responses from 10 of the 13 counties.\textsuperscript{21} The response rate is an adequate rate in comparison with other similar studies (e.g., 27\% Mozumder et al.\textsuperscript{19})

\textsuperscript{19} We conducted 2 focus groups and 12 debriefings. The final version of the questionnaire was ready to be sent out after some minor revisions in Winter 2017.

\textsuperscript{20} The sample frame came from a general list purchased from SSI and included all zip codes in which PNM offers service.

\textsuperscript{21} Assuming undelivered questionnaires were eligible, we had a response rate of 31.8\% (404/1,300).
(2011); 35% Nkansah and Collins, (2018); 28% Walter et al. (2018, forthcoming)). Table 2 summarizes the socio-demographics.

[Table 2 HERE]

On average, our respondents are 54 years old, make an annual household income of $68,000, and are predominantly male (61%). Approximately, half of our respondents have earned a Bachelor's degree or higher. The largest share of our respondents lives in urban areas (82%). Compared to the population our survey represents, our sample is older, wealthier, more educated, and contains less female. In terms of residential location, that is urban/rural, our sample is comparable to the survey population\(^{22}\).

3.2 Choice Experiment Design

In a DCE survey, individuals are asked to make decisions amongst hypothetical plans with a series of attributes subject to their budget constraints and preferences. It is prudent to provide a clear and realistic description of each attribute prior to presenting the DCE questions. Based on the existing literature, two focus groups, and twelve debriefings, we identified six attributes with their corresponding levels to define a solar energy plan. This background work allowed us to develop a DCE survey, wherein we sought to evaluate respondents’ utility gained from each solar energy plan; which derived our dependent outcome measure. Below we described the components of the survey that serves as a foundation for our investigation. Figure 1 displays a choice question used in our survey.

[FIGURE 1 HERE]

\(^{22}\) Data come from Bureau of Business & Economic Research and U.S. Census Bureau.
The first attribute, percent of electricity from renewable sources by 2040 (RPS), was intended to capture preferences towards an increase in the RPS level, especially the 80%-RPS-by-2040 bill. As described in the previous section, the current level of RPS by 2020 is 20%. We used a hypothetical 3rd level in between the proposed and current RPS, 50%. Thus, our first attribute had three levels: 20%, 50%, and 80%.

In choosing our second attribute, percent of solar energy from rooftop by 2040 (Rooftop), we were interested in discerning respondents’ preference for rooftop verses solar farm. In the description of the second attribute, we mentioned that “Increasing the share of rooftop solar means decreasing the share of solar farms.” PNM’s Procurement Plan for 2016 (the latest plan that included compliance summary) showed that it generated 31.9% of its solar requirement from solar farm and 3% from rooftop solar. In other words, rooftop solar comprised approximately 9% \( \left( \frac{3\%}{31.9\%+3\%} \right) \) of the total solar generation in 2016. Thus, we used 9% rooftop solar as the status quo level for the second attribute. The second attribute had four levels: 5%, 9%, 20%, and 30%.

Figure 1 below provides graphical representation of NM’s RPS, along with the attribute status quo levels described above for: total percent of RE by 2040 and percent of solar energy from rooftop by 2040. A change in RPS will affect the rooftop to solar farm proportion (see Figure 2). To gauge this impact, we include an interaction term between RPS and Rooftop in our analysis.

Our third attribute was credit policy for rooftop solar customers (NoCreditBanking), which stem from the current PNM policy toward its rooftop solar customers. This attribute is dichotomous, Yes and No, with Yes being rooftop customers should be allowed to save their RE credits (status quo).
Our fourth attribute, water used to generate electricity by fossil fuel (gallons per person per day) (Water), is capturing the trade-off between fossil fuel generation and RE. The water attribute levels are calculated from Albuquerque-area residents’ water use23, PNM’s annual electricity production by source, and the RPS levels proposed in the first attribute. The levels are qualitative, and each are associated with a number of gallons per person per day: Low, Medium-Low, Medium-High, and High with 1, 2, 3, and 4 gallons/person/day respectively (the lower the value, the more water saved). The status quo level is High (4 gallons/person/day). To put this into perspective for our respondents, we provided the average water consumption of Albuquerque residents (127 gallons per person per day) in the survey. We utilized Albuquerque for our calculations as it is the largest metropolitan city in NM, as well as the largest population center serviced by PNM.

Our fifth attribute is smart meter installation and feedback (SmartMeter). The survey considers not only the preference for installation, but if installed, how consumers would access hourly usage and electricity price information. There are three options for how customers could access information: 1- Customers send a phone text message to the utility company and receive information in return (SmartMeter_{text}), 2- Customers can access information after logging into their online account (SmartMeter_{online}), and 3- An in-home display will be installed that shows the information (SmartMeter_{home}) (Gerpott and Paukert, 2013). We also included the status quo scenario (no installation).

Finally, we included a payment vehicle attribute, change in monthly electricity bill (Price), to be able to calculate the marginal price along with MWTP of the attributes. We used $0, $5,

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$10, $20, $30, and $50 as levels, with no change being the status quo level. Table 1 summarizes the attributes and corresponding levels in the current study.

[TABLE 1 HERE]

RPS, Rooftop, and Water are assumed to be continuous to have a linear effect on the choice of energy plan. NoCreditBanking is dummy coded and takes a value of 1 if rooftop solar owners can only sell credits in the same month that excess electricity is generated and 0 when they can sell credits any month of the year. The smart meter attribute, however, is divided into its levels (text, online, and in-home display) to reflect the qualitative nature of the levels.

Following the best practice outlined by Kuhfeld (2007), with the attributes and levels summarized in Table 1, an orthogonal main effect design that allowed for one interaction term between attributes (RPS and Rooftop) was deployed to develop choice sets in SAS. This resulted in a total of 48 choice sets which were divided into 6 versions. The survey had four choice sets per each version of the six total versions distributed. Each choice set included two alternative plans, along with a current plan alternative. We included the business as usual plan to make our DCE questions more realistic and let our respondents express preferences for or against the status quo. We capture this by incorporating an alternative specific constant (ASC) term in the analysis.

3.3 Spatial heterogeneity and NEP scale validity

In order to capture exposure to solar energy, we utilized distance to the closest rooftop solar and solar farm to our respondents. Currently, there are 53 solar farms installed in NM (EIA, 2018b). Urban and rural respondents have median distances of about 7 km and 10.5 km
respectively to the closest solar farm (as the crow flies)\textsuperscript{24}. Moreover, PNM has more than 11,000 rooftop solar customers that are connected to its grid\textsuperscript{25}. The median urban and rural respondents live 0.15 km and 0.41 km away from the closest rooftop solar respectively. Figure 3 depicts our study area, respondents’ place of residence, and existing rooftop solar and solar farms. We utilized Geographical Information System (GIS) to calculate the distance to the closest rooftop solar and solar farm from respondents’ place of residence.\textsuperscript{26}

[FIGURE 3 HERE]

In regard to the NEP scale, we truncated the original NEP questions proposed by Dunlap et al. (2000) and used a reduced (6-item) version following Whitmarsh (2009) and Whitmarsh and O’Neill, (2010)\textsuperscript{27}. The modified NEP score has reasonably high internal consistency and is thus reliable (Cronbach’s alpha 0.7014).

To further validate our NEP score variable, we performed principle component analysis on 18 questions, of which 6 were the NEP questions. This approach identified 3 components. The 6-item NEP formed one of the components. The three components together explain 56.5% variation in the data, of which 33% comes from the NEP component. We consider this as a validation exercise of the use of the modified NEP score in our analysis.

\textsuperscript{24} Although urban respondents on average live closer to solar farms, they do not encounter with them as solar farms are usually located in the countryside.

\textsuperscript{25} We downloaded the location (lat/long) data of each rooftop from \url{http://www.nmprc.state.nm.us/index.html} (accessed 5.31.18).

\textsuperscript{26} To avoid confusion between the second attribute (Rooftop) and the distance variables, we refer to Rooftop (with capital “R”) solar only when we talk about the survey attribute.

\textsuperscript{27} Statements we included were: “The balance of nature is very delicate and easily upset”; “Modifying the environment for human use seldom causes serious problems”; “Plants and animals exist primarily to be used by humans”; “The earth is like a spaceship with only limited room and resources”; “There are limits to economic growth even for developed countries like ours”; “Humans are meant to rule over the rest of nature”.

3.4 Econometric Model

The DCE methodology is placed within Random Utility Model (RUM) (Luce, 1959; McFadden, 1973) and Lancaster’s Consumer theory (Lancaster, 1966). RUM assumes individual utility function contains an observable component (indirect utility) and a stochastic error term. The observable component is captured by the utility individual \( j \) \((j=1, \ldots, 404)\) gains from the attributes of the \( m^{th} \) alternative \((m=1, \ldots, 3, \text{including the status quo})\) in choice set \( i \) \((i=1, \ldots, 4)\). Equation 1 summarizes the RUM:

\[
U_{jm} = V_{jm} + \epsilon_{jm} \tag{1}
\]

On the other hand, Lancaster argues that individuals derive their utilities from intrinsic characteristics of goods (e.g., environmental benefits of solar energy) rather than immediate contents of the goods (e.g., solar panels). Assuming a linear in parameter indirect utility function, it is the cumulative utility obtained from each attribute, mathematically:

\[
V_{mi} = \beta_0 Price_{mi} + \sum_{a=1}^{A} \beta_i^a X_{mi}^a \tag{2}
\]

Where \( Price \) is a continuous variable indicating extra fee that customers will be required to pay for alternative \( m \) in choice set \( i \), \( X_i' \) is the \( a^{th} \) non-price attribute of the \( m^{th} \) alternative in choice set \( i \), while \( \beta_0 \) and \( \beta_i \) \((a=1, \ldots, A)\) are the vectors of parameters (including ASC) to be estimated via maximum likelihood estimation approach, representing the contribution of each attribute in the indirect utility \( V_{mi} \). Combining equations 1 and 2 leads to equation 3:

\[
U_{jm} = \beta_0 Price_{jm} + \sum_{a=1}^{A} \beta_i^a X_{jm}^a + \epsilon_{jm} \tag{3}
\]

Respondent \( j \) chooses the alternative \( m \) in choice set \( i \) that maximizes her utility, \( U_{jm} \).

There are numerous modeling methods that can be used to evaluate DCE data. The most common modeling approach is the Multinomial Logit Model (MNL). An MNL model assumes
that the stochastic error term in equation 3 is independently identically distributed (i.i.d.) with Generalized Extreme Value type I across respondents. Furthermore, an MNL model posits an unrealistic assumption (Independence from Irrelevant Alternatives (IIA)) that everyone has identical preference for an alternative (i.e., perfect substitution among all alternatives) and hence estimates a utility function for the entire population (McFadden, 1973). Random Parameter Logit model (RPL) is another widely-used modeling approach that does not assume the IIA and captures preference heterogeneity by deriving an individual-level utility function (Train, 2009). We use these two models in our analyses.

In addition, we provide the MWTP for each attribute. The estimated MWTP is the amount of money that a respondent is willing to trade for a marginal (one unit more) change in the level of an attribute. MWTP for attribute \( a \) can be calculated using equation 4:

\[
MWTP = -\left(\frac{\partial U_i/\partial x_a}{\partial U/\partial Price}\right) = -\left(\frac{\beta_a}{\beta_0}\right)
\]

where \( \beta_a \) and \( \beta_0 \) are the estimated coefficients on attribute \( a \) and price parameter in the models respectively.

Empirically, we estimate 4 models: 2 MNL and 2 RPL. Models 1 and 2 are baseline models which estimate main effects for each attribute and an interaction term between RPS and Rooftop solar attributes. Since we are interested in investigating changes from status quo levels of RPS and rooftop/solar farm, we centered the interaction term at their status quo levels. Equation 5 summarizes the global utility specification applied in models 1 and 2:

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28 For more information on the restrictions of MNL, see Train, (2003)
29 Also known as mixed logit model.
30 For a thorough explanation of the econometric modeling, see: Train (2003), Hensher et al. (2005), and Train, (2009).
31 Similar results were derived from Generalized MNL (GMNL) model. GMNL results are available upon request from the corresponding author.
\[ U = \beta_0 \text{Price} + \beta_1 \text{RPS} + \beta_2 \text{Rooftop} + \beta_3 \text{NoCreditBanking} + \beta_4 \text{Water} \]

\[ + \beta_5 \text{SmartMeter}_{text} + \beta_6 \text{SmartMeter}_{online} \]

\[ + \beta_7 \text{SmartMeter}_{home} + \beta_8 (\text{RPS} - 20) \times (\text{Rooftop} - 9) + \beta_9 \text{ASC} \]

\[ + \epsilon \]

where the \( \beta \)'s are the estimated coefficients (marginal utility) on price, RPS, Rooftop, no to credit banking, water, smart meter levels, RPS Rooftop interaction term and ASC parameters.

Recall that not only we are interested in capturing unobserved heterogeneity, but also we want to include important observed heterogeneity variables in our modeling. The latter helps with fulfilling the gaps in the literature indicated earlier. In doing so, we estimate models 3 and 4. Equation 6 presents the utility specification of the two models:

\[ U = \beta_0 \text{Price} + \beta_1 \text{RPS} + \beta_2 \text{Rooftop} + \beta_3 \text{NoCreditBanking} + \beta_4 \text{Water} \]

\[ + \beta_5 \text{SmartMeter}_{text} + \beta_6 \text{SmartMeter}_{online} \]

\[ + \beta_7 \text{SmartMeter}_{home} + \beta_8 (\text{RPS} - 20) \times (\text{Rooftop} - 9) + \beta_9 \text{ASC} \]

\[ + \beta_{10} \text{RPS} \times \text{rural} + \beta_{11} \text{Rooftop} \times \text{rural} \]

\[ + \beta_{12} \text{RPS} \times (\text{Dist}_\text{to_rooftop}) \]

\[ + \beta_{13} \text{Rooftop} \times (\text{Dist}_\text{to_rooftop}) \]

\[ + \beta_{14} \text{RPS} \times (\text{Dist}_\text{to_solar farm}) \]

\[ + \beta_{15} \text{Rooftop} \times (\text{Dist}_\text{to_solar farm}) + \beta_{16} \text{RPS} \times \text{NEP} \]

\[ + \beta_{17} \text{Rooftop} \times \text{NEP} + \beta_{18} \text{Water} \times \text{NEP} \]

\[ + \beta_{19} \text{SmartMeter}_{online} \times \text{NEP} + \beta_{20} \text{SmartMeter}_{home} \times \text{NEP} + \epsilon \]

where the first nine variables (\( \beta_1 \text{–} \beta_9 \)) are the same as in equation 5. The remaining coefficients capture the observed heterogeneity including location’s impact on respondents’ attitude towards RPS and solar energy, distance to the closest rooftop solar and solar farm on
RPS and Rooftop attributes, and NEP scale on the environmental attributes. We utilize Model 3 to test our hypotheses, $H_{\text{Rural}}$, $H_{\text{Distance}}$, and $H_{\text{NEP}}$. Table 3 summarizes the three hypotheses we have developed thus far:

**[TABLE 3 HERE]**

Recall that, we hypothesized that rural respondents will support solar farm as well as RPS as the majority of utility-scale RE development to comprise with RPS will be located in rural areas. Thus, statistically significant and positive $\beta_{10}$ would support the alternative hypothesis of $H_{\text{Rural-RPS}}$ that rural respondents distinctly support RPS. Further, given how the solar energy attribute (Rooftop) is designed, a statistically significant negative Rooftop coefficient implies that respondents support solar farm. Thus, statistically significant negative $\beta_{11}$ would support the alternative hypothesis of rural respondents distinctly support solar farm development ($H_{\text{Rural-solar farm}}$). To investigate distance to rooftop solar and/or solar farm impact on WTP ($H_{\text{Distance}}$), we interact distance to rooftop solar and solar farms with the Rooftop attribute. We are also interested in their impact on RPS (see equation 6). We examine to see if there exists distance decay effect on either rooftop solar, solar farm, or both. A negative and statistically significant $\beta_{13}$ indicates the closer to rooftop solar a respondent lives the higher utility she gains from rooftop improvement (“warm glow”). Whereas, a positive and statistically significant $\beta_{15}$ implies solar farm’s distance decay effect (Vecchiato and Tempesta, 2015), that is the farther away a respondent lives from a solar farm the lower utility she derives from solar farm development. Statistically significant and negative $\beta_{13}$ or positive $\beta_{15}$ would support the alternative hypotheses on distance hypothesis. Lastly, if the findings on the NEP scale literature persists in our DCE survey setting, one can assert that statistically significant and positive $\beta_{16}$,
\( \beta_{17}, \beta_{19}, \text{ and } \beta_{20} \) and negative \( \beta_{18} \) would support our five alternative hypotheses of the NEP scale.

Finally, in the RPL models, we assume all the attributes, including price, and the ASC variable are normally distributed and use 400 Halton draw (Train, 1999; Bhat, 2001; Scarpa et al., 2008; Train, 2009; Vecchiato and Tempesta, 2015).32

4 Results

In this section, we highlight results from the valuation analysis. Table 4 presents the definition of all the variables utilized in the models and expectations placed on the corresponding variables.

[TABLE 4 HERE]

Based on the existent RE acceptance’s literature (i.e., Sundt & Rehdanz, 2015; Ma et al., 2015; Soon and Ahmad 2015), we expected that respondents support higher level of RPS. There is no nonmarket valuation study that distinguishes between solar energy types, rooftop solar verses solar farm. Thus, we placed no expectations on the sign of the Rooftop attribute parameter prior to model estimation. Similarly, we placed no expectation on smart meter levels (text, online, in-home display). More than 88% of our respondents chose the statement, “Rooftop solar customers should be allowed to save their credits”, thus, we assumed respondents derive a negative utility from not allowing customers to bank credits. We also assumed that NM residents would oppose a policy that increases the use of water consumption by fossil fuel. Lastly, the alternative specific constant and price parameters were expected to be negative. Our hypotheses derived the remaining parameters’ expected signs.

32 All the analyses are done in Stata using Hole's (2007) clogit(), mixlogit(), and wtp() commands.
For comparison and robustness check, Table 5 summarizes results from both the MNL and the RPL models based on choices of 404 respondents. Model 1 and Model 2 specifications include the attributes. In attempting to account for the relationship between RPS and rooftop/solar farm, we included the interaction term between RPS and Rooftop. This interaction term accounts for the relationship as marginal utility gained from a one percent increase in rooftop solar level (1% decrease in solar farm) is not only impacted by rooftop itself ($\beta_2$), but also by a change from status quo level of RPS ($\beta_8 \times (RPS - 20)$) (i.e., $\frac{\partial U}{\partial R_{PV}} = \beta_2 + \beta_8 (RPS - 20)$). We centered both attributes at their status quo levels to be able to interpret changes from the current levels of RPS and Rooftop. Further, we included the ASC variable to capture business as usual effect (see equation 5).

All else being equal (ceteris paribus), respondents gain a negative utility by paying an extra monthly fee on top of their current electricity bill in both models. As expected, respondents derive a statistically significant and positive utility from increasing RPS beyond the status quo level (20%) in both models. The statistically significant and positive sign on Rooftop parameter in models 1 and 2 indicates that respondents prefer an increase in rooftop portion of the solar carve-out from its status quo level (9%). As anticipated, respondents do not support a policy that results in consuming more water for electricity generation in both models. NoCreditBanking has negative sign in both models but is only statistically significant in the MNL model. Respondents also derive less utility from the current situation (ASC) than the designed PNM’s solar energy alternatives. Lastly, the sign on the interaction term between RPS and Rooftop

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33 This stems from the large degree of preference heterogeneity among respondents. We graphed the kernel density function on Credit_no_individual-level coefficients from RPL model. The number of supports and oppositions appear to cancel each other out and hence the insignificance in RPL model.
depends on the level of RPS and Rooftop under question; an increment from status quo level of RPS decreases the utility gained from rooftop diffusion, and vice versa. In other words, marginal utility for rooftop development decreases as RPS increases beyond status quo levels. Thus, increase in rooftop (relative to solar farm) becomes less important if increasing RPS.

Recall that smart meter has three levels: text, online, and in-home display. A statistically significant and positive coefficient estimate on any of those three levels indicates that respondents derive a positive utility from smart meter installation when they access information via the corresponding type of information delivery. With that in mind, our respondents do not support smart meter installation when texting is used as the type of information delivery in both models. However, both models estimate that respondents derive a positive utility from smart meter installation when they are accessing their usage and electricity price through either online or an in-home display (SmartMeter_{online} and SmartMeter_{home})\textsuperscript{34}.

The 4\textsuperscript{th} column of Table 5 shows the standard deviations estimated from the RPL model. We assumed all of our parameters, except the RPS and Rooftop interaction term, are normally distributed. All of the standard deviations are statistically significant, except those of SmartMeter_{text} and SmartMeter_{online}. Statistically significant standard deviation indicates that respondents’ choice for the corresponding attribute are statistically significantly different and thus preference heterogeneity exists. In other words, heterogeneity results from different respondents placing different values for the potential impact of the attributes. For example, some respondents may oppose RPS because they believe RE facilities look unpleasant (or “they kill birds”), while some may support RPS due to RE’s positive environmental impact (“no water and emission”), which were ideas observed in our focus groups and debriefings. MNL model posits

\textsuperscript{34} SmartMeter_{online} becomes significant at 95\% level after including the spatial heterogeneity and the NEP variables in the MNL model. See Model 4 of Table 5.
the IIA assumption that everyone has identical preference for an alternative and fails to capture preference heterogeneity. Further, comparing the log likelihood (-1,443 vs. -1,181), the AIC (2,907 vs. 2,399), and the BIC (2,972 vs. 2,522), it is evident that RPL also outperforms MNL from a statistical standpoint. Hence, the focus of the discussion and the analysis of results is solely on the RPL model. For robustness check purposes, we include the MNL models alongside of RPL models.

To further investigate the existence of preference heterogeneity among our respondents, the third model modification additionally includes the variables describing spatial heterogeneity and the NEP scale (see equation 6). Thus, Model 3 of Table 5 accounts for location, that is rural/urban, distance to the nearest solar installation, that is distance to rooftop solar and solar farm, and the NEP scale. Spatial heterogeneity variables are interacted with only RPS and Rooftop attributes, while the NEP score is interacted with other environmental variables (i.e., Water and smart meter – online and in-home display levels only35) in addition to RPS and Rooftop. The NEP score is centered at its mean value, 23.04. The additional variables in Model 3 compared to Model 2 are assumed not to be random.

The overall findings of estimated coefficients stay similar in terms of both sign and magnitude across the attributes in the second RPL model with covariates (Model 3). However, two of the nine random parameters (Rooftop and Water) are no longer normally distributed (the 6th column of Table 5), which indicates including the spatial heterogeneity and the NEP score variables (observed heterogeneity) in the model capture more of the existing heterogeneity in preference in Model 2.

35 We did not consider SmartMeter as it is not statistically significant in Model 2.
We find that rural respondents derive statistically lower utility from Rooftop attribute. The interacted variables with the NEP scale are highly statistically significant and have the expected signs. Two out of the four interaction terms defining distance to rooftop and solar farm in Model 3 are statistically significant\textsuperscript{36}. The interaction between RPS and distance to the nearest rooftop solar indicates, \textit{ceteris paribus}, the farther away respondents live to rooftop solar, the less supportive of RPS they become. 12 km and 9 km\textsuperscript{37} away from rooftop solar will result in no support for RPS from rural and urban citizens respectively. The opposite holds for the interaction term between Rooftop attribute and distance to the closest solar farm. Respondents are weakly more supportive of Rooftop attribute as their distance to the closest solar farm increases. In other words, respondents care less about solar farms as they live farther away from them. However, distance to the closest rooftop solar and solar farm do not affect how respondents feel about Rooftop and RPS respectively. Overall, we observe a decay in support for solar farm with increasing distance from solar farm (distance decay effect), also distance to rooftop solar, and not solar farm, affects respondents’ support for RPS. In one hand, the evidence will not support the alternative hypothesis of the farther away one lives from rooftop solar, the less supportive of rooftop solar she is. On the other hand, this evidence will allow us to support the alternative hypothesis of the farther away one lives from solar farm, the less supportive of solar farm one becomes (\textbf{H}_{Distance}).

Now we turn our attention to MWTP. As indicated above, we used equation 4 to derive MWTP. Table 6 summarizes the MWTP values. The 2\textsuperscript{nd} column of Table 6 reports the MWTP

\textsuperscript{36} We first divided distance not only by solar type (rooftop and solar farm), but also by location (rural and urban), which resulted in 8 variables. We then performed t-tests on all 4-pair related coefficients (e.g., \texttt{RPS*distance to rooftop*rural} and \texttt{RPS*distance to rooftop*urban}) and failed to reject any of the four equality null hypotheses. Further, although the latter model had 4 more parameters than the current Model 3, the model fits were identical. Hence, we went with the current format Model 3.

\textsuperscript{37} \texttt{Rural} = \frac{0.015 + 0.044}{0.005} = \sim 12 \text{ km}; \texttt{Urban} = \frac{0.044}{0.005} = \sim 9 \text{ km}
for each parameter in Model 2 and the 3rd column shows the corresponding confidence interval values. We utilized Krinsky and Robb's (1986) bootstrapping approach with 50,000 simulations to estimate the confidence interval. At the status quo levels when RPS is 20% and Rooftop is 9%, the RPL model suggests that our respondents exhibit a MWTP of $0.45/month [$0.35–$0.57] and $0.76/month [$0.52–$1.07] for each 1% increase in the current level of RPS and the share of Rooftop in RPS respectively. Given the MWTP and status quo level of RPS, we can extrapolate that our respondents are willing to pay a premium of $27/month to achieve an 80% RPS. This amount is equivalent to a 36% increase in NM’s average current electricity bill38.

[TABLE 6 HERE]

Allowing for RPS and Rooftop levels to vary (i.e., not at the status quo RPS and Rooftop levels) (see Figure 1) will result in changing marginal utility magnitudes and subsequently MWTP values. Note that decreasing rooftop solar equates with increasing solar farm in our analysis. Of interest here is to examine whether RPS and Rooftop parameters change signs (no more support)39. Overall, ceteris paribus, we find that respondents are supportive ($0.07/month) of RPS even at the highest Rooftop level (30%). However, a 62%-RPS can lead to zero support for Rooftop development. The latter could very well happen; an 80%-RPS-by-2040 bill was introduced though did not pass (Stewart and Small, 2017). This indicates that our respondents are supportive of RPS and would prefer it to come from solar farm rather than rooftop, as a zero rooftop solar means 100% solar farm here. As RPS level increases, our respondents’ MWTP for rooftop (solar farm) decreases (increases).

38 Average electricity bill in NM is $75.00. Source: https://www.electricitylocal.com/states/new-mexico (accessed 5.27.18)

39 $\frac{\partial u}{\partial RPS} = 0.05 - 0.002 \times (RPV - 9) < 0 \implies RPV > 34\%; \frac{\partial u}{\partial RPV} = 0.085 - 0.002 \times (RPS - 20) < 0 \implies RPS > 62.5\%. \text{Marginal utility values are from Table 5. Further, a 9\% share of rooftop in a 60\% RPS would require many new rooftop solar installations that with the current situation there might not be enough incentives.}$
For each 1 gallon/person/day (2 million gallons/day\textsuperscript{40}) reduction in water consumed by fossil fuel to generate electricity, the RPL model (Model 2) suggests that our respondents are willing to pay a $4.77/month [$6.28, $3.55] on top of their current electricity bill. As indicated earlier, New Mexicans are supportive of smart meter as long as the information is communicated either online or via an in-home display and are exhibiting MWTP of $7.14/month [$3.52, $11.29] and $7.96/month [$4.31, $12.05] respectively.\textsuperscript{41}

Taking the mean NEP score and zero distance to rooftop and solar farm, along with RPS and Rooftop status quo levels into account in Model 3, there is not a statistically significant difference between rural verses urban respondents for the RPS attribute, though rural respondents have a higher MWTP (see Table 6). Hence, the evidence does not support the alternative hypothesis of $H_{\text{Rural-RPS}}$ that rural respondents are statistically significantly more supportive of RPS development. However, rural respondents are significantly less in favor of Rooftop solar attribute than urban at zero distance, though overall they support rooftop solar improvement (MWTP=$0.071$-$0.67= $0.04$/month). This implies that rural respondents are statistically significantly more supportive of solar farm improvement than urban respondents. As solar farms are generally located in the rural area, a decrease in their number might mean less jobs with financial and moral benefits (Dastrup et al., 2012) for the rural citizens. Conversely urban respondents have much higher MWTP ($0.71) for the Rooftop attribute, as they encounter with rooftop more and hence might be associated with the “warm glow” and psychological impact (Möllendorff and Welsch, 2017, p117). Thus, Model 3 provides us with enough reasons

\textsuperscript{40} Multiplied by NM population.
\textsuperscript{41} Rather than a categorical variable, we included a dummy coded smart meter variable that took a value of 1 if agree to smart meter installation and 0 otherwise in Model 2. This variable was significant at a 99% level indicating that our respondents are supportive of smart meter installation. Further, respondents exhibited a MWTP of $5.30/month [$2.50, $8.06].
to support the alternative hypothesis of rural (urban) residents are more supportive of solar farms (rooftop solar) \( H_{\text{Rural-solar farm}} \).

In line with other scholars’ findings on the NEP scale, Model 3\textsuperscript{42} suggests that respondents with positive environmental worldview has positive attitude toward the environment-related variables, namely RPS, Rooftop, water, and online and in-home display smart meter. For each score higher than mean, *ceteris paribus*, respondents are willing to pay an extra $0.06/month and $0.04/month for 1% increase in RPS and R_rooftop respectively. Similarly, for each score higher than the NEP average, respondents accept to pay $0.50/month, $1.23/month, and $0.75/month to reduce water consumption by fossil fuel by 2 million gallons/day\textsuperscript{43}, install smart meter and access information either online or via an in-home display respectively. Hence, the evidence supports the alternative hypotheses of \( H_{\text{NEP}} \) that higher NEP is correlated with higher support for the environment-related attributes.

Lastly, letting the interacted variables not be fixed at the status quo levels will allow us to examine different scenarios. Let us assume median distance to rooftop and solar farm for rural and urban respondents and mean NEP score, along with allowing for status quo values of RPS and Rooftop to change\textsuperscript{44}. Of interest here is to investigate whether these assumptions lead to further divergent support for RPS and Rooftop by location, that is urban and rural, and how different they are compared to the values we found from Model 2. Similar to model 2, both rural ($0.14/month) and urban ($0.01/month) respondents support RPS even at the highest-level Rooftop. For an RPS level higher than 32.6%, rural respondents are no longer willing to pay a

\textsuperscript{42} Model 4 is the MNL version of Model 3. We included this model for the purpose of comparison and robustness check.

\textsuperscript{43} 1 gallon/person/day \times \textit{NM population}.

\textsuperscript{44} Rural: Distance to rooftop=0.414 km; Distance to solar farm=10.450 km — Urban: Distance to rooftop=0.148 km; Distance to solar farm=6.892 km — Mean NEP score = 23.04.
premium to increase share of Rooftop in the RPS. Similarly, 63.4% is the highest RPS level that urban respondents would still accept to support an improvement in the share of Rooftop in RPS. In other words, our respondents, especially those who live in the rural area, want extra RPS to be fulfilled by solar farm rather than rooftop solar. Thus, we can conclude that the higher than the status quo RPS level, the lower the MWTP for rooftop solar and hence the higher the MWTP for solar farm improvements. Worth mentioning, each score higher than the mean NEP score increases the RPS percentages by 2% (34.6% and 65.4%).

5 Discussion and Conclusion

The move toward renewables is due not only to RPS, but also to cost competitiveness and consumer preferences. Consumer preferences may be a key factor in the type of renewable energy that is utilized. To estimate consumers’ preferences toward RPS and different solar energy types, we designed a DCE survey focusing on NM’s largest electric utility company. In addition to estimating households’ WTP, we assessed respondents’ attitudes towards smart meter. The survey considers not only the preference for installation (business as usual), but if installed, how consumers would access information. We further included spatial and environmental worldview heterogeneity in our analysis. Our results suggest that there is general support for diffusion of the RPS in our sample. However, there is a diminishing return in support for Rooftop solar: after a certain RPS level, our respondents are no more willing to pay for energy plans that persuade rooftop solar improvement. Thus, individuals in our sample want higher RPS to be fulfilled by solar farms rather than rooftop solar. Our respondents are also willing to pay a premium for policies that encourage smart meter installation (especially when they access information through an in-home display or via the internet) and/or reduction in water consumption by fossil fuel for electricity generation.
Using Model 2’s findings, we compare our RPS and Rooftop results to those of Mozumder et al. (2011) and Borchers et al. (2007). Mozumder et al. (2011) argue that NM residents are willing to pay $9.27/month on top of their monthly electric charge to increase the share of RE in the energy portfolio mix from 10% to 20%.\(^{45}\) We carried out a t-test to compare our MWTP calculated from the RPL model ($4.5/month for 10% increase in RPS) with that of Mozumder et al. (2011) with ($10.07)\(^{46}\) and without ($9.27) inflating the values. The t-test values (t=2.92 p-value<0.002; t=2.56 p-value<0.005) allow us to conclude that our MWTP for an extra 10% RPS is statistically significantly smaller than that of Mozumder et al. (2011) in both cases (inflated and uninflated). Considering the MWTP and status quo level of RPS, *ceteris paribus*, we extrapolated that respondents are willing to pay $27/month to achieve an 80% RPS. This is equivalent to a 36% increase in NM’s average current electricity bill. However, Mozumder et al. (2011) found an identical percentage (36%) for a 20% share of electricity to come from RE in their contingent valuation survey. Furthermore, Borchers et al. (2007) found that Delawarean consumers are willing to pay a mean premium of $19.03/month for a voluntary program of 10% solar generation, which is more than 2.5 times more than what our respondents would be willing to pay ($7.10/month) for a similar program. This might be due to either the novelty of RE during those times, the drastic change in government attitudes toward RE, different samples, or more importantly, due to the different economies under question in each survey. During the previous

\(^{45}\) We compare our results with WTP for the 2nd 10% of Mozumder et al. ($15.04$-$5.77$=$9.27$) (see footnote 13 in Mozumder et al. (2011, p1124)). To justify for the discrepancy in WTP for the first and second 10% increase in the RPS level, they argue that PNM has initiated installation of extra capacity in order to achieve the first 10%. However, no effort had been taken for the second 10% yet and thus the higher WTP for the second 10%. Since PNM is lagging behind in achieving the current RPS level (20%), hence we compare their second 10% with an extra 10% from the current level RPS in our study.

\(^{46}\) \(9.27 \times \frac{CPI_{2017}}{CPI_{2011}} = 9.27 \times \frac{237.46}{218.62} = 10.07\) CPI data are from BLS
administration, pro-environmental policies were encouraged; the current administration has the opposite view. This might have affected electricity consumers’ preferences as well.

Our findings indicate that controlling for spatial and environmental worldview heterogeneity results in a divergence of MWTP values. Consistent with similar studies (Bergmann et al., 2008; Yoo, 2011), as an increase in rooftop solar means a decrease in solar farm deployment in this research, rural respondents are more in favor of RPS and less supportive of Rooftop development. The opposite holds true for urban respondents: more support for Rooftop and less for RPS. This may be a result of the “warm glow” effect, where respondents gain moral and financial benefits from the solar type that surrounds them (Dastrup et al., 2012; Möllendorff & Welsch, 2017). Further, our findings are also consistent with those of Vecchiato and Tempesta, (2015); rural and urban respondents do not exhibit a statistically significantly positive WTP for RPS if they are 12 km and 9 km away from rooftop solar respectively. Moreover, our results suggest that there exists a distance decay effect for only solar farm. Lastly, consistent with the literature (e.g., Hawcroft & Milfont, 2010), we find that respondents with pro-environmental behavior are more supportive of policies that are environmentally friendly. This research extends the literature by differentiating solar energy types, assessing preferences on smart meter, and incorporating distance to solar installation through actual distance data rather than an artificially-introduced distance through the survey instrument.

One of the limitations of this study is that we are not able to undertake a cost-benefit analysis of different solar energy types. Future research should include not only the spatial nonmarket component (e.g., externalities, psychological and moral benefits/costs, etc.), but also the market component (e.g., social costs/benefits, rooftop solar and/or solar farm ownership status, etc.). It would be also valuable to include a distance variable within the survey and
compare results against actual distance data for different solar energy types. This is important as distance decay effect would be questionable if people generally support solar energy, hence it is unlikely that valuing solar energy is distance dependent.

Our findings suggest that our sample of NM residents are supportive of smart meter installation, however the original PNM smart meter project has been rejected at this time. This provides an opportunity to develop an alternative policy that would incorporate a voluntary smart meter program. Furthermore, to meet the desires of NM residents, our findings suggest that price and usage information provided by smart meter should be conveyed either online or through in-home display. Policies that consider everyone the same are not appropriate, as we find statistically significant differences between rural verses urban perspectives toward RE, especially solar energy. These policies are likely more effective for some groups than others. Efficient energy policy requires technological efficiency and economic viability. It also necessary that public acceptance, spatial and worldview heterogeneity be considered. For NM regulators considering either new RPS policies or altered RPS levels, this research provides improved information with which to develop efficient policy. The results also suggest that regulators in other states considering changes to their own RPS programs may find and improve understanding of consumer heterogeneity valuable.

6 Acknowledgments

We greatly appreciate valuable comments received from Ronald Cummings, Robert Berrens, along with 2018 EPRC and USAEE participants on an earlier version of this paper. We also would like to thank anonymous reviewers for their insightful comments. This research is funded by NSF Award #1345169 and NM’s Established Program to Stimulate Competitive
Research (EPSCoR). Jamal Mamkhezri gratefully acknowledges funding received from the UNM Center for Regional Studies (CRS).
7 Tables and Figures

Table 1: Attributes, levels, definitions, and expected signs.

<table>
<thead>
<tr>
<th>Attribute</th>
<th>Attribute Level*</th>
<th>Definition</th>
</tr>
</thead>
<tbody>
<tr>
<td>RPS</td>
<td>20%, 50%, 80%</td>
<td>Percent of electricity from renewable sources by 2040.</td>
</tr>
<tr>
<td>Rooftop</td>
<td>5%, 9%, 20%, 30%</td>
<td>Percent of solar energy from rooftop solar by 2040.</td>
</tr>
<tr>
<td>NoCreditBanking</td>
<td>Yes, No</td>
<td>Rooftop solar owners can only sell their credits in the same month that excess electricity is generated.</td>
</tr>
<tr>
<td>Water</td>
<td>Low (1 gal/person/day); Medium-Low (2 gal/person/day); Medium-High (3 gal/person/day); High (4 gal/person/day)</td>
<td>Water used to generate electricity by fossil fuel.</td>
</tr>
<tr>
<td>SmartMeter</td>
<td>SmartMeter_{text}, SmartMeter_{online}, SmartMeter_{home}, No installation</td>
<td>Smart meters installation and usage and price feedback by text, log into online account, or in-home display.</td>
</tr>
<tr>
<td>Price</td>
<td>No change, $5, $10, $20, $30, $50</td>
<td>Change in monthly electricity bill.</td>
</tr>
</tbody>
</table>

Note: * Levels in bold are status quo levels.

Table 2: Socio-demographics

<table>
<thead>
<tr>
<th>Variables</th>
<th>N</th>
<th>Our survey</th>
<th>Survey population</th>
</tr>
</thead>
<tbody>
<tr>
<td>Age (year)</td>
<td>404</td>
<td>53.8</td>
<td>39</td>
</tr>
<tr>
<td>Female</td>
<td>397</td>
<td>39%</td>
<td>50.6%</td>
</tr>
<tr>
<td>Education (Bachelor's degree or higher)</td>
<td>394</td>
<td>49%</td>
<td>29%</td>
</tr>
<tr>
<td>Income</td>
<td>392</td>
<td>$68,000</td>
<td>$45,500</td>
</tr>
<tr>
<td>Location (1–Urban)</td>
<td>404</td>
<td>0.82</td>
<td>0.84</td>
</tr>
</tbody>
</table>

Number of respondents = 404
Table 3: Hypothesis tested in this study

<table>
<thead>
<tr>
<th>Description</th>
<th>Null Hypotheses*</th>
</tr>
</thead>
</table>
| **H\textsubscript{Rural}** | Respondents who live in a rural area are distinctly more supportive of RPS (H\textsubscript{Rural-RPS}) and solar farm (H\textsubscript{Rural-solar farm}). | \( H_0: \beta_{10} \leq 0; H_1: \beta_{10} > 0 \)  
\( H_0: \beta_{11} \geq 0; H_1: \beta_{11} < 0 \) |
| **H\textsubscript{Distance}** | Distance to rooftop and/or solar farm impacts support for solar and RPS improvement. | \( H_0: \beta_{12} \geq 0; H_1: \beta_{12} < 0 \)  
\( H_0: \beta_{15} \leq 0; H_1: \beta_{15} > 0 \) |
| **H\textsubscript{NEP}** | Higher NEP score is associated with higher support for RPS and Rooftop, lower water usage, and smart meter implementation. | \( H_0: \beta_{16} \leq 0; H_1: \beta_{16} > 0 \)  
\( H_0: \beta_{17} \leq 0; H_1: \beta_{17} > 0 \)  
\( H_0: \beta_{18} \geq 0; H_1: \beta_{18} < 0 \)  
\( H_0: \beta_{19} \leq 0; H_1: \beta_{19} > 0 \)  
\( H_0: \beta_{20} \leq 0; H_1: \beta_{20} > 0 \) |

* Not only sign but also significance levels of the coefficients tested in these hypotheses matter.
### Table 4: Definition of variables

<table>
<thead>
<tr>
<th>Variables</th>
<th>Definition</th>
<th>Expected sign</th>
</tr>
</thead>
<tbody>
<tr>
<td>RPS</td>
<td>Percent of electricity from renewable sources by 2040.</td>
<td>+</td>
</tr>
<tr>
<td>Rooftop</td>
<td>Percent of solar energy from rooftop solar by 2040. (Increase in rooftop solar equates with decrease in solar farm)</td>
<td>(?)</td>
</tr>
<tr>
<td>NoCreditBanking</td>
<td>Rooftop solar owners can only sell their credits in the same month that excess electricity is generated.</td>
<td>–</td>
</tr>
<tr>
<td>Water</td>
<td>Water used to generate electricity by fossil fuel.</td>
<td>–</td>
</tr>
<tr>
<td>SmartMeter&lt;sub&gt;text&lt;/sub&gt;</td>
<td>Usage and electricity price information via text</td>
<td>(?)</td>
</tr>
<tr>
<td>SmartMeter&lt;sub&gt;online&lt;/sub&gt;</td>
<td>Usage and electricity price information via online account</td>
<td>(?)</td>
</tr>
<tr>
<td>SmartMeter&lt;sub&gt;home&lt;/sub&gt;</td>
<td>Usage and electricity price information via an in-home display</td>
<td>(?)</td>
</tr>
<tr>
<td>Price</td>
<td>Change in monthly electricity bill.</td>
<td>–</td>
</tr>
<tr>
<td>ASC</td>
<td>Alternative specific constant takes a value of 1 if the current plan chosen and 0 otherwise.</td>
<td>–</td>
</tr>
<tr>
<td>(RPS-20)*(Rooftop-9)</td>
<td>Interaction between RPS and Rooftop variables, centered on their status quo levels.</td>
<td>(?)</td>
</tr>
<tr>
<td>RPS*rural</td>
<td>Interaction between RPS and Rural variable*</td>
<td>+</td>
</tr>
<tr>
<td>Rooftop*rural</td>
<td>Interaction between Rooftop and Rural variable</td>
<td>–</td>
</tr>
<tr>
<td>Rooftop*Distance to rooftop</td>
<td>Interaction between Rooftop and distance to rooftop solar**</td>
<td>–</td>
</tr>
<tr>
<td>RPS*Distance to rooftop</td>
<td>Interaction between RPS and distance to rooftop solar.</td>
<td>–</td>
</tr>
<tr>
<td>Rooftop*Distance to solar farm</td>
<td>Interaction between Rooftop and distance to solar farm***.</td>
<td>+</td>
</tr>
<tr>
<td>RPS*Distance to solar farm</td>
<td>Interaction between RPS and distance to solar farm.</td>
<td>+</td>
</tr>
<tr>
<td>Rooftop*CenteredNEP</td>
<td>Interaction between Rooftop and centered NEP****.</td>
<td>+</td>
</tr>
<tr>
<td>RPS*CenteredNEP</td>
<td>Interaction between RPS and centered NEP.</td>
<td>+</td>
</tr>
<tr>
<td>Water*CenteredNEP</td>
<td>Interaction between Water and centered NEP.</td>
<td>–</td>
</tr>
<tr>
<td>SmartMeter&lt;sub&gt;online&lt;/sub&gt;*CenteredNEP</td>
<td>Interaction between SmartMeter&lt;sub&gt;online&lt;/sub&gt; and centered NEP.</td>
<td>+</td>
</tr>
<tr>
<td>SmartMeter&lt;sub&gt;home&lt;/sub&gt;*CenteredNEP</td>
<td>Interaction between SmartMeter&lt;sub&gt;home&lt;/sub&gt; and centered NEP.</td>
<td>+</td>
</tr>
</tbody>
</table>

**Notes:**

* Rural= Dummy variable that takes a value of 1 if respondent is in a rural area and zero if urban.
** Distance to rooftop solar = Distance to the closest rooftop solar as the crow flies in meter. Distance to Rooftop is divided by 1000 meter.
*** Distance to solar farm = Distance to the closest solar farm as the crow flies in meter. Distance to solar farm is divided by 1000 meter.
**** NEP score is centered at its mean, 23.04.
Table 5: Regression results of solar energy plans

<table>
<thead>
<tr>
<th>VARIABLES</th>
<th>MNL</th>
<th>RPLd</th>
<th>MNL</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Model 1</td>
<td>Model 2</td>
<td>Model 3</td>
</tr>
<tr>
<td></td>
<td>Coef. (SE)</td>
<td>Coef. (SE)</td>
<td>SD</td>
</tr>
<tr>
<td>Price^a</td>
<td>-0.040***</td>
<td>-0.112***</td>
<td>0.092***</td>
</tr>
<tr>
<td></td>
<td>(0.003)</td>
<td>(0.019)</td>
<td>(0.017)</td>
</tr>
<tr>
<td>RPS^a</td>
<td>0.022***</td>
<td>0.050***</td>
<td>0.081***</td>
</tr>
<tr>
<td></td>
<td>(0.003)</td>
<td>(0.009)</td>
<td>(0.014)</td>
</tr>
<tr>
<td>Rooftop^a</td>
<td>0.036***</td>
<td>0.085***</td>
<td>-0.039**</td>
</tr>
<tr>
<td></td>
<td>(0.007)</td>
<td>(0.019)</td>
<td>(0.017)</td>
</tr>
<tr>
<td>NoCreditBanking^a</td>
<td>-0.279***</td>
<td>-0.175</td>
<td>-0.747**</td>
</tr>
<tr>
<td></td>
<td>(0.068)</td>
<td>(0.164)</td>
<td>(0.345)</td>
</tr>
<tr>
<td>Water^a</td>
<td>-0.184***</td>
<td>-0.532***</td>
<td>-0.411**</td>
</tr>
<tr>
<td></td>
<td>(0.032)</td>
<td>(0.099)</td>
<td>(0.206)</td>
</tr>
<tr>
<td>SmartMeter^text^a</td>
<td>-0.077</td>
<td>0.262</td>
<td>0.452</td>
</tr>
<tr>
<td></td>
<td>(0.107)</td>
<td>(0.227)</td>
<td>(0.387)</td>
</tr>
<tr>
<td>SmartMeter^online^a</td>
<td>0.178</td>
<td>0.796***</td>
<td>-0.116</td>
</tr>
<tr>
<td></td>
<td>(0.118)</td>
<td>(0.256)</td>
<td>(0.459)</td>
</tr>
<tr>
<td>SmartMeter^home^a</td>
<td>0.230**</td>
<td>0.887***</td>
<td>-1.798***</td>
</tr>
<tr>
<td></td>
<td>(0.107)</td>
<td>(0.265)</td>
<td>(0.489)</td>
</tr>
<tr>
<td>ASC^a</td>
<td>-0.420***</td>
<td>-1.464***</td>
<td>2.833***</td>
</tr>
<tr>
<td></td>
<td>(0.140)</td>
<td>(0.327)</td>
<td>(0.494)</td>
</tr>
<tr>
<td>(RPS-20)*(Rooftop-9)</td>
<td>-0.001***</td>
<td>-0.003***</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.000)</td>
<td>(0.001)</td>
<td></td>
</tr>
<tr>
<td>RPS*rural</td>
<td></td>
<td>0.015</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>(0.013)</td>
<td></td>
</tr>
<tr>
<td>Rooftop*rural</td>
<td></td>
<td>-0.069***</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>(0.026)</td>
<td></td>
</tr>
<tr>
<td>RPS*Distance to rooftop</td>
<td></td>
<td>-0.005***</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>(0.002)</td>
<td></td>
</tr>
<tr>
<td>Rooftop*Distance to rooftop</td>
<td></td>
<td>0.001</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>(0.002)</td>
<td></td>
</tr>
<tr>
<td>RPS*Distance to solar farm</td>
<td></td>
<td>0.000</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>(0.001)</td>
<td></td>
</tr>
<tr>
<td>Factor</td>
<td>Coefficient 1</td>
<td>p-value 1</td>
<td>Coefficient 2</td>
</tr>
<tr>
<td>---------------------------------------------</td>
<td>---------------</td>
<td>-----------</td>
<td>---------------</td>
</tr>
<tr>
<td>Rooftop*Distance to solar farm</td>
<td>0.002*</td>
<td>(0.001)</td>
<td>0.001*</td>
</tr>
<tr>
<td>RPS*CenteredNEPb</td>
<td>0.006***</td>
<td>(0.001)</td>
<td>0.003***</td>
</tr>
<tr>
<td>Rooftop*CenteredNEPb</td>
<td>0.004**</td>
<td>(0.002)</td>
<td>0.003***</td>
</tr>
<tr>
<td>Water*CenteredNEPb</td>
<td>-0.052***</td>
<td>(0.015)</td>
<td>-0.027***</td>
</tr>
<tr>
<td>SmartMeter_{online}*CenteredNEPb</td>
<td>0.126***</td>
<td>(0.042)</td>
<td>0.057**</td>
</tr>
<tr>
<td>SmartMeter_{home}*CenteredNEPb</td>
<td>0.078*</td>
<td>(0.046)</td>
<td>0.042*</td>
</tr>
<tr>
<td>Observationsc</td>
<td>4,797</td>
<td>4,797</td>
<td>4,521</td>
</tr>
<tr>
<td>Log likelihood</td>
<td>-1443</td>
<td>-1181</td>
<td>-1072</td>
</tr>
<tr>
<td>AIC</td>
<td>2907</td>
<td>2399</td>
<td>2205</td>
</tr>
<tr>
<td>BIC</td>
<td>2972</td>
<td>2522</td>
<td>2397</td>
</tr>
</tbody>
</table>

Notes: Robust standard errors in parentheses. *** p < 0.01, ** p < 0.05, * p < 0.10.

a: Random parameters assumed normally distributed;
b: NEP score is centered at its mean (23.04);
c: Each of our 404 respondents had 12 choices to make;
d: 400 number of Halton draws were used for the RPL models.
Table 6: Marginal Willingness to Pay Values in USD/month

<table>
<thead>
<tr>
<th>Variables</th>
<th>Model 2</th>
<th></th>
<th>Model 3</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>MWTP</td>
<td>Krinsky Robb [CI]</td>
<td>MWTP</td>
<td>Krinsky Robb [CI]</td>
</tr>
<tr>
<td>Price</td>
<td>--</td>
<td>--</td>
<td>--</td>
<td>--</td>
</tr>
<tr>
<td>1% increase in RPS levels by 2040</td>
<td>$0.45***</td>
<td>[$0.35, $0.57]</td>
<td>$0.43***</td>
<td>[$0.3, $0.57]</td>
</tr>
<tr>
<td>1% increase in rooftop levels by 2040</td>
<td>$0.76***</td>
<td>[$0.52, $1.07]</td>
<td>$0.71***</td>
<td>[$0.41, $1.03]</td>
</tr>
<tr>
<td>No to Credit Banking</td>
<td>-$1.57</td>
<td>[$-4.17, $0.87]</td>
<td>-$1.06</td>
<td>[$-3.83, $1.54]</td>
</tr>
<tr>
<td>Water</td>
<td>-$4.77***</td>
<td>[$-6.28, $-3.55]</td>
<td>-$4.44***</td>
<td>[$-5.81, $-3.19]</td>
</tr>
<tr>
<td>Smart Meter installation using text</td>
<td>$2.35</td>
<td>[$-1.14, $5.51]</td>
<td>$2.30</td>
<td>[$-1.06, $5.89]</td>
</tr>
<tr>
<td>Smart Meter logging to online account</td>
<td>$7.14***</td>
<td>[$3.52, $11.29]</td>
<td>$8.48***</td>
<td>[$4.68, $12.43]</td>
</tr>
<tr>
<td>Smart Meter using an in-home display</td>
<td>$7.96***</td>
<td>[$4.31, $12.05]</td>
<td>$9.24***</td>
<td>[$5.43, $13.45]</td>
</tr>
<tr>
<td>RPS* rural</td>
<td>$0.15</td>
<td>[$0.05, $0.36]</td>
<td>$0.15</td>
<td>[$0.05, $0.36]</td>
</tr>
<tr>
<td>Rooftop*rural</td>
<td>-$0.67***</td>
<td>[$-1.09, $-0.26]</td>
<td>-$0.67***</td>
<td>[$-1.09, $-0.26]</td>
</tr>
<tr>
<td>RPS*Distance to rooftop</td>
<td>-$0.05***</td>
<td>[$-0.08, $-0.03]</td>
<td>-$0.05***</td>
<td>[$-0.08, $-0.03]</td>
</tr>
<tr>
<td>Rooftop*Distance to rooftop</td>
<td>$0.01</td>
<td>[$-0.03, $0.04]</td>
<td>$0.01</td>
<td>[$-0.03, $0.04]</td>
</tr>
<tr>
<td>RPS*Distance to solar farm</td>
<td>$0.00</td>
<td>[$-0.01, $0.01]</td>
<td>$0.02*</td>
<td>[$0, $0.04]</td>
</tr>
<tr>
<td>Rooftop*Distance to solar farm</td>
<td>$0.02*</td>
<td>[$0, $0.04]</td>
<td>$0.02*</td>
<td>[$0, $0.04]</td>
</tr>
<tr>
<td>RPS*Centered NEP</td>
<td>$0.06***</td>
<td>[$0.04, $0.08]</td>
<td>$0.06***</td>
<td>[$0.04, $0.08]</td>
</tr>
<tr>
<td>Rooftop* Centered NEP</td>
<td>$0.04**</td>
<td>[$0.02, $0.08]</td>
<td>$0.04**</td>
<td>[$0.02, $0.08]</td>
</tr>
<tr>
<td>Water* Centered NEP</td>
<td>-$0.50***</td>
<td>[$-0.78, $-0.28]</td>
<td>-$0.50***</td>
<td>[$-0.78, $-0.28]</td>
</tr>
<tr>
<td>SmartMeter_{online}* Centered NEP</td>
<td>$1.23***</td>
<td>[$0.41, $1.69]</td>
<td>$1.23***</td>
<td>[$0.41, $1.69]</td>
</tr>
<tr>
<td>SmartMeter_{home}* Centered NEP</td>
<td>$0.75*</td>
<td>[$0.02, $1.54]</td>
<td>$0.75*</td>
<td>[$0.02, $1.54]</td>
</tr>
</tbody>
</table>

Notes: *** p<0.01, ** p<0.05, * p<0.10; b: We utilized Krinsky and Robb's (1986) approach to estimate MWTP confidence intervals [CI].

Figure 1: Generation Portfolio Mix. Note: Solar requirements are: 20% solar farm and 3% rooftop.
Figure 2: An example choice question used in the survey.

Consider the following possible PNM solar energy plans. Which plan would you prefer? Check Plan A, Plan B, or Current Plan.

<table>
<thead>
<tr>
<th></th>
<th>Plan A</th>
<th>Plan B</th>
<th>Current Plan</th>
</tr>
</thead>
<tbody>
<tr>
<td>Percent of electricity from renewable sources by 2040</td>
<td>80%</td>
<td>50%</td>
<td>20%</td>
</tr>
<tr>
<td>Percent of solar energy from rooftop by 2040</td>
<td>20%</td>
<td>30%</td>
<td>9%</td>
</tr>
<tr>
<td>Credit policy for rooftop solar customers</td>
<td>Yes</td>
<td>No</td>
<td>Yes</td>
</tr>
<tr>
<td>Water used to generate electricity by fossil fuel</td>
<td>Low (1 gallon per person per day)</td>
<td>Medium-High (3 gallons per person per day)</td>
<td>High (4 gallons per person per day)</td>
</tr>
<tr>
<td>Smart meters installation and feedback</td>
<td>View in-home display</td>
<td>No installation</td>
<td>No installation</td>
</tr>
<tr>
<td>Change in monthly electricity bill</td>
<td>↑ $20/month</td>
<td>No change</td>
<td>No change</td>
</tr>
</tbody>
</table>

I would choose Plan **A**
Figure 3: Study area
Reference:


Faccioli, M., Czajkowski, M., Glenk, K., Martin-Ortega, J., 2018. Environmental attitudes and place identity as simultaneous determinants of preferences for environmental goods.


Gudding, P., Kipperberg, G., Bond, C., Cullen, K., Steltzer, E., 2018. When a Good Is a Bad (or a Bad Is a Good)—Analysis of Data from an Ambiguous Nonmarket Valuation Setting. Sustainability 10, 208. https://doi.org/10.3390/su10010208


