Consumer Preferences for Solar Energy: An Experimental 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 installed, along with whether states should reduce or expand their RPS. We develop a choice experiment survey to gain understanding of consumer preferences and their preference heterogeneity. We conduct a survey in New Mexico, a state with an RPS and ranked third for solar potential. Focusing on the consumers of the state's major utility, our choice experiment considers an increase in RPS and preference for residential solar and smart meter installation. We also consider 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 residential 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; revealed preference; spatial heterogeneity

JEL: C93; Q40

1 Introduction

Electricity generation in the U.S. is rapidly moving away from coal-fired generation to more environmentally-friendly fossil fuels and, increasingly, towards renewables. The move toward renewables is due not only to renewable portfolio standards (RPS) (currently required by 29 states), but also to cost competitiveness and consumer preferences. Consumer preferences may be a key factor in the type of renewable energy (RE) that is installed. Further, this move requires installation of "smart" equipment that could also affect consumer preferences.

Considering different approaches utilized to estimate electricity consumers' preference in terms of willingness to pay (WTP) toward embracing more RE, it is difficult to arrive at a concise conclusion. The inconsistency and preference heterogeneity stems from various factors including RE type, spatial heterogeneity, scale of RE, and sociodemographic characteristics of respondents. Regarding RE type, scholars generally find a positive WTP with various magnitudes for wind and solar (Sundt & Rehdanz, 2015; Ma et al., 2015). In regard to spatial effect, particularly distance decay, the non-market valuation literature is in its infancy (Nkansah and Collins, 2018). Moreover, studies done in Europe and Asia show a positive support for "smart" equipment that assist with RE improvement and better management (Durmaz et al., 2017; Shim et al., 2018).

In this research, we focus on preferences specifically for solar energy through a choice experiment. The survey is conducted in New Mexico (NM), a state with an RPS that requires all large electricity utilities to have at least 20% of total in-state electricity sales be from renewables by 2020. This is also a state with great potential for renewables, particularly in solar as it ranks third in the U.S. for potential. 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 meters (SM) 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, assessing preferences on SM. Further, our work incorporates distance through revealed preferences, rather than the more common stated preference approach. That is, 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, there is a positive value associated with increasing the RPS. Further, we find heterogeneity in response for location, environmental perspectives, and distance to the nearest installation.

The rest of this paper is organized into four main sections. Section 2 presents a brief background and literature review of WTP for RE and different RE types. It also includes a short background on SM. Section 3 gives a description of the study area, the choice experiment design, the survey structure and administration, theory and the econometrics model, and finally the hypotheses that our paper seeks to test. In Section 4, we briefly discuss spatial and environmental worldview heterogeneity within our respondents, and continue with the regression results. A discussion of results and conclusion will follow in the last section, Section 5.

2 Background and literature review

Studies usually do not specify an exclusive RPS goal to gauge respondents' WTP, rather investigate more RE in energy mix. Of those that do, they find that respondents are willing to pay a positive premium. For example, Mozumder et al. (2011) found that consumers are willing to pay $15.14 per month for a 20% RPS by 2020.

Numerous empirical studies have commonly found electricity consumers have positive WTP for the move to RE around the globe (e.g., Murakami et al., 2015; Möllendorff & Welsch, 2017; Shim et al., 2018)[1]. Previous research has also found and linked heterogeneity in preferences for RE to several factors including, but not limited to, energy type (e.g., Yoo & Ready, 2014; Murakami et al., 2015; Nkansah & Collins, 2018), respondents' geographic location (urban/rural) (e.g., Bergmann et al., 2006; Yoo & Ready, 2014), respondents' exposure or proximity to RE (e.g., Meyerhoff, 2013; Vecchiato and Tempesta, 2015; Kalkbrenner et al., 2017; Möllendorff & Welsch, 2017; Nkansah & Collins, 2018), environmental concerns (e.g., Clark et al., 2003; Hansla et al., 2008; Longo et al., 2008; Strazzera et al., 2012; Yoo & Ready, 2014), and sociodemographic characteristics such as income, education, age, sex, and political affiliation (e.g., Navrud & Bråten, 2007; Longo et al., 2008; Rehdanz et al., 2017).

[1] Among others see Sundt & Rehdanz (2015), Ma et al. (2015), and Soon and Ahmad (2015) for meta-analysis on WTP for RE. For example, Soon and Ahmad (2015, p882) found a mean WTP of $7.16/month to increase RE across all continents.

In regard to what type of RE is being valued, wind energy tends to have inconsistent results; researchers sometimes find support (e.g., Koundouri et al., 2009) and sometimes opposition (e.g., (Groothuis et al., 2008), whereas solar energy is the most stable with the majority supporting its use (Rehdanz et al., 2017). 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 (DD) effect (Möllendorff & Welsch, 2017; Rehdanz et al., 2017; Nkansah & Collins, 2018). The NIMBY issue implies that a proposed amenity should be sited outside of respondents' neighborhood[2]. Wind turbine externalities include but are not limited to noise, height, shadow, killing birds and bats, etc. (Möllendorff & Welsch, 2017). Distance decay effect refers to lower WTP the further away respondents live to a RE development, and vice versa. As acknowledged by other scholars (e.g., Yoo & Ready, 2014; Vecchiato and Tempesta, 2015; Welsch, 2016), preference toward utility-scale solar (PV) and/or residential solar[3] (RPV) is one of the most under-studied topics in the field of RE acceptance. This research contributes to this segment of literature gathering new data and examining whether solar energy has acceptance in a state ranked third in the U.S. for solar energy potential (NEO, 2010) and whether we observe NIMBY or DD effect for different types of solar energy in NM. Our work incorporates distance through revealed preferences, rather than the more common stated preference approach. That is, we test the impact of the actual distance to the nearest solar location, rather than an artificially-introduced distance through the survey instrument.

Furthermore, as part of the movement towards RE and the intermittency and unpredictable nature of wind and solar energy, it is anticipated that an increasing number of residential houses will be equipped with "smart" devices that are capable of reading and relaying electricity consumption in real time. Based on the Energy Information Administration (EIA, 2017a), electric companies in the U.S. owned 70.8 million SM in 2016. Residential customers made up the majority of SM installations (88%), with half of all U.S. electricity customers own SM (EIA, 2017b). Further, the former president of the U.S. in one of his speeches in 2009 admired and encouraged the use of SM in the U.S.[4]

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[2] "*Out of sight, out of mind*".
[3] We use the word "residential" solar interchangeably with "rooftop" solar. In the survey, we only used "rooftop" solar.
[4] "*Smart meters will allow you to actually monitor how much energy your family is using, by the month, by the week, by the day or even by the hour. So, coupled with other technologies, this is going to help you manage your electricity*

SM's 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, SM 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 and water usage. Some electric companies give their residential customers an opt-out option from SM program, which will cost customers extra monthly fees. Thus, altogether, these factors influence residential customers' decision-making on SM.

In the last decade, several studies have focused on the monetary estimation from the adoption of SM and public's attitudes toward SM 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 studies have 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 SM have public support, opposition, or indifference.

Building on data from a discrete-choice survey, the goal of this research is to investigate whether residents of a state with more than 300 days of sunshine and ranked 3rd amongst all states with the greatest energy potential from solar energy are willing to pay a premium to go beyond the current 20% RPS level. We further attempt to fulfill the aforementioned gaps within the non-market valuation literature for RE acceptance by testing our five hypotheses: 1- Respondents do not support SM; 2- Support for RPS has increased compared to the past; 3- Location matters; 4- We observe DD effect for different types of solar energy; and, 5. Environmental worldview affects the amount of support for environmental goods.

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use and your budget at the same time, allowing you to conserve electricity during times when prices are highest, like hot summer days." Source: "President Obama delivers remarks at solar energy center," 2009.

3 Methodology

3.1 Study Area

NM possesses substantial renewable resources, yet it lags in terms of widespread uptake of RE usage compared to other states. 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 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 adopted an RPS (Senate Bill 43) in March 2004. Under NM's RPS, all large electric utilities are required to produce 20% of total electricity sale in-state from renewable sources by 2020[5]. Of this 20%, at least 23% is mandated to come from solar energy: no less than 20% PV and at least 3% RPV[6]. In the 53rd legislative session in 2017, a new bill was introduced that would require all large utilities to generate 80% their total sales from renewables by 2040 (80% RPS by 2040) (Stewart and Small, 2017). However, this bill did not pass.

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[7]. PNM has more than 1 million solar panels (15 solar farms) and currently more than 11,000 rooftop solar connected to its grid (PNM, 2018). This company also has purchase power agreements with several solar facilities within NM to comply with its RPS requirement. Currently, RE share of PNM electricity

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[5] RPS also requires NM's rural electric cooperatives to generate 10% of total electricity sold in-state from renewable sources by 2020.
[6] In order to create a fully diversified RE portfolio, Public Regulation Commission sets RE diversity targets. Utility companies are to comprise at least 30% sourcing from wind, 20% from solar, 3% from RPV, 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 (accessed 5.31.18).
[7] In 2016, there were 762,551 households in NM. https://www.census.gov/quickfacts/NM (accessed 5.31.18).

sale is 15% and it is projected to meet its RPS goal of 20% by 2020 (PNM, 2018). We sampled our respondents from PNM's customers.

3.2 Choice Experiment Design

In a Discrete Choice Experiment (DCE) survey, individuals are asked to make decisions amongst hypothetical environmental 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.

The first attribute, percent of electricity from renewable sources by 2040 (RPS by 2040), was intended to capture preference towards an increase in the RPS level, especially the 80%-RPS-by-2040 bill. As described in the previous subsection, 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 (RPV by 2040), we were interested in discerning respondents' preference for RPV verses PV. In the description of the second attribute, we mentioned that "*Increasing the share of rooftop solar means decreasing the share of solar farms.*" Further, based on PNM's Procurement Plan for 2016 (the latest plan that included compliance summary), it generated 31.9% of its solar requirement from PV and 3% from RPV. In other words, RPV comprised approximately 9% (3%/34.9%) of the total solar generation in 2016. Thus, we used 9% RPV as the status quo level for the second attribute. The second attribute had four levels: 5%, 9%, 20%, and 30%. Figure 1 breaks down the status quo levels for the first two attributes.

[FIGURE 1 HERE]

In order to gauge the impact of a change in the proportion of the left pie of Figure 1 (RPS to non-renewable) on the proportion change in the right-sided pie (RPV to PV), we include an interaction term between RPS and RPV in our analysis.

Our third attribute was credit policy for rooftop solar customers. Currently, PNM RPV customers can save RE credits from spring (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 RPV owners can only use their credits in the same month that excess electricity is generated[8]. Thus, our third attribute is dichotomous, Yes and No, with Yes being the status quo level.

Our fourth attribute, water used to generate electricity by fossil fuel (gallons per person per day), is capturing the trade-off between fossil fuel generation and RE. Formerly, we had water and greenhouse gases to capture the trade-off. As water is a more serious issue in NM and reduction in water consumption by fossil fuel implies reduction in greenhouse gas as well, we only included the water attribute. The water attribute levels are calculated from Albuquerque-area residents' water use[9], PNM's annual electricity production by source, and the RPS levels proposed in the first attribute. The levels are: 1, 2, 3, and 4 gallons/person/day, with status quo level being 4 gallons/person/day (the lower the value, the more water saved).

Our fifth attribute is SM installation and feedback. PNM was considering installing SM for its residential customers until recently, when NM Public Regulation Commission (NMPRC, 2018) rejected the proposal in May 2018. There are three options for how customers could access hourly usage and electricity price information: 1- receive phone text, 2- log into their online account, and 3- view in-home display[10]. We also included the business as usual scenario (no installation).

Finally, we included a payment vehicle attribute, change in monthly electricity bill, to be able to calculate the marginal price along with marginal WTP (MWTP) of the attributes. We used $0, $5, $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, RPV, and water are assumed to be continuous to have a linear effect on the choice of energy plan. "Credit_no" is dummy coded and takes a value of 1 if no to saving extra credits from excess electricity is chosen and 0 otherwise. SM attribute, however, is divided into its levels (text, online, and in-home display) to reflect possible non-linear effects on the probability of choosing a solar energy plan.

The choice experiment design allowed for one interaction term between attributes (RPS and RPV). The survey had four choice sets per each version of the six total versions distributed. Each

[8] For more information on the current and the future discussion see: https://www.abqjournal.com/518250/rooftop-solar.html (accessed 5.31.18).
[9] https://www.abqjournal.com/712294/water-use-continues-to-drop.html (accessed 5.31.18).
[10] 1- Customers send a phone text message to the utility company and receive information in return. 2- Customers can access information after logging into their online account. 3- An in-home display will be installed that shows the information.

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. Figure 2 displays a choice question used in our survey.

[FIGURE 2 HERE]

3.3 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 RPV and PV and asked about preferences toward them. The third section was dedicated to the 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 two focus groups and twelve debriefings in Summer 2017. We made revisions and conducted a pre-test[11] to 100 PNM customers in Fall. The final version of the questionnaire was ready to be sent out after some minor revisions in Winter 2017.

We administered a mixed-mode survey, developed 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 sent out 4 contacts by first-class mail, with an additional "special" contact. We sent out a brief pre-notice letter, the survey packet a week later, a *thank you* and *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).

Assuming all survey recipients of unknown eligibility were not eligible to participate in the survey (Thacher et al., 2011, p74), we had a response rate of 37.1%, with responses from 10 of

[11] We sent out three contacts in the pre-test: pre-notice letter, survey module four days later, and follow-up postcard 8 days later.

the 13 counties. The response rate is an adequate rate in comparison with other similar studies (e.g., 27% Mozumder et al. (2011), 28% Walter et al. (2018, forthcoming)). Table 2 summarizes the socio-demographics.

[Table 2 HERE]

Excluding pre-test responses, overall, 404 responses were collected. On average, our respondents are 53.8 years old, have an associate degree, and an annual household income of $50,000 to $74,000. Further, 82% of our respondents live in urban areas and fewer females answered our survey (39%).

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, …, 404) gains from the attributes of the m^{th} alternative (m=1, …, 3, including the status quo) in choice set *i* (i=1, …, 4). Equation 1 summarizes the RUM:

$$U_{jmi} = V_{jmi} + \epsilon_{jmi} \tag{1}$$

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 β_0 and β_i (a=1, …, 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:

$$U_{jmi} = \beta_0 Price_{jmi} + \sum_{a=1}^{A} \beta_i^a X_{jmi}^a + \epsilon_{jmi} \tag{3}$$

Respondent *j* chooses the alternative *m* in choice set *i* that maximizes her utility, U_{jmi}.

There are numerous modeling methods that can be used to evaluate DCE data. The most common modeling approach is the Multinomial Logit Model (MNL). MNL model assumes that the stochastic error term in equation 3 is independently identically distributed with Generalized Extreme Value type I across respondents. Furthermore, 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)[12]. Random Parameter Model (RPL)[13] 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)[14]. We use these two models in our analyses.

In addition, we provide the MWTP for each attribute. MWTP for attribute *a* can be calculated using equation 4:

$$MWTP = -\left[\frac{\partial U_i/\partial x_a}{\partial U/\partial Price}\right] = -\left(\frac{\beta_a}{\beta_0}\right) \tag{4}$$

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 RPV centered at their means. Equation 5 summarizes the global utility specification applied in models 1 and 2:

$$\begin{aligned} U = ß_0 Price + ß_1 RPS + ß_2 RPV + ß_3 Credit_{no} + ß_4 Water + ß_5 SM_{text} \\ + ß_6 SM_{online} + ß_7 SM_{home} + ß_8 (RPS - 20) \times (RPV - 9) + ß_9 ASC \\ + \epsilon \end{aligned} \tag{5}$$

In Models 3 and 4, we are interested in testing our 5 hypotheses: 1- $\mathbf{H}_{SM}$; 2-$\mathbf{H}_{RPS}$; 3-$\mathbf{H}_{Rural}$; 4-$\mathbf{H}_{DD}$; and, 5- $\mathbf{H}_{NEP}$ (more detail in Section 3.5). Equation 6 presents the utility specification for model 3 and 4:

[12] For more restrictions of the MNL, see Train, (2003)
[13] Also known as mixed logit model.
[14] For a thorough explanation of the econometric modeling, see: Train (2003), Hensher et al. (2005), and Train, (2009).

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\begin{aligned}
U = ß_0 Price\ &+ ß_1 RPS + ß_2 RPV + ß_3 Credit_{no} + ß_4 Water + ß_5 SM_{text} \\
&+ ß_6 SM_{online} + ß_7 SM_{home} + ß_8 (RPS - 20) \times (RPV - 9) \\
&+ ß_9 RPS \times rural + ß_{10} RPV \times rural \\
&+ ß_{11} RPS \times (Dist\_to\_rooftop) + ß_{12} RPV \times (Dist\_to\_rooftop) \\
&+ ß_{13} RPS \times (Dist\_to\_solar\ farm) \\
&+ ß_{14} RPV \times (Dist\_to\_solar\ farm) + ß_{15} RPS \times NEP \\
&+ ß_{16} RPV \times NEP + ß_{17} water \times NEP + ß_{18} SM_{online} \times NEP \\
&+ ß_{19} ASC + \epsilon
\end{aligned} \tag{6}
$$

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)[15].

3.5 Hypothesis

We test five hypotheses as follows:

Hypothesis I ($\mathbf{H}_{SM}$) Recently New Mexico Public Regulation Commission (NMPRC) (2018) rejected PNM's SM project. One of the reasons for the rejection was that PNM failed to demonstrate its customers' support for SM. We hypothesize that NM residents do not support SM (Hypothesis I). We use Model 1 and Model 2 to test Hypothesis I. A statistically significant positive sign of any of the SM coefficients (text, online, or in-home display) would reject Hypothesis I ($\mathbf{H}_{SM}$).

Hypothesis II ($\mathbf{H}_{RPS}$) After adjusting for hypothetical bias by using Champ and Bishop's (2001) ratio (0.536), Mozumder et al. (2011) estimated that NM residents are willing to pay \$5.77/month for a 10%-RPS and \$15.04/month for a 20%-RPS (=\$9.27 for the second 10%). We use Model 2 to test the null hypothesis of the MWTP for an extra 10% of the RPS level from this study is statistically significantly higher than MWTP for the second extra 10% of Mozumder et al.[16] ($\mathbf{H}_{RPS}$).

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[15] All the analyses are done in Stata using Hole's (2007) clogit(), mixlogit(), and wtp() commands.

[16] We compare Mozumder et al. "WTP for the 2nd 10%: \$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

Hypothesis III (**H**$_{Rural}$)

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 renewable energy projects more than their counterparts. Therefore, our Hypothesis III is that respondents who live in a rural area are distinctly more supportive of PV, as PVs are mainly located in rural areas (**H**$_{Rural}$). By the same token, urban respondents are more in favor of RPV. We test this hypothesis by adding an interaction term between rural (=1 if rural, 0 otherwise) and RPS and RPV variables (see equation 6).

Hypothesis IV (**H**$_{DD}$)

In regard to respondents' exposure or proximity to RE, wind energy has been investigated the most (amongst RE) (e.g., Knapp & Ladenburg, 2015; Gudding et al., 2018)[17]. To our knowledge there are only three peer-reviewed papers that investigate proximity to solar energy (Dastrup et al. , 2012; Vecchiato and Tempesta, 2015; Möllendorff & Welsch, 2017)[18]. To contribute to this line of research, we hypothesize that distance to rooftop and/or solar farm impacts support for solar and RPS improvement (**H**$_{DD}$). To test **H**$_{DD}$, we interact actual distance to rooftop and solar farms with the survey RPV and RPS attributes (see equation 6). Statistically significant coefficients of any of the distance variables would fail to reject **H**$_{DD}$.

Hypothesis V (**H**$_{NEP}$)

Previous research indicates that environmental attitudes captured by the 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; Kennedy, Krahn, & Krogman,

achieving the current RPS level (20%), hence we compare their second 10% with an extra 10% from the current level RPS in our study.

[17] For an overview of the existing literature on distance to wind energy impact on WTP, See Table 1 of either Knapp & Ladenburg, 2015 or Gudding et al., 2018.

[18] I) Dastrup et al., (2012): Done in California, relates the positive WTP to financial and moral benefits (known as warm glow) to RPV owners, argues warm glow may counterbalance negative externalities. II) Vecchiato and Tempesta, (2015): Done in Italy, distance and size of power plants (PV and biomass) are among their attributes. They find that Italians prefer smaller plants that are "*located not very far from their place of living*". III) Möllendorff & Welsch, (2017): done in Germany, they measured exposure to PV effect on well-being (life satisfaction) and found no significant effect when in the own postcodes districts, but negative well-being effect in neighboring postcodes districts.

2015). Hence, our Hypothesis V (**H**$_{NEP}$) is that higher NEP score is associated with higher support for RE (RPS and RPV), lower water usage, and SM implementation as SM helps with easing RE management. To test **H**$_{NEP}$, we include interaction terms between NEP score and RPS, RPV, Water, and SM_online attributes (see equation 6). Statistically significant interacted coefficients would fail to reject Hypothesis V.

4 Results

4.1 Spatial heterogeneity and the NEP

In order to capture exposure to solar energy, we utilized distance to the closest rooftop 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). Moreover, PNM has more than 11,000 rooftop solar customers that are connected to its grid[19]. The median urban and rural respondents live 0.15 km and 0.41 km away from the closest rooftop respectively. Figure 3 depicts our study area, respondents' place of residence, and existing rooftop and solar farms. We utilized Geographical Information System (GIS) to calculate the distance to the closest rooftop and solar farm from respondents' place of residence. [20]

[FIGURE 3 HERE]

Furthermore, following Whitmarsh, (2009) and Whitmarsh and O'Neill, (2010), we truncated the original NEP questions proposed by Dunlap et al., (2000) and used a reduced (6-item) version[21]. The 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

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[19] We downloaded the location (lat/long) data of each rooftop from http://www.nmprc.state.nm.us/index.html (accessed 5.31.18).
[20] To avoid confusion between RPV/PV attribute and the distance variables, we refer to RPV or PV acronyms only when we talk about the survey attributes.
[21] 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".

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 NEP score in our analysis.

4.2 Regression results

In this section, we highlight results from the valuation analysis. Table 3 presents the definition of all the variables utilized in the models.

[TABLE 3 HERE]

For comparison and robustness check, Table 4 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 (linear main-effects). In attempting to account for the relationship between RPS and RPV/PV, we included the interaction term between RPS and RPV. Further, we included the ASC variable to capture business as usual effect (see equation 5).

[TABLE 4 HERE]

The coefficients for all parameters have the correct signs and are statistically significant. Exceptions are Credit_no, SM_text, and SM_online. Credit_no is highly significant in MNL model and not significant in RPL[22]. SM_online is the opposite, insignificant in MNL and highly significant in RPL[23]. SM_text parameter is positive in MNL and negative in RPL, but insignificant in both. The negative sign on Water means respondents do not support a policy that results in consuming more water for electricity generation. Similarly, the negative signs in ASC and Price suggest that our respondents are not in favor of the current solar energy policy and also, all else equal (*ceteris paribus*), they do not support a policy that requires them to pay higher energy price. The positive signs in RPS and RPV show that, *ceteris paribus*, respondents are more likely to support a policy that improves renewable energy in general and residential solar in particular. Similarly, our respondents are in favor of smart meters, especially one that is installed at home. The latter result from both Model 1 and Model 2 allows us to reject the null hypothesis of NM residents do not support SM ($\mathbf{H}_{SM}$).

[22] 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 insignificancy in RPL model.

[23] SM_online becomes significant at 95% level after including the spatial heterogeneity and the NEP variables in the MNL model. See Model 4 of Table 4.

The 5th column of Table 2 shows the standard deviations estimated from the RPL model. We assumed all of our parameters, except the RPS and RPV interaction term, are normally distributed. All of the standard deviations are statistically significant, except those of SM_text and SM_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 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.

Table 5 summarizes the MWTP values. The 2nd column of Table 5 reports the MWTP 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 RPV is 9%, the RPL model suggests that our respondents exhibit a MWTP of $.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 RPV 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 bill[24].

Allowing for RPS and RPV levels to vary (i.e., not at the status quo RPS and RPV levels) (see Figure 1) will result in changing marginal utility magnitudes and subsequently MWTP values. Note that decreasing RPV equates with increasing PV in our analysis. Of interest here is

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

to examine whether RPS and RPV parameters change signs (no more support)[25]. Overall, *ceteris paribus*, we find that respondents are supportive ($0.07/month) of RPS even at the highest RPV level (30%). However, a 62%-RPS can lead to zero support for RPV 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 PV rather than RPV, as a zero RPV means 100% PV. As RPS level increases, our respondents' MWTP for RPV (PV) decreases (increases).

Furthermore, the RPL model suggests that MWTP for decreasing water consumption to generate electricity by fossil fuel by 1 gallon/person/day (2 million gallons/day[26]) is $4.77/month [$6.28, $3.55]. New Mexicans are also supportive of SM and are exhibiting MWTP of $7.14/month [$3.52, $11.29] and $7.96/month [$4.31, $12.05] for when they can access the data online and through an in-home display respectively.

We use Model 2 to test the findings by Mozumder et al. (2011) that NM residents are willing to pay $9.27/month on top of their monthly electric charge to increase the share of RE in the energy portfolio mix from 10% to 20% ($\mathbf{H}_{RPS}$). 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)[27] and without ($9.27) inflating the values. The t-test values (t=2.92 p-value<0.004; t=2.56 p-value<0.011) allow us to reject the null hypothesis that our MWTP for an extra 10% RPS is greater than that of Mozumder et al. (2011) in both cases (inflated and uninflated). In fact, this implies that our MWTP value is statistically significantly lower than that of Mozumder et al.

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 score (see equation 6). Thus, Model 3 of Table 4 (linear main-effects with two-way interactions) accounts for location, that is rural/urban, distance to the nearest solar installation (that is, distance to rooftop or solar farm), and the NEP score. Spatial heterogeneity variables are interacted with only RPS and RPV, while the NEP score is interacted with other environmental

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[25] $\frac{\partial U}{\partial RPS} = 0.05 - 0.002 \times (RPV - 9) < 0 \Rightarrow RPV > 34\%$; $\frac{\partial U}{\partial RPV} = 0.085 - 0.002 \times (RPS - 20) < 0 \Rightarrow RPS > 62.5\%$. Marginal utility values are from Table 4. Further, a 9% share of RPV in a 60% RPS would require many new RPV installation that with the current situation there might not be enough incentives.

[26] Multiplied by NM population.

[27] $9.27 \times \frac{CPI_{2017}}{CPI_{2011}} = 9.27 \times \frac{237.46}{218.62} = \$10.07$ CPI data are from BLS

variables (i.e., Water and online SM[28]) in addition to RPS and RPV. The NEP score is centered at its mean (23.04).

The overall findings of estimated coefficients stay identical across the attributes in the second RPL model with covariates (Model 3). However, three of the nine random parameters (RPV, credit, and water) are no longer normally distributed (the 7th column of Table 4), which indicates including the spatial heterogeneity and the NEP score variables in the model capture more of the existing heterogeneity in preference in Model 2.

Taking the mean NEP score and zero distance to rooftop and solar farm into account, there is not a statistically significant difference between rural verses urban respondents for the RPS by 2040 attribute, though rural respondents have a higher MWTP (see Table 5). Rural respondents are significantly less in favor of RPV development than urban at zero distance, though overall they support RPV (MWTP= $0.05/month). This implies that rural respondents are statistically significantly more supportive of PV improvement than urban respondents. As PVs 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 ($0.71) for the RPV by 2040 attribute, as they encounter with RPV more and hence might be associated with the "warm glow"[29] and psychological impact (Möllendorff and Welsch, 2017, p117). Thus, Model 3 provides us with enough reasons to not reject the null hypothesis of rural (urban) residents are more supportive of PV (RPV) (**H**$_{\text{Rural}}$).

Furthermore, two out of the four interaction terms defining distance to rooftop and solar farm are statistically significant[30]. The interaction between RPS and distance to the nearest rooftop indicates, *ceteris paribus,* the farther away respondents live to rooftop, the less supportive of RPS they become. 10 km and 7 km[31] away from rooftop will result in no support

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[28] We included the online SM attribute rather than in-home display SM for three reasons: 1- online SM does not require any extra equipment; 2- Kernel density graph of individual coefficients from Model 2 for online SM is more parsimonious than that of in-home display; and finally, 3- including online SM leads to a better model fit. Further, including in-home display rather than the online SM would only lower the significance level (weakly significant).

[29] See footnote 18.

[30] 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., RPS*distance to rooftop*rural and RPS*distance to rooftop*urban) and could not 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.

[31] $Rural = \frac{0.015+0.044}{0.006} = \sim 10\ km$; $Urban = \frac{0.044}{0.006} = \sim 7\ km$

for RPS from rural and urban citizens respectively. The opposite holds for the interaction term between RPV and distance to the closest solar farm. Respondents are weakly more supportive of RPV development 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 and solar farm do not affect how respondents feel about RPV and RPS respectively. Overall, we observe a decay in support for PV with increasing distance from solar farm (DD effect), also distance to rooftop, and not solar farm, affects respondents' support for RPS[32]. These provide us with enough evidence to not reject the $\mathbf{H}_{DD}$ hypothesis that distance to different types of solar energy influences support for solar and RPS development.

Interacted variables with the NEP score are highly statistically significant. In line with other scholars' findings on the NEP score, Model 3[33] suggests that respondents with positive environmental worldview has positive attitude toward the environment-related variables, namely RPS, RPV, water, and online SM. 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 RPV respectively. Similarly, respondents accept to pay \$0.52/month and \$1.03/month to reduce water consumption through fossil fuel by 2 million gallons/day[34] and install online SM respectively. Hence, we also fail to reject $\mathbf{H}_{NEP}$ (Hypothesis V) 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 RPV to change[35]. Of interest here is to investigate whether these assumptions lead to further divergent support for RPS and RPV by location, that is urban and rural, and how different they are compared to the values we found for Model 2. Similar to model 2, both rural (\$0.14/month) and urban (\$0.01/month) respondents support RPS even at the highest level RPV. For an RPS level higher than 22.5%, rural respondents are no longer willing to pay a premium to increase

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[32] We created a density variable that contained the number of RPV within 1-mile buffer of our respondents. Similarly, we created another variable where it contained number of PV within 5- and 20-mile buffers. We used these variables instead of the distance variables and arrived at a similar result.
[33] Model 4 is the MNL version of Model 3. We included this model for the purpose of comparison and robustness check.
[34] See footnote 26.
[35] 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

share of RPV 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 RPV in RPS. In other words, our respondents, especially those who live in the rural area, want extra RPS to be fulfilled by PV rather than RPV. Thus, we can conclude that the higher than the status quo RPS level, the lower the MWTP for RPV and hence the higher the MWTP for PV improvements. Worth mentioning, each score higher than the mean NEP score increases the RPS percentages by 2.5% (25% and 66%).

5 Discussion and Conclusion

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 SM. We further included spatial and environmental worldview heterogeneity in our analysis. Our results suggest that, even with the highest level of RPV, there is general support for diffusion of the RPS in our sample. However, there is a diminishing return in support for RPV: after a certain RPS level, our respondents are no more willing to pay for energy plans that persuade RPV improvement. Thus, individuals in our sample want higher RPS to be fulfilled by PV rather than RPV. Our respondents are also willing to pay a premium for policies that encourage SM 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.

Moreover, we find that MWTP for RPS improvement has declined compared to 2011 (Mozumder et al. 2011). 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 for a 20% share of electricity to come from RE in their contingent valuation survey. This might be due to either the novelty of RE in 2011 or the drastic change in government attitudes toward RE. During the previous 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. As an increase in RPV means a decrease in PV deployment in this research, rural respondents are more in favor of RPS and less supportive of RPV. The opposite holds for urban respondents: more support for RPV 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). Our results also suggest that there exists a DD effect for only PV. Lastly, consistent with the literature, 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 SM, and incorporating distance to solar installation through revealed preference 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 non-market component (e.g., externalities, psychological and moral benefits/costs, etc.), but also the market component (e.g., social costs/benefits, RPV ownership status, etc.). It would be also valuable to include a distance variable within the survey and validate/compare results against revealed preference data for different solar energy types. This is important as DD effect would be questionable if people generally support solar energy and hence it is unlikely that valuing solar energy is distance dependent.

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 taken into account. 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 Appendix: Tables and Figures

Table 1: Attributes, levels, and definitions

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

Notes:
* Levels in bold are status quo levels.
**Rural is a dummy variable that takes a value of 1 if respondent is in a rural area and zero if urban.
*** Distance to RPV = Distance to the closest rooftop solar as the crow flies. Distance to RPV is divided by 1 km.
**** Distance to PV = Distance to the closest solar farm as the crow flies. Distance to PV is divided by 1 km.
***** NEP score is centered at mean (19.05).

Table 2: Socio-demographics

Characteristics		N	Our survey*
Age (year)		404	53.81
Gender (1-Female)	Male	244	61%
	Female	153	39%
Education	Less than high school	20	5%
	High school diploma or GED	55	14%
	Some college or Associate's degree	126	32%[a]
	Bachelor's degree or higher	193	49%
Household income	Less than $24,999	59	15%
	$25,000 to $34,999	50	12%
	$35,000 to $49,999	71	18%[a]
	$50,000 to $74,999	77	20%
	$75,000 to $99,999;	51	13%
	$100,000 to $149,999	60	15%
	$150,000 or greater	24	6%
Location	Urban	330	82%
	Rural	74	18%

Number of respondents: 404;
*Percentages might not sum up to 1 due to rounding.
a: The average belongs to this range.

Table 3: Definition of variables

Variables	Definition
RPS	Percent of electricity from renewable sources by 2040.
RPV	Percent of solar energy from rooftop solar by 2040.
Credit_no	Rooftop solar owners can only sell their credits in the same month that excess electricity is generated.
Water	Water used to generate electricity by fossil fuel.
SM_text	Usage and electricity price information via text
SM_online	Usage and electricity price information via online account
SM_home	Usage and electricity price information via an in-home display
Price	Change in monthly electricity bill.
ASC	Alternative specific constant takes a value of 1 if the current plan chosen and 0 otherwise.
(RPS-20)x(RPV-9)	Interaction between RPS and RPV variables, centered on their status quo levels.
Rural	Dummy variable that takes a value of 1 if respondent is in a rural area and zero if urban
RPS*rural	Interaction between RPS and Rural variable
RPV*rural	Interaction between RPV and Rural variable
RPV* Distance to rooftop	Interaction between RPV and distance to rooftop solar.*
RPS* Distance to rooftop	Interaction between RPS and distance to rooftop solar.
RPV* Distance to solar farm	Interaction between RPV and distance to solar farm.**
RPS* Distance to solar farm	Interaction between RPS and distance to solar farm.
RPV*NEP score	Interaction between RPV and centered NEP.***
RPS*NEP score	Interaction between RPS and centered NEP.
Water*NEP score	Interaction between Water and centered NEP.
SM_onlline*NEP score	Interaction between SM_online and centered NEP.

Notes:
* Distance to RPV = Distance to the closest rooftop solar as the crow flies. Distance to RPV is divided by 1 km.
** Distance to PV = Distance to the closest solar farm as the crow flies. Distance to PV is divided by 1 km.
*** NEP score is centered at mean (19.05).

Table 4: Regression results of solar energy plans

	MNL		RPL[d]			
	Model 1	Model 4	Model 2		Model 3	
VARIABLES	Coef. (SE)	Coef. (SE)	Coef. (SE)	SD	Coef. (SE)	SD
Price[a]	-0.040*** (0.003)	-0.042*** (0.003)	-0.112*** (0.019)	0.092*** (0.017)	-0.103*** (0.013)	0.089*** (0.014)
RPS by 2040[a]	0.022*** (0.003)	0.021*** (0.003)	0.050*** (0.009)	0.081*** (0.014)	0.044*** (0.009)	0.062*** (0.009)
RPV by 2040[a]	0.036*** (0.007)	0.031*** (0.009)	0.085*** (0.019)	-0.039** (0.017)	0.073*** (0.019)	-0.015 (0.036)
Credit_no[a]	-0.279*** (0.068)	-0.257*** (0.077)	-0.175 (0.164)	-0.747** (0.345)	-0.112 (0.164)	0.645* (0.385)
Water[a]	-0.184*** (0.032)	-0.188*** (0.034)	-0.532*** (0.099)	-0.411** (0.206)	-0.455*** (0.085)	-0.290 (0.260)
SM_text[a]	-0.077 (0.107)	-0.052 (0.115)	0.262 (0.227)	0.452 (0.387)	0.256 (0.217)	0.635 (0.808)
SM_online[a]	0.178 (0.118)	0.316** (0.125)	0.796*** (0.256)	-0.116 (0.459)	0.869*** (0.247)	0.102 (0.449)
SM_home[a]	0.230** (0.107)	0.312*** (0.116)	0.887*** (0.265)	-1.798*** (0.489)	0.963*** (0.264)	-1.530*** (0.447)
asc[a]	-0.420*** (0.140)	-0.516*** (0.148)	-1.464*** (0.327)	2.833*** (0.494)	-1.280*** (0.294)	2.267*** (0.423)
(RPS-20)x(RPV-9)	-0.001*** (0.000)	-0.001*** (0.000)	-0.002*** (0.001)		-0.002*** (0.001)	
RPS_rural		0.008 (0.006)			0.015 (0.013)	
RPV_rural		-0.026** (0.012)			-0.068*** (0.026)	
RPS*Distance to rooftop		-0.002*** (0.001)			-0.006*** (0.002)	
RPV*Distance to rooftop		0.000 (0.001)			0.000 (0.002)	
RPS*Distance to solar farm		0.000 (0.000)			0.000 (0.001)	
RPV*Distance to solar farm		0.001* (0.001)			0.002* (0.001)	
RPS*NEP score[b]		0.003*** (0.000)			0.006*** (0.001)	
RPV*NEP score[b]		0.003*** (0.001)			0.005** (0.002)	
Water*NEP score[b]		-0.028*** (0.008)			-0.054*** (0.015)	
SM_online*NEP score[b]		0.047** (0.022)			0.106*** (0.039)	
Observations[c]	4,797	4,521	4,797		4,521	
Log likelihood	-1443	-1249	-1181		-1074	
AIC	2907	2539	2399		2206	
BIC	2972	2667	2522		2392	

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 5: Marginal Willingness to Pay Values in USD

Variables	Model 2		Model 3	
	MWTP	Krinsky Robb [CI[a]]	MWTP	Krinsky Robb [CI[a]]
Price[a]	--	--	--	--
RPS by 2040	$0.45***	[$0.35, $0.57]	$0.43***	[$0.3, $0.57]
RPV by 2040	$0.76***	[$0.52, $1.07]	$0.71***	[$0.41, $1.03]
Credit_no	-$1.57	[$-4.17, $0.87]	-$1.09	[$-3.83, $1.54]
Water	-$4.77***	[$-6.28, $-3.55]	-$4.42***	[$-5.81, $-3.19]
SM_text	$2.35	[$-1.14, $5.51]	$2.49	[$-1.06, $5.89]
SM_online	$7.14***	[$3.52, $11.29]	$8.44***	[$4.68, $12.43]
SM_home	$7.96***	[$4.31, $12.05]	$9.35***	[$5.43, $13.45]
asc[a]	-$13.13***	[$-20.49, $-7.86]	-$12.43***	[$-18.21, $-7.62]
(RPS-20)x(RPV-9)	-$0.02***	[$-0.03, $-0.01]	-$0.02***	[$-0.03, $-0.01]
RPS_rural			$0.15	[$-0.05, $0.36]
RPV_rural			-$0.66***	[$-1.09, $-0.26]
RPS*Distance to rooftop			-$0.05***	[$-0.08, $-0.03]
RPV*Distance to rooftop			$0.00	[$-0.03, $0.04]
RPS*Distance to solar farm			$0.00	[$-0.01, $0.01]
RPV*Distance to solar farm			$0.02*	[$0, $0.04]
RPS*NEP score			$0.06***	[$0.04, $0.08]
RPV*NEP score			$0.04**	[$0.02, $0.08]
Water*NEP score			-$0.52***	[$-0.78, $-0.28]
SM_online*NEP score			$1.03***	[$0.41, $1.69]

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

Figure 1: Generation Portfolio Mix. Note: Solar requirements are: 20% PV and 3% RPV.

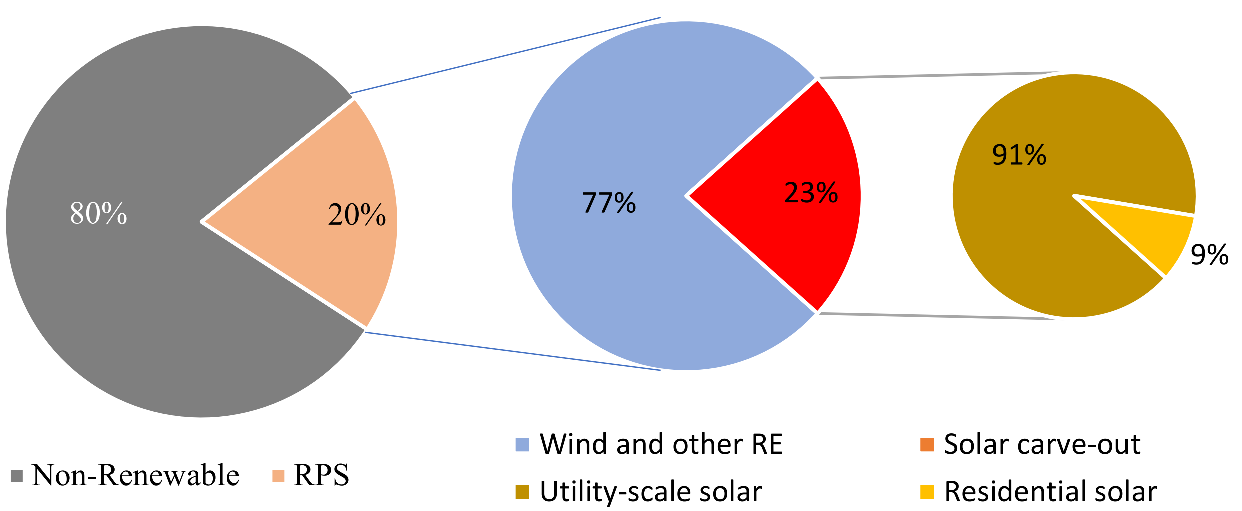
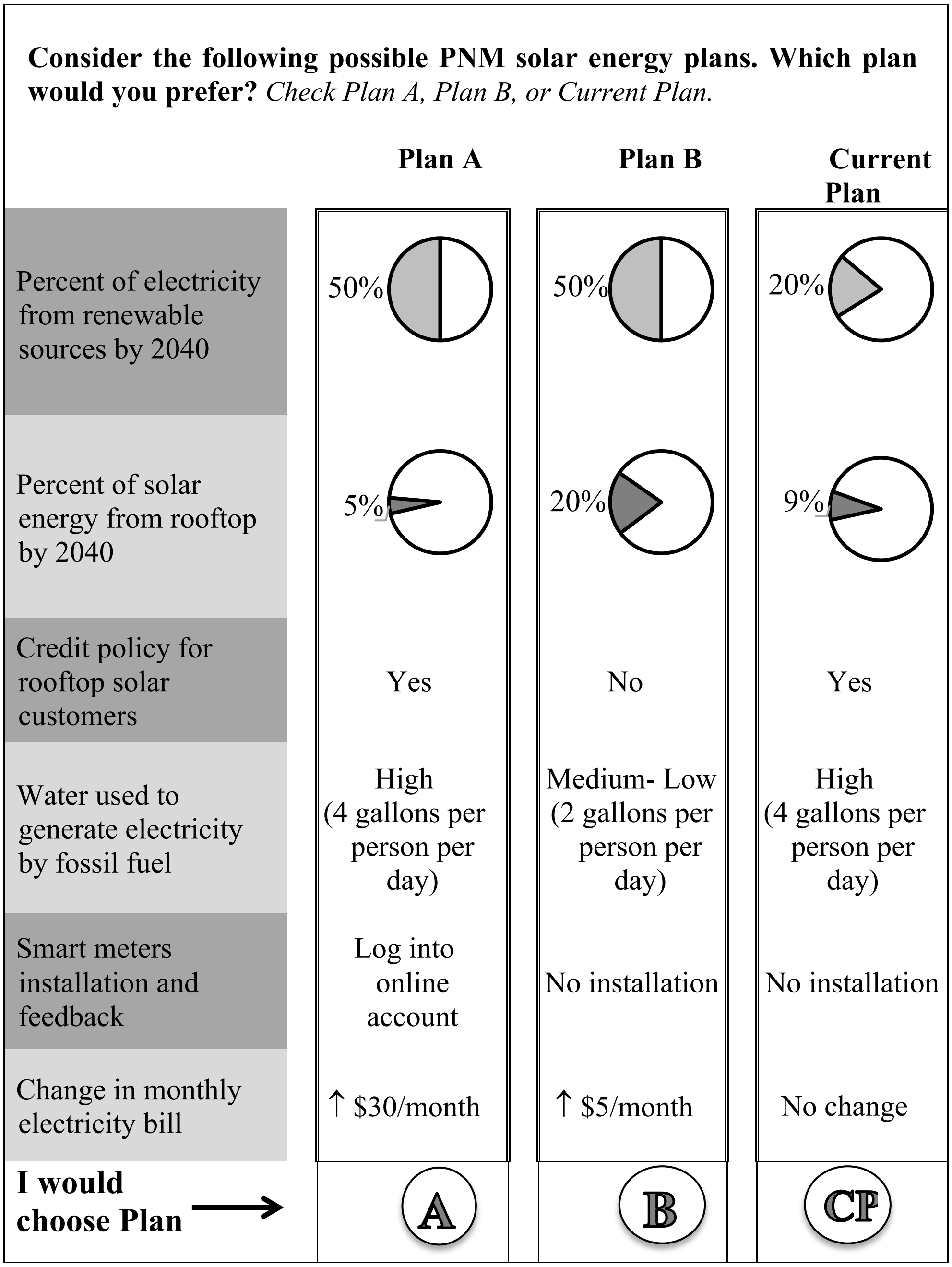


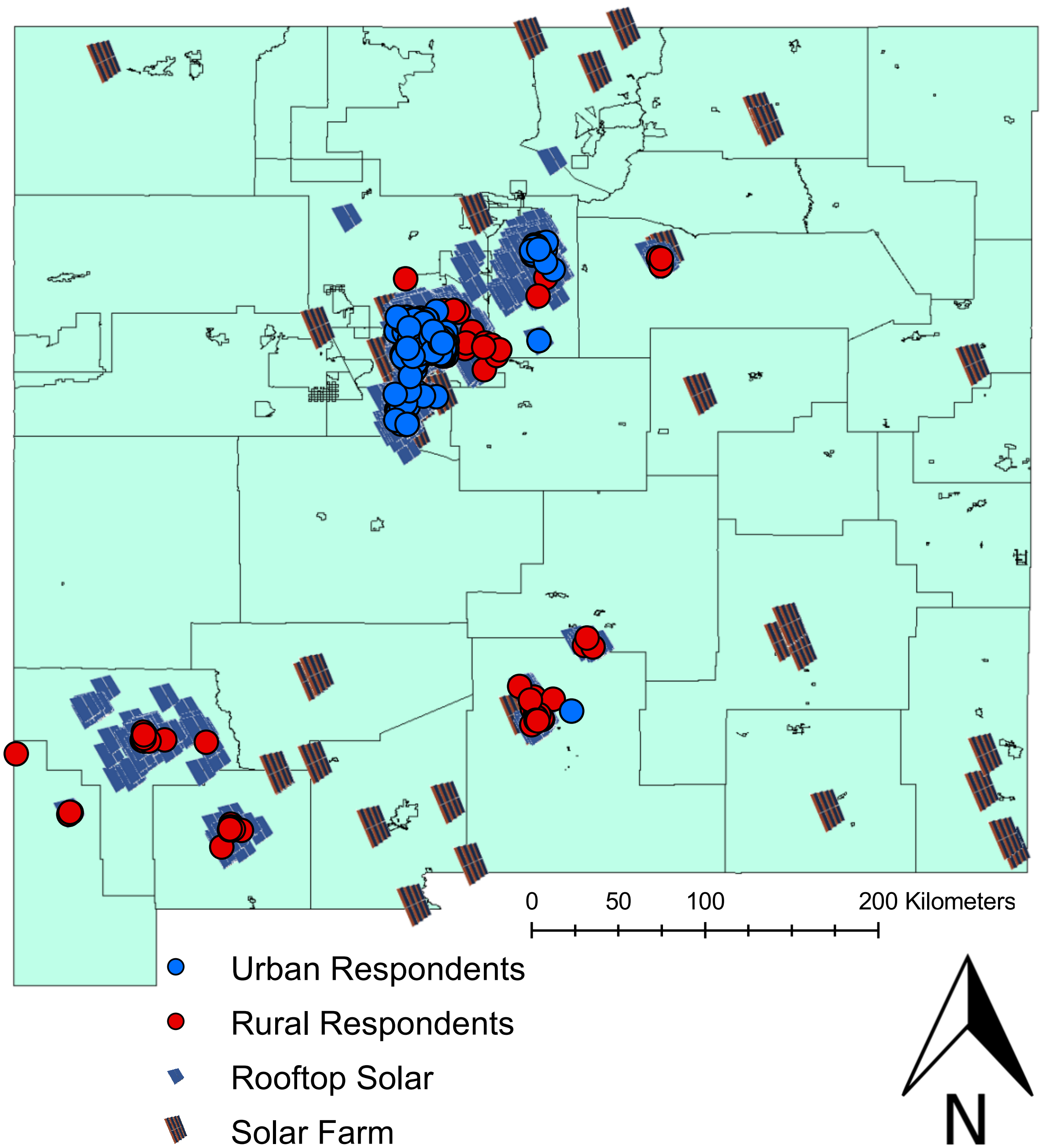
Figure 2: An example choice question used in the survey.



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

	Plan A	**Plan B**	**Current Plan**
Percent of electricity from renewable sources by 2040	50%	50%	20%
Percent of solar energy from rooftop by 2040	5%	20%	9%
Credit policy for rooftop solar customers	Yes	No	Yes
Water used to generate electricity by fossil fuel	High (4 gallons per person per day)	Medium- Low (2 gallons per person per day)	High (4 gallons per person per day)
Smart meters installation and feedback	Log into online account	No installation	No installation
Change in monthly electricity bill	↑ $30/month	↑ $5/month	No change
I would choose Plan →	A	B	CP

Figure 3: Study area



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