Discrete Choice Experiment on Renewable Portfolio Standards to Map Household Preferences

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The renewable portfolio standards (RPS) are state-mandated obligations that require electric load-serving entities to distribute a certain percentage of electricity generated from renewable sources. Recently, many states are considering reviewing their RPS policies; some states are proposing to adopt an aggressive RPS policies while other states are seeking to restrict or repeal their RPS policies. This paper employs a discrete choice experiment (DCE) technique to map public preferences about RPS for residents in New Mexico in 2017. Using attribute non-attendance (ANA) and attribute importance ranking (AIR) increases the precision of our models. Households are willing to pay $3.1/household monthly for a 10% increase in RPS requirements. Latent class models show that pro-ecological and pro-environmental households tended to prefer an increase in RPS requirement. Hotspot analysis shows pockets of homogenous responses indicating households in oil and gas rich areas tended to have lower marginal willingness to pay (MWTP) for share of renewable electricity and households in areas with extensive renewable power plants in place have higher MWTP for share of renewable electricity. This study will help policymakers to make an informed decision when updating the RPS policy of New Mexico. *Keywords: Renewable Portfolio Standards (RPS), Attribute Non-attendance (ANA), Attribute Importance Ranking (AIR), Discrete Choice Experiment (DCE), Hotspot Analysis*

The share of electricity generation from renewable sources is increasing over time. This is partly due to the retirement of fossil fuel power plants, especially coal-based power plants. Renewable sources are replacing retiring plants and meeting increased demand for electricity. Renewable sources contributed 18% of the total electricity generation in 2017, with a projected increase to 40% by 2050 (Blomberg New Energy Finance, 2018) for an annual growth of 2.1% (US Energy Information Administration, 2018). Despite lower oil and gas prices and turmoil regarding federal level policies such as the Clean Power Plan (CPP), the growth in renewable electricity (RE)

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continues due to market forces as anticipated by Obama (2017). The two most important driving forces of the RE market growth are tax credits and renewable portfolio standards (RPS) Barbose (2017). Tax credits in the form of the renewable investment tax credit (ITC) and the renewable production tax credit (PTC) aim to encourage individuals and companies to invest and produce RE, whereas RPS are state-mandated policies enforced to electric load-serving entities. RPS require that electric load-serving entities meet a minimum portion of their load with eligible forms of renewable electricity. As of 2017, 29 states and the District of Columbia have mandated RPS which apply to 56% of total US retail electricity sales Barbose (2017). The requirements of RPS vary across states, though most have a percentage-based requirement. Hawaii has the most aggressive RPS requirement with 100% renewable energy by 2045, followed by California which has 50% RPS requirement by 2030 (Database of State Incentives for Renewables & Efficiency, 2018).

Figure 1 shows the US states and territories that have mandated RPS and the key RPS requirement. The RPS requirements are time-bound and some states are planning to review their RPS as the end of term is approaching. Recently, many states legislators have proposed to increase the requirements or extend the term, while some states are seeking to decrease, repeal or freeze existing RPS policies (Barbose et al., 2016). Against this backdrop, it is imperative to know the social welfare of the policy in question. One way to get the social welfare is to conduct a cost-benefit analysis (CBA) of the RPS policy. Another way is to map public preferences towards the RPS policy. The literature is mostly concentrated on the cost-benefit analyses of RPS.

RPS compliance increases retail electricity prices as the cost of renewable electricity is higher than that of conventional sources if we consider Lazards levelized cost of electricity (LCOE). Figure 2 shows the levelized cost of energy for renewable electricity and conventional electricity. The cost of wind and solar electricity is higher than that of conventional sources. The cost of RPS compliance has a wide range of 3% to 11% increases in retail electricity prices (Morey and Kirsch, 2013; Tra, 2016; Upton Jr and Snyder, 2017; Wang, 2016). The benefits from RPS policy also have multi-faceted effects such as carbon emission reduction (Barbose et al., 2016; Heeter et al., 2014; Johnson and Novacheck, 2015), air quality improvement (Barbose et al., 2016), water withdrawal reduction (Barbose et al., 2016), and job creation (Barbose et al., 2016). Most recently, Wiser et al. (2017) conducted an extensive, national level, integrated assessment of RPS policy cost and environmental benefit. Cost-benefit studies including Wiser et al. (2017) suggest that RPS policies generate net social benefit. However, there are several issues associated with cost-benefit studies in this domain. First, it is debatable whether we can compare the states that mandated RPS with states that did not (Upton Jr and Snyder, 2017). Second, the compliance cost is a direct cost (such as purchasing renewable energy contracts (REC)) whereas the benefits are indirect. Third, RPS policies are not likely the most cost-effective policies to get the intended environmental and economic benefits (Bird et al., 2011; Fischer and Newell, 2008; Johnson, 2014; Palmer and Burtraw, 2005; Rausch and Mowers, 2014; Wiser et al., 2017). In addition to the complexity of cost-benefit studies, Upton Jr and Snyder (2017) did not find a significant benefit from RPS policies in terms of CO_2 abatement. Moreover, Considine (2016) argued that RPS policies do not provide a net social benefit if the secondary economic effect to the economy through higher electricity prices is considered. Against this backdrop, public preferences and underlying sources of preference heterogeneity can be used to facilitate communication among stakeholders, in the context of mandating binding RPS policies using bottom-up approach so that the overall social welfare can be maximized. In this paper, we have presented the results of a discrete choice experiment (DCE) to analyze the public preference towards RPS.

We conducted the discrete choice experiment (DCE) in New Mexico, where legislators proposed a bill in the NM Senate to increase RPS requirements. DCE is a widely used technique to map consumer preference toward a good, especially non-market goods (Louviere, Flynn and Carson, 2010). There is a growing body of literature employing DCE to analyze consumer preferences toward renewable energy (Bigerna and Polinori, 2014; Borchers, Duke and Parsons, 2007; Ma et al., 2015; Menegaki, 2008; Mozumder, Vásquez and Marathe, 2011; Rommel and Sagebiel, 2017; Soon and Ahmad, 2015; Sundt and Rehdanz, 2015; Zorić and Hrovatin, 2012), but none of the studies focused on mandatory renewable energy in the form of RPS. We have used a set of econometric models including sophisticated and flexible generalized multinomial logistic (GMNL), proposed by Fiebig et al. (2010) to account for individual and scale heterogeneity in preferences. Along with advanced econometric methods, we have also incorporated stated attribute non-attendance (ANA) and stated attribute importance ranking (AIR) data to tackle the reliability and the validity of the DCE method. Chalak, Abiad and Balcombe (2016) is the only study that incorporated ANA and AIR together in random parameter logistic model (RPL) in consumer food preference. In this article, we extend the existing literature by examining public preferences towards RPS policy using ANA and AIR information.

The rest of this article is organized as follows. We begin section I with an overview of RPS policies in New Mexico and then detail the survey design. The econometric models for analyzing DCE data are discussed in Section II. Section III presents results and discussions. Finally, Section IV summarizes the key findings of this study.

I. RPS DCE: Survey Design

A. Renewable Portfolio Standards in New Mexico

In 2004, the RPS policy of New Mexico was enacted under the Renewable Energy Act (S.B. 43). The policy states that by 2020, 20% of the distributed electricity of large, investor owned utility companies (IOUs) and 10% of the distributed electricity of small cooperatives (Co-op) will come from renewable sources. In 2007, several carve-outs (e.g. a minimum of 30% of the RPS requirement is met using wind energy) were also incorporated in the policy to ensure a fully diversified renewable electricity portfolio. Figure 3 shows the RPS requirement for New Mexico and compliance over time. The RPS requirement for NM in 2015 was 1.89 TWh and the compliance rate was 100% (Barbose (2017), supplementary information). Note that for several years the compliance rates were below 100%, which is due to the reasonable cost threshold policy set by the New Mexico Public Regulation Commission (NMPRC). The NMPRC states that if the cost of procuring renewable energy is more than 3% of the total revenue of a utility company then the NMPRC will not require that company to comply with the RPS requirement for that year.

In 2017, NM legislators proposed a bill stating to review and revise the RPS requirements. In the proposed bill, IOUs had to increase their RE distribution from 20% by 2020 to 80% by 2040 with several 5-year increments. The Co-ops had a 10% lower requirement of 70% RE by 2040. The bill was debated in the NM Senate on the grounds of relying on a high percentage of RE. Nevertheless, the bill was not approved. However, environmental groups working in New Mexico are campaigning to initiate the bill in the house. At this point, it is important for legislators to know the answers to central questions based on public preferences.

B. Survey Instruments

The DCE is a widely used tool in the stated preference (SP) family of non-market valuation methods. We chose the DCE approach as policymakers are interested in the preferences of individual components of the RPS policy. We developed a questionnaire based on expert opinion and careful examination of the literature. Responses from employees of the University of New Mexico and residents of New Mexico (recruited through the sites Nextdoor and Craigslist) were used to evaluate the initial questionnaire. The choice experiment consists of 5 attributes with 3, 3, 3, 3 and 6 levels. The full factorial design needs altogether 486 profiles or alternatives, which is very high. We have employed a D-efficient orthogonal factorial design based on a SAS macro (%ChoiceEff) (Kuhfeld, 2010) that produced 36 profiles. We created 18 choice sets with two alternatives and one status quo each. The block design is employed to make 6 versions where each respondent answers only 3 choice sets.

For sampling purposes, we purchased the sample from a third party who ensured a stratified random sample of 1,400 contacts [1] . The survey area and location of household shown in Figure 4 confirms that the survey is well dispersed within the geographic boundaries of New Mexico. We conducted a short pilot study (3 communications: pre-notice letter, survey questionnaire, and postcard) for a sample of 100 households chosen randomly from 1,400 households. We chose to use a mail survey because it is more convenient than a face-to-face survey in the developed world. Moreover, research shows that face-to-face, mail, telephone, and online surveys provide similar results (Berrens et al., 2003; Fleming and Bowden, 2009; Krysan et al., 1994; Szolnoki and Hoffmann, 2013). Based on the results of the pilot study, we adjusted our choice attribute levels.

At this phase, we distributed the survey to the 1,300 households. We also uploaded the survey online where only the respondent invited by mail was allowed to participate, as the online survey was protected by an individualized password. The individual password of the online survey was sent to the respondent via mail. We communicated with the respondents five times during the survey period. At the end of the survey, we had a 23.5% response rate calculated based on Americal Association for Public Opinion Research (2016). Altogether, our sample includes 306 households completing 894 useable choice questions.

C. *Survey Questionnaire*

The survey questionnaire consists of five sections. The first section asks about the general perception of New Mexicos energy future. The second section informs the respondent about different attributes of the choice experiment good and their current levels. It also subsequently asks some questions about attributes. The third section consists of 3 choice questions with three alternatives, where one of them is the status quo (SQ) or current plan (CP). Just after each choice question, respondents are asked about the certainty of their choice question answer and attribute non-attendance (ANA) related question. The fourth section starts with importance ranking questions and then asks some attitudinal questions. The survey questionnaire ends with collection of demographic information.

The success of DCE largely depends on the development of attributes and their levels Abiiro et al., 2014; Coast et al., 2012, which requires a rigorous and iterative approach including qualitative methods Coast et al., 2012; Helter and Boehler, 2016. The DCE attributes and levels are selected

[1] Note that there can still be selection bias in household selection. The third party collected the address and information of the household based on marketing campaign, which is potential for selection bias.

based on a meticulous and iterative process using literature review, expert opinion, interview with potential respondents, and pre-test. Table 1 presents the selected attributes and their levels. The main component of RPS is the share of electricity from renewable sources. We have used 3 levels of share of electricity from renewable sources (20%, 50%, and 80%). The current target of 20% by 2020 is the lowest level for continue through 2040. The other attributes in the choice questions are the effects of RPS in the state. Although nuclear electricity is clean (producing zero carbon emission), the definition of renewable electricity does not include nuclear electricity. The choice of RPS will likely impact the consumers decision on nuclear electricity. The current level of nuclear electricity in NM is 18% (calculated from the distribution plan of the 3 largest utility companies in NM). We included 18% as base, 0% as low and doubling it (36%) as high nuclear electricity. The perception of nuclear electricity can be different for different consumer depending on the fact that (1) it produces zero emission; (2) all the nuclear electricity of NM is imported from Pale Verde, AZ; and (3) consumers negative perceptions regarding nuclear electricity due to health and waste concerns and fears of nuclear accidents. The choice of RPS plan can also be impacted by perceptions of water usage by electricity producing technology. Being a desert state, water is a very important resource in NM. Research suggests that renewable electricity technology can reduce water withdrawal and consumption (Macknick et al., 2012). We have included a 10% increase, 10% decrease, and no change of water uses for the levels of water attribute. Another important factor is the economic consideration of the state plan. The economic consideration is captured through the number of jobs changed by implementing the plan. Developing and maintaining renewable electricity will have an impact on the number of jobs in the energy sector of NM. Research shows that a \$1 million investment shifted from fossil fuel to renewables can create 5 jobs (Garrett-Peltier, 2017). We have used a 2,000 jobs increase, 2,000 jobs decrease, and no change as the levels of jobs attribute. The final attribute is the increased cost that the consumer needs to pay through monthly electricity bills. Implementing higher RPS will likely increase the cost of electricity as the costs of renewable electricity are higher than the costs of conventional sources. We have used 6 levels of cost increase ranging from no change to \$60/month.

Figure 5 presents a sample choice card. Respondents are asked to choose among three alternatives, where the last one is current plan. Respondents are reminded to give serious consideration to cost and assume that they are paying the mentioned amount. Just after every choice question, we have asked two choice related questions. The first one is to know how certain the respondents are when making the choice. The second one is to get the stated attribute non-attendance (ANA) of the respondent for that particular choice situation. After all the choice questions, we have included an attribute importance ranking (AIR) question, where respondents are asked to rank the importance of attributes on a scale of 1 to 5. Next, respondents are asked about their environmental attitudes using a 6-point new ecological paradigm (NEP). The survey concludes with demographic questions about education, age, sex, voting pattern, and income. Responses are used to explore the sources of heterogeneity for the respondent.

II. Theoretical and Analytical Framework

A. *Theory Underlying Discrete Choice Experiment*

The discrete choice experiment hinges on two broad theories in economics. Lancasters modern consumer theory states that a good itself does not provide utility, rather the characteristics of a good rise in utility (Lancaster, 1966). This allows us to decompose a good into several attributes and get the value of each attribute. Random utility maximizing (RUM) is a variant of utility-maximizing theory of economics. It states that the individual rational agent chooses a good whose overall characteristics raise its utility to the maximum and the variation of individual choice can be captured through random factors.

Consider a rational, utility-maximizing individual or agent (i) is faced with a discrete choice situation ($s \in \mathbf{S}$). Given a set of alternatives ($\mathbf{J}$), the individual maps a utility (U_{ij}) with each alternative ($j \in \mathbf{J}$) and chooses the alternative that provides maximum utility. The utility given by Equation 1 has a systematic observable component, V_{ij} , and a random and unobservable stochastic component, ϵ_{ij}.

$$U_{ijs} = V_{ijs} + \epsilon_{ijs} = X_{ijs}^T \beta_i + \epsilon_{ijs} \tag{1}$$

In Equation 1, the matrix of observed variables related to alternative j and choice situation s is represented by X_{ijs}. The idiosyncratic error term, ϵ_{ijs} follows independent and identically distributed (IID) extreme value type 1 distribution. As β_i is unobserved for each i, we assume that β_i has a multivariate normal distribution, $\beta_i \sim MVN(\beta, \Omega)$. The basic form of Equation 1 for this study can be formulated as:

$$U_{ijs} = \beta_1 ASC + \beta_2 RE\_share + \beta_3 Water + \beta_4 Nuc\_in + \beta_5 Nuc\_de + \beta_6 Job + \beta_7 Job\_sq + \beta_8 Cost + \epsilon_{ijs} \tag{2}$$

Following maximizing utility theory, the individuals probability of choosing alternative $j \in \mathbf{J}$ over alternative $k \in \mathbf{J}$in choice situation s is based on Equation 1:

$$P_{ijs} = Prob(U_{ijs} > U_{iks} \forall j \in \mathbf{J}, j \neq k) \tag{3}$$

In Equation 2, ASC means alternative specific constant. RE_share is the share of electricity from renewable sources. Water represents changes in water usage. Nuc_in and Nuc_de are categorical variables indicating a change in nuclear electricity. The Job variable is defined as the change in number of jobs. Job_sq is the square of the Job variable, which is included to get the non-linear effect of employment. The Cost variable represents a monthly change in electricity bill. Table 2 provides the definition and statistics of the variables used in Equation 2.

B. *Data Analysis Methods*

The generalized multinomial logit (GMNL)

The most straightforward estimation method based on Random Utility Maximization (RUM) models is the conditional or multinomial logit model (MNL) (McFadden, 1973). Although MNL has closed-form choice probability and a likelihood function that is globally concave, it imposes constant competition across alternatives (IIA property) and cannot allow for individual specific preferences. The mixed logit model (MIXL) generalizes and extends the MNL model by allowing for preference or taste heterogeneity (McFadden and Train, 2000; Train, 2009). While MNL can be estimated using maximum likelihood estimation (MLE), MIXL requires simulated maximum likelihood estimation (SMLE) as it does not have a closed form solution. MIXL is basically a random parameter logit (RPL) model, where the taste heterogeneity of individuals is captured thorough a continuous distribution of parameters. MIXL approximates the RUM model and improves MNL by eliminating the IIA property, while keeping independent and identically distributed (IID) extreme value type 1 error term. However, researchers argue that individuals not only have differing tastes, they also exhibit heterogeneous consistency of choices depending on various factors such as familiarity with the good, the complexity of the choice task, and cognitive ability (Christie and Gibbons, 2011). Fiebig et al. (2010) proposed the scale multinomial logit model (SMNL), where the individual coefficient is adjusted based on a random scale. The SMNL is essentially a restricted case of MIXL with symmetrical mixing distribution (e.g. normal distribution; not log-normal) where the individual coefficient is not multiplied by negative values. While scale heterogeneity can better explain individual behavior than random taste heterogeneity in some contexts (Louviere et al., 2008, 2002), adjusting for scale heterogeneity in the absence of treatment for taste heterogeneity results in statistically inferior model (Greene and Hensher, 2010; Hess, Rose and Bain, 2009). The generalized multinomial logit (GMNL) model is a flexible and sophisticated model that can allow for both individual scale and taste heterogeneity (Fiebig et al., 2010).

The model estimation depends on how the parameter β_i in Equation 1 is distributed. For the GMNL model, the parameters vary across individuals according to:

$$\beta_i = \sigma_i\beta + [\gamma + \sigma_i(1-\gamma)]\eta_i \tag{4}$$

In Equation 4, σ_i is the scale of the idiosyncratic error term across individuals, γ is a scalar controller of the variance of residual taste heterogeneity η_i. The positive real value of scale (σ_i) is ensured by assuming the log-normal distribution of σ_i, with a mean and standard deviation of $\bar{\sigma}$ and τ:

$$\ln(\sigma_i) = \bar{\sigma} + \tau\nu_i, \quad \text{where} \quad \nu \sim N(0,1) \tag{5}$$

Fiebig et al. (2010) note that the estimation performance can be improved by restricting the distribution of $\nu \sim TN[-2,+2]$. Given the parameter distribution and constraints, the utility function that needs to be estimated is given in Equation 6.

$$U_{ijs} = (\beta_{0j} + \eta_{0ij}) + X^T_{ijs}[\sigma_i\beta + \{\gamma + \sigma_i(1-\gamma)\}\,\eta_i] + \epsilon_{ijs} \tag{6}$$

Note that Equation 6 has flexibility such that it can be reduced to different sub-models (MNL. MIXL, SMNL) based on the value of the structural parameters ($\sigma_i, \gamma, var(\eta_i)$) of the model. In this study, we estimated all these models and compared their results and performance. We choose the model that gives the best fit in terms of Akaike information criteria (AIC), Bayesian information criteria (BIC), and log-likelihood. The best fit model (ensuring statistical efficiency) is then used as a base case to tackle response efficiency by using stated information.

Incorporating attribute non-attendance (ANA) and attribute important ranking (AIR)

The previous section discussed the statistical efficiency of the analysis, but there is another type of efficiency that needs to be achieved. Various cognitive effects that result in poor quality responses can cause measurement error. The measurement error can arise from various sources. Although measurement error cannot be totally controlled for, the survey design and implementation should be well thought out so that it can reduce some of the measurement errors (Johnson et al., 2013). For example, a respondent can get fatigue when there is a large number of choice questions. We have eliminated this by incorporating block design so that one respondent only has to answer three sets of choice questions, and we also keep the questionnaire length to 20 minutes. We tested these in personnel interviews. However, there can be some issues associated with DCE that cannot be solved through survey design and implementation, as those issues relate to the behavioral component of respondents in applying different heuristics and decision rules to identify a preferred choice alternative. It needs additional elicitation and techniques to incorporate those issues. Often, respondents choose to ignore some information that is presented to them (e.g. attribute non-attendance) (Balcombe, Fraser and McSorley, 2015; Balcombe et al., 2017; Chavez, Palma and Collart, 2017; Chen et al., 2015; Hensher, Rose and Greene, 2005; Hole, 2011; Hole, Kolstad and Gyrd-Hansen, 2013; Krucien, Ryan and Hermens, 2017; Lagarde, 2013; Puckett and Hensher, 2009; Scarpa et al., 2012; Van Loo et al., 2015) selecting alternatives based on one specific attribute (e.g. lexicographic choice) (Campbell, Hutchinson and Scarpa, 2006; Hess, Rose and Polak, 2010; Rouwendal and de Blaeij, 2004; Sælensminde, 2006; Veisten, Navrud and Valen, 2006), or selecting the same alternative such as status quo alternative in all choice sets (e.g. no-trading) (Hess, Rose and Polak, 2010)). In this paper, we focus on attribute non-attendance (ANA).

Although there is no consensus on how ANA may be accounted for in DCE, literature on ANA implies that ignoring ANA while maintaining passive bounded rationality assumptions leads to potentially biased welfare estimates and poor model performance (Alemu et al., 2013). Literature on ANA has looked into stated ANA by eliciting questions on attribute(s) that the respondent ignore (Hole, 2011; Lagarde, 2013), inferred ANA by incorporating econometrics tools that assume zero utility for the attribute(s) that is ignored (Hensher, Rose and Greene, 2005; Hole, Kolstad and Gyrd-Hansen, 2013; Puckett and Hensher, 2009; Scarpa et al., 2012) and visual ANA by using eye tracking or brain imaging devices (Balcombe, Fraser and McSorley, 2015; Balcombe et al., 2017; Chavez, Palma and Collart, 2017; Chen et al., 2015; Krucien, Ryan and Hermens, 2017; Van Loo et al., 2015). We have opted for a stated ANA technique by eliciting an ANA question after every choice question. Dealing with stated ANA has several limitations such as ignoring an attribute may mean that respondent has very low importance on that attribute, not totally ignoring it (Balcombe et al., 2014; Hess and Hensher, 2010; Hess et al., 2013). For this reason, incorporating additional information along with dichotomous stated ANA questions is common (Balbontin, Hensher and Collins, 2017; Byrd, Widmar and Ricker-Gilbert, 2017; Caputo et al., 2016; Chalak, Abiad and Balcombe, 2016; Heidenreich et al., 2018; Sandorf, Campbell and Hanley, 2017). We have incorporated attribute importance ranking (AIR) data with dichotomous stated ANA information. Research on AIR found that the model performance is better when AIR data is used (Balcombe et al., 2014). Chalak, Abiad and Balcombe (2016) is the only study that used both ANA and AIR information together to estimate DCE. Unlike Chalak, Abiad and Balcombe (2016) and Balcombe et al. (2014), we have used AIR data such that two different attributes can have the same rank or same importance. In our questionnaire, we do not force the respondent to provide a unique rank for each attribute. The questionnaire allows respondents to assign same importance rank for more than one attributes.

Following Chalak, Abiad and Balcombe (2016), we design a contracted model where ANA and AIR data are used as a weight factor. According to the MIXL model, the random utility of person i for alternative $j \in \mathbf{J}$ and for choice situation $s \in \mathbf{S}$ is:

$$U_{ijs} = \tilde{x^{T}_{ijs}} + \epsilon_{ijs} \tag{7}$$

In Equation 7, the parameter β_i varies according to Equation 4. The matrix of latent variables ($\tilde{X^{T}_{ijs}}$) is found after multiplying the weight matrix (Λ_i) with original matrix of latent variables (x^{T}_{ijs}). The weight factor, Λ_i is defined as a diagonal matrix comprised of the weights (λ_{ik}), where $k = 1$ to K attribute. The diagonal element of weights for individual i and attribute k is comprised of the multiplication of two weight factors of ANA and AIR. The ANA weight factor is defined as:

$$\bar{\lambda_{ik}} = \rho\phi_{ik} + (1 - \phi_{ik}) \tag{8}$$

In Equation 8, $\phi_{ik} = 1$ if non-attendance is stated and $\phi_{ik} = 0$ otherwise. The value of ρ will be in between $(0, 1)$, where $\rho = 1$ makes no use of ANA data, $\rho = 1$ means ANA corresponds to zero utility and $\rho = [0, 1]$ means the use of ANA data. Another weight factor from AIR data is constructed based on the following equation:

$$\dot{\lambda_{ik}} = (1 - \mu) + \mu\frac{K - \nu_i k}{K - 1} \tag{9}$$

ν_{ik} is the importance of the k^{th} attribute by the i^{th} individual, where ν_{ik} can have a value of 1 to 5 and the rank of importance is not forced. The individual i can assign the same importance to more than one attribute. The value of μ represents the AIR parameter that varies between $(0, 1)$. When $\mu = 0$, the value of $(\dot{\lambda_{ik}})$ becomes 1 and importance data has no use. The corresponding value of multiplicative weights is:

$$\bar{\lambda_{ik}} = \bar{\lambda_{ik}} \times \dot{\lambda_{ik}} \tag{10}$$

Now we can estimate Equation 7 given the set of Equation 8 - 10. However, the value of ρ and μ are not known beforehand. We have employed a grid-search heuristic to find the optimal value of ρ and μ such that the MIXL system has maximum log-likelihood. We have incorporated ANA and AIR data systematically in 5 different restrictive models based on values of ρ and μ:
Model - 1: no use of ANA or ranking data: $\rho = 1, \mu = 0$
Model - 2: use of ranking data only: $\rho = 1, \mu = [0, 1]$ free
Model - 3: use of ANA data only, where ANA equals zero utility: $\rho = 0, \mu = 0$
Model - 4: use of ANA data only: $\rho = [0, 1], \mu = 0$
Model - 5: joint use of both ranking and ANA data: $\rho = [0, 1], \mu = [0, 1]$

Within the 5 models, the best fit model is used for calculating the marginal willingness to pay (MWTP) measures. We estimate 95% confidence intervals of MWTP using Delta, Krinsky Rob, and Fieller method. The MIXL model incorporating ANA and AIR data can determine whether taste and/or scale heterogeneity present in the household preference. It cannot explain the source of those heterogeneities. We dig more into the source of heterogeneity using geospatial technique and latent class models (LCM). The individual MWTP is used to conduct heterogeneity analysis using geospatial techniques whereas LCM is used to explain the sources of heterogeneity in the preference space.

Latent Class Models

The GMNL along with using ANA and AIR data can provide individual specific coefficients by capturing both taste and scale heteroscedasticity. Although the GMNL model has flexibility in terms of efficiency, the latent class model (LCM) is a more powerful tool to interpret results based on several classes. The LCM simplifies the results of GMNL by making the respondent segments discrete. LCM can be considered as a restrictive case of GMNL, where scale heterogeneity (σ_i) is not considered and taste heterogeneity is based on some distinct classes ($c \in \mathbf{C}$). Mathematically, if $\sigma_i = 1$ and $\beta_i = \beta_c$, then GMNL turns into LCM. Alternatively, LCM is MIXL with discrete mixing distribution. Recently Greene and Hensher (2013) and Keane and Wasi (2013), extended LCM by taking advantage of both LC and MIXL models. Greene and Hensher (2013) proposed the model as LC-MIXL, where MIXL is nested within LCM by double mixing of the logit model. LC-MIXL takes advantage of the simpler and useful interpretability of LCM and statistical flexibility of MIXL. Considering $\sigma_i = 1$ in equation (4) and we have classes within the respondents ($c \in \mathbf{C}$), the distribution of β_i will be:

$$\beta_i \sim N(\beta_c, \Sigma_c) = f_c(\beta_{i\in c}) \tag{11}$$

Consider a choice situation $s \in \mathbf{S}$ for respondent i. The probability that respondent i in class $c \in \mathbf{C}$ chooses alternative $j \in \mathbf{J}$ is:

$$P_{ijs\|c} = \frac{e^{\beta_c X_{ijs}}}{\sum_{j=1}^{J} e^{\beta_c X_{ijs}}} \tag{12}$$

The use of socioeconomic and behavioral information in LCM models are common (Borger and Hattam, 2017). If the vector Z specifies the set of socioeconomic and behavioral information, then Equation 13 defines the probability of class membership for respondent i.

$$P_{is} = \frac{\theta_s Z_i}{\sum_{s=1}^{S} \theta_s Z_i} \tag{13}$$

If the distinct classes have distinct preferences, then the socioeconomics and attitudinal information can be an explaining factor of the preference heterogeneity of the respondent.

Geospatial Analysis

We dig more into heterogeneity by investigating spatial heterogeneity using hotspot analysis. Hotspot analysis allows us to detect spatial pockets or clusters of high (or low) MWTP values by examining local spatial autocorrelation. There are several local indicators for spatial association (LISA) that can be used to conduct hotspot analysis. We have adopted Getis-Ord G_i^* statistics to determine statistically significant high (low) MWTP surrounded by high (low) MWTPs. Statistically significant high and low MWTPs are called hotspots and coldspots, respectively. Getis-Ord G_i^* is a Z-score that reflects the statistical significance of the MWTPs. The positive and negative G_i^* represent hotspots and coldspots respectively. G_i^* is defined as:

$$P_{is} = \frac{\sum_{j=1}^{n} w_{i,j} x_j - \bar{X} \sum_{j=1}^{n} w_{i,j}}{\sqrt{\frac{n \sum_{j=1}^{n} w_{i,j}^2 x_j - (\sum_{j=1}^{n} w_{i,j} x_j)^2}{n}}} \tag{14}$$

In the above setup, x_j is the MWTP for any attribute for individual j, $w_(i,j)$ is the spatial weight for MWTP of individual i and j, n is the total number of individuals, and $\bar{X}$ and S represent the mean and standard deviation. The spatial weight $w_{i,j}$ is a component of spatial weight matrix, W, which is calculated based on k nearest neighborhood and threshold distance, d. A minimum value of $k = 8$ is required to ensure normality of G_i^* (Nelson and Boots, 2008). The threshold distance can be between the minimum and the maximum nearest neighbor distance. The results of hotspot analysis can be linked to spatial and socioeconomic variables to compare the differences of those variables between hotspot and coldspot. Kriging interpolation is used to transform vector of G_i^* to a continuous raster surface.

III. Results and Discussion

A. Ensuring statistical efficiency

The choice data are analyzed using several models to get the best model. Table 3 reports the results of multinomial logit (MNL), scaled multinomial logit (SMNL), mixed logit (MIXL), and generalized multinomial logit models (GMNL). The different models are essentially estimating **??** using various structures of coefficients (β). Table 2 provides a definition of variables used and their descriptive statistics. The alternative specific constant (ASC) is included to measure the willingness to stay with the status quo or current state. The RE_share, Water and Job variables are continuous where Nuc_in and Nuc_de are categorical variables for Nuclear energy increase and decrease respectively. We use effect coding to create categorical variables. Effect coding is similar to dummy variable coding except that the interpretation of results is easier with effect coding in the presence of status quo (Bech and Gyrd-Hansen, 2005; Daly, Dekker and Hess, 2016). We use the Job_sq variable to capture the non-linearity in change in the number of jobs. The Job_sq variable is defined as the square of Job variable.

Table 3 presents results of econometric models in preference space. Column 2 of Table 3 presents the results of multinomial logit. The multinomial logit is dependent on the assumption of IIA. We have tested the IIA property using the Hausman-McFadden test as reported in Table 4. The Hausman-McFadden test shows that we can reject the absence of IIA in our data at a 90% confidence level. We cannot reject it with a higher confidence level indicating the possibility of IIA does not hold. We can circumvent this IIA property in MIXL and GMNL models by estimating the model using simulation techniques. Column 3 of Table 3 presents the results of the MIXL model. In the MIXL model all the variables are random, and the mixing distribution is normal. The MIXL model uses a simulated maximum likelihood estimation (SMLE) technique with 1,500 conventional Halton draws, where the first 15 primes are dropped. We use the GMNL model to account for scale heterogeneity along with taste heterogeneity. The estimation of the GMNL model is dependent on the choice of several inputs into the model. There are four possible input sources (random seed, number of draws, estimation method, and starting values) that can lead to computational issues in the GMNL model (Gu, Hole and Knox, 2013). Appendix A provides detailed discussion of our choice of these four inputs for the GMNL model. We use 1,500 conventional Halton draws along with the BroydenFletcherGoldfarbShanno (BFGS) estimation method and basic GMNL starting values to compute the GMNL results shown in column 4 of Table 3. Finally, the results of SMNL model are shown in column 5 of Table 3.

The best fit model, in terms of statistical efficiency, is chosen based on the statistics provided in the lower panel of Table 3. The MIXL model provides the lowest corrected Akaike Information Criteria (AICc) value. The AICc improves on AIC by imposing a penalty on the number of parameters estimated. The MIXL model improves upon the MNL model by allowing the parameter(s) to be random and bypassing the IIA property. The GMNL model estimates the scale parameters, τ and γ, in addition to the random taste parameters. However, we find that the scale parameters are not significant in our model, suggesting that we did not find scale heterogeneity in our data. We have run the SMNL model which confirms that the scale parameter is not significant in the data. Given all these considerations, and having best statistical efficiency with MIXL model, we go forward with the MIXL model to account for additional stated information.

The coefficients and significance are similar in the all the models. As the magnitudes of the coefficients are not readily explainable in the logistic model, we comment on the sign and the significance of the coefficients. The cost coefficients are negative and significant in all the models as expected. If the coefficient of any variable has opposite (same) sign of cost coefficient that means this variable is providing utility (disutility). The significant negative coefficient of ASC means that households on average have disutility to stay with the current plan. The significant RE_share coefficient indicates a positive preference for an increase in the share of renewable electricity. An increase in water usage has significant disutility, which is reasonable in a high desert area. The household associated utility (disutility) with a decrease (an increase) in nuclear electricity. An increase in Jobs is linked with utility where the Job_sq coefficient implies that the increase of utility is at a decreasing rate. The significant standard deviation of the variables shows the presence of taste heterogeneity within consumer preference. The insignificant scale parameter indicates there is no scale heterogeneity present in the data.

B. *Tackling response efficiency*

We have considered incorporating attribute non-attendance and attribute information ranking information to tackle the response efficiency. We have used stated attribute non-attendance data and stated importance rank data from the survey. At least 1 attribute is ignored in 28.92% of the choice situations, while Jobs attribute is ignored the most (8.23%) and Water attribute is ignored the least (5.45%). The average importance of the attributes shows that RE_share is the most important attribute followed by Water. Compared to Chalak, Abiad and Balcombe (2016), our ANA data has fewer occurrences of respondents ignoring an attribute. For example, in their study, one attribute is ignored in 55.1% of the choice situations. As we have constructed the attributes using rigorous qualitative techniques, only the important attributes are included in the survey. This reduces the number of occurrences of respondents ignoring an attribute. We have used 5 varieties of MIXL models to incorporate ANA and AIR data. Table 5 presents the summary statistics of the contracted models. Model 1 does not account for any new information. Model 2 only uses AIR information. Model 3 estimates ANA using the inferred technique by assigning zero utility if the respondent has ANA on that attribute. Model 4 uses ANA data only and model 5 is based on both ANA and AIR data. The contraction factors for AIR and ANA (and respectively) are estimated heuristically using a grid search approach. A detailed description of the heuristic optimization of estimating ρ and μ is provided in Appendix B. If the value of μ and ρ is equal to 0 and 1 respectively, then the data has no contraction. The estimated value of μ is 0.91 in model 2 and 0.93 in model 5, which signifies that there is very high contraction based on AIR. The estimated ρ is 0.47 and 0.48 in model 4 and model 5 respectively, representing a significant contraction of data based on AIR information. Appendix B provides detailed information on μ and ρ.

The best fit model is chosen based on Log-likelihood, AIC, BIC and AICc values. Model 2 reduces the AIC value significantly compared to model 1. This signifies that incorporating AIR information fits the model significantly better. When ANA information is used in model 3 and model 4, the AIC values reduce compared to model 1. However, model 4 fits better than model 3 where ANA assigns zero utility for that attribute. Finally, taking both ANA and AIR together fits the model best as evident by lower Log-likelihood, AIC, BIC and AICc values. Compared to the base case MIXL model, where neither ANA nor AIR data is considered, the direction and significance of the parameters of model 5 are similar. Note that some of the standard deviations are significant, suggesting that there is heterogeneity of these parameters.

We have estimated welfare measures and the marginal willingness to pay (MWTP) using model 5 considering the ANA and AIR information. Hole (2007) compared the confidence interval of MWTP measures in four ways, using delta, Fieller, Krinsky Robb, and bootstrap methods. We have used the first three methods to compute the MWTP confidence interval. Table 6 reports the MWTP with a confidence interval. We have used the delta method for further analysis[2] (estimating individual MWTP for spatial analysis) and explaining the MWTP as it is most accurate when data is well conditioned (Hole, 2007). In our case, the delta method provides the narrowest confidence interval among all three of the methods we have employed. Figure 6 presents the marginal willingness

[2]Note that the simulated maximum likelihood estimation results differ based on software packages and different computers as indicated by Gu, Hole and Knox, 2013; Lancsar, Fiebig and Hole, 2017. The confidence interval (CI) and MWTP measures are computed using Stata. All other analysis is conducted using R, gmnl package developed by Sarrias and Daziano (2017). The difference in MWTP CI and MWTP is very minimal ($< 0.01\%$)

to pay (MWTP) and confidence interval using the delta method. The box plot is constructed using a 95% confidence level. The whisker represents a 99% confidence level. The negative and significant[3] MWTP for ASC shows that households have a negative value associated with staying at the status quo level. In other words, households are willing to pay to move away from the current plan. They are willing to support another state plan that is different from the current plan. The significant MWTP for RE_share shows that households are willing to pay for renewable energy. On average, the MWTP for RE_share is $31.5/month/household for a 100% increase in RE_share. The average household uses 655 KWh of electricity a month with an average price of 11.37 cents/KWh. The willingness to pay measure translates to 4.23% increase in retail prices of electricity for a 10% increase in renewable energy in the form of RPS. This is within the bounds of cost-benefit studies (Upton Jr and Snyder, 2017; Tra, 2016; Wang, 2016; Morey and Kirsch, 2013). PNM Sky Blue, a voluntary renewable electricity program of PNM, New Mexico, sells 100 KWh for $1.7. The premium charge is 3.31% compared to the average electricity price of 11.37 cents/KWh. New Mexico households on average are willing to pay more than the premium charged by this voluntary program. Households have more MWTP for water usage than MWTP for RE_share. The MWTP for Water is $67/month/household, which means that households are willing to pay $6.7/month/household if there is a decrease in water usage of 10%. This high value associated with the Water attribute is as expected in a high desert like New Mexico. Households are willing to pay $10/month/household for an increase of 1,000 jobs in the electricity generation and distribution sector of New Mexico. However, the negative MWTP for Job_sq variable shows that the WTP for job increase will be increasing at a decreasing rate. The household shows a negative value associated with an increase in nuclear energy. This can be attributed to two reasons: (1) all the nuclear energy distributed in NM is currently imported from Pale Verde, AZ; and (2) households generally have a fear of nuclear accidents and environmental concerns regarding nuclear waste. The consumer is willing to pay $4.4/month/household if there is a decrease in nuclear energy distribution in NM. This can be explained as the households preference on non-reliability of imported nuclear electricity, rather be self-sufficient on electricity production especially using renewable sources.

C. Explaining sources of heterogeneity

The standard deviations of some of the variables are significant. This shows that there is considerable heterogeneity of parameter estimates among individuals. We have conducted the LCM and LC-MIXL model to explain the sources of heterogeneity. We have included socioeconomic and

[3]Significant at 90% confidence level.

behavioral information to construct class characteristics. Our perception is that the pro-ecological and pro-environmental household will have a positive preference towards RPS policies. We have used 6-point new ecological paradigm (NEP) questions to get the ecological perceptions of the respondent (Thornton, 2013). The ecological perception variable has 6 statements with a 5-point Likert scale. The continuous ecological attitude (EA) variable is defined as the points attained by a respondent divided by the maximum total points available (30). Often, ecological or environmental attitudes differ from the environmental practices of individuals. The environmental practice (E_prac) is a dummy variable set equal to 1 if the respondent either (a) has a hybrid car, rooftop solar panel, wind turbine, or (b) works in the energy or environment sector, or (c) has contributed to an environmental protection group. The socioeconomic variables included in LCM are Age, Male, Hispanic, High_income, and Bachelor. The definition and summary statistics of these variables are presented in Table 2.

The results from LCM and LC-MIXL are presented in Table 7. Both the LCM and LC-MIXL models reconfirm the presence of heterogeneity. Both the LCM and LC-MIXL models use 2 classes where class 2 is the reference class. The upper panel of Table 7 shows the preferences and the lower two panels report the class membership and summary statistics. The class membership links preferences with the socioeconomic and behavioral profile of the household. The slightly dominant class as indicated by the class probability (0.584) in LCM shows different preferences compared to the reference class. The dominant class prefers to move away from the current plan, to have a significant increase in RE_share, and a decrease in share of electricity from nuclear, whereas the reference class prefers to stick with the current plan and has no significant preference for RE_share and share of electricity from nuclear. Both the groups share a similar preference for the Water and Jobs variables. The characteristics of Class 1 pro-ecological, having demonstrated the environmental practice and younger compared to the class 2. It is expected that the pro-ecological class will show an inclination towards pro-environmental policies such as aggressive RPS. The result of LC-MIXL is similar to LCM in some respects. The LC-MIXL model shows that households in class 1 do not evaluate any attribute other than the cost attribute. The characteristics of class 1 households comprise of being not pro-ecological, not demonstrated the environmental practice and older compared to class 2. The class 2 households in LC-MIXL model prefer to move away from the current plan and have a significant preference towards RE_share.

The individual MWTP is estimated based on the MIXL model after considering both ANA and AIR information to conduct hotspot analysis. We have focused our effort only on MWTP for RE_share. The aim of hotspot analysis is to find statistically significant clusters of high and low MWTP. The spatial weight matrix for Getis-Ord G_i^* is calculated using k=10 neighbors and d = 10,000 meter (90th percentile distance using nearest neighborhood analysis). The results of hotspot analysis and kriging interpolation is shown in Figure 7. The left panel shows that there is a hotspot in Bernalillo and Santa Fe county, whereas a coldspot exists near to Chavez, Eddy, and Lea counties. The right panel shows kriging interpolation of the hotspot and coldspot.

The spatial and demographic differences of households in the hotspot and the coldspot are presented in Table 8. The spatial variables we have presented include household distance from a renewable power plant, distance from a conventional power plant, and distance from oil and gas lease locations. Table 2 presents the definition and summary statistics of these variables. Spatially the hotspot households are characterized by living near to renewable power plants and farther away from oil and gas lease locations compared to households in the coldspot. A similar conclusion is found by Meyerhoff (2013), indicating that households that live further from wind turbines are more likely to be opponents of wind power generation. The location of the coldspot is on the Permian basin (Chaves, Eddy, and Lea counties). A household that lives there is most likely working in the oil and gas sector and thus has a higher likelihood of supporting conventional electricity rather than RPS policies. The demographic differences suggest that the hotspot households are pro-ecological, not pro-environmental, slightly older and have a higher educational attainment than the coldspot households. The finding regarding the respondents from hotspot households being pro-ecological and educated is as expected. The LCM and LC-MIXL results also confirm that pro-ecological households prefer to support RPS policy.

IV. Policy Communication and Conclusion

The objective of this study is to estimate the welfare measure of RPS policy to inform policymakers in making further decisions regarding this policy. The literature concentrated on estimating welfare measures using cost-benefit analysis. This study uses a discrete choice experiment to map household preferences toward RPS policy in New Mexico. Using sophisticated techniques, this study answers some of the policy questions that policymakers might have in regard to updating RPS policies. The term of New Mexicos current RPS policy is 2020. The legislators proposed a bill in 2017 to increase the RPS requirement to 80% by 2040. The proposed bill was rejected by the NM Senate. Policymakers might wonder what RPS requirement may be preferred by NM residents. The result of our survey shows that New Mexico residents prefer an average of 36.15% by 2040 when asked about the preferred level of RPS. This result indicates that the proposed 80% might be too high for the state to mandate at this moment. Note that the maximum RPS requirement has been set by Hawaii (100% by 2045), followed by California (50% by 2030). Research on Californias RPS showed that a 27% RPS requirement provides higher social welfare when CO2 social cost is moderate and a 50% RPS requirement is better when CO2 social cost is high (Rouhani et al., 2016). The failure of the proposed NM RPS bill of 80% by 2040 also supports the idea of setting a lower RPS requirement for 2040 (higher than the current level 20% by 2020) might be the optimal level. However, the analysis we have performed does not allow us to comment on the optimal level but preferred level by NM residents. The results of this study might be a guiding share of electricity from renewables when considering RPS policy update.

The subsequent question this study asks is whether NM residents are willing to pay for an increase in RPS requirements. The negative and significant MWTP for ASC indicates that NM residents are willing to pay to move away from the current plan. The MWTP for RPS is $31.5/month /household, which translates to a 4.23% increase in retail prices of electricity. The cost-benefit studies of RPS policies show a 3% to 11% increase in retail prices. This study fits within the range of cost increases found in cost-benefit analyses, indicating that NM residents are willing to pay a moderate amount to increase the RPS level. The New Mexico Public Regulation Commission (NMPRC) is responsible for setting a reasonable cost threshold provision that allows electric load-serving utilities flexibility to not procure renewable electricity if the cost exceeds a certain level. The current reasonable cost threshold is 3% of the utilitys total revenue. As NM residents are willing to pay a 4.23% increase in retail electricity prices, this can guide NMPRC to formulate the reasonable cost threshold.

In addition to the willingness to pay for renewable electricity, households are willing to pay if the intended plan increases employment, decrease reliance of nuclear electricity, and decrease water usage by electricity generation in New Mexico. Investment in renewables increases jobs compared to fossil fuels (Garrett-Peltier, 2017). However, this does not account for the possible secondary employment loss due to an increase in retail electricity prices. Policymaker needs to consider the trade-off between the primary and secondary change of employment while formulating RPS policy. The preference for nuclear electricity showed that households have disutility associated with an increase in nuclear electricity. Policymakers can address the household preferences in two ways; by either reducing reliance on imported nuclear electricity or communicating with the stakeholders regarding the issues of nuclear electricity they have. The RPS policy can bring significant water savings and households are willing to pay for a decrease in the water usage of electricity generation. Policymakers can devise the RPS policy curve-outs inclined towards the renewable technology that saves the most water.

The results show considerable heterogeneity of preference among households. The geospatial analysis shows that there are some regions that have neighborhood effects such that households want to pay significantly more than households in other places. A differential electricity pricing by utility companies can get the benefit of this information. This study also finds significant taste heterogeneity among households stemming from ecological attitude, environmental practice, and age. The respondents from households with a pro-ecological attitude, having pro-environmental practice and lower age exhibit favorable preferences towards an increase of the share of electricity from renewables in RPS policy. This finding suggests that utility companies can benefit by focusing on voluntary programs. Voluntary renewable electricity programs can offer interested, pro-ecological households to purchase high priced renewable electricity. A part of the mandatory RPS requirement can be fulfilled by using voluntary participation in renewable electricity program. The cost of mandatory RPS requirement can be partially shifted towards the households that are interested in paying more to use renewable electricity.

Table 1—Discrete choice experiment attributes and levels

Attributes	Status Quo	Levels	Number of Levels
Required share of electricity from renewables by 2040	20%	20%, 50%, 80%	3
Electricity generation from nuclear power	18%	0%, 18%, 36%	3
Change in water usage for electricity generation	No change	10% increase, No change, 10% decrease	3
Change in number of New Mexico jobs	No change	Lose 2000 jobs, No change, Create 2000 jobs	3
Change in monthly electricity bill	No change	No change, \$5, \$10, \$20, \$40, \$60	6

Table 2—Definition of variables used in the econometric models

Variable	Description	Mean	Standard Deviation
ASC	=1 if Status Quo; 0 otherwise	0.33	0.47
RE_share	Required share of electricity from renewables by 2040	0.40	0.25
Water	Change in water usage for electricity generation	0.0001	0.07
Jobs	Change in number of New Mexico jobs	-0.03	1.33
Cost	Change in monthly electricity bill in dollar/household	15.26	21.67
Nuc_in	The increase in nuclear. Effect coding is used to construct this variable. Nuc_in = 1 if the level of nuclear increased from the status quo level of 18%. Nuc_in = -1 if it is status quo level of 18%. Nuc_in = 0 if it decreased to 0%.	0.09	0.81
Nuc_de	The decrease in nuclear. Effect coding is used to construct this variable. Nuc_de = 1 if the level of nuclear decreased from the status quo level of 18%. Nuc_de = -1 if it is status quo level of 18%. Nuc_de = 0 if it increased to 36%.	-0.34	0.82
Job_sq	Square of Jobs variable	1.78	1.99
Geospatial variables			
Distance_RE	Distance in km from the household location to the nearest renewable power plant. Data is collected from EIA (2018b)	27.28	32.85
Distance_Con	Distance in km from the household location to the nearest conventional power plant. Data is collected from EIA (2018b)	15.74	21.41
Distance_Oil_Gas	Distance in km from the household location to nearest centroid of oil and gas lease area. Data is collected from NMSLO (2018).	42.89	43.48
Socioeconomic variables			
Age	The age of the respondent	58.13	16.00
Hispanic	=1 if Hispanic	0.27	0.45
Male	=1 if the respondent is male	0.58	0.49
High_income	=1 if the respondent's household income is 100,000 or greater	0.43	0.50
Bachelor	=1 if the respondent has at least a bachelor degree	0.60	0.49
Environmental and ecological attitude			
EA	Ecological Attitude. Based on Thornton (2013), we have asked 6 ecological attitudinal questions. Each question has 5 points. The continuous variable is defined as the obtained points divided by the maximum point possible. The variable is bounded to 0-1.	0.63	0.14
E_prac	(1) has a hybrid car, or rooftop solar panel, or wind turbine; (2) work in energy or environment sector; or (3) contributed to environmental protection group	0.47	0.50

Table 3—Results of different models in preference space

Model	MNL	MIXL	GMNL	SMNL
Cost	-0.0213***	-0.0921***	-0.0849***	-0.0215***
	(0.0026)	(0.0225)	(0.0221)	(0.0029)
ASC	-0.1327	-1.2058***	-1.1032***	-0.1336
	(0.1379)	(0.4075)	(0.4019)	(0.1384)
RPS	1.1187***	2.4388**	1.9434**	1.1256***
	(0.2118)	(0.9714)	(0.9774)	(0.2171)
Water	-1.4089**	-4.6614**	-3.5826*	-1.4168**
	(0.6295)	(2.0005)	(2.1107)	(0.6340)
Jobs	0.2825***	0.9375***	0.8911***	0.2849***
	(0.0328)	(0.2151)	(0.2140)	(0.0358)
Job_sq	-0.0486*	-0.2412***	-0.2654***	-0.0500*
	(0.0259)	(0.0936)	(0.0954)	(0.0270)
Nuc_in	-0.1356*	-0.7035***	-0.5602**	-0.1352*
	(0.0749)	(0.2610)	(0.2674)	(0.0756)
Nuc_de	0.0321	0.4016*	0.3810	0.0336
	(0.0707)	(0.2373)	(0.2467)	(0.0717)
sd.Cost		0.0945***	0.0808***	
		(0.0235)	(0.0310)	
sd.ASC		2.2270***	2.5283***	
		(0.6165)	(0.9707)	
sd.RPS		10.4691***	11.6600***	
		(2.4254)	(4.2459)	
sd.Water		13.4600***	14.5439**	
		(4.2775)	(6.5901)	
sd.Jobs		0.8174***	0.8560**	
		(0.2556)	(0.3786)	
sd.Job_sq		0.2734*	0.2888	
		(0.1629)	(0.2019)	
sd.Nuc_in		0.3374	0.4968	
		(0.7466)	(0.5694)	
sd.Nuc_de		0.8579**	0.8318*	
		(0.3617)	(0.4293)	
Tau			0.2871	-0.1702
			(0.5123)	(0.4834)
Gamma			2.3117	
			(3.5083)	
N	894	894	894	894
Log-likelihood	-898.0372	-774.6164	-774.3267	-898.0081
$\parallel g \parallel_\infty$	8.0597E-10	8.2773E-04	3.3505E-02	4.29E-02
$gH^{-1}g$	-1.0971E-23	-1.1855E-06	-3.7511E-05	-4.66E-07
K(H)	9.8496E+04	4.1214E+05	1.0773E+06	9.7162E+04
AIC	1812.074	1581.233	1584.653	1814.016
BIC	1850.44	1657.964	1670.976	1857.177
AICc	1812.237	1581.853	1585.435	1814.22

Note:
1. MNL, MIXL, GMNL, and SMNL represents multinomial logit, mixed logit, generalized multinomial logit and scaled multinomial logit respectively.
2. *** $p < 0.01$, ** $p < 0.5$, * $p < 0.1$. Standard errors are in parenthesis.
3. MIXL and GMNL assumed Cost, ASC, RPS, Water, Jobs, Job_sq, Nuc_in, and Nuc_de are normally distributed.
4. $\parallel g \parallel_\infty$, $gH^{-1}g$, and $K(H)$ are used to know the condition of gradient and Hessian matrix so that we can infer on the convergence of simulated maximum likelihood. $\parallel g \parallel_\infty$ is the infinity norm of the largest gradient, which is the largest element of the gradient matrix in absolute value. The 2-norm condition of the Hessian, $K(H)$ is defined as $\lambda_{max}/\lambda_{min}$. λ_{max} and λ_{min} are the largest and smallest eigenvalues of $-H$ respectively.

Table 4—Hausman-McFadden test for Independence of irrelevant alternatives (IIA)

Alternative dropped	Chi-squared	Degrees of Freedom	p-value
Package A	13.97	8	0.0824
Package B	16.27	8	0.0386

TABLE 5—SUMMARY STATISTICS OF CONTRACTED MIXL MODELS

Statistics	M(1): No ANA or AIR	M(2): AIR data only	M(3): ANA data only (ANA=zero utility)	M(4): ANA data only	M(5): Both ANA and AIR data
N	863	863	863	863	863
Log-likelihood	-740.8465	-722.2269	-743.8989	-736.3773	-718.9366
$\parallel g \parallel_\infty$	5.17E-06	5.65E-08	6.58E-06	1.30E-05	4.09E-06
$g'H^{-1}g$	5.31E-10	2.61E-15	4.10E-10	3.32E-09	1.53E-10
K(H)	5.30E+05	4.31E+05	3.99E+05	3.85E+05	3.26E+05
AIC	1513.693	1476.454	1519.798	1504.755	1469.873
BIC	1589.86	1552.62	1595.964	1580.921	1546.04
AICc	1514.336	1477.097	1520.441	1505.398	1470.516
μ	0	0.91	0	0	0.93
ρ	1	1	0	0.47	0.48

Note:
1. ρ is the contraction parameter for ANA and μ is the contraction parameter of AIR.
2. The number of choice questions is reduced to 863 because we have deleted those choice question that does not have an answer of subsequent ANA and/or AIR questions.
3. $\parallel g \parallel_\infty$, $g'H^{-1}g$, and $K(H)$ are used to know the condition of gradient and Hessian matrix so that we can infer on the convergence of simulated maximum likelihood. $\parallel g \parallel_\infty$ is the infinity norm of the largest gradient, which is the largest element of the gradient matrix in absolute value. The 2-norm condition of the Hessian, $K(H)$ is defined as $\lambda_{max}/\lambda_{min}$. λ_{max} and λ_{min} are the largest and smallest eigenvalues of $-H$ respectively.

Table 6—MWTP estimates and confidence intervals using Delta, Fieller, and Krinsky Rob method

Parameter	Estimate	Delta		Fieller		Krinsky Rob	
			Lower	Upper	Lower	Upper	Lower
ASC	-3.0299*	-6.5511	0.4914	-7.2007	0.7510	-7.4449	0.7289
RE_share	31.4890***	17.5065	45.4715	17.4772	49.2345	17.8851	49.4652
Water	-66.8586***	-101.0680	-32.6492	-109.1919	-31.7008	-107.1744	-33.5178
Jobs	10.0645***	7.0892	13.0398	7.1385	13.9122	7.1013	13.8867
Job_sq	-1.5502**	-3.0023	-0.0981	-3.2064	0.0689	-3.1685	0.0578
Nuc_in	-6.2428***	-10.6919	-1.7937	-11.2452	-1.2104	-11.2061	-1.2334
Nuc_de	4.4899**	0.1790	8.8007	-0.4643	9.2604	-0.9139	9.3559

Note:
1. The confidence intervals are based on 95% confidence level.
2. *** $p < 0.01$, ** $p < 0.5$, * $p < 0.1$

TABLE 7—RESULTS OF LATENT CLASS MODEL (LCM) AND LATENT CLASS MIXED LOGIT MODEL (LC-MIXL)

Model	LCM		LC-MIXL	
	Class 1	Class 2	Class 1	Class 2
Cost	-0.0436***	-0.1218***	-0.3034*	-0.0773**
	(0.0076)	(0.0293)	(0.1835)	(0.0365)
ASC	-1.7660***	0.6168*	-0.1457	-1.6918**
	(0.2921)	(0.3473)	(1.1424)	(0.6992)
RPS	3.0743***	-0.0667	0.3693	5.8924***
	(0.4360)	(1.1035)	(5.4753)	(2.1516)
Water	-3.9928***	-7.3504**	-4.4201	-14.1942**
	(1.3985)	(3.6108)	(6.2397)	(5.7771)
Jobs	0.4596***	2.7649***	3.2979	1.1775**
	(0.0897)	(0.9636)	(2.0623)	(0.4897)
Job_sq	-0.1130*	-0.9177*	-0.8273	-0.2757
	(0.0653)	(0.4946)	(0.7921)	(0.2362)
Nuc_in	-0.8621***	0.1340	2.4728	-3.5427***
	(0.2106)	(0.4655)	(1.9736)	(1.3578)
Nuc_de	0.4749**	-0.5442	-2.8632	2.6625**
	(0.1872)	(0.5818)	(1.9796)	(1.1109)
Class membership				
EA	5.1353***		-5.8738***	
	(0.7484)		(1.1939)	
E_prac	0.4961***		-0.6270**	
	(0.1916)		(0.2972)	
Age	-0.0210***		0.0148*	
	(0.0064)		(0.0082)	
Male	0.1954			
	-0.2034	Reference class		Reference class
Hispanic	0.1493			
	-0.2267			
High_income	0.0685			
	-0.2005			
Bachelor	-0.0075			
	-0.207			
Intercept	-2.1631***		3.4211***	
	(0.6299)		(0.7618)	
Summary Statistics				
Class probability	0.584	0.416	0.556	0.444
N	741		741	
Log-likelihood	-604.9718		-580.4801	
BIC	1368.5356		1398.8483	
AIC	1257.9436		1232.9603	

Note:
1. *** $p < 0.01$, ** $p < 0.5$, * $p < 0.1$. Standard errors are in parenthesis
2. The number of choice questions reduced to 741 because we have deleted those choice question for whom we do not have socioeconomic and/or behavioral data that we have used in LCM models.
3. The standard deviation results are not presented for LC-MIXL model. Some of the standard deviations are significant.

Table 8—Spatial, Socioeconomic, and behavioral variable comparison of hotspot and coldspot household

Variables	Unit	Hotspot (n=77)	Coldspot (n=20)	Insignificant (n=195)	All sample (n=292)	Significance
Distance to renewable power plants	Km	15.52	80.25	26.50	27.28	***
Distance to conventional power plants	Km	7.58	11.65	19.38	15.74	
Distance to oil and gas lease	Km	35.56	6.38	49.53	42.89	***
Ecological Attitude (EA)	-	0.66	0.55	0.64	0.64	***
Environmental Practice (E_prac)	-	0.43	0.70	0.47	0.47	**
Age	Years	58.74	51.35	54.55	55.44	*
Male	-	0.57	0.65	0.58	0.58	
Hispanic	-	0.21	0.35	0.26	0.25	
High income	-	0.31	0.35	0.44	0.40	
Bachelor	-	0.73	0.35	0.54	0.58	**

Note:
1. All sample includes 292 households that are included in the hotspot analysis.
2. The significance levels indicate if the hotspot and coldspot group means are significantly different. This is estimated using Welch two-sample t-test. *** $p < 0.01$, ** $p < 0.5$, * $p < 0.1$

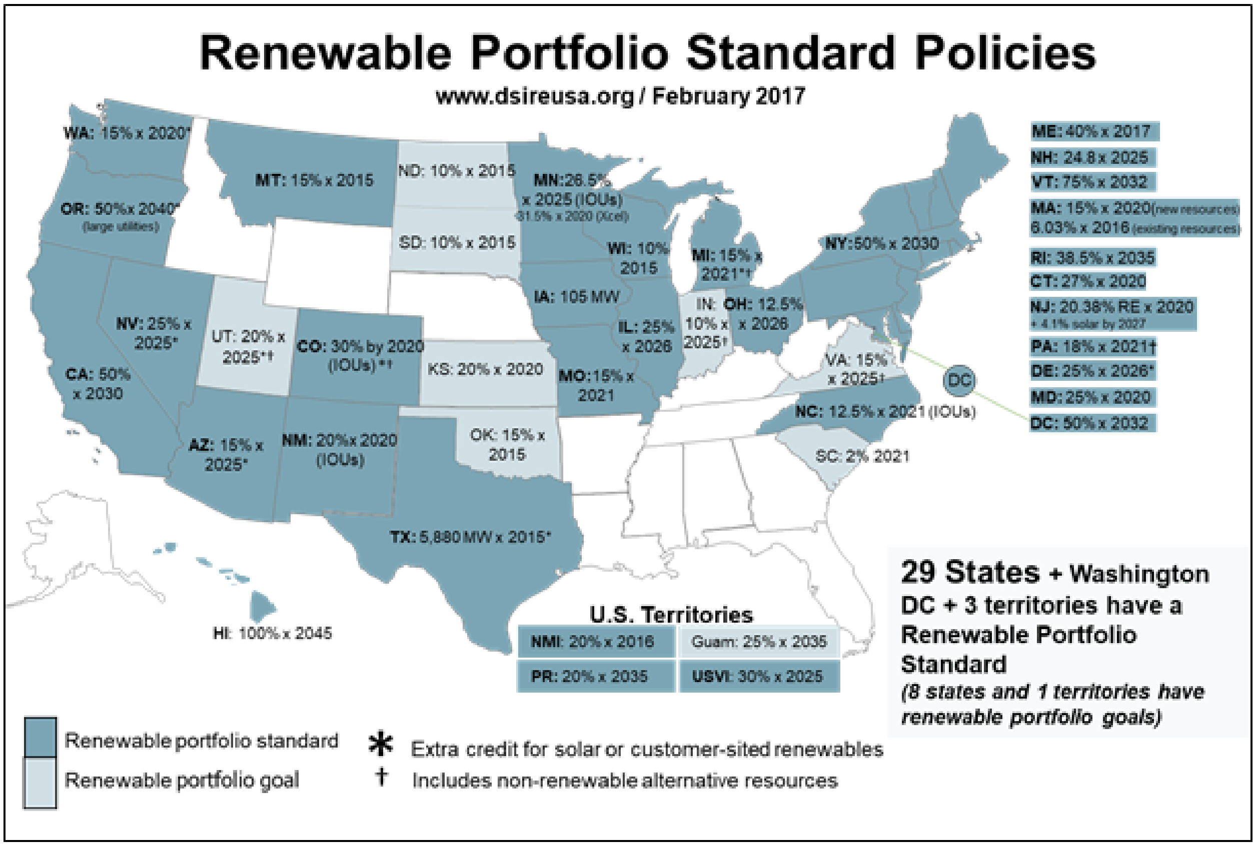


Figure 1. Renewable portfolio standards in the United States

Source: Database of State Incentives for Renewables & Efficiency (2018)

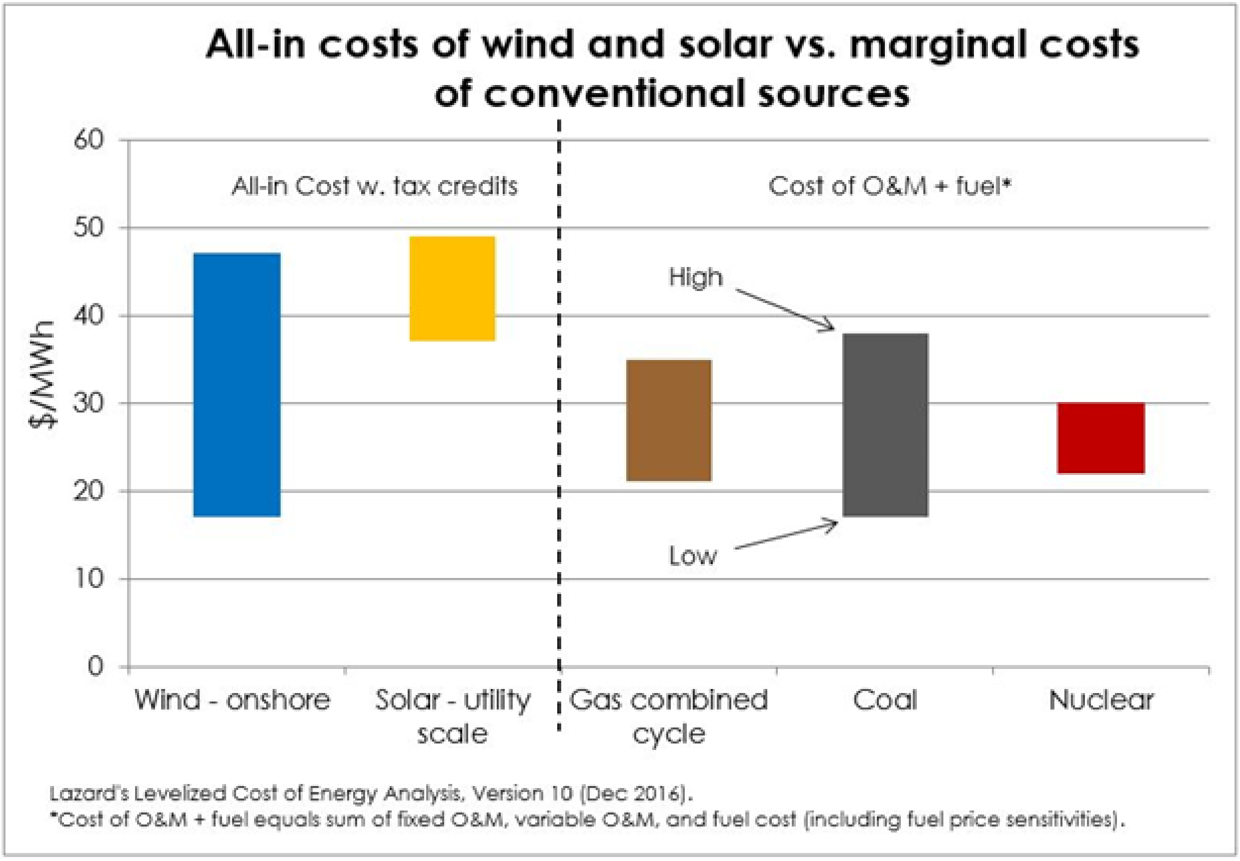


Figure 2. Lazar's levelized cost of energy, version 10

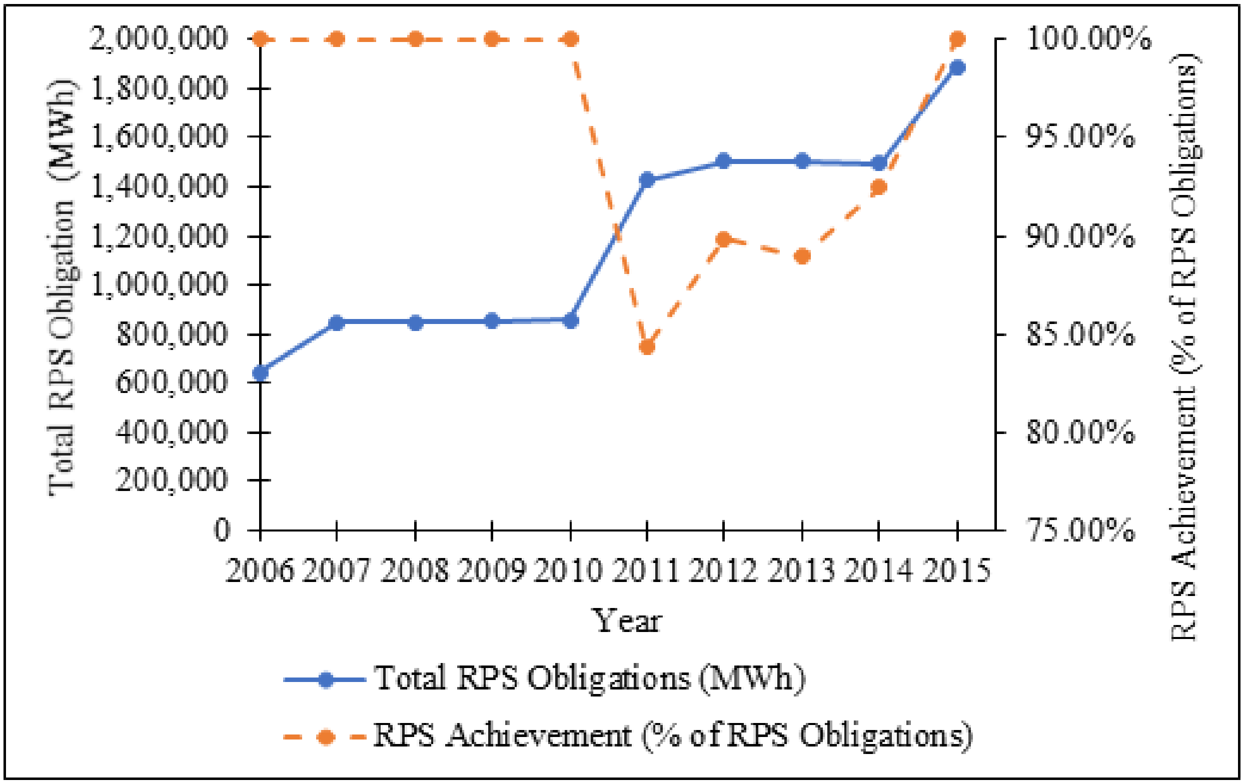


FIGURE 3. TOTAL RPS OBLIGATION AND ACHIEVEMENT IN NEW MEXICO

Source: Figure created from supplementary data of Barbose (2017)

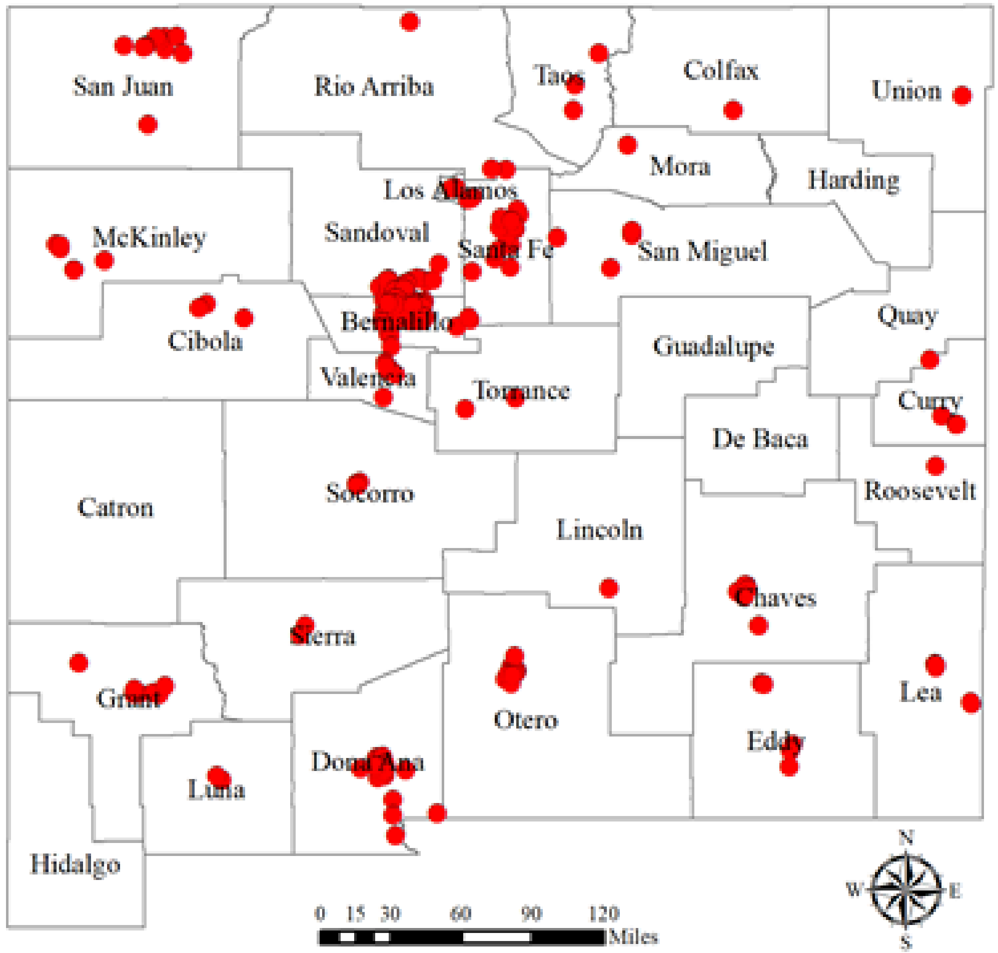
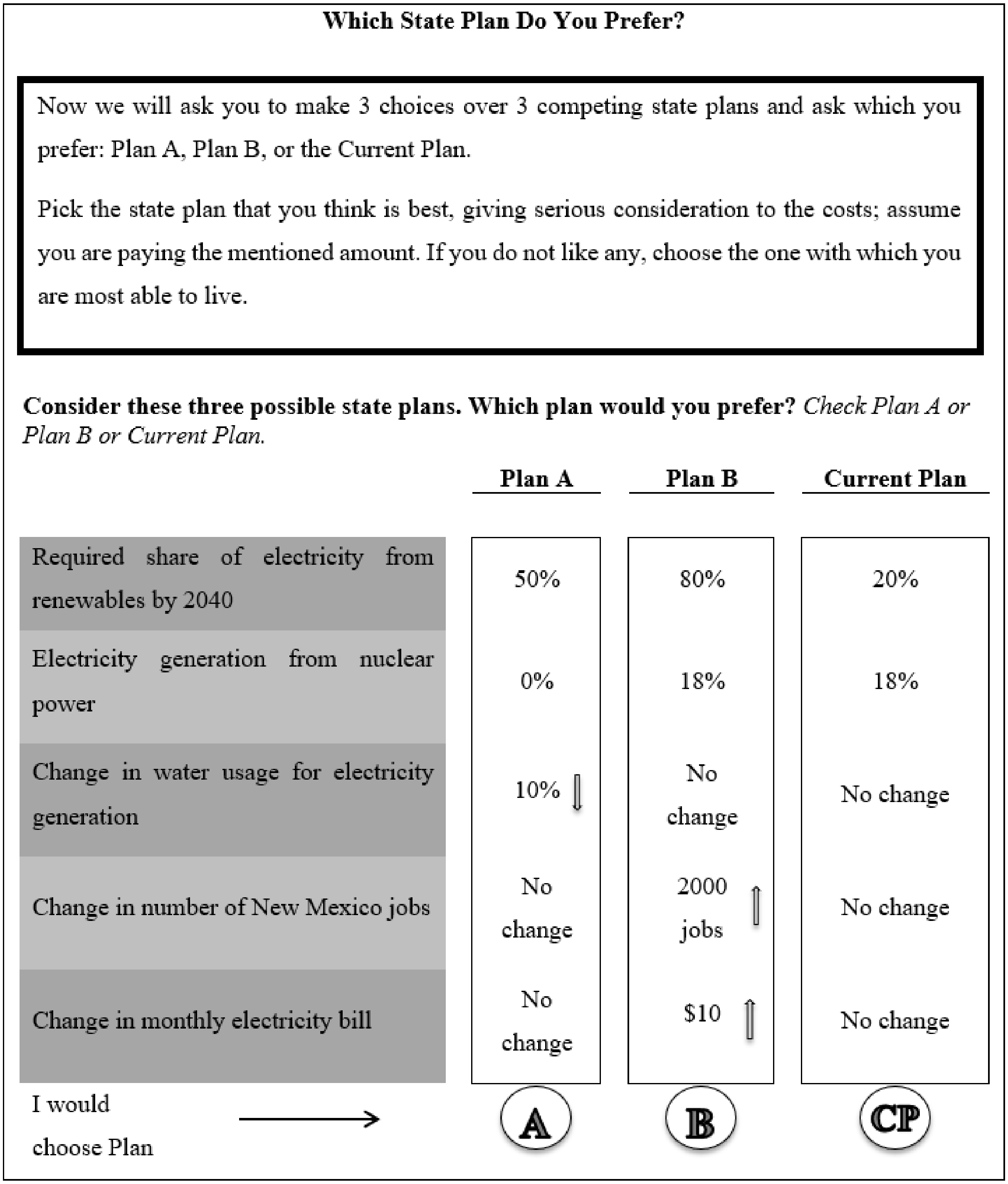


FIGURE 4. SURVEY AREA AND LOCATION OF THE RESPONDENTS



Which State Plan Do You Prefer?

Now we will ask you to make 3 choices over 3 competing state plans and ask which you prefer: Plan A, Plan B, or the Current Plan.

Pick the state plan that you think is best, giving serious consideration to the costs; assume you are paying the mentioned amount. If you do not like any, choose the one with which you are most able to live.

Consider these three possible state plans. Which plan would you prefer? *Check Plan A or Plan B or Current Plan.*

	Plan A	Plan B	Current Plan
Required share of electricity from renewables by 2040	50%	80%	20%
Electricity generation from nuclear power	0%	18%	18%
Change in water usage for electricity generation	10% ↓	No change	No change
Change in number of New Mexico jobs	No change	2000 jobs ↑	No change
Change in monthly electricity bill	No change	$10 ↑	No change
I would choose Plan →	A	B	CP

Figure 5. An example of a choice card

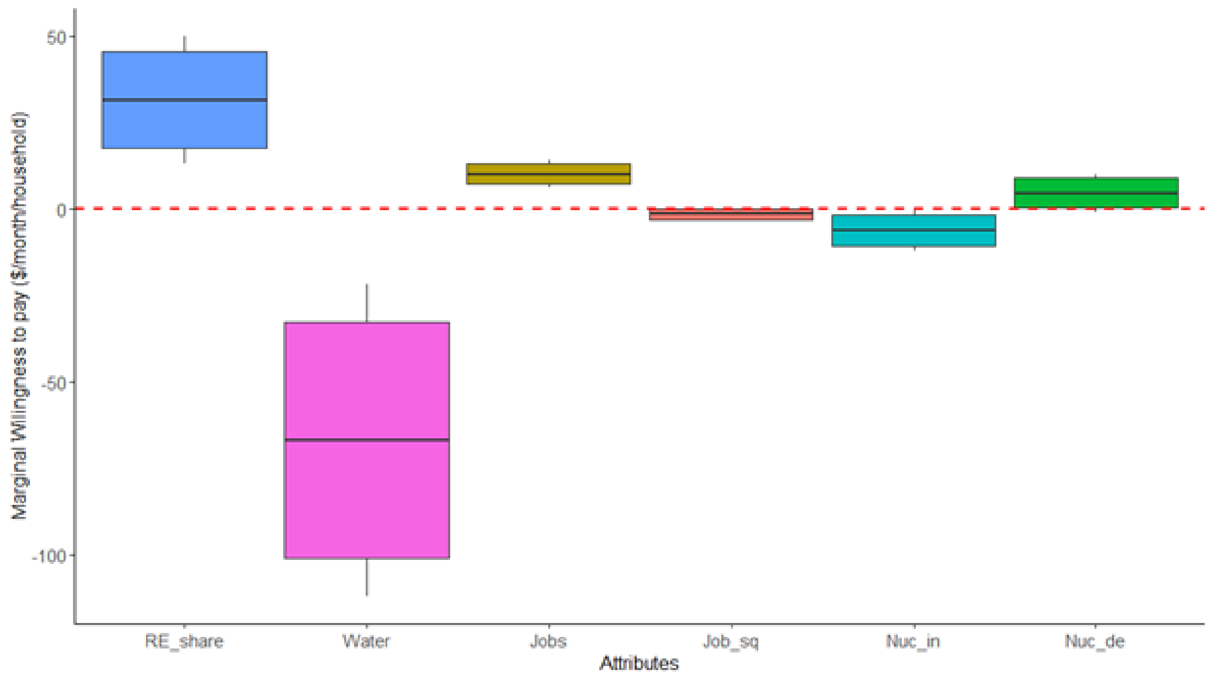


Figure 6. Willingness to pay estimate ($/month/household) for different variables

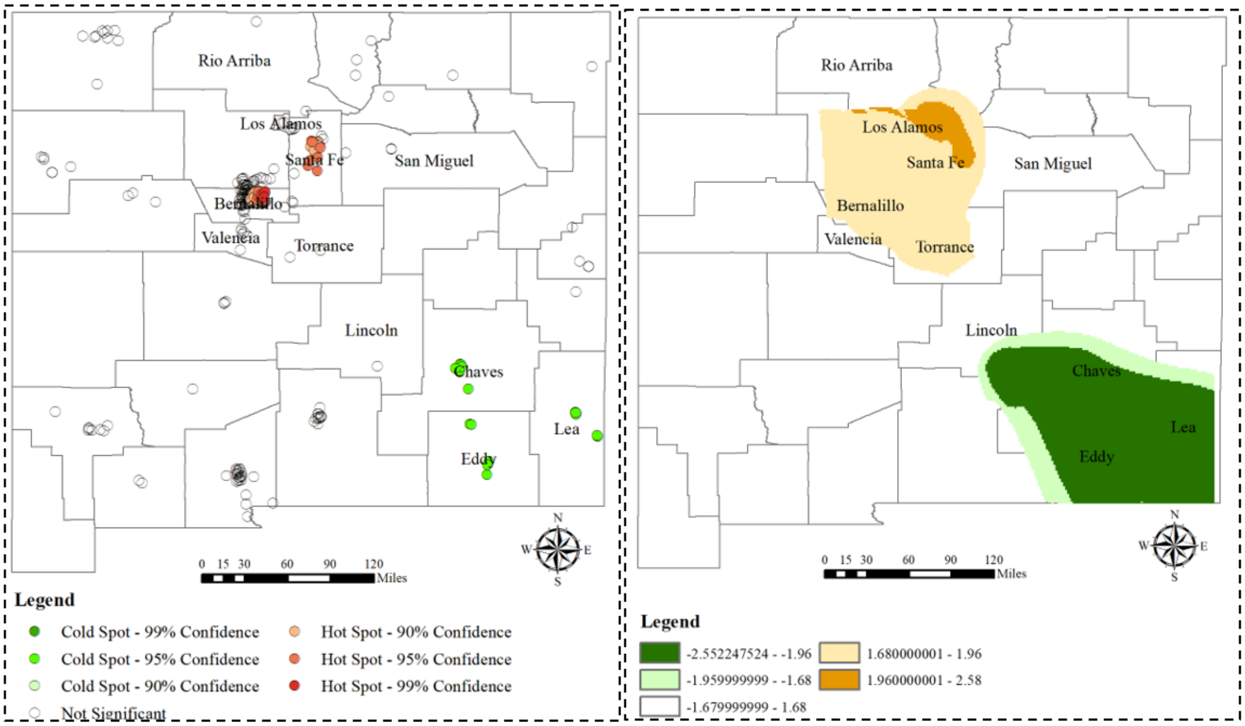


FIGURE 7. GEOSPATIAL HETEROGENEITY FOR MARGINAL WILLINGNESS TO PAY (MWTP) OF RE_SHARE

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Appendix A: Computational issues in GMNL model

The GMNL model is dependent on the choice of several input parameters (Gu, Hole and Knox, 2013). The GMNL model can be sensitive on the randomization seed. We have used 4105 for randomization seed. We have also tested 2 other seeds, but our results do not change very much in magnitude and direction. The second computational issue can arise from the number of draws and method of draws used for random parameters. Halton draws has better chances of convergence compared to random or pseudorandom draws. We have used deterministic Halton draws after burning first 15 primes for reliable estimation as argues by Sarrias and Daziano (2017). Table A1 present results of using varying number of draws. Gu, Hole and Knox (2013) suggests starting from 500 draws. We have simulated using 500 draws to 2000 draws with an increment of 250 draws. The goal of the exercise is to get a minimum number of draws that provides a consistent estimation. The choice of the number of draws depends on the quality of convergence. The first criterion is based on the 2-norm condition of the Hessian matrix, $K(H)$. If the $K(H)$ is negative the convergence signifies a non-stable saddle point instead of maximum. If the $K(H)$ is more than 1.00E+07, then the Hessian is ill-conditioned (Hole and Yoo, 2017). The second criterion is to choose the number of draws that has sufficiently lower infinity norm of the gradient ($\parallel g \parallel_\infty$) and $g'H^{-1}g$ matrix. Using both criteria, a draw of 1,500, 1,750, and 2,000 are our candidate for number of draws. We choose the minimum of 1,500 as number of draws in GMNL model.

Table A1—Summary statistics of GMNL model with varying number of Halton draws

Draws	R_500	R_750	R_1000	R_1250	R_1500	R_1750	R_2000
N	894	894	894	894	894	894	894
Log-L	-771.1871	-771.9652	-774.0919	-772.9316	-775.0731	-773.2138	-774.5997
$\parallel g \parallel_\infty$	9.01E-01	1.85E-01	2.64E-02	2.64E+00	3.86E-02	5.16E-02	3.69E-02
$g'H^{-1}g$	6.69E-03	-2.33E-02	-4.80E-05	-1.99E-02	-2.07E-06	-1.33E-05	-3.27E-05
K(H)	-1.44E+04	1.72E+07	7.56E+05	-1.11E+04	3.12E+05	6.19E+05	5.00E+05
AIC	1578.3740	1579.9300	1584.1840	1581.8630	1586.1460	1582.4280	1585.1990
BIC	1664.6970	1666.2530	1670.5060	1668.1860	1672.4690	1668.7500	1671.5220
AICc	1579.1560	1580.7120	1584.9650	1582.6450	1586.9280	1583.2090	1585.9810

Note: $\parallel g \parallel_\infty$, $g'H^{-1}g$, and $K(H)$ are used to know the condition of gradient and Hessian matrix so that we can infer on the convergence of simulated maximum likelihood. $\parallel g \parallel_\infty$ is the infinity norm of the largest gradient, which is the largest element of the gradient matrix in absolute value. The 2-norm condition of the Hessian, $K(H)$ is defined as $\lambda_{max}/\lambda_{min}$. λ_{max} and λ_{min} are the largest and smallest eigenvalues of $-H$ respectively.

The third issue associated with GMNL model is the starting point. The convergence of GMNL models is highly sensitive to the starting point. We have followed Hole and Yoo (2017) to get the starting point using the conventional method. The parameter choice is shown in Table A2 and the result of the simulation is shown in Table A3. Based on the quality of convergence criteria, we

Table A2—The starting parameter values for GMNL models

Parameter	MNL	SMNL	MIXL	GMNL I	GMNL II	GMNL
Coefficients (β)	Est	Est	Est	Est	Est	Est
Standard deviation (σ)	0.1	0.1	Est	Est	Est	Est
Scale parameter $-\tau$	0.1	Est	0.1	Est	Est	Est
Scale parameter $-\gamma$	0.1	0.1	0.1	0.1	0.1	Est

Note: Est means that parameters are estimated using the specified model

choose a GMNL model where the starting point of GMNL model will be the base case of GMNL model. Although GMNL II staring values provide better AICc, it is ill-conditioned as indicated by a $K(H)$ more than 1.00E+07.

Table A3—The summary statistics of GMNL model with different staring values

Starting value	MNL	SMNL	MIXL	GMNL I	GMNL II	GMNL
Log-L	-775.07	-774.52	-774.35	-774.35	-771.73	-774.33
$\parallel g \parallel_\infty$	4.32E-05	9.90E-05	1.46E-05	1.96E-04	3.24E-04	3.75E-05
$g'H^{-1}g$	3.08E-08	2.77E-07	3.37E-09	5.05E-07	1.86E-06	2.54E-08
K(H)	3.12E+05	3.67E+07	1.24E+06	6.06E+05	1.80E+07	1.08E+06
AIC	1586.15	1585.03	1584.69	1584.69	1579.45	1584.65
BIC	1672.47	1671.35	1671.01	1671.01	1665.78	1670.98
AICc	1586.93	1585.81	1585.47	1585.47	1580.23	1585.44

Note:
1. $\parallel g \parallel_\infty$, $g'H^{-1}g$, and $K(H)$ are used to know the condition of gradient and Hessian matrix so that we can infer on the convergence of simulated maximum likelihood. $\parallel g \parallel_\infty$ is the infinity norm of the largest gradient, which is the largest element of the gradient matrix in absolute value. The 2-norm condition of the Hessian, $K(H)$ is defined as $\lambda_{max}/\lambda_{min}$. λ_{max} and λ_{min} are the largest and smallest eigenvalues of H respectively.
2. GMNL I and GMNL II have three different starting values. GMNL I or GMNL II model predicted with (1) MNL starting values; (2) SMNL starting values; and (3) MIXL starting values. Only the best of GMNL I and best of GMNL II starting values are reported.

The last issue in GMNL model that we have taken care of is the method of optimization. There are 4 popular optimization methods in simulated likelihood estimation: (1) Newton-Raphson (NR). (2) BerndtHallHallHausman (BHHH); (3) DavidonFletcherPowell (DFP), and (4) BroydenFletcher-GoldfarbShanno (BFGS). We have tested three of them as BFGS is a refined DFP method where BFGS nearly always works better (Train, 2009). The results of alternative optimization methods are shown in Table A4.

All the three methods tested (NR, BFGS, and BHHH) provides similar results in terms of coefficients, significance and AICc. The time taken to get the results is fast with BHHH and very slow with NR compared to BFGS. The infinity norm ($\parallel g \parallel_\infty$) and $g'H^{-1}g$ of NR and BHHH method is much higher compared to the BFGS method. The higher values of these lead to unstable convergence, where it reached flat region. Moreover, Train (2009) argued that BFGS works better than all other methods. In this note, we have chosen to use BFGS method.

TABLE A4—THE SUMMARY STATISTICS OF GMNL MODEL FOR VARYING OPTIMIZATION METHOD

Parameter	NR	BHHH	BFGS
N	894	894	894
Log-L	-775.7276	-775.66019	-775.0731
$\parallel g \parallel_\infty$	2.2852E+02	2.8699E+01	3.8626E-02
$g'H^{-1}g$	-1.8322E-01	-2.2983E+01	-2.0748E-06
K(H)	-1.1408E+04	6.9215E+05	3.1153E+05
AIC	1587.455	1587.32038	1586.146
BIC	1673.778	1673.64308	1672.469
AICc	1588.237	1588.10209	1586.928

Note: $\parallel g \parallel_\infty$, $g'H^{-1}g$, and $K(H)$ are used to know the condition of gradient and Hessian matrix so that we can infer on the convergence of simulated maximum likelihood. $\parallel g \parallel_\infty$ is the infinity norm of the largest gradient, which is the largest element of the gradient matrix in absolute value. The 2-norm condition of the Hessian, $K(H)$ is defined as $\lambda_{max}/\lambda_{min}$. λ_{max} and λ_{min} are the largest and smallest eigenvalues of H respectively.

Appendix B: Fitting response efficiency (ANA and AIR) data

Table B1—The summary statistics of GMNL model for varying optimization method

Attributes	ANA	AIR
RE_share	0.066741	3.881188
Nuclear	0.074527	3.184564
Water	0.054505	3.765101
Jobs	0.082314	3.601329
Cost	0.061264	3.413333

Note: ANA and AIR represent attribute non-attendance and attribute important ranking respectively

Table B1 provides the summary statistics of ANA and AIR information. At least one attribute is not considered in 28.92% of the choice situation. We have analyzed 5 different restrictive models where we have considered ANA and/or AIR information. Table 5 presents the summary statistics of the restrictive models. Model 1 does not use ANA and AIR data. Model 2 uses AIR data only where we have found the value of using heuristic optimization. The grid search value of with corresponding AIC values are presented in the left panel of Figure B1. As the increases, the AIC values increases up to the value of μ is 0.91. After that, the AIC value bounces back.

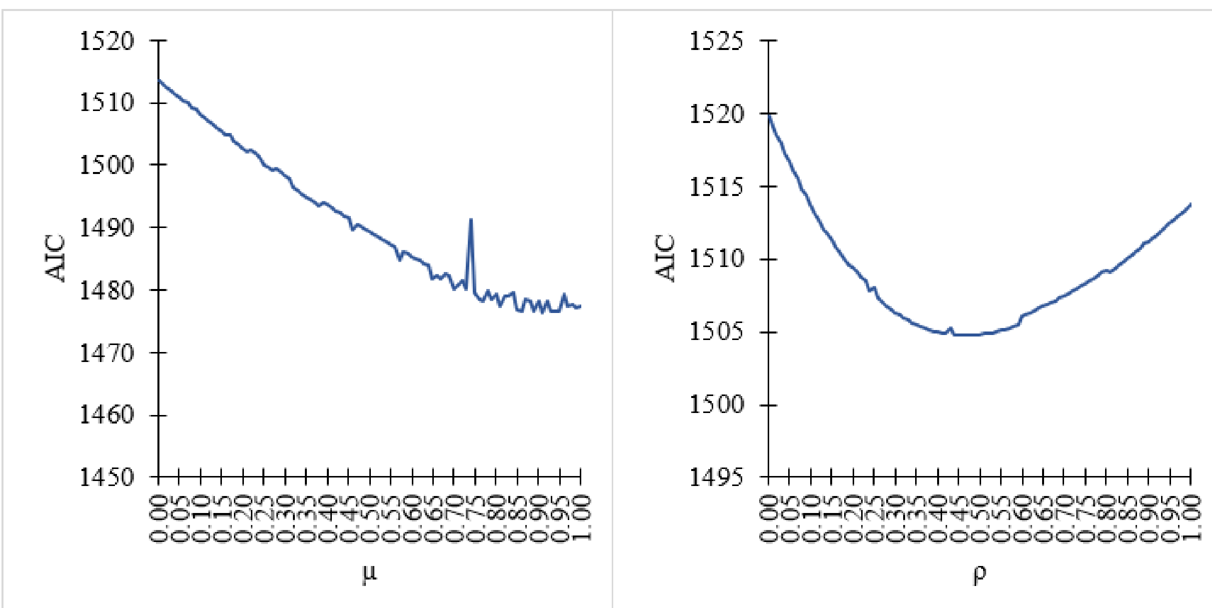

Figure B1. The AIC value corresponding contraction factor of AIR () and ANA () in model 2 and 4 respectively

Note:

Source:

The heuristics grid search optimization of shows that the minimum AIC value is attained when

ρ is equal to 0.47. When considering both μ and ρ, the model 5 heuristic optimization gives the lowest value of AIC when μ and ρ are 0.93 and 0.48 respectively. These values are used to get the optimized model 5, where we consider both ANA and AIR information.