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Analysis

Heterogeneity in Preferences for Woody Biomass Energy in the US Mountain West

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1. Introduction

The United States has passed legislation aimed at reducing greenhouse gas emissions (United States Congress, 2005; United States Congress, 2007; EPA, 2015). In order to achieve the goals set by these commitments, significant amounts of fossil fuel energy will need to be replaced with renewable energy. There are multiple renewable technologies from which to choose, and each option has associated costs and benefits. In order to maximize the social benefits from investments in renewable energy technologies, the external costs and benefits must be quantified and included in the decision making process.

One option for increasing renewable energy production is woody biomass, which can be used to produce electricity, thermal energy, or liquid biofuels. Woody biomass is already used to produce about 2% of the energy in the United States (EIA, 2017) and has the potential to supply up to 10% (Zerbe, 2006). The high cost of production relative to fossil fuels has been a major barrier to expansion of woody biomass energy in the US (Gan and Smith, 2006). However, there are external effects that are not captured in markets and these costs and benefits can affect the socioeconomic efficiency of woody biomass energy relative to other energy options. Because these effects are not captured in markets, nonmarket valuation techniques are needed to quantify the value that society has for them.

Throughout the Western United States there are large areas of public forest that are departed from historic conditions as a result of past management decisions that include wildfire exclusion, poor timber harvesting practices, and over-grazing (Wienk et al., 2004; Hutto, 2008).These overgrown and structurally homogenous forests are less resilient to natural and manmade disturbances, less able to support a variety of native plant and animal communities (Huntzinger, 2003; Hiers et al., 2007), and are more likely to experience unusually severe and damaging wildfires (Schwilk et al., 2009) that can threaten numerous human and ecological values (Graham et al., 2004). Fire-adapted forests that are departed from historic fire regimes are characterized by increased tree density, structural homogenization, and woody fuels buildup (Taylor, 2004). These conditions contribute to high fire severity and are typically mitigated using mechanized thinning treatments, prescribed fire, or a combination of the two (Rummer et al., 2005). Mechanized thinning treatments use heavy equipment to remove excess fuels. They sometimes generate merchantable forest products like sawlogs for lumber, pulpwood for paper, and woody biomass, which consists of the limbs, tops, needles, leaves, and other parts of trees and woody plants that are byproducts of forest management.

Treatment of forestland to improve forest health or reduce wildfire risk produces substantial amounts of woody biomass feedstock that could potentially be used for energy generation. There are however, potential negative effects associated with woody biomass harvest, including potential negative impacts to soils from compaction and erosion and resulting lower site productivity (Thiffault et al., 2011). Additionally, emissions from woody biomass energy facilities may reduce air quality in communities where they are located (Chum et al., 2011). In order to adequately assess the socioeconomic efficiency of any management action that would increase the amount of woody biomass harvested from public forests, public preferences toward the potential outcomes need to be quantified.

The purpose of this paper is to quantify public preferences for an increase in the production of woody biomass energy from public forestland in the Mountain West region, and the potential environmental and socioeconomic outcomes associated with it. Public preferences are quantified in terms of willingness to pay (WTP) using the choice modeling method and econometric modeling techniques that allow sources of preference heterogeneity, which is the degree to which preference structures vary across respondents, to be identified and accounted for. Choice modeling is well suited to this task because it provides the ability to separately quantify preferences toward the multiple different effects associated with an increase in woody biomass energy.

The paper proceeds with a review of studies that have used similar nonmarket valuation methods to analyze preferences toward renewable energy and their findings regarding preference heterogeneity. Next, the methods used to conduct the study are presented, starting with a description of the survey instrument, followed by the econometric models used to analyze the data. Next, the results of the study are presented,

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Table 1
Summary of stated-preference valuation studies on renewable energy preferences.

Study	Method	Energy type	Location	Key findings
Álvarez-Farizo and Hanley (2002)	CM[a], CR[b]	Wind	Spain	Significant WTP to protect scenic cliffs, fauna & flora and landscapes
Bergmann et al. (2006)	CM	Hydro-power, wind, biomass	Scotland	Significant WTP for landscape quality, air quality, and wildlife diversity
Cicia et al. (2012)	CM	Wind, solar, agricultural biomass, nuclear	Italy	Positive preferences for wind and solar, mixed results for biomass, and negative preferences for nuclear
Ku and Yoo, (2010)	CM	Renewable energy	Korea	Significant WTP to avoid wildfire and air pollution, and to generate employment.
Li et al. (2009)	CVM[c]	Renewable energy	United States	Significant WTP for increase in green energy research and development
Longo et al. (2008)	CM	Renewable energy	England	Significant WTP for energy security, and mitigation of climate change and air pollution
Roe et al. (2001)	CM	Green electricity	United States	Significant WTP to reduce emissions through increases in renewable energy
Scarpa and Willis (2010)	CM	Solar pv, micro-wind, solar thermal, heat pumps, biomass boilers and pellet stoves	UK	Significant WTP for micro-generation renewable energy adoption
Solino et al. (2012)	CM	Forest biomass	Spain	Positive and significant WTP to avoid wildfire, reduce pollution, and reduce pressure on non-renewable resources
Solomon and Johnson (2009)	CVM	Biomass ethanol	United States	Positive WTP for climate change mitigation
Strazzera et al. (2012)	CM	Wind	Spain	Significant heterogeneity in preferences toward the visual impacts of wind farms, explained by respondent attitudes
Susaeta et al. (2011)	CM	Woody biomass	Southeast United States	Positive but insignificant WTP for greenhouse gas emissions reductions, forest attributes (wildfire and pests), and biodiversity protection
Yoo and Ready (2014)	CM	Solar, wind, biomass, other	United States	Significant heterogeneity in preferences for renewable energy, especially solar

[a] Choice modeling.
[b] Contingent rating.
[c] Contingent valuation.

and finally, the study's findings and implications for public policy are discussed.

2. Public Preferences for Renewable Energy

Nonmarket valuation has been used to quantify the value of a wide range of nonmarket goods and services associated with renewable energy generation a summary of stated-preference studies is provided in Table 1. Attributes valued in these studies include: reduced greenhouse gas emissions (Roe et al., 2001; Longo et al., 2008; Solomon and Johnson, 2009; Susaeta et al., 2011; Solino et al., 2012), improved air quality (Roe et al., 2001; Bergmann et al., 2006), preservation of landscapes (Álvarez-Farizo and Hanley, 2002; Bergmann et al., 2006), reduced wildfire risk (Bergmann et al., 2006; Solino et al., 2012), preservation of wildlife habitat and biodiversity (Álvarez-Farizo and Hanley, 2002, Bergmann et al., 2006), energy security (Longo et al., 2008; Li et al., 2009), and rural employment (Solino et al., 2012). Studies of public preferences toward woody biomass energy specifically, have been conducted in Spain (Solino et al., 2012) and the southeastern United States (Susaeta et al., 2010). Solino et al. (2012) found positive WTP in Spain for reduced greenhouse gas emissions, reduced risk of forest fire and reduced pressure on natural resources associated with the utilization of woody biomass for electricity generation. Susaeta et al. (2010) found positive (but statistically insignificant) WTP for improved forest health, reductions in CO_2 emissions and improvement of forest habitat from reduced wildfire risk. No previous studies have quantified public preferences for woody biomass energy from public lands in the western US, nor have previous studies evaluated preferences specifically toward feedstock generated by forest restoration treatments on public forests. The US west has unique geographic, ecological, and socioeconomic characteristics, including a high proportion of public lands compared to other parts of the country. Not only is optimal decision making with regards to biomass harvesting likely to differ between private landowners and public land managers because of differences in private and social accounting of other amenities provided by forests, but public preferences more relevant to, and can be more readily accommodated within, management and policy of public lands.

Choice modeling data sets are often analyzed using a multinomial logit model (MNL), which assumes that preferences are homogeneous across the population. However, studies have commonly found heterogeneity in preferences that can be explained by geographic location, environmental attitudes, political viewpoints and sociodemographic characteristics. Significant predictors of preference heterogeneity have been found to include age (Ek, 2005; Bergmann et al., 2008; Longo et al., 2008), gender (Solomon and Johnson, 2009; Susaeta et al., 2010), education (Bergmann et al., 2008; Susaeta et al., 2010), income level (Álvarez-Farizo and Hanley, 2002; Ek, 2005; Bergmann et al., 2006), urban *versus* rural place of residence (Bergmann et al., 2008), and environmental attitudes (Álvarez-Farizo and Hanley, 2002; Longo et al., 2008), including climate change beliefs (Solomon and Johnson, 2009).

Failure to account for preference heterogeneity with the use of MNL can lead to biased estimates of average preferences across the population and an inability to consider distributional effects across different classes within the population (Boxall and Adamowicz, 2002). The simplest and most commonly used approach to relaxing the assumption of homogeneous preferences is to include interaction terms between individual-specific respondent characteristics and case-specific attribute levels in MNL. While this approach can account for the influence that sociodemographic and attitudinal characteristics have on preferences, it does nothing to relax the potentially unrealistic assumptions of Independence of Irrelevant Alternatives (IIA) and uncorrelated unobserved error over time (Yoo and Ready, 2014). Two models exist which relax not only the assumption of homogeneous preferences, but also of IIA and uncorrelated error terms. One is the random parameter logit model (RPL), which accounts for heterogeneity assuming that preference parameters are randomly distributed across the population and allows model parameters to vary randomly across individuals (Train, 1998). The second is the latent class logit model (LCL), which assumes that multiple distinct classes exist in the population, between which preferences vary, but within which preferences are homogenous. The latent class model accounts for preference heterogeneity by simultaneously estimating probability of class membership and preference parameters based on individual characteristics (Boxall and Adamowicz, 2002). The LCL and RPL frameworks can also be combined to allow within-class heterogeneity in the LCL to be accounted for using the randomly distributed preference parameters used in the RPL (Bujosa et al., 2010; Greene and Hensher, 2013).

Multiple studies have used LCL, RPL, or both to examine preferences for renewable energy. Susaeta et al. (2011) found evidence of heterogeneity in preferences toward woody biomass energy, using both MNL with interactions and RPL. Bergmann et al. (2008) used RPL to account for heterogeneity in preferences for renewable energy generation arising from differences between urban and rural residents in Scotland. Strazzera et al. (2012) used LCL in an analysis of preferences toward visual impacts of wind farms in Spain, finding that groups with distinct preferences could be defined by attitudinal variables. Yoo and Ready (2014) used multiple model specifications (LCL, RPL, and a RPL-LCL hybrid) in an investigation of preferences toward multiple sources of renewable energy in Pennsylvania. Using LCL, Cicia et al. (2012) analyzed preferences toward multiple renewable energy sources in Spain and found that three distinct groups existed in the population that could be defined by both their sociodemographic characteristics and their preferences for different renewable energy sources.

In addition to accounting for preference heterogeneity, the latent class framework can be used to address issues of attribute non-attendance (ANA), in which respondents ignore one or more of the attributes when making their choices (Scarpa et al., 2009; Campbell et al., 2011; Yoo and Ready, 2014). Non-attendance can range from ignoring a single attribute, up to complete non-attendance, in which all attributes are ignored and alternatives are selected randomly (Scarpa et al., 2009). ANA can result from respondents simply ignoring attributes that are not relevant to them, or using heuristics to reduce the cognitive effort required when faced with complex choice tasks (Hensher, 2006). Choice modeling relies on the assumption that respondents consider the levels of all attributes and weigh the tradeoffs that exist between alternatives in a choice set (Scarpa et al., 2009). If respondents ignore an attribute for reasons other than deriving zero utility from it, their behavior is inconsistent with random utility theory. Therefore, these behaviors can have consequences that include biased estimates and the inability to accurately estimate trade-offs between attributes (Scarpa et al., 2009).

3. Choice Modeling Survey Instrument

Three states (Arizona, Colorado, and Montana) were selected for sampling purposes to represent the region. To determine what types of socioeconomic and environmental effects associated with woody biomass energy were most important to residents of the study area, focus group workshops were held in Missoula, MT, Denver, CO, and Flagstaff, AZ, between July and September of 2013. The meetings were attended by stakeholders from the United States Forest Service (USFS), state agencies, universities, the forest industry, wildlife and land conservation groups, and local recreation groups.[1]

Based on feedback from participants at the three workshops, the five attributes selected for inclusion in the survey were: homes powered with wood in the state (abbreviated HOMES); forest health in the state (FORESTS); large wildfires in the state (WILDFIRES); unhealthy air days experienced locally (AIRDAYS); and household monthly energy bill (BILL).[2] The attributes are defined along with their status quo and alternative levels in Table 2. Each attribute was defined over a ten-year time horizon to provide a realistic time-frame in which to adopt and implement new forest management strategies, while also remaining relevant to respondents. Although the state-specific status quo levels for each attribute varied between the three study states, they were similar enough that a single status quo level for each of the attributes was selected and used for all three states. Having a single status quo level ensured that the data from all three study states could be pooled into a single dataset, with sampling stratified by state.

The amount of biomass energy produced was defined in terms of the number of home equivalents powered with woody biomass annually (HOMES). This metric was chosen because it was determined that the number of homes powered would be more easily interpreted than a unit of electric or thermal generation, such as kilowatt hours (KWh) or British thermal units (Btus). Respondents were informed that the woody biomass energy would replace energy that is currently produced using fossil fuels, and the ability to offset fossil fuel use and reduce long-term impacts of climate change was presented as a benefit associated with HOMES. Climate change mitigation benefits are based on consensus in the scientific literature that the utilization of forest biomass residues from land that stays in forested land use, like the public lands that are the focus in this study, has the potential to provide long-run climate benefits with no negative short-term carbon balance effects (Gustavsson et al., 1995; Jones et al., 2010; Sathre and Gustavsson, 2011).

FORESTS was defined as the proportion of healthy forests in the state, across all ownerships. The definition emphasized the fact that healthy forests support a greater diversity of native plant and animal species and are more resilient to disturbances such as fire, insects and disease. The proportion of healthy forests in each study state was determined using the Vegetation Condition Class classification system, which categorizes the level of departure of current vegetation conditions from a historic reference (Barrett et al., 2010).

Large wildfires were defined in the survey as wildfires that burn at least 1000 acres and threaten homes and structures. The status quo level of WILDFIRES was determined using spatial data from the Monitoring Trends in Burn Severity project (MTBS, 2012). The definition highlighted the average number of homes destroyed annually over the past decade in each study state, but also emphasized that the majority of homes were destroyed by a small number of very destructive fires, that the number of fires each year is highly variable, and that wildfires are an important beneficial natural disturbance present in healthy forest ecosystems.

AIRDAYS was defined as average the number of days annually that are “unhealthy for sensitive groups” in the respondent's community. The status quo was based on the average number of days from 2008 through 2012 that air quality was documented as “unhealthy for sensitive groups” at United States Environmental Protection Agency (EPA) monitoring stations throughout the study area. This represents the average number of days that the average household is exposed to levels of air pollutant concentrations high enough to pose a health risk to older adults, young children and people with specific health concerns (EPA, 2013a, 2013b). Consistent with findings by Pope et al. (2009), the definition explained that long-term exposure to air quality that is “unhealthy for sensitive groups” may pose health risks to all members of the community and reduce life expectancy.

[1] Representatives from a number of organizations representing tribal forestry (3), private forest owners (3), and environmental groups with a strong anti-biomass energy stance (12) were contacted about attending the meetings, but were either unavailable or uninterested in attending.

[2] A sixth attribute, “Rural Job Creation” was ranked as important and initially included in the survey, but was dropped after peer-review suggested that the survey was overly-complex. “Rural Job Creation” was dropped, rather than one of the attributes, because the economic value of job creation can be estimated from markets, while the other attributes are not presently traded in markets.

Table 2
Definitions of choice attributes.

Variable	Definition	Levels	Units
HOMES	The amount of woody biomass energy produced annually. Defined as electric or thermal energy produced using residues from restoration treatments on public forests.	10,000, 20,000[a], 30,000, 50,000	Homes per year
FORESTS	The percent of healthy forestland, across all forest ownership categories.	10, 20[a], 30, 60	Percent
WILDFIRES	The number of wildfires per year that burn at least 1000 acres and threaten homes and watersheds.	6, 9, 12[a], 15	Wildfires per year
AIRDAYS	The number of days per year when air quality is unhealthy for sensitive groups in your community.	5, 10[a], 15, 30	Days per year
BILL	Household average monthly energy bill in US dollars.	80, 100[a], 120, 150, 200, 400	US dollars

[a] Status quo attribute level.

The payment vehicle was defined as the respondent's average monthly household energy bill (BILL), an obligatory payment mechanism that is less likely to induce protest responses than a government tax or fee. The average monthly household energy bill in the study states was used to define the status quo (EIA, 2011). The annual equivalent of BILL was also provided in the choice sets to decrease the likelihood of respondents interpreting the monthly amounts as inconsequential. BILL was defined to include electricity, natural gas, and other fuels used for heat. Presenting the level of the payment vehicle as an absolute amount was meant to serve a specific purpose. Unlike some applications of choice modeling, where the status quo represents an “opt-out” or “no-purchase option”, the status quo in these choice sets does not represent zero-cost option and this approach provides a reminder to respondents that the status quo is not free (see Banzhaf et al., 2001 for more discussion of opt-out alternatives).

With 4 attributes varying across 4 levels each and 1 attribute varying across 6 levels, there were 1536 ($4^4 \times 6^1$) possible combinations of the attributes and their levels. From the full set of possible combinations, an efficient fractional factorial experimental design of 48 alternative profiles was created using SAS statistical analysis software (SAS Institute Inc., 2015) and the macros described by Kuhfeld (2010). An efficient design size with 48 alternatives was developed with 1 status quo and 2 non-status quo alternatives per choice set, and four choice sets arranged in six survey blocks. Respondents were randomly assigned one of the six versions of the questionnaire.

The survey instrument contained four sections in 16 pages. Section 1 provided an introduction and collected information on respondent opinions about energy generation, public land management, and climate change. Section 2 provided background information about energy consumption in the US, forest management, details about how woody biomass can be used to produce energy, sustainable levels of woody biomass harvest from public forests, and the costs and benefits associated with woody biomass energy. The attributes were defined and the choice sets were presented in Section 3. Respondents were reminded to consider their budget constraints and alternative uses of their income. In Section 4, information about the respondents' experience with the survey and sociodemographic information was collected, which allowed comparison between the collected sample and the general population of the state.

A mixed-mode data collection strategy was employed to obtain a stratified random sample of the study population. All potential respondents were contacted with an invitation letter mailed to their home explaining the purpose of the research and randomly presented with one of the following response options: (a) a web address and unique identification (ID) number that served as a password to complete the survey online, (b) a notification that they would soon be receiving a physical survey packet in the mail, or (c) both a web address with ID number *and* the option to wait and receive a physical copy of the questionnaire in the mail if they did not respond online. Individuals in the online-only group (a) who had not completed the survey after about two weeks received a reminder post-card in the mail. Individuals in groups b and c were contacted using the four-contact method described in Dillman (2007). The second mailing included the survey, the third mailing was a reminder postcard, and, if a response had still not been received, the fourth and final mailing included a second hardcopy of the survey.

The sample was stratified to ensure coverage of people who live in forested areas and people who live in airsheds with a history of poor air quality because these characteristics were hypothesized to affect preferences toward the attributes of interest. Residents of forested areas were identified using US EPA level III Ecoregions (EPA, 2013a, 2013b). Poor air-quality airsheds were identified as EPA non-attainment airsheds, which have failed to meet national ambient air quality standards (EPA, 2013a, 2013b). Because of the large number of Spanish speaking residents in Arizona and Colorado, for census tracts with at least 50% Hispanic population, respondents were provided with the option to complete the Spanish language version of the survey.

4. Econometric Models

Two econometric models were fitted to the data. The first is the multinomial logit model (MNL), which is the most commonly used model for CM data. The theoretical foundations of the MNL are random utility maximization (Mcfadden, 1973) and the characteristics theory of value (Lancaster, 1966). Random utility explains that the utility associated with a particular alternative from a choice set is composed of both an observable and a random component,

$$U_j = V(x_j, p_j; \beta) + \varepsilon_j \tag{1}$$

where U_j is the true but unobservable utility associated with the consumption of profile j, V is the systematic indirect utility function, x_j is a vector of the attribute levels associated with profile j, p_j is the cost of profile j, β is a vector of preference parameters, and ε_j is a random error term. An individual will only select alternative i over alternative j if the utility associated with alternative i is greater than the utility from alternative j.

Assuming the errors in the regression can be described by a Gumbel distribution and are independently and identically distributed, the probability that an individual will select alternative i over alternative j, can be expressed as

$$P(i \mid C) = \frac{\exp(\mu V_i)}{\sum \exp(\mu V_{j)}} \tag{2}$$

where μ is a scale parameter inversely proportional to the variance of the error term. By assuming constant error variance, this parameter can be set to equal one (Ben-Akiva and Lerman, 1985). This can be expanded and expressed as

$$P_n(i \mid C_n) = \frac{\exp(\beta_{ni} X_{ni} + \tau Q_{ni})}{\sum \exp(\beta_{nj} X_{nj} + \tau Q_{nj})} \tag{3}$$

where X_n is a vector of terms for the attribute levels encountered by individual n; β_n is a vector of associated estimated coefficients; Q_n is an alternative specific constant (ASC), taking a value of 1 for status quo alternatives and zero otherwise, with an associated coefficient of τ.

In the model represented by Eq. (3), preference structures are

Table 3
Sociodemographic and Attitudinal characteristics.

Variable	Definition	Sample (%)	Study population (%)[a]
HIGHINC	Dummy variable = 1 if household annual income > $100 k	25.9	21.5[b]
COLLEGE	Dummy variable = 1 if have at least a bachelor's degree	59.0	31.2[b]
SKEPTIC	Dummy variable = 1 if do not believe in anthropogenic climate change	47.6	49.2[c]
FORESTED	Dummy variable = 1 if live in a forested ecoregion	53.6	N/A
AIRQUALITY	Dummy variable = 1 if think that smoke and other air pollution negatively impacts community	23.2	N/A
RESTORATION	Dummy variable = 1 if think that public forests are in need of restoration treatments	89.8	N/A
CONFUSED	Dummy variable = 1 if think that the survey was confusing	27.3	N/A

[a] Based on the weighted average of the populations of Arizona, Colorado, and Montana.
[b] Source: Census Bureau (2010).
[c] Source: Howe et al. (2015)..

assumed to be homogeneous across respondents, which may not hold true because there are individual characteristics that are likely to explain some portion of the preferences that people have toward environmental goods. This assumption can be relaxed through the inclusion of individual-specific characteristics, R, that are interacted with the alternative-specific attribute-levels.

$$P_n(i \mid C_n) = \frac{\exp(\beta_{ni}X_{ni} + \tau Q_{ni} + \gamma R_n X_i)}{\sum \exp(\beta_{nj}X_{nj} + \tau Q_{nj} + \gamma R_n X_j)} \tag{4}$$

The second model used to examine preference heterogeneity in this paper is the latent class model, which provides the ability to identify subsets of the population with similarities in preference structures. The LCL framework assumes that individuals are members of a group that has particular preferences, independent from the choice problem being analyzed (Swait, 1994). Preferences differ across groups, but are homogeneous within groups. Given S classes in the population and individual n belonging to class $s(s = 1, \ldots, S)$, the indirect utility function can be written as:

$$U_{in\mid s} = \beta_s X_{in} + \varepsilon_{in\mid s} \tag{5}$$

where β_s is the vector of preference parameters for class s, X_{in} is a vector of individual and alternative specific characteristics and $\varepsilon_{in\mid s}$ represents the random component of utility for individual n of class s. The probability of individual n selecting alternative i is now partially dependent on what class of the population the respondent belongs to, with preference parameters varying by class:

$$P_{n\mid s}(i) = \frac{\exp(\beta_s X_i)}{\sum_{n=1}^{N} \exp(\beta_s X_k)} \tag{6}$$

Inclusion in a particular class is defined by socioeconomic, demographic and attitudinal characteristics hypothesized to affect preferences. Described in Table 3, the characteristics included in the final model were selected based on data exploration and preliminary models, which revealed them to be significant predictors of preferences. As outlined by Holmes and Adamowicz (2003), identification of class membership is accomplished through the following logit model:

Table 4
Response rates by mode.

	Internet	Mail	Mixed
Invitations sent	16,775	511	1019
Undeliverable invitations	1451	57	125
Delivered invitations	15,324	454	894
Complete responses	692	189	345[a]
Overall response rate	4.5%	42%	39%
MT response rate	5.9%	54%	50%
CO response rate	4.5%	35%	36%
AZ response rate	3.1%	35%	29%

[a] 291 mixed-mode responses were completed with mail hard-copy and 54 were completed on the internet.

$$P_{ns} = \frac{\exp(\lambda_s Z_n)}{\sum_{s=1}^{S} \exp(\lambda_s Z_n)} \tag{7}$$

where Z is a set of individual characteristics and λ is a vector of parameters. Selection of the number of classes is informed by the Bayesian information criterion (BIC) and Akaike information criterion (AIC) (Swait, 1994). *A priori* assumptions about the underlying elements of preference heterogeneity and the practical explanatory interpretation of the classes can also be taken into account.

The joint probability of individual n belonging to class s and selecting alternative i can also be defined as the expected value of the product of the probabilities defined in Eqs. (6) and (7),

$$P_n(i) = \sum_{s=1}^{S} [P_{n\mid s}(i) P_{ns}] = \sum_{s=1}^{S} \left(\frac{\exp(\lambda_s Z_n)}{\sum_{s=1} \exp(\lambda_s Z_n)} \right)^* \prod_{k=1}^{K} \left(\frac{\exp(X_{ink}\beta_s)}{\sum_{j=n} \exp(X_{ink}\beta_s)} \right) \tag{8}$$

where $k = 1, \ldots K$ are the choice sets presented to individual i. In order to account for ANA within a latent class framework, parameters of some or all of the attributes can be restricted for certain classes. Restricting the parameter of an attribute to zero represents the attribute being ignored and having a marginal utility of zero. Following Scarpa et al. (2009), a class is estimated in which the parameters on all of the attributes are restricted to zero, which implies ANA, and accounts for respondents who appeared to have ignored all attributes and made their choices randomly. ANA behavior was identified in preliminary model specifications, when a class of respondents was found to have the wrong sign on the parameter for BILL, indicating that these respondents were either acting irrationally by indicating a preference for higher energy bills, all else equal, or that they were exhibiting ANA behavior. Later model specifications suggest the latter explanation to be true.

In order to obtain policy relevant interpretations of the estimated coefficients, the marginal effects of each attribute must be calculated. Based on the model represented by Eq. (4), the average household marginal willingness to pay (MWTP) for a one-unit improvement in any attribute can be estimated as

$$-\left(\frac{\beta_{n\,\widehat{attribute}} + \sum_{m=1}^{M} \gamma_{nm} G_m}{\beta_{n\,\widehat{cost}} + \sum_{m=1}^{M} \theta_{nm} G_m} \right) \tag{9}$$

where G represents the fraction of the study area population that falls into each of the m socioeconomic or attitudinal categories accommodated in Eq. (3), and all other parameters are defined as above. Based on the method used by Han et al. (2008), Eq. (9) produces adjusted average household MWTP that corrects for the potential that survey respondents were not representative of the demographic characteristics of the study area as a whole. From the estimated coefficients produced by Eq. (6), for each class *1* through S, MWTP for each attribute can be estimated as.

$$-\left(\frac{\beta_{s\,\widehat{attribute}}}{\beta_{s\,\widehat{cost}}} \right). \tag{10}$$

Table 5
MNL regression results.

	Base MNL		MNL interactions	
	Coefficient	Std. err.	Coefficient	Std. err.
HOMES	0.00796***	0.00169	− 0.00582	0.00643
AIRDAYS	− 0.0461***	0.00341	− 0.0484***	0.0142
WILDFIRES	− 0.0356***	0.00837	− 0.0191	0.0323
FORESTS	0.0316***	0.00131	0.0156***	0.00474
BILL	− 0.00533***	0.000329	− 0.00454***	0.00146
ASC	0.307***	0.0435	0.314***	0.0449
SKEPTIC × HOMES			− 0.00496	0.00315
SKEPTIC × AIRDAYS			0.0167**	0.00730
SKEPTIC × WILDFIRES			0.0139	0.0174
SKEPTIC × FORESTS			− 0.0113***	0.00267
SKEPTIC × BILL			− 0.00207***	0.000717
HIGHINC × HOMES			0.00485	0.00360
HIGHINC × AIRDAYS			− 0.00921	0.00891
HIGHINC × WILDFIRES			− 0.0250	0.0199
HIGHINC × FORESTS			0.00499	0.00320
HIGHINC × BILL			0.000364	0.000793
COLLEGE × HOMES			0.00320	0.00332
COLLEGE × AIRDAYS			− 0.0265***	0.00720
COLLEGE × WILDFIRES			0.000292	0.0175
COLLEGE × FORESTS			0.00797***	0.00269
COLLEGE × BILL			− 0.00134*	0.000727
FORESTED × HOMES			0.00479	0.00310
FORESTED × AIRDAYS			− 0.00270	0.00698
FORESTED × WILDFIRES			− 0.0284*	0.0167
FORESTED × FORESTS			0.00407	0.00258
FORESTED × BILL			0.000385	0.000684
AIRQUALITY × HOMES			− 0.00464	0.00377
AIRQUALITY × AIRDAYS			0.0154**	0.00773
AIRQUALITY × WILDFIRES			0.0157	0.0196
AIRQUALITY × FORESTS			0.00256	0.00299
AIRQUALITY × BILL			0.000888	0.000825
RESTORATION × HOMES			0.0132**	0.00555
RESTORATION × AIRDAYS			0.00779	0.0123
RESTORATION × WILDFIRES			− 0.00822	0.0286
RESTORATION × FORESTS			0.0151***	0.00411
RESTORATION × BILL			0.000292	0.00124
Log-likelihood	− 4135.7		− 3997.5	
AIC	8283.5		8067.2	
BIC	8328.4		8336.0	
N	13,116		12,933	

Standard errors in second column.
* $p < 0.10$.
** $p < 0.05$.
*** $p < 0.01$.

5. Survey Response Characteristics

An equal number of surveys of each mode were sent to each of the three study states. The survey yielded 1226 total complete responses. Response rates varied by contact mode and across the three study states. Response rates were 42% for the mail-only contact group, 39% for the mixed contact-mode, and 4.5% for the internet-only contact mode. Overall, response rates were highest in Montana and lowest in Arizona, resulting in 540 responses in MT, 404 responses in CO, and 282 responses in AZ. Survey respondents were on average, older, better educated and more likely to have a household income at least $100,000 per year than the population as a whole.

Respondents were strongly in favor of restoration treatments in public forests, with almost 90% in support of forest restoration treatments. A majority (71%) of respondents were also in favor of utilizing more woody biomass from public forests for energy generation. When it comes to renewable energy production, 73% of respondents indicated a preference for more renewable energy production, but only 45% indicated that they would pay higher energy bills for renewable energy. A small majority (52%) of respondents believe that the climate is changing and that it is being caused by human activities. This is very close to the percent of people in the study area population that believe in anthropogenic climate change (Howe et al., 2015). Responses to a preliminary question regarding preferences for preferred sources of household energy revealed that respondents may view woody biomass as an inferior energy option when it comes to mitigating emissions leading to climate change. When asked to rank their top three sources of household energy, respondents ranked woody biomass 6th out of 10 options, behind hydroelectric, solar, wind, natural gas and geothermal.[3]

Responses were collected using three different modes in a stratified random design, which was stratified by state. A detailed discussion of the effects of survey mode and sample stratification by state are beyond the scope of this paper, but several things are worth noting here, and are considered in evaluation of the results. An MNL with covariate interactions was run to evaluate the effects of state and survey mode on preferences. The model yielded three significant interactions. Relative to respondents from Montana, those from Arizona had weaker preferences for forest heath and were more sensitive to increases in monthly energy bill. Relative to internet respondents, respondents to the mail-only survey had stronger preferences for forest health. However, MWTP did not differ significantly for any attributes between

[3] Woody biomass ranked ahead of nuclear, coal, oil, and crop biomass.

Table 6
Latent class model results.

	Woody biomass skeptics (class 1)		Woody biomass supporters (class 2)		Low WTP (Class 3)		Attribute non-attenders (class 4)	
	Coefficient	Std. err.	Coefficient	Std. err.	Coefficient	Std. err.	Coefficient	std. err.
Marginal utilities								
HOMES	− 0.00109	0.00371	0.0637***	0.0120	0.0437***	0.00968		
AIRDAYS	− 0.0264***	0.00891	− 0.312***	0.0409	− 0.143***	0.0264		
WILDFIRES	− 0.0540***	0.0200	− 0.166***	0.0489	− 0.326***	0.0536		
FORESTS	0.0473***	0.00642	0.0760***	0.00771	0.0836***	0.0140		
BILL	− 0.00365***	0.000650	− 0.0120***	0.00164	− 0.0696***	0.00940		
ASC	− 0.547***	0.131	1.121***	0.221	1.173***	0.226	1.050**	0.455
Class membership parameters								
SKEPTIC			0.218	0.285	1.097***	0.245	1.002***	0.314
HIGHINC			0.131	0.244	− 0.561**	0.285	− 0.926**	0.417
COLLEGE			0.816***	0.274	− 0.0887	0.238	− 0.159	0.374
FORESTED			0.0390	0.235	− 0.451**	0.226	− 0.729**	0.303
AIRQUALITY			− 1.111**	0.443	− 0.0424	0.263	− 0.226	0.381
RESTORATION			− 0.760*	0.423	− 1.268***	0.399	− 1.498***	0.478
CONFUSED			− 0.184	0.295	0.00551	0.255	0.627**	0.312
Constant			− 0.165	0.524	0.589	0.497	0.620	0.811
Posterior membership probability	35.7%		24.1%		23.0%		17.2%	
Log-likelihood	− 3786.4							
AIC	7668.7							
BIC	8027.2							
N	12,933							

* $p < 0.10$.
** $p < 0.05$.
*** $p < 0.01$.

the survey modes.

To assess the potential for nonresponse bias, the characteristics of late-respondents were compared with those who responded earlier, based on the assumption that late-respondents are more similar to non-respondents than they are to early-respondents (Armstrong and Overton, 1977). Late-respondents were identified as those who responded after receiving the reminder post card, and they represent 40% of the sample. Late-respondents were compared to the 60% of the sample who responded before the reminder post-card. Comparison of sociodemographic and attitudinal characteristics revealed that late-respondents were similar to other respondents in some ways, but differed significantly in others. Late-respondents were significantly less likely to be male, senior citizens, high income earners, or have a college degree. They were also significantly less likely to believe in anthropogenic climate change, or believe that public forests are in need of restoration, which suggests that the survey topic may have resonated less with late-respondents. However, no statistically significant differences were found between the preferences of late-respondents and others in terms of MWTP. Therefore, nonresponse bias does not appear to have a statistically significant effect on estimates of MWTP in this case.

6. Results and Discussion

Three model specifications were estimated. Two variations of the MNL were estimated and their results are presented in Table 5. Results from the latent class specification are presented in Table 6. It was expected that increases in the level of HOMES and FORESTS would be associated with increased likelihood of an alternative being selected because higher levels of both attributes are benefits (indicated by positive coefficients). Increases in AIRDAYS, WILDFIRES, and BILL, on the other hand, make the respondent worse off and are expected to decrease the likelihood of an alternative being selected (indicated by negative coefficients).

6.1. MNL and MNL-interaction Results

The base specification of the MNL utilizes only the attribute levels and the ASC to explain the alternatives selected by respondents in the choice sets. The coefficients in the MNL model are all statistically significant at better than a 1% level ($\alpha = 0.01$) and their signs are consistent with expectations. The positive coefficient on the ASC in the base model is statistically significant, suggesting a significant status quo effect.

In the MNL interactions model, HOMES and WILDFIRES are statistically insignificant, and HOMES does not have the expected sign. AIRDAYS, FORESTS and BILL are all statistically significant and have the expected signs. In this model, the coefficients on choice attributes represent the preferences of base-case respondents. Here, the base case represents respondents who believe in climate change, are not high income earners, do not have a college degree, do not live within a

Table 7
Household marginal willingness to pay per month, by class.

	Woody biomass skeptics (class 1)			Woody biomass supporters (class 2)			Low WTP (class 3)		
Attribute	Mean MWTP	95% CI		Mean MWTP	95% CI		Mean MWTP	95% CI	
HOMES	− 0.30	− 2.28	1.69	5.31	3.17	7.46	0.63	0.40	0.85
AIRDAYS	− 7.22	− 13.50	− 0.94	− 26.01	− 32.87	− 19.15	− 2.05	− 2.52	− 1.57
WILDFIRES	− 14.76	− 27.84	− 1.68	− 13.85	− 22.55	− 5.15	− 4.68	− 5.79	− 3.57
FORESTS	12.93	6.86	19.00	6.34	4.74	7.94	1.20	0.99	1.42
ASC	− 149.68	− 227.56	− 71.80	93.55	51.64	135.45	16.85	11.10	22.60

Note: MWTP for class 4 (attribute non-attenders) is constrained to zero for all attributes.

Table 8
Average monthly household MWTP.

Attribute[c]	LCL mean[a]			MNL-base[b]			MNL-interaction[b]		
	Average household MWTP ($)	95% CI		Average household MWTP ($)	95% CI		Average household MWTP ($)	95% CI	
HOMES	1.32	0.04	2.60	1.49	0.87	2.12	1.66	− 0.16	3.48
AIRDAYS	− 9.32	− 13.32	− 5.31	− 8.64	− 10.16	− 7.12	− 6.96	− 11.18	− 2.74
WILDFIRES	− 9.68	− 16.71	− 2.66	− 6.67	− 9.64	− 3.70	− 8.88	− 17.67	− 0.11
FORESTS	6.42	3.82	9.02	5.93	5.15	6.70	8.21	4.57	11.84
ASC	− 27.01	− 66.24	12.21	57.54	4.11	134.11	69.11	4.11	134.11

[a] Mean MWTP and confidence intervals for LCL model are calculated as the sum of the MWTP and confidence intervals from each group, multiplied by the respective membership probability.
[b] MWTP estimates with 95% confidence intervals for the MNL-base and MNL-interaction models were estimated with 500 bootstrap iterations using the method describe by Efron and Tibshirani (1986).
[c] MWTP for HOMES and FORESTS are for marginal increases in the level of the attribute. MWTP for AIRDAYS and WILDFIRES, on the other hand, represents willingness to pay to avoid increases in the levels of the attributes. This is consistent with the negative coefficients on AIRDAYS and WILDFIRES in Tables 4 & 5.

Table 9
Aggregate annual marginal willingness to pay.

Attribute	Annual household MWTP ($)[a]	Aggregate MWTP ($M)[b]	10% improvement from status quo in each state[c]	WTP for 10% improvement from status quo ($M)[d]
LCL model				
HOMES	15.81	75.15	2000 homes	150.30
AIRDAYS	− 111.81	− 531.48	1 fewer day	531.48
WILDFIRES	− 116.20	− 552.36	1.2 fewer wildfires	662.83
FORESTS	77.04	366.20	2 percentage points	732.40
ASC	− 324.18	− 1540.94	na	na
MNL-interactions				
HOMES	19.92	94.69	2000 homes	189.38
AIRDAYS	− 83.52	− 397.00	1 fewer day	397.00
WILDFIRES	− 106.56	− 506.52	1.2 fewer wildfires	607.83
FORESTS	98.52	468.31	2 percentage points	936.61
ASC	829.32	3942.09	na	na
MNL-base				
HOMES	17.88	84.99	2000 homes	169.98
AIRDAYS	− 103.68	− 492.83	1 fewer day	492.83
WILDFIRES	− 80.04	− 380.46	1.2 fewer wildfires	456.56
FORESTS	71.16	338.25	2 percentage points	676.50
ASC	690.48	3282.13	na	na

[a] Annual household MWTP is monthly household MWTP from Table 8, multiplied by 12 months.
[b] Aggregate annual MWTP is annual household MWTP multiplied by the 405,525 households in the Montana.
[c] Ten percent improvement is the status quo level, multiplied by 0.1 for HOMES and FORESTS, and multiplied by − 0.1 for AIRDAYS and WILDFIRES.
[d] WTP for 10% improvement from status quo is unit change for 10% improvement, multiplied by aggregate MWTP.

forested ecoregion, and do not think poor air quality negatively affects their community. As in the base MNL, the interactions model has a positive and significant ASC, indicating that respondents had a preference for the status quo option, regardless of the change in the levels of the attributes.

Coefficients on the interaction terms describe the effects that individual characteristics have on preferences for each attribute. The significant negative coefficient on COLLEGE × BILL indicates that people with a college education are more sensitive to increases in BILL than respondents without a college education. This may be a result of these respondents better accounting for their budget constraints. Although they have a higher sensitivity to BILL, the significant positive coefficient on COLLEGE × FORESTS and the significant negative coefficient on COLLEGE × AIRDAYS indicate that college graduates have higher MWTP than others for FORESTS and AIRDAYS. The significant negative coefficient on SKEPTIC × BILL indicates that people who do not believe in climate change are more sensitive to increases in BILL than others. The significant negative coefficient on SKEPTIC × FORESTS and the significant positive coefficient on SKEPTIC × AIRDAYS indicate that these people also have lower MWTP for FORESTS and AIRDAYS.

The positive and significant coefficient on AIRQUALITY × AIRDAYS suggests that people who think that their community is negatively affected by poor air quality actually have lower WTP to avoid increases in poor air quality days than respondents who do not think poor air quality affects their community. People who live in forested areas have stronger preferences for avoiding increases in the number of large wildfires, as indicated by the significant negative coefficient on FORESTED × WILDFIRES. The interactions produced with the forest restoration opinion variable show that people who think that public forests are in need of restoration have higher WTP for both HOMES and FORESTS.

6.2. Latent Class Model

The LCL model was specified using all of the variables that appear in the MNL-interactions model. Model specifications ranging from two to six classes were run and a four-class model was selected as the best specification based on AIC and BIC. The need for a restricted class was recognized when the sign on BILL was positive and significant in one of the classes in earlier iterations of the LCL model, suggesting a class of respondents were ignoring the cost associated with each alternative, or selecting alternatives with higher cost, all else constant. Multiple levels of ANA and various numbers of restricted classes were explored. The specification with a single class representing complete ANA was found to best fit the data. Consequently, class 4 in the final model specification represents complete ANA, with all attribute parameters restricted to zero. In an attempt to explain the behavior of the ANA class, the variable CONFUSED, defined in Table 3, was added to the model.

As shown in Table 6, with the exception of the coefficient on HOMES for class 1, all coefficients for all choice attributes are statistically significant and have the expected sign, for all classes. All classes have reserved their lowest MWTP for HOMES. MWTP with 95% confidence intervals were estimated for each class using the delta method (Hole, 2007), and are presented in Table 7.

Class 1 is the reference class and represents the largest share of respondents with 36%. Determinants of class membership for the other classes are interpreted with respect to class 1. Members of class 1 are the most concerned about climate change and the need for forest health restoration treatments. They have a strong preference for change away from status quo management of public forests (negative ASC); however, they are also the class that is least interested in generating energy from woody biomass. This suggests members of class 1 support active management to restore forest health, but view woody biomass energy as an unappealing or ineffective method for addressing these issues. The characteristics and preferences that define class 1 suggest that it represents respondents who are skeptical or uncertain about woody biomass energy. This class has been labelled "woody biomass skeptics."

Class 2 is the second largest of the classes, representing 24% of respondents. They have been labelled "woody biomass supporters." Members of class 2 are highly educated and were least confused by the survey. They have statistically significantly higher mean MWTP for HOMES and AIRDAYS than any other class. The fact that class 2 has the highest mean MWTP for AIRDAYS, while also being the least likely to feel that their community is negatively affected by poor air quality, conforms with the positive coefficient on AIRQUALITY × AIRDAYS in the MNL interactions model. It seems that people who live in communities with better air quality are less willing to accept reduced air quality than people who live in communities with poorer air quality to begin with. The lower willingness to accept degraded air quality amongst residents of communities without a history of poor air quality may be explained by loss aversion, which states that once an individual owns or possesses something, giving it up feels like a loss. Loss aversion is one explanation for the endowment effect, in which individuals value an item more highly if they already own it.

Classes 3 and 4 have similar class membership parameters to one another and together account for 40% of respondents. They are characterized as having low or zero MWTP for all attributes. The attributes in the survey instrument did not resonate with members of classes 3 and 4. Relative to classes 1 and 2, member of classes 3 and 4 are significantly less likely to believe in anthropogenic climate change, earn more than $100,000 per year, or live in a forested ecoregion. Relative to members of class 1, they are also significantly less likely to believe forests are in need of restoration treatments. Although not statistically significant, members of classes 3 and 4 are also less likely than classes 1 and 2 to have a college education. These people are skeptical about climate change and do not live in forested ecoregions, so forest health, wildfire risk and woody biomass energy appear to be less relevant to them.

Classes 3 and 4 are distinguished from one another by the fact that that while members of class 3 do report small MWTP for all choice attributes, MWTP estimates for class 4 members are not statistically significantly different from zero as a result of restrictions placed to account for ANA. The parameter coefficients for all attributes for class 4 were constrained to zero, representing respondents making random choices with no regard to the levels of the attributes in the alternatives. Members of class 4 are statistically significantly more likely to be confused by the survey than the members any other class. The significantly higher likelihood for members of class 4 to have felt that the survey was confusing suggests that the apparently random choices made by these respondents is due, at least in part, to confusion or lack of willingness to invest the cognitive effort required by the survey.

Constraining MWTP estimates for class 4 to zero is justified under either of two potential explanations for the attribute non-attendance. First, because the constraints on class 4 represent complete ANA, it may be that none of the attributes are relevant to the respondent and the WTP for these respondents is truly zero. Second, if the non-attendance is related to cognitive burden and the use of heuristics, as suggested by the higher levels of confusion for this class, then although the true WTP for these respondents may be greater than zero, the respondents did not express their true preferences and welfare estimates will be biased by their inclusion in the analysis. Without certainty about their true preferences, the most conservative approach is to constrain WTP for all attributes to zero for the 17.2% of respondents represented by class 4.

6.3. Aggregate Willingness to Pay and Model Comparison

Estimates of MWTP from the LCL, MNL-interaction, and MNL-base models are shown in Table 8. Mean MWTP values and 95% confidence intervals from the LCL have been calculated as the sum of the mean MWTP and associated confidence intervals from each group, multiplied by the respective membership probability. Even with 17.2% of the sample constrained to a mean MWTP of zero for all attributes (representing the restricted ANA class), the LCL produced higher mean estimates for AIRDAYS, and WILDIRES. Mean MWTP for HOMES and FORESTS are higher in the MNL interaction model. However, mean MWTP for HOMES is not statistically different from zero in the MNL interactions model.

According to three measures of goodness of fit (log-likelihood, AIC, and BIC), the LCL model provides a better fit to the data than the MNL models and therefore the remainder of the discussion focuses on the results of the LCL model.

Because of the differing units by which the attributes are defined, it is difficult to directly compare the magnitudes of the MWTP estimates across attributes. However, calculating WTP for a ten percent improvement in each attribute can facilitate a more direct comparison. As shown in Table 9, mean annual household MWTP for each attribute is aggregated for the 4.75 million households in the three states that were sampled to represent the study area (Census Bureau, 2010). This is then multiplied by the number of units in a 10% improvement from the status quo. For comparison, results are provided for all three model specifications in Table 9. Based on the results from the LCL, according to this metric, WTP for improved forest health is the largest amongst all of the attributes, at little over $732 million annually. This is followed by aggregate annual WTP for WILDFIRES and AIRDAYS at $663 million and $531 million, respectively. Viewed through this lens, it is clear that WTP for HOMES is substantially smaller than the other attributes, at $150 million annually. Note that the MWTP values for AIRDAYS and WILDFIRES are negative, indicating a MWTP for decreases, or to avoid increases, in the levels of those attributes. Total WTP for a 10% improvement, on the other hand, is positive for all attributes, because the change in the attribute levels has been defined as an improvement from the status quo.

7. Conclusion

The primary goal of this study was to quantify the preferences that residents of the US Mountain West have toward the utilization of woody biomass harvested from public forests for energy generation and the potential environmental effects associated with it. The findings have important policy implications for the social acceptance of utilizing woody biomass from public forests in this region for energy generation. A choice modeling survey was used to estimate MWTP for attributes representing four variables: amount of energy generated with woody biomass, forests health, avoided increases in the number of large wildfires, and avoided days experiencing degraded air quality. Multiple models were fit to the data and the latent class logit model was found to provide the best fit of the data.

Results from the LCL revealed positive mean MWTP for all of the attributes in the study. Positive mean MWTP for HOMES suggests that from a socioeconomic perspective, the production of more energy from woody biomass than the free market will provide is likely more efficient because of the failure of the free market to account for nonmarket benefits. However, MWTP for HOMES is smaller than for the other attributes, suggesting that the public would not be willing to accept significant decreases in forest health, increases in the likelihood of large wildfire, or reduced air quality in order to achieve higher amounts woody biomass energy. On the other hand, the MWTP for the non-energy attributes suggests that if increased woody biomass energy generation can facilitate more forest treatments that improve the condition of public forests, substantial additional benefits may be gained.

Results also revealed significant heterogeneity in preferences that are tied to respondent sociodemographic and attitudinal characteristics. Preferences toward woody biomass energy can be described in terms of

4 distinct classes: "woody biomass supporters", "woody biomass skeptics", "respondents with low WTP", and "attribute non-attenders". The presence of multiple classes of preference structures suggests that distributional effects may exist with regards to the impacts of changes in public land management and energy policies. Given the size of the "woody biomass skeptics" class, it is likely that managing public forests for woody biomass energy could produce conflict, and thus considerable work toward collaboration amongst groups with disparate positions would likely be needed. The members of the "skeptics" class have a high level of interest in public forest land management and the potential effects associated with woody biomass energy. The concerns of this class may be related to the sustainability and negative environmental impacts of woody biomass harvest, and if biomass energy can be shown to have a positive ecological influence on public forestland, the views of biomass skeptics may become more positive toward woody biomass energy. This suggests both the need for increased efforts to educate the public about potential benefits of woody biomass energy and the necessity to put in place the types of biomass energy policies that avoid or mitigate potential negative effects on the environment, including forest ecosystems and airsheds. The "low WTP" and "ANA" classes appear to be somewhat disengaged on the issue of public forestland management for energy due to a combination of beliefs about climate change and geography. Given their low level of concern for the attributes in this study, the "low WTP" and "ANA" classes will be challenging to target with outreach campaigns designed to inform people of the characteristics and potential benefits of woody biomass energy.

The potential benefits associated with woody biomass energy are more likely to be generated in certain situations than others. As a result, there are some cases where woody biomass energy generation is likely to be socioeconomically efficient, and some cases in which it is likely to be inefficient. Forest health can be improved and the risk of large wildfires reduced through thinning of forests that are currently departed from historic conditions, and air quality can be improved through the utilization of treatment residues that would otherwise be burned in open piles in the forest for disposal. In this instance, biomass energy is likely to deliver multiple benefits to stakeholders in the region who have a significant willingness to pay. In other situations, such as chipping whole green trees from land clearing to produce energy feedstock, or converting natural forest to plantation to grow trees specifically for energy, the benefits for which residents of the Mountain West are willing to pay are less likely to generated, and woody biomass energy is less likely to be socioeconomically efficient. This nuance is the crux of future biomass energy economics and policy in the region.

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