Measuring Heterogeneous Preferences for the Preservation of Prime Farmland With and Without Agrivoltaics

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Abstract: This study fills a gap in cultural ecosystem service (CES) assessment of prime farmland located in peri-urban areas by presenting results from a choice experiment recently conducted in Utah's Wasatch Front region. The choice experiment was designed to account for heterogeneous effects associated with a wide array of socio-demographic and attitudinal characteristics on household preferences for farmland preservation, including farmland used for the joint production of solar power and agricultural products. We apply a mixed-logit model to our data that controls for preference heterogeneity among Wasatch Front households along two dimensions – at the individual household level and according to different household types. We find that the typical household is willing to pay a non-trivial annual fee to preserve the region's existing peri-urban farmland, and to a lesser extent is willing to pay for agrivoltaics on that land. We also find extensive preference heterogeneity among different types of households for farmland preservation and agrivoltaics. These findings can serve as crucial components of broader land-use studies designed to account for the full range of agri-environmental ecosystem services.

Keywords: cultural ecosystem services; choice experiment; preference heterogeneity

JEL Classifications: Q15, Q24, Q57

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1 INTRODUCTION

In addition to supplying us with food, farms provide a variety of public goods conferring environmental, social, and cultural benefits, many of which are declining over time due to urbanization. In particular, peri-urban farmlands are under persistent threat of development (c.f., United Nations, 2014; Malano et al., 2014; d'Amour, 2017). According to d'Amour (2017), unchecked urban expansion is expected to result in farmland losses of up to 2.5% globally by 2030 relative to the area of peri-urban farmlands existing in 2000. From 2000-2030, the US is projected to have lost roughly 3.7 million acres due to urban expansion, translating into losses of roughly 1% of both its peri-urban farmland and associated total crop production.

Understanding the full impacts of farmland loss, including the inherent tradeoffs associated with containing it, can benefit from an ecosystem service (ES) assessment. The ES framework is designed to measure both market and non-market goods and services, and as a result has the potential to produce a more holistic valuation of agricultural and developed (e.g., residential and commercial) lands (Bateman et al., 2013; Crossman et al., 2013). A handful of assessments along these lines – assessments focusing on sustained agro-ecological systems and resilient rural communities at both the watershed and individual farm levels – can be found in the literature pertaining to other regions in the world (c.f., Fezzi and Bateman, 2011; Bateman et al., 2013; Wainger and Ervin, 2017). These assessments target provisioning (e.g., food supply), regulating (e.g., air and water quality, soil formation and nutrient regulation, etc.), and supporting (e.g., refugium and nursery functions) services, with far less attention paid to cultural ecosystem services (CES) (e.g., services attributable to aesthetics, heritage, and recreation)(Chan and Satterfield, 2020).[5] Excluding the estimation of CES associated with agricultural production runs the risk of biasing any assessment of the economic tradeoffs associated with preserving peri-urban farmland, particularly in regions incurring high land conversion rates (Daniel et al., 2012; Chan et al., 2012; Narducci et al., 2019).[6] Results from an ES assessment including CES could be used by local policymakers to ascertain a comprehensive value of prime farmlands located within the region's peri-urban areas.

For this study we focus on an agricultural region located in the US state of Utah. Utah has the 10th lowest proportion of agricultural lands in the US and is experiencing rapid urbanization, having lost over 20% of its farmland acreage from 1982 to 2015 (USDA, 2018 and 2020). The majority of Utah's prime farmland is located along the Wasatch Front (extended Salt Lake City metropolitan area), which also faces intense population pressures and potential for climate change impacts (NRCS, 1997; UDAF, 2005). The Wasatch Front is the third fastest growing region in the US, representing a significant threat to the preservation of farmland in the

[5]See de Groot et al. (2002 and 2012), MEA (2005), Gomez-Baggethun and Barton (2013), and Crossman et al. (2013) for background on the common classifications of ecosystem services.

[6] Nahuelhual et al. (2014) observe that among households in more highly developed countries CESs are frequently ranked ahead of other types of ecosystem services in terms of their importance to human welfare. Although commonly overlooked in terms of determining their value monetarily (due to their intangibility and the inherent difficulties associated with their measurement), CESs are more accessible and intuitively appreciated by people in their daily lives than other agroecosystem services (Plieninger et al., 2015; Willcock et al., 2017). See Woods et al. (2020) for further exploration of these types of issues surrounding the valuation of CESs. See Baulcomb et al. (2015) for methods used to identify different types of CESs.

region's peri-urban areas (Envision Utah, 2017; Kem C. Gardner Policy Institute, 2016, U.S. Census Bureau, 2019). Busch et al. (2005) predict that by 2030, loss of prime farmland in the Wasatch Front will reach over 12% relative to the area of prime farmland in 2000. Further, in 2016, Envision Utah (2017) reported that citizens are deeply concerned about potential impacts on food production and preservation of farming and ranching culture due to urban-development pressures and climate change.

With these trends in mind, this study centers at the juxtaposition of limited regional agriculture, the soaring loss of farmland to housing in peri-urban areas, and a citizenry concerned about the future of local agriculture and the potential ramifications of climate change. This juxtaposition depicts the interrelated challenges currently faced by numerous communities throughout the world. Our contribution to better understanding these challenges evolves from the blending of three domains: 1) the measurement of heterogeneous household preferences for alternative farmland scenarios that account for a host of unique socio-demographic and attitudinal variables; 2) the use of photorealistic visualizations to portray the farmland scenarios; and 3) a topical application of agrovoltaics, i.e., the co-development of the same area of land for the production of both solar photovoltaic energy and agriculture (Goetzburger and Zastrow, 1982).[7]

In this paper we examine the aforementioned juxtaposition within the context of a choice experiment, applying a standard mixed-logit (ML) model to our data that controls for preference heterogeneity among Wasatch Front households along two dimensions: 1) at the individual household level, and 2) according to different household types. Results from our baseline (or parsimonious) ML specification, which controls for latent preference heterogeneity at the individual household level, indicate that Wasatch Front households are willing to pay for CES associated with both existing peri-urban farmland preservation and agrivoltaics. Specifically, the typical household is willing to pay an annual fee of approximately $182 to preserve 50% (or $364 to preserve 100%) of existing peri-urban farmland within their locality, all else equal. The typical household is also willing to pay an annual fee of approximately $45 for agrivoltaics on not more than 10% of existing peri-urban farmland, again all else equal. Interestingly, if confronted with the choice of preserving an additional 50% of existing peri-urban farmland with and without agrivoltaics, we find that the typical household's welfare is unaffected. In other words, the typical household is unwilling to pay extra to secure farmland preservation in its pristine state, without agrivoltaics.

In the remainder of this paper we discuss the details of the survey instrument, the choice experiment, and the methods used to account for heterogeneous effects associated with a wide array of socio-demographic and attitudinal characteristics on household preferences for farmland preservation, development density, and the use of farmland for conventional agriculture as well as its joint use in agrivoltaics.[8] To reiterate, this study fills a gap in CES assessment of prime farmland located in peri-urban areas by presenting results from a choice experiment recently conducted in Utah's Wasatch Front region. It is also the first study to

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[7] According to Adeh et al. (2019), farmlands in general exhibit enormous potential for this type of joint production.
[8] Lopez et al. (2012) propose that joint solar production is most relevant for regions such as the Wasatch Front given its prodigious supply of solar energy.

investigate preferences with choice experiment methods regarding agrivoltaics —co-location of solar photovoltaic (PV) energy production with agriculture.

1.1 LITERATURE REVIEW

A handful of recent choice-experiment studies have been used to estimate CES associated with the preservation of farmland, but they do not account for preference heterogeneity to any great extent (Duke et al., 2012; Jianjun et al., 2013; Rewitzer et al., 2017; Sayadi et al., 2009; Wang and Swallow, 2016; Yuan et al., 2015), and they pertain to regions located outside the US Intermountain West.[9]

Duke et al. (2012) investigate the non-market benefits associated with integrated farmland preservation and management practices in a peri-urban area of northern Delaware, US. Their results suggest substantial benefits for land preservation alone. These are nonetheless similar in magnitude to the benefits obtained from a combination of management practices. The authors estimate mean household willingness-to-pay (WTP) for preservation alone to be roughly $60 per year. The study's payment vehicle is a "preservation contract" to which respondents contribute via increases in state taxes and fees (ranging from $2 to $100 per year). Duke et al. (2012) do not include visualizations of the different preservation/management scenarios in the choice experiment to mitigate potential informational bias.

By contrast, Rewitzer et al. (2017) utilize near-photo realistic images of landscape development in the Swiss Alps to distinguish their experiment's choice alternatives. Visualizations depict regionally typical vistas of alternative development scenarios to represent visual impacts of landscape change. The authors find relatively strong preferences for farmland preservation driven by CES values, as well as natural hazard protection in the mountainous region.

Wang and Swallow (2016) similarly report considerable interest among surveyed households for farmland conservation in the Alberta Capital Region of Canada. The authors estimate that a one-time increase in property taxes or rent generating $CAD 17.6 million would be acceptable to 75% of the population. WTP for conservation is highest for land used for commercial vegetable production, located near primary highways and outside of city limits. Interestingly, the authors find that the difference in WTP to conserve such land generally does not offset the higher costs of that type of land, and efficient use of limited conservation funds would result in the targeting of lower-cost grazing lands located further from the main population centers.

The limited number of related studies provides a narrow benchmark against which our empirical results can be compared. Further, we have found little research addressing the extent to which people view agrivoltaics as an amenity or disamenity. Farmland has enormous potential for joint energy and food production (Adeh et al., 2019, Dinesh and Pearce, 2016). As such, agrivoltaics could conceivably play a role in helping to meet increasing demand for low-carbon electricity generation while simultaneously preserving productive agricultural land (Majumdar et al., 2018). To our knowledge, only a handful of recent studies explore the

[9]Bergstrom and Ready (2008) review earlier stated- and revealed-preference studies valuing farmland preservation in the eastern US and Canada, and in general find results qualitatively similar to those reported in these more recent studies. See Milcu et al. (2013) for a literature review of the broader CES literature.

environmental and aesthetic impacts of photovoltaic landscapes (Salak et al., 2021; Scognamiglio, 2016; Taylor, 2015). As Salak et al. (2021) point out, renewable-energy driven landscape transformation can lead to highly relevant visual-aesthetic impacts, the perceptions of which are heterogeneous (e.g., perceptions depend upon individuals' current and previous residences, how they have been socialized, where they spend their leisure time, etc.). Ultimately, renewable-energy landscapes can be perceived as environmentally-friendly, clean and inexhaustible, safe and socio-economically beneficial on the one hand, but associated with injustice, cost increases, yield limitations and loss of competitiveness on the other. Further, these landscapes can be perceived as contributing to sustainable development on a global scale, but also as contributing to unwanted mechanization. In other words, globally renewable-energy landscapes may be linked more to opportunities than threats, yet viewed negatively at the local level.

Visual representations offer a unique medium to convey alternative future scenarios and can augment text-based descriptions to increase understanding. Visualizations have been used in related research in environmental management (e.g. Orland 1992, Chamberlain and Meitner 2012), policy making (Shaw et al. 2009), future scenario modeling for eliciting landscape preferences (Meitner et al. 2005), and community engagement (Schroth et al. 2011, Sheppard 2012). Related choice-experiment research has applied visual techniques to survey values related to land-use change (Bateman et al 2009) and trade-offs for flood protection (Ryffel et al. 2014). However, the implementation of visualizations within choice experiments for the evaluation of farmland CES is limited (Rewitzer et al. (2018) is a rare exception).

1.2 STUDY LOCATION: UTAH'S WASATCH FRONT REGION

The Wasatch Front is Utah's largest metropolitan region (see Figure 1). It is located in the north-central part of the state, comprising Weber, Davis, Salt Lake, and Utah Counties. The region stretches along, and is hemmed in by, the Wasatch Mountain range to the east and the Great Salt Lake to the west. Proximity to the mountains provides readily available access to freshwater in one of the driest states in the US. The region has experienced considerable population growth since the 1950s—its population increasing by over 300% to its current three million residents, with projections of the population reaching six million residents by 2065 (Perlich et al., 2017). Much of the remaining undeveloped land and farmland is rapidly being converted to housing, likely due to the continued demand for single family housing (Tian et al, 2015) coupled with population growth.

[INSERT FIGURE 1 HERE]

We focus on two cities within this region – Spanish Fork in the south and Layton toward the north (see Figure 2). These communities have experienced high rates of population growth and land-use change since 2000, yet they retain extensive tracts of adjacent farmland. This retention of farmland has occurred in spite of the agricultural sector currently employing only 0.5% of the population in Spanish Fork and 0.2% in Layton (U.S. Census Bureau, 2019). Details and rationale for selecting these two communities as our study area are elaborated on in Woods et al. (2020).

[INSERT FIGURE 2 HERE]

Between 2000 and 2010 population in Spanish Fork grew by more than 70%. Currently, 40,000 residents (U.S. Census Bureau, 2019) reside in Spanish Fork, with population expected to increase by another 80 percent by 2050. Agricultural production is still prominent in Spanish Fork. The city lies within Utah County, which ranks second in the state for total agricultural products sold (NASS, 2017a). The city of Layton has a population of over 77,000 and experienced growth of 15% between 2000 and 2010 (U.S. Census Bureau, 2019). The city's population is anticipated to increase by an additional 40% by 2050. Layton lies within Davis County, which ranks in the middle of total agricultural products sold by county (NASS, 2017b). Between 2012 and 2017, both Davis (Layton) and Utah Counties (Spanish Fork) witnessed decreases in total farmland acreage and average parcel sizes; decreases ranging from 6 to 12%.

Broadly speaking, the combination of economic and population growth currently being experienced in the region, coupled with households' attitudes and preferences for farmland preservation, present urban and regional planners with ample opportunities to design alternative neighborhood- and watershed-level configurations, but with associated risk. Urban and regional planning strategies need to be aligned with the key determinants of residents' quality of life—transportation to and from places of employment, access to social amenities, related environmental impacts, and salient neighborhood characteristics. Impending population growth stands to exacerbate any misalignments. To hone their models and designs, planners require information about quality-of-life determinants directly from the region's households; information obtained through surveys and experiments, such as the choice experiment to which we now turn our attention.

2 METHODS

We begin this section with a discussion of the survey instrument and embedded choice experiment designed to elicit heterogeneous household preferences for different farmland preservation scenarios. We then discuss the procedures used to recruit residents of Spanish Fork and Layton to participate in the survey.

2.1 THE SURVEY INSTRUMENT AND CHOICE EXPERIMENT

The survey instrument developed for this study uses a socio-cultural valuation approach to identify and better understand CESs in the cities of Spanish Fork and Layton (Infield et al., 2018; Gould et al., 2015). To ensure that our survey design elicited a wide range of values associated with agroecosystem CESs, we operationalized the survey questions and had experts and stakeholders review and revise our survey. We then piloted a web version of the survey instrument, created in Qualtrics XM, with graduate students and professors at Utah State University (USU).[10] This round of testing was essential for flagging potential design flaws and informing any needed final revisions to the self-administered online survey.

As discussed more fully in Woods, et al. (2020), operationalization separates latent variables into subdomains that can then be unpacked into measurable concepts (Dillman et al., 2014).

[10] A copy of the web-based survey instrument is available as a supplementary online appendix.

For this study, CESs were divided into eight operationalization subsets, six of which had been previously delineated by the Millennium Ecosystem Assessment (MEA, 2005), encompassing cultural identity, heritage values, spiritual and religious values, inspiration, aesthetics and recreation. Educational opportunities and local productivity (i.e., opportunities for purchasing locally grown food or fiber) subsets were added, as they are recognized as emerging concepts within the CES literature (Chan et al., 2012; Fish et al., 2016). Following Cheng et al. (2019) and Gould et al. (2015), our survey considers the range of commonly recognized CES categories. Specific CES questions were adapted from Schmidt et al. (2017). Standard socio-demographic questions, drawn from the U.S. Census American Community Survey (ACS), composed the final section of the survey.

The choice experiment was designed as part of a broader study that evaluates individuals' use of and preferences for land development and farmland preservation. For the experiment, we developed three different choice blocks consisting of six unlabeled choice sets. The blocks and sets were randomized for each respondent. Each choice set consisted of two separate alternatives (A and B) and an "opt-out" status quo option (Alternative C).[11] The status quo option depicted a fully developed residential area, indicating a complete conversion of land use from agricultural to residential. This was intentional, for two reasons: 1) the trajectory of residential housing developments in our study sites is expected to replace agriculture in much of the urban fringe areas in the future, and 2) the experiment was designed to elicit household preferences for this inherent dynamic change. These culminate in the current reality where there are no city or countywide zoning protections against farmland conversion. Employing this forward-looking status quo option enables the depiction of an explicit, uniform, future status quo across all respondents. Further, the forward-looking nature of this option mitigates potential bias associated with implicit, household-specific, current (and therefore effectively unmeasurable) notions of the status quo for each participant.

Each choice alternative consisted of four separate attributes representing pertinent characteristics of the farmland-preservation decision. Table 1 provides information about each attribute – their variable names for the ensuing empirical analysis and the respective intervals of their values. These variables were provided to survey participants in text and image form. As indicated in the table, the attribute *Preserve* refers to the percentage of existing peri-urban farmland preserved (ranging from 0% to 100%). This attribute represents different development densities, applying similar residential design vernacular as nearby developments for each study site. Attribute *Practice* refers to the type of farming practice and represents CESs provided by agricultural heritage, as well as landscape aesthetics.

[INSERT TABLE 1 HERE]

As mentioned in the table's footnotes, we convert this attribute to *Practice4* = 1 if existing peri-urban farmland is managed as a horse pasture, zero otherwise. We created a dummy variable for horse pasturage because until the Agricultural Improvement Act (Farm Bill) of 2018

[11] See Adamowicz et al. (1998), Boxall et al. (1996), and Hensher et al. (2015) for broad perspectives on the choice-experiment method.

horses were not officially designated as livestock at the federal level. Yet, perceptually, horse pasturage may be considered unique to residents from other *Practice* categories. Implementing horse pasturage as *Practice4* is designed to control for the perceptual effects.[12] The attribute *Energy* refers to whether or not solar panels are installed. We indicate that solar panels would occupy no more than 10% of preserved agricultural land. The percentage represents a middle ground between some existing state regulations (e.g., Rhode Island 20%, A.B. S0570, 2017, New York 1%, A.B. S1538, 2009). Lastly, the *Cost* attribute reflects an alternative's annual cost of farmland preservation (ranging from $10 to $200) based upon ranges of costs found in the literature (e.g., Duke et al., 2012, and Wang and Swallow, 2016).

One of the unique features of this study concerns how we contextualize the collection mechanism associated with the *Cost* attribute. Rather than predetermine the mechanism, we queried the respondent's preferred method of funding local public goods (such as farmland preservation) in a previous survey question. The text of the question reads as follows,

> *"One way to preserve farmland in [Layton or Spanish Fork] is through new taxes. These taxes can leverage existing resources so farmland or development rights can be purchased. With either of these purchases, some or all existing farmland would be maintained as farm or open space instead of housing or commercial development. If preserving farmland in [Layton or Spanish Fork] required your taxes to increase, which type of tax would you prefer?"*

Possible answers to this question include property tax, income tax, and sales tax, as well as the statements (1) "I support taxation for this purpose, but do not have a tax preference", (2) "I am fundamentally opposed to using taxation for this purpose", and (3) "Unsure". Later, when comparing actual choice alternatives, respondents are instructed to imagine paying for their preferred alternative according to their preferred payment method (as indicated by their respective answers to the above question). As a result, this question provides two 'layers of control' for potential protest voting. One layer, which registers potential protest voting explicitly, is the opportunity for a respondent to choose statement (2) in answer to the question, and then choose the status quo option in each of the subsequent six choice situations. The other layer, which controls for protest voting implicitly, is that in choosing between alternatives the respondent's choice is in no way confounded by a predetermined, universal payment method that the respondent may not prefer. Therefore, when a respondent chooses the status quo, we are confident that the choice was not influenced by a predetermined payment method. The issue of potential protest voting is further explored in Section 3.

For each of the different choice sets and alternatives (including the status quo) a visual representation augments the text-based description. The graphical representations of CES were developed using Adobe Photoshop software with Google Street View imagery of one location for each study site. The image was modified through combinations of different housing

[12] We also created dummy variables for each farming practice, e.g., *Practice1* = 1 if the existing peri-urban farmland is managed cut hay, zero otherwise; *Practice2* = 1 if the land is managed for an early-season dryland crop, zero otherwise; etc. Running our regressions with these dummy variables in place of *Practice4* did not qualitatively change our results.

development densities, solar panels, and a range of different farming practices (e.g. ranching, orchard, alfalfa).

An example choice situation is provided in Figure 3. In this particular situation the respondent is asked to choose between Alternative A, which preserves 50% of existing peri-urban farmland in an orchard with agrivoltaics (i.e., solar panels installed on no more than 10% of the land) at an annual cost of $10, Alternative B, which preserves 100% of the existing peri-urban farmland as horse pasturage with no agrivoltaics at an annual cost of $50, and the status quo (Alternative C), which depicts full residential development on existing peri-urban farmland with no annual cost to the respondent's household. The status quo is always designated Alternative C, and is associated with no annual cost. By contrast Alternatives A and B consist of some percentage of farmland preservation (either 50% or 100%) with or without agrivoltaics at a non-zero annual cost.

[INSERT FIGURE 3 HERE]

We developed a D-efficient fractional factorial design for the experiment (which corresponds to a 3x5x2x6 full factorial design matrix, as indicated by Table 1) using the Fedorov algorithm (Cook and Nachtsheim, 1980; Zwerina et al., 1996, and Carlsson and Martinsson, 2003). Following the method developed by Hole (2015), we created a design consisting of three blocks of six choice situations, where blocks were randomly assigned across respondents (i.e., each respondent was assigned one randomly chosen block of six choice situations). The design's D-efficiency score after eight iterations was 1.373.[13]

2.2 PARTICIPANT RECRUITMENT

The survey was administered to a simple random sample of residents in Spanish Fork and Layton. Sample frames were developed from residential address point data available through the Utah Automated Geographic Reference Center (AGRC 2019). Slightly less than 500 households were sampled in each city. Sample sizes were determined to obtain a precision level ±5% with a 95% confidence level and $p = 0.05$, but were increased by 25% to account for potentially low response rates (Israel, 1992; Grala et al., 2012). A modified Dillman method (Dillman et al., 2014) was used to accommodate budgetary limitations (less than $2,000 available for recruitment). Selected households received three invitations to complete an online self-administered survey, with the option of completing a print version. A financial incentive was offered in the form of a raffle for a gift voucher to increase response rates.

We contacted participants between November 25, 2019 and January 3, 2020. Our recruitment materials included two letters, the initial and final mailings, and a reminder postcard sent between letters. Households were limited to one submission. A total of 29 surveys were completed online from our Spanish Fork sample frame, and 37 surveys completed for Layton, resulting in initial response rates of approximately 6% and 8%, respectively.[14]

[13] We applied Stata's *Dcreate* routine to create the design (Stata/IC 14.2 for Windows (64-bit x86-64). It is commonly believed that an efficiency score above one indicates an efficient design.

[14] Duke et al. (2012) and Rewitzer et al. (2017) report response rates of 47% and 43%, respectively. Wang and Swallow (2016) do not report their survey's response rate. In their meta-analysis of response rates from choice

As a result of our relatively low initial response rates and potential selection bias, we tested for the presence of both biases in our sample (Smyth et al., 2010).[15] Due to budget limitations, we restricted our test to the Spanish Fork subsample. Following Grala et al. (2012), we randomly sampled a subset of non-respondent households, but instead of contacting them by phone we distributed self-administered surveys in early February 2020 using the drop-off pick-up method (DOPU) (Trentelman et al., 2016), which has demonstrated high response rates in Utah. The DOPU method resulted in 26 more surveys (total 11% response rate in Spanish Fork). We then conducted Pearson's chi-square and Mann-Whitney U tests to detect differences across original Spanish Fork respondents who submitted their surveys online and respondents who completed their surveys during the non-response DOPU testing phase in Spanish Fork.

The Pearson's chi-square tests indicate no statistically significant difference between online and DOPU respondents in Spanish Fork in terms of gender ($\chi^2(1) = 0.121$, $p = 0.728$), education ($\chi^2(5) = 5.003$, $p = 0.416$), religious affiliation ($\chi^2(3) = 1.396$, $p = 0.706$), race/ethnicity ($\chi^2(3) = 2.038$, $p = 0.565$) or annual income ($\chi^2(4) = 7.431$, $p = 0.115$). A Mann-Whitney U test confirms the Pearson's chi-square findings, and further reveals that age for online respondents does not significantly differ from DOPU respondents ($U = 287.500$, $p = 0.265$). These results suggest that the null hypothesis of no relationship existing between survey-administration approach (online vs. DOPU) and survey responses cannot be rejected.[16]

2.3 THEORETICAL MODEL

Choice decisions in our experiment can be depicted by a random utility model (Hensher et al., 2015). The participant representing household i selects the alternative j in each choice situation k that yields the highest utility level for the household, expressed as,

$$\underset{\{\boldsymbol{w}_{ijk}\}}{Max}\ U_{ijk}(\boldsymbol{w}_{ijk}) + \varepsilon_{ijk}, i = 1, \dots, N, j = 1, \dots 3, k = 1, \dots, 6. \quad (1)$$

Specifically, household i's utility $U_{ijk}(\boldsymbol{w}_{ijk})$ is a function of explanatory variables $\boldsymbol{w}_{ijk}$, where $j = 1, \dots, 3$ denotes that each choice situation consists of three alternatives, $k = 1, \dots, 6$ denotes that each participant is presented with six randomly provided choice situations, and a total of N households are represented in the choice experiment. Matrix $\boldsymbol{w}_{ijk}$ in turn consists of two sub-matrices, $\boldsymbol{x}_{ijk}$ and $(\boldsymbol{x}_{ijk} \cdot \boldsymbol{z}_{ijk})$, with $\boldsymbol{x}_{ijk}$ containing alternative-specific attributes and their corresponding levels from Table 1 (including interactions among the different attributes in order to explicitly measure trade-offs existing among them), and $(\boldsymbol{x}_{ijk} \cdot \boldsymbol{z}_{ijk})$ containing household-specific socio-demographic and attitudinal variables taken from Table 2 and 4

experiment studies in general, Watson et al. (2016) report an average response rate of roughly 50% for experiments consisting of at most four attributes.

[15] Potential sample selection bias also exists because even though 98% of residents in both Layton and Spanish Fork have access to wired broadband of 25 mpbs or faster, respondents must nevertheless be computer-literate to participate in online surveys (U.S. Census Bureau, 2019; Willcock et al., 2017).

[16] See Woods et al. (2020) for further information about the outcomes of these statistical tests.

(denoted by matrix $\boldsymbol{z}_{ijk}$) interacted with a subset of attributes from $\boldsymbol{x}_{ijk}$ (the specific subset depending upon the particular regression equation being estimated).

Lastly, random component ε_{ijk} in equation (1) accounts for the econometrician's uncertainty in estimating household i's set of marginal utilities associated with matrices $\boldsymbol{x}_{ijk}$ and $(\boldsymbol{x}_{ijk} \cdot \boldsymbol{z}_{ijk})$. For estimation purposes, ε_{ijk} is assumed to be independently and identically distributed extreme value across all households and alternatives, and uncorrelated with matrices $\boldsymbol{x}_{ijk}$ and $(\boldsymbol{x}_{ijk} \cdot \boldsymbol{z}_{ijk})$. As pointed out by Williams and Ortuzar (1982), Hicks and Strand (2000), Louviere et al. (2005), and Guevara and Ben-Akiva (2006), to the extent that relevant attributes are included in, and irrelevant attributes are omitted from, the study's experimental design, this latter assumption of ε_{ijk} being uncorrelated with matrices $\boldsymbol{x}_{ijk}$ and $(\boldsymbol{x}_{ijk} \cdot \boldsymbol{z}_{ijk})$ is justifiable, i.e., under these conditions we can assume an absence of endogeneity in the empirical model that might otherwise bias estimates of the marginal utilities associated with $\boldsymbol{x}_{ijk}$ and $(\boldsymbol{x}_{ijk} \cdot \boldsymbol{z}_{ijk})$.

Within the ML framework we are able to control for preference heterogeneity in two dimensions. First, the coefficients associated with $\boldsymbol{x}_{ijk}$ are estimated as random parameters across individual households. Second, the coefficients associated with $(\boldsymbol{x}_{ijk} \cdot \boldsymbol{z}_{ijk})$ are estimated as constants. The first set of coefficients controls for latent, household-specific preference heterogeneity, while the second set identifies specific sources of the heterogeneity across different household types (Alpizar et al., 2003). Following Revelt and Train (1998) and Caplan et al. (2007), we specify the utility function in (1) in linear form,

$$U_{ijk}(\boldsymbol{w}_{ijk}) = \boldsymbol{\alpha}_i \boldsymbol{x}_{ijk} + \boldsymbol{\beta}(\boldsymbol{x}_{ijk} \cdot \boldsymbol{z}_{ijk}) + \varepsilon_{ijk}, \quad (2)$$

where matrix $\boldsymbol{\alpha}_i, i = 1, \dots, N$, and vector $\boldsymbol{\beta}$ contain our empirical model's respective coefficient estimates. Specifically, $\boldsymbol{\alpha}_i$ represents the matrix of household-specific marginal utilities associated with the different attributes and attribute levels contained in Table 1, which in turn are represented by matrix $\boldsymbol{x}_{ijk}$. We assume that $\boldsymbol{\alpha}_i = \boldsymbol{\alpha} + \boldsymbol{\sigma}\boldsymbol{v}_i$, where $\boldsymbol{\alpha}$ represents a vector of constant mean coefficient estimates of $\boldsymbol{\alpha}_i$ (derived across households $i = 1, \dots, N$ from an MNL specification of the model), $\boldsymbol{\sigma}$ denotes the vector of standard deviations of the corresponding attribute levels, and $\boldsymbol{v}_i$ is a vector of associated error terms, distributed standard normal (Hensher et al., 2015). Vector $\boldsymbol{\beta}$ in equation (2) represents the average household's marginal utilities associated with the set of interaction terms included in matrix $(\boldsymbol{x}_{ijk} \cdot \boldsymbol{z}_{ijk})$. Equation (2) is estimated using Stata/IC 14.2 for Windows (64-bit x86-64).

For future reference, we denote $\bar{\alpha}^c$ as the mean estimate of the marginal disutility of a 10% increase in Home/Rental Cost, and $\bar{\alpha}^a$ as the mean estimate of the marginal utility associated with attribute level a from Table 1 (each measured across their respective household-specific coefficient estimates contained in $\boldsymbol{\alpha}_i$). Similarly, coefficient β_z^c represents an estimate of the added marginal disutility of a 10% increase in Home/Rental Cost interacted with socio-demographic or lifestyle variable z, and β_z^a represents an estimate of the added marginal utility associated with the interaction between variable z and attribute level a.

2.4 EMPIRICAL MODEL

Denoting the deterministic portion of equation (2) as V_{ijk}, i.e., $V_{ijk} = \boldsymbol{\alpha}_i \boldsymbol{x}_{ijk} + \boldsymbol{\beta}(\boldsymbol{x}_{ijk} \cdot \boldsymbol{z}_{ijk})$, the logit model defines household i's conditional choice probability for the first alternative, $j = 1$, in comparison k as,

$$p_{i1k}(\boldsymbol{\alpha}_i, \boldsymbol{\beta}) = \frac{e^{V_{i1k}}}{e^{V_{i1k}} + e^{V_{i2k}}}, \tag{3}$$

where $p_{i1k}(\cdot)$ represents the conditional probability that household i ranks alternative 1 over alternative 2 in choice comparison k, and e is Euler's number (Rouwendal and Meijer, 2001).[17] Following Rouwendal and Meijer (2001), Revelt and Train (1998), and Hole (2007), the probability that household i ultimately makes the particular sequence of choices over the six choice situations conditional on knowing $\boldsymbol{\alpha}_i, i = 1, \ldots, N$, and $\boldsymbol{\beta}$ can be expressed as,

$$P_i(\boldsymbol{\alpha}_i, \boldsymbol{\beta}) = \prod_{k=1}^{6} p_{ij^*k}(\boldsymbol{\alpha}_i, \boldsymbol{\beta}), \tag{4}$$

where j^* represents the alternative ($j = 1$ or $j = 2$) actually chosen in situation k.

The unconditional probability of the observed sequence of choices for household i is then conditional probability $P_i(\boldsymbol{\alpha}_i, \boldsymbol{\beta})$ integrated over the distribution for $\boldsymbol{\alpha}_i$, with the $\boldsymbol{\beta}$ estimates effectively serving as constants of integration. This probability can be expressed as,

$$\mathcal{L}(\boldsymbol{\alpha}, \boldsymbol{\sigma}) = \int P_i(\boldsymbol{\alpha}_i, \boldsymbol{\beta}) f(\boldsymbol{\alpha}_i | \boldsymbol{\alpha}, \boldsymbol{\sigma})\, d\boldsymbol{\alpha}_i, \tag{5}$$

where $f(\boldsymbol{\alpha}_i | \boldsymbol{\alpha}, \boldsymbol{\sigma})$ is household i's conditional density function for $\boldsymbol{\alpha}_i$, assumed standard normal via our previously stated distributional assumptions on $\boldsymbol{v}_i$. As Train (2003) and Hole (2007) show, this expression cannot be solved analytically across $i = 1, \ldots, N$, and is therefore approximated using simulation methods. The simulated log likelihood function, $\mathcal{LL}_s(\boldsymbol{\alpha}, \boldsymbol{\sigma})$, is expressed as,

$$\mathcal{LL}_s(\boldsymbol{\alpha}, \boldsymbol{\sigma}) = \sum_{i=1}^{N} ln\left[\frac{1}{R}\sum_{r=1}^{R} P_i(\boldsymbol{\alpha}_i^r, \boldsymbol{\beta})\right], \tag{6}$$

where R is the number of replications for the simulation (in our case 500) and $\boldsymbol{\alpha}_i^r$ is the r^{th} draw from conditional density $f(\boldsymbol{\alpha}_i | \boldsymbol{\alpha}, \boldsymbol{\sigma})$.

Based upon previously defined $\bar{\alpha}^c$ and $\bar{\alpha}^a$, the marginal willingness to pay (MWTP) of attribute level a can then be expressed as,[18]

$$MWTP_a = -\frac{\bar{\alpha}^a}{\bar{\alpha}^c}. \tag{7}$$

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[17] In like fashion, household i's choice probability for the second alternative, $j = 2$, in comparison k is written as $p_{i2k}(\boldsymbol{\alpha}_i, \boldsymbol{\beta}) = (1 - p_{i1k}(\cdot)) = \frac{e^{V_{i2k}}}{e^{V_{i1k}} + e^{V_{i2k}}}$.

[18] MWTP can be calculated as the ratio of the two coefficients due to the linear-preference assumption expressed in equation (2). See Hensher et al. (2015) and Alpizar et al. (2003) for further details.

For example, if attribute level a represents *Preserve* from Table 1, then $MWTP_a$ measures the household's MWTP for an additional 50% of farmland preserved. Further, using previously defined β_z^c and β_z^a, the MWTP for attribute level a associated with interaction term (a x z), which we henceforth denote as "Differential MWTP", is calculated as,

$$MWTP_{az} = -\frac{\beta_z^a}{\bar{\alpha}^c + \beta_z^c}, \tag{8}$$

Hence, if attribute level a again represents *preserve* and demographic variable z represents *highinc* from Table 2, then $MWTP_{az}$ measures a high-income household's Differential MWTP for an additional 50% of farmland preserved relative to a low-income household's MWTP for the same attribute level.[19]

As mentioned in Secton 2.1, our experimental design resulted in 18 different choice situations, and thus 18 degrees of freedom for our ensuing analysis (Hensher et al., 2015). We are therefore precluded from estimating a single "giant" model that simultaneously includes all of the attributes and associated interaction terms. Instead, we estimate separate regression models in Section 3.4 for each socio-demographic and attitudinal variable of interest. For example, the *gender* variable from Table 2 is interacted with each attribute from Table 1 in a model separate from the models interacting other attribute levels and socio-demographic/attitudinal variables. While running separate regressions obviates concerns of potential multicollinearity afflicting our results, we note that all combinations of socio-demographic or attitudinal variables included in Tables 2 and 4 exhibit correlation coefficients below 0.5 in magnitude.

3 RESULTS

Descriptive statistics of demographic data are reported in Table 2 with the US Census data for the region identified in Table 3. As Table 2 shows, *gender* is split 50%-50% (male-female) mirroring the census data. Ethnic composition (93% identify their ethnicity as being *white*), percentage *employed* (66%), and percentage of high-income (*highinc*) households (13%) closely mirror respective estimates for the region. Further, regional percentages corresponding to *gender, white,* and *employed* are relatively uniform across the specific counties comprising the region, while *highinc* is relatively low in Weber County and high in Salt Lake County.

[INSERT TABLES 2 AND 3 HERE]

Tables 2 and 3 also reveal over-representation of some household characteristics. For example, senior and middle-aged individuals represent 47% and 38% of our sample, respectively, while regional census estimates are 18% and 24%, respectively. The percentage of households in our sample identifying as members of Utah's predominant religious faith, the Church of Jesus Christ of Latter-Day Saints (78%) align with the census percentages for Davis

[19] The absence of a specific variable defined for low-income households in Table 2 defines this class of households as the baseline household income category for this study.

and Utah Counties (71% and 82%, respectively), but differ for the region overall. Further, 69% of our sampled households identify as either high-middle or low-middle income (i.e., middle income), which is slightly higher than the region's 56%. Respondents having earned a college degree make up 59% of our sample, while the census indicates 35% across the region (reaching as low as 24% in Weber County and as high as 42% in Utah County). Lastly, while 99% of our sample consists of homeowners, the corresponding US Census percentage is only 69% for the region. Our empirical results should be interpreted with these differences – between our sample and the census estimates for the Wasatch Front population – in mind.

Table 4 describes the attitudinal information collected from our participants. We note from the table that 83% of participants "strongly" or "somewhat" agrees with the statement, "Purchasing locally produced food and/or fiber is beneficial to the environment." Similarly, 77% generally believes that it is "moderately" to "very" important to preserve farmland." In contrast, only 22% of our participants self-identified as being "fundamentally opposed to using taxation to preserve farmland", and 26% would "support higher-density housing in his or her community if it resulted in more farmland preservation."

[INSERT TABLE 4 HERE]

A total of 91 households participated in the survey, resulting in a total of approximately 1,640 (91 x 18) observations initially available for analysis. Of these households, only one was removed from our sample due to what we perceive as conspicuous protest voting (by virtue of the respondent having (1) self-identified as being fundamentally opposed to using taxation to fund public goods, and (2) chosen the status quo option, Alternative C, for each of the six choice situations the individual was presented with). Again, as indicated in Table 4 over 20% of our respondents identify themselves as being fundamentally opposed to using taxation to preserve farmland (i.e., *notax* = 1). As described in Section 3, we control for these potential protest voters by including *notax* as an interaction term with the experiment's attributes to measure the extent to which this variable potentially impacts the typical household's preferences for farmland preservation.

In the following subsections, we present additional results. In Section 3.1 we present results for parsimonious specifications of equation (2), where only the marginal effects associated with the choice experiment's attributes – *preserve, practice4, energy,* and *cost* – are estimated (in effect, we assume $\boldsymbol{\beta} = \mathbf{0}$ in (2) from Section 2.3). The parsimonious model enables us to establish a baseline for these effects. We compare results across the standard multinomial logit (MNL) and mixed-logit (ML) specifications of the model, demonstrating the latter specification's improvements in both overall fit and the reliability of the individual coefficient estimates.[20]

In Section 3.2, we present results for the interactive effects of the different socio-demographic and attitudinal variables contained in Tables 2 and 4 on household preferences for farmland preservation and agrivoltaics. It is important to note that while the parsimonious ML specification controls for latent preference heterogeneity across individual households, the

[20] The MNL specification can be considered a special case of the ML specification, where estimation of the coefficient matrix $\boldsymbol{\alpha}_i$ in equation (2) is effectively restricted to equal a vector of constants $\boldsymbol{\alpha} = \boldsymbol{\alpha}_1 = \cdots = \boldsymbol{\alpha}_N$.

ML models with interaction terms further account for heterogeneous effects associated with explicit household types.

In Section 3.3 we discuss the results of internal validity tests conducted on our empirical models. The internal validity tests entail comparing the respondents' actual choices in the experiment with their stated attitudes toward farmland preservation and proximity to agrivoltaics in general.

3.1 THE PARSIMONIOUS MODEL

Table 5 presents our results for both a benchmark Multinomial Logit (MNL) and ML specifications of the parsimonious model. Note the inclusion of two previously undefined variables in these two specifications. Variable *choiceA* equals one if the respondent chooses Alternative A, zero otherwise. This alternative-specific constant is included in order to account for potential idiosyncratic "left-hand choice bias", whereby, all else equal, respondents are neurologically drawn to choosing the first (left-hand) alternative in any given choice situation (Lebovich et al., 2019). The second variable, *choiceA_duration*, further refines the potential effect of *choiceA* on respondents' idiosyncratic choices through its interaction with the amount of time respondents spend completing the survey, the hypothesis being that the shorter the survey's duration, the more likely a respondent will have chosen Alternative A in any given choice situation.[21]

[INSERT TABLE 5 HERE]

As indicated in columns two and three of Table 5, the estimated coefficient values are qualitatively similar across the two specifications of the parsimonious model in terms of sign and statistical significance. However, the ML coefficient estimates for *preserve* and *energy* are roughly three- and two-times larger than the corresponding MNL estimates, and the MNL estimate for *choiceA* is roughly three-times larger than the corresponding ML estimate. As expected, both specifications indicate positive marginal utilities associated with *preserve* and *energy*, and negative marginal utility associated with *cost*, i.e., all else equal the typical household in our sample prefers more preservation of existing peri-urban farmland and joint production of solar power, but dislikes incurring higher annual costs to obtain these goods.

The typical household is guilty of left-hand choice bias (the coefficient for variable *choiceA* is positive in both specifications), although those households completing the survey more quickly are not more prone to exhibiting this bias (the coefficient for *choiceA_duration* being statistically insignificant). Similarly, the typical household does not exhibit a statistically significant preference for farmland preserved as horse pasture (compared with a non-equine agricultural alternative) in either specification.

Summary statistics reported in Table 5 evince the ML specification's better overall fit of the data. The value of the ML specification's log-likelihood function at convergence is considerably larger than that of the MNL's (-369.42 vs. -427.77), as is the ML specification's McFadden R^2 measure (0.16 vs. 0.10). Further, the standard deviations associated with the mean coefficient

[21] The average duration for completing the survey was just under 5,000 seconds (83 minutes), with a minimum of 162 seconds (3 minutes) and a maximum of slightly more than 36,000 seconds (600 minutes).

estimates for *preserve*, *energy*, and *cost* derived for the ML specification are each statistically significant, indicating that treating these estimates as household-specific random parameters is econometrically valid (Hensher et al, 2015).[22] As a result, we henceforth confine our ensuing discussions to ML specifications of the data.

The fourth column of Table 5 reports corresponding MWTP values from the ML specification derived according to equation (7), with attendant 95% confidence intervals calculated using the Delta method (Oehlert, 1992; Rice, 2007). As indicated, the typical household is, all else equal, willing to pay an annual fee of approximately $182 to preserve 50% (or $364 to preserve 100%) of existing peri-urban farmland within their locality. The typical household also is willing to pay an additional annual fee of approximately $45 for agrivoltaics, again all else equal.

With results for the ML specification of the parsimonious model serving as our benchmark, we now turn to the results for models accounting for preference heterogeneity associated with a variety of household types.

3.2 MODELS ACCOUNTING FOR PREFERENCE HETEROGENEITY BY HOUSEHOLD TYPE

Table 6 contains results for preference heterogeneity as it affects the attribute *cost*. The first column of the table lists the specific socio-demographic/attitudinal variable respectively interacted with *cost*. Due to the sizeable number of variables included in the analysis (see Tables 2 and 4), we present solely those variables exhibiting a statistically significant relationship with *cost* (and similarly for attributes *preserve* and *energy* in subsequent tables).[23] The second column in Table 6 provides the coefficient estimates for each respective interaction term with *cost*. As an example of how the coefficient estimates in Table 6 are derived, consider the estimate for the socio-demographic variable *white*. To obtain this estimate we regressed a household's choice of alternative on randomized parameters for *preserve*, *energy,* and *practice4*, and constant parameters for *cost*, *choiceA*, *choiceA_duration* and the interaction term *cost_white*, and so forth for each variable listed in the table.

[INSERT TABLE 6 HERE]

As indicated in Table 6, households located in urban and suburban areas, households that generally believe farmland preservation is important, and households containing at least one member belonging to an environmental group are less sensitive to increases in the cost associated with peri-urban farmland preservation and/or agrivoltaics. Households whose respondents identify their ethnicity as being white, who grew up in an urban environment, and who are "fundamentally opposed to using taxation to preserve farmland" are more sensitive to cost increases. The strongest negative effect on sensitivity-to-cost arises among households

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[22] We estimated a wide variety of additional ML specifications, including models with controls for correlated coefficients (Hole, 2007) and scale heterogeneity (Gu et al., 2013). We also estimated the ML model in willingness-to-pay space (Hole, 2007). Results were qualitatively similar across each specification, signifying the robustness of the specifications reported on in this paper. The results for these alternative specifications are available from the authors upon request.

[23] The full suite of results for the regressions run to produce the results contained in Tables 6 – 9 are available upon request from the authors.

that generally believe farmland preservation is important, while households that are fundamentally opposed to taxation to preserve farmland exhibit the strongest positive effect.

Table 7 likewise contains our preference-heterogeneity results associated with attribute *preserve*. In addition to presenting solely the statistically significant coefficient estimates in column 2, Table 7 also presents the corresponding Differential MWTP estimates. As explained in equation (8), Differential MWTP for *preserve* represents the addition to (or subtraction from) a given reference household's MWTP estimate. As an example of how the Differential MWTP estimates in Table 7 are derived empirically, consider the estimates for the socio-demographic variables *highinc* and *lowmidinc* (the coefficient estimate corresponding to *himidinc* was found to be statistically insignificant). To obtain these estimates we regress a household's choice of alternative on randomized parameters for *energy* and *practice4*, constant parameters for *preserve*, *cost*, *choiceA*, *choiceA_duration*, and interaction terms *preserve_highinc*, *preserve_lowmidinc*, *cost_highinc*, and *cost_lowmidinc*. We then use equation (8) to calculate respective Differential MWTP values for *highinc* and *lowmidinc* (where the reference household is low-income).[24]

[INSERT TABLE 7 HERE]

From Table 7 we see that households stating general beliefs that farmland preservation is important and that there is currently not enough farmland preserved in Utah, as well as households that would support higher-density housing in their communities if it resulted in more farmland preservation are each willing to pay more to preserve existing peri-urban farmland than households that do not share these beliefs and preferences – on average $124, $82, and $43 more in annual fees, respectively. Households identifying themselves as being "fundamentally opposed to using taxation to preserve farmland" and that are located in urban or suburban areas are willing to pay less than households not sharing a fundamental opposition to taxation and that reside in rural areas – on average $68 and $241 less in annual fees, respectively. Surprisingly, higher- and lower-middle-income households are willing to pay less than low- and higher-middle-income households for farmland preservation – on average $102 and $84 less in annual fees, respectively. The unexpected result for *highinc* suggests that high-income households in the Wasatch Front are not as concerned about the loss of existing peri-urban farmland as they may be for other types of environmental goods.[25]

Table 8 presents preference-heterogeneity results associated with attribute *energy*.[26] As indicated, households that support agrivoltaics on nearby farmland and that would support higher-density housing in their communities if it resulted in more farmland preservation are generally willing to pay more for agrivoltaics on existing peri-urban farmland than households that do not share such support – on average $69 and $33 more per year in annual fees. Households located in urban or suburban areas are willing to pay roughly $67 more per year for

[24] In our empirical calculations, we only include the estimate for β_z^c in the numerator of equation (8) for the variables listed in Table 6, i.e., the variables whose interaction with *cost* was previously found to be statistically significant. Otherwise, we effectively assume $\beta_z^c = 0$.

[25] For example, see Kramer and Mercer (1997) and Aadland and Caplan (2006b).

[26] We also ran preference-heterogeneity models associated with attribute *practice4*, but decided not to present them here due to space limitations and the absence of *practice4*'s statistical significance in the parsimonious model. The results are available from the authors upon request.

agrivoltaics than rural households. And households that have lived in their current residences for not more than five years and whose respondent has earned a college degree are likewise willing to pay \$104 and \$64 more per year, respectively, than households that have lived in their current home for more than five years and whose respondent has not earned a college degree. Lastly, households whose respondent's age is between 35 and 54 years-old, who claims to have had a "history of farming in his or her family", and who visits farmland "to connect with local heritage" are, respectively, willing to pay \$71, \$33, and \$77 less annually for agrivoltaics.

[INSERT TABLE 8 HERE]

Finally, Table 9 presents our results for the explicit tradeoff between the attributes *preserve* and *energy*. Our tradeoff measure is calculated as a "Conditional Marginal Rate of Substitution" (CMRS) of farmland preservation for agrivoltaics (where we adjust equation (8), which was originally defined to measure Differential MWTP) to account for the marginal utility associated with additional farmland preservation conditional on (or, given) the presence agrivoltaics. Specifically, equation (8) becomes,

$$CMRS_{az} = -\frac{\bar{\alpha}^a + \beta_z^a}{\bar{\alpha}^c + \beta_z^c}, \tag{9}$$

where in this case a refers to attribute *preserve* and z refers to attribute *energy*. Thus, $\bar{\alpha}^a$ represents the (mean of the random) ML coefficient estimate corresponding to *preserve*, β_z^a refers to the (fixed) ML coefficient estimate corresponding to interaction term (*preserve * energy*), $\bar{\alpha}^c$ denotes the (mean of the random) ML coefficient estimate corresponding to *cost*, and β_z^c represents the (fixed) ML coefficient estimate corresponding to interaction term (*energy * cost*).[27]

[INSERT TABLE 9 HERE]

As mentioned in Section 1, if confronted with the options of preserving an additional 50% of existing peri-urban farmland with and without agrivoltaics, we find that the typical household's Differential CMRS is unaffected, in particular the tradeoff between these two options is statistically insignificant (the 95% confidence interval includes zero). Alternatively stated, the typical household is unwilling to pay extra to secure farmland preservation in its pristine state, without agrivoltaics.

3.3 INTERNAL VALIDITY OF SURVEY RESPONSES

We test the internal validity of our survey responses by assessing three separate relationships between actual choices made in the choice experiment, on the one hand, and attitudinal claims made previously in the survey instrument, on the other (Brewer, 2000). The first relationship we consider is between a household's support for agrivoltaics situated on nearby farmland (i.e.,

[27] In theoretical terms, i.e., in relation to utility function $U(\cdot)$ specified in equation (1) of Section 3.1, $CMRS_{az} = -\frac{(\partial U(\cdot)/\partial a)|_z}{\partial U(\cdot)/\partial c}$, where $(\partial U(\cdot)/\partial a)|_z$ denotes the change in $U(\cdot)$ with respect to an incremental change in attribute a's level for a given level of variable z, and $\partial U(\cdot)/\partial c$ denotes the change in $U(\cdot)$ with respect to an incremental change in cost level c. In our case, attribute level a represents the level of *preserve* and z represents *energy* = 1.

whether variable *solarnear* from Table 4 equals one or zero), and the probability of that household choosing an alternative (A or B) when it includes agrivoltaics situated on nearby farmland, i.e., when *energy* equals one.

To perform this test, we create a variable named *solarpref* that equals one when *energy* equals one for a given alternative and the respondent chooses that alternative in the choice experiment, and then run a simple Pearson's χ^2 test between the two variables. We ultimately find a statistically significant relationship between the two variables ($\chi^2(1) = 8.88$ ($p = 0.003$)), indicating that *solarnear* and *solarpref* are positively related to each other, which in turn means that respondents who indicate positive support for agrivoltaics situated on nearby farmland were, all else equal, more likely to choose an alternative including agrivoltaics. We consider this outcome as internal validation of the participants' responses to survey questions concerning their preferences for joint production of farmland preservation and solar power.

We similarly check for internal validation of participants' responses to survey questions concerning their preferences for farmland preservation and their attitudes about whether enough farmland is preserved in the Wasatch Front. Here, we consider the relationship between a household's belief about whether there is enough farmland currently preserved in the region (i.e., whether variable *enough* from Table 4 equals one or zero), and the probability of that household choosing an alternative when it includes 100% of the farmland preserved, i.e., when *preserve* = 1.

To perform this test we create a variable named *preservepref1* that equals one when *preserve* equals one for a given alternative and the respondent chooses that alternative in the choice experiment, and again run a simple Pearson's χ^2 test between the two variables. We ultimately find a statistically significant relationship between the two variables ($\chi^2(1) = 4.79$ ($p = 0.029$)), indicating that *enough* and *preservepref1* are positively related to each other, which in turn means that respondents who either "strongly" or "somewhat" disagree with the statement, "There is enough farmland in Utah", were, all else equal, more likely to choose an alternative including full preservation of farmland. We consider this outcome as internal validation of the respondents' responses to survey questions concerning their preferences for farmland preservation because households that do not believe there is currently enough preserved farmland in the region prefer to preserve existing farmland.

Interestingly, in our final internal validity check, we find that this positive relationship between *enough* and *preservepref1* is no longer statistically significant when we loosen the definition of *preservepref1* to also equal one when *preserve* equals either 0.5 or one for a given alternative and the respondent chooses that alternative. We call this variable *preservepref2*. We do not find a statistically significant relationship between *preservepref2* and *enough* in this case ($\chi^2(1) = 1.45$ ($p = 0.228$)), indicating that, in conjunction with our previous findings for *preservepref1* versus *enough*, households that do not believe there is currently enough preserved farmland in the region are not necessarily more likely to choose an alternative including partial (50%) preservation of farmland.

4 DISCUSSION

Hanley et al. (1998) point out that choice experimentation offers advantages over the traditional contingent valuation method (CVM) because of the ability to estimate a good's characteristic values. The choice-experiment approach is predicated upon the notion that dissimilar attributes of an environmental good such as land preservation can be used to understand the different margins upon which individuals are willing to make tradeoffs. According to Streever et al. (1998), the use of CVM in situations where multiple land-use options and attributes of those options are under consideration is generally problematic. When juxtaposed with Sayadi et al.'s (2009) observation that an aesthetic valuation of agriculture "is complex, and may be expressed directly in monetary values only in the extreme cases of homogeneous, specific landscapes, spatially localized and in a situation of evident aesthetic contrast," it is evident that choice experimentation incorporating high-resolution visualizations of different land-use scenarios is a requisite approach to eliciting accurate, household-level estimates of farmland CES. This is one of the reasons our visualizations were developed as locally germane with the surrounding landscape and depicting real-world agricultural practices.

The purpose of this study is to fill a gap in the assessment of CES associated with prime farmland located in peri-urban areas. Toward this end, we have presented results from a choice experiment recently conducted in Utah's Wasatch Front region. The choice experiment was designed to account for heterogeneous effects associated with a wide array of socio-demographic and attitudinal characteristics on household preferences for farmland preservation, including farmland used for the joint production of solar power and agricultural products. We have applied a mixed-logit model to our data that controls for preference heterogeneity among Wasatch Front households along two dimensions – at the individual household level and according to different household types.

We have found ample evidence of preference heterogeneity among the Wasatch Front's households with respect to farmland preservation and the adoption of agrivoltaics, or joint production of solar power on these farmlands. Our parsimonious model indicates that latent heterogeneity exists at the individual household level, and that on average households are willing to pay four times as much for the preservation of existing peri-urban farmland than for agrivoltaics – roughly \$180 versus \$45 in annual fees, respectively. The typical household is indifferent between preserving an additional 50% of existing peri-urban farmland with and without agrivoltaics. Results from ML specifications allowing for heterogeneity by household type identify a host of socio-demographic and attitudinal factors that influence the valuation of these CES on household preferences. Specifically, households that (1) are located in urban and suburban areas, (2) generally believe farmland preservation is important, and (3) contain at least one member belonging to an environmental group, are less sensitive to increases in the cost associated with peri-urban farmland preservation and/or agrivoltaics. Households whose respondent (1) identifies his or her ethnicity as being white, (2) grew up in an urban environment, and (3) identifies as being "fundamentally opposed to using taxation to preserve farmland" are more sensitive to cost increases.

Households that (1) generally believe farmland preservation is important, (2) believe that there is not enough farmland currently preserved in Utah, and (3) would support higher-density housing in its community if it resulted in more farmland preservation are, all else equal, willing to pay more to preserve existing peri-urban farmland. Households identifying themselves as being "fundamentally opposed to using taxation to preserve farmland" and are located in urban or suburban areas (as opposed to rural areas) are willing to pay less. Surprisingly, higher-income and lower-middle-income households are willing to pay less than low-income and higher-middle-income households for farmland preservation.

Lastly, households that (1) support agrivoltaics on nearby farmland, (2) would support higher-density housing in their communities if it resulted in more farmland preservation, and (3) are located in urban or suburban areas, are generally willing to pay more for agrivoltaics on existing peri-urban farmland, as are households that have lived in their current residences for not more than five years and whose respondent has earned a Bachelor's or Master's degree. Households whose respondent's age is between 35 and 54 years-old, who identifies with having a "history of farming in his or her family" and who visits farmland "to connect with local heritage" are willing to pay less for agrivoltaics.

This estimated range of values for farmland preservation in the Wasatch Front region of Utah must be tempered by two caveats. First, our study oversampled senior and middle-aged individuals, college-educated individuals, homeowners, middle-income households, and households identifying as members of the Church of Jesus Christ of Latter-Day Saints. Second, although our estimated average household valuation of farmland preservation can serve as a baseline for what idealistically might be invested on a per-household basis in the region, our results concerning preference heterogeneity among households can be used by policymakers to target region-wide messaging about the saliency of farmland preservation, e.g., as political advertising for a multi-county ballot measure in favor of a farmland-preservation bond.

Several previous CES studies have expounded upon the importance of incorporating CES valuations in land-use studies of a region's more traditional provisioning, regulating, and supporting ecosystem services, in order to mitigate against biasing the overall value of an ecosystem downward (c.f., Petway et al., 2020; Narducci et al., 2019). Indeed, in some cases CES are considered to be the most valuable of an ecosystem's services (c.f., Power, 2010; Swinton et al., 2007; Howley et al., 2012). This study's results echo these concerns, by having estimated monetary values based upon the administration of an innovative choice experiment that controlled not only for the effects of a wide array of household-level socio-demographic characteristics, but also for several unique attitudinal attributes. With these estimates in hand, the Wasatch Front's policymakers and stakeholders have an accurate assessment of the CES at stake, and thus a fuller picture of the extent of ecosystem services at risk as the region continues to develop its prime farmlands into new residential and commercial land uses.

This study's main limitation – sample size – points the way forward on one avenue of future research. It behooves the Wasatch Front's stakeholders to support a replication of the survey across a wider swath of households in the region. Moreover, the survey instrument could be designed to incorporate a host of methodological advances pertaining to the visual depiction of alternative scenarios, as well as mitigation of potential biases afflicting these types of field experiments; hypothetical, informational, and strategic biases long associated with stated-preference surveys, as well as response uncertainty (Meginnis, et al., 2020; Aadland and Caplan, 2006a; Blumenschein et al., 1998). The goal here is to extend and improve upon both our experimental design and the statistical power of our estimates of household preferences for farmland preservation in the Wasatch Front region, and to extend our choice-experiment methodology to the estimation of CES associated with farmland preservation in other regions of the world.

5 CONCLUSION

Our study elucidates how residents value CES associated with peri-urban farmland, which is threatened in many regions around the world due to urbanization. Results from our choice experiment reveal household preferences in support of Envision Utah's (2017) goals regarding the preservation of peri-urban agriculture in Utah County, the rapidly developing heart of the Wasatch Front region. These goals point to a need for extensive land-use planning in the county; planning that accounts for the CES associated with peri-urban farmland preservation. Insufficient data on the trade-offs associated with different planning scenarios creates challenges for local governments, Envision Utah, and other key stakeholders. Our research provides empirical evidence that can be leveraged into land-use policy changes associated with peri-urban agricultural preservation, by providing accurate and timely estimates of its associated CES. Given its emphasis on the measurement of CES and attendant tradeoffs in CES values associated with land-use change, our study therefore provides an essential "piece of the puzzle" to aid and inform Utah's land-use planning process. More broadly, our methods to assess the value of various CES, including photo-realistic farmland and agrivoltaic scenarios, could easily be adapted to other locations to inform land-use policy.

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Figure 1. The Counties Comprising the Wasatch Front Region (Left Frame) and its Relative Location Within the State (Lower-Right Frame) and the US (Upper-Right Frame)

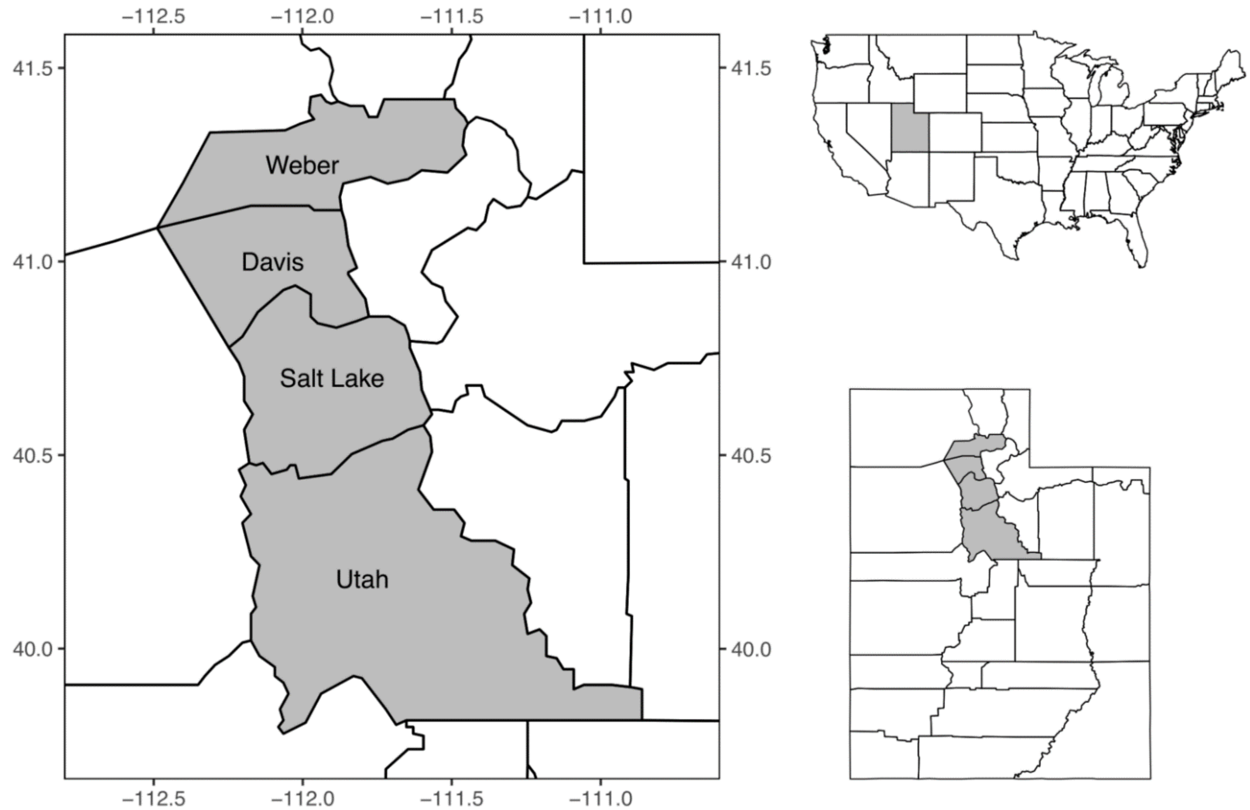

Figure 2. Locations of Surveyed Communities (Layton and Spanish Fork) and Their Locations Relative to Utah's Capital, Salt Lake City

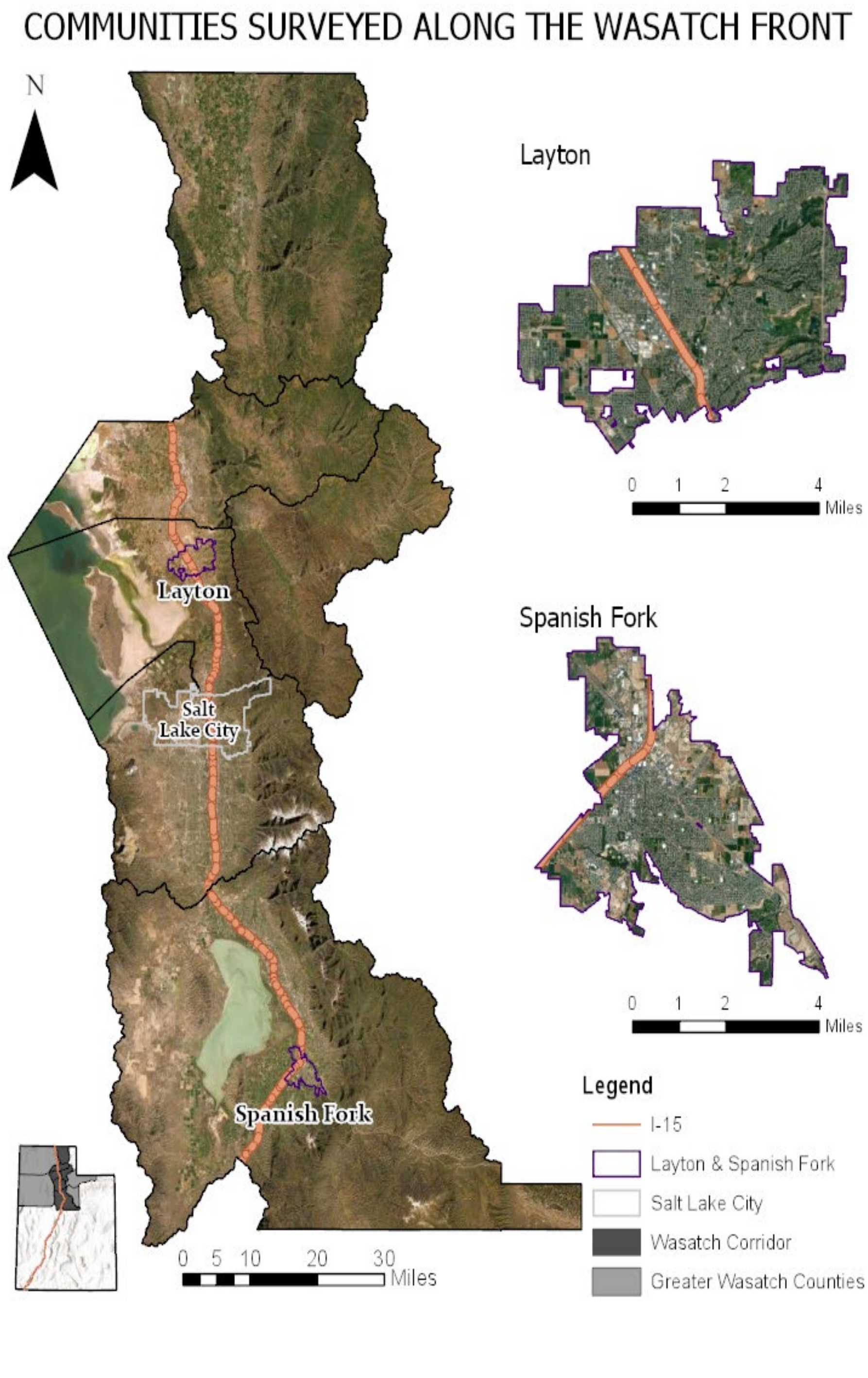

Figure 3. Example Choice Situation

Choice A (above): With an annual tax of $10, 50% of existing farmland in Layton is preserved. Orchards are the primary crop type and no more than 10% of the farmland has solar panels.

Choice B (above): With an annual tax of $50, 100% of existing farmland in Layton is preserved. Horses graze the land and no renewable energy is present.

Figure 3 Continued

Choice C (above): With no annual tax, all farmland in Layton will be converted to single-family residential.

Table 1. Choice experiment attributes (and corresponding *Variable Names*).

Extent of Farmland Preservation (*Preserve*)

- No development on existing peri-urban farmland.
- 50% of existing peri-urban farmland is developed into single-family homes.
- 100% of existing peri-urban farmland is developed into single-family homes (status quo).

Farming Practice (*Practice*)*

- Existing peri-urban farmland is managed for cut hay.
- Existing peri-urban farmland is managed for an early-season dryland crop.
- Existing peri-urban farmland is managed as pasture for cattle.
- Existing peri-urban farmland is managed as a horse pasture.
- Existing peri-urban farmland is managed as an orchard.

Renewable Energy (*Energy*)

- No solar panels are installed on existing peri-urban farmland (i.e., no agrivoltaics).
- Solar panels are installed on no more than 10% of existing peri-urban farmland.

Annual Cost of Farmland Preservation/Renewable Energy (*Cost*)

- $0
- $10
- $25
- $50
- $100
- $200

Notes: Variable names are provided in parenthesis (in italics). *This variable is changed to *Practice4* for the ensuing empirical analysis, where *Practice4* = 1 if existing peri-urban farmland is managed as a horse pasture, zero otherwise.

Table 2. Socio-Demographic Variable Names, Descriptions, and Sample Percentages

Variable Name	Description	% of Sample
gender	=1 if respondent is male, 0 otherwise.	50
senior	=1 if respondent's age is 55 years or older, 0 o.w.	47
midage	=1 if respondent's age is between 35 and 54 years, 0 o.w.	38
LDS	=1 if respondent is a member of the Church of Jesus Christ of Latter-Day Saints, 0 o.w.	78
white	=1 if respondent identifies as White/Caucasian, 0 o.w.	93
employed	=1 if respondent is currently employed full-time, 0 o.w.	66
retired	=1 if the respondent is retired, 0 o.w.	26
homemaker	=1 respondent identifies as a homemaker, 0 o.w.	7
highinc	=1 household's gross annual income is no less than $150,000, 0 o.w.	13
himidinc	=1 if household's gross annual income is at least $100,000 and no greater than $150,000, 0 o.w.	31
lowmidinc	=1 if household's gross annual income is at least $50,000 and no greater than $100,000, 0 o.w.	38
collegegrad	=1 if respondent has obtained either a Bachelor's or graduate degree, 0 o.w.	59
own	=1 if household owns its residence, 0 o.w.	99
location	=1 if household resides in the city of Spanish Fork, 0 o.w.	59
shortlive	=1 if household has resided in current location for no greater than 5 years, 0 o.w.	56
midlive	=1 if household has resided in current location for no less than six years and no greater than 15 years, 0 o.w.	19
nonrural	=1 if household currently resides in urban area or suburb, 0 o.w.	84
grewupurban	=1 if respondent grew up in an urban area, 0 o.w.	10
grewupsuburb	=1 if respondent grew up in a suburban area, 0 o.w.	37
histfarm	=1 if there is a "history of farming" in respondent's family, 0 o.w.	58
envorg	=1 if any member of the household belongs to an environmental club, group, or organization, 0 o.w.	7
familiar	=1 if respondent is familiar with a map of their city (shown to them as part of the question), 0 o.w.	97

Table 3. Census data for Wasatch Front counties (percentages).

	Wasatch Front Counties				
Variable Name	**Weber**	**Davis**	**Salt Lake**	**Utah**	**Regional Total**
gender	50	50	50	50	50
senior	22	17	20	14	18
midage	24	24	26	21	24
LDS	54	71	51	82	62
white	92	92	87	93	90
employed	67	68	71	68	69
retired & hmkr	33	32	29	32	31
highinc	7	13	16	11	12
medinc	53	59	57	54	56
collegegrad	24	36	33	42	35
own	72	77	67	68	69

Table 4. Attitudinal Variable Names, Descriptions, and Sample Percentages

Variable Name	Description	% of Sample
heritage	=1 if respondent visits farmland "To connect with local heritage (traditions passed down through the landscape and land uses)", 0 o.w.	64
notax	=1 if respondent is "fundamentally opposed to using taxation to preserve farmland", 0 o.w.	22
solarnear	=1 if respondent would support a solar installation situated on nearby farmland ("not to occupy more than 10% of the landscape allowing for continued farming practices or open space"), 0 o.w.	64
enough	=1 if respondent either "strongly" or "somewhat" disagrees with the statement, "There is enough farmland in Utah", 0 o.w.	61
environgood	=1 if respondent either "strongly" or "somewhat" agrees with the statement, "Purchasing locally produced food and/or fiber is beneficial to the environment", 0 o.w.	83
preserveimp	=1 if respondent generally believes that it is "moderately" to "very" important to preserve farmland, 0 o.w.	77
moredense	=1 if the respondent would support higher-density housing in his or her community if it resulted in more farmland preservation, 0 o.w.	26

Table 5. Regression Results for the Parsimonious Model

	MNL Model	ML Model	MWTP ($)
Mean Coefficient Estimates			
preserve	1.36*** (0.239)	4.54*** (0.684)	181.64 (128.83, 234.45)
energy	0.58*** (0.104)	1.11*** (0.343)	44.53 (14.13, 74.92)
practice4	-0.12 (0.133)	0.22 (0.218)	8.89 (-7.83, 25.62)
cost	-0.01*** (0.002)	-0.02*** (0.005)	---
choiceA	1.34*** (0.101)	0.34** (0.155)	---
choiceA_duration	0.00 (0.000)	0.00 (0.000)	---
Standard Deviations			
preserve	---	2.93*** (0.563)	---
energy	---	2.63*** (0.442)	---
practice4	---	0.52 (0.578)	---
cost	---	0.02*** (0.006)	---
Observations	1,605	1,605	---
McFadden's R^2	0.10	0.16	---
Log Likelihood	-427.77	-369.42	---
LR Test	300.70***	144.28***	---

Notes: Standard errors are in parentheses, except for MWTP, where lower and upper bounds of 95% confidence interval are reported (derived using the Delta method). Coefficients for *choiceA* and *choiceA_duration* are estimated as constant terms in the ML specification, hence standard deviations are not calculated for these coefficients. The LR Test for the MNL model is based upon a Wald χ^2 test statistic rather than the LR χ^2 test statistic. *p<0.10, **p<0.05, ***p<0.01.

Table 6. Heterogeneous Effects Associated with Attribute *cost*

Interaction Term	**Coefficient Estimate**
white	-0.01* (0.007)
nonrural	0.02** (0.007)
grewupurban	-0.02* (0.009)
envorg	0.02** (0.010)
notax	-0.03*** (0.007)
preserveimp	0.03*** (0.006)

Notes: Standard errors are in parentheses. *p<0.10, **p<0.05, ***p<0.01.

Table 7. Heterogeneous Effects Associated with Attribute *preserve*

Interaction Term	**Coefficient Estimate**	**Differential MWTP**
highinc	-2.09^{**} (0.989)	-102.22 (-203.55, -0.90)
lowmidinc	-1.71^{**} (0.055)	-83.67 (-168.49, 1.15)
location	-1.04^{*} (0.555)	-48.04 (-99.87, 3.79)
nonrural	-2.08^{**} (0.939)	-241.30 (-445.73, -36.87)
notax	-3.30^{***} (0.533)	-68.29 (-125.29, -11.28)
enough	1.74^{***} (0.532)	81.89 (27.39, 136.40)
preserveimp	2.86^{***} (0.526)	124.16 (42.93, 205.39)
moredense	0.91^{*} (0.558)	42.76 (-10.35, 95.91)

Notes: Standard errors are in parentheses for the coefficient estimates. The lower and upper bounds of the 95% confidence interval are in parentheses for Differential MWTP. $^{*}p<0.10$, $^{**}p<0.05$, $^{***}p<0.01$.

Table 8. Heterogeneous Effects Associated with Attribute *energy*

Interaction Term	Coefficient Estimate	Differential MWTP
midage	-1.03** (0.407)	-71.14 (-132.66, -9.61)
collegegrad	1.00*** (0.280)	64.27 (24.00, 104.55)
shortlive	0.98** (0.425)	103.78 (54.81, 152.76)
nonrural	0.77** (0.380)	66.58 (-0.80, 133.96)
histfarm	-0.50* (0.274)	-33.33 (-70.24, 3.57)
heritage	-1.27*** (0.297)	-77.27 (-119.58, -34.96)
solarnear	1.01*** (0.280)	68.68 (23.11, 114.24)
moredense	0.49* (0.274)	32.49 (-4.42, 69.39)

Notes: Standard errors are in parentheses for the coefficient estimates. The lower and upper bounds of the 95% confidence interval are in parentheses for Differential MWTP. *p<0.10, **p<0.05, ***p<0.01.

Table 9. Tradeoff Between *preserve* and *energy*

Trade-Off	Differential MWTP
preserve vs. *energy*	-21.05 (-96.60, 54.51)

Notes: The lower and upper bounds of the 95% confidence interval are in parentheses for MWTP.