UNDERSTANDING PUBLIC PREFERENCES FOR NON-NATIVE SPECIES MANAGEMENT AND WILDFIRE RISK MITIGATION IN ARIZONA

by

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A Thesis Submitted to the Faculty of the

DEPARTMENT OF AGRICULTURAL AND RESOURCE ECONOMICS

In Partial Fulfillment of the Requirements

For the Degree of

MASTER OF SCIENCE

In the Graduate College

THE UNIVERSITY OF ARIZONA

2025

THE UNIVERSITY OF ARIZONA
GRADUATE COLLEGE

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ACKNOWLEDGMENTS

I would like to express my deepest gratitude to my committee co-chair, Dr. Aaron Lien, for his invaluable guidance, mentorship, and consistent support throughout this research process. I am also sincerely thankful to my co-chair, Dr. George Frisvold, for his expertise in applied economics and his thoughtful input at every stage of the project.

I am especially grateful to Dr. Anna Josephson for joining my committee under unexpected circumstances and generously dedicating her time to reviewing and improving this research.

I would also like to thank Dr. Jose Soto for his early guidance and helpful feedback in refining the survey instrument and shaping the methodological framework. I am deeply appreciative of the time, insight, and encouragement offered by each of my committee members over the past year.

This research would not have been possible without the collaboration of key informants and survey participants in Arizona, particularly those from the Globe region. Their lived experiences and local knowledge were essential in grounding this study in real-world challenges and perspectives.

Finally, I gratefully acknowledge the financial support provided by the Natural Resource Users Law and Policy Center (NRULPC), without which this research could not have been conducted.

LAND ACKNOWLEDGMENT

We respectfully acknowledge the University of Arizona is on the land and territories of Indigenous peoples. Today, Arizona is home to 22 federally recognized tribes, with Tucson being home to the O'odham and the Yaqui. Committed to diversity and inclusion, the University strives to build sustainable relationships with sovereign Native Nations and Indigenous communities through education offerings, partnerships, and community service.

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ABSTRACT

Wildfires in Arizona are increasing in frequency and severity, often fueled by invasive plant species such as buffelgrass. This thesis explores public preferences for wildfire mitigation strategies, particularly invasive species management, using a Best-Worst Scaling (BWS) survey supported by Conditional Logit (CLM) and Random Effects Logit (REL) models. The study focuses on high-risk communities near the Tonto National Forest, using a stakeholder-informed survey design.

Results show that residents prioritize tangible safety outcomes over institutional or financial considerations—especially "Protection of Homes," "High to Medium Risk Reduction," and "Mechanical Thinning." These attributes consistently ranked highest in the BWS and were statistically significant in the CLM model. In contrast, respondents expressed strong opposition to utility tax increases, regardless of magnitude. The CLM results confirmed that price was a significant negative predictor of preference, alongside positive preferences for safety-focused attributes.

However, the REL model, used to simulate actual voting behavior under cost constraints, revealed that price alone was statistically significant. Non-price attributes, such as the type of administering agency, prevention method, or prioritization goal, had no measurable influence on voting outcomes once cost was introduced. This suggests a divergence between symbolic support for mitigation strategies and willingness to pay—likely driven by the public goods nature of wildfire protection, in which individuals may support collective benefits in principle but prefer to free ride when financial contributions are required.

This work suggests that policymakers should consider designing low-cost, high-impact programs and explore non-fee-based or collectively funded mechanisms to align wildfire mitigation strategies with public preferences. Doing so may improve political feasibility and reduce resistance among cost-sensitive or lower-income households.

Chapter 1

Introduction

Wildfires have long been a natural component of ecosystems in the Western United States (Westerling et al., 2006; Littell et al., 2009). Historically, these fires were frequent but low in intensity, playing a vital role in reducing fuel accumulation and maintaining ecological balance (Millar et al., 2007; Hessburg et al., 2005). However, over the past century, human intervention has dramatically altered fire regimes (Keeley et al., 1999; North et al., 2015). Fire suppression policies, land-use changes, and climate change have contributed to the accumulation of hazardous fuel loads and increased fuel aridity, leading to a sharp rise in wildfire frequency and severity (Burke et al., 2021; Essen et al., 2023). As a result, the burned area in the U.S. has quadrupled over the last four decades, with climate change further exacerbating this trend by extending fire seasons, intensifying drought conditions, and raising temperatures (Wilder et al., 2021). Despite extensive fire suppression efforts, many regions remain highly vulnerable, underscoring the need for proactive wildfire adaptation and mitigation strategies (Misal et al., 2023). This study provides a preference-based framework for evaluating invasive species control measures under wildfire risk conditions.

This study examines how wildfire mitigation strategies, specifically the management of invasive plants, align with public preferences in fire-prone regions of Arizona, such as the Tonto National Forest. Using a Best-Worst Scaling (BWS) survey approach, we address three questions: (1) Which agency garners the highest public support for leading invasive plant control efforts?; (2) What types of invasive plant control measures do residents prefer?; and (3) How cost affects support for wildfire risk reduction? By analyzing stakeholder preferences, this study identifies the most publicly acceptable and effective strategies for the management of invasive species in fire-prone regions.

Support for wildfire prevention policies is shaped by factors such as individual risk perception, socioeconomic status, and direct wildfire experience (Hui et al., 2022; Sánchez et al., 2022). However, paradoxes arise, such as the ‘risk paradox‘, in which residents of high-risk areas may resist mitigation policies despite their heightened exposure (Alló and Loureiro, 2020). Understanding these dynamics is essential for designing effective wildfire management strategies that align with public preferences.

Beyond their ecological impact, wildfires impose far-reaching economic and societal burdens. In Arizona, wildfire suppression costs alone reached nearly $9.6 million in 2023 (Arizona Department of Forestry and Fire Management, 2023), yet suppression efforts represent only a fraction of total wildfire-related expenditures. Studies estimate that suppression accounts for just nine percent of total wildfire costs, while nearly half of the financial burden falls on local communities through long-term damages, including property value declines, water shortages, and lost ecosystem services (Barrett, 2018). Furthermore, wildfire smoke poses a significant but often overlooked health cost, with annual economic losses from smoke-related illnesses estimated at $16 billion in the U.S. (WEF, 2021). Compounding these risks, invasive species, such as buffelgrass in Arizona, worsen fire hazards and require coordinated management efforts that depend on public awareness and participation (Plecki et al., 2021). Invasive species like buffelgrass and red brome have transformed fire regimes in desert and semi-arid regions, increasing both fire frequency and severity (Wilder et al., 2021). These species thrive under changing climatic conditions, benefiting from longer growing seasons, record high temperatures, and prolonged droughts to out-compete native vegetation (Fusco et al., 2019). As a result, Arizona communities, particularly those near fire-prone areas such as the Tonto National Forest, face escalating threats from wildfires and complex management challenges.

The survey results reveal that respondents placed the greatest importance on wildfire mitigation strategies that offer direct safety benefits, particularly “Protection of Homes” and “High to Medium Wildfire Risk Reduction.” “Mechanical Thinning” was moderately preferred, while “Herbicide Treatment” received mixed support. In contrast, respondents expressed strong resistance to paying for mitigation through increased utility taxes, indicating a general aversion to fee-based funding mechanisms. Notably, smaller tax increases (e.g., $1 or $4) were sometimes viewed less favorably than larger ones, suggesting symbolic opposition to fee-based funding mechanisms rather than purely economic trade-offs.

While "Administrative Agency" was ranked lower in perceived importance, the CLM model showed statistically significant differences between governmental and non-governmental entities, reflecting subtle but relevant preferences for institutional trust. However, the REL model results indicated that cost entirely dominated voting behavior. None of the non-price attributes significantly affected referendum support. Support dropped sharply as tax levels increased from $1 to $10, despite respondents previously assigning high importance to certain attributes in the BWS task.

These findings contribute to broader discussions on the societal and economic costs of wildfires, emphasizing their indirect and long-term consequences. Arizona's experience reflects a larger regional and global trend, with wildfire risks intensifying due to climate change and the proliferation of invasive species. With nearly 50 million homes in the U.S. now located in the wildland-urban interface, a number that grows by one million every three years (Burke et al., 2021), developing integrated management policies that reflect public preferences is essential. This study informs the design of mitigation strategies that are both effective and publicly viable, especially in high-risk regions where invasive species and wildfires intersect.

Chapter 2

Literature Review

2.1 BWS Method

Best Worst Scaling (BWS), first introduced by Louviere and Woodworth (1991), is an extension of the paired comparison method. It has since been widely applied in various fields, including healthcare (Flynn et al., 2007, 2008), marketing research (Lusk and Briggeman, 2009), and environmental valuation (Soto et al., 2016, 2018), as a novel approach to measuring utility, offering advantages over traditional discrete choice experiments (DCEs). Unlike DCEs, which require respondents to choose between full bundles of attributes, BWS asks participants to identify the single most and single least preferred items within a given set. This produces more discriminative data by capturing both ends of the preference scale rather than just a top choice or ordinal ranking. It reduces cognitive burden compared to full rankings while avoiding potential centrality bias, and provides clearer trade-off information that supports estimation of relative utility differences (Marley and Louviere, 2005; Thomas et al., 2017; Loureiro and Arcos, 2012; Louviere et al., 2015)

BWS models can become cognitively burdensome for respondents when a large number of attributes or levels are included, as the number of best-worst combinations grows. However, structured experimental designs, such as orthogonal arrays and balanced block designs, help reduce this burden while maintaining statistical efficiency and attribute orthogonality (Hedayat et al., 2012; Soto et al., 2016, 2018; Flynn et al., 2007, 2008). In this study, we mitigate respondent fatigue by limiting the number of choice sets to eight using an orthogonal design.

Soto et al. (2018) employ the Best-Worst Scaling (BWS) method to reduce survey bias while producing utility estimates for both ecosystem services and disservices. Their approach demonstrates how BWS can be used to quantify trade-offs in environmental preferences, particularly when respondents are faced with complex or unfamiliar terminology. In a similar fashion, this study uses a Best-Worst Choice (BWC) survey to estimate the relative importance of ecosystem services (ES) by framing questions around specific and concrete management practices. This strategy is designed to reduce confusion among respondents who may not be familiar with abstract ES terms.

Parallel research by Lusk and Briggeman (2009) applied the BWS technique to evaluate consumer preferences for novel food attributes, including naturalness, taste, price, convenience, nutrition, tradition, origin, appearance, and environmental impact, as well as for organic food. Their econometric analysis employed both Random Parameter Logit (RPL) and Multinomial Logit (MNL) models to estimate the relative importance of each attribute. Preferences were reported as shares, which allowed for more intuitive interpretation of relative attribute preferences. Their findings revealed that food safety was the most valued attribute, while the origin of food ranked lowest. Furthermore, respondents who prioritized price showed a lower likelihood of preferring organic options, suggesting that income plays a key role in shaping consumer choices.

Burton et al. (2024) employs a discrete choice experiment (DCE) embedded in a national survey to assess the preferences of Greek residents' for wildfire prevention and management policies. The study utilizes a conditional logit model to estimate preferences based on observed choices, a mixed multinomial logit model to account for individual heterogeneity, and a latent class model to identify distinct respondent groups with similar preferences. Instead of a willingness-to-accept (WTA) framework, Burton et al. (2024) estimates willingness-to-pay (WTP) for different policy attributes, including tax increases, management entities, and policy types. The WTP estimates derived from the logit models provide a robust measure of public valuation for wildfire mitigation efforts. While the latent class model offers additional insight into preference heterogeneity, the use of a DCE allows for the estimation of relative attribute importance without the need for direct price solicitation, aligning with methodologies used in environmental policy research.

2.2 Choice of Attributes

Attribute selection in choice experiments is fundamental for understanding public policy preferences. Prior research identifies five key attributes that influence support for fire management policies: prevention measures, administrative agency, risk reduction, cost, and administrative priority. Prevention measures, such as mechanical thinning and prescribed burns, are widely recognized for reducing wildfire intensity, tree mortality, and hazardous fuel loads (Chang et al., 2023; North et al., 2015; Kalies and Kent, 2016). Public preferences for these strategies vary: some favor proactive education campaigns, while others support regulatory approaches like mandatory vegetation management (Burton et al., 2024)

The administrative agency responsible for wildfire prevention plays a significant role in public acceptance of fire policies. Studies indicate that public trust in the managing entity, whether a national fire service, a local government agency, or a non-profit organization, affects support for mitigation strategies (Burton et al., 2024; Holmes et al., 2012). Individuals tend to prefer established agencies with clear authority, particularly national-level fire and forest services, over decentralized or non-governmental entities. Additionally, the perceived effectiveness of wildfire policies is often linked to their expected reduction in risk. Holmes et al. (2012) found that willingness to pay for wildfire mitigation increases when policies are expected to yield substantial risk reduction. However, risk perception varies across demographic groups, with some communities underestimating their vulnerability despite residing in high-risk areas (Alló and Loureiro, 2020).

Cost remains a central factor shaping policy support. While some are willing to pay higher taxes for effective programs, others, particularly lower-income households, may require incentives to participate (Sánchez et al., 2022). The prioritization of wildfire administration also affects policy outcomes, as funding allocations and decision-making authority determine the implementation and long-term success of mitigation efforts (Chang et al., 2023). This study builds on existing literature by exploring how public preferences vary across these five attributes, prevention measure, administration agency, risk reduction, cost, and administrative priority, interact to shape public preferences for wildfire mitigation strategies.

Chapter 3

Methodology

3.1 Non-Econometric Framework

Following Dawes et al. (2018), a BWS mean score is used as a non-econometric measure of importance. In this context, 'non-econometric' refers to a summary statistic calculated from best-minus-worst counts across all respondents. This score provides an intuitive indicator of how often an attribute level was selected as most or least important. A BWS score is calculated using the following formula:

$$BWS\ Score = \frac{(Count_b - Count_w)}{f \cdot n}. \tag{3.1}$$

Here, the numerator is the difference between the number of times a level is selected as the best and worst in all sets. f is the number of times a level is presented as an option in a set and n is the number of respondents. To see the frequency of each level, refer to Table B.1 in Appendix.

3.2 BWS Econometric Framework

Best-Worst Scaling (BWS) choice modeling is a valuable tool in market research, with applications in product development, healthcare, business strategy, and forest management practices (Louviere et al., 2015; Flynn et al., 2007; Lusk and Briggeman, 2009; Soto et al., 2016, 2018). Unlike traditional ranking methods, BWS reduces ambiguity by requiring respondents to identify only the most preferred and least preferred options within a set. This forced-choice design minimizes middle ranking ambiguity and forces respondents to make clear trade-offs among competing attributes. The utility derived from each attribute and level reflects the extent to which a respondent is willing to forgo one feature to retain another. In this framework, the least preferred (worst) choice can be interpreted as the cost or trade-off that respondents are willing to accept to secure their most preferred (best) choice. This structure allows researchers to capture the maximum difference in importance, commonly referred to as MaxDiff, between options. As noted by Marley and Louviere (2005), most MaxDiff models are estimated using a multinomial logit (MNL) framework, which assumes an underlying maximum utility u. The MNL model is then used to estimate the combination of attribute levels that produce the largest difference in perceived importance:

$$B_C(x) = \frac{e^{u(x)}}{\sum_{z \in C} e^{u(z)}} \tag{3.2}$$

Where $B_C(x)$ is the probability that attribute y is chosen as the best in C, *u(x)* is the utility for x, and *u(z)* is the overall utility for all the other elements in C. Likewise, there is a probability $W_C(y)$ for y to be chosen as the worst attribute in C (Marley and Louviere, 2005):

$$W_C(y) = \frac{e^{-u(y)}}{\sum_{z \in C} e^{-u(z)}} \tag{3.3}$$

The MaxDiff model assumes that the probability of a choice for the worst option in C is the negative balance of the best option in C. This makes the probability of x and y picked as *best* and *worst*:

$$BW_C(x, y) = \frac{e^{[u(x)-u(y)]}}{\sum_{\{p,q\} \in C} e^{[u(p)-u(q)]}}, \quad x \neq y,\ p \neq q \in C. \tag{3.4}$$

The denominator represents the sum of all BWS combinations p, q where $p = q$. The utility difference equation for x as the most important and x as the least important attribute level in choice set C, of BWS profile t, for respondent i, can be measured following Soto et al. (2018):

$$U^i_{mnt} = \beta_m x^i_{tm} - \beta_n x^i_{tn} + \epsilon^i_{tm} - \epsilon^i_{tn}, \quad m \neq n \tag{3.5}$$

Where β_m and β_n are parameters for estimation and the ϵ is the error term. This can be applied to the earlier equation for calculating the probability of each choice set by replacing x and y in (3.5) for m and n, respectively:

$$BW_C(m,n) = \frac{e^{[\beta_m x_{tm} - \beta_n x_{tn}]}}{\sum_{\{p,q\}\in C} e^{[\beta_p x_{tp} - \beta_q x_{tq}]}} \tag{3.6}$$

Using maximum likelihood estimation, we can calculate the β parameters. We can modify the BWS pairs to estimate the level scale impact (LSV) from the BWS. The LSV estimates the effect on importance from each level. This survey has five attributes and 12 levels. The estimation is done for only 11 levels, selecting a level as a base of reference to avoid the "dummy variable trap" (Soto et al., 2018). The following is the utility function expressing importance through the LSV:

$$U^i_{mnt} = \beta^i_{a^2}\delta^i_{a^2} + ... + \beta^i_{e^3}\delta^i_{e^3} + \epsilon^i \tag{3.7}$$

Here, β attached to the $\delta^i_{a^2..e^4}$, shows us the attribute impact when δ^i takes on the value of 1 if selected as the best level in a choice set, -1 if selected as the worst level, and 0 otherwise.

Interactions can be estimated using the conditional logit model (CLM) following Soto et al. (2016). The CLM is used to estimate the utility (or importance) of an attribute level in the presence of alternate attribute levels. There is a specific number of possible combinations for J attributes in each comparison (choice set), J(1-J). For this experiment, we used 5 attributes, therefore J(J-1) = 20. The variable representing the chosen outcome was expanded 20 times per choice set, with a 1 indicating the selected BWS combination. This means that there were 20 alternatives to each choice. There were 8 choice sets (or questions) in the BWS, resulting in 160 possible outcomes per respondent.

To aid in interpretation, the coefficients are rescaled into a common metric known as the 'share of preference' (Lusk and Briggeman, 2009). This transformation expresses each attribute's relative importance proportionally. For example, a share value of 2.00 indicates that the attribute is considered twice as important as the reference category. This approach can also be applied to co-variates, provided they are compared against the same baseline level.

$$Share\ of\ preference = \frac{e^{\beta_i}}{\sum_{i=1}^{11} e_i^{\beta}} \tag{3.8}$$

3.3 WTP Econometric Framework

For every choice set, there is a binary choice where respondents will either agree or disagree to increasing the price of their monthly utility tax by \$1, \$4, \$7, or \$10, considering the choice set C. We can define the probability of agreeing to pay as $P(yes)$ and model it in the following equation:

$$P(yes) = P(U_y > U_n) \tag{3.9}$$

Where $P(\text{yes}) = P(U_y > U_n)$ is the probability of the utility for yes (U_y) being greater than the utility for no (U_n). To simplify this, we can normalize U_n to equal zero without compromising the significance of this model by subtracting it from U_y:

$$U_y^* = U_y - U_n \tag{3.10}$$

$$P(yes) = P(U_y - U_n > 0) \tag{3.11}$$

Now, $U_y - U_n$ can be redefined as U_i, and the probability of choosing *yes* based on the utility of individual i becomes:

$$P(yes) = P(U_i > 0) \tag{3.12}$$

Integrating this identity with the survey model, we will use a random effects logit (REL) to represent the utility equation for an individual i, and the binary choice t:

$$U_{it} = \beta' x_{it} + \alpha_i + \epsilon_{it} \tag{3.13}$$

$$Y_{it} = (U_{it} > 0) \tag{3.14}$$

Where the individual specific error a_i, and the overall error term ϵ_{it}, are added to the attribute that was selected x_{it}. β represents the vector for the estimated parameters, and Y_{it} is the outcome of the binary choice, taking the value of 1 if selected and 0 otherwise. We can assume that the error terms are independent random variables that are uncorrelated with X_{it}. Additionally, we want to identify the differences in WTP among groups of interest. We can represent this model with the following equation:

$$P(Y = 1|x_{it}) = \frac{e^{(\beta' x_{it} + \gamma P_{it} + \alpha_i)}}{1 + e^{(\beta' x_{it} + \gamma P_{it} + \alpha_i)}} \tag{3.15}$$

The first portion of this equation, $P(Y = 1|x_{it})$, denotes the probability that a respondent answered yes, $Y = 1$, given the individual choosing from choice set t. The second portion is the logistic distribution for the estimated parameters β for the selected attribute x_{it}. P_{it} represents the utility tax amount shown in the referendum scenario for respondent i at time t, the additional cost of \$1, \$4, \$7, or \$10 to increase utility tax to fund the invasive species removal program attributes.

The respondents' WTP can be calculated in a dollar value using the negative ratio of the coefficient of a non-price attribute over the coefficient price. Below, β_i is the resulting coefficient from the REL model for attribute i, while β_p represents the price coefficient. This allows for interpretation of the estimates' proportional importance. If a share of preference is twice as big for one attribute level in comparison to another, it can be considered twice as important.

$$WTP = -\frac{\beta_i}{\beta_p} \tag{3.16}$$

Chapter 4

Survey Design & Data

4.1 Survey Description

The survey was launched in January of 2025. The survey instrument was developed using the online platform, Qualtrics, and a mail-in survey form to ease respondent effort, following the Dillman method (Dillman et al., 2014). In addition to the hypothetical referendum questions described below, the survey included a section eliciting respondents' knowledge of invasive plant species; another on respondents' level of trust towards government agencies' ability to prevent and manage wildfires; demographic information; and a series of questions probing whether and how respondents were affected by recent wildfires.

To identify potential 'policy attributes' that policy makers could plausibly consider when designing such a referendum, we consulted key informers. We first conducted key informant interviews with personal from the United States Forest Service, the Arizona Department of Forestry and Fire Management, municipal governments, and residents of the target area (n = 11). We asked participants about their experiences with wildfires, the perceived drivers of recent wildfires, and the current actions being taken to manage the risk of wildfires. Second, we pre-tested our survey instrument using an initial sample of 16 individuals, including residents of Gila, Pinal, and Pima counties, survey design experts, and subject matter experts, to assess the reliability of our questions. No significant changes were made to the survey following the pre-test, and no major revisions were necessary. Minor edits were made to improve wording clarity and streamline the flow of questions. The BWS was composed of a series of eight 5-attribute choice sets in which respondents chose which attribute was their least and most preferred of the list set.

Based on the input of practitioners and previous literature, we identified five potential attributes that could vary by referendum. The following attributes were used to develop the hypothetical referendum programs: a) administrative agency (2 levels; governmental and non-governmental); b) change in wildfire risk (2 levels; high to medium and medium to low); c) prevention measure (2 levels; mechanical thinning and herbicide treatment); d) prioritization (2 levels; protection of homes and protection of ecosystem); and e) increase in utility tax (4 levels; $1, $4, $7, and $10). Table 4.1 details these attributes.

Table 4.1: A list of attributes and levels used to create choice experiment questions.

Attribute	**Definition**	**Levels**
Administrative Agency	Organization or agency responsible for implementing invasive plant management program.	Governmental Non-Governmental
Change in Wildfire Risk	The expected change in wildfire risk.	High-to-Medium Medium-to-Low
Prevention Measure	The primary technique employed to control invasive plants.	Mechanical Thinning Herbicide Treatment
Prioritization	The primary objective of the management program.	Protection of homes Protection of ecosystem
Increase in Utility Tax	Increase in monthly utility tax to fund the Invasive plant management program.	$1 $4 $7 $10

Respondents had the opportunity to complete surveys at a time that is most convenient for them and through preferred platforms: tablets, cell phones, computer, or the provided physical survey mailed directly to them. As mentioned above, this research followed the Dillman Method (Dillman et al., 2014), which offers a guideline for online surveys, and received the approval of The University of Arizona's Institutional Review Board (STUDY00005255).

The survey began with an informed consent form, followed by a series of background questions relating to invasive plant species and the impact they have on wildfire risk, for the purpose of evaluating their knowledge of the subject matter (i.e., wildfires and invasive species). In the section that followed, respondents answered a series of background questions relating to their experience with wildfires. There was then the choice experiment block, followed by a section of demographic information.

The number of observations available for the choice experiment modeling (i.e., unique responses to each of the eight unique hypothetical referendum questions) were 568 (each respondent answered 8 design questions; 71 respondents; 8 x 71 = 568 total observations).

Given that a choice experiment that accounts for all combinations, or full factorial, would include $2 \times 2 \times 2 \times 2 \times 4 = 64$ hypothetical scenarios. This study instead used the Neil Sloan orthogonal array design, in order to use a balanced factorial design orthogonal design with 8 choice tasks per respondent (Table B.1). Figure 1 illustrates an example choice task.

Figure 4.1: Example Best-Worst Choice Question with Referendum Vote

Step 1: List out most and least important attributes

Most Important		Least Important
○	**Administration Agency**: Non-governmental	○
○	**Change in wildfire risk**: High to Medium	○
○	**Prevention Measure**: Herbicide Treatment	○
○	**Prioritization**: Protection of homes	○
○	**Increase in Utility Tax**: $7	○

Step 2: Would you vote for or against this program?

○ I would vote YES to this referendum.
○ I support the goal of this referendum, but I am not prepared to pay $7/month and thus would vote NO.
○ I support the goal of this referendum, but I cannot afford $7/month and thus would vote NO.
○ I support the goal of the initiative, but I would vote NO for the following reason:
○ I would vote NO to this referendum.

4.2 Demographics

The final section of the survey gathered demographic information from respondents. Table 4.2 presents a breakdown of survey participants alongside comparative data from the 2023 U.S. Census for the city of Globe, Arizona. As is common in voluntary survey-based research, the sample does not perfectly align with the Census demographic profile. In particular, the sample is older, with respondents 65 years and older comprising nearly 45% of the sample (28.2% 65-74 years and 16.9% 75+), compared to a combined 20.2% in the Census data. In contrast, individuals under 35 years of age were underrepresented, accounting for just 2.8% of the respondents versus 34.7% of the population.

The educational attainment among the respondents was relatively high: 36.6% had a bachelor's degree or higher, and 28.2% had completed some college or an associate's degree. Gender distribution slightly favored women (46.5%) over men (36.6%), with 7.0% preferring not to respond and 9.9% marked as not applicable. Racial and ethnic representation also diverged from local Census data. White/Caucasian respondents made up 52.1% of the sample compared to 41.0% in the Census, while Hispanic respondents were underrepresented (22.5% in the survey versus 46.0% in the Census). Other racial and ethnic groups, including Native American and Asian populations, were not represented in the sample.

Income distribution revealed a higher proportion of middle-income respondents, with 23.9% earning between $50,000 and $99,999 annually. Only 12.7% of respondents reported an annual household income under $25,000, compared to 20.7% in the Census. A substantial portion (16.9%) preferred not to disclose their income, and 9.9% did not answer. While Table 4.2 compares overall Census data, it is important to note that our target population primarily includes homeowners, who tend to be older than the general population. As a result, the age distribution of survey respondents skews older.

Table 4.2: Survey Respondent Demographics Compared to 2023 U.S. Census

Category	Survey Resp.	Survey Resp. %	2023 U.S. Census %
Age			
Under 25 years	0	0.0%	25.6%
25–34 years	2	2.8%	9.1%
35–44 years	7	9.9%	15.0%
45–54 years	5	7.0%	16.8%
55–64 years	10	14.1%	13.3%
65–74 years	20	28.2%	12.2%
75+ years	12	16.9%	8.0%
Prefer not to answer	8	11.3%	–
N/A	7	9.9%	–
Education			
Less than 12th grade	0	0.0%	–
High school graduate or GED	15	21.1%	–
Some college or associate's degree	26	28.2%	–
Bachelor's degree or higher	20	36.6%	–
Prefer not to answer	3	4.2%	–
N/A	7	9.9%	–
Gender			
Male	26	36.6%	53.6%
Female	33	46.5%	46.4%
Prefer not to answer	5	7.0%	–
N/A	7	9.9%	–
Ethnicity			
White/Caucasian	37	52.1%	41.0%
African American	1	1.4%	2.6%
Hispanic	16	22.5%	46.0%
Asian	0	0.0%	1.7%
Native American	0	0.0%	5.6%
Pacific Islander	0	0.0%	0.0%
Other	0	0.0%	2.7%
Prefer not to answer	9	12.7%	–
N/A	8	11.3%	–
Income			
Less than $25,000	9	12.7%	20.7%
$25,000–$49,999	15	21.1%	18.7%
$50,000–$99,999	17	23.9%	37.0%
$100,000–$199,999	8	11.3%	19.3%
$200,000 or more	3	4.2%	4.3%
Prefer not to answer	12	16.9%	–
N/A	7	9.9%	–

Chapter 5

Results

5.1 BWS Mean Score

The BWS mean scoring indicates relative importance by directly comparing the frequency with which respondents selected attribute levels as most and least important. Mean scores were calculated using the difference in best and worst selections for each level, normalized by the number of tasks and respondents. This non-econometric approach offers a clear, interpretable ranking of attributes and levels as perceived by respondents.

Table 5.1: Best-Worst Scores for Each Attribute Level

Level	Best Count	Worst Count	BWS Diff	BWS Score
Administrative Agency				
Governmental	7	83	-76	-0.35185
Non-Governmental	14	73	-59	-0.27315
Change in Wildfire Risk				
High to Medium	80	8	72	0.33333
Medium to Low	59	13	46	0.21296
Prevention Measure				
Mechanical Thinning	46	22	24	0.11111
Herbicide Treatment	35	43	-8	-0.03704
Prioritization				
Protection of Homes	88	15	73	0.33796
Protection of Natural Resources	55	18	37	0.1713
Increase in Utility Tax				
$1	6	40	-34	-0.31481
$4	4	45	-41	-0.37963
$7	22	34	-12	-0.11111
$10	16	38	-22	-0.2037

Among all attributes, ‘Protection of Homes’ and ‘High to Medium Risk Reduction’ were rated most important, with BWS scores of 0.33796 and 0.33333, respectively. These results suggest that respondents place a high value on both personal safety and tangible wildfire risk reduction. Similarly, 'Mechanical Thinning' emerged as an important fire prevention method (BWS = 0.11111), while 'Herbicide Treatment' was viewed far less favorably and had a slightly negative BWS score (–0.03704), indicating respondents selected it as least important more often than most important. This pattern aligns with previous research documenting longstanding public concerns about herbicide use in forest management, which often center on ecological and health risks and have led to restrictions in many North American regions (Buse et al., 1995).

Notably, the utility tax increase levels were ranked lowest across all attributes. The additional $4 and $1 tax increases were the least preferred, with BWS scores of –0.37963 and –0.31481, respectively. Surprisingly, the $1 increase had a lower BWS score than the $10 increase (–0.2037), which contradicts conventional economic expectations that larger costs would be more heavily penalized in importance rankings. This suggests that the symbolic nature of a fee increase, even if small, may elicit strong opposition from certain respondent groups, particularly those who may perceive any added cost as inequitable or unnecessary.

The 'Administrative Agency' attribute was also rated low in relative importance. Both governmental and non-governmental entities had negative BWS scores (–0.35185 and –0.27315, respectively), indicating low confidence in administrative actors relative to tangible outcomes like risk reduction or home protection.

In comparison to other themes in the survey, risk reduction and protection-related attributes consistently outperformed institutional or financial trade-offs. For example, the difference in BWS score between the most preferred (Protection of Homes) and least preferred (Additional $4) attribute levels is over 0.71, signaling a wide gap in how respondents weigh management goals versus financial contribution.

Overall, the results suggest that tangible wildfire mitigation strategies, especially those that directly reduce risk and protect property, carry the highest importance. In contrast, price sensitivity and agency identity were viewed as less consequential. These findings have implications for designing wildfire prevention programs and fee structures, particularly for ensuring public support among lower-income stakeholders who may view even small cost increases as barriers to access.

Table 5.2: Conditional Logit Model Results from Best-Worst Scaling

Attribute	Coef.	Exp(Coef.)	SE(Coef.)	z-value	p-value
Admin	-0.20815	0.81209	0.07767	-2.680	0.00736 **
Risk	0.60290	1.82742	0.09196	6.556	$5.53e-11$ ***
Measure	0.19110	1.21059	0.07835	2.439	0.01472 *
Priority	0.21991	1.24596	0.07836	2.806	0.00501 **
$1 Tax	-0.81457	0.44283	0.15860	-5.136	$2.81e-07$ ***
$4 Tax	-1.00202	0.36714	0.16256	-6.164	$7.09e-10$ ***
$7 Tax	-0.28685	0.75062	0.15349	-1.869	0.06164 .

Note: *** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$

Reference categories: Governmental agency, Medium-to-Low risk, Herbicide Treatment, Protection of Natural Resources, $10 Tax.

5.2 CLM Model

Table 5.2 presents the results from the Conditional Logit Model (CLM), where coefficients are interpreted relative to omitted reference levels. The Administrative Agency attribute omits "Governmental," so the coefficient for "Admin" reflects preferences for non-governmental organizations relative to government agencies. Similarly, the risk attribute omits "Medium-to-low", so the coefficient for "Risk" reflects preferences for "High-to-Medium" risk reduction. The measure attribute omits "Herbicide Treatment" use, so the coefficient for "Measure" reflects preferences for "Mechanical Thinning" of invasive grasses. While the priority attribute omits "Protection of Natural Resources", so the coefficient for "Priority" reflects preferences for "Priority" of program administration. Utility tax levels include dummy variables for $1, $4, and $7, with $10 as the omitted reference category to avoid multicollinearity.

Most non-price attributes are positively signed and statistically significant, indicating strong preferences for programs emphasizing risk reduction, mechanical thinning, and home protection. The coefficient for Risk Reduction: High to Medium was the largest in magnitude, followed by Priority: Protection of Homes. The significant and positive coefficient for Mechanical Thinning indicates that it was preferred over Herbicide Treatment. In contrast, all utility tax levels ($1, $4, and $7) had negative coefficients, with strong statistical significance, indicating consistent resistance to fee-based wildfire mitigation programs.

All non-price attributes, with the exception of Administrative Agency, were positively signed and statistically significant, indicating general support for risk reduction, mechanical thinning, and home protection across the full sample. Risk reduction from high to medium had the largest coefficient, suggesting it was especially important to respondents. Utility tax increases were all negatively signed and statistically significant, confirming strong resistance to paying for mitigation through higher fees.

Differences in preferences emerge when analyzing subgroups of respondents. Notably, attitudes toward public agency involvement, risk reduction measures, and taxation levels vary, suggesting that policy approaches to wildfire risk management may need to be tailored to different stakeholder groups.

5.3 REL Model

To analyze respondents' likelihood of voting 'Yes' on each referendum scenario, a Random Effects Logit (REL) model was estimated using a binary dependent variable (Binary_Y), with a random intercept for each respondent (R_ID). This model accounts for unobserved heterogeneity in baseline voting tendencies across individuals. The model included all five policy attributes, with the price attribute (utility tax increase) entered as a categorical factor variable. The $1 tax level was set as the reference category, with the $4, $7, and $10 levels included as binary indicators.

The results are presented in Table 5.3. The random intercept had substantial variance (σ^2 = 25.95; SD = 5.09), indicating considerable between-individual variation in baseline voting propensity. The intercept was positive and highly significant (p < 0.001), suggesting that respondents were overwhelmingly inclined to vote 'Yes' when the cost was low (i.e., at the $1 reference level).

Among the five attributes, none of the non-price variables—administrative agency, wildfire risk reduction, prevention method, or prioritization—were statistically significant. This suggests that these attributes did not independently influence voting behavior in the referendum framework once cost was controlled for. However, price levels had a strong and statistically significant impact. Compared to the $1 tax level, support dropped sharply at $4 ($\beta$ = –4.00, $p < 0.001$), $7 ($\beta$ = –6.85, $p < 0.001$), and $10 ($\beta$ = –10.98, $p < 0.001$).

Table 5.3: Random Effects Logit Model for Referendum Voting Behavior

Attribute	**Estimate**	**Std. Error**	**z-value**	**p-value**
(Intercept)	6.665	0.894	7.453	< 0.001 ***
Administrative Agency	0.015	0.174	0.087	0.931
Risk Reduction	-0.061	0.174	-0.348	0.728
Prevention Measure	0.000	0.169	0.000	1.000
Prioritization	0.000	0.169	0.000	1.000
$4 Tax Increase	-4.001	0.304	-13.163	< 0.001 ***
$7 Tax Increase	-6.848	0.376	-18.200	< 0.001 ***
$10 Tax Increase	-10.982	0.567	-19.384	< 0.001 ***

Note: *** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$

Reference categories: Governmental agency, Medium-to-Low risk, Herbicide Treatment, Protection of Natural Resources, $1 Tax.

These results indicate that cost was the dominant driver of referendum support. Shown in Table 5.4, at a $1 tax level, the predicted probability of voting 'Yes' was above 90%, whereas at $10, it dropped below 20%. This steep decline aligns with the descriptive summary of vote patterns, which showed that 93.6% of respondents supported the $1 proposal, compared to just 19.2% for the $10 option. The findings reinforce the conclusion that financial commitment was a key barrier to support, even for programs that aligned with respondents' preferences in the BWS task.

Table 5.4: Descriptive Vote Support by Cost Level

Utility Tax Level	**% Voting Yes**	**% Voting No**
$1	93.6%	6.4%
$4	61.8%	38.2%
$7	41.2%	58.8%
$10	19.2%	80.8%

Chapter 6

Discussion

These results underscore the central role of cost in referendum decisions. While BWS and CLM models revealed strong stated preferences for wildfire risk reduction and mitigation strategies, these preferences did not translate into financial support in the REL framework. One likely explanation is that respondents perceive abstract ranking tasks differently from real-choice scenarios. In BWS, individuals signal symbolic or idealized preferences, but in REL-style referendum, where financial commitment is explicit, cost sensitivity dominates. This distinction reflects a well-documented divergence between stated and revealed preferences in environmental economics, particularly in contingent valuation and choice modeling contexts (Carson and Groves, 2007; Loomis, 2011).

Another interpretation is that respondents faced budget constraints or equity concerns, leading them to oppose even modest tax increases for programs they otherwise supported in principle. Prior studies of environmental referendum have shown that cost is often the primary determinant of voting behavior, even when non-price attributes such as ecological benefit or risk reduction are emphasized (Kotchen, 2009).

The REL model, in particular, highlights a behavioral shift: price was the only statistically significant predictor of support. Non-price attributes, including risk reduction, agency type, and prioritization, had no measurable effect on actual voting decisions. Support declined sharply as tax levels increased, even when packages included highly valued components. This suggests that financial realism overrides symbolic support, echoing concerns about affordability that commonly arise in public goods funding (Samuelson, 1954).

This divergence may also reflect a threshold perception or scope neglect, where respondents infer that low-cost increases (e.g., $1) are insufficient to generate meaningful impact. In this context, \$1 may signal minimal investment, whereas \$10 implies a more serious or effective intervention. These perceptions align with behavioral findings in willingness-to-pay literature, where under-reaction to small cost differentials reflects skepticism about low funding levels (Bateman, 1993; Jorgensen et al., 2001). Future research could test this more directly through conjoint designs that explicitly tie tax amounts to program scale (e.g., acres treated, number of homes protected).

BWS and CLM models, by contrast, revealed strong stated preferences for tangible safety outcomes. "Protection of Homes" and "High to Medium Risk Reduction" consistently ranked highest across models, while "Mechanical Thinning" received moderate support. In contrast, both small and large tax increases were penalized in importance rankings, with smaller taxes often viewed more negatively. This suggests resistance not only to mandatory contributions, but also to programs perceived as ineffective.

Another notable finding is the limited role of administrative agency identity. Although CLM results detected modest preferences for non-governmental over governmental actors, these effects were not significant in the REL model. This suggests that trust in institutions, while relevant in some wildfire studies (Burton et al., 2024), may be secondary to cost and outcome clarity in determining public support.

Taken together, the integration of BWS, CLM, and REL models reveals meaningful distinctions between symbolic preferences and real-world support under budgetary constraints. These models provide a holistic view of how residents in fire-prone Arizona communities prioritize wildfire mitigation strategies, both in theory and when financial stakes are introduced. Such findings carry important policy implications. Symbolic support in surveys may not translate into behavioral endorsement when funding is involved. Programs must therefore balance visible, high-impact outcomes with affordability. Additionally, the lack of significant effects for institutional identity implies that communication strategies and cost transparency may matter more than the agency delivering the program.

Ultimately, designing wildfire mitigation strategies that gain public traction will require not only effective messaging about benefits, but also creative financing approaches, such as cost-sharing, matching grants, or opt-in fee structures, that reduce perceived burden while maintaining credibility and scope.

Chapter 7

Conclusion

This study examined public preferences for wildfire mitigation strategies in Arizona using a Best-Worst Scaling (BWS) framework, followed by Conditional Logit (CLM) and Random Effects Logit (REL) models. It assessed the relative importance of key policy attributes and evaluated whether these preferences translated into support when financial costs were introduced.

The results revealed that residents strongly prioritize tangible benefits, especially "Protection of Homes" and "High to Medium Wildfire Risk Reduction." These attributes were consistently rated highest in the BWS and were statistically significant in the CLM model. Prevention methods like "Mechanical Thinning" also received moderate support, while financial attributes, including even modest tax increases, were rated least favorably.

However, the REL model introduced a striking contrast. Despite the high stated importance assigned to certain attributes, actual support collapsed when utility tax increases were included. Support dropped dramatically from $1 to $10 tax levels, and none of the non-price attributes significantly influenced vote outcomes. These findings indicate that financial cost, not program content, was the dominant determinant of support when real tradeoffs were involved.

Rather than a methodological failure, this disconnect reflects rational behavior consistent with the economics of public goods. Wildfire mitigation exhibits classic non-excludable, non-rival properties, meaning that once implemented, all members of a community benefit—regardless of whether they contribute. As such, respondents may express strong preferences in symbolic ranking tasks (e.g., BWS), but in scenarios requiring personal payment, may prefer to free ride, assuming others will cover the cost. This challenge is well documented in environmental policy and contingent valuation research, where stated support often exceeds actual willingness to pay (Carson and Groves, 2007; Kotchen and Moore, 2007).

Future studies could probe this free-riding tendency more directly by incorporating experimental framing treatments that emphasize collective responsibility, social norms, or conditional contribution mechanisms such as tax-matching scenarios or community-level funding thresholds. These approaches may help policymakers design funding strategies that align symbolic preferences with real behavioral support.

Importantly, this study underscores that symbolic approval does not always translate into behavioral endorsement, particularly when personal costs are involved. Public-facing wildfire mitigation programs must therefore balance affordability with clear communication about tangible benefits. The lack of influence from administrative agency identity in the REL model suggests that institutional trust, while not irrelevant, may be secondary to cost and perceived impact in shaping support.

This research also highlights opportunities for further work on behavioral mechanisms. For example, the apparent penalization of low-cost options (e.g., $1) may reflect a form of "scope neglect," in which respondents perceive small costs as insufficient to deliver meaningful results. Alternatively, it may signal symbolic protest against fee-based approaches altogether. Future work should test whether respondents interpret low-cost programs as ineffective or simply reject them on principle.

In sum, the divergence between stated attribute importance and revealed support underscores the complexity of funding public goods like wildfire mitigation. While participants value mitigation outcomes, their reluctance to pay likely reflects a mix of perceived inefficiency, financial constraint, and classic free-rider behavior. Moving forward, strategies that integrate behavioral realism into preference modeling, and explicitly link cost levels to service scale, will be critical for designing cost-effective, publicly acceptable wildfire mitigation policies.

Appendix A

Final Survey Instrument

Informed Consent to Participate in Research
Study Title: Understanding Public Preferences for non-native Species Management in Arizona
Principal Investigator: Ayden Macleod
Consent Version: 11/01/2024

You are being asked to participate in a research study**.** Your participation in this research study is voluntary and you do not have to participate. This document contains important information about this study and what to expect if you decide to participate. Please consider the information carefully. Feel free to ask questions before making your decision to participate.

Thank you for taking the time to participate in this survey. It is designed to gather information about the public's view on invasive plant species. Your answers will assist in generating knowledge from diverse points of view to inform invasive plant management practices.

Information collected about you will not be used or shared for future research studies.

The information that you provide in the study will be handled confidentially. Your participation is completely voluntary, confidential, and anonymous. However, there may be circumstances where this information must be released or shared as required by law. The University of Arizona Institutional Review Board may review the research records for monitoring purposes.

If you have any questions, concerns, need clarification, or complaints about the study, you may contact the principal investigator:

Ayden Macleod, University of Arizona, Graduate Student, Department of Agricultural and Resource Economics. Email: aydenmacleod@arizona.edu

Note: For questions about your rights as a participant in this study or to discuss other study-related concerns or complaints with someone who is not part of the research team, you may contact the Human Subjects Protection Program at the University of Arizona – using the following information: Phone (520)-626-8630 or online at https://research.arizona.edu/compliance/human-subjects-protection-program.

By participating in this survey, you are agreeing to our use of the data for research on public attitudes about non-native plant species management.

Instructions

Thank you for taking the time to complete this survey.

Mark Answer Like This: ●
Not Like This: ⊗

Background Questions

1. What is the passcode in your survey packet (see postcard)?

2. What city/town do you live in?

◯	Globe
◯	Claypool
◯	Miami
◯	Superior
◯	None of these
◯	Prefer not to answer

3. How long have you lived in this city/town?

◯	Less than 1 year
◯	1-5 years
◯	More than 5 years
◯	Prefer not to answer

4. Have you or members of your family been impacted by any of these events in the past five years?

	Yes	No
Wildfire	◯	◯
Flood	◯	◯

5. Are you aware of the presence of invasive plant species in Arizona?

◯	Yes
◯	No

6. Are you aware of the wildfire dangers associated with invasive plant species?

◯	Yes
◯	No

7. Are you aware of any programs or efforts, where you live, aimed at removing invasive plants to reduce wildfire risk?

◯	Yes
◯	No

8. Were you, or your family members, affected by the Telegraph Wildfire of 2021? **[If no, please skip to the section titled Policy Questions]**.

◯	Yes
◯	No

9. During the time that the Telegraph Fire was burning, did you or members of your household evacuate or leave the area overnight?

◯	Yes
◯	No

10. Did you or members of your household evacuate any domestic animals or pets during the time that the Telegraph Fire was burning?

◯	Yes
◯	No

11. Did anyone in your household lose wages due to the Telegraph Fire Event? [If wages were lost, please do not include paid annual leave]

◯	Yes… Estimate total household wages lost: [$]
◯	No

12. Was your home/property damaged as a result of the Telegraph Fire or post-wildfire flooding?

◯	Yes
◯	No

13. If you had damages to your property, due to the Telegraph Fire or post-wildfire flooding, what would you estimate the costs of damage to be? [leave blank if no damages were done]

$

Background Questions

Now we will ask about a hypothetical new utility tax aimed at reducing wildfire risk.

Imagine that there is a new referendum ballot initiative to raise money for invasive plant management projects through a **utility tax**. This cost would come directly from your household's budget. We are interested in understanding whether you would vote "yes" or "no" and what aspects of the program are most important to you.

Below you will find additional information about various invasive plant management programs and instructions on how to provide feedback. Please read these carefully before continuing.

Key Features of Invasive Plant Management Programs:

Invasive plant management programs supported by the referendum typically vary in terms of goals and methods. Below are descriptions of key programmatic features, potential effectiveness, and costs:

Administrative Agency: An invasive plant management program could be handled by a governmental agency or a non-governmental organization (NGO).

Wildfire Risk Reduction: Programs' effectiveness can vary. Depending on the program, wildfire risk reduction could be lowered from high-to-medium risk or medium-to-low risk.

Types of Risk Reduction Measures: Programs could reduce risk using different approaches to wildfire prevention, such as:

- **Mechanical Thinning:** Using specialized equipment to remove invasive plants and other invasive vegetation, reducing fire fuel loads; or
- **Herbicide Treatment:** Applying targeted herbicides to eliminate invasive plants and vegetation that serve as fuel for wildfires.

Prioritization: What areas should be prioritized for the removal of invasive plant species? Prioritizing near homes may benefit homeowners directly by reducing the risk of fire. Prioritizing near natural resources may protect native wildlife and vegetation from wildfire harm.

Utility Tax Increase: Funding for these programs would come from an increase in your utility tax. Program costs could increase taxes from $1 to $10 per month.

Below are 8 different hypothetical referendum invasive plant management programs, each varying in terms of various levels of: Administrative Agency, Wildfire Risk Reduction, Utility Tax Increase, Prioritization, and Prevention Measures. **Please treat each question as unique from the others.**

Taking these considerations into account, please respond to the following questions. For each of the following 8 questions, please complete the following steps:

Step 1: Select one feature of the program you think is the **most important** feature and one feature of the program you think is the **least important**.

Step 2: Indicate whether you would vote **for**, or vote **against** this program if it was on the ballot this year

An Example question is provided on the next page.

Example Question:

Step 1: Please indicate which feature is the **most important** and which feature is the **least important**.

Most Important		Least Important
●	**Administration Agency:** Non-governmental	○
○	**Change in wildfire risk:** High to Medium	○
○	**Prevention Measure:** Herbicide Treatment	●
○	**Prioritization:** Protection of homes	○
○	**Increase in Utility tax:** $10 per month	○

Step 2: Would you vote **for** or **against** this program?

● I would vote **YES** to this referendum.

○ I support the goal of this referendum, but I am not prepared to pay $10/month and thus would vote **NO**.

○ I support the goal of this referendum, but I cannot afford $10/month and thus would vote **NO**.

○ I support the goal of the initiative, but I would vote **NO** for the following reason [________________________]

○ I would vote **NO** to this referendum

Plant Management Program 1. **Step 1:** Please indicate which feature is the **most important** and which feature is the **least important** to you.

Most Important		Least Important
○	**Administrative Agency:** Governmental	○
○	**Change in wildfire risk:** High to Medium	○
○	**Prevention Measure:** Mechanical Thinning	○
○	**Prioritization:** Protection of homes	○
○	**Increase in Utility tax:** $1 per month	○

Step 2: Would you vote **for** or **against** this program?

○ I would vote **YES** to this referendum.

○ I support the goal of this referendum, but I am not prepared to pay $1/month and thus would vote **NO**.

○ I support the goal of this referendum, but I cannot afford $1/month and thus would vote **NO**.

○ I support the goal of the initiative, but I would vote **NO** for the following reason [________________________]

○ I would vote **NO** to this referendum.

Plant Management Program 2. **Step 1:** Please indicate which feature is the **most important** and which feature is the **least important** to you.

Most Important		Least Important
○	**Administrative Agency:** Non-Governmental	○
○	**Change in wildfire risk:** Medium to Low	○
○	**Prevention Measure:** Herbicide Treatment	○
○	**Prioritization:** Protection of natural resources	○
○	**Increase in Utility tax:** $1 per month	○

Step 2: Would you vote **for** or **against** this program?

○ I would vote **YES** to this referendum.

○ I support the goal of this referendum, but I am not prepared to pay $1/month and thus would vote **NO**.

○ I support the goal of this referendum, but I cannot afford $1/month and thus would vote **NO**.

○ I support the goal of the initiative, but I would vote **NO** for the following reason [________________________]

○ I would vote **NO** to this referendum.

Plant Management Program 3. **Step 1:** Please indicate which feature is the **most important** and which feature is the **least important** to you.

Most Important		Least Important
◯	**Administrative Agency:** Governmental	◯
◯	**Change in wildfire risk:** High to Medium	◯
◯	**Prevention Measure:** Herbicide Treatment	◯
◯	**Prioritization:** Protection of natural resources	◯
◯	**Increase in Utility tax:** $4 per month	◯

Step 2: Would you vote **for** or **against** this program?

◯ I would vote **YES** to this referendum.

◯ I support the goal of this referendum, but I am not prepared to pay $4/month and thus would vote **NO**.

◯ I support the goal of this referendum, but I cannot afford $4/month and thus would vote **NO**.

◯ I support the goal of the initiative, but I would vote **NO** for the following reason [________________________]

◯ I would vote **NO** to this referendum.

Plant Management Program 4. **Step 1:** Please indicate which feature is the **most important** and which feature is the **least important** to you.

Most Important		Least Important
◯	**Administrative Agency:** Non-Governmental	◯
◯	**Change in wildfire risk:** Medium to Low	◯
◯	**Prevention Measure:** Mechanical Thinning	◯
◯	**Prioritization:** Protection of homes	◯
◯	**Increase in Utility tax:** $4 per month	◯

Step 2: Would you vote **for** or **against** this program?

◯ I would vote **YES** to this referendum.

◯ I support the goal of this referendum, but I am not prepared to pay $4/month and thus would vote **NO**.

◯ I support the goal of this referendum, but I cannot afford $4/month and thus would vote **NO**.

◯ I support the goal of the initiative, but I would vote **NO** for the following reason [________________________]

◯ I would vote **NO** to this referendum.

Plant Management Program 5. **Step 1:** Please indicate which feature is the **most important** and which feature is the **least important** to you.

Most Important		Least Important
◯	**Administrative Agency:** Governmental	◯
◯	**Change in wildfire risk:** Medium to Low	◯
◯	**Prevention Measure:** Mechanical Thinning	◯
◯	**Prioritization:** Protection of natural resources	◯
◯	**Increase in Utility tax:** $7 per month	◯

Step 2: Would you vote **for** or **against** this program?

◯ I would vote **YES** to this referendum.

◯ I support the goal of this referendum, but I am not prepared to pay $7/month and thus would vote **NO**.

◯ I support the goal of this referendum, but I cannot afford $7/month and thus would vote **NO**.

◯ I support the goal of the initiative, but I would vote **NO** for the following reason [________________________]

◯ I would vote **NO** to this referendum.

Plant Management Program 6. **Step 1:** Please indicate which feature is the **most important** and which feature is the **least important** to you.

Most Important		Least Important
○	**Administrative Agency:** Non-Governmental	○
○	**Change in wildfire risk:** High to Medium	○
○	**Prevention Measure:** Herbicide Treatment	○
○	**Prioritization:** Protection of homes	○
○	**Increase in Utility tax:** $7 per month	○

Step 2: Would you vote **for** or **against** this program?

○ I would vote **YES** to this referendum.

○ I support the goal of this referendum, but I am not prepared to pay $7/month and thus would vote **NO**.

○ I support the goal of this referendum, but I cannot afford $7/month and thus would vote **NO**.

○ I support the goal of the initiative, but I would vote **NO** for the following reason [________________________]

○ I would vote **NO** to this referendum.

Plant Management Program 7. **Step 1:** Please indicate which feature is the **most important** and which feature is the **least important** to you.

Most Important		Least Important
○	**Administrative Agency:** Governmental	○
○	**Change in wildfire risk:** Medium to Low	○
○	**Prevention Measure:** Herbicide Treatment	○
○	**Prioritization:** Protection of homes	○
○	**Increase in Utility tax:** $10 per month	○

Step 2: Would you vote **for** or **against** this program?

○ I would vote **YES** to this referendum.

○ I support the goal of this referendum, but I am not prepared to pay $10/month and thus would vote **NO**.

○ I support the goal of this referendum, but I cannot afford $10/month and thus would vote **NO**.

○ I support the goal of the initiative, but I would vote **NO** for the following reason [________________________]

○ I would vote **NO** to this referendum.

Plant Management Program 8. **Step 1:** Please indicate which feature is the **most important** and which feature is the **least important** to you.

Most Important		Least Important
○	**Administrative Agency:** Non-Governmental	○
○	**Change in wildfire risk:** High to Medium	○
○	**Prevention Measure:** Mechanical Thinning	○
○	**Prioritization:** Protection of natural resources	○
○	**Increase in Utility tax:** $10 per month	○

Step 2: Would you vote **for** or **against** this program?

○ I would vote **YES** to this referendum.

○ I support the goal of this referendum, but I am not prepared to pay $10/month and thus would vote **NO**.

○ I support the goal of this referendum, but I cannot afford $10/month and thus would vote **NO**.

○ I support the goal of the initiative, but I would vote **NO** for the following reason [________________________]

○ I would vote **NO** to this referendum.

Additional Information

1. Please tell us how vulnerable you feel for each of the following statements: (scale of 1 to 5, 1 being not at all vulnerable, 5 being extremely vulnerable)

	1	2	3	4	5
How vulnerable do you feel that your life is due to wildfires?	○	○	○	○	○
How vulnerable do you feel that the lives of your family members are due to wildfires?	○	○	○	○	○
How vulnerable do you feel that your home is to wildfires?	○	○	○	○	○

2. Rank how effective you think each of the following types of efforts would be to address wildfire prevention goals: (scale of 1 to 5, 1 being very low effectiveness, and 5 being extremely effective)

	1	2	3	4	5
Mechanical thinning	○	○	○	○	○
Herbicide treatment	○	○	○	○	○
Controlled Burns	○	○	○	○	○

3. Please tell us the level of trust you have in the following entity's ability to prevent wildfires: (scale of 1 to 5, 1 being no trust, and 5 being complete trust).

	1	2	3	4	5
U.S. Forest Service	○	○	○	○	○
State Forestry	○	○	○	○	○
Local Fire Department	○	○	○	○	○
Non-Governmental Organizations	○	○	○	○	○

4. Please tell us the level of trust you have in the following entity's ability to manage wildfires: (scale of 1 to 5, 1 being no trust, and 5 being complete trust).

	1	2	3	4	5
U.S. Forest Service	○	○	○	○	○
State Forestry	○	○	○	○	○
Local Fire Department	○	○	○	○	○
Non-Governmental Organizations	○	○	○	○	○

Demographic Information

Please tell us a little about yourself. No identifying information will be collected, ensuring that your responses remain anonymous and cannot be linked back to you.

1. What is your home zip code?

○	85501
○	85539
○	85532
○	85135
○	85553
○	85502
○	85541
○	Prefer not to answer

2. What is your age?

○	18-24 years
○	25-34 years
○	35-44 years
○	45-54 years
○	55-64 years
○	65-74 years
○	75 years or older
○	Prefer not to answer

3. What is your gender?

◯	Male
◯	Female
◯	Other, please specify:
◯	Prefer not to answer

4. Which category best describes you?

◯	Hispanic or Latino
◯	Asian
◯	Black or African American
◯	American Indian or Alaska Native
◯	White (Non-Hispanic/Latino)
◯	Native Hawaiian or Other Pacific Islander
◯	Another race, ethnicity or origin, please specify: [ ]
◯	Prefer not to answer

5. What is the highest degree or level of school you have completed?

◯	Some high school
◯	High school graduate or GED
◯	Some college or associate's degree
◯	Bachelor's degree or higher
◯	Other, please specify:
◯	Prefer not to answer

6. What was your total household income before taxes last year?

◯	Less than $25,000
◯	$25,000 - $49,999
◯	$50,000 - $99,999
◯	$100,000 - $199,999
◯	More than $200,000
◯	Prefer not to answer

7. What best describes your housing situation?

◯	I own my home
◯	I rent my home
◯	Prefer not to answer

8. Is your home insured against wildfire damage?

◯	Yes
◯	No
◯	Prefer not to answer

Is there anything else you would like to tell us about how the Telegraph fire affected you or additional comments on this survey?

Thank you for your time.
Please return the survey in the paid-postage envelope no later than Friday, February 14, 2025.

Appendix B

Orthogonal Array

Attribute 1	Attribute 2	Attribute 3	Attribute 4	Attribute 5
0	0	0	0	0
1	1	1	1	0
0	0	1	1	1
1	1	0	0	1
0	1	0	1	2
1	0	1	0	2
0	1	1	0	3
1	0	0	1	3

Table B.1: Orthogonal Array for 8 run choice experiment

Appendix C

Respondents' Trust in Public Institutions

Question	Mean	SD
Rank the following government entities by how much trust you have in their ability to prevent wildfires (5 = most trust).		
U.S. Forest Service	3.20	1.19
State Forestry	3.27	1.05
Local Fire Department	3.10	1.21
Non-Governmental Organization	2.13	1.11
Rank the following government entities by how much trust you have in their ability to manage wildfires (5 = most trust).		
U.S. Forest Service	3.57	1.19
State Forestry	3.53	1.04
Local Fire Department	3.13	1.28
Non-Governmental Organization	2.10	1.13
Rank how effective you think each of the following efforts would be in addressing fire prevention goals (5 = most effective).		
Mechanical Thinning	3.97	0.96
Herbicide Treatment	2.53	1.50
Controlled Burns	3.33	1.06

Table C.1: Descriptive Statistics for Trust in Public Organizations and Policy Effectiveness

Appendix D

Respondents' Perceived Vulnerability to Wildfire

Question	Mean	SD
How vulnerable do you feel that your life is due to wildfires? (1 = not at all vulnerable, 5 = extremely vulnerable)	2.80	1.06
How vulnerable do you feel that the lives of your family members are due to wildfires? (1 = not at all vulnerable, 5 = extremely vulnerable)	2.73	1.08
How vulnerable do you feel that your residence is to wildfires? (1 = not at all vulnerable, 5 = extremely vulnerable)	3.10	1.06

Table D.1: Perceived Vulnerability to Wildfires

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