Linking Forests to Airsheds: Investigating Public Support and Willingness to Pay for Reducing Wildfire Smoke Exposure

Ahmed Amine Jawhari [a], Benjamin A. Jones [b], Robert P. Berrens [c]

[a] PhD Candidate, Department of Economics, The University of New Mexico, jawhari@unm.edu (corresponding author).

[b] Associate Professor and Regents' Lecturer, Department of Economics, The University of New Mexico, bajones@unm.edu.

[c] Regents' Professor, Department of Economics, The University of New Mexico, rberrens@unm.edu.

Abstract

Wildfire smoke reduction in the western United States presents a regional public good challenge, as local fires send smoke across state lines. This study evaluates households' willingness-to-pay (WTP) to reduce smoke through forest fuel treatments. A contingent-valuation referendum (N=1,023; WTP n=623) with *ex-ante*/*ex-post* choice-purification screens yields a conservative median WTP of \$94 to \$123 (2021 USD) per year for one avoided smoke day. Valuations are higher among households who trust agencies, report health concerns, and support treatments. Preferences are polarized: 15% reject the prescribed fire smoke tradeoff, showing near-zero WTP. These benefit estimates can inform benefit-cost analysis and budgetary appropriations.

Keywords: Wildfire Smoke; Wildfire Mitigation; Prescribed Fire; Contingent Valuation; Willingness-to-Pay; Consequentiality Measures.

doi:10.3368/le.102.4.042225-0032R1

1. Introduction

Wildfires in the western United States (US) have escalated in both frequency and intensity, propelled by overabundant forest fuels, changing climate conditions, and the expansion of the wildland-urban interface (Crockett & Westerling, 2018; Mockrin et al., 2022). Although large blazes ignite locally, the smoke they generate disperses widely, crossing state and even national borders (Bruce et al., 2025). Thus, wildfire damages are not confined to the flame zone. This creates a risk externality dilemma (whose reduction provides a public good): local ignition sites produce costs (e.g., respiratory health burdens, reduced visibility, and degraded recreation opportunities) borne by households scattered across multiple states.

Forest managers typically address the risk of severe wildfires, and thus future smoke, through forest fuel treatments, particularly prescribed fire paired with mechanical thinning (Stephens et al., 2012). Yet prescribed fire remains well-below recommended levels in the western US (Schultz, McCaffrey, & Huber-Stearns, 2019). Two principal barriers explain this shortfall: (i) insufficient financing to conduct large-scale burns, and; (ii) limited public acceptance of intentionally introduced smoke (Miller, Field, & Mach, 2020). This "smoke today vs. smoke tomorrow" tradeoff (Jones et al., 2022) is significant, as decision makers must weigh the localized, but short-term, emissions from prescribed fire against cross-continental and potentially severe wildfire smoke.

Research shows that wildfire smoke imposes sizable non-market damages, and that avoiding smoke yields important welfare gains (i.e., health, recreation, visibility, wildlife habitat, climate co-benefits) (e.g., Gellman, Walls, & Wibbenmeyer, 2022; Sanderfoot et al., 2022; Crowley et al., 2023). However, existing valuations monetize health outcomes (e.g., symptom days

) and do not capture the broader airshed bundle of benefits from "less smoke," nor do they condition values on the mechanism that delivers those reductions (fuel treatments).

This study fills that gap by eliciting western US households' willingness-to-pay (WTP) for one fewer annual smoke day when the reduction is explicitly delivered through large-scale fuel treatments. It addresses two critical questions: (i) How does support for forest fuel treatments and trust in federal agencies influence WTP?, and; (ii) Does resistance to short-term prescribed fire smoke undermine the political and economic feasibility of a regional financing mechanism? To address these questions, we conducted a contingent valuation (CV) referendum survey of N=1,023 households across 11 western US states.[1] Our analysis incorporates *ex-ante* measures promoting incentive-compatibility in the survey design, and *ex-post* measures for preference "purification." The *ex-post* measures include a rational consistency check, recoding low-certainty votes, and applying the discrete knife-edge approach used in Mohr et al. (2023) to split the sample based on perceived survey consequentiality (Carson & Groves, 2007; Herriges et al., 2010). Based on the "purified" preferences, the study aims to derive welfare estimates that reflect choices made under *epistemically favorable conditions* (Lades et al., 2025).

Results indicate that the median annual household WTP to avoid one day of wildfire smoke ranges from about $35 to over $200, depending on the strictness of uncertainty recoding and perceptions of consequentiality. Even under conservative assumptions, median WTP estimates cluster around $94 to $123.[2] These valuations, when aggregated across western US households, correspond to $2.6 billion to $3.4 billion in annual benefits. Preferences are polarized: about 15% of respondents reject any short-term prescribed fire smoke and report near-zero WTP, which can constrain large-scale deployment. Trust in implementing agencies and tolerance for short-term smoke are strong correlates of WTP. Findings show the potential for broader airshed-wide financing mechanisms, in the sense that households' valuations are large enough to justify meaningful investments and to inform budget planning and multi-jurisdiction cost sharing.

2. Background and Literature Review

From Forest Fuels to Regional Airsheds

Historically, natural wildfires have supported ecosystem health. However, the legacy of fire suppression has disrupted natural fire cycles, leading to an overabundance of forest fuels (Parks et al., 2018). Rising temperatures and prolonged droughts have created favorable conditions for severe and harder-to-control wildfires (Crockett & Westerling, 2018; see also Appendix Figure 1a). Although large fires ignite in local forested areas, monitors show that their smoke routinely crosses state and even national borders, turning a local ignition into a regional airshed problem (Jaffe et al., 2020; Bruce et al., 2025). Western US states bear the largest share of the growing burned acreage in the US, making their downwind populations especially vulnerable to wildfire smoke (Appendix Figure 1b).

Smoke pollutants degrade air quality, leading to respiratory health damage and increased all-cause mortality (Gould et al., 2024). Vulnerable populations, especially the elderly, face heightened health risks (Liu et al., 2015; 2017) and the damage extends beyond human health. Wildfire smoke reduces households' life quality by affecting scenery visibility, outdoor recreation, wildlife health, and habitats (Gellman, Walls, & Wibbenmeyer 2022; Sanderfoot et al., 2022). Such amenities hold significant value, although they are not typically traded in markets (Segerson, 2017).

The growth in wildfires in the western US and their attendant external effects has meant an increasing need for mechanisms to scale and finance smoke reduction (Jones et al., 2022). More generally, various sources have argued for managing air pollution from a regional airshed perspective, accounting for prevailing wind and weather patterns (Zirnhelt et al., 2014; Guttikunda, 2024), including with respect to wildfire smoke (Schweizer et al., 2017; Wen et al., 2023). Although regional airsheds are not used for Clean Air Act attainment standards in the US, where the geographic resolution is the county level (Cropper et al., 2025), they are being pursued in other countries (e.g., Tripathi, Yadav, & Sharma, 2024; Basumatary, Dhote, & Bansod 2025). Such an approach could reduce wildfire smoke more effectively while better targeting payments from downwind beneficiaries.

Watersheds and airsheds do not always align geographically, but experiences with forested watersheds and downstream drinking water protection illustrate feasible solutions. Funding models that span large regions are increasingly applied in the arid western US to support water-source protection of forested areas (e.g., Adhikari et al., 2017; Hjerpe et al., 2024). Because effective forest treatments often cross ownership boundaries—federal, tribal, state, municipal, and private—collaborative programs and cost-sharing are needed. The core argument is that delineating prevailing airsheds, just as with watersheds, and looking beyond the wildland urban interface (WUI), could become central to financing wildfire-risk mitigation and smoke reduction.

Valuing Cleaner Airsheds: Use and Nonuse Benefits

Assigning a monetary value to avoided smoke exposure days expresses a diffuse airshed benefit as a welfare-consistent measure on a monetary scale, which permits comparison with program costs and could inform investment in upstream fuel treatments. Non-market valuation captures the worth of goods not traded in markets, such as clean air, lower health risks, and clearer vistas (Boyle, 2017). These values are essential for conducting benefit-cost analyses of wildfire management policies. Non-market values fall into two primary classes. Use values reflect direct gains such as fewer hospital visits or better recreation days, plus indirect gains like climate regulation. Nonuse values reflect satisfaction from knowing ecosystems and future generations are spared smoke (Segerson, 2017).

Studies confirm that households value avoiding wildfire smoke impacts, but value estimates are largely for health outcomes (e.g., symptom days) without conditioning on how the reductions are achieved (i.e., the mitigation mechanism). The stated preference literature stresses that respondents' valuation depends on the credibility and perceived implementation pathway of the proposed program, not merely the end outcomes (Carson & Groves, 2007; Herriges et al., 2010; Boyle, 2017, p. 97). Richardson, Loomis, and Champ (2013) found southern Californians would pay $95 per avoided symptom day following the 2009 Station Fire wildfire, but the data predate today's larger fires and omit hypothetical bias controls. Jones et al. (2016) estimated a $130 WTP for reduced health effects from smoke in Albuquerque, New Mexico, using a defensive behavior approach (household averting actions to reduce exposure), yet the result is site-specific. Shrestha et al. (2021) is the lone study to mention prescribed fire explicitly, reporting $41 per acre in Mississippi, a state with minimal recent wildfire growth as shown in our Appendix Figure 1b. The study focuses solely on private forests. Its results may not apply to western US states, where most forests are publicly owned (Nelson, Liknes, & Butler, 2010). In contrast, the present study targets the full bundle of smoke-related benefits relevant at the airshed scale (health, visibility, outdoor recreation, and nonuse benefits). It estimates households' WTP for one fewer annual smoke day when the reduction is delivered, specifically, by scaling forest fuel treatments (prescribed fire and mechanical thinning) on public lands in the western US.

The "Smoke Today" vs. "Smoke Tomorrow" Dilemma: Economic Valuation and Barriers to Scaling Prescribed Fire

Forest managers typically reduce future wildfire severity and thereby total smoke by combining prescribed fire with mechanical thinning (Stephens et al., 2012). Despite its proven benefits, the use of prescribed fire in the western US remains well-below recommended levels. Parks et al. (2025) recommend increases between 10 and 100 times in prescribed fire combined with thinning. Reported treated acreage increased about 5% yearly from 1998 to 2018, but 70% of all treated acres and 98% of the growth were in the southeastern US (Kolden, 2019). Schultz, McCaffrey, and Huber-Stearns (2019) revealed two primary obstacles explaining this shortfall: (i) insufficient financing and human resources, and; (ii) lack of public support. Surprisingly, their study showed that air quality standards are not barriers to implementation. We argue that these obstacles reinforce each other because broader public acceptance can shape legislative priorities and, consequently, funding allocations for fuel treatments.

A key challenge is the “smoke today” against “smoke tomorrow" tradeoff (Jones et al., 2022). Prescribed fire releases short-term smoke, which can provoke health concerns and community pushback. By lowering fuel loads, it can also reduce the scale and intensity of future wildfire smoke. Preliminary findings indicate that the net air-quality gains are positive: Higuera-Mendieta and Burke (2025) report that reductions in severe wildfire smoke can outweigh the smoke from low-severity prescribed fires. Empirical findings diverge on the extent of short-term health impacts: some studies find no statistically significant link between prescribed fire and hospitalizations (Raab et al., 2023), while others report associations with asthma, cardiovascular outcomes, and adverse births (Huang et al., 2019; Jones & Berrens, 2021).

The present study takes an important first step towards addressing the financing gap and the “smoke today” against “smoke tomorrow” dilemma by gauging households’ public support and WTP for a program that scales up fuel treatments. If households accept some short-term smoke to avoid more severe future smoke episodes, their aggregated WTP could justify efforts to expand revenue sources for scaling up prescribed fire. Quantifying this tradeoff, and how trust in government or attitudes toward fuel treatments shape valuation, provides policy-relevant information for designing effective "Forests to Airsheds" financing solutions.

3. Theoretical Considerations

Downwind households across the regional airshed benefit from wildfire smoke reduction as it introduces improvements to health, outdoor recreation, scenery visibility, wildlife habitats, and future climate impacts (Liu et al., 2015; 2017; Gellman, Walls, & Wibbenmeyer, 2022; Sanderfoot et al., 2022; Gould et al., 2024). Let $Q = (E, q_{WS}, q_{PF})$ be the bundle of environmental attributes entering the household's utility, where E is a vector of the non-smoke environmental attributes affecting welfare, q_{WS} denotes wildfire smoke exposure, and q_{PF} denotes short-term smoke exposure from prescribed fire. In the status quo, these attributes are at levels $Q^0 = (E^0, q^0_{WS}, q^0_{PF})$. The *Wildfire Smoke Reduction Program* considered in our contingent valuation survey would shift the environmental attributes to Q^1 using fuel treatments.

The household's maximum WTP to reduce wildfire smoke is defined as the Hicksian Compensating Surplus (HCS) measure of welfare change:

$$WTP_{\text{HCS}} = \mathrm{e}(p, Z, Q^0, U^0) - \mathrm{e}(p, Z, Q^1, U^0) \qquad [1]$$

where $e(.)$ is the household's expenditure function, p is the price vector for market goods, Z is a vector of exogenous household attributes, and U^0 is the baseline utility level. Paying WTP_{HCS} leaves the household at U^0 while enjoying the net environmental change $(Q^1 - Q^0)$. Although prescribed fire may introduce some short-term smoke in the treatment areas, the referendum question instructs households to disregard this effect ($\Delta q_{\text{PF}} \approx 0$). The rationale is to isolate the benefits of long-term, airshed-wide reductions in wildfire smoke. This way, the study avoids a valuation that would otherwise conflate the increment (future smoke reduction) with the decrement (localized treatment smoke). This assumption aligns with evidence that prescribed fire smoke is more localized and short-lived than wildfire smoke (Navarro et al., 2018). However, it is possible that some households can reject this net-positive framing because of their latent aversion to smoke from prescribed fire. Let

$$d_{\mathrm{i}} = \begin{cases} 1 \text{ if household } i \text{ rejects the smoke tradeoff,} \\ \qquad\qquad 0, \text{otherwise.} \end{cases} \qquad [2]$$

The survey elicits d_{i} in a follow-up question, which is later used to explore heterogeneity in WTP by acceptance of the "smoke today" against "smoke tomorrow" tradeoff.

A well-known critique of stated preference valuations is hypothetical bias; the divergence between hypothetical and actual behavior. Experimental evidence shows the bias is largest when respondents doubt that survey outcomes will guide real policy or payments; credible policy and payment links significantly reduce it (Haab, Lewis, & Whitehead, 2020). Recent work proposes three complementary safeguards: (i) preference "purification", which removes answers demonstrably driven by cognitive error; (ii) restriction of the welfare analysis to responses given under *epistemically favorable conditions*—that is, when respondents are informed, attentive and free of obvious biases; and, (iii) adoption of the Bernheim-Rangel framework, which treats only such bias-free responses as "welfare-relevant choices" (Bernheim & Rangel, 2009; Lades et al., 2025).

The present study implements these three safeguards through the *ex-ante*/*ex-post* framework of Loomis (2014). *Ex-ante* measures promote incentive-compatibility and consequentiality in the survey design. *Ex-post* measures purify responses by testing for rational consistency, adjusting for uncertainty, and survey consequentiality. Together, these measures allow for a robust estimation of welfare change.

4. Survey Design and Data

This study uses a public advisory referendum administered using an online Qualtrics panel. The survey instrument was reviewed and approved by the Institutional Review Board at the University of New Mexico. The survey was launched in July 2021 after a pilot test (n = 100, June 2021) to refine clarity and technical quality. Each respondent answered the survey for their entire household. Quota sampling ensured representativeness by age, gender, race, and state-of-residence across the 11 contiguous western US states (Arizona, California, Colorado, Idaho, Montana, Nevada, New Mexico, Oregon, Utah, Washington, and Wyoming; see Appendix Table A1). In total, N=1,023 respondents completed the survey.[3]

Participants began with an eligibility screener confirming residence in the western US and age≥18. They next received information on wildfire smoke's health and environmental impacts, followed by a description of the proposed *Wildfire Smoke Reduction Program* and its potential benefits. The program would use prescribed fire and mechanical thinning on public forests to reduce each household's smoke exposure by one-day annually for 20 years.[4]

Two-Stage Advisory Referendum

Respondents answered a two-stage referendum question. First, they voted 'Yes,' 'No,' or 'Not Sure' on a no-cost referendum for the program, which would reduce household smoke exposure by one-day annually at zero monetary expense. Next, a single-bounded, closed-ended referendum introduced a randomly assigned annual federal tax t_i to fund the program:[5]

> *The Wildfire Smoke Reduction Program would be costly to operate and requires financing [...]*
>
> *Q: Would you vote for or against [...] in an advisory referendum if adoption of this program reduced your exposure to wildfire smoke by an average of 1 day per*

year and would cost your household {\$$t_i$} in increased Federal taxes every year for the next 20 years?

The survey design promoted incentive-compatibility *ex-ante* through various measures. The survey implemented a closed-ended valuation format, consistent with evidence from Hanemann et al. (2025), to elicit valid welfare-change measures. The referendum was framed as advisory to federal agencies. It was linked to a coercive federal tax if it passed with a 50% majority rule. The survey also reminded respondents to consider household budget constraints and alternative uses of income (Carson, Groves, & List, 2014). These elements promote policy and payment consequentiality in the sense of Carson and Groves (2011) and conform to best practices for consequential CV surveys (Harrison, 2007; Loomis 2014; Lades et al., 2025).

Full voting results are provided in Appendix Table A3 (N = 1,023); about 78% of respondents supported the program at zero cost, but support dropped to 47% when a positive payment amount (t_i) was introduced. This sharp decline underscores voters' sensitivity to cost, consistent with theoretical expectations for valid welfare estimates in CV.

Follow-up Questions

Immediately after the valuation question, the survey presented three follow-up questions that are used *ex-post* to purify responses. First, respondents rated their certainty in payment decisions on a discrete 0 (*not at all certain*) to 10 (*completely certain*) scale. Second, participants answered two questions probing perceptions of policy and payment consequentiality, consistent with the conceptual framework established by Carson and Groves (2007), Herriges et al. (2010), and Mohr et al., (2023):

Q: Do you believe these survey results will affect Federal wildfire policy and reduce the level of wildfire smoke?

Q: Do you believe that your Federal taxes will actually increase to pay for the proposed Wildfire Smoke Reduction Program, if implemented?

Third, they were asked to consider the "smoke today" vs. "smoke tomorrow" tradeoff:

We ask you to consider the tradeoff between using prescribed burning to reduce future wildfire activity with the fact that prescribed burning, like any type of fire, creates smoke.

Q: […] Indicate agreement or disagreement to the statement: I am willing to accept some exposure to smoke from prescribed burns as a tradeoff for reducing future wildfire activity in the US

This question relaxes the initial assumption of "no direct treatment smoke," revealing whether respondents would still accept short-term smoke to achieve long-term benefits across the regional airshed. Approximately 85% accepted, while 15% rejected the tradeoff (Table 1). The vote-certainty scale and the two consequentiality prompts are applied as *ex-post* validity filters in the econometric analysis presented under Choice Purification in Section 5.

After the referendum, respondents who voted 'No' to the payment amount were asked a follow-up question on their most important reason for voting against the program. To be consistent with the CV literature (e.g., Halstead, Luloff, & Stevens, 1992; Johnston et al., 2017), we classify as potential protest 'No' votes those reporting reasons orthogonal to the value provided by the program (e.g., payment vehicle objections, institutional distrust, etc.). Since protest status for 'Yes' is unobserved, protest comparisons are interpreted conditional on voting 'No.' We use protest information (Appendix Table A11) for diagnostics rather than a primary choice purification measure to avoid upward bias in WTP from dropping potential protest 'No' votes; however, we note that misclassifying protest responses can bias welfare estimates in either direction (Meyerhoff & Liebe, 2006).

Descriptive Statistics

Table 1 summarizes the characteristics of the N=1,023 respondents who completed the survey. The average age was 49 years, and half the sample identified as female. Around 76% of respondents reported White race, 46% held at least a bachelor's degree, and 14% lived in rural areas. Households averaged 2.6 members, with an average annual income of $77,000 (2021 USD) but with a sizable standard deviation of $49,000, indicating broad economic diversity. Most respondents (77%) believed they had smelled wildfire smoke at home and outdoors, and 38% felt that smoke had negatively affected their health; 11 % had visited a doctor for smoke-related issues, and 14% had missed work. Nearly a quarter (25%) used a portable air filter, and 73% lived with individuals considered especially vulnerable to smoke (e.g., children, seniors, or people with medical needs). Knowledge and attitudes about wildfire management were also prevalent: 74% were aware of prescribed fire or mechanical thinning prior to the survey, 75% supported expanding these practices, and 62% expressed confidence in the federal government's ability to implement the proposed *Wildfire Smoke Reduction Program* effectively. Overall, these statistics highlight that wildfire smoke is a familiar concern for most households in the western US, and there is substantial openness to proactive fuel treatments as a means of mitigating future smoke episodes.

<<Table 1 about here>>

5. Methodology

The proposed *Wildfire Smoke Reduction Program* can provide households with nonuse values (e.g., improved wildlife habitat, climatic impacts) as well as use values (e.g., improved health, scenery visibility, outdoor recreation). Thus, this study implements the CV method through a public referendum-style, trichotomous choice format contingent on a payment amount (t_{i}). Let the vote of respondent i be $Y_{\mathrm{i}} = \{0,1,2\}$: =1 if they vote 'Yes' to support the program at cost t_{i}, =0 if they vote 'No,' and =2 if they vote 'Not Sure.'

Choices Purification

Following Bernheim and Rangel (2009) and Lades et al. (2025), the analysis seeks to identify choices given under *epistemically favorable conditions*. These include choices that are internally consistent, confident, and made by respondents who believe the survey could translate into real policy and payments. The choice purification proceeds in four *ex-post* steps.

First, to determine whether 'Not Sure' (N=258) responses could be pooled with 'Yes' or 'No' categories, we apply Cramer and Ridder's (1991) likelihood ratio test. The null hypothesis posits that estimated coefficients for 'Not Sure' responses are statistically identical to those of either 'Yes' or 'No,' implying no loss of fit when merging response categories. Two constrained multinomial logit models were estimated:[6] one forcing 'Not Sure' coefficients to equal 'Yes' and another equating them to 'No.' These were compared to an unconstrained three-category model. Each constrained model imposes 18 equality constraints (17 slope coefficients as in Table 2 plus the intercept), resulting in 18 degrees of freedom. The likelihood ratio tests rejected pooling 'Not Sure' with 'Yes' ($\chi^2(18) = 221.18,\ p < 0.01$). Merging 'Not Sure' with 'No' was not rejected at the same threshold ($\chi^2(18) = 33.13,\ p > 0.01$). Figure 1 reinforces this result. The predicted probability of 'Not Sure' responses aligns closely with 'No' votes across payment amounts, particularly at higher costs where uncertainty diminishes. We therefore recode 'Not Sure' as 'No,' effectively reducing the referendum to a dichotomous format ($Y_{\mathrm{i}} = \{0,1\}$) for all the subsequent analyses performed below.[7]

<<Figure 1 about here>>

Second, rational-consistency screening drops votes that violate monotonicity: eleven (11) respondents who voted ‘No’ to the program at zero cost but supported it at a positive cost are excluded, leaving a final analytic sample of N=1,012 households.

Third, the analysis addresses vote uncertainty. Let $Y_i^\tau = \{0,1\}$ take $Y_i^\tau = 1$ when respondent i both approves the cost referendum ($Y_i = 1$) and reports a certainty score ≥ τ on the 0-10 scale, and $Y_i^\tau = 0$ otherwise. Such that:

$$Y_i^\tau = \begin{cases} 1, & Y_i = 1 \text{ and certainty}_i \geq \tau, \\ 0, & \text{otherwise.} \end{cases} \qquad [3]$$

This asymmetric recoding rule (Champ, Moore, & Bishop, 2009) converts low-certainty ‘Yes’ votes to ‘No’ while leaving all ‘No’ votes intact. The study reports results for the no-recoding baseline ($\tau = 0$), as well as for the $\tau = \{6,7\}$ thresholds that are shown empirically (e.g., Poe et al., 2002; Wang et al., 2016) to approximate actual payment behavior.

Fourth, we implement the discrete knife-edge consequentiality split of Mohr et al. (2023). Define two binary indicators: $\text{Affect}_i = 1$ if respondent i believes the survey could affect federal wildfire policy, and $\text{Payment}_i = 1$ if they assign a non-zero probability to having to pay increased taxes if the program is implemented. The intersection of these beliefs yields three groups: the “Completely Inconsequential” group who meets neither condition $(\text{Affect}_i \cap \text{Payment}_i) = 0$, the “Weakly Consequential” group who meets a minimum of policy consequentiality $(\text{Affect}_i = 1)$, and the “Strongly Consequential” group who meets both conditions $(\text{Affect}_i \cap \text{Payment}_i) = 1$. This approach is consistent with the definitions and rationale outlined in Carson and Groves (2007) and Herriges et al. (2010).

Willingness-to-Pay (WTP) Estimation

Following Cameron (1988), this study employs a log-linear (exponential) specification for the underlying WTP, consistent with the net-positive framing of the program ($\mathrm{WTP_{HCS}} \geq 0$). We specify the WTP function as:

$$\log(WTP_i) = X_\mathrm{i}\beta + \eta_\mathrm{i} \qquad [4]$$

where X_i is a vector of characteristics, β is a vector of coefficients to be estimated, and $\eta_\mathrm{i} \sim Logistic(0, \kappa)$. A respondent votes 'Yes' if $WTP_\mathrm{i} \geq t_\mathrm{i}$, such that:

$$\Pr(Y_\mathrm{i}^\tau = 1|X, t_i) = \Pr(X_\mathrm{i}\beta + \eta_\mathrm{i} \geq \ln(t_i)) \qquad [5]$$

$$\Pr(Y_\mathrm{i}^\tau = 1|X, t_i) = 1 - \Pr\left(\frac{\eta_\mathrm{i}}{\kappa} \leq \frac{1}{\kappa}\ln(t_\mathrm{i}) - \frac{1}{\kappa}X_\mathrm{i}\beta\right) \qquad [6]$$

where $\kappa > 0$ is the scale parameter standardizing the error term η_i.[8] This equation is equivalent to that of a binary logistic regression with $\ln(t_i)$ as a covariate along with *X*. This regression estimates the parameters $(\beta_{\mathrm{payment}}, \beta^*) = (-\frac{1}{k}, \frac{1}{k}\beta)$ where β_{payment} is the coefficient on the logged payment amount $\ln(t_i)$, and β^* is the coefficient on the rest of covariates, *X*. The parameter of interest, β, is in WTP space and is recovered in two main steps: (i) recover $\kappa = -\frac{1}{\beta_{\mathrm{payment}}}$; and, (ii) scale β^* such that $\beta = \kappa\beta^*$. The results section reports estimates of (β, κ).[9] The initial vector $(\beta_{\mathrm{payment}}, \beta^*)$ is estimable by maximizing the log-likelihood function:[10]

$$\log L(\beta^*) = \sum \left\{Y_\mathrm{i}^\tau \log\left(1 - \mathrm{F}\left(\beta_{\mathrm{payment}}, \beta^*, t_\mathrm{i}, X_\mathrm{i}\right)\right) + (1 - Y_\mathrm{i}^\tau)\log\left(F\left(\beta_{\mathrm{payment}}, \beta^*, t_\mathrm{i}, X_\mathrm{i}\right)\right)\right\} \qquad [7]$$

The exponential functional form (Eq. 4) allows interpretation of the estimated coefficients multiplicatively rather than assuming constant marginal effects; a one unit increase in the explanatory variable X_j multiplies median WTP by a factor of $\exp(\widehat{\beta_\mathrm{j}})$.[11] The median (MD) WTP is adopted as the central tendency measure since it is less sensitive to extreme values and distributional assumptions (Boman, 2022). In a public referendum, the payment amount yielding majority support (50%) is the MD WTP, which is defined as:

$$\widehat{\mathrm{MD}}(WTP|\bar{X}) = \exp(\bar{X}\hat{\beta}) \quad [8]$$

The Krinsky and Robb procedure (1986) is used to construct a 95% confidence interval for the estimated MD WTP.[12]

Sensitivity to Functional Form and Distributional Assumptions

To assess the sensitivity of our MD WTP estimates, we implement two complementary checks. First, MD WTP is re-estimated using a linear specification:

$$WTP_i = X_i\beta + \eta_i \quad [9]$$

A well-known feature is that, when the observed support at the lowest payment amount ($1) is below 50%, the linear WTP specification can imply a non-positive median (Haab & McConnell, 2002; Whitehead et al., 2024).

Second, we additionally estimate the Turnbull non-parametric estimator as a conservative, distribution-free estimator and robustness check (Turnbull, 1976; Haab & McConnell, 1997, 2002; Whitehead et al., 2024). Let t denote the payment amount and $S^{\tau}(t) = \Pr(Y^{\tau}|\, t)$ the observed acceptance rate at uncertainty threshold τ. Since sampling variability can violate the theoretical requirement for acceptance to be weakly decreasing in t, we pool adjacent payment amounts whenever a higher amount shows greater acceptance than the neighboring lower amount (Kriström, 1990; Haab & McConnell, 1997). The Turnbull median is taken as the lower endpoint of the first pooled block at which the pooled acceptance falls to ≤0.5; we construct 95% bootstrap confidence intervals by resampling respondents (100,000 replications). Estimator-specific results are reported in Appendix Table A10 and briefly summarized in the results section.

6. Results

Baseline Estimates and Uncertainty

Table 2 presents the results of the $\log(WTP)$ regressions for the full analytical (N=1,012) sample under the three uncertainty specifications.[13] Regardless of specification, 'Yes' votes to the WTP eliciting question are decreasing in the payment amount, adhering to economic theory ($\kappa = -1/\beta_{\text{payment}}$). The baseline specification provides the least statistical power ($\chi^2(17) = 244.58$) compared to $\tau = \{6,7\}$. Nevertheless, all uncertainty specifications $\tau = \{0,6,7\}$ point to the same significant drivers of households' underlying WTP for wildfire smoke reduction. For brevity, we present the results of the strictest uncertainty specification ($\tau = 7$).[14]

<<Table 2 about here>>

Among all the explanatory variables, policy attitudes and health-related factors emerge as the strongest determinants of WTP.[15] Support for proactive fuel treatments *('General support')* shows a significant coefficient of $\beta = 2.800$ ($p < 0.01$) , translating to a $\exp(2.800) \approx 16.4$-fold increase in the household's underlying WTP. Trust in federal government implementation (*'Confidence fed'*) is significantly ($p < 0.01$) associated with a 3.9-fold increase in WTP. The presence of sensitive groups (e.g., households with young children or seniors) is significantly ($p < 0.05$) associated with a 2.6-fold increase in the households' WTP. Expectedly, expressing health concerns about wildfire smoke significantly ($p < 0.01$) correlates with a 7.2-fold increase in WTP, which is almost identical to the effect of a recent doctor visit following exposure to wildfire smoke (a proxy for need of medical care). The use of air filters as a mitigation strategy is also marginally ($p < 0.10$) linked to a higher household WTP.[16]

Some socio-demographics, such as liberal orientation, show a strong positive effect on WTP, with an estimated coefficient of $\beta = 1.149$ ($p < 0.01$). Financially, a \$1,000 USD increase in the household's total income is significantly ($p < 0.01$) associated with a 1% higher WTP for the *Wildfire Smoke Reduction Program*. In contrast, other demographic variables (age, gender, race, education) appear to have statistically insignificant effects under all three specifications.

MD WTP estimates, however, vary across uncertainty specifications. Under the baseline, the median household WTP for a one-day reduction in wildfire smoke exposure each year is $65 (95% CI [$40.28, $90.79]). MD WTP decreases to $55 under the stricter uncertainty specification ($\tau = 6$), and to $35 under the strictest specification adopted ($\tau = 7$).[17]

Consequentiality Splits

Table 3 presents the results of $\log(WTP)$ regressions stratified by respondents' perceived survey consequentiality. The analysis reveals heterogeneity in the drivers of underlying WTP and its median estimates across consequentiality groups.

<<Table 3 about here>>

The "Completely Inconsequential" group (Column 1) who doubts the referendum could affect policy or result in actual tax increases, shows poor fit: $R^2_{\mathrm{McF}} = 0.15$ and a statistically insignificant likelihood ratio test ($\chi^2(17) = 25.94$). No covariates, including typically influential variables such as *'Income,' 'Doctor visit,'* or *'General support,'* achieve significance ($p > 0.10$). This aligns with the group's statistically insignificant MD WTP of $1.79 for a one-day reduction in smoke exposure, suggesting responses are noise-driven rather than reflective of structured preferences ($\kappa = 3.509,\ t = 1.32$).

In contrast, the "Weakly Consequential" (Column 2) and "Strongly Consequential" (Column 3) groups show robust model fit ($\mathrm{R}^2_{\mathrm{McF}} = 0.19$) and significant LR statistics ($p < 0.001$). The typical positive factors driving household WTP emerge again. MD WTP increases sharply with perceived consequentiality: $165 for "Weakly Consequential" respondents, and $208 for those who are "Strongly Consequential", reported as annual household WTP for a one-day reduction in smoke exposure. These findings show the potential downward bias introduced by including non-engaged inconsequential respondents.[18]

Joint Uncertainty-Consequentiality Results

Table 4 and Figure 2 summarize MD WTP under the three levels of uncertainty recoding, $\tau = \{0,6,7\}$, and consequentiality groups. For the full analytical sample (N=1,012), MD WTP declines sharply from \$65 ($\tau = 0$) to \$55 ($\tau = 6$) and \$35 ($\tau = 7$). Among the inconsequential group, MD WTP remains insignificant and near zero regardless of the uncertainty recoding. In contrast, "Weakly" and "Strongly Consequential" respondents continue to express much higher MD WTP levels, even under strict uncertainty specifications $\tau = \{6,7\}$.

<<Figure 2 about here>>

<<Table 4 about here>>

Relative to our baseline exponential specification (Eq. 4), the linear specification (Eq. 9) and the Turnbull estimator yield statistically indistinguishable full sample WTPs under the strict uncertainty recoding ($\tau = 7$). The exponential MD WTP is \$35.26 (95% CI [\$19.37, \$50.71]); the linear specification yields \$37.65 (95% CI [-\$22.68, \$71.15]); and the Turnbull estimator gives \$20.00 (95% CI [\$17.00, \$59.00]). Although intervals overlap, the point estimates differ economically: the Turnbull is 43.3% lower than the exponential, while the linear is 6.9% higher. The differences in estimates are consistent with each approach's mechanics. The linear MD WTP specification is estimated on the level scale and does not impose non-negativity. It has greater sensitivity to the upper tail; this can yield larger point estimates and wider confidence intervals. When acceptance $S^{\tau}(t)$ at the lowest amount (\$1) is below 0.5, the implied median can be non-positive (Haab & McConnell, 2002; Whitehead et al., 2024). The Turnbull estimator is distribution-free and can identify a median bracket (under monotonicity), whose lower endpoint is reported as a conservative (lower-bound) median estimate (Turnbull, 1976; Kriström, 1990; Haab & McConnell, 2002). The qualitative ordering in Table 4 is preserved across approaches: medians decline under stricter uncertainty recoding and increase under stricter consequentiality conditions.

Prescribed Fire Smoke Tradeoff Segmentation

A majority of respondents (85%) accept short-term prescribed fire smoke to secure fewer and less intense wildfires in the future ("Acceptors"), while 15% reject any additional smoke ("Rejectors"). The heterogeneous preferences of these two groups shed light on whether the minority opposed to short-term smoke might still pay to reduce future wildfire emissions.[19]

Table 5 presents $\log(WTP)$ estimates for each group, based on the strictest uncertainty threshold ($\tau = 7$). Among "Acceptors," typical WTP drivers remain significant: higher household income ($\beta^A = 0.012$), general support for fuel treatments ($\beta^A = 2.636$), and confidence in government implementation ($\beta^A = 1.272$) all increase households' underlying WTP. These coefficients follow the same pattern observed in the full sample and in the consequential groups: 'Yes' votes decline with rising payment amounts ($\kappa = 2.039, p < 0.01$). The median annual WTP for a one-day reduction in smoke exposure among "Acceptors" is \$52, which remains positive and significant across uncertainty recodings and specifications (see Appendix Table A10).

Strikingly, none of the explanatory variables significantly affect "Rejectors" WTP, even though this subset shows a higher model fit ($R^2_{McF} = 0.34$). The payment amount does not meaningfully predict their 'Yes' votes ($\kappa^R = 2.294, p > 0.10$), suggesting minimal interest in the program. The median annual WTP for a one-day reduction among "Rejectors" is \$0.70 (95% CI [\$0.00, \$14.11]). This estimate is statistically indistinguishable from zero under the parametric specifications, which we interpret as a non-compensatory aversion to any additional prescribed-fire smoke (see Appendix Table A10). Under $\tau = 7$, the linear specification yields -\$440.49 (95%

CI [-$887.09, $799.59]). For the Turnbull, the median is $23.00 (95% CI [$1.00, $28.00]). The confidence interval is bounded below by $1 (the lowest payment amount offered), hence it cannot include zero. This polarization implies that, beyond absolute WTP levels, the distribution of acceptance versus rejection of short-term smoke could be decisive for the passage of a regionwide referendum on prescribed fire funding.

<<Table 5 about here>>

Protest Diagnostics

Among ‘No’ voters (N=287), 75.61% state reasons orthogonal to the program’s value (payment-vehicle or institutional objections), which we classify as potential protest ‘No’ votes (Appendix Table A11). This corresponds to 21% of the analytical sample (N=1,012); the statistic does not imply that three-quarters of the sample protested. Conditional on a ‘No’ vote, the incidence of potential protests is statistically indistinguishable across consequentiality groups ($\chi^2(2) = 0.31, p = 0.855$), and across the “Acceptors” and “Rejectors” of the prescribed fire smoke tradeoff ($p = 0.941$; Appendix Table A12). In summary, the absence of differential protest behavior across the WTP segmentation groups suggests the reported between-group differences in WTP are not likely attributable to heterogeneity in protest responses among ‘No’ voters.

7. Discussion

Main Findings

This study estimates western US households’ valuations for one fewer day of wildfire smoke per year, when reductions are delivered through large-scale fuel treatments. Because smoke reduction is a regional public good that transcends state lines (Bruce et al., 2025), these valuations could help inform benefit-cost analysis, airshed-scale appropriations, and intergovernmental cost-sharing. The results indicate potential for a “Forests to Airsheds” arrangement in which downwind households' benefits could justify investment in upstream fuel treatments, helping to bridge budget gaps underlying shortfalls from recommended treatment levels (Schultz, McCaffrey, & Huber-Stearns, 2019). This potential is conditional on public support for the treatment methods and trust in implementing agencies, and on acceptance of the tradeoff between "smoke today" and "smoke tomorrow" (Jones et al., 2022).

Across multiple specifications addressing hypothetical bias, the median household WTP to avoid one day of wildfire smoke annually ranges from \$35 to over \$200. We derive our conservative estimate using the stricter uncertainty threshold ($\tau = 7$) among the "Weakly Consequential" group (Table 4), yielding a median WTP of \$94 per household. Since households with income ≥\$150,000 are under-represented in both the full sample and the consequential groups (Appendix Tables A2, A6), this estimate is plausibly conservative. What scale of aggregate benefits does this imply? Applying this cautious valuation across 27.8 million households in the 11 western states (US Census, 2021) implies \$2.6 billion in aggregate annual benefits. On a back-of-the-envelope basis, that magnitude is comparable to the cost of treating about 4 million acres at \$656 per acre (2021 USD; deflated from \$747 as reported by Wear, Wibbenmeyer, & Zhu, 2025).[20]

The analysis also reveals significant heterogeneity. Respondents who viewed the survey as inconsequential reported near-zero WTP, which reflects skepticism that the referendum would lead to an actual program or tax. This heterogeneity illustrates the influence of perceived policy realism on stated values, mirroring the pattern reported by Mohr et al. (2023), who also found that more consequential groups provide higher and more consistent WTP estimates. Another source of heterogeneity emerged in the "smoke today" against "smoke tomorrow" tradeoff (Jones et al., 2022): about 85% would tolerate some short-term prescribed fire smoke, while 15% rejected any such tradeoff. We interpret the latter group's near-zero MD WTP as a non-compensatory refusal to tolerate additional prescribed-fire smoke: price responsiveness is weak and imprecise in all specifications. Protest diagnostics show similar protest ‘No’ rates for “Acceptors” and “Rejectors” ($p = 0.941$), so the between-group WTP difference is unlikely to be driven by protest behavior. Accordingly, the relative shares of “Acceptors” versus “Rejectors” will condition the political and economic feasibility of policies like the *Wildfire Smoke Reduction Program*.

Practical Implications

From a policy perspective, these findings indicate potential for broader airshed-wide financing mechanisms, in the sense that households’ valuations are large enough to justify meaningful investments. In a “Forests to Airsheds” finance loop, jurisdictions that routinely experience transported smoke could contribute to the costs of fuel treatments undertaken in upstream (source-region) landscapes, and agencies could receive dedicated appropriations or intergovernmental transfers to implement those treatments. This structure addresses the public-good nature of smoke abatement: ignitions send plumes beyond local boundaries, creating benefits for multiple states when fuel loads are managed proactively.

Federal land management agencies face binding financial constraints. Under the Anti-Deficiency Act (GAO, n.d.), agencies such as the US Forest Service may not obligate or expend funds in in excess of enacted appropriations. In severe wildfire seasons, meeting suppression needs has often required supplemental congressional appropriations (Preisler et al., 2011). Within that federalist structure, a substantial share of financing may fall to state and local governments and could also involve regional and multi-state collaboratives.

To make such financing strategies feasible, two main factors emerge. First, trust in federal agencies shapes households’ WTP; those who believe agencies can successfully implement fuel treatments exhibit valuations up to 16 times higher than those who do not (based on our findings). Second, public acceptance of short-term smoke as a tradeoff is critical. The minority rejecting the tradeoff can influence local opposition and erode the political support needed to scale up fuel treatments. Outreach efforts clarifying how prescribed fires are conducted, monitored, and mitigated (US EPA, 2021) may help convert some "Rejectors"; otherwise, their opposition could undermine policy adoption at local or state levels.

Limitations and Future Research

This study has several limitations. CV is susceptible to hypothetical bias, although several *ex-ante* and *ex-post* procedures are adopted here to mitigate it. Absent a perfectly consequential (real-setting) public referendum, bias cannot be ruled out. However, given the composite (use and nonuse) nature of benefits from reducing wildfire smoke, CV remains the most suitable approach to monetize welfare changes. Additionally, quota sampling increases demographic representativeness, yet it may introduce selection bias if respondents and non-respondents differ on relevant characteristics (Cumming, 1990). Arguably, carefully designed quota samples can perform comparably to probability samples (Deville, 1991; Groves et al., 2011, pp.409-410). The survey design has some potential limitations. First, the possibility of an anchoring effect from the two-stage referendum, which presents the program at no cost first, then at a monetary cost second. Second, the net-positive framing of the survey assumes no direct exposure to prescribed fire smoke. A follow-up question allowed for relaxing that assumption, showing that respondents can carry a latent aversion to prescribed fire smoke. Finally, data were collected in July 2021, capturing preferences at a specific time period. Since then, wildfire conditions and public awareness could have shifted. For example, the 2022 Hermit's Peak/Calf Canyon Fire—a controlled burn that became New Mexico's largest wildfire—sparked national media attention and led to a four-month suspension of US Forest Service prescribed fires.

Future research could explore how major wildfire events, including prescribed fire escapes, shift public support for forest fuel treatments across regions and over time. Repeated survey waves implemented as a longitudinal household panel could permit within-household estimation of changes in valuations for fewer smoke days. They could also assess whether variation in realized smoke exposure is associated with those changes. Such panel evidence could refine benefit estimates and add a longitudinal perspective to contingent valuation. Finally, research could characterize the "Rejector" subgroup's preferences and constraints (e.g., health vulnerability, household composition, local exposure, institutional trust) to identify when expected reductions in wildfire smoke do not offset the perceived costs of short-term prescribed fire smoke.

8. Conclusions

As the western US faces increasingly intense wildfires, downwind communities find themselves caught in a struggle for cleaner air and a sustainable quality of life. Each year, smoke clouds drift over cities and towns, obscuring the skies and increasing health risks for millions of western US residents. This study measures downwind households' stated willingness-to-pay for fewer smoke days when reductions are achieved through prescribed fire and mechanical thinning.

Findings indicate that large segments of the public place substantial value on reducing their wildfire smoke exposure vis-à-vis forest fuel treatments. Aggregated across the region, the implied benefits are sizable and relevant for airshed-scale appropriations and intergovernmental cost-sharing. A majority of households accept more prescribed fire and thinning to reduce future smoke, providing the first rigorously documented evidence on this tradeoff in line with calls by Jones et al. (2022). However, trust in federal agencies emerged as a key determinant of WTP; when that trust is lacking, valuations plummet. Acceptance of short-term smoke from prescribed fire proves critical: about 85% of households are willing to tolerate short-term emissions, whereas 15% reject them entirely, expressing negligible WTP. These results highlight the dual challenge of financing and public acceptance.

Looking ahead, a full benefit-cost analysis of forest fuel reduction programs remains necessary to evaluate whether such programs are worthwhile to society. That analysis could combine per-acre program costs with smoke-avoidance benefits, relevant co-benefits (e.g., smaller burned area, avoided damages and suppression costs), and potential disamenities (e.g., escape risk, episodic smoke).

Acknowledgments

The authors acknowledge funding support from the New Mexico Legislature. The views expressed in this paper are those of the authors and do not necessarily reflect the views of the funding entity. The authors thank Dr. Yuting Yang (University of New Mexico) and several anonymous reviewers for helpful comments and suggestions that improved the quality of this paper.

References

Adhikari, D., Thacher, J. A., Chermak, J. M., & Berrens, R. P. (2017). Linking forest to faucets in a distant municipal area: Public support for forest restoration and water security in Albuquerque, New Mexico. *Water Economics and Policy*, *3*(01), 1650019. https://doi.org/10.1142/S2382624X16500193

Balcombe, K., & Fraser, I. (2009). Dichotomous-choice contingent valuation with 'don't know' responses and misreporting. *Journal of Applied Econometrics*, *24*(7), 1137-1152.

Basumatary, J., Dhote, M., & Bansod, S. D. (2025). GIS-Based Delineation of Air Basins, Airsheds, and Air Zones. In *Smart Buildings and Cities with Remote Sensing and GIS, Chapter 18,* pp. 297-312. Chapman and Hall/CRC, Boca Raton, FL, USA.

Bernheim, B. D., & Rangel, A. (2009). Beyond revealed preference: choice-theoretic foundations for behavioral welfare economics. *The Quarterly Journal of Economics*, *124*(1), 51-104.

Boman, M. (2022). The sample median as an estimator of population mean true willingness to pay under valuation uncertainty: a synthesis and analysis of the literature. *Applied Economics*, *54*(55), 6393-6405.

Boyle, K. J. (2017). Contingent valuation in practice. In *A primer on nonmarket valuation*, 2nd edition, Chapter 4, pp. 83-131. Springer, Dordrecht, Netherlands.

Bruce, E. D., Folorunsho, A., Jaisawal, N., Gaw, E., & Li, Y. (2025). Intra-Continental Transport of Western Wildfire Smoke Heightens Health Risks Across North America. *International Journal of Environmental Research and Public Health*, *22*(2), 226. https://doi.org/10.3390/ijerph22020226

Cameron, T. A. (1988). A new paradigm for valuing non-market goods using referendum data: maximum likelihood estimation by censored logistic regression. *Journal of Environmental Economics and Management*, *15*(3), 355-379.

Carson, R. T., & Groves, T. (2007). Incentive and informational properties of preference questions. *Environmental and Resource Economics*, *37*(1), 181-210.

Carson, R. T., & Groves, T. (2011). Incentive and information properties of preference questions: commentary and extensions. In *The International Handbook on Non-Market Environmental Valuation*, Chapter 15, pp. 300-321. Edward Elgar, Cheltenham, United Kingdom.

Carson, R. T., Groves, T., & List, J. A. (2014). Consequentiality: A theoretical and experimental exploration of a single binary choice. *Journal of the Association of Environmental and Resource Economists*, *1*(1/2), 171-207.

Champ, P. A., Moore, R., & Bishop, R. C. (2009). A comparison of approaches to mitigate hypothetical bias. *Agricultural and Resource Economics Review*, *38*(2), 166-180.

Cramer, J. S., & Ridder, G. (1991). Pooling states in the multinomial logit model. *Journal of Econometrics*, *47*(2-3), 267-272.

Crockett, J. L., & Westerling, A. L. (2018). Greater temperature and precipitation extremes intensify Western US droughts, wildfire severity, and Sierra Nevada tree mortality. *Journal of Climate*, *31*(1), 341-354.

Cropper, M. L., Hu, M., Park, Y., & Muller, N. Z. (2025). *Geographic Resolution in Environmental Policy: EPA's Shift from Regions to Counties Under the Clean Air Act* (No. w33412). National Bureau of Economic Research. https://doi.org/10.3386/w33412

Crowley, C., Miller, A., Richardson, R., & Malcom, J. (2023). Increasing damages from wildfires warrant investment in wildland fire management. *Department of the Interior, 1-16. US Government*.

Cumming, R. G. (1990). Is probability sampling always better? A comparison of results from a quota and a probability sample survey. *Australian and New Zealand Journal of Public Health*, *14*(2), 132-137.

Deville, J. C. (1991). A theory of quota surveys. *Survey Methodology*, *17*(2), 163-181.

Gellman, J., Walls, M., & Wibbenmeyer, M. (2022). Wildfire, smoke, and outdoor recreation in the western United States. *Forest Policy and Economics*, *134*, 102619. https://doi.org/10.1016/j.forpol.2021.102619

Gould, C. F., Heft-Neal, S., Johnson, M., Aguilera, J., Burke, M., & Nadeau, K. (2024). Health effects of wildfire smoke exposure. *Annual Review of Medicine*, *75*(1), 277-292.

Groves, R. M., Fowler Jr, F. J., Couper, M. P., Lepkowski, J. M., Singer, E., & Tourangeau, R. (2011). FAQs About Survey Methodology. In *Survey methodology*. Chapter 12, pp. 409-410. John Wiley & Sons, Hoboken, NJ, USA.

Guttikunda, S. K. (2024). Designating Airsheds in India for Urban and Regional Air Quality Management. *Air*, *2*(3), 247-257.

Haab, T. C., & McConnell, K. E. (1997). Referendum models and negative willingness to pay: alternative solutions. *Journal of Environmental Economics and Management*, *32*(2), 251-270.

Haab, T. C., & McConnell, K. E. (2002). The Distribution of Willingness to Pay. In *Valuing Environmental and Natural Resources: The Econometrics of Non-Market Valuation*. Chapter 4, pp. 84-113. Edward Elgar, Cheltenham, United Kingdom and Northampton, MA, USA.

Haab, T., Lewis, L. Y., & Whitehead, J. (2020). State of the art of contingent valuation. In *Oxford Research Encyclopedia of Environmental Science*. Oxford University Press, Oxford, United Kingdom. https://doi.org/10.1093/acrefore/9780199389414.013.450

Halstead, J. M., Luloff, A. E., & Stevens, T. H. (1992). Protest bidders in contingent valuation. *Northeastern Journal of Agricultural and Resource Economics*, *21*(2), 160-169.

Hanemann, M., Krosnick, J., Wichgers, L., Wooldridge, J., Lampron, S., Schneider, D., Shaeffer, E. M., Tompson, T., & Visser, P. (2025). Ben Franklin's Whistle, Cost Expectations, and the Choice of Valuation Format. *Environmental and Resource Economics, 88*, 1375-1406.

Harrison, G. W. (2007). Making choice studies incentive compatible. In *Valuing Environmental Amenities using Stated Choice Studies*, Chapter 4, pp. 67-110. Springer, Dordrecht, Netherlands.

Herriges, J., Kling, C., Liu, C. C., & Tobias, J. (2010). What are the consequences of consequentiality? *Journal of Environmental Economics and Management*, *59*(1), 67-81.

Higuera-Mendieta, I., & Burke, M. (2025). *The air pollution benefits of low severity fire* [Preprint]. EarthArXiv. https://doi.org/10.31223/X52M9N

Hjerpe, E. E., Colavito, M. M., Waltz, A. E., & Meador, A. S. (2024). Return on investments in restoration and fuel treatments in frequent-fire forests of the American west: A meta-analysis. *Ecological Economics*, *223*, 108244. https://doi.org/10.1016/j.ecolecon.2024.108244

Huang, R., Hu, Y., Russell, A. G., Mulholland, J. A., & Odman, M. T. (2019). The impacts of prescribed fire on PM2. 5 air quality and human health: application to asthma-related emergency room visits in Georgia, USA. *International Journal of Environmental Research and Public Health*, *16*(13), 2312. https://doi.org/10.3390/ijerph16132312

Jaffe, D. A., O'Neill, S. M., Larkin, N. K., Holder, A. L., Peterson, D. L., Halofsky, J. E., & Rappold, A. G. (2020). Wildfire and prescribed burning impacts on air quality in the United States. *Journal of the Air & Waste Management Association*, *70*(6), 583-615.

Johnston, R. J., Boyle, K. J., Adamowicz, W. (Vic), Bennett, J., Brouwer, R., Cameron, T. A., Hanemann, W. M., Hanley, N., Ryan, M., Scarpa, R., Tourangeau, R., & Vossler, C. A. (2017). Contemporary Guidance for Stated Preference Studies. *Journal of the Association of Environmental and Resource Economists*, *4*(2), 319-405.

Jones, B. A., Thacher, J. A., Chermak, J. M., & Berrens, R. P. (2016). Wildfire smoke health costs: a methods case study for a Southwestern US 'mega-fire'. *Journal of Environmental Economics and Policy*, *5*(2), 181-199.

Jones, B. A. (2018). Willingness to pay estimates for wildfire smoke health impacts in the US using the life satisfaction approach. *Journal of Environmental Economics and Policy*, *7*(4), 403-419.

Jones, B. A., & Berrens, R. P. (2021). Prescribed burns, smoke exposure, and infant health. *Contemporary Economic Policy*, *39*(2), 292-309.

Jones, B. A., McDermott, S., Champ, P. A., & Berrens, R. P. (2022). More smoke today for less smoke tomorrow? We need to better understand the public health benefits and costs of prescribed fire. *International Journal of Wildland Fire*, *31*(10), 918-926.

Kolden, C. A. (2019). We’re not doing enough prescribed fire in the Western United States to mitigate wildfire risk. *Fire*, *2*(2), 30. https://doi.org/10.3390/fire2020030

Krinsky, I., & Robb, A. L. (1986). On approximating the statistical properties of elasticities. *The Review of Economics and Statistics*, 715-719.

Kriström, B. (1990). A non-parametric approach to the estimation of welfare measures in discrete response valuation studies. *Land Economics*, *66*(2), 135-139.

Lades, L. K., Zawojska, E., Johnston, R. J., Hanley, N., Delaney, L., & Czajkowski, M. (2025). Anomalies or expected behaviors? Understanding stated preferences and welfare implications in light of contemporary behavioral economics. *Review of Environmental Economics and Policy*, *19*(1), 48-68.

Liu, J. C., Pereira, G., Uhl, S. A., Bravo, M. A., & Bell, M. L. (2015). A systematic review of the physical health impacts from non-occupational exposure to wildfire smoke. *Environmental Research*, *136*, 120-132.

Liu, J. C., Wilson, A., Mickley, L. J., Dominici, F., Ebisu, K., Wang, Y., Sulprizio, M. P., Peng, R. D., Yue, X., Son, J.-Y., Anderson, G. B., & Bell, M. L. (2017). Wildfire-specific fine particulate matter and risk of hospital admissions in urban and rural counties. *Epidemiology, 28*(1), 77-85.

Loomis, J. B. (2014). Strategies for overcoming hypothetical bias in stated preference surveys. *Journal of Agricultural and Resource Economics*, 34-46.

Meyerhoff, J., & Liebe, U. (2006). Protest beliefs in contingent valuation: explaining their motivation. *Ecological Economics*, *57*(4), 583-594.

Miller, R. K., Field, C. B., & Mach, K. J. (2020). Barriers and enablers for prescribed burns for wildfire management in California. *Nature Sustainability*, *3*(2), 101-109.

Mockrin, M. H., Helmers, D., Martinuzzi, S., Hawbaker, T. J., & Radeloff, V. C. (2022). Growth of the wildland-urban interface within and around US National Forests and Grasslands, 1990–2010. *Landscape and Urban Planning*, *218*, 104283. https://doi.org/10.1016/j.landurbplan.2021.104283

Mohr, T. M., Groothuis, P. A., Whitehead, J. C., Cockerill, K., Anderson Jr, W. P., & Gu, C. (2023). Discrete and continuous measures of consequentiality. *Journal of Environmental Economics and Policy, 12*(3), 342-362.

Navarro, K. M., Schweizer, D., Balmes, J. R., & Cisneros, R. (2018). A review of community smoke exposure from wildfire compared to prescribed fire in the United States. *Atmosphere*, *9*(5), 185. https://doi.org/10.3390/atmos9050185

Nelson, M. D., Liknes, G. C., & Butler, B. J. (2010). Map of forest ownership in the conterminous United States.[Scale 1: 7,500,000]. *Res. Map NRS-2. Newtown Square, PA: US Department of Agriculture, Forest Service, Northern Research Station.*, *2*, 1-2.

Parks, S. A., Holsinger, L. M., Panunto, M. H., Jolly, W. M., Dobrowski, S. Z., & Dillon, G. K. (2018). High-severity fire: evaluating its key drivers and mapping its probability across western US forests. *Environmental Research Letters*, *13*(4), 044037. https://doi.org/10.1088/1748-9326/aab791

Parks, S. A., Guiterman, C. H., Margolis, E. Q., Lonergan, M., Whitman, E., Abatzoglou, J. T., Falk, D. A., Johnston, J. D., Daniels, L. D., Lafon, C. W., Loehman, R. A., Kipfmueller, K. F., Naficy, C. E., Parisien, M.-A., Portier, J., Stambaugh, M. C., Williams, A. P., Wion, A. P., & Yocom, L. L.

(2025). A fire deficit persists across diverse North American forests despite recent increases in area burned. *Nature Communications*, *16*(1), 1493. https://doi.org/10.1038/s41467-025-56333-8

Poe, G. L., Clark, J. E., Rondeau, D., & Schulze, W. D. (2002). Provision point mechanisms and field validity tests of contingent valuation. *Environmental and Resource Economics*, *23*, 105-131.

Preisler, H. K., Westerling, A. L., Gebert, K. M., Muñoz-Arriola, F., & Holmes, T. P. (2011). Spatially explicit forecasts of large wildland fire probability and suppression costs for California. *International Journal of Wildland Fire*, *20*(4), 508-517.

Raab, H., Moyer, J., Afrin, S., Garcia-Menendez, F., & Ward-Caviness, C. K. (2023). Prescribed fires, smoke exposure, and hospital utilization among heart failure patients. *Environmental Health*, *22*(1), 86. https://doi.org/10.1186/s12940-023-01032-4

Richardson, L., Loomis, J. B., & Champ, P. A. (2013). Valuing morbidity from wildfire smoke exposure: a comparison of revealed and stated preference techniques. *Land Economics*, *89*(1), 76-100.

Sanderfoot, O. V., Bassing, S. B., Brusa, J. L., Emmet, R. L., Gillman, S. J., Swift, K., & Gardner, B. (2022). A review of the effects of wildfire smoke on the health and behavior of wildlife. *Environmental Research Letters*, *16*(12), 123003. https://doi.org/10.1088/1748-9326/ac30f6

Schultz, C. A., McCaffrey, S. M., & Huber-Stearns, H. R. (2019). Policy barriers and opportunities for prescribed fire application in the western United States. *International Journal of Wildland Fire*, *28*(11), 874-884.

Schweizer, D., Cisneros, R., Traina, S., Ghezzehei, T. A., & Shaw, G. (2017). Using National Ambient Air Quality Standards for fine particulate matter to assess regional wildland fire smoke and air quality management. *Journal of Environmental Management*, *201*, 345-356.

Segerson, K. (2017). Valuing environmental goods and services: an economic perspective. In: *A Primer on Nonmarket Valuation*, 2nd edition, Chapter 1, pp. 1-25. Springer, Dordrecht, Netherlands.

Shrestha, A., Grala, R. K., Grado, S. C., Roberts, S. D., Gordon, J. S., & Adhikari, R. K. (2021). Nonindustrial private forest landowner willingness to pay for prescribed burning to lower wildfire hazards. *Forest Policy and Economics, 127*, 102451. https://doi.org/10.1016/j.forpol.2021.102451

Stephens, S. L., McIver, J. D., Boerner, R. E. J., Fettig, C. J., Fontaine, J. B., Hartsough, B. R., Kennedy, P. L., & Schwilk, D. W. (2012). The effects of forest fuel-reduction treatments in the United States. *BioScience, 62*(6), 549-560.

Tripathi, S. N., Yadav, S., & Sharma, K. (2024). Air pollution from biomass burning in India. *Environmental Research Letters*, *19*(7), 073007. https://doi.org/10.1088/1748-9326/ad4a90

Turnbull, B. W. (1976). The empirical distribution function with arbitrarily grouped, censored and truncated data. *Journal of the Royal Statistical Society: Series B (Methodological)*, *38*(3), 290-295.

US Bureau of Labor Statistics. (2025). CPI inflation calculator.

US Census Bureau. (2021). *American Community Survey, 1-year estimates (ACS 2021), Subject Table S1101: Households and Families* [Data set]. US Department of Commerce.

US Department of Health and Human Services, Office of the Assistant Secretary for Planning and Evaluation. (2016). *Guidelines for regulatory impact analysis*. https://aspe.hhs.gov/sites/default/files/private/pdf/242926/HHS_RIAGuidance.pdf

US Government Accountability Office. (n.d.). *Antideficiency Act resources*. https://www.gao.gov/legal/appropriations-law/resources

US Environmental Protection Agency. (2021). Comparative assessment of the impacts of prescribed fire versus wildfire (CAIF): A case study in the western US.

US Environmental Protection Agency. (2025). *About air data reports*. https://www.epa.gov/outdoor-air-quality-data/about-air-data-reports

Wang, P. W., Ya, J., Zhong, L. S., & Mei, R. (2016). Respondent uncertainty and reliability in contingent valuation—A case of the Dalai Lake protected area. *Limnologica*, *58*, 59-68.

Wen, J., Heft-Neal, S., Baylis, P., Boomhower, J., & Burke, M. (2023). Quantifying fire-specific smoke exposure and health impacts. *Proceedings of the National Academy of Sciences*, *120*(51), e2309325120. https://doi.org/10.1073/pnas.2309325120

Whitehead, J. C., Haab, T., Lewis, L., Richardson, L., & Schuhmann, P. (2024). *A meta-analysis of single-bound contingent valuation: Willingness to pay estimates, determinants of reliability and split-sample hypothesis tests* [Unpublished manuscript].

Wear, D. N., Wibbenmeyer, M., & Zhu, Y. (2025). *The Costs of Achieving Forest Resilience in California* (No. 25-03). Resources for the Future.

Zirnhelt, N., Angle, R. P., Bates-Frymel, D. L., Gilbert, M., Melancon, S., Suzuki, N., & Freedman, R. (2014). Airshed management. *Air Quality Management: Canadian Perspectives on a Global Issue*, Chapter 17, pp. 329-348. Springer, Dordrecht, Netherlands.

Table 1. Survey Summary Statistics for Relevant Variables (N=1,023).

Variables	Description	Mean	*SD*
Age	Respondent's age	49.28	18.33
Female	Respondent' gender (survey allows for a non-binary option)	0.50	0.50
White	Respondent of white race	0.76	0.43
College	Respondent has a bachelor's degree or higher	0.46	0.50
Liberal	Respondent self-identifies as liberal	0.40	0.49
Rural	Respondent's primary location being rural	0.14	0.35
Household size	Respondent's household size	2.63	1.21
Income ($1,000s)	Mid-point of the respondent's total household income range in thousands of dollars (2021 US dollars)	77.26	49.46
Sensitive groups	Household includes sensitive individuals	0.73	0.44
School miss	Child ever missed a school day due to wildfire smoke	0.18	0.38
Work miss	Respondent ever missed a workday due to wildfire smoke	0.14	0.34
Smoke home	Respondent thinks they smelled wildfire smoke at home	0.77	0.42
Smoke outdoor	Respondent thinks they smelled wildfire smoke outdoors	0.76	0.42
Health affect	Respondent thinks wildfire smoke affected their health	0.38	0.48
Doctor visit	Respondent ever visited a doctor due to wildfire smoke	0.11	0.31
Health concern	Respondent concerned about future wildfire smoke health impacts	0.93	0.26
Air filter	Respondent is using an air filter	0.25	0.43
Forest visit	Respondent ever visited a National Forest, National Park, National Monument, or National Wilderness Area	0.89	0.32
Prior knowledge	Respondent has prior knowledge about using prescribed fire and mechanical thinning to reduce future wildfire	0.74	0.44
General support*	Respondent generally supports expanding use of both prescribed fire and mechanical thinning	0.75	0.43
Accept Pburn	Respondent is willing to accept some exposure to smoke from prescribed burns as a tradeoff for reducing future wildfire	0.85	0.36
Confidence fed	Respondent is confident in the federal government implementing the Wildfire Smoke Reduction Program	0.62	0.49
Share	Respondent believes that survey results will be shared with Federal policymakers	0.79	0.40

Notes: This table presents full sample means and standard deviations for relevant variables. Only Age, Household size, Income ($1,000s) are continuous, other variables are binary (Yes=1, No=0). *General support is the only item that originally allowed a 'Not sure' answer; 'Not sure' is coded as 'No' to as explained in the main text.

Table 2. WTP Estimation Results for Full Sample by Uncertainty Recoding.

Log (*WTP*)	$\tau = 0$		$\tau = 6$		$\tau = 7$	
	Coef.	**T-stat.**	**Coef.**	**T-stat.**	**Coef.**	**T-stat.**
Intercept	-1.910	-1.17	-1.861	-1.26	-2.668*	-1.72
Age	-0.005	-0.52	-0.006	-0.66	-0.011	-1.19
Female	-0.274	-0.79	-0.316	-1.01	-0.293	-0.95
Non-white	-0.414	-1.03	-0.350	-0.97	-0.227	-0.65
Liberal	1.497***	3.29	1.438***	3.60	1.152***	3.16
College	-0.154	-0.42	-0.070	-0.21	0.156	0.48
Income ($1,000s)	0.008**	2.06	0.009**	2.47	0.010***	2.85
Sensitive groups	0.848**	1.97	0.652*	1.73	0.966**	2.50
School miss	-1.141*	-1.83	-1.158**	-2.06	-0.863	-1.62
Missed work	1.057	1.53	1.094*	1.77	0.348	0.60
Health concern	1.231*	1.66	1.636**	2.27	1.977***	2.58
Doctor visit	1.707**	2.24	1.731**	2.56	1.969***	3.00
Air filter	1.204**	2.44	1.006**	2.36	0.697*	1.74
General support	2.882***	4.29	2.665***	4.61	2.800***	4.75
Forest visit	-0.534	-0.96	-0.689	-1.36	-0.378	-0.76
Confidence fed	1.869***	3.65	1.513***	3.60	1.372***	3.40
Share	0.441	0.98	0.568	1.38	0.229	0.57
κ (scale parameter)	2.332***	5.29	2.058***	5.87	2.016***	6.07
Sample Size	1,012		1,012		1,012	
McFadden R^2_{McF}	0.17		0.19		0.19	
LR test (χ^2)	244.58 (*df*=17)		267.67 (*df*=17)		253.94 (*df*=17)	
Median WTP	$ 65.03		$ 55.03		$ 35.26	
95% Confidence interval	[$40.28, $90.79]		[$34.48, $75.24]		[$19.37, $50.71]	

Notes: Logistic regression results for binary vote (Yes $= 1$) for the *Wildfire Smoke Reduction Program*. WTP is modeled as $\log(WTP) = X\beta$, with coefficients scaled by $\kappa = (-1/\beta_{\text{payment}})$, where β_{payment} is the coefficient on the log payment amount. Specifications differ in treating uncertain 'Yes' votes: $\tau = 0$ (no recoding), $\tau = 6$, and $\tau = 7$ (recoding 'Yes' to 'No' if $\text{certainty} < \tau$ on a 0-10 scale). 'School miss' is interpreted conditional on missed work; variance inflation diagnostics indicate no multicollinearity (all VIFs < 2; Table A9).
* *p*<0.1; ** *p*<0.05; *** *p*<0.01.

Table 3. WTP Estimation Results by Consequentiality Group ($\tau = 0$).

Log (WTP)	Completely Inconsequential (Affect ∩ Payment) =0		Weakly Consequential (Affect = 1, Payment = 0,1)		Strongly Consequential (Affect ∩ Payment) =1	
	Coef.	**T-stat.**	**Coef.**	**T-stat.**	**Coef.**	**T-stat.**
Intercept	-9.164	-0.79	1.764	1.40	3.028**	2.07
Age	0.020	0.42	-0.005	-0.52	-0.018*	-1.82
Female	0.593	0.37	-0.124	-0.41	0.027	0.08
Non-White	-3.335	-1.25	-0.194	-0.56	-0.286	-0.77
Liberal	1.691	0.79	0.995***	2.83	0.833**	2.30
College	-0.193	-0.11	-0.257	-0.81	-0.339	-1.01
Income ($1,000s)	0.041	1.14	0.004	1.35	0.005	1.43
Sensitive groups	2.482	0.94	0.736**	2.01	0.709*	1.84
School miss	-0.281	-0.11	-0.806	-1.56	-1.013*	-1.80
Missed work	4.189	0.94	0.838	1.48	0.578	0.97
Health concern	1.325	0.51	-0.610	-0.75	-1.254	-1.21
Doctor visit	-0.540	-0.19	1.383**	2.11	1.978**	2.56
Air filter	2.350	0.89	1.047**	2.52	0.949**	2.16
General support	3.397	1.07	2.409***	4.43	2.512***	4.24
Forest visit	0.197	0.10	-0.568	-1.11	-0.475	-0.83
Confidence fed	0.654	0.32	0.858**	2.22	0.586	1.37
Share	-0.608	-0.38	0.493	0.78	0.733	0.95
κ (scale parameter)	3.509	1.32	1.552***	5.53	1.495***	5.12
Sample Size	145		623		511	
McFadden R^2_{McF}	0.15		0.19		0.19	
LR test (χ^2)	25.58 (*df*=17)		160.92 (*df*=17)		132.92 (*df*=17)	
Median WTP	$ 1.79		$ 164.98		$ 207.75	
95% C.I.	[$0.00, $24.25]		[$123.30, $250.74]		[$148.18, $364.29]	

Notes: Logistic regression results for binary vote (Yes = 1) for the *Wildfire Smoke Reduction Program*. WTP is modeled as $\log(WTP) = X\beta$, with coefficients scaled by $\kappa = (-1/\beta_{\text{payment}})$, where β_{payment} is the coefficient on the log payment amount. Sample is split using two indicators: Affect (1 = believe survey could influence policy) and Payment (1 = believe payment would be levied if referendum passes). No uncertainty recoding (τ=0) applied.
* p<0.1; ** p<0.05; *** p<0.01.

Table 4. Median WTP of Households to Reduce Wildfire Smoke Exposure by One Day Annually, Classified by Uncertainty Recoding and Consequentiality Groups.

		Uncertainty Recoding			Sample Size
		$\tau = 0$	$\tau = 6$	$\tau = 7$	
	Full Sample	$ 65.03 [$40.28, $90.79]	$ 55.03 [$34.48, $75.24]	$ 35.26 [$19.37, $50.71]	1,012
Conseq. Group	**Completely Inconsequential (Affect ∩ Payment) =0**	$ 1.79 [$0.00, $24.25]	$ 2.28 [$0.00, $24.51]	$ 1.42 [$0.00, $20.68]	145
	Weakly Consequential (Affect = 1, Payment = 0,1)	$ 164.98 [$123.30, $250.74]	$ 132.20 [$101.84, $180.90]	$ 94.12 [$70.87, $123.04]	623
	Strongly Consequential (Affect ∩ Payment) =1	$ 207.75 [$148.18, $364.29]	$ 169.08 [$125.95, $258.88]	$ 123.28 [$92.80, $171.69]	511

Notes: The table summarizes MD WTP estimates for reducing wildfire smoke exposure by one day using fuel treatments, classified by uncertainty recoding (columns) and consequentiality groups (rows). MD WTP is the payment amount eliciting 50% support in the referendum. $\widehat{\mathrm{MD}}(WTP|\bar{X}) = \exp(\bar{X}\hat{\beta})$, where $\bar{X}\hat{\beta}$ is the mean covariate vector multiplied by regression coefficients (95% Krinsky-Robb confidence intervals in brackets).

Table 5. WTP Regression by Prescribed Fire Smoke Acceptance ($\tau = 7$).

Log (*WTP*)	"Acceptors"		"Rejectors"	
	Coef.	**T-stat.**	**Coef.**	**T-stat.**
Intercept	-2.420	-1.45	-2.861	-0.46
Age	-0.013	-1.32	-0.061	-0.97
Female	-0.401	-1.20	-0.041	-0.03
Non-White	-0.111	-0.29	0.009	0.01
Liberal	1.308***	3.14	-0.196	-0.14
College	-0.044	-0.13	3.294	1.18
Income ($1,000s)	0.012***	2.95	-0.014	-0.72
Sensitive groups	1.040**	2.47	2.230	0.97
School miss	-0.608	-1.06	-3.986	-1.11
Missed work	0.568	0.91	-4.304	-0.97
Health concern	2.022**	2.46	1.121	0.40
Doctor visit	1.444**	2.17	12.845	1.31
Air filter	0.529	1.23	3.452	1.23
General support	2.636***	4.16	2.950	1.20
Forest visit	-0.542	-0.99	0.482	0.24
Confidence fed	1.272***	2.97	2.909	1.19
Share	0.527	1.18	-1.962	-0.96
κ (scale parameter)	2.039***	5.60	2.294	1.42
Sample Size	859		153	
McFadden $R^2_{\mathbf{McF}}$	0.18		0.34	
LR test (χ^2)	207.29 (*df*=17)		50.43 (*df*=17)	
Median WTP	$ 52.21		$0.70	
95% Confidence interval	[$31.25, $72.85]		[$0.00, $14.11]	

Notes: This table presents log (WTP) regression results for "Acceptors" and "Rejectors" of some prescribed fire smoke as a tradeoff for less wildfire smoke in the future. Sample is split using the indicator 'Accept Pburn.' Vote outcome adjusts for the strict uncertainty threshold ($\tau = 7$).
* *p*<0.1; ** *p*<0.05; *** *p*<0.01.

Figure 1. Predicted Voting Probability for the *Wildfire Smoke Reduction Program* by Cost ($).

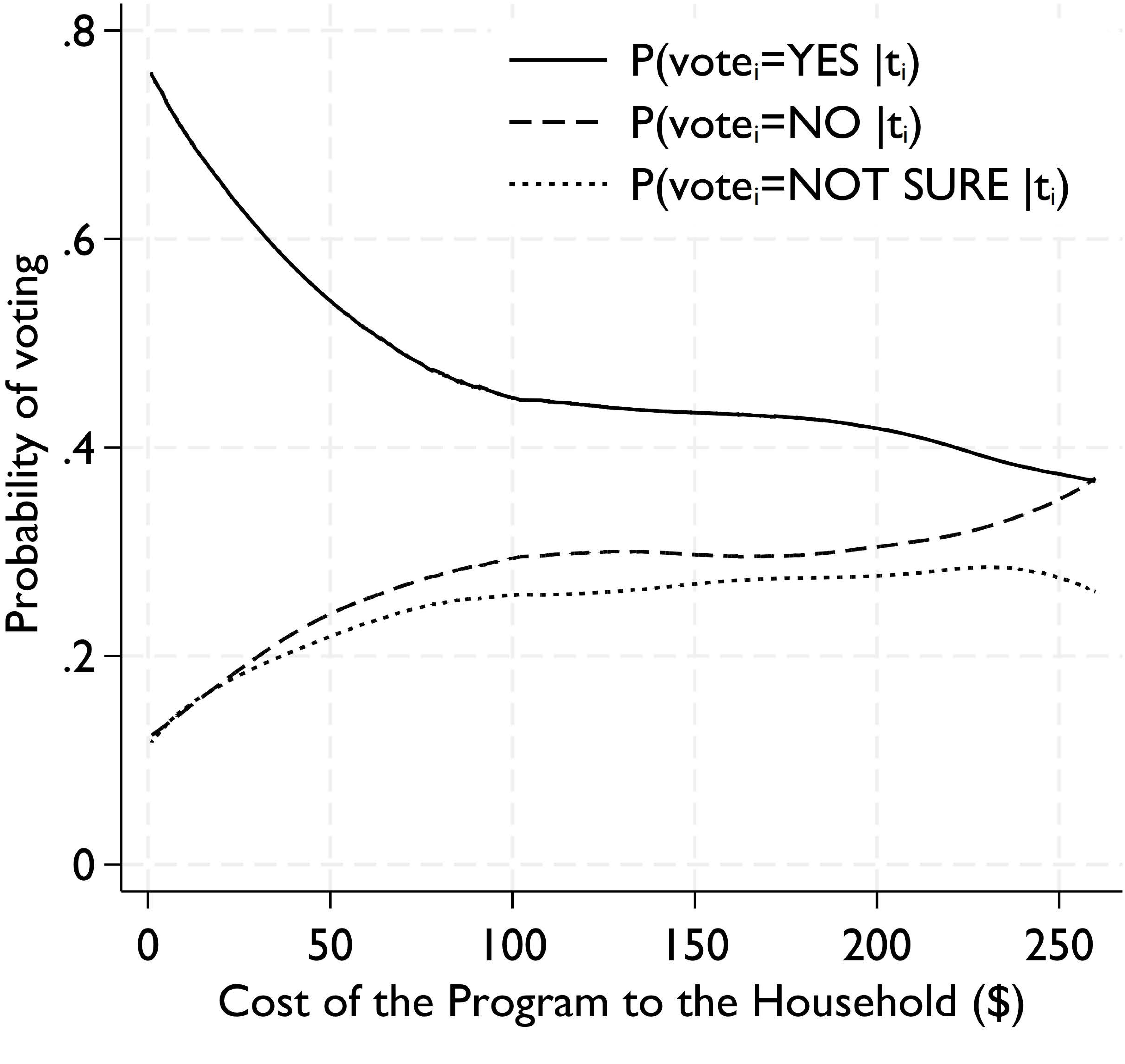
Notes: The figure plots LOWESS-smoothed predicted probabilities of ‘Yes,’ ‘No,’ and ‘Not Sure’ votes by payment amount; exact zero ‘Yes’ responses at the upper end are shown in Appendix Figure A3.

Figure 2. Distribution of Median WTP for a One-Day Reduction in Wildfire Smoke by (A) Uncertainty Thresholds and (B) Consequentiality Groups.

Notes: Kernel density estimates of median WTP. Estimates derived from 100,000 Monte Carlo draws of regression coefficients.

Endnotes

[1] Arizona, California, Colorado, Idaho, Montana, Nevada, New Mexico, Oregon, Utah, Washington, and Wyoming.
[2] Note that all monetary estimates in this paper are in 2021 USD unless otherwise stated.
[3] Quota sampling produces unbiased estimates comparable to those of probability sampling as long as respondents and non-respondents do not differ on relevant attributes (Cumming, 1990). Despite minor deviations, the sample aligns sufficiently with US Census benchmarks for analytical inference (Appendix Table A2).
[4] We use a one-day outcome to elicit a marginal, easily interpretable WTP. Smoke-days are a policy-relevant unit used in US air-quality reporting (US EPA, 2025). The 20-year horizon aligns with federal regulatory impact analysis guidance (US HHS, 2016).
[5] The payment amount for each respondent is randomly drawn from a continuous uniform distribution ranging from \$1 to \$260. This range was selected to be plausible for households in the survey context and to bracket central-tendency WTP estimates for a one-day reduction in wildfire smoke reported in prior studies (e.g., Richardson, Loomis, & Champ, 2013; Jones et al., 2018).
[6] Note: models are estimated with all covariates as in Table 2.
[7] This outcome differs from Shrestha et al. (2021) who concluded that 'Not Sure' votes could not be pooled with neither 'No' nor 'Yes' votes, and from Balcombe & Fraser (2009) who concluded that 'Not Sure' votes are more likely to be 'Yes' votes. This divergence shows the context-dependent nature of uncertainty treatment and suggests that pooling decisions should be made based on statistical evidence rather than a universal rule.
[8] η is standardized with the scale parameter $\kappa = (\mathrm{sd}(\eta)\sqrt{3})/\pi$.
[9] Variances are calculated using Taylor series approximations following Cameron (1988, p. 362).
[10] The logistic cumulative density function is expressed as: $F\left(\beta_{\mathrm{payment}}, \beta^{*}, t_{\mathrm{i}}, X_{\mathrm{i}}\right) = \frac{\exp\{\beta_{\mathrm{payment}} \ln(t_{\mathrm{i}}) - X_{\mathrm{i}}\beta^{*}\}}{1+\exp\{\beta_{\mathrm{payment}} \ln(t_{\mathrm{i}}) - X_{\mathrm{i}}\beta^{*}\}}$.
[11] If X_{j} is an indicator, moving from 0 to 1 multiplies the median WTP by $\exp\left(\widehat{\beta}_{\mathrm{j}}\right)$.
[12] $\widehat{\mathrm{MD}}(WTP|\bar{X})$ values are simulated by repeatedly drawing (100,000 times) from the asymptotic multivariate normal distribution of the coefficients. We then select the 2.5th and 97.5th percentiles (Haab & McConnell, 2002, p.110). For all simulation-based procedures (e.g., Krinsky-Robb draws, bootstrapping), we fix the seed at s = 2025.
[13] Covariates show no evidence of multicollinearity; variance-inflation factors (VIF) are all <2 (Appendix Table A9).
[14] Note that results are robust to employing state fixed effects (see Appendix Table A4).
[15] Coding of attitudinal variables: '*General support*', '*Confidence fed*', and '*Share*' are Yes/No indicator variables (1 = 'Yes', 0 = otherwise). '*Health concern*' recodes the 1-5 Likert item ("Overall, how concerned are you about future potential impacts of wildfire smoke to your personal health?") to a dummy (=1 if ≥ 'Slightly concerned'; =0 if 'Not at all concerned').
[16] Having smelled smoke either indoors or outdoors does not statistically affect the households' underlying WTP under all uncertainty specifications. Appendix Tables A5.a and A5.b show MD WTP by stated smoke exposure (survey variable 'numbertimes'). Point estimates rise with exposure, but group differences are not statistically significant. This self-reported measure is omitted from the baseline econometric models because it is likely to contain substantial measurement error.
[17] The model with only socio-demographics is estimated; MD WTP is robust to including the attitudinal variables (Appendix Table A4).
[18] Similarly to the full sample, consequential respondents (Affect = 1) are representative of the western US population (Appendix Table A6).
[19] Note that "Acceptors" and "Rejectors" differ in various aspects (age, political orientation, exposure to wildfire smoke, and support for forest fuels treatments). See Appendix Table A7 for details.
[20] Treatment cost is the per-acre sum of mechanical thinning (\$577/acre) and prescribed fire (\$170/acre) based on US Forest Service cost records. It includes labor and equipment but excludes environmental review/compliance.



P(vote$_i$=YES |t$_i$)
P(vote$_i$=NO |t$_i$)
P(vote$_i$=NOT SURE |t$_i$)
Probability of voting
.8
.6
.4
.2
0
0
50
100
150
200
250
Cost of the Program to the Household ($)


A) Uncertainty
B) Consequentiality
τ =0 (baseline)
τ =6 recoding
τ =7 recoding
Full Sample
Weakly Conseq.
Strongly Conseq.
Density
MD WTP ($)
MD WTP ($)
.05
.04
.03
.02
.01
0
0
50
100
150
.03
.02
.01
0
0
100
200
300
400