

Research article

Valuing shifts in the distribution of visibility in national parks and wilderness areas in the United States



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ABSTRACT

Environmental regulations often have the objective of eliminating the lower tail of an index of environmental quality. That part of the distribution of environmental quality moves somewhere above a threshold and where in the original distribution it moves is a function of the control strategy chosen. This paper provides an approach for estimating the economic benefits of different distributional changes as the worst environmental conditions are removed. The proposed approach is illustrated by examining shifts in visibility at Class I visibility areas (National Parks and wilderness areas) that would occur with implementation of the U.S. Environmental Protection Agency's Regional Haze Program. In this application we show that people value shifts in the distribution of visibility and place a higher value on the removal of a low visibility day than on the addition of a high visibility day. We found that respondents would pay about \$120 per year in the Southeast U.S. and about \$80 per year in the Southwest U.S. for improvement programs that remove the 20% worst visibility days.

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1. Introduction

Many environmental amenities are not constant and for some they are not constant over relatively short periods of time. Nowhere is this more obvious than with air pollution and visibility where an atmospheric inversion can produce conditions where large skyscrapers cannot be discerned by city residents one day and then the city's skyline becomes visible from distant suburbs the next day. A less obvious example is water quality in a river where quality can change with changes in pollution loading, ambient temperature and volume of flow. Thus, summary statistics such as average visibility or average water quality might not always be the best way to characterize environmental conditions because people may care about the distribution of quality over space or time. For example, the impact of climate change, which might include high variability in daily temperatures, may be better characterized by the number of days that would fall into particular temperature bins than the mean temperature shift. In addition, different distributions of days

could have the same average temperature.

Government agencies often operationalize regulatory objectives in terms of reducing or eliminating the low quality end of the distribution of an environmental quality indicator. Examples include the U.S. Environmental Protection Agency's (USEPA) 8-h maximum threshold for ozone that can induce stricter regulatory action when the specified ozone threshold is exceeded and the maximum contaminant levels (MCLs) for different drinking-water contaminants. In valuing environmental quality improvements associated with such threshold policies it may be important to go beyond valuing the removal of low quality conditions to also consider the new distribution of environmental quality, i.e., where in the distribution does the improvement occur.

In the current paper we investigate an application based the USEPA's Regional Haze Program (42 U.S. Code § 7491 - *Visibility protection for Federal class I areas*).¹ Haze is a visibility impairment caused when the particles from air pollution emissions reduce the ability to see distant objects, and affect the clarity and color of what

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¹ "EPA's Regional Haze Program", <http://www.epa.gov/airquality/visibility/program.html>, accessed May 19, 2014.

people see. The Regional Haze Program applies to visibility in 156 Class I visibility areas across the U.S., which are national parks and wilderness areas.² The goal of this program is to remove human-induced haze conditions occurring on the 20% of days with the lowest visibility during the year. The value the public places on removing the 20% worst visibility days may depend on the resulting visibility distribution. A change where the 20% worst days move to the highest visibility conditions is likely valued more than a change where the days have only a moderate improvement in visibility. The ability to look at the benefits of different distributional shifts becomes particularly important when there are control options that differentially shift the visibility distribution and have different regulatory costs.³

Estimation of the benefits of reducing haze is complex because the policy goal of removing anthropogenic haze from the 20% worst visibility days shifts the distribution of visibility over the year; actions that reduce or remove haze on the 20% worst days increases the number of days in the other 80% of the initial quality distribution. Valuing a threshold, such as removing the 20% worst days, may not be sufficient because it may matter to respondents what the distribution of visibility is after the removal of the worst days. Where do these days move in the other 80% of the initial distribution? Further, mean visibility is not a sufficient statistic for characterizing shifts in the visibility distributions as different distribution shifts can result in the same mean visibility.

Our study is the first to investigate how characteristics of shifts in the distribution of visibility conditions influence value estimates and link value estimates for those shifts to the Regional Haze Rule for Class I visibility areas. Two parallel studies were implemented to estimate values for visibility improvements in Class I visibility areas that face quite different visibility conditions; the Four Corners region in the Southwest and the Appalachian Mountains region in the Southeast. To foreshadow our results, we find that people do consider dimensions of the shift in the distribution of visibility (reductions in the number of lowest visibility days and increases in the number of highest visibility days). We also found that potential human health effects affect value estimates in both study regions, while ecological effects only affect value estimates in the Southwest region. Overall, we find that our approach is a promising way to use stated-preference methods to value changes in the distribution of visibility and to effectively control for changes in auxiliary attributes, such as human health and ecosystem effects, in benefit and cost analyses. We believe our general approach can be adapted to value other policies that effect changes in the distribution of environmental amenities or disamenities.

2. Previous visibility valuation research

While there is some literature on portraying distribution information to respondents in stated-preference surveys, this literature is rather limited and primarily occurs in the valuation of changes in risks. Some have used risk ladders that portray changes in thresholds of risk (Corso et al., 2001), while others have used risk cards

that portray the chance in 100 that an event will occur (Krupnick et al., 2002). These approaches present changes in probabilities for binary outcomes, risk outcomes that occur or not, and are not directly transferable to valuing changes in the distribution of visibility where the change involves a continuous variable.

2.1. Previous visibility valuation studies

There have been a small number of previous studies that investigated the value of visibility improvements, and we will focus on the two most recent studies (Chestnut and Rowe, 1990; Smith et al., 2005), which are the only studies that provide value estimates for visibility improvements in Class I visibility regions (Table 1). We will refer to these as the Chestnut and the Smith studies for expositional convenience hereafter. The report from the Chestnut study, in addition to documenting their own study, provided an overview of other visibility valuation studies conducted prior to 1990.⁴

Portraying changes in visibility to respondents in a stated-preference survey is a challenging task. Respondents must be presented with the current and improved visibility conditions. Further, there is not a unique visibility improvement outcome; the worst visibility days, when improved, can be spread across the remaining distribution of days. Thus, it is a complicated design issue to consider what dimension of the distribution shift to present in a survey and how this information should be presented. The Chestnut and Smith studies used sets of four photographs to convey visibility under different conditions during the summer months. The Chestnut study estimated values for visibility improvements in Class I areas in California, the Southwest and the Southeast and their photographs were of scenes in Yosemite, Grand Canyon and Shenandoah National Parks, respectively (the California treatment is excluded from Table 1 as it is not comparable to the Smith study and the current study). The photographs represented 15%, 20%, 40% and 25% of summer days (Table 1). The Smith study replicated the Chestnut study using four photographs to depict the same categories of visibility conditions.

While the Chestnut study used words, as shown in Table 1, to describe the initial distributions of visibility days, the Smith study, in addition to replicating the Chestnut study, had a treatment where they used a histogram (Fig. 1) to present the number and percentage of days in each category of the initial visibility distribution. They also added a category for bad weather days, 12 days (~10%). Both the Chestnut and Smith studies asked respondents to value improvements in average visibility conditions, with average visibility improving from conditions shown in photograph C to B and C to A, as well as to prevent a decline in average visibility from C to D (see Table 1 and Fig. 1).

A key difference between the Chestnut and Smith studies is that Chestnut used different photographs that approximated the visibility conditions in each category (A, B, C and D), while Smith used a single photograph that was digitally manipulated to portray actual mean visibility condition within each category.

Neither the Chestnut study nor the Smith study explicitly controlled for factors that could confound estimates of value for visibility improvements such as concerns about effects on human health and ecosystems. For example, the USEPA (2010) states:

“Air pollution can affect our health in many ways. Numerous scientific studies have linked air pollution to a variety of health

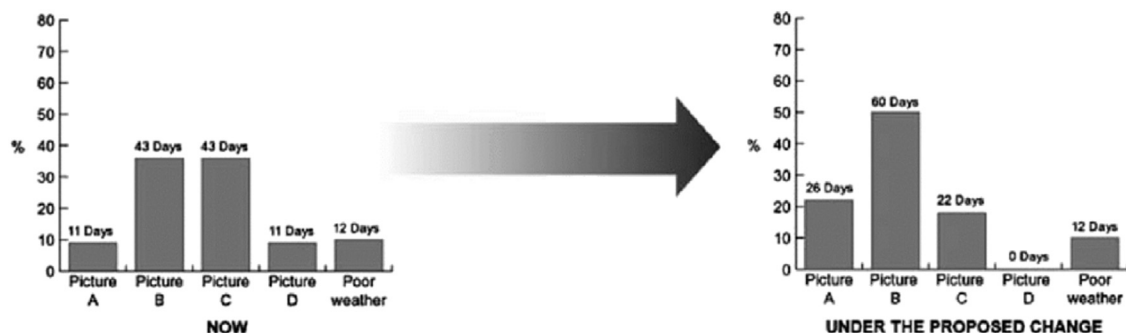
² “List of 156 Mandatory Class I Federal Areas”, <http://www.epa.gov/airquality/visibility/class1.html>, accessed May 19, 2014.

³ Most control policies and nonmarket valuation applications have been aimed at delivering overall improvements. There are some key policy exceptions that affect the spatial and temporal distribution of pollution. One example is the reformulation of gasoline in the summer to reduce ozone (Auffhammer and Kellogg, 2011). There have also been some efforts to get people to voluntarily reduce driving when it is predicted that a threshold standard will be violated (Cutter and Neidell, 2009). Cropper et al. (2014) look at the implications of a plan that would require drivers to buy special permits in advance to use their vehicles on high ozone days.

⁴ Two studies were initiated that would have valued visibility in Class I visibility regions, but values were never estimated, the studies never progressed beyond the initial design stages (Balson et al., 1990; Carson et al., 1990).

Table 1
Summaries of key previous visibility valuation studies.

	Chestnut and Rowe (1990)		Smith et al. (2005)
Year study conducted	1988		2003
Locations Valued	Southeast National Parks	Southwest National Parks	Southeast National Parks
States Included in Region	- Alabama - Delaware - Florida - Georgia - Kentucky - Maryland - Mississippi - North Carolina - South Carolina - Tennessee - Virginia - West Virginia	- Arizona - Colorado - Nevada - New Mexico - Utah	- Alabama - Delaware - Florida - Georgia - Kentucky - Maryland - Mississippi - North Carolina - South Carolina - Tennessee - Virginia - West Virginia
National Parks Identified	- Great Smoky Mountains - Mammoth Caves - Shenandoah	- Arches - Bandelier - Bryce Canyon - Canyonlands - Carlsbad Caverns - Chiricahua - Capitol Reef - Mesa Verde - Petrified Forest - Rocky Mountain - Saguaro - Zion	- Great Smoky Mountains - Mammoth Caves - Shenandoah
Target population	Virginia Residents	Arizona Residents	U.S. (contiguous 48 states)
Visibility Image (identified to respondents and referenced in valuation question)	Shenandoah	Grand Canyon	Shenandoah
Visibility Portrayed	- Photograph A, almost no haze, 17 deciviews, 18 summer days, 15% of time, - Photograph B, a little haze, 21 deciviews, 24 summer days, 20% of time, - Photograph C, average visibility, 28 deciviews, 48 summer days, 40% of time - Photograph D, a lot of haze, 37 deciviews, 30 summer days, 25% of time		See Fig. 1 below
Use Histograms to Portray Visibility Distributions	No	No	No & Yes
Type of Survey	Mail	Mail	Internet Panel (Knowledge Networks)
Valuation Approach	Contingent Valuation, Payment Card	Contingent Valuation, Payment Card	Contingent Valuation, Payment Card
Visibility Change Valued	- Average increases from C to B conditions - Average increases from C to A conditions		- Average increases from C to B conditions - Average increases from C to A conditions



^aDepicts a change from photograph C to B as described in Chestnut and Rowe (1990).

Fig. 1. Sample Histogram of Changes in Visibility from Smith et al. (2005) (Fig. 3, p. 1772). Depicts change in distribution of visibility from photograph C to B as described for Chestnut and Rowe (1990) in Table 1.

problems including: (1) aggravation of respiratory and cardiovascular disease; (2) decreased lung function; (3) increased frequency and severity of respiratory symptoms such as difficulty breathing and coughing; (4) increased susceptibility to respiratory infections; (5) effects on the nervous system, including the brain, such as IQ

loss and impacts on learning, memory, and behavior; (6) cancer; and (7) premature death“ (chapter 1, p. 1).

This is a general statement and is not specific to reducing haze to

improve visibility in Class I visibility areas where associated human health effects are likely negligible to nonexistent. Yet, statements like the one above can lead the public to assume that a visibility improvement program would have associated improvements in human health. To address this potential concern the Chestnut study included the following statement in their survey:

“These questions concern only visibility at national parks in the Southwest and assume there will be no change in visibility at national parks in other regions. Other households are being asked about visibility, human health and vegetation protection in urban areas and at national parks in other regions” (p. 7, Appendix A).

This statement was, we believe, intended to preclude respondents from including considerations of other parks outside the Southwest, human health and ecosystem improvements in valuation responses. The Smith study employed language similar to the Chestnut study, and asked respondents in one version of the survey to allocate values across programs targeted at human health, harm to plant life, and scenic vistas. Smith found that values for visibility using this allocation procedure were significantly lower than values estimated without this allocation procedure (see Smith et al., Table 5, p. 1776), which indicates that omitting considerations for human health and ecosystem effects may overestimate values.

Valuing visibility enhancements also involves concerns regarding the temporal and geographical extent of the improved visibility. While the Chestnut and Smith studies focused on visibility improvements during the summer months, the assumptions their respondents used regarding visibility in other months of the year are unknown.

Further, air pollution and the haze component can cover large geographic regions (Malm, 1992). The Chestnut study, which Smith followed, used the following language in the Southwest version of the survey:

“These questions concern only visibility at national parks in the Southwest and assume there will be no change in visibility at national parks in other regions” (p. 7, Appendix A).⁵

This text was preceded in the surveys by a map showing the Southeast region and national parks within this region.

2.2. Key difference between previous visibility valuation studies and the current study

In the study discussed below we designed a survey instrument to be explicit about the dimensions of visibility subjects were asked to value. Like the Chestnut and Smith studies, we used photographs to display visibility conditions under different levels of haze. Similar to the Smith study, we used actual photographs with computer-simulated modifications to show how visibility would change under differing levels of haze for the same scene, and used histograms to portray the number of days in different categories of visibility.

Our research differs from these previous studies in important dimensions. First, we binned the distribution of days into equal quintiles to align the design with the national policy goal of removing the 20% worst visibility days. The Chestnut and Smith studies binned the 25% lowest visibility days together, which limits the use of these studies from providing value estimates aligned with the goal of the Regional Haze Program.

Second, we consider changes in the distribution of haze over a full year, not just the summer months. Actions to reduce haze may have effects on visibility throughout the year and advanced modeling enables the prediction of changes in haze throughout the year (Molenar et al., 1994; Hand et al., 2014; Tesche et al., 2006).

Third, we asked respondents to value changes in the distribution of visibility, not just a shift in the mean. This approach allows value estimates to be explicitly linked to visibility improvement programs, which is not possible for value improvements in mean visibility where different improved distributions could have the same mean.

Finally, we use a choice experiment that offers respondents a sequence of binary choices where one of the choices was always the current status quo and the other choice featured a distribution of visibility as well as other attribute levels. The use of a choice experiment, instead of contingent valuation as used in the Chestnut and Smith studies, allows for the explicit control of human health and ecosystem effects in the design of the valuation study and the statistical analysis of the response data. While economists have long believed that all sources of economic benefits should be comprehensively taken into account, environmental legislation often takes a different tactic. In our case, haze reductions in Class I visibility areas are unlikely to affect human health and natural ecosystems, but survey respondents may be inclined to think that haze reductions will lead to improvements in human health and ecosystem conditions. The temptation for the analyst, in light of such policy considerations, is to tell survey respondents that there are no such effects. These types of statements may strain the credibility of a survey instrument to respondents. The approach adopted here is to take what respondents in focus groups indicated was a more credible approach and tell them that different air quality improvement programs can have different influences on human health and ecosystems.

3. Study design

We start by specifying a preference function people may hold for reductions in haze as:

$$V = U_i(v(\alpha), h(\alpha), g(\alpha), z, I) + \varepsilon_i \quad (1)$$

where V is a utility function for individual i , v , h and g are arguments for visibility, human health and ecosystems, respectively, which are all affected by haze (α). All other goods and services consumed are denoted by the numeraire, z , I is income, and ε is a random error. We assume that people prefer better visibility and less undesirable human health and ecosystem effects such that the following conditions hold:

$$\frac{\partial V}{\partial \alpha} = \left(\frac{\partial U}{\partial v} \right) \left(\frac{\partial v}{\partial \alpha} \right) + \left(\frac{\partial U}{\partial h} \right) \left(\frac{\partial h}{\partial \alpha} \right) + \left(\frac{\partial U}{\partial g} \right) \left(\frac{\partial g}{\partial \alpha} \right) < 0 \quad (2)$$

which implies that reductions in haze (α) will increase utility, i.e., all arguments in equation (2) are negative. To investigate if these relationships hold and to estimate the value people place on visibility improvements in Class I regions we implemented a choice experiment (Hanley et al., 1998) where the attributes of the choices included visibility improvements and possible human health and ecosystem impacts.

In a survey, respondents were given a choice between maintaining current conditions with no cost to their household and improving visibility conditions with a specified cost to their household. The probability that respondents would choose the program with improved visibility conditions (ic), reduced haze, is given by:

⁵ This text is an excerpt from one version of their surveys and is replicated in Appendix A of Chestnut and Rowe (1990).



Fig. 2. Visibility images insert from the southwest survey version.

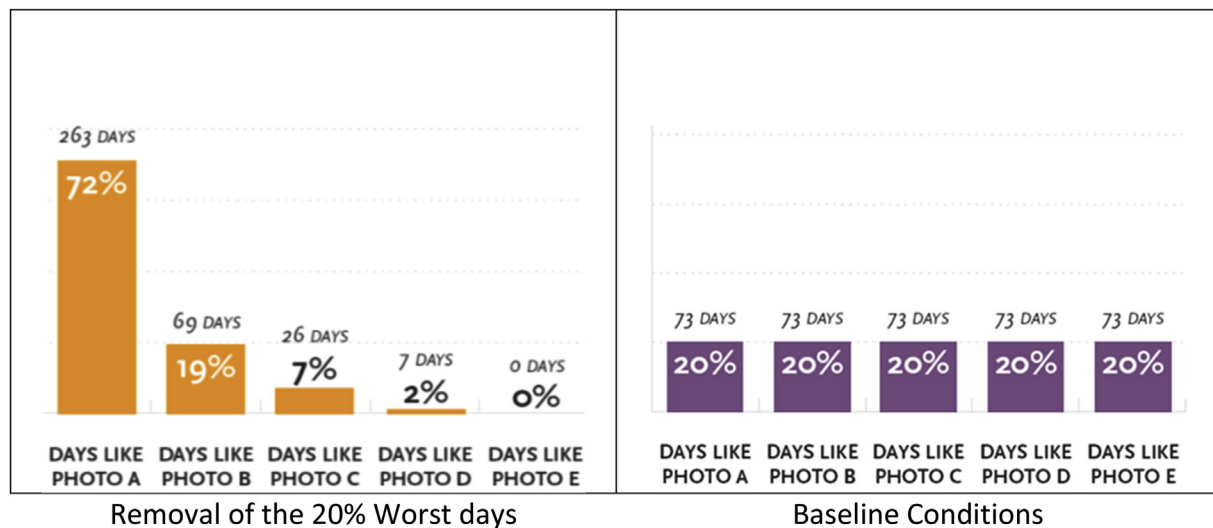


Fig. 3. Sample histograms from the southwest version of the survey.

$$\Pr(\text{choose } ic) = (V_{ic} - V_{cc} > \varepsilon_{cc} - \varepsilon_{ic}) \quad (3)$$

where cc denotes current conditions. A logit model is used to analyze responses to the binary yes/no responses to the choice experiment questions.

The value of visibility improvements we compute is defined as follows:

$$wtp_{v|h=0,g=0} = \frac{\partial V(h=0,g=0)}{\frac{\partial V}{\partial t}} \quad (4)$$

This approach is used because human health and ecosystem effects from improving visibility in Class 1 visibility regions are extremely small to nonexistent.

3.1. Survey design

The survey design process involved the conduct of five sets of focus groups in Atlanta, Chicago, Sacramento, Denver, and Boston. Four focus group sessions (two, two-hour sessions per evening on two consecutive evenings) were held in each location, for a total of 20 groups. All respondents were recruited at random from listed telephone numbers and the groups were led by a professional moderator. The target was to have 8 to 10 participants per group.

The first groups were conducted in Atlanta and explored concepts, terminology, images and graphics in an open-ended format. The focus group effort concluded in Boston with participants responding to a full questionnaire. Key insights were observed from the focus groups include the following.

The first was that photographs with computer simulations of visibility conditions helped respondents understand what views

would look like under different visibility conditions. The selected photograph (Canyonlands for the Southwest and Great Smoky Mountains for the Southeast) for each region of the country was chosen from a vantage point where a visitor to the area could actually experience the view and the scene provided features at varying depths within the photo. Photographs were 4" by 6" in size. The five visibility images shown to subjects in the Southwest version of the survey are shown in Fig. 2. Photo A shows average visibility conditions for the best 20% of days throughout the year and photograph E shows the average visibility conditions for the worst 20% of days.

Second, "binning" visibility days into quintile categories established baseline visibility conditions for respondents that clearly identified the policy-relevant 20% worst visibility days (Photo E). We used five bins of equal size in our study for baseline conditions (current conditions), one for each quintile of the annual distribution of visibility days. Each respondent was provided with a set of five photographs that represented baseline visibility conditions within each bin; explained as current conditions in the survey.⁶ The photographs were from a single image and digitally manipulated to portray mean visibility for the respective interval of visibility (Fig. 2).

Third, we found that focus-group participants understood the change in the distribution of visibility days when this information was shown using histograms, one that showed current conditions and one that showed improved conditions (Fig. 3). Current condition bars were purple and improved condition bars were yellow.

⁶ Current conditions were based on monitoring data from the Interagency Monitoring of Protected Visual Environments (IMPROVE) network for the period 2000 to 2004.

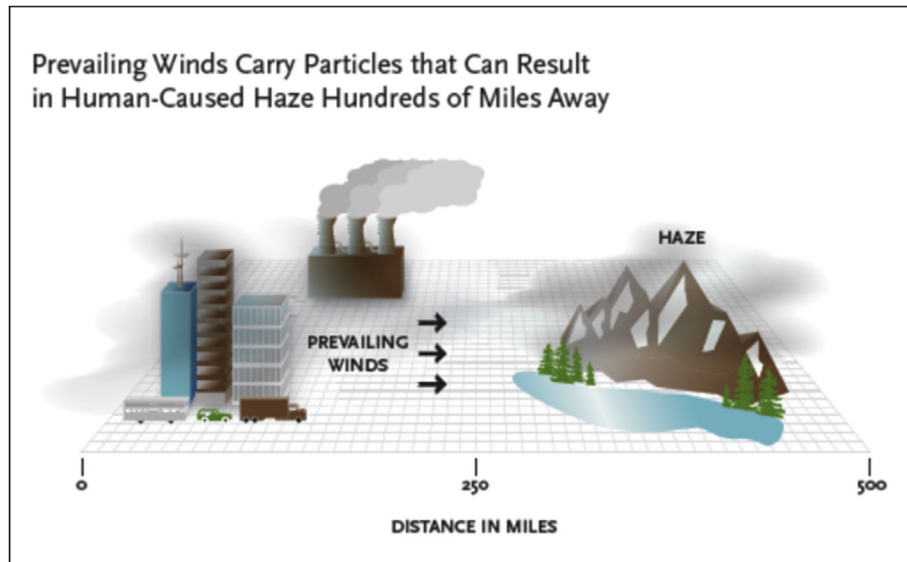
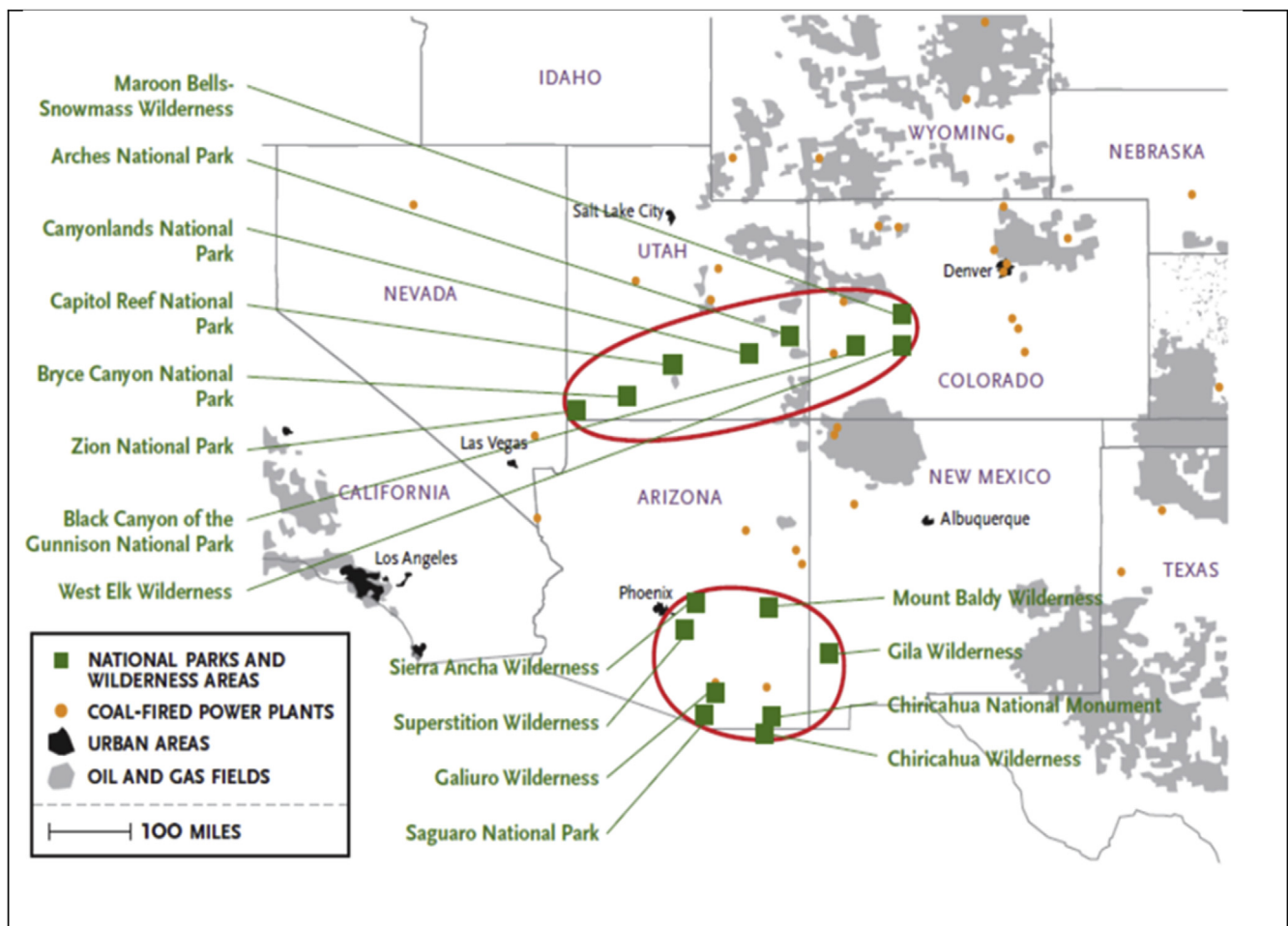


Fig. 4. Air pollution dispersion diagram from the surveys.

Photographs and histogram bars were labeled A to E to align pictures with the bars; the bars denoted the percentage and number of days in each bin. Under baseline conditions, the bar for each

quintile had the same percentage (number) of days, but the visibility images, as shown in Fig. 2, varied across the bins. The improved condition histograms portrayed reduced numbers of



^a Included as an insert with the surveys.

Fig. 5. Map of national parks and wilderness areas in the southwest study Area.

PROGRAM 5

Choice Question

19. Please compare the current conditions without a program to conditions with Program 5. Then answer the question below as if Program 5 is the only program available.

	CURRENT CONDITIONS ▼	CONDITIONS WITH PROGRAM 5 ▼
VISIBILITY CONDITIONS IN THIS REGION	73 DAYS 20% 73 DAYS 20% 73 DAYS 20% 73 DAYS 20% 73 DAYS 20% DAYS LIKE PHOTO A DAYS LIKE PHOTO B DAYS LIKE PHOTO C DAYS LIKE PHOTO D DAYS LIKE PHOTO E	263 DAYS 72% 69 DAYS 19% 26 DAYS 7% 7 DAYS 2% 0 DAYS 0% DAYS LIKE PHOTO A DAYS LIKE PHOTO B DAYS LIKE PHOTO C DAYS LIKE PHOTO D DAYS LIKE PHOTO E
IMPACTS ON ECOSYSTEMS	<i>No Change</i>	<i>A Small Reduction</i>
HEALTH IMPACTS ON VISITORS	<i>No Change</i>	<i>No Change</i>
YEARS TO REACH IMPROVEMENT	<i>No Improvement</i>	<i>10 Years to Reach</i>
COST TO YOUR HOUSEHOLD EACH YEAR	<i>\$0</i>	<i>\$115</i>

If there was a vote today to decide whether to do Program 5 or not do this program, how would you vote?

(CIRCLE ONE NUMBER)

1 I would vote **FOR** Program 5

2 I would vote **AGAINST** Program 5

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Fig. 6. Sample choice question for southwest study Area.

days in lower visibility bins and higher numbers of days in higher visibility bins.⁷ Thus, the photographs used were constant for each respondent and changes in the distributions of visibility were

shown through the bar graphs associated with each photograph.

The fourth insight was that telling respondents that the purpose of the study was to value changes in visibility after all human health and ecosystem effects of air pollution had been removed was not believed by some respondents. This is despite the fact that resource managers indicated that human health and ecosystem effects were highly unlikely in any dimension experienced or viewed by

⁷ As the distribution of visibility days is divided into quintiles for baseline conditions (purple bars in Fig. 3), we continue to refer to the bins as quintiles when we move to the improved conditions (yellow bars in Fig. 3).

Table 2
Choice question attributes and levels.

Attributes	Descriptions/Definitions	Levels
Visibility Improvements	Shift in distribution of visibility (see Appendix Table A1)	Southwest – 7 visibility programs Southeast – 6 visibility programs
Ecosystem Impacts	Particles that form haze can affect water quality, soil, plants, and in turn, the growth and variety of plants and animals.	• No Change • A Small Reduction
Health Impacts	Some park visitors who have respiratory problems may experience coughing or shortness of breath on days with high levels of human-caused haze.	• No Change • A Small Reduction
Timing	Numbers of years until program improvements are realized.	• 10 Years • 20 Years
Cost	Recurring annual cost to household.	\$15, \$35, \$65 or \$115

humans, respectively. Thus, we added human health and ecosystem attributes to the choice experiment design so respondents chose over changes in the distribution of visibility that had or did not have associated human health and ecosystem effects. While some respondents would not accept being told there was no human health or ecosystem effects associate with visibility improvements, many of these individuals were able to accept that different policies might have different effects on human health and ecosystems with small impacts.

The fifth insight was helping people understand the geographical dispersion of air pollution (haze). We found early in the design process that some people thought very locally, but perhaps in different dimensions. Some, but not all, thought of affected areas as local forested areas, not necessarily National Parks and wilderness areas, while another segment thought that haze was caused locally in national parks and wilderness areas by visitors vehicle exhaust and campfires. Thus, we inserted a diagram in the survey to portray how air pollution can travel hundreds of miles ([Fig. 4](#)). A second component of the geographical representation was a map showing locations of National Parks and wilderness areas, and that portrayed where most people live and sources of haze ([Fig. 5](#)). The areas where haze would be reduced were portrayed by red-outlined ovals. This helped respondents to understand that human health effects would likely be minimal and that the benefits of any policy action would be geographically constrained.

3.2. Choice questions

The choice questions presented binary choices comparing current visibility conditions and a visibility improvement program; this was a change from the purple-bar histogram of current conditions to the yellow-bar of improved conditions as portrayed in [Fig. 6](#). This is what has become known as discrete-choice experiment; a discrete-choice response format variant of a choice experiment where respondents choose between the status-quo condition and an improvement or decrement from current conditions.

The visibility improvement programs were described in terms of five attributes ([Table 2](#)). The first attribute portrayed the change in the distribution of visibility using the bar graphs with the five bins. The left column presented current conditions with the visibility days equally divided across the five bins (purple bars in [Fig. 6](#)). The panel of five visibility photographs was enclosed with the survey and the images were labeled A to E, like the bars in the choice question, and subjects were told that the A conditions were the highest visibility and E conditions were the lowest visibility. The right column showed how visibility improved; there were more days in the higher visibility bins and fewer in the lower visibility bins (yellow bars in [Fig. 6](#)).

To ensure adequate variation of visibility improvements across and within choice sets, three programs were taken directly from the path where there is an equal improvement in visibility during

each year of the improvement programs. Four additional programs were created by perturbing the improvements so that they were not on the linear path with equal visibility improvements in all years. Because two programs turned out to be very close for the Southeast region, only six programs are used in the final experimental design for that region. The Southwest region included the full seven programs. The alternative shifts (improvements) in the distribution of visibility relative to current conditions are shown in [Appendix Tables A1](#) (Southwest) and [A2](#) (Southeast). Program 1 for both regions represents the full federal program of removing the worst 20% of days.

Only two levels were used for ecosystem and human health impacts, no change or a small reduction. Two levels were used to obtain a “clean” estimate of the value of visibility improvements. We wanted to be able to exclude ecosystems and human health considerations, the no change levels, when computing value estimates to align with the national policy. Small changes in human health and ecosystems were used to be consistent with scientific information that indicates a visibility improvement program would have little to no effect on ecosystems and human health.⁸

Time was included because the haze reduction programs can be more or less aggressive in reducing haze, which would make visibility improvements occur sooner or later. The cost attribute is included to estimate the marginal utility of income, which is necessary to compute the values of visibility improvements (see [Equation \(4\)](#)). Respondents were told the costs would be passed on to households through higher prices and taxes, and they would pay higher prices and taxes each year while the program is being implemented.

This choice question asks for a total value that includes any use and nonuse values respondents might hold for visibility improvements in Class 1 areas ([Champ et al., 2003](#)). Thus, the samples that will be described below for study implementation are not limited to those who visit Class 1 areas or live in close proximity to these areas.

To derive choice sets, a 24-row, orthogonal, main-effects design matrix was drawn from an on-line catalog of orthogonal matrices.⁹ The size of this design matrix allows for orthogonal placement of the three two-level attributes (human health impacts, ecological impacts, and time), one four-level attribute (program cost), and one six-level attribute (the visibility programs).¹⁰ The design contained 24 choice sets, which were divided among four different survey

⁸ Atmospheric scientists and ecologists from the National Park Service who study these issues advised us that any change that might occur in ecosystems would be so small and take so long that visitors would not be able to detect the changes. The visibility improvement actions are not designed to protect human health and people visit the areas for a short period of time and would not be exposed to air quality for an extended period of time.

⁹ http://support.sas.com/techsup/technote/ts723_Designs.txt.

¹⁰ Since the design matrix only accommodates a six-level attribute, variation over the seven programs is manufactured by mixing information from two additional two-level columns from the design matrix into the perturbation routine.

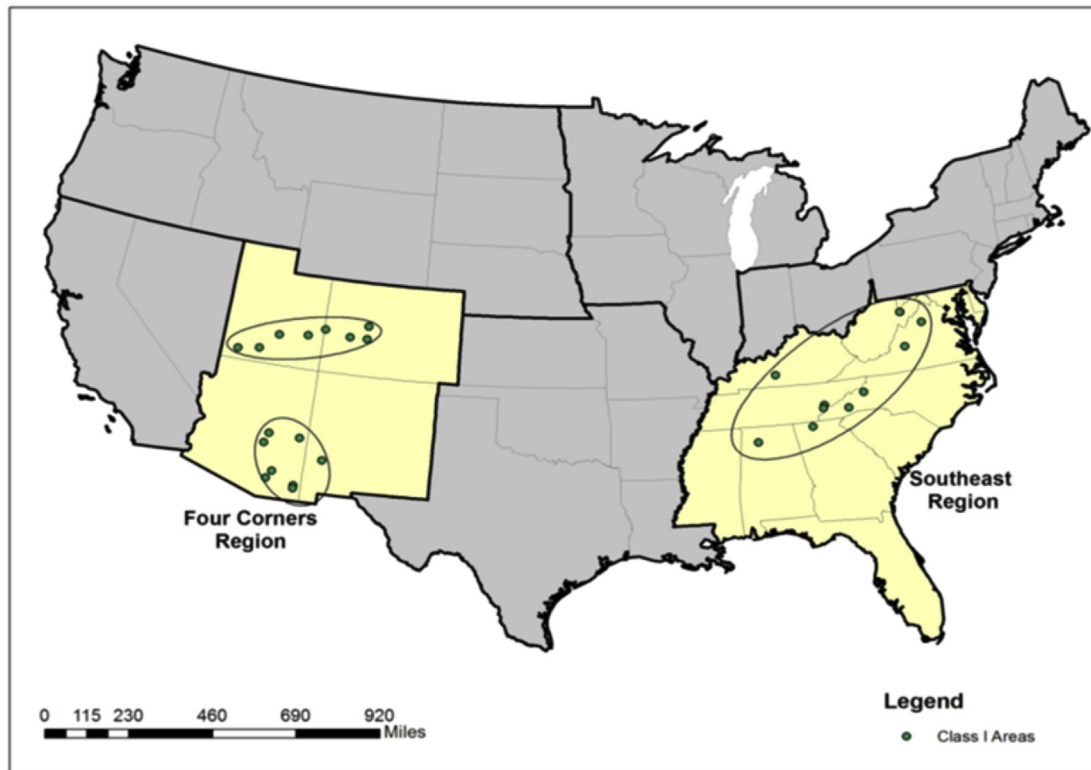


Fig. 7. Map designating southwest and southeast study areas.

versions with six questions per survey and randomly assigned to respondents.¹¹

To verify that the experimental design would identify all parameters, simulations were run on the Southwest experimental design for the four perturbation scenarios with 1000 replications. Each replication assumed a sample size of 400 (100 responses to each of the four survey versions) and utilized representative utility parameters from focus group data. Results indicated that all parameters could be estimated precisely.

A final consideration was that we wanted the choice question to be incentive compatible and the survey to be consequential (Carson and Groves, 2007). Incentive compatibility included having respondents answer binary questions where they choose a visibility improvement program or to remain with baseline conditions. Consequentiality was reinforced by cover letters from the national park Service telling subjects:

"The National Park Service is conducting a study to determine how best to protect and improve scenic vistas in National Parks and other wilderness areas."

And the choice questions were framed as follows:

"If there was a vote today to decide whether to do Program X or not do this program, how would you vote?"

Thus, the survey was framed as influencing decision making and the choice was immediate.

3.3. Survey implementation

The survey was implemented in the Four Corners area of the Southwest (Utah, Arizona, New Mexico and Colorado) and Southeast (Delaware, Maryland, Virginia, West Virginia, Kentucky, Tennessee, North Carolina, South Carolina, Georgia, Alabama, Mississippi and Florida) (Fig. 7). For each region a sample of 2000 residential addresses from the U.S. Postal Service Computerized Delivery Sequence File was acquired from Survey Sampling International. The survey was administered by the Center for Survey Research at Virginia Tech. Sample members received a personalized pre-survey letter, the survey (including a cover letter, fold-out picture set for the quintiles of the current distribution of visibility, \$2 incentive, and pre-paid return envelope), a reminder postcard, and a replacement survey if no response was received within about two weeks of the initial survey mailing.

4. Empirical results and discussion

The response rate, as a percent of deliverable surveys, was 39% for the Southwest sample and 32% for the Southeast sample.

Respondent characteristics generally differ between the two samples. Southwest respondents are more likely to have experienced haze reducing visibility and visited a Class I area, but have a similar level of concern as Southeast respondents (Table 3). Southeast respondents are less likely to be male, less likely to be college educated and have lower annual incomes, but have the same average age as Southwest respondents. As these results are from random samples of different populations there is no reason

¹¹ While a binary question can be incentive compatible (Carson and Groves, 2007), any sequence of choice questions, which is standard in choice experiments, generally violate this property from a theoretical perspective. However, Vossler et al. (2012) suggest that there are assumptions under which this approach can be incentive compatible.

Table 3
Respondent characteristics.

Characteristics	Southeast (n = 590)	Southwest (n = 681)	Test statistic for comparison of regions ^a
Percent reporting that they have experienced haze reducing their ability to view a scenic vista	81%	89%	t = −4.1***
Percent reporting that they have visited a Class I area within the visibility improvement region	67%	84%	t = −7.2***
Percent somewhat or very concerned about human-caused haze in national parks and wilderness areas	54%	51%	z = 1.0
Percent male	51%	63%	z = −3.9***
Mean age	54 years	54 years	t = 0.3
Percent college graduates	42%	52%	z = −3.4***
Mean annual income ^b	\$63,000	\$69,000	t = −2.2**

^a Single, double and triple asterisks indicate significance at the 10%, 5%, and 1% significance levels, respectively.

^b Income responses were categorical and data were coded to the midpoint of the categories, with the top category (\$150,000 or more) coded as \$150,000, to compute means.

that the sample demographics should be the same across the samples, and these differences further indicate that value estimates cannot be directly compared across the two study regions.

4.1. Econometric model

Responses to the choice questions were analyzed using a linear specification of the utility function (equation (1)) as follows:

$$U = \beta_c(C) + \sum_{k=1}^K \beta_k X_k + \varepsilon \quad (5)$$

where C is the cost attribute, X is a vector of the other attributes and the β_k are coefficients to be estimated. The attribute variables are defined as:

Cost = annual cost in dollars,
Health = 1 if small improvement and 0 no effect,
Ecological = 1 if small improvement and 0 no effect, and
Time = 1 if 20 years and 0 if 10 years.

Two coding procedures for visibility were considered:

$$\beta_{mean} Mean_j, \quad (6a)$$

and

$$\beta_{Adays} Adays_j + \beta_{Edays} Edays_j \quad (6b)$$

The visibility variables are defined as:

Mean = mean visibility for the respective improved visibility distribution measured in deciviews, and
Adays/Edays = number of days associated with the A and E photographs (best and worst visibility, respectively).

A deciview is a measure of visibility used by atmospheric

scientists (Henry, 2002). (Mean deciviews for current conditions and each improved visibility distribution are documented in Appendix Table A3.) Higher deciviews imply less visibility, which implies $E(\beta_{mean}) < 0$. It is also expected that the following two relationships hold: $E(\beta_{Adays}) > 0$ and $E(\beta_{Edays}) < 0$; more high visibility days and fewer low visibility days are preferred. Considering these alternative specifications allows for an investigation of whether respondents considered different characteristics of the changes in the visibility distributions or responses are simply related to a single summary statistic. We choose these specification because the Chestnut and Smith studies asked respondents to value changes in mean visibility and focus group participants tended to focus on the number of days associated with the *Adays* and *Edays* images. In addition, the *Adays/Edays* specification allows for the analysis to explicitly address the policy goal of removing the 20% worst visibility days.

4.2. Estimation results

When estimating Equation (5) using a logit model the cluster option in STATA was used to account for possible correlation in the responses each respondent made to the six choice questions. Separate models were estimated for the Southwest and Southeast samples. This was done because each region had different current conditions for visibility and different changes in visibility to meet the goal of removing the worst 20% of visibility days. Thus, we cannot compare the results from the two regions statistically and did not estimate a pooled model to test equality of parameter estimates.

Both visibility specifications indicate significant, positive values for improvements in visibility (Table 4). *Mean* is significant and negative, as expected, in both samples. *Adays* are significant and positive and *Edays* are significant and negative in both samples. Thus, reducing *Edays* and increasing *Adays* increases value.

Turning to the other attributes in the choice models, *Health* is significant and positive in both samples. *Ecosystem* is only

Table 4
Logit model parameter estimates.

Variables	Southwest	Southeast
Mean	−0.407*** ^a (0.055) ^b	−0.211*** (0.020)
Adays	0.008*** (0.003)	0.015*** (0.002)
Edays	−0.038*** (0.008)	−0.020* (0.010)
Health	0.206*** (0.055)	0.216*** (0.068)
Ecosystem	0.172** (0.083)	0.020 (0.089)
Time	0.039 (0.055)	−0.152** (0.066)
Cost	−0.014*** (0.001)	−0.013*** (0.001)
Constant	2.889*** (0.410)	4.063*** (0.371)
N	3902	3351
χ^2	175	219

^a Asterisks denote significance at the 10% (*), 5% (**) and 1% (***) levels.

^b Numbers in parentheses are standard errors.

Table 5
Annual Household Willingness to Pay (2012\$).

Model							
Southwest							
Programs							
Mean Visibility	5.3 dV ^a	6.3 dV	6.5 dV	6.7 dV	6.9 dV	7.1 dV	8.0 dV
Adays/Edays	263/0	179/11	179/29	135/15	110/11	110/29	58/62
Willingness to Pay							
Mean	\$79 (61, 100) ^b	\$50 (38, 62)	\$44 (33, 55)	\$37 (28, 47)	\$32 (24, 40)	\$26 (20, 33)	−\$1 (−1, −1)
Adays/Edays	\$88 (69,109)	\$66 (50, 83)	\$51 (40, 64)	\$56 (40, 73)	\$54 (36, 74)	\$40 (28, 54)	\$6 (1, 11)
Southeast							
Programs							
Mean Visibility	13.7 dV	15.7 dV	16.1 dV	16.8 dV	17.2 dV	20.6 dV	
A days/E days	365/0	234/0	234/18	179/0	179/18	69/51	
Willingness to Pay							
Mean	\$118 (94, 147)	\$86 (69, 108)	\$80 (64, 100)	\$68 (55, 86)	\$62 (50, 78)	\$7 (6, 9)	
Adays/Edays	\$118 (93, 149)	\$78 (55, 105)	\$71 (53, 92)	\$62 (36, 89)	\$54 (36, 74)	\$8 (−2, 17)	

^a dV = deciview.
^b 95% confidence intervals estimated using the Krinsky-Robb method with 5000 iterations.

significant for the Southwest sample, and *Time* is only significant for the Southeast sample. The coefficients for these variables are robust to different specifications of visibility in terms of significance and magnitude.

Cost, the marginal utility of money, is negative and statistically significant. This is true for both samples and this finding is robust to the specification of visibility.

Overall, the *Adays/Edays* specifications have somewhat larger log likelihood values (larger chi-square statistics) indicating that this specification fits the data better and information is lost when mean visibility is used as the visibility explanatory variable. That is, the *Adays/Edays* model has two variables to describe the distributions, rather than one with the *Mean* specification. Despite this suggestive evidence that one model specification might fit the data best, welfare estimates presented in the next section are approximately the same from both model specifications. We cannot estimate a pooled model with *Mean*, *Adays* and *Edays* variables due to the correlation between *Mean* and the *Adays/Edays* variables.¹²

4.3. Welfare estimates

Welfare estimates (*wtp*) are calculated for each of the seven visibility improvement programs considered by the Southwest sample and the six programs for the Southeast sample. Values are computed using both specifications of visibility, which implies a different functional specification of equation (4) for each specification of visibility:

$$wtp_{v|h=0,g=0}^{Mean} = (\beta_{Mean})(Mean_{ic} - Mean_{cc})/|\beta_{Cost}| \tag{7a}$$

$$wtp_{v|h=0,g=0}^{days} = \sum_k (\beta_{kdays}*(kdays_{ic} - kdays_{cc})/|\beta_{Cost}|, \; k = A, E \tag{7b}$$

where each value is a change from current visibility conditions (*cc*) to improved visibility conditions (*ic*). The current condition mean visibility for the Southwest region is 8.0 deciviews and the comparable figure for the Southeast region is 21.1 deciviews. Current conditions have the number of *Adays* and *Edays* binned into equal quintiles of days, while each visibility improvement scenario increases the number of *Adays* and decreases the number of *Edays*

relative to current conditions.

Welfare estimates are reported in Table 5. Two immediate insights arise from the values reported. First, value estimates using the *Adays/Edays* specification are higher than those for the mean specification in the Southwest, but this is not the case for the Southeast sample. The *Adays/Edays* program value estimates for the Southwest sample range from 11% for the 5.3 deciview (263 *Adays*) program to 69% for the 6.9 deciview (110 *Adays*) program greater than the respective *Mean* value estimates; excluding the 8.0 (58 *Adays*) program with a negative value for the *Mean* specification. For the Southwest sample, value estimates are approximately the same for the *Mean* and *Adays/Edays* specifications for the 13.7 deciview (365 *Adays*) and 20.6 deciview (69 *Adays*) scenarios. For the other four scenarios, the *Mean* values are about 11% larger than the *Adays/Edays* values. While there is suggestive evidence that the *Adays/Edays* specifications in Table 4 might fit the data better than the *Mean* specifications, the welfare estimates presented in Table 5 indicate that value estimates from the two model specifications are approximately the same.

Second, values for the Southeast sample are larger than for the Southwest sample for the scenario that meets the policy goal of removing the 20% worst visibility days (13.7 deciview and 5.3 deciview scenarios, respectively). This result may suggest non-linearities in preferences for visibility improvements as the Southwest region is starting from a much higher level of visibility than the Southeast region (8.0 versus 21.1 deciviews). However, this intuition must be tempered by the fact that the visibility improvement in the Southwest region is much smaller than the visibility improvement in the Southeast region (2.7 versus 7.4 deciview improvements). In addition, as shown in Table 3, there are significant differences between respondents in the two regions, which may suggest differing preferences for visibility improvements between the regions. Thus, with the available data, we cannot conclusively explain why value estimates are larger in the southeast region than in the southwest region.

We present summaries of the value estimates from the Chestnut and Smith studies for comparisons with the value estimates from the current study (Table 6). Direct comparisons are not possible because the studies valued different changes in visibility, had different definitions of parks in the Southeast and Southwest regions and had different samples. The Chestnut and Smith value estimates were converted to 2012 dollars so that they would be the same year as the present study. In the current study, the Southeast value estimates range from \$7 to \$118, which includes all but one of the Chestnut Southeast estimates. The exception is the improvement from C to A conditions for Virginia residents, which is \$3 more

¹² The correlation between *Adays* and *Edays* is −0.75 in the both data sets. The correlations in the original experimental designs were −0.77 and −0.76 for the *Adays* and *Edays* variables in the southwest and southeast samples, respectively.

Table 6
Summary of Visibility Value Estimates from Chestnut and Smith Studies (2012\$).^a

Value estimates ^b	Chestnut and Rowe (1990)		Smith et al. (2005)	
	Mean WTP (standard errors)		Mean WTP (standard errors)	
Survey Response Rate	61%	57%	73%	
Target Population, Improvement Region	Virginia Residents, Southeast Parks	Arizona Residents, Southwest Parks	U.S. Residents, Southeast Parks	
Improve from C to B Mean Visibility	\$97 (19)	\$73 (12)	NA	
Improve from C to A Mean Visibility	\$121 (21)	\$106 (17)	NA	
Sample Frame	U.S. Residents, Southeast Parks	U.S. Residents, Southwest Parks	Without Histograms	With Histograms
Improve from C to B Mean Visibility	\$66 (8)	\$68 (8)	\$95 (27)	\$85 (13)
Improve from C to A Mean Visibility	\$93 (11)	\$91 (10)	\$146 (67)	\$131 (24)

^a Converted to 2012 dollars to match the year for the current study using the “Gross Domestic Purchases Price Index” from the 2015 *Economic Report of the President*.

^b Definitions of A, B and C conditions for value estimation are presented in Table 1.

than the estimate for 13.7 deciview (365 *Adays*) scenario (\$121 vs. \$118). Our Southwest value estimates range from –\$1 to \$88. Here, the Chestnut estimates for the improvement from C to A conditions exceed the current study estimate of \$88 for the 5.3 deciview (263 *Adays*) scenario (\$106 and 91 versus \$88). Given the confidence intervals and standard errors reported, none of these differences would be statically significant. Thus, while there are differences in study designs that do not make value estimates directly comparable, we can say that our value estimates and those reported by Chestnut are of the same range of magnitude. The same can also be said when the current study value estimates are compared to those from the Smith study. Thus, different design features do change value estimates, but the different design features do not appear to result in dramatically different value estimates.

We also computed value estimates for the human health (*h*) and ecosystem (*g*) attributes as:

$$wtp_{h|v=0,g=0} = \beta_h / \beta_{cost} \quad (8a)$$

and

$$wtp_{h|v=0,g=0} = \beta_h / \beta_{cost} \quad (8b)$$

A small improvement in human health would add about \$17 to value estimates for both the Southeast and Southwest samples. A small ecosystem improvement would add about \$12 to value estimates for the Southeast sample and this variable was not significant in the Southwest sample. Thus, if human health was not controlled in the experimental design and at least some respondents assumed that the visibility improvement program would improve human health, our values may have been overstated for a program designed purely to enhance the esthetic of improved visibility. The same can be said for ecosystem considerations for the Southeast sample.

4.4. Considerations for values of shifts in the distribution of visibility

Several insights are relevant here. The first is that both the *Adays* and *Edays* variables are significant, and this model specification yields similar value estimates to the *Mean* visibility specification. The significance of the *Adays* and *Edays* variables is robust to both the Southeast and Southwest samples, and suggests that respondents do consider shifts in the distribution of visibility when valuing changes in visibility. The *Adays/Edays* specification allows for calibrating value estimates more closely to policy analyses because the *Mean* specification could give the same value to policies that would have different values for *Adays* and *Edays*. Depending on the numbers in the B, C and D visibility categories, different pairings of *Adays* and *Edays* could have the same mean

visibility.

Second, there is asymmetry between how respondents evaluate increase in *Adays* versus decrease in *Edays*. Consider the ratio of the estimated coefficients on *Edays* to the estimated coefficients on *Adays* ($|\beta_{Edays}| / \beta_{Adays}$). For the Southeast sample, this ratio is 4.75 and the comparable ratio for the Southwest sample is 1.33. This means that a day reduction in *Edays* is worth 4.75 (1.33) more than a day increase in *Adays* in the Southeast (Southwest) region. This result clearly supports the policy priority of removing the worst visibility days with an added benefit of moving these to the best visibility conditions.

Finally, in most cases, the *Adays/Edays* value estimates were not dramatically different from the *Mean* value estimates. However, a difference of even 10% can have a substantial impact on aggregate value estimates and might affect whether a policy produces a positive or negative net present value when program benefits are compared to program costs. Thus, we would argue for using models that take account of more information in the shift in the distribution of visibility than simply a change in mean visibility conditions. As noted previously, different distribution shifts can result in the same mean visibility whereas the *Adays/Edays* specification allows for values that are more customized to the distributional shifts in visibility. The *Adays/Edays* specification does omit days in the B, C and D bins, but we observed that focus-group participants were not nearly as concerned about the days in the middle of the distribution and they were with the best and worst conditions in the tails of the distributions.

5. Conclusions

This study demonstrates an approach, in the context of valuing visibility improvements, for using a choice experiment to estimate values for policies and programs that result in a shift in the distribution of environmental outcomes. Our focus groups revealed that careful consideration is needed when designing information to portray the distribution of current and improved conditions. Our results suggest that simply using the mean of the distribution to analyze responses may not be sufficient because people may care about other characteristics of the distribution shift and this was confirmed by the results of the *Adays/Edays* model estimates. In addition, controlling for human health and ecosystem effects, by including these considerations as attributes in a choice experiment, enhanced the credibility of the survey scenario with focus group participants and provides an empirical procedure for excluding these considerations when they are not part of the benefits of a program being evaluated. To better understand how study design features affect visibility value estimates more research is needed beyond our study and the Chestnut and Smith studies.

Beyond these methodological suggestions, our research

provides insight into the potential benefits of the national policy to improve visibility in Class 1 areas in the U.S. (National Parks and wilderness areas). Because baseline visibility conditions and changes in visibility vary by region of the country, and likely public preferences as well, the results presented here suggest that region-specific value estimates are needed to support computation of benefits of progress toward meeting Regional Haze Program goals. Our results suggest that conservative estimates of the aggregate annual benefits accruing with a move from current conditions to fully meeting the goals of the Regional Haze Program using the *Adays/Edays* models would be \$1115 million in the Southeast region and \$206 million in the Southwest region. These estimates are conservative because we only aggregate over the share of households from sampled states that responded to the survey (32% in the Southeast and 39% in the Southwest). These aggregate estimates differ because the per household value is higher in the Southeast (\$118 vs. \$88) and there are more households in the southeast (25.5 million vs. 6.0 million). Further empirical work is needed to estimate the benefits of visibility improvements in Class I visibility improvement areas in other regions of the U.S.

While our empirical example is done in the context of visibility improvements, our general approach should be readily adaptable, with case-specific modifications, to other types of applications where valuing a shift in the distribution of environmental conditions is required.

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Appendix A. Supplementary data

Supplementary data related to this article can be found at <http://dx.doi.org/10.1016/j.jenvman.2016.01.042>.

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