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Perspective

Illustration of a Method to Incorporate Preference Uncertainty in Benefit–Cost Analysis

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Benefit–cost analysis is widely used to evaluate alternative courses of action that are designed to achieve policy objectives. Although many analyses take uncertainty into account, they typically only consider uncertainty about cost estimates and physical states of the world, whereas uncertainty about individual preferences, thus the benefit of policy intervention, is ignored. Here, we propose a strategy to integrate individual uncertainty about preferences into benefit–cost analysis using *societal preference intervals*, which are ranges of values over which it is unclear whether society as a whole should accept or reject an option. To illustrate the method, we use preferences for implementing a smart grid technology to sustain critical electricity demand during a 24-hour regional power blackout on a hot summer weekend. Preferences were elicited from a convenience sample of residents in Allegheny County, Pennsylvania. This illustrative example shows that uncertainty in individual preferences, when aggregated to form societal preference intervals, can substantially change society's decision. We conclude with a discussion of where preference uncertainty comes from, how it might be reduced, and why incorporating unresolved preference uncertainty into benefit–cost analyses can be important.

KEY WORDS: Benefit–cost analysis; preference uncertainty; societal decision making

1. INTRODUCTION

Benefit–cost analysis (BCA) is widely used in policy analysis and government decision making to examine whether a specific policy is justified, or to compare several alternative policies with different outcomes and time horizons. The most useful analyses take uncertainty into account (Boardman, Greenberg, Vining, & Weimer, 2017; Morgan, 2017; Morgan & Henrion, 1992), yet typically only uncertainty about cost estimates and physical states of the world is considered, neglecting uncertainty about the value that the public places on policy outcomes. When a decision is to be made by a single decisionmaker who is uncertain about an appropriate value (e.g., the value of a statistical life), the best practice is to use parametric analysis so as to display the consequences of alternative value choices (Morgan & Henrion, 1992). However, when the values involved are those of a population, no framework exists to incorporate uncertainty in individual preferences into the societal decision-making process. In this article, we propose such an approach that incorporates preference uncertainty using *individual preference intervals*, along with different *aggregation rules*, to express *uncertainty in societal preferences*. Cost estimates are then compared with those societal preference intervals to determine whether society will surely accept (or reject) an option, or whether an additional analytic-deliberative process should be invoked to reach a collective societal decision (Arvai, 2003; Cox, 2012; Dreyer & Renn, 2014; National Research Council, 1996; Renn, 1999, 2004).

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2. INCORPORATING PREFERENCE UNCERTAINTY INTO POLICY ANALYSIS

BCA typically uses engineering and economic models to quantify the consequences of alternative policy choices in monetary terms. To illustrate uncertainty in societal preferences, we consider an example that involves augmenting smart grid and distributed generation technologies to allow a region to operate as an isolated island to provide residential electric customers with limited power when none is available from the central grid (see Baik, Morgan, & Davis, 2018 for details). In this and similar cases, cost estimates are determined by factors such as the prices of raw materials, manufacturing, labor, and maintenance. Assuming that engineering analyses can determine the required technology and units with relative certainty, uncertainty in the cost estimates comes from two sources: (1) uncertainty in prices and (2) errors in estimating the cost function, such as that knowledge about how technology will evolve in the future is not precisely known (Boardman, Greenberg, Vining, & Weimer, 2017).

Quantifying the benefits can be much trickier. In this illustration, the majority of benefits only accrue if a grid blackout occurs but customers continue to receive (some) power. Thus, the expected value of benefit is $B = P(blackout) \times value(blackout)$, where *P(blackout)* is the probability of a blackout over a given time frame and *value(blackout)* is the value that community members place on their reliable electric services during the blackout. Although much effort is spent on estimating the probability of blackouts (e.g., through simulations or by using bounding analysis) (Morgan, 2001; Xu & Brown, 2008), the value of the lost electricity is more difficult to estimate. Typically, the value that residential electricity customers place on electric services is assumed to be a known quantity that can be elicited using surveys, where customers are asked for their willingness to pay (WTP) to avoid blackouts. Yet, it is not hard to see that there exists uncertainty in these values arising from several sources. Traditional issues include sampling error, where the true distribution of WTP across individuals, or true population average WTP, is unknown from any particular sample of individuals, and statistical inference must be used for the population value (Davis, 2018). There may also be uncertainty arising from respondents not understanding questions in survey instruments or, despite efforts made in designing clear unambiguous instruments, respondents may not be able to fully envision the circumstances they would face during a blackout (Baik, Davis, & Morgan, 2018; Baik, Morgan, et al., 2018). Both add measurement error on top of sampling error.

We have found that fundamental uncertainty in the value of blackouts is present when members of a community simply do not know exactly how much they would value their electric services during a hypothetical blackout (Baik, Davis, et al., 2018). Suppose that there is a large regional blackout and you cannot get power for 24 hours. We guess that for the 24 hours you would surely be willing to pay \$1 to have electricity to power your high-priority loads—such as a few lights, your refrigerator, and air conditioning during summer. You also would probably pay \$5 or even up to \$20. But \$40 might give you pause. Is this too much? How much is usually spent on similar goods and services? Unless it is for a very unusual situation (e.g., a planned wedding reception at your home), it is almost certainly too much to pay \$500 to get the electricity back for 24 hours. Suppose \$150 is the largest amount you might consider, and you are certain you would not pay more. Between these numbers, \$40 you would surely pay and amounts above \$150 that you would surely not pay, is a range (\$40–\$150) where you are unsure about paying. This is a general pattern we have found in surveying members of the lay public. People tend to have clear bounds to their WTP but are unsure about what they would do between those bounds.

To address such situations, we propose an approach to handle individual preference uncertainty and capture that uncertainty in aggregated social preferences. Suppose the population consists of N individuals (in our case, residential electricity customers) indexed $i = 1, 2, \ldots, N$. Each individual has a lower bound L_i that is the maximum of what he or she would *surely* trade in exchange for a good or service (i.e., where the individual switches from "definitely buy" to "may consider buying"), and has an upper bound U_i that is the minimum of what the individual would surely not trade in exchange for the good or service (i.e., where the individual switches from "may consider buying" to "definitely will not buy"). Further, assume that L_i and U_i are measured on an interval scale for all individuals such that L_i and U_i are well defined up to affine transformations. The range L_i to U_i is the *individual's preference interval*, which can be interpreted as the range of values for which the individual is unsure about whether he or she is willing to pay any amount between L_i and U_i

(Bernheim & Rangel, 2007; Braun, Rehdanz, & Schmidt, 2016; Dost & Wilken, 2012; Wang, Venkatesh, & Chatterjee, 2007).

To construct a *societal preference interval* (L, U), representing society's uncertainty about the value of avoiding a blackout (where in this case "society" is everyone served by the feeder), we must aggregate L_i and U_i in some way. If L_i and U_i are measured on an interval scale and individuals are interpersonally comparable so that changes in lower (upper) bounds are equivalent from person to person, the measures satisfy *cardinal full comparability* (Roberts, 2009). Because we assume cardinal utilities with full interpersonal comparability, individuals' preferences can be combined to make social decisions without contradicting Arrow's impossibility theorem, which applies only when individual preferences are ordinal and noncomparable (Arrow, 1950; Sen, 1999).

The most common aggregation from individual to societal preferences is the average or median (Black, 1948), but the summation rule is by no means the only valid mathematical or ethical rule. Instead, cardinal full comparability also admits other aggregation rules. Two important ones that yield a transitive social welfare function and provide interesting bounds on what society might care about are the minimum and maximum (Roberts, 2009; Sen, 1999). There are arguments for and against each one. If, for example, individuals' lower bounds are strongly associated with wealth, the individuals with greater lower bounds may simply be more affluent. In this case, society might care more about individuals with smaller lower bounds (if no arrangements exist for cross-subsidies), and the minimum aggregation function should be used. If, on the other hand, individuals' lower bounds are more strongly correlated with need (e.g., the need for an electrically operated medical respirator), society might care more about the individuals with larger lower bounds, and the maximum aggregation rule would be more appropriate.

For these reasons, we suggest aggregating individuals' preference intervals to construct societal preference intervals. When community members' WTP is highly correlated with their need, a decisionmaker might make a decision based on the maximum aggregation rule (favoring those who need the most). Using the minimum aggregation rule, we calculate *society's minimum preference interval* from the *minimum lower bound* ($\text{MinLB} = \min(L_i)$) to the *minimum upper bound* ($\text{MinUB} = \min(U_i)$; the vertically striped area in Fig. 1). On the other hand, when community members' WTP is highly correlated with their wealth, a decisionmaker might make a decision based on the minimum aggregation rule (favoring those who can pay the least). The same process can be used to construct *society's maximum preference interval* from the *maximum lower bound* ($\text{MaxLB} = \max(L_i)$) to the *maximum upper bound* ($\text{MaxUB} = \max(U_i)$; the horizontally striped area in Fig. 1). In between the two intervals, it is also possible to construct *the interval of intermediate preference* from MinUB to MaxLB (the shaded area in Fig. 1).

Once the intervals are calculated, it is possible to determine whether society as a whole would definitely reject an option, definitely accept an option, or is unsure. As addressed in a large literature on stochastic dominance (Henry, 1974; Pindyck, 1990; Ramani & Richard, 1993), uncertainty about states of the world does not matter if one alternative is better than another in every state of the world, or always worse than another in every state of the world (i.e., statewise dominant). Translating this insight to our context, preference uncertainty will not matter if paying the cost stochastically dominates rejecting the alternative (the cost of an alternative is below the minimum WTP for every member, thus in the "definitely accept" area in Fig. 1) or rejecting the alternative stochastically dominates paying the cost (the cost of an alternative is above the maximum WTP for every member, thus in the "definitely reject" area in Fig. 1). Only two of the three possible outcomes permit a definitive decision (accept or reject), while society being unsure (the cost is in between MinLB and MaxUB) means that some form of additional deliberation is needed. In the unsure case, the outcome of BCA might be determined by whether and how strongly individuals' preferences are correlated with their wealth and need. Although we only consider the most common case when individuals who are the least interested and the most interested in a project are fairly distinguishable and both have some amount of preference of uncertainty, in general, the number and type of preference intervals are determined by the distance between the two groups of individuals and how much preferences are spread out within each group.

3. CASE STUDY: PROVIDING LIMITED LOCAL ELECTRIC SERVICE IN THE EVENT OF LARGE LONG-DURATION OUTAGES IN THE BULK POWER SYSTEM

For our illustration using the value of lost services provided by electricity during a large power

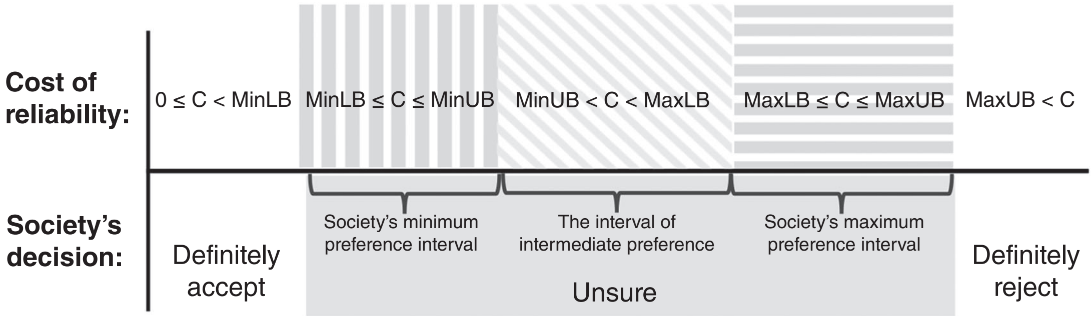

Fig. 1. This diagram summarizes the three different regions of society's decisions depending on society's preference intervals. If the required cost is lower than the minimum of society's minimum preference interval or higher than the maximum of society's maximum preference interval (i.e., the required cost per outage per household located in the white regions), society can definitely accept or reject an option. However, if the required cost is within the unsure region (i.e., the required cost is located in the shaded region), additional considerations, such as whether and how strongly respondents' preferences are correlated with their wealth and need, should be addressed before making the decision.

outage of long duration, we draw on numerical results from Baik, Davis, et al.'s (2018) face-to-face interviews in which we elicited the value of lost load for residential customers during a hypothetical 24-hour power outage on a hot summer weekend in western Pennsylvania. Because of the several assumptions we make to perform this illustration, readers should place no credence in the specific numerical results obtained. They should be viewed as *strictly illustrative* of the method and should *not* be used as a basis for any decision making about improving power system resilience.

As seen in Fig. 2, Baik, Davis, et al. (2018) used a multiple-bounded discrete choice preference elicitation method, which allowed respondents to express uncertainty in their preferences in the form of an interval (the upper limit from the "yes" column (L_i) to the upper limit from the "not sure" column (U_i)) (Cubitt, Navarro-Martinez, & Starmer, 2015; Johnston et al., 2017). Respondents provided their *conditional* WTP (assuming that the blackout already occurred and then were asked to value turning their power back on) either to receive full or partial (<20 A) backup service.

For illustration, we arbitrarily assume that the preferences we elicited are not different across regions, and construct societal preference intervals using the following approach:

- First, we extract each individual's lower and upper bound (L_i and U_i). Fig. 3(A) shows the distribution of L_i and U_i.
- Next, we compute MinLB, MaxLB, MinLB, and MaxUB.
- Then, we construct the society's minimum (from MinLB to MinUB) and maximum preference interval (from MaxLB to MaxUB).
- Finally, we calculate the interval of intermediate preference (from MinUB to MaxLB).

Following Baik, Morgan, et al. (2018), we assume that in each of several parts of the United States, there is a distribution feeder that serves 2,500 customers and the incremental investment cost of modifications needed to supply backup power is recovered through service payments. To simplify the example, we do not consider the length of disruptions or time value of money. Because different regions face different types of risks, we count the number of major electric emergency incidents and disturbances in each state that: (1) occurred between 2000 and 2017, (2) directly resulted in losses to customers (either demand loss or number of customers affected is greater than zero), and (3) required ≥24 hours to fully restore the power (Department of Energy, Office of Electricity Delivery and Energy Reliability, 2017).

Fig. 3(B) shows the cost required per respondent per outage to implement the backup service on the horizontal axis, plotted against the number of outages on the vertical axis. Here, we assume that individual preferences are the same in all regions and select the following five cases (indicated by points along the curve in Fig. 3(B)): (1) a state that experienced the largest number of long outages (70 long outages during the past 17 years, square), (2) Pennsylvania, for which the value was elicited (37 outages, dot), (3) four states that experienced the average number of long outages (10 outages, triangle), (4) three states that provide additional insights

	Would you be willing to pay this amount to get partial (about one-fifth of your normal power) service on a hot summer weekend day?		
	Yes	Not sure	No
Less than $5	✔	❑	❑
$5 – $9.99	✔	❑	❑
$10 – $14.99	✔	❑	❑
$15 – $19.99	✔	❑	❑
$20 – $24.99	✔	❑	❑
$25 – $29.99	❑	✔	❑
$30 – $34.99	❑	✔	❑
$35 – $39.99	❑	✔	❑
$40 – $44.99	❑	✔	❑
$45 – $49.99	❑	❑	✔
$50 – $54.99	❑	❑	✔
$55 – $59.99	❑	❑	✔
$60 – $64.99	❑	❑	✔
$65 – $69.99	❑	❑	✔
$70 – $74.99	❑	❑	✔

Fig. 2. Multiple-bounded discrete choice question that was used in Baik, Davis, et al. (2018), eliciting respondent's willingness to pay (WTP) for partial backup service during a 24-hour large regional blackout that had occurred on a hot summer weekend. In this example, the respondent would surely pay at least $25 and might be willing to pay as much as $45 for the low-amperage backup service.

about the societal investment decision (five outages, diamond), and (5) four states that experienced only one long outage (star).

To determine which aggregation rule(s) should be used, we check the correlations between income levels and WTP. Because the respondents' WTP was slightly correlated with their income levels ($\gamma_{Income\_L_i} = 0.15$, $\gamma_{Income\_U_i} = 0.14$) and electricity need (without any limitation: $\gamma_{Full\,Amps\_L_i} = 0.19$, $\gamma_{Full\,Amps\_U_i} = 0.30$, under 20 A constraint: $\gamma_{Limited\,Amps\_L_i} = 0.27$, $\gamma_{Limited\,Amps\_U_i} = 0.29$), all the three preference intervals need to be considered to make a societal decision. As shown in Fig. 3(B), the required cost per outage per household always lies within the interval of intermediate preference if a region experiences more than one long outage (the shaded area). In this case, the decisionmaker may need additional information, such as the distribution of individuals' lower and upper bounds, to determine the proportion of the population that supports the policy (see Fig. 3(A) and Table I). However, because the required cost per outage per household for regions that experience only one long outage always exceeds the upper bound of the interval of intermediate preference (i.e., MaxLB, which is $75), the decisionmaker should definitely reject the investment in this region.

A more traditional aggregation approach is to use the median and average of lower and upper bounds (Figs. 3(C) and (D)), treating everyone equally. In this case, the results suggest that regions suffering more than five long outages should make the investment because the lower bound of the interval lies above the cost curve (median: $30/outage-household, average: $35/outage-household), but regions suffering less than three long outages should reject the investment because the upper bound of the interval lies below the cost curve (median: $45/outage-household, average: $46/outage-household). However, both strategies hide individuals who are vulnerable to long-lasting outages and need the backup services but cannot afford the service payments.

Our illustration shows why incorporating preference uncertainty can be important, especially when individuals' preferences are not sufficiently strong. In some regions that suffer a large enough number of long outages and require relatively low service payments (because the incremental investment cost is evenly distributed across the outages), most individuals are either definitely willing to pay more than the required cost per outage per household or are unsure. For example, if, as we assume in this illustration, the preferences of residential customers in the state with the largest number of large long-duration outages are the same as those of respondents in Baik, Davis, et al. (2018), 86% (using lower bounds) to 89% (using upper bounds) of customers

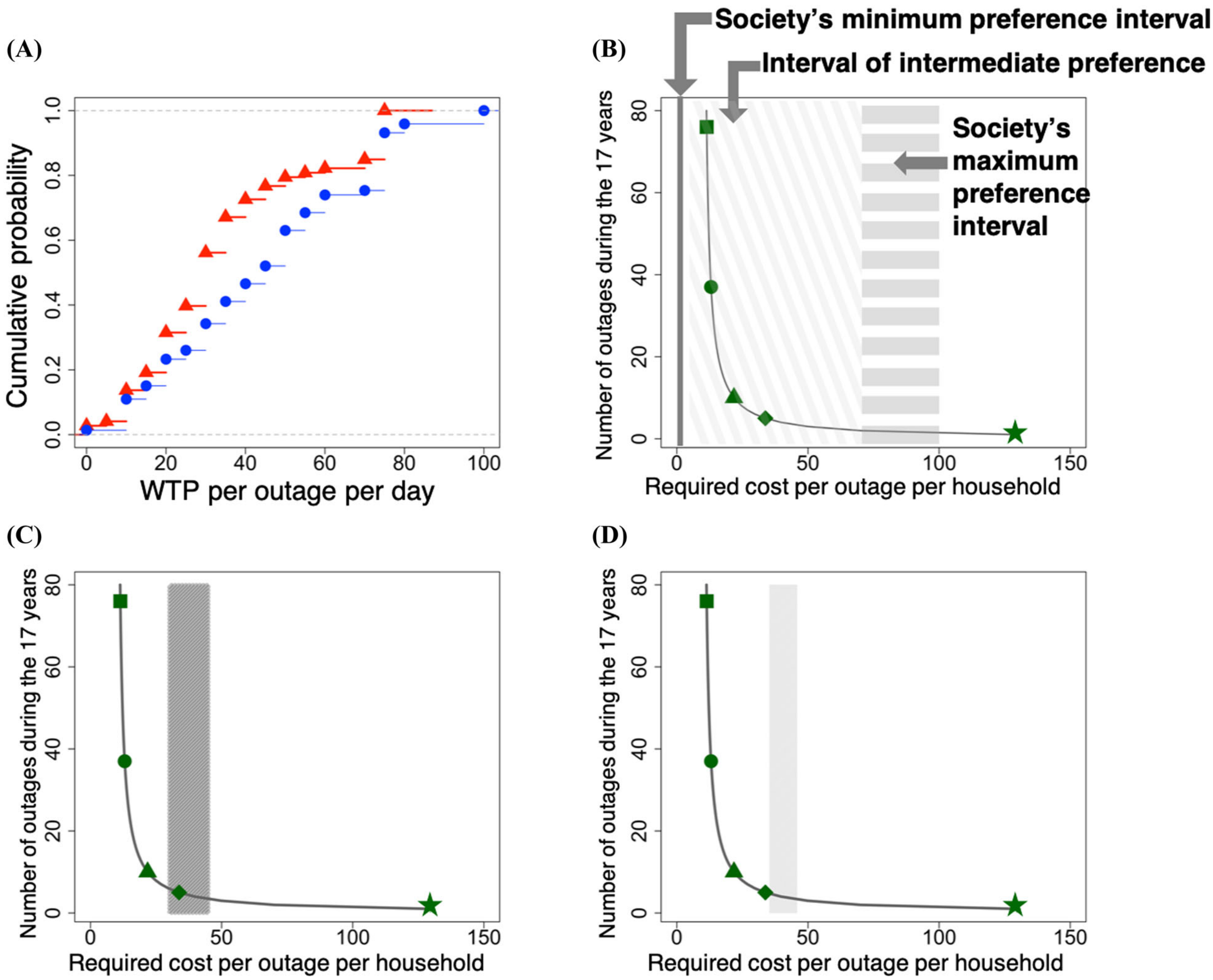

Fig. 3. (A) Cumulative distribution of the respondents who were surely (L_i, red triangles) or might (U_i, blue dots) be willing to pay for the low-amperage backup service against a 24-hour outage on a hot summer weekend (data compiled by Department of Energy, Office of Electricity Delivery and Energy Reliability, 2017). (B) The required incremental cost per outage per household to implement the low-amperage backup service (solid curve) compared to the interval of the society's maximum preference interval (horizontally striped area), minimum preference interval (vertically striped area in Fig. 1 and the vertical line at zero), and intermediate preference (shaded area). The dots along the curve indicate the required incremental investment cost per outage per household for the five example states discussed in the article. (C) The required incremental cost per outage per household to implement the low-amperage backup service (solid curve) compared to the median of the respondents' preferences (dark gray box). (D) The required incremental cost per outage per household to implement the low-amperage backup service (solid curve) compared to the average of the respondents' preferences (light gray box). Because of the assumptions, we have had to make to perform this analysis, all results should be viewed as illustrative. No credence should be given to the specific numerical results.

would support the investment, and preference uncertainty does not make a significant difference in decision making (see Table I). However, in the case of other regions that experience fewer long outages, the required service payment increases, and the proportion of individuals who support the backup service using the two different bounds can change substantially. For instance, in this example, the three states expected to suffer five long outages would require ~\$34/customer-outage. In this case, the individuals' upper bounds suggest that more than 65% of individuals would be supportive, whereas the lower bound suggests that only 44% of the individuals would be supportive (see Table I). A decision based on majority preference would flip depending on both uncertainty in preferences and the aggregation rules.

Table I. The Required Payment per Outage per Household and Percentage of the Respondents Who Would Be Willing to Pay More than the Required Incremental Investment Cost per Outage per Household Before and After Providing More Information and Exercises

States/Number of Large Long-Duration Outages During the Lifetime of Technology	Required Payment per Outage per Household	After Providing More Information		Before Providing More Information	
		Lower Bound	Upper Bound	Lower Bound	Upper Bound
A state that experienced the largest number of large long-duration outages (70 outages)	$12	86%	89%	70%	79%
Pennsylvania (37 outages)	$13	86%	89%	70%	79%
Average (10 outages)	$22	68%	77%	44%	64%
Five outages	$34	44%	66%	16%	51%
Minimum (one outage)	$130	0%	0%	0%	0%

Note: For illustration, we arbitrary assume that the preferences elicited in Baik, Davis, et al. (2018) are not different across regions. Preference uncertainty arises from using individuals' lower or upper bounds or providing more information and exercises do not substantially influence decision making in high-risk regions, but low-risk regions' decisions can be substantially influenced by both factors.

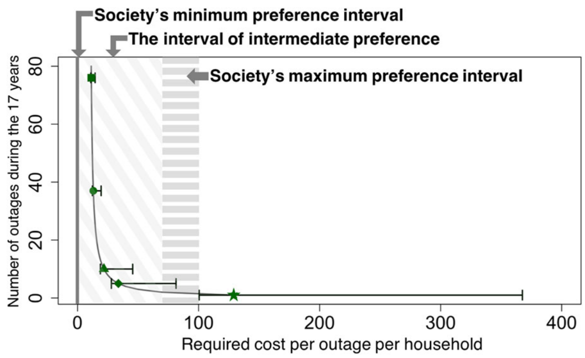

Fig. 4. Similar to Fig. 3(B) but including uncertainty that arises from cost estimates. The error bars indicate the upper and lower bound of the required cost per outage per household. Results are illustrative. No credence should be given to the specific numerical results.

Although we have focused on preference uncertainty, the approach can also be used to incorporate cost uncertainty (Fig. 4) (Boardman, Greenberg, Vining, & Weimer, 2017). In our case, the number of customers served by a distribution feeder and the incremental investment cost per distribution feeder to enable islanding are the two largest sources of cost uncertainty. We treat both factors parametrically (1,500, 2,500, and 3,000 residential customers per feeder) (Baik, Morgan, et al., 2018; Willis, 1997; XCel Energy, 2014), and as low as $70,000 and as high as $300,000 (Gellings, 2011; Junlakarn & Ilić, 2013). The horizontal error bars on each point in Fig. 4 indicate the maximum and minimum required costs when the number of outages occurred is fixed. Society should definitely reject the investment if a region experiences less than one large long-duration outage in 17 years because the lowest cost required per outage per household (slightly over $100) exceeds the upper bound of the society's maximum preference interval ($100). Even if a region experiences more than one long outage in 17 years, in this example, the region still could not definitely accept the project because the required cost is always higher than the society's minimum preference interval ($0, the vertical line), and additional deliberation would be required.

4. DISCUSSIONS AND POLICY IMPLICATIONS

BCA has been widely used to support choice between policy options, but there has been no systematic attempt to incorporate preference uncertainty of the affected population. Although there have been studies exploring individuals' uncertainty about their preferences, especially in stated preference data and in the use of different methods rather than mean, traditional BCA approaches often assume no uncertainty in preferences and use averages. Such approaches assume a level of precision in the public's preferences that often does not exist, can hide the tails of the distribution, and neglect income effects. The method that we propose aggregates individuals' uncertainty about their preferences, applies the aggregation results in policy decision-making problems in a novel way, and extends the generality of BCA. This strategy can be used to help decisionmakers understand when society can make a definite decision. When it cannot, it can help identify what else needs to be considered, such as exploring the role of preference uncertainty and aggregation rules on individual preference intervals in making a societal decision. Thus, the method we propose could help society make more informed and collective policy and investment decisions.

Although the approach generalizes BCA, it remains unclear where preference uncertainty comes from, and whether it is possible to help individuals resolve that uncertainty. Key issues include the hypothetical nature of contingent valuation studies (Fischhoff & Furby, 1988), inherent biases and measurement error in each elicitation technique (Venkatachalam, 2004), and qualitative descriptions that are translated differently than intended (Broberg & Brännlund, 2008). Among the likely causes of preference uncertainty, familiarity with the alternatives is probably the most important for long-duration blackouts. Preference uncertainty for goods and services available in the market is usually relatively small (Kealy & Turner, 1993), while people find it difficult to express preferences over novel alternatives (Fischhoff, 1991; Schulze, McClelland, Waldman, & Lazo, 1996). Such unfamiliarity has been proposed as a reason for violating expected utility theory's axioms, although empirical investigations have found little support for preference uncertainty (in the form of intervals) as an explanation for preference anomalies (Butler & Loomes, 2011; Cubitt et al., 2015).

The value that community members place on reliable electric services is an ideal case for illustrating the importance of preference uncertainty, where consequences are significant but poorly understood. Although most people are familiar with electric services, many have not experienced long outages, nor thought much (if at all) about losing the services that are usually taken for granted (like heating and refrigeration) during those outages. Providing respondents with detailed information about a prolonged blackout and the electric services available during the blackout decreased about 20% of the uncertainty in their preferences and reduced the gap in the proportion of individuals who support the investment using two different bounds (as shown in Table I, the investment decision can be flipped) (Baik, Davis, et al., 2018), but uncertainty and inconsistencies persisted throughout the study even with the additional effort. The results suggest that while some uncertainty in preferences can be resolved by helping respondents think through the various aspects of the hypothetical outage and articulate their values, for many respondents there is an upper bound on the precision with which they can express their preferences for novel services. This shows the importance of incorporating the inherent uncertainty in respondents' preferences into analysis and understanding how much such uncertainty influences the investment decisions.

Although we limit our illustration to a hypothetical 24-hour blackout of electric service, the framework we propose could also be used to construct societal preference intervals for longer and larger outages under a variety of conditions. The consequences of having almost no backup services for longer periods (e.g., a week or more) are typically very different than those of shorter periods, both economically and socially, and individuals' familiarity with large outages of long duration decreases with the duration and scale of outages (Baik, 2018). Individuals' economic and social preferences for backup services can be expected to be more uncertain under such conditions, so the benefits from incorporating uncertainty in the public's judged preferences into decision making would be increased considerably. Thus, the framework we propose should be able to help decisionmakers in making more informed and socially responsible investment decisions in such situations.

5. CONCLUSION

BCA and other forms of analysis are widely used to compare policies that affect society. Although most analyses consider the uncertainty in cost estimates and states of the world, uncertainty in individual preferences is rarely taken into account. Further, because typical BCA treats everyone in a population the same, individuals who need the most assistance and care, both in expressing their preferences and weighing those preferences once expressed, are often neglected. The method we propose can help decisionmakers figure out when society as a whole can and cannot make a definite decision. If society cannot make a definite decision and requires additional deliberation, the method can help explore how much preference uncertainty—the gap resulting from using individuals' lower and upper bounds—and aggregation rules on individual preference intervals could affect the cost effectiveness of an investment project. The method we propose could help society to make more informed and collective policy and investment decisions.

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