

Overcoming Learning-Aversion in Evaluating and Managing Uncertain Risks

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ABSTRACT

Ambiguity-aversion and related decision biases distort cost-benefit evaluations of uncertain risks and can lead to poor risk management policy decisions, i.e, to decisions which predictably will have high retrospective regret. This research synthesizes research on decision-analytic and behavioral economics relations among several well-documented decision biases and argues that they lead to what we call *learning-aversion*: predictably sub-optimal learning and premature decision-making in the face of high uncertainty about the costs, risks, and benefits of proposed changes. We argue that ambiguity-averse preferences, together with other biases such as overconfidence, confirmation bias, optimism bias, and hyperbolic discounting of the immediate costs and delayed benefits of learning, contribute to deficient individual and group learning, avoidance of information-seeking, under-estimation of the value of further information, and hence needlessly inaccurate risk-cost-benefit estimates and poor risk management decisions. We examine how such biases create predictable regret in selection of potential risk-reducing regulations, and how *low-regret learning strategies* (based on computational reinforcement learning models) can be used to overcome these suboptimal decision processes by replacing aversion to uncertain probabilities with optimized learning, i.e, with actions calculated to balance exploration (deliberate experimentation and uncertainty reduction) and exploitation (taking actions to maximize the sum of expected immediate reward, expected discounted future reward, and value of information). We illustrate the proposed framework for understanding and overcoming “learning-aversion” and for implementing low-regret learning strategies using regulation of air pollutants with uncertain health effects (concentration-response functions) as a case study.

Key words: decision biases, ambiguity aversion, learning aversion, no-regret learning, benefit-cost analysis

Introduction

For most of the past century, economists have sought to apply methods of benefit-cost analysis (BCA) (Portney, 2008) to help policy makers identify which proposed regulations, public projects, and policy changes best serve the public interest. BCA provides methods to evaluate quantitatively, in dollar terms, the total economic costs and benefits of proposed changes. In versions commonly used by regulators and analysts, BCA prescribes that decisions be made to *maximize the expected net present value* (NPV) of resulting time streams of net benefits (i.e., monetized benefits minus costs), with delayed and uncertain impacts being appropriately discounted to yield a net present value for each option being evaluated (e.g., Treasury Board of Canada Secretariat, 1998). Similarly, in law-and-economics analyses of negligence torts, the Learned Hand Rule prescribes a duty to take care to prevent or reduce risk if the cost of doing so is less than the expected benefit (Grossman et al., 2006). In regulatory BCA, benefits are typically measured as the greatest amounts that people who want the changes would be willing to pay (WTP) to obtain them. Costs are measured by the smallest amounts that people who oppose the changes would be willing to accept (WTA) as full compensation for them (Portney, 2008). Recommending alternatives with the greatest expected NPV helps to adjudicate the competing interests of those who favor and those who oppose a proposed change.

Example: A Simple BCA Justification for Banning Coal Burning

In 2002, a study in the *Lancet* suggested that a relatively simple public health measure, banning burning of coal in Dublin County, Ireland, created substantial health benefits ([Clancy et al., 2002](#)). The study concluded that “Reductions in respiratory and cardiovascular death rates in Dublin suggest that control of particulate air pollution could substantially diminish daily

death....Our findings suggest that control of particulate air pollution in Dublin led to an immediate reduction in cardiovascular and respiratory deaths.” In a press release, one of the authors, Douglas Dockery, explained that "The results could not be more clear, reducing particulate air pollution reduces the number of respiratory and cardiovascular related deaths immediately" ([Harvard School of Public Health, 2002](#)). Citing these estimated benefits, policy makers extended the bans more widely, reasoning that “Research has indicated that the smoky coal ban introduced in Dublin in 1990 resulted in up to 350 fewer deaths...per year. It has clearly been effective in reducing air pollution with proven benefits for human health and our environment... ” (Department of the Environment Community and Local Government, 2012).

As a simple example to illustrate BCA ideas and principles, suppose that “350 fewer deaths per year” is well-defined, with each such postponed death being valued at \$1M for purposes of BCA. (Technically, what actually changes is presumably the *ages* at which deaths occur, rather than the *number* of deaths per year. In steady state, the deaths postponed from this year to next year would be exactly offset by the number of deaths postponed from last year to this year, so the number of deaths per year would actually remain unchanged (and on average equal to the number of births per year, since each birth eventually generates one death), even though everyone now lives a year longer. However, for purposes of illustration, we will assume that total benefits of \$350M per year from increased longevity is a realistic estimate of the benefits in question.) Assume that extending the coal-burning ban to a wider area is estimated to double the effect of the original ban, creating another “350 fewer deaths per year.” Also for simplicity, suppose that that the total costs of the proposed extended coal ban are estimated as \$100M per year (e.g., from diminished coal producer and consumer surpluses, increased costs of gas and electricity as these are substituted for coal burning, unsatisfied demand for more heat at an affordable price in the winter, etc.) For purposes of illustration, only these costs and benefits will be considered. Since total estimated benefits from extending the ban greatly exceed total estimated costs, creating a total net benefit per year from extending the ban that is estimated to be $\$350M - \$100M = \$250M$ per year, the BCA recommendation would be to extend the ban. Even if the estimated cost were doubled or the estimated benefit were halved (but not both), the estimated net benefit would still be positive. Such sensitivity analysis is often used to check whether policy recommendations are robust to plausible uncertainties, as they appear to be here. (This example is continued below.)

Arguably, seeking to maximize net social benefit in this fashion promotes a society in which everyone expects to gain from public decisions on average and over time, even though not everyone will gain from every decision. Hence, BCA offers a possible approach to collective choice that appears to meet minimal standards for justice (it might be favored by everyone from an initial position behind Rawls's veil of ignorance) and economic efficiency (those who favor an adopted change gain more from it than those who oppose it lose). At first glance, BCA appears to have developed a decision-making recipe that circumvents the daunting impossibility theorems of collective choice theorists (e.g., [Hylland and Zeckhauser 1979](#); Mueller 2003; Man and Takayama, 2013; [Nehring 2007](#); Othman and Sandholm, 2009), which imply that no satisfactory way exists in general to use individual preferences to guide economically efficient social choices while protecting other desirable properties (such as voluntary participation and budget balance). For that is precisely what BCA seeks to do.

However, this paper argues that, whatever its conceptual strengths and limitations might be for *homo economicus*, or purely rational economic man, BCA for real-world regulations or projects with risky outcomes often leads to *predictably regrettable* collective choices in practice (and does not really succeed in bypassing impossibility results in principle). More useful recommendations can be developed by seeking to *minimize expected rational regret*, rather than to maximize expected NPV, especially when probabilities for different costs and benefits are unknown or uncertain. This criterion, explained further in Section 4, is also better suited to the needs of real decision-makers with realistically imperfect information about the costs and benefits of proposed changes than is the principle of maximizing expected NPV.

Example (Cont.): A BCA Justification for Banning Coal Burning May Be Regrettable

In the Dublin study, the original researchers' conclusion that "The results could not be more clear, reducing particulate air pollution reduces the number of respiratory and cardiovascular related deaths immediately" ([Harvard School of Public Health, 2002](#))" was later questioned by methodologists, who noted that the study lacked key elements, such as a control group, needed to draw valid causal conclusions. [Wittmaack, 2007](#) pointed out that mortality rates were already occurring long before the ban, and occurred in other parts of Europe and Ireland not affected by it, and concluded that "Serious epidemics and pronounced trends feign excess mortality previously attributed to heavy black-smoke exposure." Similarly, [Pelucchi et al., 2009](#) noted that "However, during the same period, mortality declined in several other European countries. Thus, a causal link between the decline in mortality and the ban of coal sales cannot be established." As of 2012, when the ban was extended to additional areas and towns, there was thus some reason to question whether the original health benefits estimates were credible, or whether they might be simply an artifact of poor statistical methodology. However, the question was primarily of interest to methodologists, and played no significant role in policy-making, which assumed that the original health benefits estimates were at least approximately correct (DECLG, 2012).

Such discrete uncertainties (e.g., will proposed interventions actually cause their intended and projected consequences?) cannot be resolved by simple BCA sensitivity analyses that vary inputs over ranges around the best point estimates of their values. They require confronting the discrete possibility that the true benefits might be zero, or extremely different from the estimated levels (here, around \$350M/yr.), due to flaws in the underlying assumptions of the BCA. How best to incorporate such discrete uncertainties into BCA has long been a challenge and topic of controversy among BCA scholars (Graham,1981). It is no easy task to assess and justify specific probabilities for them, and any such probability would be based on information and assumptions that others might disagree with. Thus, the question arises of how to do BCA when there are substantial uncertainties about the underlying premises, modeling assumptions, and policy-relevant conclusions of the cost and benefits models (here, for health risk reductions) being used.

If the original data are available for reanalysis, then methodological issues and challenges can be openly surfaced and discussed, and whether the original BCA conclusions and recommendations change when different methodological choices can be examined. For air pollution studies, original data are not always made available to other investigators. In the case

of the Dublin study, however, the Health Effects Institute (HEI) funded the original investigators to re-do their analysis, taking into account methodological considerations such as the need to compare declines in mortality inside and outside the areas affected by the ban. The main result (HEI, 2013) was that, "...In contrast to the earlier study, there appeared to be no reductions in total mortality or in mortality from other causes, including cardiovascular disease, that could be attributed to any of the bans. That is, after correcting for background trends, similar reductions were seen in ban and non-ban areas. The study by Dockery and colleagues shows that accounting for background trends in mortality can be crucial, since the earlier Dublin study appears likely to have overestimated the effects of the 1990 coal ban on mortality rates from diseases that were already declining for other reasons." Thus, when uncertainty about benefits from a coal ban was finally reduced by further investigation in 2013, it turned out that the originally projected health benefits that had seemed to provide a strong BCA rationale for coal-burning bans were no longer supported. The decision to extend the bans might be considered regrettable, if, in hindsight, the true benefits of doing so turned out to be less than the true costs.

A striking feature of this example is that the analysis done in 2013, comparing reductions in mortality risks from before to after the ban across areas affected and not affected by the ban, could have been done just as easily in 2002 as in 2013. However, there was no felt need to do so. The investigators and the recipients of the analysis believed that the correct interpretation was at hand and was obviously correct ("could not be more clear"), justifying prompt action (the ban) intended to protect the public interest, and making further investigation both unnecessary and undesirable.

The following sections suggest that this pattern is no accident. Rather, there is a strong tendency, which we refer to as *learning aversion*, to stop BCA calculations and data collection prematurely (Russo and Schoemaker, 1989). Confident recommendations for action may be based on BCA estimates in which the sign of estimated net benefits could easily be reversed by further data or analysis. Sensitivity or uncertainty analyses and additional information may be presented that bolster confidence in results (e.g., by showing that even if the best estimates of costs and benefits are changed by some factor, the recommendations do not change) while doing little to highlight fundamental remaining uncertainties about whether the key premises of the BCA calculations are correct (e.g., that banning coal burning measurably reduces all-cause and cardiovascular mortality risks). In short, rather than, or in addition to, "analysis-paralysis," the reverse problem of making high-stakes decisions prematurely, when more information having high decision-analytic value-of-information (VOI) is readily available, is also a threat to effective use of BCA. This behavior is unsurprising in light of findings from behavioral

economics on how people respond to uncertainties (especially “ambiguous” ones that cannot easily be quantified via known probabilities). Once recognized, it is easily avoided, e.g., by shifting the driving metaphor for BCA away from maximizing expected net benefits based on present information, and toward minimizing later regrets (Russo and Schoemaker, 1989).

The remainder of the paper is structured as follows. Section 1 discusses common aspirations and motivations for BCA and discusses its promise and limitations for improving collective choices in societies of *homo economicus*. Section 2 recalls key features of purely rational individual decision-making and some impossibility results from collective choice theory for purely rational agents. Section 3 discusses how real people make decisions, including many “predictably irrational” ones (Ariely, 2009). It argues that the resulting web of well-documented decision heuristics and biases invalidates the usual normative prescriptive use of elicited or inferred WTP and WTA amounts in many practical applications. Both WTP and WTA amounts are sensitive to details of framing, context, perceptions of fairness and rights, feelings about social obligations and entitlements, and other factors that depart from the simplified economic models (e.g., quasi-linear preferences with additively separable costs and benefits) envisioned in the usual foundations of BCA. Section 3 also notes that psychological phenomena such as ambiguity aversion (reluctance to bet on unknown or highly uncertain subjective probabilities) imply several forms of what we will call *learning aversion*, i.e., refusal to use available information to improve decision-making. Simple examples illustrate mechanisms of learning-aversion for organizations as well as individuals. Section 3 argues that, in following the prescriptions of BCA, real people and organizations (whether individuals, companies, regulatory agencies, or legislators and policy-makers) typically spend too much to get too little, for a variety of reasons rooted

in decision psychology and political theory. We not only systematically over-estimate the prospective value (net benefit) of projects with uncertain outcomes (as in the planning fallacy (Kahneman and Tversky, 1979)), but we also typically fail to test and learn enough about the likely consequences of alternative courses of action before acting (Russo and Schoemaker, 1989). Hence we make collective bets on social programs and regulations that are excessively risky, in the sense that their benefits do not necessarily, or with high probability, outweigh their costs. We also usually fail to study and learn enough after acting to optimally improve decision-making models and assumptions over time. In effect, our policy-making and regulatory institutions are often *learning-averse*, with a strong bias toward premature action and insufficient prospective investigation of alternatives or retrospective learning and evaluation of decisions and outcomes (Russo and Schoemaker, 1989). They show a revealed preference for acting as if we already have sufficient information to identify the best course of action with confidence now, even if available information is actually inadequate to do so, and even if a careful decision analysis (based on value-of-information analysis for maximizing expected utility) would prescribe postponing a choice.

Section 4 considers how to do better. For deciding which alternative action to take next (from among those being considered, e.g., to pass or not to pass a proposed new regulation), the BCA prescription “*Choose the alternative that maximizes expected NPV*” is often less good than the advice from other rules, such as: “*Choose the alternative that minimizes expected rational regret,*” or “*Do not choose yet, but continue to learn from small-scale trials before making a final choice for large-scale deployment.*” Section 4 also reviews results from machine learning and psychology, suggesting that

seeking to minimize regret can be a highly adaptive strategy for uncertain environments in which relevant probabilities of decision outcomes are initially unknown – that is, environments where ambiguity-aversion is likely to be especially important in decision-making. Section 5 concludes with comments on the prospects for using regret minimization as an alternative to expected NPV maximization as a foundation for more practical and valuable BCA.

1. Aspirations and Benefits of BCA

To improve the rationality and effectiveness of collective choices, such as whether to implement a costly regulation or to undertake a costly public works project, economic benefit-cost analysis (BCA) attempts to calculate and compare the total cost of each alternative being considered to the total benefit that it would produce. If an alternative's costs clearly exceed its benefits, it can be rejected outright. Conversely, it can be considered further for possible adoption if its benefits exceed its costs, and if no other feasible alternative would create a clearly preferable distribution of costs and benefits. Even if costs and benefits are uncertain, one can seek to implement only those alternative(s) that produce preferred probability distributions of net benefits (e.g., distributions that are not stochastically dominated by the distributions from other choices). Thus, BCA seeks to inject rationality, objectivity, and optimization into public discourses about what to do with limited resources.

BCA comparisons are admittedly complicated by the need to make trade-offs over time, under uncertainty, and across individuals and groups, especially when those

who bear most of the costs of an intervention do not receive most of its benefits. Despite these difficulties, a welcome element of common sense and benign rationality seem to infuse basic BCA prescriptions, such as *Don't take actions whose costs are expected to exceed their benefits*; or *Take actions to produce the greatest achievable net benefits*. People may argue about how best to quantify costs and benefits, including how to evaluate opportunity costs, delayed or uncertain rewards, real options, and existence values. They may disagree about how best to characterize uncertainties – e.g., what information, models, and assumptions should be used in estimating the probabilities of different possible outcomes. But the key concept of submitting proposed courses of action to the relatively objective-seeming tests of quantitative BCA comparisons, rather than letting pure politics or other processes drive public decisions about expensive actions, has appealed powerfully to many scholars and some policy makers over the past half century.

It is easy to understand why. Without such guidance, collective decisions – even those taken under a free, democratic rule of law – may harm all involved, as factional interests and narrow focusing on incremental changes take precedence over more dispassionate and comprehensive calculations for identifying which subsets of changes are most likely to truly serve the public interest.

Example: Majority rule without BCA can yield predictably regrettable collective choices

Table 1 shows five proposed changes that a small society, consisting of individuals 1-3 (“players,” in game theory terminology) is considering adopting. The proposed changes, labeled A-E, are shown in the rows, of the table. These might represent proposed regulatory acts, investment projects, initiatives, mandates, etc. The table presents resulting changes in annual

incomes for player if each measure is adopted, measured in convenient units, such as thousands of dollars per year. (For simplicity, the impacts of the different measures are assumed to be independent of each other.) For example, project A, if implemented would cost player 1 three units of income (perhaps in the form of a tax on player 1's business or activities), and would produce benefits valued at one unit of income for each of players 2 and 3. Thus, its costs are narrowly concentrated but its benefits are widely distributed. Conversely, project D would impose a tax, or other loss of income, of one unit of income on each of players 2 and 3, but would produce three units of income for player 1. E is the *status quo*.

Table 1. A hypothetical example of changes in annual incomes (e.g., in thousands of dollars) for each of three people from each of five alternatives

Proposed change	Player 1's income change	Player 2's income change	Player 3's income change
A	-3	1	1
B	1	-3	1
C	1	1	-3
D	3	-1	-1
E	0	0	0

If the collective choice process used in this small society is direct majority rule, with each participant voting for or against each proposed change, A-E, then which proposed changes will be approved? Assuming that each voter seeks to maximize his own income (or minimize his own loss), measures A-C will be adopted, since a majority (two out of three) of the players prefer each of these to the *status quo*. Summing the changes in incomes for all three of the adopted measures A-C shows that each player would receive a net loss of 1 unit of income from these three adopted collective decisions. Thus, applying simple majority rule to each proposed change A-E creates a *predictably regrettable outcome*: it is clear that changes A-C will be adopted (the outcome is *predictable*) and it is clear that this will make all voters worse off than they would have been had they instead rejected the changes and maintained the status quo (the adopted changes are, in this sense, jointly *regrettable*).

The problem illustrated here is familiar: each voter is willing to have "society" (as embodied in the collective choice process) spend other people's money to increase his own benefit. Yet, when each faction (a coalition, or subset of players, such as players 2 and 3, for change A) has the political power to adopt a measure that achieves gain for all its members at the expense of its non-members, the portfolio of alternatives that end up being adopted harms everyone, in the sense that everyone would have preferred the *status quo*. Political theorists

have recognized this possibility for centuries; it loomed large in Federalist Paper Number 10, and in concerns about tyranny of the majority.

BCA seeks to remedy this ill by subjecting each alternative to a cost-benefit test. A familiar example is the potential compensation test: *Do the gainers gain more than the losers lose?* Would those who prefer adoption of a proposed alternative still prefer it if they had to fully compensate those who preferred the *status quo*? (This question makes sense under the usual assumptions of quasi-linear preferences (utility can be expressed as benefits minus costs) and if utility is assumed to be transferable and proportional to money. Although these assumptions, in turn, may be difficult to defend, they suffice to illustrate some key points about strengths and limitations of BCA even under such idealized conditions.) Alternatives A-C in Table 1 fail this test, but alternative D – which would not be selected by majority rule – passes. For example, if a tax of one income unit taken from each of individuals 2 and 3 allows individual 1 to gain a benefit (such as socially subsidized healthcare) evaluated as equivalent to three income units, it might be deemed an alternative worth considering further, since individual 1 could (at least in principle) pay one unit of income to each of individuals 2 and 3 and still be better off (by one income unit) than before the change. BCA practitioners often apply such tests for potential Pareto improvements to determine whether a proposed change is worth making (Feldman, 2004).

Of course, taking from some to benefit others, especially if potential compensation remains only a theoretical possibility, raises questions about rights and justice (e.g., is enforced wealth transfer a form of theft? Would individuals voluntarily choose to adopt procedures that maximize estimated net social benefits, if they made

the choice from behind the veil of ignorance in Rawls's initial position?) Moreover, it is well known that potential compensation criteria can lead to inconsistencies when a proposed alternative to the *status quo* increases one good, e.g., clean air, but reduces another, e.g., per-capita income. (Those who prefer a change in the *status quo* might still do so if they had to fully compensate those who prefer it; and yet those who prefer the *status quo* might still do so if they had to fully compensate those who do not (Feldman, 2004).) Thus, potential compensation tests are by no means free of conceptual and practical difficulties. Nonetheless, the idea that a proposed change should not be adopted unless its benefit (defined as the sum of willingness-to-pay (WTP) amounts from those who want it) exceeds its cost (defined as the sum of willingness-to-accept (WTA) amounts needed to fully compensate those who don't) provides a plausible and much-cited screen for eliminating undesirable proposals (Portney, 2008).

2. *Homo Economicus*

BCA was developed by economists, and is most applicable to societies of purely rational individual decision-makers. *Homo economicus*, or ideally rational economic man, has several admirable characteristics not widely shared by real people (Gilboa and Schmeidler, 1989; Smith and von Winterfeldt, 2004); these are briefly recalled now. He does not engage in activities whose costs are clearly greater than their benefits, or make purchases or lifestyle choices that he is certain to regret later – unlike many rueful real-world recipients of predictable credit card bills and doctor's admonishments. He

does not over-value present as opposed to delayed rewards, or certain as opposed to uncertain ones, or losses compared to gains (neither of which distracts him from a dispassionate focus on final outcomes, independent of framing and reference point effects). He does not succumb to temptations that he knows are against his rational long-term self-interest, in the sense of making current choices that he knows he will later regret. He welcomes any relevant information that increases the *ex ante* expected utility of his decisions, whether or not it supports his preconceptions. He seeks and uses such information rationally and effectively whenever the cost of acquiring it is less than its benefits in increased expected utility. He learns from new information by conditioning crisp, coherent priors on it and then acts optimally – that is, to maximize subjective expected utility (SEU) – in light of the resulting posteriors and what is known about future opportunities and constraints.

Homo economicus is a dispassionate fellow, unswayed by useless regrets (no crying over spilt milk), endowment effects (grapes are not sweetened by ownership), status quo bias (he neither fears nor seeks change for its own sake), or sunk cost bias (being in for a penny does not affect his decision about whether to be in for a pound. No business or investment strikes him as being too big to fail if failure has become the rational choice). He experiences neither thrills nor anxiety from gambling once his bets have been optimally placed; he does not hold on to losing stocks to avoid the pain of selling them and acknowledging a loss; and he never seeks to win back with an unfavorable bet what he has already lost. His Prospect Theory weighting function for probabilities is a 45-degree line, so that he neither over-estimates the probabilities of rare events (thus driving over-investment in protecting against them), nor

underestimates the probabilities of more common and familiar ones (thus driving under-investments in prudent investments to protect against predictable risks, e.g., from floods or hurricanes). He does not especially favor his own prior opinions, intuitions and beliefs (no confirmation bias) or eschew uncertain probabilities or outcomes compared to known ones (no Allais or Ellsberg paradoxes, no ambiguity aversion). His choices are dynamically consistent: what he plans today for his future self to do, it actually does when the future arrives. These and other characteristics of *homo economicus* can be succinctly summarized by saying that he is a *subjective expected utility (SEU) decision-maker*, conforming to the usual (Savage-style) axioms for rational behavior (Gilboa and Schmeidler, 1989; Smith and von Winterfeldt, 2004).

However, perfect individual rationality does not necessarily promote effective collective choice. Numerous impossibility results in game theory and the theory of collective choice reveal the difficulty of constructing collective choice procedures (“mechanisms”) that will produce desirable results based on voluntary participation by rational people. Tradeoffs must be made among desirable characteristics such as budget balance (a mechanism should not run at a net loss), *ex post* Pareto-efficiency (a mechanism should not select an outcome that every participants likes worse than one that was rejected), voluntary participation, and nondictatorship (a mechanism should reflect the preferences of more than one of the participants) (e.g., Mueller 2003; Man and Takayama, 2013; Othman and Sandholm, 2009). Similar tradeoffs, although less well known, hold when collective decisions must be made by rational individuals with different beliefs about outcomes ([Hylland and Zeckhauser 1979](#); [Nehring 2007](#)), as well as when they have different preferences for outcomes.

Example: Pareto-Inefficiency of BCA with disagreements about probabilities

Suppose that members of a society (or an elected subset of members representing the rest) must collectively decide whether to pay for an expensive regulation with uncertain health benefits (or other uncertain benefits). Uncertainties for individuals will be represented by subjectively assessed probabilities, and the fact that these probabilities are not objectively determined is reflected in the fact that different people assess them differently. For concreteness, suppose that the collective choice to be made is whether to implement a costly proposed regulation to further reduce fine particulate air pollution in order to promote human health and longevity. Each individual believes that the benefits of the proposed regulation will exceed its costs if and only if (a) Air pollution at current levels causes significantly increased mortality risks; and (b) The proposed regulation would reduce those (possibly unknown) components of air pollution that, at sufficiently high exposure concentrations and durations, harm health. Each individual favors the regulation if and only if the joint probability of events (a) *and* (b) exceeds 20%. That is, the product of the probabilities of (a) and (b) must exceed 0.2 for the estimated benefits of the proposed regulation to exceed its costs (as these two events are judged to be independent).

As a mechanism to aggregate their individual beliefs, the individuals participating in the collective choice have agreed to use the arithmetic averages of their individual probabilities for relevant events, here (a) and (b). They will then multiply the aggregate probability for (a) and the aggregate probability for (b) and pass the regulation if and only if the resulting product exceeds 0.2. (Of course, many other approaches to aggregating or reconciling expert probabilities can be considered, but the point illustrated here with simple arithmetic averaging holds generally.)

Individual beliefs can be described by two clusters with quite different world views and subjective probability assessments. Half of the community (“pessimists”) fear both man-made pollution and our inability to control its consequences: they believe that air pollution probably does increase mortality risk, but that not enough is known for a regulation to reliably target and control the unknown components that harm human health. Specifically, they assign probability 0.8 to event (a) (exposure causes risk) and probability 0.2 to event (b) (regulation reduces relevant components of exposures). The other half of the community (“optimists”) is skeptical that that exposure increases risk, but believe that, if it does, then it is probably the components targeted by the regulation that do so (i.e., fine particulate matter rather than sulfates or something else). They assess a probability of only 0.2 for event (a) and a probability of 0.8 for event (b). Note that both sets of beliefs are consistent with the postulates that all individuals are perfectly rational, since the axioms of rationality do not determine how prior probabilities should

be set (in this case, reflecting two different world views about the likely hazards of man-made pollution and our ability to control them).

Using arithmetic averaging to combine the subjective probability estimates of participating individuals (assumed to be half optimists and half pessimists), the average probability for event (a) is $(0.8 + 0.2)/2 = 0.5$, and the average probability for event (b) is likewise $(0.2 + 0.8)/2 = 0.5$. These group probability assessments imply that the collective joint probability of events (a) and (b) is $0.5 * 0.5 = 0.25$. Since this is above the agreed-to decision threshold of 0.2, the regulation would be passed. On the other hand, every individual computes that the joint probability of events (a) and (b) is only $0.8 * 0.2 = 0.16$. Since this is below the decision threshold of 0.2 required for projected benefits to exceed costs, no individual wants the regulation passed. Thus, aggregating individual beliefs about events leads to a decision that no one agrees with – a regrettable outcome.

The important point illustrated by this example is not that one should not average probabilities, or that other mechanisms might work better. To the contrary, an impossibility theorem due to Nehring (2007) demonstrates that *no* method of aggregating individual beliefs and using them to make group decisions can avoid selecting dominated decisions (other than such trivial procedures as selecting a single individual as a “dictator” and ignoring everyone else’s beliefs). For *any* aggregation and decision rule that treats individuals symmetrically, one can construct examples in which the group’s decision is not favored by any of its members. (For example, using a geometric mean instead of an arithmetic means would resolve the specific problem in this example, but such a procedure would also select dominated choices in slightly modified versions of the example.) Thus, the general lesson, illustrated here for the specific aggregation mechanism of averaging individual probabilities to get collective ones, is that when probabilities of events are not known and agreed to, and opinions about them are sufficiently diverse, then calculations (collective decision mechanisms) that combine the probability judgments of multiple experts or participants to determine what acts should be taken in the public interest risk producing regrettable collective choices with which no one agrees.

Example: Impossibility of Pareto-Efficient choices with sequential selection

A possible remedy for the Pareto-inefficient outcomes in the preceding example would be not to combine individual beliefs about component events at all, but instead to elicit from individuals their final, holistic preferences for, or evaluations of, collective actions. For example, each individual might estimate his own net benefit from each alternative action (pass or reject

the proposed regulation, with a proposed tax or other measure to pay for it if it is passed), and then society might take the action with the largest sum of estimated individual net benefits. This would work well in the preceding example, where everyone favors the same collective choice (albeit for different reasons, based on mutually inconsistent beliefs). But it leaves the resulting decision process squarely in the domain of other well-known impossibility theorems that apply when individuals directly express preferences for alternatives.

As an example, suppose a society of three people (or a Congress of three representatives of a larger society) makes collective choices by voting among various proposed regulatory alternatives as the relevant bills are brought forward for consideration. Suppose that the legislative history is such that, in the following list of possible alternatives, the choice between A and B comes to a vote first (e.g., because advocates for PM_{2.5} reduction organize themselves first or best), and that later the winner of that vote is run off against alternative C (perhaps because O₃ opponents propose their bill later, and it is assumed that the current cost-constrained political environment will allow at most one such pollution reduction bill to be passed in the current session). Finally (maybe in the next session, with an expanded regulatory budget, or perhaps as a rider to an existing bill), alternative D is introduced, and run off against whichever of alternatives A-C has emerged as the collective choice so far. Here are the four alternatives considered:

- A: Do not require further reductions in any pollutant
- B: Require further reductions in fine particulate matter (PM_{2.5}) emissions only
- C: Require further reductions in ozone (O₃) only
- D: Require further reductions in both PM_{2.5} and O₃.

Individual preferences are as follows (with ">" interpreted as "is preferred to"):

1. $A > D > C > B$
2. $B > A > D > C$
3. $C > B > A > D$

For example, individual 1 might believe that further reducing air pollution creates small (or no) health benefits compared to its costs, but believes that, if needless costs are to be imposed, they should be imposed on both PM_{2.5} and O₃ producers (with a slight preference for penalizing the latter, if a choice must be made). Individual 2 believes that PM_{2.5} is the main problem, and that dragging in ozone is a waste of cost and effort; individual 3 believes that ozone is the main problem.

Applying these individual preferences to determine majority votes, it is clear that B will be selected over A (since B is preferred to A by both of individuals 2 and 3). Then, B will lose to

C (since 1 and 3 prefer C to B). Finally, D will be selected over C (since 1 and 2 prefer D to C). So, the predictable outcome of this sequence of simple majority votes is that alternative D will be the society's final collective choice, i.e., require further reductions in both pollutants. But this choice is clearly Pareto-inefficient (and, in that sense, regrettable): everyone prefers option A (no further reduction in pollutants), which was eliminated in the first vote, to option D (further reductions in all pollutants), which ended up being adopted.

A central theme of collective choice theory for societies of rational individuals is that such perverse outcomes occur, in the presence of sufficiently diverse preferences, for all possible collective choice mechanisms (including those in which BCA comparisons are used to compare pairs of alternatives), provided that non-dictatorship or other desired properties hold (e.g., Mueller 2003; Man and Takayama, 2013).

3. How Real People Evaluate and Choose Among Alternatives

Real people are quite different from *homo economicus* (Gilboa and Schmeidler, 1989; Smith and von Winterfeldt, 2004). Psychologists, behavioral economists, marketing scientists, and neuroscientists studying choices have demonstrated convincingly that most people (including experts in statistics and decision science) depart systematically from all of the features of purely rational decision-making discussed above (e.g., Kahneman, 2011). To a very useful first approximation, most of us can be described as making rapid, intuitive, emotion-informed judgments and evaluations of courses of action ("System 1" judgments, in the current parlance of decision psychology), followed (time and attention permitting) by slower, more reasoned adjustments ("System 2" thinking) (*ibid*).

The Affect Heuristic Effects Risky Choice and BCA Evaluations via a Network of Decision Biases

Much of System 1 thinking, in turn, can be understood in terms of the *affect heuristic*, according to which gut reaction – a quick, automatically generated feeling about whether a situation, choice, or outcome is good or bad – drives decisions. For most decisions and moral judgments, including those involving how to respond in risky situations, the alternative choices, situations, or outcomes are quickly (perhaps instinctively) categorized as “bad” (to be avoided) or “good” (to be sought). Beliefs, perceptions, and System 2 rationalizations and deliberations then tend to align behind these prompt evaluations. This approximate account, while over-simplified, successfully explains many of the departures of real preferences and choice behaviors from those prescribed by expected utility theory, and is consistent with evidence from neuroeconomics studies of how the brain processes risks, rewards, delays, and uncertainties (including unknown or “ambiguous” ones) in arriving at decisions. For example, immediate and certain rewards are “good” (positive valence). They are evaluated by different neural circuits than rewards that are even modestly delayed, or uncertain, perhaps explaining the observed “certainty effect” of relative over-weighting of rewards received with certainty. Conversely, immediate, certain losses are typically viewed as “bad” and are disproportionately avoided: many people will not buy with cash (immediate loss) what they will buy with credit cards (delayed loss). More generally, real people often exhibit time preferences that exhibit approximately hyperbolic discounting, and hence dynamic inconsistency: someone who would always prefer \$1

now to \$2 six months from now may nonetheless also prefer \$2 in 36 months to \$1 in 30 months. The conflict between the high perceived value of immediate temptations and their lower perceived value (or even negative net benefit) when viewed from a distance in time explains many a broken resolution and resulting predictable regret.

Figure 1 provides a schematic sketch of some suggested relations among important decision biases. Although there are numerous details and a vast literature about relations among biases, the core relations in Figure 1 can be summarized succinctly as:

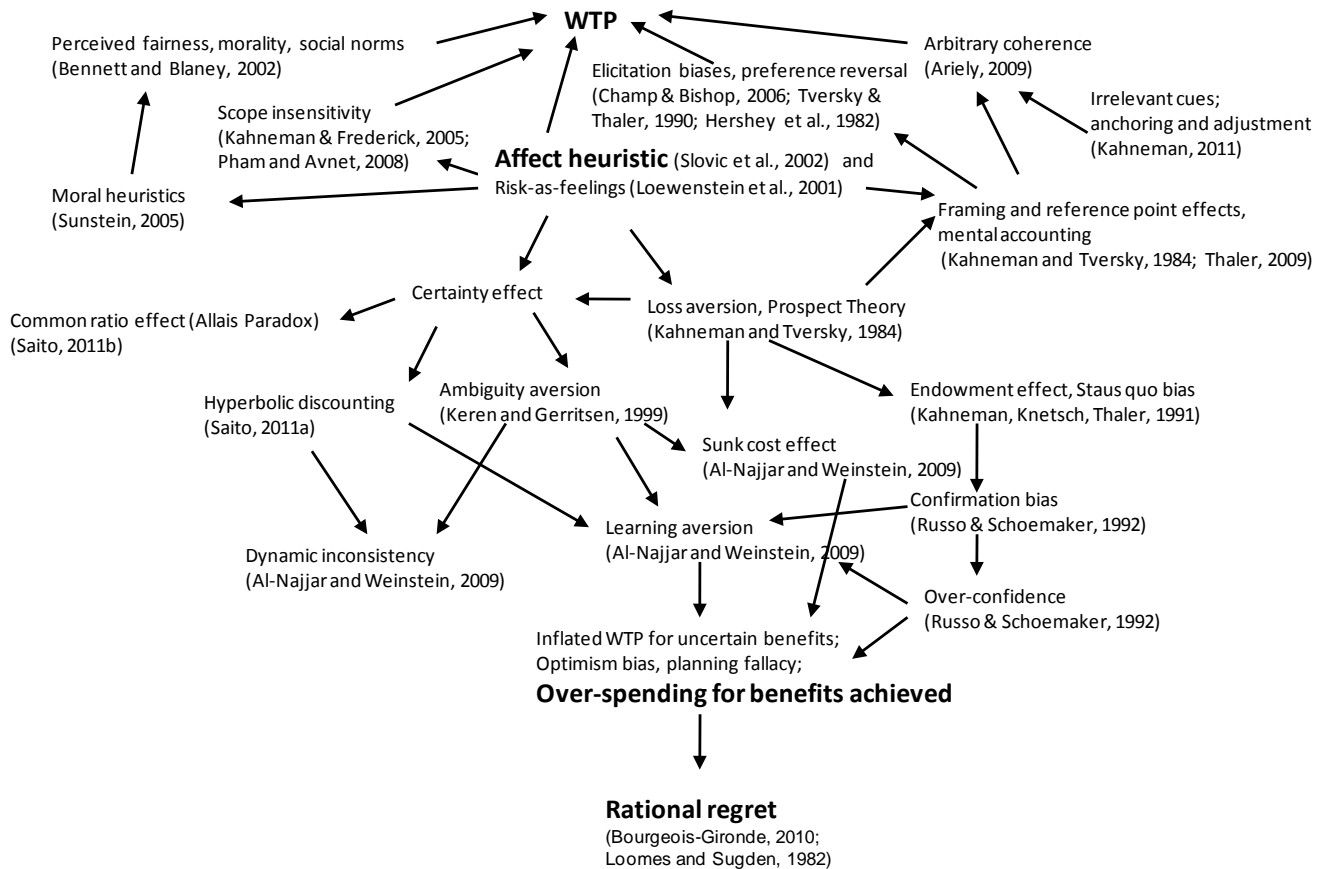
WTP ← *Affect heuristic* → *Learning aversion* → *Overspending* → *Rational regret*.

These components are explained next. The arrows in Figure 1 indicate a range of implication relations of various strengths and degrees of speculation, ranging from relatively weak (the bias at the tail of an arrow plausibly contributes to, facilitates, or helps to explain the one its head) to strong (the bias at the tail of an arrow mathematically implies the one at its head under quite general conditions). For example, it may seem plausible that the certainty effect helps to explain hyperbolic discounting if delayed consequences are interpreted by the brain as being uncertain (since something unknown might happen in the future to prevent receiving them – one might be hit by a bus later today) (Prelec and Loewenstein, 1991; Saito, 2011a).

Establishing or refuting such a speculation empirically might take considerable effort for an experimental economist, behavioral economist, or neural economist (Dean and Ortoleva, 2012; Epper and Fehr-Duda, 2014). But mathematical conditions under which the certainty effect implies hyperbolic discounting (and also the common ratio effect found in the Allais Paradox) can be established fairly easily, e.g., Saito, 2011a and b).

The arrows in Figure 1 suggest several such implications having varying degrees of support in the literature; the cited references provide details.

Figure 1. Suggested relations among decision biases. (An arrow from A to B indicates that bias A implies, contributes to, or facilitates bias B.)



Some of the most striking implications in Figure 1 concern the consequences of *ambiguity aversion*, i.e., reluctance to take action based on beliefs about events with unknown objective probabilities (and willingness to pay to reduce uncertainty about probabilities before acting). An ambiguity-averse decision maker would prefer to use a coin with a known probability of heads, instead of a coin with an unknown probability of heads, whether betting on heads or on tails; this is inconsistent with SEU (since

revealing a preference for the coin with known probability of heads when betting on heads implies, in SEU, that one considers the other coin to have a smaller probability of heads, and hence a larger probability of tails). Proposed normative models of decision-making with ambiguity aversion lead to preferences for acts that can be represented as *maximizing the minimum possible subjective expected utility* when the probabilities of consequences for acts, although unknown, belong to a set of multiple priors (the Gilboa-Schmeidler multiple priors representation); or to more general representations in which an additional penalty is added to each prior (Maccheronia et al., 2006). However, recent critiques of such proposed “rational ambiguity-aversion” models have pointed out the following implications (Al-Najjar and Weinstein, 2009):

- *Ambiguity aversion implies that decisions do not ignore sunk costs*, as normative theories of rational decision-making would prescribe;
- *Ambiguity aversion implies dynamic inconsistency*, i.e., that people will make plans based on assumptions about how they will behave if certain contingencies occur in the future, and then not actually behave as assumed.
- *Ambiguity aversion implies learning aversion*, i.e., unwillingness to receive for free information that might help to make a better (SEU-increasing) decision.

Decision Biases Invalidate Straight-Forward Use of WTP Values

One clear implication of the network of decision biases in Figure 1 is that they make WTP amounts (both elicited and revealed) untrustworthy as a normative basis for quantifying the benefits of many risk-reducing measures, such as health, safety, and

environmental regulations (Casey JT, Delquie P. 1995). Important, systematic departures of elicited WTP from normative principles include the following:

- *Affect heuristic.* People (and other primates) are willing to pay more for a small set of high-quality items than for a larger set that contains the same items, with some lower-quality one added as well (Kralik et al., 2012). (More generally, in contrast to the prescriptions of SEU theory, expanding a choice set may change choices even if none of the added alternatives is selected, and may change satisfaction with what is chosen (Poundstone, 2010).)
- *Proportion dominance.* Willingness-to-pay is powerfully, and non-normatively, affected by use of proportions. For example, groups of subjects typically are willing to pay more for a safety measure described as saving “85% of 150 lives” in the event of an accident than for a measure described as saving “150 lives” (Slovic et al., 2002, 2005) (Similarly, one might expect that many people would express higher WTP for saving “80% of 100 lives” than for saving “10% of 1000 lives,” even though all would agree that saving 100 lives is preferable to saving 80.) The high percentages act as cues triggering positive-affect evaluations, but the raw numbers, e.g., “150 lives,” lack such contextual cues, and hence do not elicit the same positive response. This aspect of choice as driven by contextual cues is further developed in Ariely’s theory of arbitrary coherence (Ariely, 2009).
- *Sensitivity to wording and framing.* Describing the cost of an alternative as a “loss” rather than as a “cost” can significantly *increase* WTP (Casey and Delquie, 1995). The opportunity to make a small, certain payment that leads to a large return value with small probability, and else to no return, is assessed as more valuable when it is called “insurance” than when it is called a “gamble” (Hershey et al., 1982). Describing the risks of medical procedures in terms of mortality probabilities instead of equivalent survival probabilities can change preferences among them (Armstrong et al., 2002), since the gain-frame and loss-frame trigger loss-averse preferences differently, in accord with Prospect Theory.
- *Sensitivity to irrelevant cues.* A wide variety of contextual cues that are logically irrelevant can nonetheless greatly affect WTP (Poundstone, 2010). For example, being asked to write down the last two digits of one’s Social Security Number significantly affects how much is willing to pay for consumer products (with higher SSNs leading to higher WTP amounts) (Ariely, 2009). The “anchoring and adjustment” heuristic (Kahneman, 2011) allows the mind to anchor on irrelevant cues (as well as relevant ones) that then shape real WTP amounts and purchasing behaviors (Poundstone, 2010).

- *Insensitivity to probability.* If an elicitation method or presentation of alternatives gives different salience to attributes with different effects on affect (e.g., emphasizing amount vs. probability of a potential gain or loss), then choices among the alternatives may change (the phenomenon of *elicitation bias*, e.g., Champ and Bishop, 2006). Similarly, although rational (System 2) risk assessments consider the probabilities of different consequences, System 1 evaluations may be quite insensitive to the magnitudes of probabilities (e.g., 1 in a million vs. 1 in 10,000), and, conversely, overly sensitive to the change from certainty to near-certainty: “When consequences carry sharp and strong affective meaning, as is the case with a lottery jackpot or a cancer... variation in probability often carries too little weight. ...[R]esponses to uncertain situations appear to have an all or none characteristic that is sensitive to the possibility rather than the probability of strong positive or negative consequences, causing very small probabilities to carry great weight.” (Slovic et al., 2002)
- *Scope insensitivity.* Because the affect heuristic distinguishes fairly coarsely between positive and negative reactions to situations or choices, but lacks fine-grained discrimination of precise degrees of positive or negative response, WTP amounts that are largely driven by affect can be extraordinarily insensitive to the quantitative magnitudes of benefits involved. As noted by Kahneman and Frederick (2005), “In fact, several studies have documented nearly complete neglect of scope in CV [contingent valuation stated WTP] surveys. The best-known demonstration of scope neglect is an experiment by Desvougues et al. (1993), who used the scenario of migratory birds that drown in oil ponds. The number of birds said to die each year was varied across groups. The WTP responses were completely insensitive to this variable, as the mean WTP’s for saving 2,000, 20,000, or 200,000 birds were \$80, \$78, and \$88, respectively. ... [Similar], Kahneman and Knetsch (see Kahneman, 1986) found that Toronto residents were willing to pay almost as much to clean up polluted lakes in a small region of Ontario as to clean up all the polluted lakes in Ontario, and McFadden and Leonard (1993) reported that residents in four western states were willing to pay only 28% more to protect 57 wilderness area than to protect a single area.”
- *Perceived fairness, social norms, and moral intensity.* How much individuals are willing to pay for benefits typically depends on what they think is fair, on what they believe others are willing to pay, and on whether they perceive that the WTP amounts for others reflect moral convictions or mere personal tastes and consumption preferences (e.g., Bennett and Blaney, 2002). The maximum amount that a person is willing to pay for a cold beer on a hot day may depend on whether the beer comes from a posh hotel or a run-down grocery store, even though the product is identical in either case (Thaler, 1999).

Many other anomalies (e.g., preference reversal, endowment effect, *status quo* bias, etc.) drive further gaps between elicited WTP and WTA amounts, and between both and normatively coherent preferences (see Figure 1). Taken together, they rule out any straight-forward use of WTP values (elicited or inferred from choices) for valuing uncertain benefits. Indeed, once social norms are allowed as important influencers of real-world WTP values (unlike the WTPs in textbook BCA models of quasi-linear individual preferences), the question arises of whether coherent (mutually consistent) WTP values necessarily exist at all. Simple examples show that they may not.

Example: Non-existence of WTP in a social context

As a trivial example of the non-existence of mutually consistent individual WTP amounts when social influences are important, consider a society of two people with the following preferences for funding a proposed project:

1. Individual 1 is willing to pay up to the maximum WTP amount that anyone else pays (in this case, just individual 2), so that no one can accuse him of failing to pay his fair share. If no one else pays anything, then individual 1 is willing to pay \$100.
2. Individual 2 is willing to pay what he considers his fair share, namely, the total social benefit of the project (which he defines as the sum of WTPs from everyone else – in this case, just individual 1 – divided by the number of people in society, in this case, 2).

With these preferences, there is no well-defined set of individual WTP amounts. Letting A denote the WTP for individual 1 and B the WTP for individual 2, there is no pair of WTP amounts, $(\$A, \$B)$, satisfying the individual preference conditions that $A = B$ for $B > 0$, else $A = 100$; and $B = A/2$.

Multiple Decision Biases Contribute to Learning Aversion

The network of decision biases in Figure 1 shows a prominent role for what we call *learning aversion*, meaning reluctance to seek or use information that might change a decision for the better. The term “learning aversion” (Louis, 2009) is not widely used in decision science. However, we believe it is central to understanding how to avoid premature action and to improve the practice and outcomes of BCA. For example, Table 2 summarizes ten well-documented “decision traps,” or barriers to effective decision-making by individuals and organizations, discussed in a popular book (Russo and Schoemaker, 1982). Most of these traps involve failing to take sufficient care to collect, think about, appropriately use, and deliberately learn from relevant information that could improve decisions. Not keeping track of decision results (number 9), failing to make good use of feedback from the real world (number 8), failing to collect relevant information because of overconfidence in one’s own judgment (number 4), and trusting too much in the most readily available ideas and information (number 5) are prominent examples of failure to learn effectively from experience. Although most of the examples in the *Decision Traps* book (Russo and Schoemaker, 1989) are drawn from the world of business, the same failings are pervasive in applied risk analysis, policy analysis, and BCA. For example, in the Dublin coal-burning ban example previously considered, the original researchers failed to collect relevant information (what happened to mortality rates outside the ban area over the same period?), while expressing great confidence in their own judgments that the correct interpretation of the data was obvious (“could not be more clear”) ([Harvard School of Public Health, 2002](#)).

Table 2. Ten Decision Traps (from Russo and Schoemaker, 1989)

- 1) **Plunging In** – Beginning to gather information and reach conclusions without first taking a few minutes to think about the crux of the issue you're facing or to think through how you believe decision like this one should be made.
- 2) **Frame Blindness** – Setting out to solve the wrong problem because you have created a mental framework for your decision, with little thought, that causes you to overlook the best options or lose sight of important objectives.
- 3) **Lack of Frame Control** – Failing to consciously define the problem in more ways than one or being unduly influenced by the frames of others.
- 4) **Overconfidence in Your Judgment** – Failing to collect key factual information because you are too sure of your assumptions and opinions.
- 5) **Shortsighted Shortcuts** – Relying inappropriately on “rules of thumb” such as implicitly trusting the most readily available information or anchoring too much on convenient facts.
- 6) **Shooting From The Hip** – Believing you can keep straight in your head all the information you've discovered, and therefore “winging it” rather than following a systematic procedure when making the final choice.
- 7) **Group Failure** – Assuming that with many smart people involved, good choices will follow automatically, and therefore failing to manage the group decision-making process.
- 8) **Fooling Yourself About Feedback** – Failing to interpret the evidence from past outcomes for what it really says, either because you are protecting your ego or because you are tricked by hindsight.
- 9) **Not Keeping Track** – Assuming that experience will make its lessons available automatically, and therefore failing to keep systematic records to track the results of your decisions and failing to analyze these results in ways that reveal their key lessons.
- 10) **Failure to Audit Your Decision Process** – Failing to create and organized approach to understanding your own decision-making, so you remain constantly exposed to all the above mistakes.

Figure 1 suggests that such learning-aversion is not only a product of overconfidence (which, in turn, might reflect a predilection to consider only information and interpretations that support the views with which one is already endowed, to avoid the loss of those comfortable views and the negative affect associated with such a loss). Hyperbolic discounting and ambiguity aversion are also shown as contributors to

learning aversion. Hyperbolic discounting implies that the immediate costs of learning (e.g., costs of having to collect new information that might disconfirm current beliefs, and costs of having to update current beliefs and decision rules that depend on them) may overwhelm (at present) the potential future benefits of being able to make better decisions based on the new information – even if, in retrospect, the potential (but delayed) benefits would be judged much larger than the costs of learning. Ambiguity aversion, as axiomatized by Gilboa and Schmeidler (1989) and others (Maccheronia et al., 2006) implies that a decision-maker will sometimes refuse free information that could improve decisions (Al-Najjar and Weinstein, 2009). For example, in principle, an ambiguity-averse decision-maker might refuse sufficiently informative, free genetic information that is highly relevant for decisions on lifestyle, healthcare planning, and insurance purchasing (Hoy et al., 2014). Empirically, fuller disclosure of scientific uncertainties to women facing cancer treatment choices does not necessarily improve the quality of their decisions (by any measure evaluated), but does significantly reduce their subsequent (post-decision) satisfaction with the decisions that are eventually made (Polti et al., 2011).

BCA facilitates learning-averse decision-making. Its golden rule is to choose the action (from among those being evaluated) that maximizes the *expected* discounted net benefit. There is no requirement that expected values must be calculated from adequate information, or that more information collection must continue until some optimality condition is satisfied before a final BCA comparison of alternatives is made. In this respect, BCA differs from other normative frameworks, including decision analysis with explicit value-of-information calculations, and optimal statistical decision models (such

as the Sequential Probability Ratio Test) with explicit optimal stopping rules and decision boundaries for determining when to stop collecting information and take action. Since learning-averse individuals (Hoy et al., 2014) and organizations (Russo and Schoemaker, 1989) typically do not collect enough information (as judged in hindsight) before acting, prescriptive disciplines should explicitly encourage optimizing information collection and learning as a prelude to evaluating, comparing, and choosing among final decision alternatives (Russo and Schoemaker, 1989). Helping users to overcome learning aversion is therefore a potentially valuable direction for improving the current practice of BCA.

In a collective choice context, learning aversion may be strategically rational if discovering more information about the probable consequences of alternative choices could disrupt a coalition's agreement on what to do next (Louis, 2009). But collective learning aversion may also arise because of free-rider problems or other gaps between private and public interests.

Example: Information externalities and learning aversion in clinical trials

In clinical trials, a well known dilemma arises when each individual seeks his or her own self-interest, i.e., the treatment that is expected to be best for his or her own specific case, given presently available information. If everyone uses the same treatment, then the opportunity to learn about potentially better (but possibly worse) treatments may never be taken. Given a choice between a conventional treatment that gives a 51% survival probability with certainty and a new, experimental treatment that is equally likely to give an 80% survival probability or a 20% survival probability, and that will give the same survival probability (whichever it is) to all future patients, each patient might elect the conventional treatment (since $51\% > 0.5 \cdot 0.2 + 0.5 \cdot 0.8 = 50\%$). But then it is never discovered whether the new treatment is in fact better. The patient population continues to endure an individual survival probability of 51% for every case, when an

80% survival probability might well be available (with probability 50%). The same remains true even if there are many possible treatment alternatives, so that the probability that at least some of them are better than the current incumbent approaches 100%. Ethical discussions of the principle of clinical equipoise (should a physician prescribe an experimental treatment when there is uncertainty about whether it performs better than a conventional alternative, especially when opinions are divided?) recognize that refusal to experiment with new treatments (possibly due to ambiguity-aversion) in each individual case imposes a costly burden from failure to learn on the patient population as a whole, and on each member of it when he or she must choose among options whose benefits have not yet been well studied (Gelfand, 2013). The principle that maximizing expected benefit in each individual case can needlessly reduce the expected benefit for the entire population is of direct relevance to BCA, as discussed further in the next example.

Example: Desirable interventions with uncertain benefits become undesirable when they are scaled up

Many people who would be willing to pay \$1 for a 50-50 chance to gain \$3 or nothing (expected net value of \$1.50 expected benefit - \$1 cost = \$0.50) might balk at paying \$100,000 for a 50-50 chance to gain \$300,000 or nothing. Indeed, for risk-averse decision-makers, scaling up a favorable prospect with uncertain benefits by multiplying both costs and benefits by a large enough factor can make the prospect unacceptable. (As an example, for a decision-maker with exponential utility function evaluating a prospect with normally distributed benefits having mean M and variance V , the certainty equivalent of n copies of the prospect, where all of n of them share a common uncertainty and the same outcome, has the form $CE = nM - kn^2V$, where k reflects subjective relative risk aversion. Since the first term grows linearly and the second term grows quadratically with the scaling factor n , the certainty equivalent is negative for sufficiently large n .) Now consider a local ordinance, such as a ban on coal-burning, that has uncertain health benefits and known implementation costs, such that its certainty equivalent is assessed as positive for a single county. If the same ban is now scaled up to n counties, so that the same known costs and uncertain benefits are replicated n times, then the certainty equivalent will be negative for sufficiently large n . A bet worth taking on a small scale is not worth taking when the stakes are scaled up too many times. Yet, top-down regulations that apply the same action (with uncertain benefits) to dozens, hundreds, or thousands of counties or individuals

simultaneously, based on assessment that $CE > 0$ for each one, implies that essentially the same bet is being made many times, so that the total social CE will be negative if the number of counties or individuals is sufficiently large. This effect of *correlated uncertainties* in reducing the net benefits of regulations with uncertain benefits that are widely applied is omitted from BCA calculations that only consider expected values.

Learning Aversion and Other Decision Biases Inflate WTP for Uncertain Benefits

The decision biases network in Figure 1 has a potentially surprising implication: Real people typically over-estimate highly uncertain benefits and under-estimate highly uncertain costs, and hence are willing to pay too much, for projects (or other proposed changes) with unknown or highly uncertain benefits and/or costs. Intuitively, one might expect exactly the reverse: that ambiguity aversion would reduce the perceived values or net benefits of such projects. But in fact, ambiguity aversion (and other drivers of learning aversion) mainly cut off information collection and analyses needed for careful evaluation, comparison, and selection of alternatives, leading to premature and needlessly risky decisions (see Table 2). Then, overconfidence and optimism bias take over (Figure 1). From the perspective of obtaining desirable outcomes, members of most decision-making groups spend too much time and effort convincing each other that their decisions are sound, and increasing their own confidence that they have chosen well. They spend too little effort seeking and using potentially disconfirming information that could lead to a decision with more desirable outcomes (Russo and Schoemaker, 1989). Moreover, in assessing the likely future outcomes of investments in risky projects, individuals and groups typically do *not* focus on the worst plausible scenario (e.g., the worst-case probability distribution for completion times of future

activities), as theoretical models of ambiguity aversion suggest (Gilboa and Schmeidler, 1989). To the contrary, they tend to assign low subjective probabilities to pessimistic scenarios, and to base plans and expectations on most-favorable, or nearly most-favorable, scenarios (e.g., Newby-Clark et al., 2000).

This tendency toward overly-optimistic assessment of both uncertain benefits (too high) and uncertain costs or delays (too low) has been well documented in discussions of optimism bias (and corollaries such as the planning fallacy). For example, it has repeatedly been found that investigators consistently over-estimate the benefits (treatment effects) to be expected from new drugs undergoing randomized clinical trials (e.g., Djulbegovi et al., 2011; Gan et al., 2012); conversely, most people consistently underestimate the time and effort needed to complete complex tasks or projects, such as new drug development (Newby-Clark et al., 2000). These psychological biases are abetted by statistical methods and practices that routinely produce an excess of false positives, incorrectly concluding that interventions have desired or expected effects that, in fact, they do not have, and that cannot later be reproduced (Nuzzo, 2014; Sarewitz, 2012; Lehrer, 2012; Ioannidis, 2005). Simple Bayesian calculations suggest that more than 30% of studies with reported P values of ≤ 0.05 may in fact be reporting false positives (Goodman, 1991). Indeed, tolerance for, and even encouragement of, a high risk of false-positive findings (in order to reduce risk of false negatives and to continue to investigate initially interesting hypotheses) has long been part of the culture of much of epidemiology and public health investigations supposed to be in the public interest (e.g., Rothman, 1990).

The bottom of Figure 1 suggests that learning aversion and several related decision biases contribute to a willingness to take costly actions with highly uncertain benefits and/or costs. Other prominent decision biases that favor such willingness to bet on a positive outcome under substantial uncertainty include the following:

- (a) *Overconfidence* in subjective judgments when objective facts or probabilities are not available (Russo and Schoemaker, 1992);
- (b) *Sunk-cost effect* (propensity to throw good money after bad, or escalating commitment to an uncertain project as past investment increases, in preference to stopping and acknowledging failure and the need to move on) (Navarro and Fantino, 2005); and
- (c) *Optimism bias* (e.g., underestimating the probable effort, cost, success probability, or uncertainty to complete a complex undertaking; and overestimating the probable benefits of doing so).

These biases favor premature decisions to pay to achieve uncertain benefits, even in situations where free or inexpensive additional investigation would show that the benefits are in fact almost certainly much less than the costs.

Example: Overconfident Estimation of Health Benefits from Clean Air Regulations

Overconfidence and confirmation biases can be encoded in the modeling assumptions and analytic procedures used to develop estimates of cost and benefits for BCA comparisons. For example, the U.S. EPA (2011 and b) estimated that reducing fine particulate matter (PM2.5) air pollution in the United States has created close to 2 trillion dollars per year of annual health benefits, mainly from reduced elderly mortality rates. This is vastly greater than the approximately 65 billion dollars per year that EPA estimates for compliance costs, leading them

to conclude that “***The extent to which estimated benefits exceed estimated costs*** and an in-depth analysis of uncertainties ***indicate that it is extremely unlikely the costs of 1990 Clean Air Act Amendment programs would exceed their benefits under any reasonable combination of alternative assumptions or methods identified during this study***” (emphasis in original). However, the benefits calculation used a quantitative approach to uncertainty analysis based on a Weibull distribution (assessed using expert guesses) for the reduction in mortality rates per unit reduction in PM2.5. The Weibull distribution is a continuous probability distribution that is only defined over non-negative values. Thus, the quantitative uncertainty analysis implicitly assumes a 100% certainty that reducing PM2.5 does in fact cause reductions in mortality rates (the Weibull distribution puts 100% of the probability mass on positive values), in direct proportion to reductions in PM2.5 pollutant levels, even though EPA’s qualitative uncertainty analysis states (correctly) such a causal relation has not been established. An alternative uncertainty analysis that assigns a positive probability to each of several discrete uncertainties suggests that “EPA’s evaluation of health benefits is unrealistically high, by a factor that could well exceed 1000, and that it is therefore very likely that the costs of the 1990 CAAA [Clean Air Act Amendment] exceed its benefits, plausibly by more than 50-fold. The reasoning involves re-examining specific uncertainties (including model uncertainty, toxicological uncertainty, confounder uncertainty, and uncertainty about what actually affects the timing of death in people) that were acknowledged qualitatively, but whose discrete contributions to uncertainty in health benefits were not quantified, in EPA’s cost-benefit analysis” (Cox, 2011). If this analysis is even approximately correct, then EPA’s highly confident conclusion results from an uncertainty analysis that disregarded key sources of uncertainty. It implicitly encodes (via the choice of a Weibull uncertainty distribution) overconfidence and confirmation biases that may have substantially inflated estimated benefits from Clean Air Act regulations by assuming, similar to the Dublin coal ban analysis, that reducing PM2.5 concentrations causes reductions in mortality rates, while downplaying (by setting its subjectively assessed probability to zero) the possibility that this fundamental assumption might be wrong.

In the political realm, the costs of regulations (or of projects or other proposed expensive changes) can also be made more palatable to decision-makers by a variety of devices, long known to marketers and politicians and increasingly familiar to behavioral economists, that exploit the decision biases in Figure 1 (Poundstone, 2010).

Among these are the following: postponing costs by even a little (to exploit hyperbolic discounting, since paying now provokes an adverse reaction that paying even slightly later does not); emphasizing annual costs instead of larger total costs; building in an annual rate increase (so that increases become viewed as part of the *status quo*, and hence acceptable without further scrutiny); paying from unspecified, obscure, or general funds (e.g., general revenues) rather than from specific accounts (so that trade-offs, opportunity costs and outgoing payments are less salient); adding comparisons to alternatives that no one would want to make the recommended one seem more acceptable; creating a single decision point for committing to a stream of expenses, rather than instituting multiple review and decision points (e.g., a single yes/no decision, with a limited time window of opportunity, on whether to enact a costly regulation that will last for years, rather than a contingent decision for temporary funding with frequent reviews to ask whether it has now served its purpose and should be discontinued); considering each funding decision in isolation (so that proposal can be evaluated based on its affect when viewed outside the context of competing uses to which the funds could be put); framing the cost as protecting an endowment, entitlement, or option (i.e., as paying to avoid losing a benefit, rather than as paying to gain it); and comparing expenditures to those of others (e.g., to how much EU or Japan is spending on something said to be similar). These and related techniques are widely used in marketing and advertising, as well as by business leaders and politicians seeking to “sell” programs to the public (Gardner, 2009). They are highly effective in persuading consumers to spend money that, in retrospect, they might feel would have been better spent on something else (Ariely, 2009; Poundstone, 2010).

4. Doing Better: Using Predictable Rational Regret to Improve BCA

Figure 1 and the preceding discussion suggest that a variety of decision biases can lead to both individual and collective decision processes that place too little value on collecting relevant information, rely too heavily on uninformed or under-informed judgments (which tend to be over-optimistic and over-confident), and hence systematically over-value prospects with uncertain costs and benefits, creating excessive willingness to gamble on them. One result is *predictable disappointment*: consistent over-investment in uncertain and costly prospects that, predictably, will be seen in retrospect to have (on average) cost more and delivered less than expected. A second possible adverse outcome is *predictable regret*: investing limited resources in prospects with uncertain net benefits when, predictably, it will be clear in hindsight that the resources could have been better spent on something else. Standard BCA facilitates these tendencies by encouraging use of current expected values to make choices among alternatives, instead of emphasizing more complex, but potentially less costly (on average), optimal sequential strategies that require waiting, monitoring, and inaction until conditions and information justify costly interventions (Stokey, 2009 for economic investment decisions; Methany et al. 2011 for hospital operations). This section considers how to do better, and what “better” means.

A long-standing tradition in decision analysis and normative theories of rational decision-making complements the principle of maximizing expected utility with various versions of minimizing expected rational regret (e.g., Loomes and Sugden, 1982; Bell, 1985). Formulations of rational regret typically represent it as a measure of the

difference between the reward (e.g., net benefit, in a BCA context) that one's decision *actually* achieved and the greatest reward that *could* have been achieved had one made a different (feasible) decision instead (Hart, 2005; Hazan and Kale, 2007).

Adjusting decision rules to reduce rational regret plays a crucial role in current machine-learning algorithms, as well as in neurobiological studies of human and animal learning, adaptation, and decision-making, within the general framework of computational reinforcement learning (e.g., Li and Daw, 2011; Schönberg et al., 2007). (By contrast, related concepts such as elation or disappointment (Delquié and Cillo, 1986) reflect differences between expected or predicted rewards and those actually received. They do not necessarily attribute the difference to one's own decisions, or provide an opportunity to learn how to make more effective decisions.)

Intuitively, instead of prescribing that current decisions should attempt to maximize prospective expected reward (or expected discounted net benefits), rational regret-based theories prescribe that they should be made so that, even in hindsight, one has no reason to change the decision process to increase average rewards. In effect, instead of the advice "Choose the alternative with the greatest expected value or utility," normative theories of regret give the advice "Think about how, in retrospect, you would want to make decisions in these situations, so that no change in the decision procedure would improve the resulting distribution of outcomes. Then, make decisions that way." In this context, a no-regret rule (Chang, 2007) is one that, even in retrospect, one would not wish to modify before using again, since no feasible modification would lead to a preferred distribution of future consequences. Equivalently, if various options are available for modifying decision rules to try to improve the frequency distribution of

rewards that they generate, then a no-regret rule is one that cannot be improved upon: it is a fixed point of the decision rule-improvement process (Hazan and Kale, 2007). (These concepts apply to what we are calling rational regrets, i.e., to regrets about not making decisions that would have improved reward distributions.)

Example: Rational vs. Irrational Regret

Suppose that a decision maker’s reward (or “payoff,” in the game-theoretic terminology often used) is determined by her choice of an act, A or B, together with a random state of nature (e.g., the outcome of one toss of a fair die, with faces 1-6 being equally likely, revealed only after the choice has been made. Possible payoffs range between 1 and 6.1 dollars, as described by the following table.

	<u>State: 1 2 3 4 5 6</u>					
<u>Decision</u>						
Act A:	1	2	3	4	5	6.1
Act B:	2	3	4	5	6	1

Expected utility theory unequivocally prescribes choosing act A (since its probability distribution of rewards stochastically dominates that of act B, as $6.1 > 6$), even though act B yield a higher payoff than A 5/6 of the time. Minimizing rational regret also prescribes choosing act A, since any decision rule that prescribes choosing B in this situation (always or sometimes) will yield a payoff frequency distribution that is inferior to (stochastically dominated by) the payoff distribution from always choosing act A. In this simple case, choosing act A and then observing that choosing B would have yielded a higher reward provides no reason for a rational decision-maker to deviate from the optimal strategy of always choosing act A. Thus, minimizing rational regret recommends A, not B.

Other concepts of regret and regret-avoidance are linked to personality psychology. These include making decisions with low potential for regret to protect damaging already low self-esteem (Josephs et al., 1992), as well as preferring to avoid

learning outcomes in order to avoid possible regrets. From a biological perspective, it has been proposed that the *emotion* of regret, when used as an error signal to adaptively modify decision rules in individual decision-making, is a “rational emotion” that helps us to learn and adapt decision-making effectively to uncertain and changing environments (e.g., Bourgeois-Gironde, 2010). Although these psychological and biological aspects of regret are important for some kinds of decision-making under risk, it is primarily proposed concepts of rational regret, as just discussed, that we believe are most useful for improving the practice of BCA. The rest of this section explains how.

Does the shift in perspective from maximizing prospective expected net benefits to minimizing expected retrospective regret make any practical difference in what actions are recommended? Not for *homo economicus*. For an ideally rational SEU decision-maker, the principle of maximizing SEU, while optimally taking into account future plans (contingent on future events) and the value of information, is already a no-regret rule. But for real decision-makers (whether individuals or groups) who are not able to formulate trustworthy, crisp, agreed-to probabilities for the consequences of each choice, the shift to minimizing regret has several powerful practical advantages over trying to maximize expected net benefits. Among these are the following:

- *Encourage prospective hindsight analysis.* A very practical aid for reducing over-confidence and optimism bias is for decision-makers to imagine that a contemplated project or investment ends badly, and then to figure out what could have caused this and how it might have been prevented. Such “prospective hindsight” or “premortem” exercises have been used successfully in business to help curb under-estimation of costs and over-estimation of benefits when both are highly uncertain (Russo and

Schoemaker, 1989). In the domain of regulatory benefit-cost analysis, they prompt questions such as: Suppose that, twenty years from now, we rigorously assess the health benefits and economic costs actually achieved by extending Clean Air Act amendments, and find that the costs were on the order of a trillion dollars (EPA, 2011), but that the projected benefits of reduced mortality rates caused by cleaner air never materialized. How might this have happened? Could it have been discovered sooner? What might we do now or soon to prevent such an outcome? When such questions are asked on a small scale, as in the Dublin coal-ban example, they lead to simple answers, such as to use a control group (people outside the affected area) to determine whether the bans actually produced their predicted effects (HEI, 2013). On a national level a similar openness to the possibility of errors in projections, and vigilance in frequently testing uncertain assumptions against data as the effects of expensive regulations become manifest, might likewise be used to anticipate and prevent the BCA failure scenarios imagined in premortem exercises. In the U.S., for example, learning from the experiences of cities, counties, or states (such as California) who are early adopters of policies or initiatives that are later proposed for national implementation provides opportunities to check assumptions against data relatively early, and to modify or optimally slow-roll (Stokey, 2009) the implementation of national-level policies as needed to reduce expected regret.

- *Increase feedback and learning.* Items 8-10 in Table 2 describe failures to learn from real-world feedback based on the gaps between what was expected and what actually occurred, or between what was achieved and what could have been

achieved by better decisions (if this is known). Formal models of how to adaptively modify decision processes or decision rules to reduce regret – for example, by selecting actions next time a situation is encountered in a Markov decision process, or in a game against nature (with an unpredictable, possibly adversarial, environment) using probabilities that reflect cumulative regret for not having used each action in such situations in the past – require explicitly collecting and analyzing such data (Robards and Sunehag, 2011; Hazan and Kale, 2007). Less formally, continually assessing the outcomes of decisions and how one might have done better, as required by the regret-minimization framework, means that opportunities to learn from experience will more often be exploited instead of missed.

- *Increase experimentation and adaptation.* An obvious possible limitation of regret-minimization is that one may not know what would have happened if different decisions had been made, or what probabilities of different outcomes would have been induced by different choices (Jaksch et al., 2010). This is the case when relevant probabilities are unknown or ambiguous. It can arise in practice when no states or counties have been early (or late) adopters of a proposed national policy, and so there is no comparison group to reveal what would have happened had it not been adopted. In this case, formal models of regret reduction typically require exploring different decision rules to find out what works best. Such learning strategies (called “on-policy” learning algorithms, since they learn only from experience with the policy actually used, rather than from information about what would have happened if something different had been tried) have been extensively developed and applied successfully to regret reduction in machine learning and

game theory (Chang, 2007; Yu et al., 2009; Robards and Sunehag, 2011). They adaptively weed out the policies that are followed by the least desirable consequences, and increase the selection probabilities for policies that are followed by preferred consequences. Many formal models of regret-minimization and no-regret learning strategies (e.g., Chang, 2007; Jaksch et al., 2010 for Markov decision processes) have investigated how best to balance exploration of new decision rules and exploitation of the best ones discovered so far. Under a broad range of conditions, such adaptive selection (via increased probabilities of re-use) of the decision rules that work best empirically soon leads to discovery and adoption of optimal or near-optimal (“no-regret”) decision rules (i.e., maximizing average rewards) (Chang, 2007; Robards and Sunehag, 2011; Hazan and Kale, 2007). Of course, translating these mathematical insights from the simplified world of formal decision models (e.g., Markov decision processes with initially unknown transition and reward probabilities and costs of experimentation) to the real world requires caution. But the basic principle that the policies that will truly maximize average net benefits per period (or discounted net benefits, in other formulations) may initially be unknown, and that they should then be discovered via well-designed and closely analyzed trials, has powerful implications for the practice of BCA and policy making. It emphasizes the desirability of conducting, and carefully learning from, pilot programs and trial evaluations (or natural experiments, where available) before rolling out large-scale implementations of regulations or other changes having highly uncertain costs or benefits. In effect, the risk of failure or substantially sub-optimal performance from programs whose assumptions and expectations about costs and

benefits turn out to be incorrect can be reduced by small-scale trial-and-error learning, making it unnecessary to gamble that recommendations based on BCA using current information will turn out to coincide with those that will be preferred in hindsight, after key uncertainties are resolved.

- *Asymptotic optimization of decision rules with initially unknown probabilities for consequences.* In formal mathematical models of no-regret reinforcement learning with initially unknown environments and reward probabilities, swift convergence of the prescriptions from empirical regret-minimization algorithms to approximately optimal policies holds even if the underlying process tying decisions to outcome probabilities is unknown or slowly changing (Yu et al., 2009). This makes regret-minimization especially relevant and useful in real-world applications with unknown or uncertain probabilities for the consequences of alternative actions. It also provides a constructive approach for avoiding the fundamental limitations of collective choice mechanisms that require combining the subjective probabilities (or expected values) of different participants in order to make a collective choice ([Hylland and Zeckhauser 1979](#); Nehring, 2007). Instead of trying to reconcile or combine discrepant probability estimates, no-regret learning encourages collecting additional information that will clarify which among competing alternative policies work best. Again, the most important lesson from the formal models is that adaptively modifying policies (i.e., decision rules) to reduce empirical estimates of regret based on multiple small trials can dramatically improve the final choice of policies and the final results produced (e.g., average rewards per period, or discounted net benefits actually achieved). From this perspective, recommending

any policy based on analysis and comparison of its expected costs and benefits to those of feasible alternatives will often be inferior to recommending a process of trials and learning to discover what works best. No-regret learning (Chang, 2007) formalizes this intuition.

In summary, adjusting decision processes to reduce empirical estimates of regret, based on actual outcomes following alternative decisions, can lead to much better average rewards or discounted net benefits than other approaches. Real-world examples abound of small-scale trial and error leading to successful adaptation in highly uncertain business, military, and policy environments (e.g., Harford, 2011).

5. Conclusions

This paper has argued that a foundational principle of traditional BCA, choosing among proposed alternatives to maximize the expected net present value of net benefits, is not well suited to guide public policy choices when costs or benefits are highly uncertain. In principle, even if preferences are aligned (so that familiar collective choice paradoxes and impossibility results caused by very different individual preferences do not arise) – for example, even if all participants share a common goal of reducing mortality risks – there is no way (barring such extremes as dictatorship) to aggregate sufficiently diverse probabilistic beliefs to avoid selecting outcomes that no one favors ([Hylland and Zeckhauser 1979](#); Nehring, 2007). BCA does not overcome such fundamental limitations in any formulation that requires combining probability

estimates from multiple participants to arrive at a collective choice among competing alternatives – including using such probabilities to estimate which alternative has the greatest expected net benefit.

In practice, a variety of well-known decision biases conspire to make subjectively assessed expected value calculations and WTP estimates untrustworthy, with highly uncertain benefits often tending to be over-estimated, and highly uncertain costs tending to be under-estimated. Biases that contribute to unreliable expected net benefit and WTP estimates range from the affect heuristic, which we view as fundamental, to optimism, over-confidence, and confirmation biases, ambiguity aversion, and finally to what we have called learning aversion (Figure 1). As a result of this network of biases, it is predictable that projects and proposals with highly uncertain costs and benefits will tend to be over-valued, leading to potentially regrettable decisions, meaning decisions that, in retrospect, and upon rational review, one would want to have made differently. Similar results have been demonstrated for groups and for individuals (Russo and Schoemaker, 2009). The net result is a proclivity to gamble on excessively risky proposals when the benefits and costs are highly uncertain.

To help overcome these difficulties, we have proposed shifting to a different foundation for BCA calculations and procedures: minimizing rational regret. Regret minimization principles have been developed in both decision analysis (e.g., Loomes and Sugden, 1982; Bell, 1985) and extensively in more recent machine learning, game theory, and neurobiological models of reinforcement learning (Hart, 2005; Chang, 2007; Hazan and Kale, 2007; Li and Daw, 2011; Schönberg et al., 2007). Although the idealized mathematical models and analyses of these fields are not necessarily directly

applicable to real-world BCA settings, they do suggest several practical principles that have proved valuable in improving real-world individual and collective decisions when potential costs and benefits are uncertain enough so that the best course of action (given clarity on goals) is not clear. In particular, we propose that BCA under such conditions of high uncertainty can be improved by greater use of prospective hindsight (or “premortem”) analyses to reduce decision biases; explicit data collection and careful retrospective evaluation and comparison of what was actually achieved to what was expected, and to what could have been achieved by different choices (when this can be determined); and deliberate learning and adaptation of decision rules based on the results of multiple small-scale trials in settings for which this is practical. Not all of these principles are applicable in all BCA situations, of course. Whether to build a bridge in a certain location cannot be decided by multiple small-scale trials, for example. But for many important health, safety, and environmental regulations with substantial costs and substantial uncertainty about benefits, learning from experiences on smaller scales (e.g., from the changes in mortality rates following different histories of pollution reductions in different counties) can powerfully inform and improve BCA analyses that are intended to guide larger-scale (e.g., national) policy-making. The main proposed shift in emphasis is from *guessing* what will work best (in the sense of maximizing the expected NPV of net benefits, as assessed by experts or other participants in the decision-making process), and then perhaps betting national policies on the answer, to *discovering* empirically what works best, when it is practical to do so and when the answer is initially highly uncertain.

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