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The Value of Formal Quantitative Assessment of Uncertainty in Regulatory Analysis

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Executive Summary

The U.S. Office of Management and Budget's Circular A-4 introduced a new requirement for the treatment of uncertainty in Regulatory Impact Analyses (RIAs) of proposed regulations. The Circular requires agencies to perform a formal quantitative assessment of uncertainty regarding a regulation's benefits and costs if either is expected to reach $1 billion annually. Despite relatively frequent use in other contexts, formal assessments of uncertainty are rarely employed in RIAs. In fact, treatment of uncertainty in RIAs typically has been inadequate. Consequently, this new requirement has the potential to improve significantly regulatory analysis conducted under Executive Order 12866.

In this paper, we discuss how formal quantitative assessments of uncertainty can be conducted, and we examine the additional effort that they would require of agencies developing RIAs. In doing so, we focus on Monte Carlo analysis, a common method of performing such assessments.

We examine how information regarding uncertainty can improve the evaluation of regulations. Not only can it provide important contexts for interpreting point estimates of regulations' economic impacts, in certain circumstances it can lead to different, more accurate point estimates of those impacts. An improved understanding of key sources of uncertainty in regulatory analysis also can help establish research priorities.

To highlight how Monte Carlo analysis can provide better characterizations of uncertainty than can methods typically used in RIAs, we compare these two approaches in the context of evaluating uncertainties regarding the economic impact of EPA's recently finalized Nonroad Diesel Rule.

The use of improved analytical methods, as required by Circular A-4, is not the only step necessary to improve treatment of uncertainty in RIAs. To more fully obtain the benefits of such methods, their results must be presented more prominently in RIAs than discussions of uncertainty typically have been in the past.

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1. Introduction

Benefit-cost analysis provides valuable information that is critical for the evaluation of proposed regulations.[1] It is a core component of a Regulatory Impact Analysis (RIA), which Presidential Executive Order 12866 requires for all "economically significant" proposed Federal regulations.[2] To estimate proposed regulations' benefits and costs, analysts frequently rely on projections and other inputs that are uncertain — sometimes substantially so. Uncertainties in these underlying inputs are propagated through analyses, leading to uncertainty in ultimate benefit and cost estimates. Despite this uncertainty, the most prominently displayed results of RIAs are often single, apparently precise "point estimates" of benefits, costs, and net benefits. Such point estimates can mask uncertainties inherent in their calculation and thereby obscure tradeoffs among competing policy options.

Uncertainty is inevitable in the estimation of benefits and costs, and many regulations should be finalized even in the face of significant uncertainty. Nonetheless, a well-informed understanding of the nature and extent of uncertainty in benefit and cost estimates can be essential to sound policymaking.

Historically, efforts to address uncertainty in RIAs have been limited. New guidance set forth in the U.S. Office of Management and Budget's (OMB) Circular A-4 on Regulatory Analysis has the potential to enhance greatly the information provided in RIAs regarding uncertainty in benefit and cost estimates.[3] Circular A-4 requires the development of a formal quantitative assessment of uncertainty regarding a regulation's economic impact if either annual benefits or costs are expected to reach $1 billion. Over the years, the use of formal quantitative uncertainty assessments has become common in a variety of fields, including engineering, finance, and a number of scientific disciplines. In particular, Monte Carlo analysis has become a widely used method for developing formal assessments of uncertainty. Monte Carlo analysis

[1] See Arrow et al. (1996).
[2] In cases where benefits cannot be monetized adequately, a cost-effectiveness analysis, rather than a benefit-cost analysis, may serve as the primary economic analysis of a regulation. Our discussion of the treatment of uncertainty in RIAs is equally applicable to both types of analyses.

also has been found to be useful in certain regulatory contexts. For example, the U.S. Environmental Protection Agency (EPA) has recognized that it can be an important element of risk assessments.[4] But efforts to formally quantify uncertainties rarely have been made in the context of RIAs. Instead, uncertainty typically has been addressed qualitatively or through sensitivity analysis. Further, regardless of the analytical approach used to address uncertainty, discussion of uncertainty has been given little prominence in RIAs.

In this paper, we address the role that formal quantitative assessment of uncertainty can play in regulatory analysis. In Section 2, we provide a brief overview of how a formal quantitative assessment of uncertainty can be developed. In particular, we focus on the execution of Monte Carlo analysis. In Section 3, we discuss the benefits of uncertainty assessments for policymaking, and in Section 4, we demonstrate how formal quantitative assessments are better at providing these benefits than are typical means of addressing uncertainty in RIAs. To do so, we draw upon the results of three Monte Carlo analyses of uncertainty in the economic analysis of EPA's Nonroad Diesel Rule, which became effective on August 30, 2004. We performed one of these Monte Carlo analyses,[5] and EPA performed two others as a part of the RIA that accompanied its final rulemaking. In Section 5, we discuss the additional effort that Monte Carlo analysis would require of agencies, and in Section 6, we address the need for agencies to make assessments of uncertainty more prominent in RIAs. In Section 7, we conclude.

2. <u>Implementation of Monte Carlo Analysis in RIA</u>

Monte Carlo analysis is a common method of conducting formal quantitative uncertainty assessments that can be implemented with relative ease. The first step in a Monte Carlo analysis involves the development of probability distributions of uncertain inputs to an analysis. These probability distributions reflect the implications of uncertainty regarding an input for the range of its possible values and the likelihood that each value is the true value.

A number of sources of uncertainty can influence an input's probability distribution. One possible source, statistical variation, is imprecision in the estimate of an input due to a

[3] U.S. Office of Management and Budget (OMB) (2003).
[4] U.S. Environmental Protection Agency (EPA) (1997).
[5] Stavins et al. (2004).

combination of random variation in data used to develop the estimate and limitations in the quantity of available data. The possibility that an incorrect framework or model was applied to available data to develop an estimate for an input — often called model uncertainty — is another key source of uncertainty. In the measurement of a relationship between two phenomena, one example of such uncertainty is the possibility that the measurement did not account for a third, confounding factor that is responsible for some of the perceived relationship between the two phenomena. A measurement that incorporates that third factor may result in a different estimate of the relationship. Finally, even if existing estimates were developed using an appropriate model, analysts are often required to apply them to contexts that differ from those in which they were developed. The possibility that appropriate adjustments are not made in transferring estimates to different contexts introduces another source of uncertainty. These three sources of uncertainty are among the types that can influence an input's probability distribution. They can be accounted for in developing an input's probability distribution by using a variety of methods that rely on existing data, expert judgment, or a combination of the two.[6]

Once probability distributions of inputs to a benefit-cost analysis are established, a Monte Carlo analysis determines the resulting probability distribution of the regulation's net benefits by carrying out the calculation of benefits and costs thousands, or even millions, of times.[7] With each iteration of the calculations, new values are randomly drawn from each input's probability distribution and used in the benefit and/or cost calculations. Over the course of these iterations, the frequency with which any given value is drawn for a particular input is governed by that input's probability distribution.[8] If a sufficient number of iterations are performed, the range of resulting net benefit estimates and the frequency of particular estimates within that range can be used to determine the probability distribution of net benefits arising from those input uncertainties that have been characterized in the analysis.

3. Value of Uncertainty Assessments for Policymaking

Assessments of uncertainty in regulatory analysis can lead to both short-term and long-

[6] For a discussion of methods of characterizing these uncertainties, see Morgan and Henrion (1990).
[7] Monte Carlo analysis also can be used to characterize probability distributions of components of net benefits, including benefits or costs.
[8] For example, if an input has a 30 percent chance of being ten, then, on average, ten will be used as the value for

term gains for policymaking. In the short-term, such assessments allow more informed evaluations of proposed regulations and comparisons among regulatory alternatives. In the long-term, such assessments can help establish research priorities.

Assessments of uncertainty can provide valuable information for policymakers evaluating a proposed regulation in at least two respects. First, findings regarding uncertainty in a net benefits estimate can provide valuable context for interpreting that estimate. Second, consideration of uncertainties in underlying inputs, and how those uncertainties interact, can lead to different point estimates of net benefits than would a purely deterministic analysis that relies on single values for each input.

Uncertainty assessments provide insights regarding the distribution of possible net benefits associated with a regulation. Similar point estimates can be associated with vastly different distributions of possible outcomes around those estimates. The distribution of possible outcomes can significantly affect perceptions of an estimate of a regulation's net benefits. For example, if a point estimate of the expected value of a regulation's net benefits is $10 billion, one would likely view this estimate differently if there were virtually no possibility that net benefits could be less than zero than if there were a 20 percent probability of such an outcome.[9] There may even be occasions where the distribution of possible outcomes associated with a regulation should be given equal or greater consideration than the most likely or average outcome. Such occasions could arise where there is a low probability of an outcome involving either extraordinarily high costs or benefits. This potentially important characteristic of a regulation could not be discerned without going beyond an estimate of the expected value of its net benefits to consider the full distribution of possible outcomes.

Assessments of uncertainty in benefit and cost estimates also can aid the evaluation of alternative approaches to proposed regulatory actions. Differences in the benefits and/or costs of alternatives may be one of many factors that influence which alternative is chosen. It is critical that policymakers understand the degree of confidence that can be placed in estimates of those differences. If two alternatives achieve the same objective and the first alternative is estimated to cost less than the second, the weight that policymakers give to this difference, relative to other

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that input in 30 out of every 100 calculations.

[9] When the true value of a variable such as net benefits is uncertain, different point estimates of that variable reflect different characteristics of its distribution of possible values. The "mean" or "expected value" is the weighted average of all possible values, where the weight assigned to each possible value reflects the probability that that

factors, should be influenced by the probability that the second alternative's cost could, in fact, be no more than that of the first.

In addition to providing important context for interpreting point estimates from a benefit-cost analysis, there are circumstances in which consideration of uncertainty can lead to different point estimates than would be developed in a deterministic analysis that does not account for uncertainty. First, careful consideration of uncertainty in inputs to benefit-cost analyses, which is necessary in the context of Monte Carlo analysis, can lead to different point estimates for those inputs than may be used in deterministic analyses. For example, the point estimate of an input used in a deterministic analysis may represent that input's expected value using one particular estimation model. But, consideration of model uncertainty may reveal that other plausible models would yield significantly different point estimates. Therefore, a point estimate of the input's expected value that accounts for the distribution of possible values resulting from model uncertainty would differ from an estimate based on just one model, which might be used in a deterministic analysis.

Second, an input may factor into an analysis in a manner in which the ultimate net benefit estimate will differ depending on whether only a point estimate is used for the input, or the distribution of that input's possible values is explicitly incorporated in the analysis. This is because for certain mathematical functions applied to uncertain inputs in a benefit-cost analysis, an estimate of the expected value of the function that accounts for the distribution of the input's possible values will differ from an estimate resulting from applying the function to a single value equal to the input's expected value. For example, the present value of benefits that is calculated by using a point estimate for an uncertain discount rate will differ from the expected present value of benefits that would be calculated if one explicitly accounted for the distribution of possible discount rates.

Third, correlations among uncertain inputs can cause the expected value of net benefits resulting from those uncertain inputs to differ from a net benefits estimate developed by using point estimates for the inputs.[10] For example, if the values of two uncertain inputs are positively

value is the true value. The "most likely" value is the value that has the highest probability of being the true value.

[10] Two uncertain inputs are correlated if the probability that one input's true value falls within a particular range of its possible values is related to, rather than independent of, another uncertain input's true value. Correlations can result from either the direct effect of one input's value on that of the other input, or from indirect relationships. Two inputs are positively (negatively) correlated if "high" values of one tend to be associated with "high" ("low") values of the other.

correlated, then the expected value of their product — accounting for uncertainties and this correlation — would be greater than the product of point estimates equal to each input's expected value. Thus, if that product were a component of benefits, an analysis that does not account for uncertainties in the inputs and correlations between them would underestimate the expected value of benefits.

Uncertainty assessments also can help identify the most significant determinants of uncertainty regarding a regulation's net benefits, and thereby the potential for future research to reduce that uncertainty. In the short-term, this information can be used to determine whether there may be benefits to delaying a rulemaking, in anticipation of future improvements in knowledge that will allow for more informed decision-making. In the long-term, the cumulative information gained from uncertainty assessments in RIAs can be used to identify sources of uncertainty that have the greatest effect on our ability to understand the economic impacts of regulations. This knowledge can be used to help establish research priorities.

4. Advantages of Formal Quantitative Uncertainty Assessments Relative to Typical Means of Addressing Uncertainty in RIAs

Formal quantitative methods, such as Monte Carlo analysis, can provide more reliable and richer characterizations of the implications of uncertainty than can the typical, more limited, means of addressing uncertainty in RIAs. In the same way that determinants of a regulation's net benefits interact in complex ways that require a benefit-cost analysis to assimilate and understand, the implications of interactions among uncertainties in those determinants often only can be addressed sensibly and effectively by using formal quantitative methods.[11] Consequently, the gains from addressing uncertainties in regulatory analysis described in Section 3 can be better achieved through the use of formal quantitative methods.

Along with qualitative discussions, sensitivity analysis is one of the most common methods used to characterize uncertainty in regulatory analysis. A sensitivity analysis often involves examining the effect on the ultimate estimate of net benefits of changing the value(s)

[11] Discussions of the advantages of formal uncertainty assessments often focus on their capacity to account correctly for interactions among uncertainties in key inputs, but this takes for granted another advantage of these assessments. Without requirements for such assessments, careful evaluation of uncertainties in the underlying inputs themselves may not be conducted, let alone assessments of how those uncertainties interact.

chosen for one or more key inputs to the highest or lowest values within a plausible range. To evaluate the insights that can be gained from formal quantitative assessments of uncertainty, relative to those available from sensitivity analysis, we examine the application of these two approaches in a recent regulatory analysis.

During the same period that OMB was finalizing its new guidance for regulatory analysis contained in Circular A-4, EPA was finalizing its Nonroad Diesel Rule.[12] Along with other investigators, we performed a Monte Carlo analysis of uncertainty in the net benefits of EPA's proposed Nonroad Diesel Rule.[13] In addition, in the RIA that accompanied EPA's final rulemaking, EPA presented the results of two Monte Carlo analyses that address uncertainty in certain determinants of that Rule's benefits.[14] In the RIAs for the proposed and final rulemaking, EPA also used methods of assessing uncertainty that are more typical of RIAs. Thus, the Nonroad Diesel Rule provides a good context for assessing the merits of Monte Carlo analysis, relative to typical means of addressing uncertainty in RIAs.[15]

Our Monte Carlo analysis of EPA's proposed Rule incorporates probability distributions for more than 60 inputs to EPA's analysis, including inputs to both cost and benefit estimates.[16] These probability distributions are largely limited to characterizations of statistical variation, using readily available data that EPA relied on in developing the RIA. We do not address many potentially important sources of uncertainty that could be characterized in a Monte Carlo analysis using data available to EPA or methods that require more time than was available for

[12] This Rule establishes new emissions standards for land-based, nonroad diesel engines, such as those used in construction and agricultural equipment. To facilitate the use of technologies needed to meet these standards, which begin in 2008, the Rule requires significant reductions in the sulfur content of diesel fuel used in nonroad engines. The Rule also requires reductions in the sulfur content of locomotive and marine diesel fuels.

[13] See Stavins et al. (2004).

[14] EPA (2004), Appendix 9B.

[15] This section provides examples of how Monte Carlo analysis can improve information regarding uncertainty in point estimates and reveal how uncertainties in inputs can affect the values of those estimates. The process of performing a Monte Carlo analysis also can improve point estimates by uncovering inconsistencies or flawed assumptions in their calculation. In performing a Monte Carlo analysis, one must pay attention to how inputs' mean values are derived, rather than simply identify those values. This additional attention may reveal flaws in deterministic benefit-cost analyses that are otherwise not readily apparent. While performing our Monte Carlo analysis, our identification of aspects of EPA's analysis that could be improved illustrates this additional benefit of formal uncertainty assessments.

[16] While we performed three Monte Carlo analyses of the Nonroad Diesel Rule's net benefits, all references in this paper refer to the first of those analyses. In our first analysis, no changes were made to the underlying benefit-cost analysis conducted by EPA. It therefore offers the best opportunity for comparing a Monte Carlo analysis with methods that EPA employed to address uncertainty in the proposed Rule's RIA. In our second Monte Carlo analysis, corrections were made to flaws in EPA's analysis. In our third analysis, we explored the implications of an alternative model for estimating the Rule's health effects. As a result, the second and third analyses could not be compared directly with EPA's uncertainty assessment.

our analysis. Therefore, each input's probability distribution likely understates overall uncertainty regarding the input's true value. Likewise, the resulting probability distributions of the Rule's costs and benefits likely understate the extent of uncertainty in those estimates. EPA's Monte Carlo analyses only address uncertainty in the Rule's benefits resulting from reductions in ambient concentrations of particulate matter (PM). In particular, EPA analyzes the implications for its benefits estimate of uncertainty in concentration-response (C-R) functions[17] for certain PM-related health effects — most importantly premature mortality — and uncertainty in economic values of those effects.

There is one important difference between EPA's first and second Monte Carlo analyses. In EPA's first analysis (and in our analysis), only statistical variation is considered in characterizing uncertainty in the C-R function for PM-related premature mortality. These characterizations of uncertainty are based on the results of a single, observational epidemiologic study, and thereby do not account for uncertainty as to whether the model used in the study is the correct model for estimating the C-R function. Model uncertainty, however, can be a major, even dominant source of overall uncertainty regarding the estimation of relationships between health effects and low-level ambient PM concentrations.[18] In EPA's second Monte Carlo analysis, its characterization of uncertainty in the C-R function for premature mortality is based on expert judgments that account for some aspects of model uncertainty in that function.[19] For example, the overall characterization of uncertainty in the C-R function in the second analysis reflects uncertainty as to whether there is a constant relationship between changes in ambient PM concentrations and changes in health effects at all ambient PM concentrations.

Estimation of the Range of Possible Economic Impacts Associated with a Regulation

Due to the number of sources of uncertainty in a regulatory analysis and the complexity of their interactions, assessments of the extent of uncertainty in a regulation's net benefits — or components thereof — that are conducted without formal quantitative analyses are unlikely to represent accurately the true extent of uncertainty. For example, in the draft RIA for the proposed Nonroad Diesel Rule, EPA's quantitative consideration of uncertainty regarding the

[17] C-R functions describe the relationship between changes in ambient PM levels and changes in particular health effects, such as premature mortality. They are used to estimate reductions in adverse health effects that can be expected from emissions reductions following the Rule's implementation.
[18] For example, see Koop and Tole (2004).

Rule's cost is limited to an assessment of the impact on net benefits of actual costs being between 20 percent lower and 20 percent higher than its primary estimate.[20] This range of possible costs appears to be the result of expert judgment, perhaps informed by sensitivity analysis regarding key cost inputs. But without a formal quantitative assessment of uncertainty, one cannot reliably judge whether costs could be outside that range. No sensitivity analysis or expert judgment is likely to be able to account for the implications of all the sources of uncertainty in inputs to the cost estimate, which can be incorporated in a Monte Carlo analysis. Indeed, our Monte Carlo analysis indicates that there is more than a five percent probability that costs could be 20 percent greater or less than EPA's primary estimate. Given that our analysis omits several significant sources of uncertainty in the cost estimate, it is likely that our analysis understates the probability that costs will be outside the range defined by EPA. Therefore, EPA's range does not represent adequately the extent of uncertainty regarding the Rule's cost that could be discerned based on uncertainties in underlying inputs.

EPA also presents an assessment of the implications for its benefits estimate of scenarios in which reductions in fine particulate matter ($PM_{2.5}$) emissions resulting from the Rule are five percent below and five percent above its primary estimate.[21] Our analysis finds that there is more than a 75 percent probability that those emissions reductions could be outside the range of plus or minus five percent of EPA's estimate.

As it is unlikely that a Monte Carlo analysis in a RIA will comprehensively address all sources of uncertainty in the estimation of a regulation's economic impact, even the results of such an analysis will likely understate the range of possible outcomes that could result from a regulation. But ranges produced by such an analysis would still provide substantially more reliable information about the implications of known uncertainties than would less rigorous means of addressing uncertainty. In turn, these ranges can better inform judgments by policymakers as to the overall implications of uncertainty for their decisions.

Evaluation of the Likelihood of Particular Outcomes within a Range

Monte Carlo analysis also provides information on the likelihood of particular outcomes within a range. Indeed, an understanding of the likelihood of values within a range is essential to

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[19] EPA (2004), p. 9-218.
[20] EPA (2003), p. 9-49.
[21] EPA (2003), pp. 9-49 - 9-51.

any meaningful interpretation of that range. Without such an understanding, inappropriate conclusions may be drawn from the presentation of a range of possible outcomes. For example, when a range of possible net benefits is provided, some may assume that all values within that range are equally likely to be the ultimate outcome. But this is rarely the case. Others may assume that the distribution of possible net benefits is symmetric. That is, while various outcomes may have different likelihoods of occurring, actual net benefits would be just as likely to fall somewhere in the first half of the range of possible values as in the second half. This, too, often may not be the case. For example, EPA's second Monte Carlo analysis found that, given the sources of uncertainty that it assessed, there would be more than a 90 percent probability that actual benefits in 2030 would fall within the first half of its estimated range of possible benefits.[22]

Typical methods of addressing uncertainty in a RIA, such as sensitivity analysis, often cannot provide meaningful guidance as to the likelihood that a regulation's net benefits will exceed or fall below certain values.[23] In fact, such analyses can sometimes inadvertently provide misleading suggestions as to the likelihood of certain outcomes. For example, in exploring uncertainty in its estimate of the proposed Nonroad Diesel Rule's benefits, EPA examines the implications of uncertainty in three income elasticities for the economic unit values of avoiding particular health effects.[24] To do so, EPA determines the benefit estimate that results from setting all three elasticities to the lowest value within the range that EPA believes to be plausible for each elasticity. In turn, EPA also examines the consequences of setting all elasticities to the high end of their respective ranges.

In conducting this exercise, EPA is examining extremely unlikely scenarios. Even if, for each income elasticity, there were as much as a 20 percent probability that its true value is less than the low estimate that EPA employs, there still would be less than a one percent probability

[22] EPA (2004), p. 9-245, Figure 9B-9. EPA's analysis of the Nonroad Diesel Rule's benefits focused on benefits in two years, 2020 and 2030. Because it will take several decades for the fleet of existing nonroad engines to be completely replaced with new engines incorporating the required emissions controls, benefits in 2030 are more representative of the Rule's long-run annual benefits.
[23] There can be some circumstances in which sensitivity analysis may provide insights of this type, particularly when there are very few uncertain inputs and the sensitivity analysis explores the implications of uncertainties in all inputs simultaneously. In practice, however, benefit-cost analyses will rarely be simple enough for sensitivity analysis to offer these kinds of insights.
[24] EPA (2003), pp. 9-196 - 9-197. These income elasticities are used to estimate how individuals' willingness to pay to avoid PM-related health effects will increase with increases in per-capita income over time.

that the true values of all three elasticities are at or below these low values.[25] This may lead some to believe that there is a low likelihood of benefits falling outside the range of estimates that EPA establishes in this exercise. But the fact that the specific scenarios that EPA examines are highly improbable does not imply that there is a low probability that benefits could be outside the range that EPA establishes. While the probability of the particular scenarios may be small, uncertainties in many other inputs that are not considered in the exercise can lead to a high probability of benefits being outside that range. Indeed, the range that EPA establishes in this exercise is from 82 percent to 141 percent of its primary point estimate for 2030 benefits.[26] Our Monte Carlo analysis indicates that there is at least a 73 percent probability that 2030 benefits will be outside that range.

The above comparisons are examples of how sensitivity analysis cannot offer meaningful information regarding the range and likelihood of a regulation's possible net benefits. Instead, sensitivity analysis can indicate the extent to which uncertainty in particular inputs contributes to overall uncertainty in net benefits. However, the implications of uncertainty in one input cannot be put in context without the use of a formal quantitative assessment of uncertainty to characterize that overall uncertainty. Absent such an assessment, there is a risk that results of sensitivity analyses may be perceived incorrectly as providing information regarding overall uncertainty in net benefits.

Effect of Uncertainty Assessments on Point Estimates

In some circumstances uncertainty assessments can change point estimates. EPA's second Monte Carlo analysis provides an example. In that analysis, EPA develops a characterization of uncertainty in the C-R function for premature mortality that goes beyond uncertainty arising from statistical variation. This leads to a probability distribution for anticipated reductions in premature mortality whose expected value is nearly 30 percent less than the point estimate that EPA calculates in an analysis that does not account for these broader sources of uncertainty.[27]

As this demonstrates, Monte Carlo analysis can reveal when uncertainties in inputs to a benefit-cost analysis cause the expected value of a regulation's net benefits to differ from what

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[25] This assumes that these income elasticities are uncorrelated.
[26] EPA (2003), p. 9-197, Table 9B-6.
[27] EPA (2004), pp. 9-213 – 9-245. In particular, see Figure 9B-4.

would be suggested by a deterministic analysis. Sensitivity analysis may explore the implications of uncertainties that can bring about such results, but it cannot address all possible outcomes resulting from those uncertainties or indicate the probability associated with any one outcome. Therefore, unlike Monte Carlo analysis, sensitivity analysis cannot provide policymakers with useful insight as to whether uncertainties in inputs cause the expected value of a regulation's net benefits to differ substantially from the primary net benefits estimate that would result from a deterministic analysis.

5. <u>Additional Efforts Required to Produce a Monte Carlo Analysis</u>

Implementation of a Monte Carlo analysis imposes two requirements that are not strictly necessary to develop point estimates of benefits and costs. First, instead of requiring a single point estimate for each input to a benefit-cost analysis, Monte Carlo analysis requires the development of probability distributions for important, uncertain inputs. Second, numerous repetitions of the calculations in a benefit-cost analysis must be performed. These requirements may appear burdensome, but to a large degree, Monte Carlo analysis can entail little additional effort, relative to what is already expended on RIAs. To the extent that it does require significant additional effort, much of this effort may be of equal importance to the effort devoted to developing a deterministic analysis of economic impacts.

As with benefit-cost analysis, a Monte Carlo analysis does not need to be exhaustive to offer important insights. For example, EPA's Monte Carlo analyses for its Nonroad Diesel Rule addressed the implications of limited types of uncertainty in just a few of the numerous uncertain inputs in its regulatory analysis. Nonetheless, as was described above, those Monte Carlo analyses offer a much more informative assessment of uncertainty than can be gained from methods typically used to address uncertainty in RIAs.

In developing probability distributions for uncertain inputs to a regulatory analysis, uncertainty from statistical variation can often be characterized with little additional effort relative to that needed to develop point estimates. Much of the data necessary for such characterizations already will have been collected for the development of point estimates.

Characterizing other sources of uncertainty in inputs can require more effort. For example, EPA's second Monte Carlo analysis required an expert elicitation to characterize uncertainty in the C-R function for premature mortality beyond that attributable to statistical variation. Expert elicitation involves a "formal, highly structured and well documented process whereby expert judgments … are obtained."[28]

The amount of additional effort necessary to develop a Monte Carlo analysis can be minimized through careful consideration of which input uncertainties are worthwhile addressing in the analysis, since valuable insights can be gained even if the uncertainties in only a few inputs are characterized. Evaluation of how an input factors into an analysis and a preliminary assessment of uncertainty may make clear that efforts to characterize uncertainty in the input would have little affect on the findings of a Monte Carlo analysis. Thus, significant efforts to characterize uncertainty in that input would not be warranted. Such an assessment also could lead to the opposite conclusion, thereby justifying additional effort. The importance of fully characterizing uncertainty in the C-R function for premature mortality in EPA's analysis of the Nonroad Diesel Rule is made clear by the fact that reductions in premature mortality account for ninety percent of the Rule's quantified benefits.[29] Some inputs may be significant elements of numerous regulatory analyses, providing additional justification for efforts to develop more complete characterizations of uncertainty in their values.

While a Monte Carlo analysis can require additional effort to characterize uncertainty in inputs to a benefit-cost analysis, that effort often may be warranted even in the absence of the needs of a Monte Carlo analysis. Such characterizations of uncertainty may be necessary just to develop an accurate point estimate for an input, as was demonstrated by EPA's second Monte Carlo analysis. If a point estimate represents an input's expected value, the development of that point estimate requires an implicit judgment about that input's probability distribution. Characterizations of uncertainty required in a Monte Carlo analysis simply make those implicit judgments explicit. Therefore, in addition to making possible quantification of uncertainty in the results of a benefit-cost analysis, these characterizations will likely improve the empirical basis for, and quality of point estimates used as inputs to the analysis.

Developments in computer performance and software over the years have substantially reduced the amount of effort required to conduct calculations for a Monte Carlo analysis, once input uncertainties have been characterized. Widely available software allows the execution of

[28] EPA (2004), p. 9-214.
[29] EPA (2004), p. 9-28.

Monte Carlo analysis in common spreadsheet programs on a desktop computer.[30] Also, modern programming techniques allow the writing of Monte Carlo computer programs with minimal additional effort, relative to that needed to produce point estimates.

In summary, there are many means of minimizing the additional effort required to develop a Monte Carlo analysis that can still provide important insights regarding uncertainty in estimates of a regulation's benefits and costs. Moreover, some of the effort required for such an analysis is justified simply to improve the reliability of point estimates of benefits and costs.

6. Prominence of Uncertainty Assessments in RIAs

Point estimates of regulations' net benefits have been given far greater prominence in RIAs than discussions of uncertainty associated with them. Uncertainty assessments are often relegated to appendices and discussed in a manner that makes it difficult for readers to discern their significance. This is perhaps inevitable given that single point estimates can be communicated more easily than lengthy qualitative assessments of uncertainty or a series of sensitivity analyses. The ability of Monte Carlo analysis to produce quantitative probability distributions of a regulation's net benefits provides a means of summarizing uncertainty that can be communicated nearly as concisely as point estimates. The need for and means of communicating uncertainty in such a fashion has been addressed in the existing literature.[31] If a summary of uncertainty in an estimate is not given equal prominence relative to the estimate itself, essential context for interpreting the estimate and opportunities to learn from uncertainty associated with it will be lost. OMB should therefore strive to ensure that, coincident with adopting its guidance for performing formal quantitative uncertainty assessments, agencies take advantage of the opportunity such assessments provide to more prominently and concisely summarize uncertainties associated with point estimates in RIAs.

Some resistance to the use of Monte Carlo analysis and prominent presentation of its results has arisen based on the perception that such analysis requires more expert judgment and therefore makes the results presented in a RIA more speculative.[32] Also, some have expressed

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[30] Examples of such software include Crystal Ball® and @Risk.

[31] For example, see Morgan and Henrion (1990), Chapter 9; EPA (1997); and National Research Council (NRC) (2002), Chapter 5.

[32] NRC (2002), p. 134.

concern that, given the inevitably incomplete nature of any Monte Carlo analysis, prominently presenting its results would incorrectly lead readers to conclude that results of a benefit-cost analysis are more certain than they are. Both concerns are unfounded. First, as was described in Section 5, developing characterizations of uncertainty in inputs for a Monte Carlo analysis often simply involves making explicit and transparent expert judgments that necessarily already must be made to develop point estimates for those inputs. Moreover, to the extent that a Monte Carlo analysis is thought to be incomplete in its characterization of uncertainty regarding a regulation's net benefits, that can be communicated qualitatively or through sensitivity analysis, just as the implications of uncertainty typically have been communicated in RIAs. But for those uncertainties in inputs that are known and can be quantified, a Monte Carlo analysis' quantitative results offer a much more reliable and transparent characterization of those uncertainties' implications.

7. Conclusion

Uncertainty is inevitable in estimates of regulations' economic impacts. Assessments of the extent and nature of such uncertainty can provide important information for policymakers evaluating proposed regulations. Such information offers a context for interpreting benefit and cost estimates, and can lead to point estimates of regulations' benefits and costs that differ from what would be produced by a purely deterministic analysis. In addition, these assessments can provide information that can help establish priorities for research.

Due to the complexity of interactions among uncertainties in inputs to benefit-cost analysis, it is often the case that an accurate assessment of uncertainty can be gained only through the use of formal quantitative methods, such as Monte Carlo analysis. Such analysis involves relatively straightforward extensions to benefit-cost analysis. Its use can offer significant insights, while requiring only limited additional effort relative to that already expended on RIAs. Many of these insights cannot be gained using methods of addressing uncertainty that have typically been employed in RIAs, such as sensitivity analysis.

The analysis of EPA's Nonroad Diesel Rule provides a good example for the evaluation of differences between the information that can be offered by Monte Carlo analysis and that offered by more typical means of addressing uncertainty in RIAs. We compared findings from the two methods and found that formal quantitative methods offer policymakers a richer and more reliable characterization of uncertainty regarding a regulation's economic impact. While our Monte Carlo analysis only accounted for limited aspects of uncertainty in several inputs to EPA's benefit-cost analysis, the resulting characterizations of uncertainty in EPA's estimates of the Rule's benefits and costs differed significantly from those that EPA developed through less formal methods. These differences result, in part, from the capacity of Monte Carlo analysis to account appropriately for interactions among the numerous uncertain inputs to the benefit-cost analysis. EPA's own Monte Carlo analysis of the Rule's benefits suggests that, when the effects of uncertainty in inputs to the benefit-cost analysis are accounted for appropriately, the expected value of the Rule's benefits may differ significantly from EPA's primary estimate, which did not explicitly account for uncertainty.

The new requirement for formal quantitative assessments of uncertainty that is incorporated in OMB's Circular A-4 marks a significant step forward in enhancing regulatory analysis under Executive Order 12866. It has the potential to improve substantially our understanding of uncertainty regarding the economic impact of regulations, and thereby to lead to more informed policymaking. To ensure the greatest benefit from this new guidance on the treatment of uncertainty in RIAs, the results of uncertainty assessments must be given more emphasis and prominence.

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