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From Data to Decision: The Three Elements of Policymaking Illustrated by The Case of Global Warming

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This article studies the process from data acquisition to policy decisions exemplified by studying an optimum policy on global warming. Policymakers must be reasonably skeptical before proposing remedies to curb warming, but policymakers cannot await the final proof of any proposal's merit. Balancing evidence with doubt requires an informed approach, in which information is converted to knowledge and used to illuminate and compare human welfare connected to different scenarios. This article suggests, normatively, three essential elements for data based policies: evidence, consequence, and strategy. The presented framework for data based policymaking combines results from decision theory, economics, and political theory.

Keywords: data based, decision making, global warming, loss function, policymaking, social welfare, strategy, type-I error

JEL classification: C44, D78, H10, Q28

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> 'But many scientists are still far from convinced by warming theories. I believe the U. S. and other countries should heed these skeptics and wait before implementing major restrictions on carbon emissions.'
> *Nobel laureate Gary Becker (1992)*

> 'An organization called Redefining Progress enlisted five economists – the Nobel laureates Robert Solow and Kenneth Arrow, together with Harvard's Dale Jorgenson, Yale's William Nordhaus, and myself – to circulate an «Economists' Statement on Climate Change,' calling for serious measures to limit the emission of greenhouse gases.'
> *Professor Paul Krugman (1997)*

Global warming is a hot topic. On the one hand, skeptics urge us to keep our cool. On the other hand, it might not be an option we have. Curbing human activities may – or may not – come with high costs and because of the uncertainty, policymakers hesitate before suggesting remedies. But the harm from waiting looms large and it may become irreversible. Therefore, environmentalists and international treaties demand action. Balancing evidence with doubt requires acute abilities in the political economy of global warming. In this article, we shall propose to approach the issue of global warming and implementing remedies by utilizing a framework of optimum data based policy-making. We use global warming as an example of the more general case when a phenomenon possibly requires policy action, but when both action and inaction may come with uncertain and potentially imbalanced costs. We aim to shed light on the general themes rather than specific details in the intricate process from data acquisition to policy decision.

Fernandez and Rodrik (1991) raised the important issue of status quo bias in decision making and policy formation. They asked why governments so often failed to adopt policies that economists considered efficiency enhancing. Their answer entailed the concept of a status quo bias, an inclination to remain inactive until too late. We go further and ask: What must a benevolent, welfare-oriented policymaker know in order to dismiss an acceptance of status quo and implement economic measures? We use climate change and associated policies as the concrete example to illuminate the process. In this article we develop a framework within which to formulate policy on the basis of evidence, allowing for considerations of social consequences, and taking account of scenario probabilities by employing a social strategy mandate arising from general elections.

Policymaking as public action stands at the intersection of three large branches of knowledge: decision theory, economics, and political theory. Although there is a large body of literature on the three different strains of thought, e.g. as far-apart bodies of knowledge as statistical inference and the theory of justice, few studies have sought to investigate the lines along which a framework, combining the three traditions and with particular relevance to policy, can be constructed. Such a synthesis must track the process from the initial exploration of data to the final implementation of policy. Let us explore why it would be useful to present the elements of that process at a high level of abstraction. Collection and use of data in policy in general can be non-existent, uncoordinated, or misdirected. It can also be well targeted, measured, and welfare enhancing. Consequently, it would be desirable to obtain a framework within which characteristics of optimum data based policies can be explored. The global warming question lies at the meeting point of several scientific traditions, so policy recommendations vary. In this article, we shall put forward an economic basis.

There has been considerable research in all three mentioned branches of knowledge. However, an attempt at reviewing all the policy relevant research here would not be adequate use of space. Nevertheless, some general comments may be allowed. Since the political economy of global warming policies relies on insights gained in diverse fields, the challenge is to identify the interface and construct combinations of those fields. In decision theory, results have been obtained on how to approach decision making under risk and uncertainty when many scenarios are possible. Central tools are the loss function and strategies with which to choose action rules; see e.g. Rice (1995) for an introduction. However, decision theory is silent on how economic policymakers can acquire social welfare measures of costs and how to obtain socially acceptable strategies. Economics and political theory complement decision theory by studying total costs, distribution of costs, and political mandates. Thus, a policymaker or an international agency may invoke results from the three fields when considering implementation of a global warming policy.

Let us briefly mention a few relevant recent studies. Chamberlain (2000) and Brown (2000) may be consulted for studies on the application of decision theory. Keuzenkamp and Magnus' (1995) work on tests contributes to understanding the need for balancing evidence against doubt, earlier raised by Hall and Selinger (1986). In fact, Neyman and Pearson (1933, p. 296) suggested already seven decades ago that «...how the balance [between error types] should be struck must be left to the investigator.» The balance mentioned in that statement refers to the weighting of the evidence of absence with the absence of evidence concerning global warming. In this article, we demonstrate the important role of a proper loss function for policymakers when they seek to strike the socially optimum balance between different kinds of evidence. In short, a loss function is a function that sums up the consequences to society of an action resulting from an implemented decision. The loss function is introduced as a tool to evaluate and compare outcomes. Thus, the construction of measures of social welfare is the bridge between economics and decision theory, and is key to the political economy of the question. Consult Hanemann (1994) for an excellent exposition of why economists have developed a tool like contingent valuation to address some questions that emerge from welfare considerations of non-market situations. Geweke et al. (2000) offer useful additional comments upon the link between statistical inference and decision making. In economics there is a long-standing tradition of performing cost-benefit analyses, but Tol (2001) points out the remarkable lack of attention equity concerns have received in climate change issues. These concerns are related to justice, but exactly what is a just distribution of the costs and benefits remains unclear and unresolved. Ultimately, it is a question for political theory and philosophy; a question e.g. Rawls (1971) addressed. In the real world, politicians who are elected by an electorate give the mandate for social strategy to policymakers. We realize, then, that an examination of the process from data to policy must build on separate studies in subfields that may lie far apart, an argument similar to the one Baumol (2000) calls the marriage of theory, data analysis, and application to serve as a new foundation of our discipline's applied work. Consequently, it is a challenge to students of political economy to contribute towards an integration of the specialized studies.

The thrust of our argumentation can be summarized thus. A policymaker should acquire evidence on global warming from the scientific community. The evidence will consist of scenario probabilities and scenario effects. The effects must then be interpreted in terms of social welfare considerations, and as a result social costs represent the target loss function. Social costs include in principle both the total amount of burdens and the distribution of burdens. In order to implement a policy rule, the policymaker must, ultimately, make use of a political mandate on handling expectations and distributions, both current and intergenerational. That mandate represents public sentiment on how to balance welfare. In short, the three elements that a policymaker needs are: evidence, consequence, and strategy. Let us term this approach the optimum data based policy formation. This is not an empty or self-evident scheme because there do exist several alternatives to optimum data based policy making. One alternative is an ideologically formed policy that is not data based. Another one is a policy that does not use social welfare as the loss function or measuring yardstick, but for example a personal or partisan loss function. One example of the latter is the adoption of a conservative scientist's fear of too early rejection. By using these alternatives as yardsticks that we may use to investigate the content of the proposed framework, we will comprehend the benefits of using data in decision-making and the social justice in using social welfare in distinguishing between different decisions.

Let us say in advance where we are headed. The next section motivates the need for this study and presents the contextual background upon which it should be interpreted. Section three introduces the methodology and the nomenclature. In section four, we go on to present the framework of an optimum data based global warming policy. In the subsequent sections five and six, we discuss the loss function and social strategies. Section seven discusses problems and further research, and the final section concludes.

Background, Motivation, and Literature

Even though our aim in this article is to study the broader background of policy formation, it would serve our argumentation if we relate certain insights on a specific problem. Thus, let us in the remainder focus on the problem of global warming. If the null hypothesis of no link between human activity and global warming is true, then measures are unnecessary and costs are misdirected. However, if the null hypothesis is false, and humans do in fact contribute to global warming by their actions – by economic processes and the way we organize society – the consequences of not reducing the polluting discharges may be devastating. It is crucial that society is able to differentiate between the two, or at least present balanced policies that weigh different probabilities. To that end, many approaches can be thought of. One would be the academic approach of focusing attention towards one type of mistake, the mistake of falsely rejecting a true hypothesis. In this approach, rejection should come only when the conjecture at hand has been thoroughly falsified. Similarly, some commentators believe, in the same spirit, that a new policy should not be implemented until its merits have been demonstrated beyond doubt. This view entails requiring very solid proofs of humanly generated global warming before acting. The requirements may be so strict that they exceed the demands from reasonable doubt. We shall see below that the key word is reasonable, and that it must be associated with social consequence of outcomes. Others go further and refuse intervention as a matter of principle. This attitude may be founded on ideology. While the first, conservative approach is based on data, the second is not. It is based on a pre-analytic principle. A similarly pre-analytic policy suggestion is found at the other extreme. Some commentators suggest intervention and implementation of policies without scrutinizing data. This eagerness is often founded on personal belief systems. A fourth approach is the precautionary better-safe-than-sorry attitude of watching particularly that part of the outcome matrix in which the most devastating consequences occur. As the first approach, this is also based on data, the only difference being how probabilities and consequences are weighted. This approach may imply policy implementation *before* the hypothesis of no humanly generated global warming has been scientifically rejected.

How should an ideal policymaker choose between the four different approaches? There is no obvious answer, but this article suggests that there are three necessary elements contained in the answer. There exists an array of additional policy options, combining and extending the mentioned four, but there also do exist basic similarities that help us construct an approach to optimum policymaking. Choosing an approach is, however, a highly complex problem that is founded in a variety of political economy considerations. This article examines such considerations.

Let us inspect some views on statistical inference in economics because the policymaker first faces an inference problem. In empirical economics, there is a convention of accepting those empirical results that show statistical significance at a pre-specified level, conventionally five percent. A policy version of this convention could be similar to the conservative, scientific approach mentioned above. It would recommend a policy only to the degree it relied on statistically significant reports on global warming effects. However, an important literature originated when McCloskey (1985) explained to the economic profession the old insight that statistical significance is an attractive name for more arcane, technical matters related to sample size and testing procedures. It is not to be confused with economic or substantial significance; see McCloskey and Ziliak (1996) for a review of current economic practice. McCloskey claimed that the loss function had been mislaid. By that McCloskey meant that analysts must not forget what they ultimately want to optimize, and said that in policymaking, the interest generated by empirical estimates is less connected to t-values and more connected to economic meaning, relevance, and impact. In fact, Wald (1939) stated the challenge clearly: «The statistician who wants to test certain hypotheses must first determine the relative importance of all possible errors, which will entirely depend on the special purpose of his investigation.» Thus, the observation that the loss function has been mislaid still begs the question of where it is and what it looks like. The loss function may be defined as a function that sums up the results and consequences of any action taken, and this is a core topic to which we will devote much space. In policymaking, the loss function may translate into costs to social welfare. In cost-benefit terms, a benefit surplus may be expressed as negative loss. In other words, the loss function is what policymakers want to minimize. Of course, even though it is sometimes quantifiable, it often represents only an attempt to translate judgments about outcomes into operationally commensurable terms. Historically, economists have used many types of loss functions and different forms have generated debate. For example, in regression analysis analysts invariably use loss functions like the sum of absolute deviations or the sum of squared differences in order to evaluate models and fit, although many other loss functions may be fathomed. Statistically, the loss function is a function of the state of the world and the decisions taken and so it is a mapping from a space of states and decision rules into a one-dimensional, and therefore readily comparable, scale. This is a necessary condensation of available knowledge since practitioners in policymaking are in great need of tools to assess results from their actions. Thus, in this article we shall focus attention on the unique profile of the loss function policymakers must target. In the problem at hand, that of global warming, any policy approach will entail consequences, and the consequences must be considered along with the probabilities. Moreover, decisions must be made, often without much time to ponder the issue and investigate proofs. Society cannot escape the difficulty of computing all the consequences by refusing to deal with them. The enormity of the calculus involved allows no escape, however tempting it is to refuse undertaking computations. Even a decision of passivity – of doing nothing – is, fundamentally, a policy decision. This is very different from the consequences resulting from refusing to investigate a difficult problem in science or refusing to reject a generally believed scientific hypothesis. Summers (2000) captured the inescapability of policymaking when he said: «...as an academic, if a problem is too hard and does not admit of a satisfactory solution, there is an obvious response: work on a different problem. That is not a luxury that one has in government.» Thus, there is a need for a systematic way of looking at the policy balance of probability and outcome.

Uncertainty is one aspect that is frequently addressed in the policy issues in general and in the environmental literature in particular. That literature is relevant to the computations of the consequence matrix. An important strain in that literature arose with Arrow and Fisher (1974). They made the point that when decisions must be made in the presence of uncertainty, the value of information is enhanced. Quasi-option value is a concept designed to capture the value of that information. The knowledge that knowledge will be gained in the future is thus incorporated into the decision of waiting until decision-makers are more certain, implying that the probable value inherent in waiting outweighs the potential costs of waiting. Unfortunately, the literature does not investigate where the balancing rod should come from. We address that issue. However, Arrow and Fisher's early contribution has spurred an enormous activity in specific sub-fields dealing with what actions to take in the face of the unknown, but we shall not attempt a review.

Methodology and Nomenclature

Let us establish the nomenclature. A null hypothesis, a null for short, is an assumption about the world and which mechanisms the world or society operate under. The null hypothesis may also be an idea about certain relationships relevant for policy or a guess about the magnitude of an effect or a parameter. Its complement is called the alternative hypothesis. They cannot both be true. Since the alternative hypothesis comprises the complement of the null hypothesis it may in fact be a set of hypotheses. Here, we shall make it as simple as possible, without loss of generality, and consider only two states of the world, the one in which the null hypothesis is true and the one in which the null hypothesis is false, regardless of how false it is. Observe that we allow the null hypothesis to be an interval, a vector, or a set.

It is important to notice that when the null hypothesis is a point assumption about a parameter or a strict statement such as «there is no global warming» it may frequently be wrong, maybe always. Many commentators thus urge observers to realize that using a null hypothesis is most often only a tool for generating results and something to compare evidence with. Then, it does not matter that the null is false and thus rejected, because it often is. What matters is *how* false it is. In our binary set-up degrees of truthfulness are lost. What we gain is simplicity and transparency. The set-up can easily be generalized from a binary one to a continuous one, but it would require more abstraction and thus lead to less availability. This article embraces the view that a null hypothesis is an apparatus to generate comments. But we also believe that to fix ideas it is useful to maintain and employ the concept of a null since by doing so observers may have a point of departure when statements about the world shall be made. In consequence, the dichotomous set-up this article uses, in which a null is either true or false, is only a mental heuristic we use in order to illustrate the delicate point that scientific evidence must be balanced by social consequences when it is to be used in policy. The continuous case follows exactly the same framework.

A type-I error is the type of error that is committed when one rejects a true null hypothesis. A type-II error occurs when a false null hypothesis fails to be rejected. The probability of making a type-I error, given a specific test procedure, is conventionally assigned the Greek letter alpha. Sometimes it is called the p-level. The probability of making a type-II error is denoted by the Greek letter beta. By tradition, alpha is also known as statistical significance or size. It can be computed under the assumption that the null is true and that a specified empirical procedure is followed a given number of times. Naturally, the beta level is a function of just how false the null is. It is more likely that the testing procedure will detect the falsity of a null if it is far from the truth. Statistical convention, going back some decades, typically gives an alpha of five percent a special status. It is sometimes considered a mistake to reject a null if the computed alpha is above five percent. Another view says that an empirical result, for example a coefficient estimate, which comes with a low t-value should be distrusted. In truth, at what level a researcher decides to reject the null, or find a coefficient estimate significant, is completely a matter between her, the loss function involved, and the strategy employed. Statistical convention is at best an easy-to-use and sometimes-right heuristic rule. Statistical inference is the position taken concerning the belief in the validity of the null hypothesis. We will consider two types of inference, rejection and acceptance. A rejection occurs when the investigator believes that the null is false. An acceptance entails a belief that the null is true. This dichotomy is imposed as a matter of simplicity. We may substitute the binary inference universe with a continuous spectrum, reflecting the fact that some test outcomes may show larger departure from

Table 1.
Rejection or Acceptance of Scientific Hypotheses

Inference	*State-of-the-world*	
	Null is true	*Null is false*
Reject null	Type-I error	
Accept null		Type-II error

the assumed null than other outcomes. Thus, an investigator may be more or less certain of rejection. Such a continuity of the decision space would not enhance our understanding here and it would complicate the presentation. Therefore, we keep it binary. Finally, the state-of-the-world is a term that denotes the unobservable truth about what state the world exists in. Again, the binary space of states is a simplification that comes with no loss of generality. It might also have been a continuous spectrum, but that would obfuscate, not facilitate, comprehension. The nomenclature is illustrated in Table 1.

Notice that there are four possibilities. They are exhaustive of all combinations of state and action. We say that if the null is not explicitly rejected, it is accepted. The combinations are (true, reject), (true, accept), (false, reject), and (false, accept). Whatever the investigator or decision-maker decides upon, the decision has a corresponding cell in Table 1. This is a crucial point, since some analysts seem to believe that one may escape the positioning simply by refusing to take a position. In our system, a refusal to take a position would be equivalent to an implicit acceptance of the null, which corresponds to the lower row. The position may be true or false, and would be so randomly or ideologically, without data scrutiny. Thus, Table 1 is the graphical equivalent of the truism that any position taken – also the refusal to take a position – necessarily precludes another position. In our context, if the null hypothesis is that human activity does not contribute to global warming, an unwillingness to form an opinion on the matter is translated to a belief that there is no relation between human activity and global warming.

In Table 2, we have depicted the policy parallel to a scientific position. Letters a through d denote the four outcome types. In

Table 2.
Results of Retaining the Position of No Policy or Implementing Policy, Null Hypothesis: No Global Warming

Policy decision	*State-of-the-world*	
	Null is true, having no policy is adequate	*Null is false, having no policy is inadequate*
Implement policy	Type-I policy mistake, W_a, P_a	W_b, P_b
No policy	W_c, P_c	Type-II policy mistake, W_d, P_d

data based policymaking policymakers may mimic hypothesis testing by linking policy decisions to having no policy or implementing a new policy to accepting or rejecting a null hypothesis. Table 2 is this article's version of comparable tables in DeLong and Lang (1992) and Zellner (1990). A combination of state and policy (state, policy) yields consequences for all people involved. In the table, we denote welfare consequences W. Later, we shall apply the decision theoretic term loss to welfare consequences. The policymaker believes, or an analyst tells her after having seen the evidence, that each combination of state and policy will be realized with a certain (subjective) probability P. This is a perceived probability, as imagined by humans studying the evidence. It may or may not be a function of frequentist probabilities from repeated investigations or simulations. Upon realization of one state-of-the-world, the world is necessarily in one state or another. No probabilities are involved after realizations. However, which state it is remains undisclosed to investigators. Analysts have guesses based on instruments and indicators. Analysts then assign (subjective) probabilities to each state.

Should policymakers emphasize the type-I error relatively more than the type-II error, as scientists do? There is no a priori basis for such a status quo bias. An ideal policymaker should not necessarily wait until consensus is reached and established descriptions of the world are at hand. It may be too late. While waiting, policy must be based on balancing available evidence with reasonable doubt. This stance finds an early eloquent proponent in Friedman (1953): «…policy conclusion necessarily rests on a prediction about the consequences of doing one thing rather than the other, a prediction that must be based – implicitly or explicitly – on positive economics.»

Thus, policy should be founded on data and in theory. Let us examine the roles of the policymaker and the analyst. Let us call data X. The data X may be stochastic, and thus have distributions. Using data, analysts estimate, theorize, test, and ultimately form a belief about the vector (P_a, ..., P_d) of the probabilities associated with each outcome. The data may indicate that surely, the world is in a state in which the null is true. Then the sum of the subjective probabilities in the first column will be large, possibly close to unity. Or data may hint that it is unclear which state the world is in. In that case, the subjective probabilities assigned may be evenly distributed between the two columns. Thus, when using data in policy one must start with analysis. The data X offer a window into natural phenomena, economic mechanisms, and social processes that allows analysts to form an opinion about what the state of the world is. In order to form such opinions, they use measurements, or metrics in short notation, m(X), and a theory t(m(X)) that are transformations of the data X into scalars, vectors or sentences that condense the data X into something meaningful and interpretable. When the data X are stochastic, so is any metric m(X). The metric has a distribution, and when analysts inspect it, they do not know with certainty its distribution. In other words, there may be false alarms and missing alarms. Analysts may believe that humans have generated global warming because their measurements indicate that it is the case. It might be otherwise, and then the instruments are giving false alarms. Analysts may believe there is no relation between human activity and global warming because data and theories suggest variation has been going on for millennia. Then, the data and our handling of them, would fail to trigger the alarm. Ultimately, the policymaker must take all this into account, compare it with consequences and social acceptance of risk, uncertainty, and distribution of burdens, and then make a decision. Let us study the process in more detail.

Optimum Data Based Policymaking

We employ the decision theoretic approach and terminology as described by Rice (1995). For simplicity and no loss of generality, let us compare four different decision rules: two data based rules and two ideological rules. The first rule we shall study is what we may call the *ideological laissez-faire* decision rule. Using it, policymakers are curbed by rules set out ex ante not to interfere with market solutions. The second we shall call the *statistical significalist* or *conservative* decision rule. Using it, policymakers side with conservative scientists, and act only when a null hypothesis of no relation between human activity and global warming has been rejected at a low alpha-level. The third rule we term the *better-safe-than-sorry* rule or the *precautionary* rule. Using it, policymakers act much sooner on indicators of a possible relation between human activity and warming than is allowed by the significalist rule. The fourth is the *radical interventionist* rule. Using it, policymakers try to preempt humanly generated global warming regardless of what indicators say. The first and the last rule are pre-analytic rules and not based on data. The second and the third rule are analytic rules, based on evidence. There are, of course, many other possible rules. We use these four to fix ideas, and to ease understanding by having concrete specifications since simple rules enhance transparency and aid comprehension.

Assume that the analysts possess an index that can combine all the instrument readings of global warming. This index is a metric m(X), and it is a function m() of the data X. The data X contain both observations on natural phenomena and possible human interaction with nature. Analysts must try to disentangle what nature sets up with no human assistance on the one hand, and how nature responds to human processes on the other. Let us focus attention on the human contribution. The aggregate metric of human contribution may be discrete or continuous. It may be a scalar or a vector. For simplicity, assume that the vector can be compressed into a meaningful scalar, and that its scale is translatable into easily understood intervals. Let the index be normalized to run from 0 through 20, keeping algebra at a minimum and reserving it to the compression of the index. Further, let a metric score of around 10, for example from 8 to 12 indicate no humanly generated global warming, a score below 6 humanly generated global cooling, and a score above 14 humanly generated global warming. In this system, global warming without human cause would lie in the first interval. For now, we use global warming as short for humanly generated global warming. Let there be gray zones of doubt from 6 to 8 and 12 to 14. When the metric falls between 8 and 12, we assign to it the score m_0. For the cases when it falls into intervals 12 to 14 and above 14, we say that the metrics score m_1 and m_2.

Of course, the question of what policy to implement is most controversial when the metric – as a symbolization of all accumulated human knowledge at the time – lies in the gray zone. In Table 3 we list the four decision rules and what policy actions correspond to what levels of the metric. Using Occam's razor – the doctrine in the philosophy of science, named after the philosopher Occam, urging investigators to keep things as simple as possible – we do not describe the nature of the policy actions here.

Table 3.
Four Decision Rules and Policy Actions Based on Metric Signal

Rule	*Data based?*	*Action when m_0*	*Action when m_1*	*Action when m_2*
d_1 Ideological laissez-faire	No	No policy, a_0	No policy, a_0	No policy, a_0
d_2 Statistical significalist	Yes	No policy, a_0	No policy, a_0	Policy, a_1
d_3 Better-safe-than-sorry	Yes	No policy, a_0	Policy, a_1	Policy, a_1
d_4 Radical interventionalist	No	Policy, a_1	Policy, a_1	Policy, a_1

We realize that policy actions may form a continuous spectrum in the same way any metric can. Thus, a realistic description or an operational recipe would make policy a continuous function of the metric. We simplify by substituting the continuous function with a discrete one.

From Table 3 we observe that the most interesting differences occur in the cells of row three and four and column four. The two data based rules statistical significalist and better-safe-than-sorry specify different policies when the metric is in the gray zone of doubt, namely when the score is m_1. The statistical significalist rule commands policymakers to await more evidence. The better-safe-than-sorry rule states that society should err on the safe side, and implement policy even when the evidence has not confirmed a relation between global warming and human activity.

First Element: Evidence

In economics, data and theory combine to offer a better position than a blind guess. The world is a risky and uncertain place so analysts compile data in order to understand the world, but the data may contain stochastic elements because they may be non-experimental samples from a much larger population universe or because they contain random noise. It follows that the metric m(X) is stochastic. A policymaker needs to acquire a rudimentary grip on the distribution of the observed metric signal. She needs to know how reliable the metric is, and how often it makes erratic calls.

The analysts face an inference problem. They know that even if there is no humanly generated global warming and the metric (our aggregate evidence) would show 10 or m_0, there exist stochastic processes that come in between the state of the world and the signal they receive. Sometimes then, the metric shows 14 or m_2 even when the state of the world is no warming. Most often, however, when the metric shows 14, there is global warming. Analysts know this, but do not know which is which when they encounter a score of 14. Based on simulations, theories, experiments, and experience they will assign probabilities p of how to interpret the measurement signal. Thus, the subjective probabilities p are functions of the state of the world, metric signal, and the experience of the scientists. We tabulate the different possible p-functions in Table 4. In the following, we shall expand upon the nature of the p-function. Let us refer to the state of the world with the letter s for state, and let the number 0 represent the state-value of no humanly generated global warming. We give the complement, humanly generated global warming, state-value 1. Again, policy relevance may be gained by using many degrees of human contribution, and so a sophistication of this simple model would utilize a continuous scale instead of a binary pair of 0 and 1. The p-function p(s,m) has two elements: state s and metric signal m. Thus, p(0,0) denotes the probability of analysts observing a signal m_0 when the state of the world is no global warming, or s=0. Similarly, p(0,2) denotes the probability of analysts observing a false alarm, a signal of m_2 when the state of the world is no global warming. In contrast, p(1,0) symbolizes the probability of a signal m_0 when in fact there is global warming, i.e. a missing alarm. For each state of the world, there must be a signal, so the probability of different signal type must sum to unity for both states of the world.

From Table 4 we realize that it is of the essence how precise the metric signal is and that the degree of imprecision is known to some extent. There will be false alarms and missing alarms and these constitute obstacles to ideal policymaking.

Second Element: Consequence

Since policy involves the welfare of people, ideal policymakers need a gauge of how people are affected. To ideal policymakers, social consequence should be the measuring rod, not arbitrary statistical conventions. Here we shall define a loss function to be a function that sums up all effects on society for a given policy. A loss function is a decision theoretic term for a function that encapsulates all the consequences, such as economic costs or utility losses, of actions taken. Here, it could also be called the welfare function, but we retain the standard terminology. Constructing such a loss function of social welfare is a challenge. However, in the minds of any policymaker, politician, and economist lies the idea that some policies are preferable to others. Here, we project that idea into an application. We propose that some ranking between social outcomes is possible, and that some approximation of relative importance must be attempted. We claim that it is human nature to rank and compare outcomes, and that societies – as aggregates of human nature – seek to rank and compare outcomes. However, Arrow (1963) has shown that the aggregation of an individual ranking to a collective ranking is a complex, not always feasible, problem. Nevertheless, we postulate that a congregation of two or more individuals can agree on a ranking between at least two social outcomes. In addition, the different outcomes are comparable in some (unspecified) sense. Measures of loss can be assigned. It is a necessary, but not sufficient condition, for the idea of an optimum data based policy. If or when no rankings of aggregate, social outcomes are attainable, policy may as well be decided upon using a game board with dice. An example of the

Table 4.
Metric in States of the World and Subjective Probabilities

Metric signal	*No global warming, s=0*	*Global warming, s=1*
m_0	p(0,0)	p(1,0)
m_1	p(0,1)	p(1,1)
m_2	p(0,2)	p(1,2)
Sum	1	1

Table 5.
The Loss Function of Social Welfare

Policy action	*State-of-the-world*	
	No global warming, s=0	*Global warming, s=1*
Implement policy, a_1	Unnecessary costs	Status quo restored
No policy, a_0	Status quo	Catastrophe

contours of social welfare is tabulated in Table 5.

We observe that Table 5 is especially imbalanced on the northwest to southeast diagonal when the unnecessary costs are very different from the costs of a catastrophe. The hard part in gauging the consequences is to establish the relative losses and distribution of losses associated with each outcome. Let us for now suppose that the loss function is thought to be what is tabulated in Table 6. Below, we shall discuss the nature of the loss function in more detail.

The state-policy combination of (no warming, no policy) entails no changes from the status quo. We assign the outcome a loss of 0. There are two cases of policy implementation. In the first, the policies are redundant because warming is unaffected by human activity. Since resources are scarce there exist many alternative ways to use resources. Thus, societies assume costs without any benefits. Suppose careful consideration gives this outcome a loss of absolute magnitude a. The minus sign in the table indicates loss. In the second case, the policies are needed because human activities do in fact contribute to global warming. Thus, societies assume costs and reap the benefits. If the policies restore status quo, a conscientious scrutiny of costs and benefits may deem the loss to be of magnitude b. The worst outcome results from a type-II policy error associated with the failure to reject a false hypothesis. When there in fact is a connection between human activity and warming, but society fails to detect it and does nothing, the loss may be estimated at an absolute magnitude of c. That loss may be daunting. In essence, Table 6 constitutes a summary of how humans deem the different outcomes. The four scalars a, b, c, and 0 can be thought of as one-dimensional summaries, or elements in the value domain of the loss function, of both aggregates of costs and highly complicated distributions of costs among societies and individuals. Here, loss comprises numerical attempts at measuring

Table 6.
Relative Magnitudes in the Loss Function of Social Welfare

Policy action	*State-of-the-world*	
	No global warming, s=0	*Global warming, s=1*
Implement policy, a_1	-a	-b
No policy, a_0	0	-c

social welfare. Philosophically, the scalars may represent our need to rank outcomes in terms of the hazards each encompasses, but they may also represent a more ambitious attempt at actually estimating the loss involved, in economic terms. In any event, as we shall see below the relative magnitudes of the loss associated with each outcome are of key importance and that comparison between different decision rules is facilitated when each outcome is assigned loss on a numerical scale. For example, policymakers may want to embrace one decision rule if c is small compared to b and another decision rule if c is very large compared to b. Thus, it is adamant to policymakers to launch attempts at ranking and quantifying the loss involved in all outcomes, which is mirrored in a the relative magnitudes of a, b, c, and 0, and compare the inherent adversity in each scenario.

Let us now contemplate the problem of picking a rule to balance probabilities and consequences.

Third Element: Strategy

Society faces a dynamic, sequential game against nature in which what Nature plays initially is partly hidden to the observer, but Nature's historic plays will be revealed as time goes by. Here, we make it simple. We study only a one-shot game in order to illustrate the importance of evidence and consequence in policy. Society is the other player, and has at its disposal a whole range of plays. For our purpose, the range is compressed to a binary choice of policy or no policy. Let us study the details of different decision rules. In order to compare outcomes, we must establish an apparatus to do so. In decision theory, risk R is one such measure. There may be alternatives. Rice (1995: 575) defines risk as:

$$(1)\quad R(s=k,d\_i)\equiv E_j[l(s=k,d\_i(m\_j))]$$
$$=\sum_{j=0}^{2} l(s=k,d\_i(m=m\_j))\,p(s=k,m=m\_j);$$
$$k=0,1;\quad i=1,\ldots,4;\quad j=0,1,2,$$

in which loss l is the loss associated with a state s and a policy originating in a decision d and p is the subjective probability assigned to the assumed state-of-the-world based on metric m. Subscript k runs over the two states of the world, subscript i denotes one of the four decision rules, and subscript j represents one of the three levels of the metric m. Let loss l(s=k,d_i(m_j)) be defined as the costs to social welfare at state k following decision rule i after having observed a metric signal of m_j compared to an initial state of no warming with no policy. Below, we shall discuss the underpinnings of the loss function and elaborate on its position in economics.

Let us inspect the definition in equation (1) closely. From the equation we observe that risk is defined as a function of the state-of-the-world and the decision rule employed. Thus, there is a risk for each combination of state and decision rule. More specifically, it is defined as the expected loss over metric signals for a given decision rule in a given state of the world. Risk is the sum of the products of loss and probability of loss in a given state of the world. Another way to understand the social relevance of risk is to think of it as the expected social welfare in a given state of the world given the measurement apparatus and scientific knowledge we are able to utilize for each of the different decision rules policymakers employ. To see this, contemplate first the risk inherent in a laissez-faire decision rule when there is no global warming. The decision rule says that policymakers should not look to data and measurement signals, but simply maintain, for ideological reasons, their no-policy approach. In essence, the laissez-faire decision rule states that policymakers be inactive, regardless of evidence, in the belief that markets eventually will price events such that a social optimum will be reached. Thus, the risk or expected loss over different measurement signals is 0 since the loss associated with each signal is 0 when there is no warming, and the policy is the same for all signals. In contrast, the risk or expected loss over different measurement signals is -c when the state of the world is global warming. This risk emerges from the rule that laissez-faire commands policymakers to remain inactive regardless of signals, and thus the expected outcome is -c, the loss associated with doing nothing in the face of global warming. In comparison, a conservative statistical significalist decision rule involves an analytical policymaking process in which policymakers scrutinize data before making decisions. However, they require solid evidence for global warming before action is taken since the decision rule only recommends policy implementation when the signal warns strongly, m_2, of global warning. In Table 7a we see that the expected loss of the significalist decision rule is very different when the state is no warming compared with the state of global warming. More technically, from inserting terms into equation (1) we observe that the loss associated with the significalist decision rule when there is no global warming, then, simply is the product of the loss associated with the

Table 7a.
Risk For 4 Decision Rules When There Is No Global Warming

Decision rule	*Loss given metric signal and policy action under decision rule, to be multiplied with probability p(0,m_j), j=0,1,2*			*Risk*
	loss; m_0, p(0,0)	*loss; m_1, p(0,1)*	*loss; m_2, p(0,2)*	
d_1	0	0	0	0
d_2	0	0	-a	-a[p(0,2)]
d_3	0	-a	-a	-a[p(0,1)+p(0,2)]
d_4	-a	-a	-a	-a

Table 7b.
Risk For 4 Decision Rules When There Is Global Warming

Decision rule	*Loss given metric signal and policy action under decision rule, to be multiplied with probability p(1,m_j),j=0,1,2*			*Risk*
	loss; m_0, p(1,0)	*loss; m_1, p(1,1)*	*loss; m_2, p(1,2)*	
d_1	-c	-c	-c	-c
d_2	-c	-c	-b	-c[p(1,0)+p(1,1)]-bp(1,2)
d_3	-c	-b	-b	-cp(1,0)-b[p(1,1)+p(1,2)]
d_4	-b	-b	-b	-b

unnecessary costs, -a, multiplied with the probability of receiving an m_2 signal when state equals 0, p(0,2). On the other hand, as Table 7b uncovers the loss associated with the significalist decision rule when there is in fact global warming, is a more complicated sum of several terms. The first term is the loss associated with inaction in face of global warming, namely the product of loss -c and the probability of having no policy implemented. The latter is also the sum of two terms, the probability p(1,0) of receiving a no-warming signal, m_0, when there is warming plus the probability p(1,1) of receiving a gray-zone signal, m_1. The second term is the loss associated with action in the face of global warming, namely the product of loss in cleaning-up and curbing emissions, -b, and the probability p(1,2) of seeing a warming signal m_2 in the state of global warming. Similarly, we may calculate the risks involved in the other two decision rules and compare them.

Let us inspect more closely the risk involved with each decision rule. In Table 7a we compute the risk levels for each decision rule in the state-of-the-world no humanly generated global warming, s=0, and in Table 7b we compute the risk levels for each decision rule in the state-of-the-world in which human activity contributes to global warming, s=1.

We observe from Tables 7a and 7b that the risk involved is very different for each decision rule and state. Unfortunately, the state-of-the-world is hidden to society, and the need for strategy originates from the need to deal with the unknown. When society uses the metric m as an indicator, it uses available evidence to navigate. Using the metric, subjective probabilities for which state the world is in are proposed. Combinations of state and policy yield social loss, and the expected loss or risk for each decision rule in each of the two states of the world can then be computed. However, a policymaker does not know how to approach the risk. The policymaker needs a strategy. To see this, compare Tables 7a and 7b above. The laissez-faire decision rule involves no risk when there is no global warming, but a risk of absolute magnitude at possibly catastrophic levels, c, when there is warming. The better-safe-than-sorry decision rule has a negative risk when there is no warming, and is therefore worse than the laissez-faire in that state of the world. However, when there is warming, the risk associated with the better-safe-than-sorry decision rule may be much smaller than the catastrophic risk of the laissez-faire decision rule. Thus, it may seem tempting for a risk-averse policymaker to prefer the better-safe-than-sorry decision rule to the laissez-faire rule. However, it does depend on the magnitude of c, whether it is at the magnitude of an inconvenience or at the magnitude of a catastrophe. Moreover, whether to embrace a better-safe-than-sorry decision rule or a conservative, significalist decision rule depends on the scalars a, b, and c in concert with society's strategy. For example, a risk-averse policymaker, representing a risk-averse government, administration, or nation may decide to use an correspondingly risk-averse strategy, for example one we may call a minimax strategy. In that strategy, the minimum risk – or the worst-case scenario – for each state-of-the-world is identified, and the decision rule that comes with the maximum minimum risk – or the best worst-case scenario – is chosen.

However, if one state is highly improbable given prior knowledge or earlier experience the society may not want to pay too much attention to it. Guarding against the terrible, but highly unlikely, is not necessarily a wise approach or something society wishes to do. Another strategy is what we may call the Bayes strategy. It involves the computation of risk terms for each decision rule using a basis of a prior distribution of subjective probabilities: the distribution of state-of-the-world probabilities. In our example, there are two such subjective probabilities. The prior probability that the world is in a state of no humanly generated global warming π_0 and the prior probability of a relationship between human activity and global warming π_1.Using those prior probabilities, another way of identifying a strategy to choose the decision rule can be arrived upon: Use the decision rule with the most attractive expected risk given the prior. The formula for computing such statistics is given in equation (2).

$$(2)\quad E_s(R(s,d\_i \mid \pi_0,\pi_1)=R(s=0,d\_i)\pi_0 + R(s=1,d\_i)\pi_1, \quad ,i= 1,\ldots,4.$$

In Table 8, we give a simple illustration of the difference between the two strategies. In the table we realize that what decision rule to use depends on what strategy lies underneath. For certain choices of loss, subjective probabilities, and priors the statistical significalist may be a better decision rule. That is why it is preferred by many academics. In their private loss function there is great shame attached to being caught in a type-I error. Thus, for scientists the absolute magnitude of the scalar a is large, and –a consequently constitutes a huge loss. The loss associated with the other error, type-II, is small since it is likely to be shared with many other scientists. For society, however, the absolute magnitude of scalar a may often be much smaller than the number c. Consequently, society as a whole may wish to use another decision rule than an individual, for example the better-safe-than-sorry rule. Furthermore, the loss function involved may differ greatly from situation to situation, and from society to society. The strategy employed may be different from general election to general election.

The outline above raises several questions. For example, by introducing the prior distribution in the Bayes strategy, the careful observer may ask what would be the

Table 8.
Risk Comparison Chart of Two Strategies to Choose Decision Rule: Minimax and Bayes

Rule	*Loss in state-of-the-world* *No warming, s=0*	*Warming, s=1*	*Minimum risk*	*Bayes risk*
Ideological laissez-faire d_1	0	-c	-c	$-c\pi_1$
Strict significalist d_2	-a[p(0,2)]	- c[p(1,0)+p(1,1)]-bp(1,0)	Depends on parameters	$-a[p(0,2)]\pi_0$-{c[p(1,0+p(1,1)]-bp(1,0)}π_1
Better-safe-than-sorry d_3	-a[p(0,1)+p(0,2)]	-cp(1,0)-b[p(1,1)+p(1,2)]	Depends on parameters	- a[p(0,1)+p(0,2)]π_0-{cp(1,0)-b[p(1,1)+p(1,2)]}π_1
Radical interventionist d_4	-a	-b	-max(a,b)	$-a\pi_0-b\pi_1$

difference between the prior π and the posterior p when the world does not repeat itself. To answer we must enter the debate on Bayesian inference, which we will avoid here; see Zellner (1990) or Rice (1995). It is not our purpose to settle such issues, only illustrate the use of different strategies in order to describe the elements of optimum data based policy formation. More importantly, risk or expected loss in one state-of-the-world is only *one* of many potentially relevant measures of the social consequences involved. But one measure that is widely accepted for one type of application may not be accepted for another, especially when people are involved. Moreover, instead of entering a scalar loss in each cell we might want to enter the whole distribution of population welfare, and thus distribution of individual loss, or at least a multidimensional vector. These are paramount questions to resolve, but they are not crucial to our purpose. Our purpose is smaller in scope; to identify and outline the basic elements of policymaking.

The Loss Function

In economics, the concept of welfare has become a cornerstone in applied work, and Baumol (2000) attributes the current understanding of the term to Pigou (1912). Here, the founding idea of social consequence or social welfare is that at least two social systems may be imagined such that an electorate would prefer one to the other. That idea is appealing because the alternative seems inadmissible. To see why, assume conversely that all social systems imaginable are in principle indistinguishable in terms of social welfare. Then social science collapses to mere description, with no purpose, no motivation, and no anchor in the improvement of society. As a corollary of that position, we need not worry about global warming since any social organization is as acceptable as any other, a position that intuitively feels unacceptable. This motivates accepting the contrary, the original assumption that there do exist at least two development paths in relation to climate change that entail different social welfare or loss. Society would like to identify such paths, even when identification challenges the available apparatus.

Let us focus attention to the loss function. In optimum data based policy formation, the loss is defined as:

$$(3)\quad l(s=k, d\_i(m)), \qquad k=0,1; \quad i=1,\ldots,4,$$

in which state s denotes the true state of the world, decision d the policy decision taken, and metric m the scientific signal. This is a model simplification. More fundamentally, the loss function l is a function l(s=k, d_i(m); μ) of state and decision given the utility structure μ, representing a vector consisting of the individual utility functions, or social preference orderings, of the members of society. We may not constrict ourselves to current members, but may also include future inhabitants. Thus, the utility structure μ is given by:

$$(4)\quad \mu=(\mu_1,\ldots\mu_n), \quad n\in N,$$

in which N is the set of all current and future members of society. The individual utility levels are given by μ_n. This utility structure is in much need of condensation. Otherwise, the multidimensionality of the loss l makes it a formidable, and contemporaneously impossible, task to represent it in policy by estimation. That does not alter the fact that any decision affects welfare and has loss associated with it. Thus, condensation using state-of-the-art techniques is a necessity in optimum data based policymaking. Condensation is what cost-benefit analyses attempt to do, by assigning equal weight to each monetary unit.

Typically, economists use estimates of the expectation of net cost, but there is no reason why not, except for tractability reasons, the whole distribution of costs should be employed. The cost-benefit concept is itself limited in scope as it usually represents estimates of tangible values, i.e. transformations of market, actual or hypothetical, bids. In theory, any concept of social consequence may be used. Economists increasingly accept that utility is extracted not only from consumption streams, but also from knowledge about the state of the world, existence of certain features and natural phenomena, options of opportunities, and distribution of welfare. As a consequence, methods have been developed and are under improvement to assess such values. Hanemann (1994) discusses the use of one such method, the contingent valuation method and comments upon the controversies the method has evoked. Hanemann, even if controversial, is in accordance with earlier authors. For example, Kenneth Arrow (1963: 17) wrote: «The individual may order all social states by whatever standards he deems relevant.» Moreover, Gary Becker (1993: 386) stated: «Individuals maximize welfare as they conceive it, whether they be selfish, altruistic, loyal, spiteful, or masochistic.» Finally, Schelling (1968) suggested an eclectic approach to obtaining priority lists by saying that the price system is only one way to find out what things are worth to people. Another one is to ask them. And asking is performed in a referendum; it is a mechanism designed to elicit preference rankings from society. Potentially, then, approaches emulating the contingent valuation method or actively using public referenda may be employed to obtain the perceived or experienced loss from much wider sources than has been attempted so far. In obtaining a social loss function in policymaking, it is a necessary requirement that light be shed on the welfare associated with different outcomes.

Social Strategy

The economy is an apparatus society use to produce welfare. By clever organization and good arrangement of institutions society inspires effort and performance from its members. Intermediate products are goods and services, and they are distributed to people for their private disposition. The end product is welfare. How to ensure welfare to the members of society is one of the most studied topics in all of economics, political science, and philosophy. One main strain in the literature is the application of a *strategy* to use in the construction of welfare. In an influential contribution, Rawls (1971) outlined a theory of justice. In the theory, he discussed strategies that could be employed when addressing equity and distribution questions. There are many potential strategies so the goal becomes to obtain social strategies that represent individual attitudes in some specified way. Arrow (1963) showed that is a complex issue, and some permutations of individual preferences cannot be aggregated without imposing specific constraints. Recently, Barbera (2001), and Knoblauch (2001) examine some aspects of the social choice inherent in adopting such social strategies. Barbera is concerned with establishing collective choices that best correspond to the member individuals and characterize classes of social choice functions for different models. Knoblauch studies how elections can represent preferences and investigate properties of elections. The contributions demonstrate the inherent difficulty. Nevertheless, the need for strategy is inescapable since a policymaker may choose not to embrace a strategy, but that would also be a strategy. Thus, in optimum data based policymaking the strategies employed are sought to represent the opinion of the electorate. The social strategy is constructed to pick a decision rule on the basis of the appropriate measure of outcome, so it is a mapping from a possibility space of states and decisions rules to one particular decision rule, symbolized in compact notation:

$$(5)\quad (s=k,d\_1,\ldots,d\_4;\mu)\xrightarrow{s} d\_i,$$

$$k=0,1;\qquad i=1,\ldots,4,$$

in which S denotes social strategy. Above, risk was one example of measure M that is a function of a combination of state and decision that would augment the choice of strategy. Maximum minimum risk and maximum Bayes risk were two examples of goals for social strategies, defined on the measure M. There are many other issues to consider, i.e. many other measures M_j, the subscript j being element in large set containing what humans care about. Current equity is one. Intergenerational justice and sustainability is another. Option values and irreversibility are yet others. The list may become as large as societal concerns are numerous. Still, it becomes clear that in order to perform optimum data based policymaking strategies must be employed to choose among the many different decision rules.

Discussion

The process from data to policy is intricate, as the above has illustrated. We have compressed the process down to three essential elements: evidence, consequence, and strategy. Such simplification enhances comprehension, but entails overlooked important facets and issues. Thus, there are weaknesses in a general framework. Let us discuss some. First, the framework considers merely one iteration of the process from data to policy. In reality, the process is an ongoing exchange between implemented policy and reception of new data. A multiple iteration model would show that a process may converge towards a reflective equilibrium between policy and data or diverge for political or other reasons. The difference between convergence and divergence cannot be portrayed in our framework. Second, we have considered a binary model in which the state-of-the-world and the decision universe have two categories, leading to a four-cell outcome space. Making both continuous would have reflected the world better and made the framework more realistic. However, sophistication is warranted only when it invites deeper insights. Here, the introduction of continuity in the models would have facilitated a gradual increase in policy realism and made the application of the framework more operational, but it would have weakened the emphasis on the broader policy scheme.

Another concern is the utopian ideal of an ideal policymaker. Principal-agent models and public choice theory have shown that policymakers may have private loss functions and hidden agendas. In fact, a whole field of thought emerged with Buchanan and Tullock (1962) to study many such aspects descriptively. But this does not preclude an exposition of an optimum data based policy formation process normatively. Further, most policymakers probably operate on a convex combination of public and personal loss functions. Then there is a need to acquire an overview of the interplay between the public loss function and data, and present a special clarification when public policy must be distinguished from private strategies because of different loss functions.

Concluding Remarks

In policymaking, making errors may be more dramatic than in research. Therefore, a policy may sometimes be implemented without scientific proofs of the policy's merits. Additionally, while scientists often are concerned with type-I-errors, a policymaker must weigh both type-I and type-II in each and every policy proposal according to the social outcome. For example, failing to implement a necessary policy directed at global warming can be much more dangerous to humankind than falsely implementing an unnecessary policy. In policymaking committing a type-II error may sometimes be perilous while making a type-I error merely annoying. For a scientist, it may be the opposite. Falsely rejecting a true null (type-I-error) may entail loss of prestige, while failing to reject a false null (type-II-error) is shared with many other scientists, thus comes with low cost. Thus, a policymaker must distinguish between the different kinds of loss functions. To balance data with doubt, to consider social consequences, and to project public opinion on welfare matters, a policymaker needs assessment of three elements: evidence, consequence, and strategy.

The three elements may be illustrated in a sequence of three steps. First, the evidence found in data yield scenarios and probabilities emerging from scientific scrutiny and the employment of metrics and instruments. Second, the policymaker attaches social consequences to each scenario. The consequences comprise the loss function and have the role of weights in comparing the outcomes. Third, to choose between different actions and decision rules the policymaker uses a strategy that mirrors a public mandate from an electorate. The three-step process comprises the basic elements of an optimum data based policy.

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