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Epistemic Values and the Argument from Inductive Risk*

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Critics of the ideal of value-free science often assume that they must reject the distinction between epistemic and nonepistemic values. I argue that this assumption is mistaken and that the distinction can be used to clarify and defend the argument from inductive risk, which challenges the value-free ideal. I develop the idea that the characteristic feature of epistemic values is that they promote, either intrinsically or extrinsically, the attainment of truths. This proposal is shown to answer common objections to the distinction and provide a principled basis for separating legitimate from illegitimate influences of nonepistemic values in scientific inference.

1. Introduction. The ideal of science as insulated from social, political, and moral values has been debated from a variety of perspectives in the philosophical literature in recent years (Lacey 1999; Longino 2002; Machamer and Wolters 2004; Kincaid, Dupré, and Wylie 2007). One of the strongest challenges to the ideal of value-free science is posed by what I call *the argument from inductive risk*, according to which nonepistemic values *should* influence standards of evidence required for accepting or rejecting hypotheses when there are significant social costs associated with errors. This argument, inspired by the practice in statistics of setting rates of type I and type II errors on the basis of their relative costs, was a lively topic of dispute in the philosophy of science literature in the 1950s and 1960s (Rudner 1953; Churchman 1956; Jeffrey 1956; Levi 1960, 1962, 1967; Hempel 1965). More recently, the argument has been revived by philosophers concerned with scientific assessments of risks posed by toxic chemicals (Shrader-Frechette 1991; Cranor 1993, 2006; Douglas 2000, 2007).

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However, the argument from inductive risk stands in need of elaboration with respect to the contested distinction between epistemic and nonepistemic values. After all, the argument's chief purpose is to convince us of the unavoidable role of nonepistemic values in scientific inference. Moreover, since not all impacts of nonepistemic values on scientific inferences are salutary, advocates of the argument from inductive risk must distinguish good intrusions of nonepistemic values from bad ones. Yet the distinction between epistemic and nonepistemic values is often associated with the ideal of value-free science (Rooney 1992; Longino 1996; Douglas 2007, 2009). As Douglas puts it, "A clear demarcation between epistemic (acceptable) and non-epistemic (unacceptable) values is crucial for the value-free ideal" (2009, 89–90). And indeed, proponents of the ideal do invoke the distinction in defense of their views (McMullin 1982; Lacey 1999). It is tempting, therefore, to assume that a critic of the value-free ideal must also object to the distinction between epistemic and nonepistemic values. In what follows, I show that this assumption is not only mistaken but also unfortunate because it obscures the usefulness of the epistemic/nonepistemic distinction for a positive account of the role of values in science.

First, I propose and defend a distinction between epistemic and nonepistemic values that can support the argument from inductive risk. I develop the idea that epistemic values are distinguished on the grounds that they promote the attainment of truth. Central to my proposal is a distinction between what I call intrinsic and extrinsic epistemic values. An epistemic value is intrinsic if manifesting that value constitutes an attainment of or is necessary for truth. For example, empirical accuracy is an intrinsic epistemic value because an empirically accurate theory is a theory whose consequences for observable phenomena are mostly true. In contrast, testability is not an intrinsic epistemic value, but a preference for testable hypotheses arguably promotes the attainment of truth indirectly by enhancing the efficiency of scientific inquiry (Popper 1963). Thus, testability is an extrinsic epistemic value. I explain how this approach answers objections to the epistemic/nonepistemic distinction. In addition, I consider a recent defense of the argument from inductive risk that attempts to avoid relying on the distinction between epistemic and nonepistemic values and argue that it does not succeed.

Next, I explain how my proposal leads to a principled account of the difference between epistemically legitimate and illegitimate influences of nonepistemic values on scientific inference. Influences of nonepistemic values on scientific inferences are epistemically bad if and only if they impede or obstruct the attainment of truths. Since there are many aspects of scientific inference that are not dictated by epistemic values, the influence of nonepistemic values can often be epistemically harmless. For example, epistemic values rarely dictate exactly how much data to collect before accepting or rejecting a hypothesis. Thus, there may be several epistemically reasonable methods or procedures that differ with regard to the speed with which they draw inferences. In such a case, nonepistemic values may influence which procedure is adopted. I argue that a similar case can be made for procedures that are designed to favor some types of errors over others, a point I illustrate with a discussion of the use of uncertainty factors in assessing the toxicity of chemicals.

2. The Argument from Inductive Risk. The classic statement of the argument from inductive risk in the philosophy of science literature occurs in a (1953) paper by Richard Rudner titled "The Scientist *qua* Scientist Makes Value Judgments."[1] After explaining why he finds previous arguments on both sides of the issue unsatisfactory, Rudner proceeds to offer what he describes as "a much stronger case . . . for the contention that value judgments are essentially involved in the procedures of science" (2). That argument leads off with the following assertion: "Now I take it that no analysis of what constitutes the method of science would be satisfactory unless it comprised some assertion that the scientist as scientist accepts or rejects hypotheses" (2).

Rudner then discusses several examples in which decisions about what level of certainty one demands before accepting a particular hypothesis depend on the practical or ethical consequences of being mistaken. For instance, he suggests that a level of certainty that suffices for accepting that a belt buckle stamping machine is not defective would not be enough to justify accepting that the level of a toxic constituent in a drug is sublethal (1953, 2). These examples lead to the second premise of Rudner's argument: "In general then, before we can accept any hypothesis, the value decision must be made in the light of the seriousness of the mistake, that the probability is *high enough* or that, the evidence is *strong enough*, to warrant its acceptance" (3). From these two premises, Rudner concludes that value judgments about the seriousness of mistakes are an unavoidable aspect of accepting a scientific hypothesis. He notes that this reasoning is implicit in widely used statistical significance tests (3), wherein one decides which of the two errors is worse (the type I error), then sets the rate of that error at an acceptably low level, and then makes probability of the other error (type II) as low as possible given the error rate of the first. Normally, the type I error consists of rejecting the null hy-

1. Other philosophers also published versions of the argument from inductive risk around the same time as Rudner (cf. Braithwaite 1953, Chapter 7; Churchman 1956). However, Rudner's formulation stands apart in virtue of its clarity, concision, and engaging style.

pothesis when it is in fact true. For instance, in assessing the toxicity of a chemical, the null hypothesis might be that a specific level of exposure to the chemical has no toxic effect. The type II error would then be the failure to reject the null hypothesis when it is in fact false.

It will be helpful to have a concise paraphrase of Rudner's argument in the language used here.

1. One central aim of scientific inference is to decide whether to accept or reject hypotheses.
2. Decisions about whether to accept or reject a hypothesis should depend in part on nonepistemic value judgments about the costs of accepting the hypothesis when it is false and rejecting it when it is true.
3. Therefore, nonepistemic values should influence scientific inference.

To avoid ambiguity, I substitute "nonepistemic values" for Rudner's "values," since the argument is controversial only to the extent that the values in question are not epistemic but rather concern such things as avoiding harms to human health. I also interpret Rudner's claim that values are "essentially involved" in scientific inference as a normative claim, that is, as the claim that nonepistemic values *should* influence standards of evidence demanded for accepting and rejecting hypotheses. Finally, the term acceptance should be understood in a cognitive and not merely practical sense. That is, what makes the argument from inductive risk controversial is its claim that nonepistemic values should influence what hypotheses and theories scientists *believe*, not merely what research projects they choose to pursue or hypotheses they choose to investigate. There are at least two accounts of acceptance in the literature that are compatible with the proposal advanced here (Harsanyi 1985; Maher 1993).

Various objections have been raised against the argument from inductive risk (Jeffrey 1956; Levi 1960, 1962, 1967; McMullin 1982; Lacey 1999). I will not review these objections here for reasons of space and because I think that other defenders of the argument from inductive risk, especially Douglas (2000, 2007, 2009), have done a good job of responding to them.

3. Epistemic versus Nonepistemic Values. Since its conclusion makes reference to nonepistemic values, a thorough defense of the argument from inductive risk cannot avoid taking some stance on that controversial distinction. In this section, I defend the idea that the characteristic feature of epistemic values is that they promote the attainment of truth, either intrinsically or extrinsically. I explain how this proposal is not undermined by objections to the epistemic/nonepistemic distinction. Finally, I argue that a recent attempt to defend the argument from inductive risk without the epistemic/nonepistemic distinction is unsuccessful.

3.1. Epistemic Values and Truth. Epistemic values are naturally understood as values that promote the acquisition of true beliefs (Goldman 1999). Truth should be understood in connection with truth content: a true and very informative belief is more epistemically valuable than a true but trivial belief. However, truth does not necessarily mean true theories. For instance, the ability to make accurate predictions is an example of the attainment of truth, since accurate predictions are true or approximately true statements about the future. Hence, defining epistemic values in terms of the attainment of truth does not imply any commitment to scientific realism. Some values may promote true predictions about observable things while other values frustrate that aim, and hence fervent antirealists and table-thumping scientific realists alike can care about epistemic values.

In addition, the distinction between intrinsic and extrinsic epistemic values requires some explanation. Intrinsically valuable things are good in their own right, whereas extrinsic goods are valuable because they are means for promoting intrinsic goods (Anderson 1993, 19–20). Thus, a value is intrinsically epistemic if exemplifying that value either constitutes an attainment of truth or is a necessary condition for a statement to be true. For example, predictive accuracy is an intrinsic epistemic value, because to be able to make accurate predictions is to have attained an important truth-seeking aim, namely, the ability to form true beliefs about the future. The epistemic status of consistency is somewhat more complex. Consistency is commonly divided into two subtypes: internal and external. Internal consistency means an absence of self-contradictions, while external consistency refers to an absence of contradictions with other accepted beliefs. Internal consistency is a straightforwardly intrinsic epistemic value, since it is a necessary condition for truth. Whether external consistency is an epistemic value, however, depends on the truthfulness of the accepted background beliefs. If those beliefs are significantly false (e.g., that the earth is the center of the universe and is no more than 10,000 years old), then external consistency can be a major impediment to the attainment of truth.

Epistemic values are extrinsic when they promote the attainment of truth without themselves being indicators or requirements of truth. A good example of an extrinsic epistemic value is Popper's criterion of testability. The more precise and informative a theory's empirical predictions are, the greater its testability. Testability alone is not an intrinsic epistemic value, because a theory that makes a wide range of precise yet false predictions is nevertheless very testable and an untestable theory might be true. However, Popper (1963) argued that a preference for testable theories promotes the attainment of truths by increasing the efficiency of scientific inquiry. An untestable theory, even if true, is a scientific dead end that leads to no further gains in empirical knowledge, while highly testable theories, even if false, generate predictions that may spur scientific discoveries.

As another example of an arguably extrinsic epistemic value, consider simplicity. Simplicity would be an intrinsic epistemic value only if the world were simple, since otherwise there would be no reason to judge simplicity as an indicator of or requirement for truth. Yet a general presumption that we inhabit a simple world hardly seems a promising basis for simplicity as an important epistemic value. But simplicity might be an extrinsic epistemic value even if it is not an intrinsic one. There are in fact two approaches for making this case with regard to examples, such as fitting curves to a scatter of data, in which simplicity can be given a reasonably precise meaning. One approach is to show (subject to various qualifications) that minimizing expected predictive errors requires selecting a curve that strikes the right balance between simplicity and closeness of fit with the data (Forster and Sober 1994). That is, while closer fit with data can normally be had by selecting a more complex curve, "overfitting" the data with an excessively complex curve increases the chance of a greater mismatch between future data and predictions. A second account of simplicity explains how a preference for simpler hypotheses promotes efficient convergence to the truth, where efficiency is understood in terms of minimizing the maximum number of times the investigator can switch from conjecturing one hypothesis to another (Kelly 2007a, 2007b). Both of these accounts, then, defend simplicity as an extrinsic epistemic value. In both cases, a preference for simpler hypotheses is argued to promote the attainment of truth (either of approximately true predictions or efficient convergence to true hypotheses), yet neither approach presumes that the world is simple.

There are some other aspects of epistemic values as understood here that are worth making note of. Epistemic values can be manifested by things other than theories and hypotheses, such as methods, social practices, and community structures. For example, several philosophers have proposed that open debate among peers who represent a diversity of viewpoints is more likely to promote the acquisition of truth than a hierarchical system in which investigators must defer to authorities (Popper 1966, 217–218; Longino 1990). If that is right, then values that promote free and open discussion in science are epistemic values. Another important feature of epistemic values is that they often interact with one another. For example, testability *alone* is not an intrinsic epistemic value, but testability is an intrinsic epistemic value when combined with empirical accuracy. For theories that are empirically accurate, greater testability means more informative true empirical consequences. But testability is not an intrinsic epistemic value for highly inaccurate theories: for such theories, greater testability merely translates into more precise falsehoods. Some epistemic values, such as empirical accuracy, are very robust in the sense of being epistemic in almost any setting. Other epistemic values are contextual in the sense that their capacity to promote the attainment of truth depends on occurring within a specific set of circumstances. That point is illustrated by external consistency: its status as epistemic depends on the truthfulness of our background beliefs. Contextual epistemic values also raise the possibility that a value might be epistemic in one historical period but not in another. For example, external consistency might fail to be an epistemic value in a period in which background beliefs are seriously mistaken but become an epistemic value at a later time when the quality of background beliefs has improved.

Some may have the intuition that an epistemic value in one place and time must be an epistemic value everywhere and always and hence that there can be no contextual epistemic values.[2] But this idea cannot be maintained by anyone who holds that epistemic values are distinguished by their capacity to promote the acquisition of true beliefs. For what is truth promoting and what is not can depend on the actual state of the world, which is evidently not always and everywhere the same. That point is illustrated by external consistency: whether background beliefs are mostly truthful depends on what those beliefs are and what the world is like. One might object that allowing contextual epistemic values leads to undesirable consequences, for example, that fundability could count as an epistemic value if funding is necessary for research. However, I do not think that this consequence is a genuine problem. If I must choose between research projects A and B, where A will produce new knowledge and B will not, then I have an epistemic reason to pursue A. And fundability is one factor that can influence whether a research project will generate knowledge. Thus, I see no good reason to deny that fundability can be an epistemic value, as long as one keeps in mind that it is a reason to choose a research project and not a reason for believing that what is funded is true. One might attempt to sharpen the objection by observing that funding sources could refuse to support some worthwhile topics of research. But this shows only that a social system can create individual incentives that result in bad consequences overall. (For example, each researcher has an epistemic incentive to choose A, but it would be epistemically best for science as a whole if some chose A and others chose B.) In such circumstances, the only remedy is to change the system.

As drawn here, the distinction between epistemic and nonepistemic values differs from a number of other distinctions with which it is often

2. This viewpoint was expressed by an anonymous referee.

associated. For instance, the distinction between epistemic and nonepistemic values does not correspond to a distinction between facts and values. Epistemic values are not distinguished by being factual rather than evaluative: they are distinctive in virtue of promoting the acquisition of truths. The difference between epistemic and nonepistemic values is also not the same as Longino's distinction between constitutive and contextual values (1990, 4–7). Constitutive values are grounded in the aims of science itself, while contextual values are features of the broader social environment of which science is a part. This is not the same as the epistemic/nonepistemic distinction, because a contextual value might promote the attainment of truths and a constitutive value might fail to do this if truth is not the sole aim of science.

A word on the concept of truth assumed in this discussion is in order. All that I assume about truth is that it satisfies the following transparency condition: "*P*" is true if and only if *P*.[3] For example, "Ice is cold" is true if and only if ice is cold. Despite its seemingly trivial nature, the transparency condition does conflict with some theories of truth. For instance, consider a pragmatic theory of truth according to which whatever is useful for a person to believe is true. That this pragmatic theory of truth violates the transparency condition can be seen by examples such as the following: it is useful for Tom, who is 5 feet 10 inches, to believe that he is 6 feet tall, since this belief enhances his self-esteem. There are several theories of truth that satisfy the transparency condition, and for the present purposes there is no need to express favor for any one of them over the others.[4] Finally, I should say something about how the term "value" is used here. Values function as what Solomon calls "decision vectors," that is, factors that "influence the outcome (direction) of a decision" (2001, 53). However, not all decision vectors would normally be thought of as values. For example, sexist bias is a decision vector but would not be a value in a social setting in which sexism is frowned on. Values, then, are decision vectors that are favorably regarded in a community.

3.2. Answers to Critiques. In this subsection, I explain how my account of epistemic values answers objections that have been raised against the epistemic/nonepistemic distinction. One line of objection claims that there is no clear distinction between epistemic and nonepistemic values. For example, Rooney argues that the lack of agreement among proposed lists of epistemic values provides evidence of this: "The fact that there is no consensus about what exactly the epistemic values are surely provides our

3. I follow Maher (1993, 208–209) in this.

4. See Blackburn and Simmons 1999 for a survey of the leading theories.

first clue here. We haven't seen anything resembling a clear demarcation of epistemic values because there is none to be had" (1992, 15). But disagreement about the application of a concept is not necessarily evidence that it lacks a reasonably clear definition. For example, spectators at football games sometimes disagree about whether a ball carrier scored a touchdown on a particular play. But this is not evidence that there is no clear definition of what constitutes a touchdown (the criterion is that the ball must break the plane of the end zone while in the grasp of the carrier). Rather, disagreements result from the fact that, in some cases, it is difficult to know whether the definition is satisfied, for instance, when the view of the ball carrier is obscured by a crowd of other players. Similarly, disagreements about epistemic values are not necessarily evidence that there is no clear definition of epistemic. According to the account of epistemic values proposed here, disagreements occur because it is sometimes a very complex and difficult question whether a particular value promotes the attainment of truth. Moreover, my proposal can explain why some values are regarded by almost everyone as epistemic while other values are more controversial. Every list of epistemic values that I know prominently includes empirical accuracy or some close variant. Since empirical accuracy is a robust and intrinsic epistemic value, this is exactly what one would expect given my approach. However, the status of simplicity as an epistemic value is far more contentious. That is also not surprising. Simplicity is usually not an intrinsic epistemic value, and attempts to show that simplicity is an extrinsic epistemic value require a heavy dose of technical concepts and complex mathematical or logical reasoning. So, the uncontroversial epistemic values are obviously truth conducive, while the controversial epistemic values are ones whose connection to truth is much more complex. This situation is more easily explained by the approach defended here than by the claim that there is no clear distinction whatever between epistemic and nonepistemic.

Another argument that there is no clear distinction between epistemic and nonepistemic values points out that it is impossible to disentangle social from epistemic (Machamer and Douglas 1999; Machamer and Ozbeck 2004). I think that this line of criticism has merit as an objection to some proposals about how to distinguish epistemic from nonepistemic values, but it is not an objection to the account advanced here.[5] Given my account, social is not the appropriate contrast with epistemic. Epistemic values are contrasted with values that do not promote the attainment of truth, either because they have no impact whatever on that goal or because they obstruct it. Both epistemic and nonepistemic values can

5. See, e.g., Machamer and Douglas's (1999) critique of Lacey's attempt to distinguish cognitive values from social values by means of "materialist strategies" (1999, 68).

be and typically are social. Indeed, an epistemic value must be embedded in the social practices and norms of a scientific community if it is to have any impact on science. Epistemic, therefore, should not be contrasted with social, historical, contingent, or contextual. An epistemic value may be a social norm with a complex history, and its status as epistemic may depend on contingent facts about the world and the context of social practices within which it operates. Sometimes the thrust of the can't-disentangle-social-from-epistemic objection seems to be that the nonepistemic values prevalent in a social milieu can influence what a person thinks the epistemic values are (Rooney 1992; Douglas 2009, 90). It seems very probable that this claim is true, but that is no reason for concluding that there is no clear distinction between epistemic and nonepistemic values. To continue the football analogy, a person's allegiances may influence whether she thinks a touchdown was scored, but this does not show that the term "touchdown" lacks a clear definition.

Another objection is that epistemic values are too anemic to guide scientific inquiry toward consensus and, consequently, that other sorts of values must influence scientific judgments (Rooney 1992, 15–20; Longino 1996; Laudan 2004; Douglas 2009, 93–94). This objection is a challenge to the usefulness of the concept of epistemic values rather than to the cogency or existence of that concept. The thought behind the objection seems to be that defenders of epistemic values believe that, in a perfect world, epistemic values alone would guide scientific inference. Hence, the objection goes, if epistemic values can be shown incapable of this, the reason for distinguishing epistemic from nonepistemic vanishes, and the distinction is useless. However, the objection shows, at best, only that the distinction between epistemic and nonepistemic values is not useful for defending the ideal of value-free science. But I think it should be clear that this is not the only use to which the epistemic/nonepistemic distinction might be put. For example, my purpose in upholding that distinction is to provide a better defense and articulation of the argument from inductive risk, which attempts to show that nonepistemic values *should* influence decisions to accept or reject hypotheses. In addition, I think that these critics tend to exaggerate the incapacity of epistemic values to guide scientific inference. For instance, they often do not consider the possibility of extrinsic epistemic values. Thus, Longino insists that simplicity could be an epistemic value only if the world were simple (1996, 53). Another mistake is to neglect the difference between truth content and probability. From an epistemic perspective, the more truth the better, and hence it is epistemically valuable for an empirically accurate theory to be highly informative regardless of whether it is highly probable. Laudan misses this point when he suggests that there can be no epistemic reason for saying that a theory is good but false and no epistemic grounds judging a theory with greater scope to be superior to one that is more narrowly restricted (2004, 18–19). After all, Laudan reasons, the probability of the false theory is zero, and the probability of the more restricted theory must be greater than or equal to the probability of the one with greater scope. But this shows only that probability is not the same as truth content. A false theory may be of epistemic value if it makes many true predictions (as the case of Newtonian mechanics illustrates), and the wider the range of accurate predictions, the better.

3.3. Without Epistemic Values? A final objection charges that the epistemic/nonepistemic distinction is unnecessary because a better understanding of the role of values in science can be achieved through abandoning it. This idea is elaborated in greatest detail and sophistication in a recent book by Douglas (2009). While Douglas differentiates ethical, social, and cognitive values, the key distinction in her account is not between distinct types of values but between what she calls direct and indirect *roles* of values in scientific work (87–88). A value plays a direct role in a decision if it is a reason for choosing one of the alternatives over the other (96). For example, a scientist might choose a research project because it stands the best chance of getting funded, or she might accept a hypothesis because it makes more accurate predictions than its rivals. In these cases, funding and accurate predictions, respectively, play a direct role in the decisions. A value plays an indirect role in a decision when it is a reason for choosing standards that are directly applied in the decision-making process (96–98). For example, the desire to protect human health could justify setting a low threshold of evidence for detecting carcinogens, but it is not itself a reason that could be given to favor a particular hypothesis. Finally, Douglas distinguishes values from what she terms "criteria," such as internal consistency and empirical accuracy, that are directly tied to the ultimate aim of science to produce "reliable knowledge" (94). Douglas's central claim, then, is that values should play a direct role *only* in such contexts as judgments about which research projects to pursue, which to fund, which methodologies to employ, and what standards of evidence to adopt (98–102). She is unequivocal in demanding that values should never play a direct role in deciding which hypothesis or theory to accept: "Our values, whether social, ethical, or cognitive, have no direct bearing on the way the world actually is at any given time. Thus, when deciding upon which empirical claims to make on the basis of the available data or evidence, values should play only an indirect role" (103). Instead, only empirical criteria such as compatibility with the evidence should play a direct role in decisions about which hypotheses to accept or reject.

I think that Douglas's account of the proper role of values in science does not succeed in dispensing with the distinction between epistemic and nonepistemic values. Her proposal crucially relies on a distinction between values and what she characterizes as criteria for acceptable science. The centerpiece of her account is the claim that only epistemic criteria, such as compatibility with the data or internal consistency, should be allowed to play a direct role in the evaluation of scientific hypotheses. But then "epistemic criteria" are playing the role of "epistemic values," and the only difference seems to be a switch from "value" to "criterion." Douglas provides the following reason to think that this is more than a terminological change: "so-called 'epistemic values' are less like values and more like criteria that all theories must succeed in meeting. One must have internally consistent theories; one must have empirically adequate/conforming/predictively competent theories. Without meeting these criteria, one does not have acceptable science" (2009, 94). I do not think that this is a reason for denying the label "epistemic value" to consistency and empirical accuracy. Values that are deeply intertwined with core aims of science are still values. Moreover, they possess characteristics associated with values by Kuhn (1977, 330–333); most important, they function as decision vectors rather than as categorical rules. Unlike categorical rules or absolute criteria, decision vectors can be balanced against one another. For example, empirical accuracy might be balanced against external consistency or simplicity.

The proposal advanced here differs from Douglas's account in several ways. The role of epistemic values is explicitly acknowledged, and their complexities—such as context dependence and interactions—are explored. Furthermore, Douglas's division between direct and indirect roles does not correspond to my distinction between intrinsic and extrinsic epistemic values. For example, testability is an extrinsic epistemic value, but according to my proposal, it can legitimately play a direct role in deciding which hypothesis to accept.

4. Nonepistemic Values and Nonobstruction of Truth. In this section, I explain how the distinction between epistemic and nonepistemic values drawn in the previous section leads to an account of the proper role of nonepistemic values in scientific inference. The main theme is that influences of values on science are epistemically bad when and only when they hinder or obstruct the attainment of truth. This leads to the question of how nonepistemic values might influence scientific inferences without compromising epistemic aims. I focus on two possibilities that are relevant to the argument from inductive risk, the first having to do with how long one waits before drawing an inference and the second with judging some errors as worse than others and adjusting one's methods accordingly.

4.1. How Long to Wait? According to the approach advanced here, intrusions of nonepistemic values are epistemically bad if and only if they interfere with, block, or obstruct the acquisition of truths. Of course, epistemic goods are far from being the only type of good there is. For example, moral values are often thought to trump epistemic values, as is illustrated by commonly accepted prohibitions on unethical experimentation. Not everything that is epistemically good, therefore, is good, all things considered. However, the argument from inductive risk is not intended as a justification for preventing particular sorts of data from being collected or certain types of experiments from being performed. Instead, it concerns the processes by which inferences are drawn from those data that do become available. In that context, it is reasonable to place greater weight on epistemic values. Thus, the influences of nonepistemic values supported by the argument from inductive risk should endeavor to avoid compromising epistemic ends.

Nonepistemic values can influence scientific inference without conflicting with epistemic values only if epistemic values do not completely determine all aspects of scientific inference. Epistemic values must allow some leeway, some wiggle room for nonepistemic values to operate. There are several ways this might occur. The simplest would be if epistemic values placed virtually no constraints whatever on scientific inference. However, I do not find this idea very plausible, and, in any case, the argument from inductive risk has no need for grand claims about underdetermination. Uncertainties arising from practical challenges faced by specific scientific fields, such as toxicology or climate science, are more than sufficient (Lemons, Shrader-Frechette, and Cranor 1997). Suppose, then, that epistemic values normally do place some genuine restrictions on what could and could not be reasonably inferred in a given scientific setting. In such circumstances, nonepistemic values might still have room to operate without obstructing epistemic ends. One example of this that is relevant to the argument from inductive risk concerns how long one waits, and how much evidence one demands, before drawing an inference.

The aim of forming true beliefs while avoiding falsehoods inevitably requires a balance between drawing an inference quickly and waiting for further evidence that reduces uncertainties. Very high standards of evidence can postpone the acceptance of truths, but those same high standards may save us from errors. Lower standards of evidence will have the opposite effect. While it is obvious that avoiding error is an epistemic good, it is worth explaining why speed of inference is also epistemically valuable. Since knowledge is the good with which epistemology is concerned, the longer the time spent in the possession of knowledge, the better from an epistemic standpoint. By analogy, health is the good with which medicine is concerned, and hence the more time a person spends in a state of health, the better from a purely medical perspective. Thus, if two scientific methods A and B are equally reliable but A is quicker, then A is better on purely epistemic grounds. Furthermore, it would be a mistake to suppose that stricter standards of evidence are always epistemically preferable, since extremely high standards can stifle the growth of knowledge. For example, modern science would be impossible if mathematical proof were the criterion for acceptance of scientific theories. The trade-off between the speed and reliability of scientific methods, therefore, is a trade-off between two epistemic values. Hence, if A is slightly more reliable but B is quicker, there may be no clear answer as to which is epistemically preferable.

A slower, more cautious approach to balancing the reliability and speed of inference is commonly thought to be adopted in research science. One reason given for this is that an accepted scientific belief is a potential building block for further results, so that one scientific error will have a tendency to generate more errors (Cranor 1993, 25–26; Peterson 2007, 7–8). However, this "building block" argument does not show that very high standards of evidence are always epistemically preferable. Even when results are used as a basis for further results, the desire to avoid error must still be balanced against the epistemic costs of suspending judgment for too long. Excessively stringent standards of evidence would impede science by giving scientists very few "blocks" of accepted beliefs to build on. In addition, not all scientific results are used as foundations for further research. Some are used primarily for some practical purpose, such as setting allowable exposure levels to toxic chemicals or predicting climate trends. Claims about reference doses of chemicals are more like scientific endpoints than building blocks for future knowledge.

In many cases of concern to the argument from inductive risk, therefore, the building block argument does not provide an epistemic reason for insisting that false beliefs should be considered far more costly than postponing acceptance of truths. In fact, the "building block" argument illustrates the often contextual nature of epistemic values described above. Whether more stringent standards are preferable from an epistemic perspective may depend on the uses to which the results of inquiry will be put. Consequently, methods that generate results more quickly at the cost of a higher rate of errors may be more acceptable on purely epistemic grounds when those results are to be used for some practical application rather than as a basis for further scientific knowledge. This in turn opens up a broader space of alternative methods, thereby allowing nonepistemic considerations greater opportunity to influence which method is chosen without conflicting with epistemic values.

The argument from inductive risk is often illustrated by cases in which a pressing nonepistemic value, such as the protection of human health, provides a powerful reason to draw inferences more quickly. For example, Cranor (1993, Chapter 4) argues against following conventional, cautious norms of research science when performing risk assessments of potentially toxic chemicals. Useful risk assessment not only requires drawing reasonably accurate inferences about toxic effects but also demands that those inferences be drawn in a timely manner. As Cranor observes, the result of slow, cautious approaches is widespread public exposure to a large number of potentially toxic chemicals for which no risk assessment has been performed. Thus, he recommends, "The regulatory challenge is to use presently available, expedited, approximation methods that are nearly as 'accurate' as current risk assessment procedures, but ones which are much faster so that a larger universe of substances can be evaluated" (103). Cranor considers two such expedited procedures and compares their results to those produced by slower, more conventional risk assessment approaches, finding that they do not differ too greatly (137–146). His argument, therefore, is a good example of how nonepistemic values could influence scientific inferences without compromising epistemic values. From a purely epistemic point of view, the choice between expedited and slower risk assessment methods is a trade-off: quicker inferences versus a somewhat greater chance of error. Cranor's strategy is to argue that the expedited procedures he describes fall into the class of methods that strike a reasonable balance between these two epistemic concerns (142). Thus, from a purely epistemic perspective, neither has a clear advantage over the other, whereas the expedited procedures are far superior when it comes to reducing the public's exposure to toxic substances, thereby making the expedited procedures the best option overall.

4.2. Bias and Epistemic Values. But the argument from inductive risk is not limited to suggesting that nonepistemic values should influence across-the-board standards of evidence, for instance, by adopting less stringent standards so that inferences may be drawn more quickly. It also recommends judging some errors more costly than others for nonepistemic reasons and consequently setting a higher standard of evidence for some alternatives than for others. For example, we might demand higher standards of evidence for accepting that a chemical is not toxic than for accepting that it is toxic because we think that it is better to overprotect than to underprotect against risks to human health (Shrader-Frechette 1991, Chapter 9). Varying standards of evidence for nonepistemic reasons is more controversial than uniformly raising or lowering the evidential bar, since it seems to amount to a kind of bias. This brings up a number of interesting questions. Is it a bad thing from an epistemic standpoint to favor some errors over others? Is it always epistemically bad to be biased? The answers to these questions are quite nuanced, and it is possible for nonepistemic values to influence judgments about which errors are worse without obstructing the attainment of truth.

There is in fact little plausibility to the idea that a proper scientific attitude requires judging all errors equally bad. That point is illustrated by Popper's account of testability. It is better, epistemically, to accept a false yet highly testable hypothesis than to accept a false and untestable hypothesis, because the testable hypothesis is a more effective means for advancing scientific knowledge. Similarly, it is epistemically better to accept a false hypothesis that is close to the truth than to accept a false hypothesis that is very far from the truth. For example, suppose that the actual reference dose for a chemical is 0.01 milligram per kilogram of body weight per day. Then the hypothesis that the reference dose is 0.011 is closer to the truth than the hypothesis that it is 1.1. The important question, then, is whether there is something epistemically bad about the specific type of favoring of errors advocated by the argument from inductive risk. For example, if 0.01 milligram per kilogram per day is the actual reference dose, then we might think it worse to accept 0.015 as the reference dose than to accept 0.005. Yet neither of these two hypotheses is more testable than the other, and there do not seem to be any reasonable grounds for claiming that 0.005 is closer to 0.01 than 0.015 is. So, there does not appear to be any *epistemic* reason for thinking it worse to accept 0.015 than 0.005 when the actual reference dose is 0.01. However, saying that there is no epistemic reason for it is not the same as saying that there is an epistemic reason against it. Let us turn, then, to a consideration of the epistemic value of absence of bias.

In everyday talk, a person is said to be biased when her commitment to a particular viewpoint makes her exaggerate favorable evidence and disregard contrary evidence. However, for the present purposes, psychological explanations of bias are less important than getting clear about what is epistemically bad about it. Intuitively, bias is bad because it results in a systematic tendency to either overshoot or undershoot a target, as in the case of an archer whose arrows consistently land too high. In statistics, an estimator is said to be unbiased if its expected value equals the value of the unknown parameter one wishes to estimate. To extend the archery analogy, the average value of an unbiased estimator is the bull's-eye. While lack of bias is commonly treated as a good feature of estimators in statistics, it is far from being the only desirable quality for an estimator to have. It is also important that the estimator be efficient, that is, that it be unlikely to vary too much from its expected value. An unbiased yet very inefficient estimator may be a very poor guide; by analogy, the majority of an archer's shots may be far off the mark even if their average is exactly on target. But the epistemic appeal of an unbiased *and* efficient estimator is easy to grasp: since it is efficient, the value of the estimator is very likely to be close to its expected value, and since it is unbiased, its expected value equals the actual value of the parameter. However, unbiased estimators are not always the best option. For example, there may be a trade-off between absence of bias and efficiency, and the best estimator might allow some bias in order to be more efficient. In fact, the justifications of simplicity in terms of minimizing expected predictive error mentioned above hinge on precisely this point.

Let us consider how this works in the standard example of fitting a polynomial curve to a scatter of data points. The concept of bias is somewhat more complex in this case, because the number of parameters to be estimated depends on the degree of the polynomial. For example, a linear function has two parameters, the intercept and the slope, while a second-degree polynomial, a parabola, would have three parameters. An unbiased estimator in this context is one that is unbiased for each of the parameters. An estimator that selects from the set of linear functions, then, assumes that the coefficient on x^n is zero for any $n > 1$. Thus, if the actual curve is a parabola (so the coefficient on x^2 is not equal to zero), then any estimator that considers only linear functions is biased. However, an estimator that selects from the set of linear functions is less sensitive to randomness in the data and hence will typically have less variance (i.e., be more efficient) than one that selects from a set including higher-order polynomials. And this advantage in efficiency may outweigh the costs of being biased. As a result, it may be better, from the perspective of expected predictive accuracy, to choose a linear function even when it is known that the actual curve is more complex. Thus, an unbiased estimator is preferable, other things being equal, but there are many cases in which other things are not equal and consequently in which the best estimator may be biased.

Consider the implications of all this for the question of whether to err on the side of caution, for example, by using default uncertainty (also known as safety) factors in estimating acceptable exposure levels to chemicals. Uncertainty factors are a commonly used device for erring on the side of protecting human health and the environment in the estimation of reference doses (Nielson and Ørevbø 2008). A reference dose is defined as a quantity of daily exposure over a lifetime that is without appreciable risk of harmful effects, including to susceptible subgroups. Reference doses typically cannot be estimated directly from human data and hence are usually based on extrapolation from animal experiments. One approach is to estimate a *no observed adverse effect level* (NOAEL) from animal data and then to divide that number by an uncertainty factor to arrive at the reference dose. This approach is intended to accommodate a variety of uncertainties inherent in this inference, including cross-species differences and the possibility of especially susceptible human subgroups.

Although uncertainty factors can be adjusted to the specifics of individual cases, a common practice is to apply a default uncertainty factor of 100.

Consider how the statistical concept of bias would apply in this case. The estimator could be a NOAEL derived from animal experiments and divided by the uncertainty factor, and the unknown parameter would be the reference dose. The question, then, would be how to choose the default uncertainty factors so as to minimize the bias of the estimator. But it is difficult, if not impossible, to know how to do this. For example, the toxic effects of a chemical in animals will typically differ from its toxic effects in humans, and it is almost never possible to say by exactly how much. Thus, there is no reason to think that an unbiased estimator would assume that effects in animal models and humans are the same. In fact, given what we know, it is very likely that such an approach would typically be biased toward underestimating toxic effects in humans.

Since the early use of uncertainty factors in the 1950s, there have been a number of reasons to think that humans are often more susceptible to the toxic effects of chemicals than are laboratory animals (Lehman and Fitzhugh 1953; Dourson and Stara 1983; Walton, Dorne, and Renwick 2004; Dorne and Renwick 2005). However, the state of knowledge on this topic has never sufficed to indicate how to assign numerical values to uncertainty factors so as to make estimates of reference doses unbiased. At best, it suggests a broad range of possible values. In this context, a priority on protecting human health can be a reason for selecting default uncertainty factors from the higher end of this range without compromising any epistemic values.

An additional question is why a default uncertainty factor (e.g., 100) should be widely used. One might think that it would be better from an epistemic point of view to devise uncertainty factors in an entirely case-by-case manner, since such an approach could potentially reduce the difference between the parameter and the expected value of the estimator, that is, reduce bias. But the discussion of curve fitting should make us realize the weakness of this reasoning. Even if a case-by-case approach to uncertainty factors would reduce bias, it still remains that a biased but efficient estimator may have lower expected predictive error than an unbiased but very inefficient estimator. And the use of standardized default uncertainty factors can be viewed from this perspective. Standard default uncertainty factors make estimates of reference doses less sensitive to random variations in the data and hence would decrease the variance of these estimates (which is to say, increase their efficiency). Default uncertainty factors, then, amount to a kind of simplifying assumption. Thus, a certain amount of extra bias resulting from the use of default uncertainty factors might be an epistemically reasonable price to pay for increased efficiency.

The examples from this and the preceding section illustrate that scientific inferences involve trade-offs among epistemic values and that there is often no clearly best way to strike the balance. In such cases, there is more than one epistemically acceptable method or procedure that could be used, and nonepistemic values can legitimately play a role in deciding which one to select. The method desired for ethical or practical reasons should be one of those that could have been adopted even if epistemic values were our sole concern. According to this proposal, then, the scientific merits of research influenced by nonepistemic values should be defensible on strictly epistemic terms. That places a burden on one who proposes to allow nonepistemic values to influence some aspect of scientific inference: science in which nonepistemic values have an impact must still be good science. Of course, there is no simple recipe to define "good science," and which methods are epistemically legitimate is sometimes a subject of genuine scientific controversy. However, notorious examples of bad influences of nonepistemic values on science involve obvious and gross violations of epistemic values, such as concealing unwelcome findings, harassing scientists whose research leads to undesired results, or tailoring studies to reach predetermined conclusions (McGarrity and Wagner 2008). Finally, the claim that nonepistemic values should operate within the confines of what is epistemically acceptable pertains primarily to questions about which inferences to draw from data. Legitimate ethical considerations—for example, about the rights of human subjects to provide informed consent—can trump epistemic values when deciding what sorts of experiments to allow and what data to collect.

5. Conclusion. The argument from inductive risk is one of the strongest challenges to the ideal of value-free science. And since the epistemic/nonepistemic distinction is often called on to support the value-free ideal, it is tempting to suppose that an advocate of the argument from inductive risk must also be a critic of the distinction between epistemic and nonepistemic values. In this essay, I have argued that this assumption is mistaken. What the argument from inductive risk says and whether it is defensible depends on how the distinction between epistemic and nonepistemic values is drawn. I develop the idea that the characteristic feature of epistemic values is that they promote, either intrinsically or extrinsically, the attainment of truths. I show how this proposal answers common objections to the distinction and supports the argument from inductive risk by providing a principled basis for separating legitimate from illegitimate influences of nonepistemic values in scientific inferences.

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