Review of risk and uncertainty concepts for climate change assessments including human dimensions

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Abstract

This paper discusses aspects of risk and uncertainty relevant in an interdisciplinary assessment of climate change policy. It opposes not only the objective approach (viewing probabilities as degrees of truth) versus the subjective approach (viewing them as degrees of certainty), but also situations of risk (when precise probabilities are well founded) versus situations of uncertainty (broader forms of ignorance such as Knightian or deep uncertainty, incompleteness, vagueness). It argues that the evolution of the IPCC guidelines on risk and uncertainties from the third to the fourth report can be read as a move away from a core objective and probabilistic position, to include more complex aspects of uncertainty. Still, many human dimensions such as strategic uncertainties, surprises, metaphysics, taboos and epistemic uncertainties remain missing from the IPCC guidelines' systematic typology.

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1. Introduction

Debates on risk and uncertainty often mingle two deep but distinct questions:

The first is the question of objective versus bayesian probabilities. This paper argues that these are different in nature, as the former defines degrees of Truth, while the later define degrees of Certainty. The social sciences literature relevant to climate policy uses both notions, so none can be dismissed out of hand. The example of weather risk management will show that knowing what the market believe can be as useful as knowing objective historical frequencies.

The second question is about the difference between risk and uncertainty. It is often agreed that risk refers to situations in which probabilities are well defined, while uncertainty refers to a broader form of ignorance. This means that probability theory is only one paradigm among others, which is appropriate to describe risk but (by definition, so there should be no controversy here) not uncertainty. This paper exhibits a few mathematical tools for situations in which probabilities are not well defined, but not totally unknown either. It discusses examples of contributions to the climate change literature using imprecise probabilities.

Third, in a global environmental issue such as climate change, risk and uncertainty issues do not solely come from imperfect of knowledge about the state of the world. This paper expands the discussion beyond mere `errors' to aspects of ignorance caused by human will. The relevance of these human dimensions to climate policy assessment is discussed, starting with the strategic use of information, and then extending to the notion of surprise, metaphysical issues and taboos.

It might be tempting to segregate the human dimensions of uncertainty as relevant only to the so-called soft or social sciences (i.e. those of IPCC Working Group III), with the idea that with enough time, `hard' sciences (i.e. those of Working Group I) will always end up providing precise and objective probabilities. This paper's rejects this idea by reviewing a few basic notions of the epistemology of science. With limited data (and there is only one Earth's climate change experiment), even hard science produce imprecise results. And the biggest scientific advances are also those that vastly increase, rather than decrease, the number of open questions.

2. Epistemic differences : objective truth vs. subjective certainty

The classical starting point of the discussion about risk and uncertainty is the foundation of mathematical probability theory. This foundation is the notion of equiprobability, a mathematical idealization of physical situations of perfect symmetry. Theoretically, equiprobability can be taken as a self-evident intuitive notion, in the same way as points and lines can be considered self-evident intuitive notions in Euclidean geometry.

But in practical applications involving probabilities, the numbers rarely come from such ideal models. When assessing the likelihood that the oil price is above 80$/barrel in 2010, dividing the world in equally probable events makes little practical sense. So where do the probability numbers comes from ? There is a variety of procedures to measure levels of uncertainty. So in addition to the probabilities based on symmetry, this paper will distinguish subjective probabilities, frequentist probabilities and personal probabilities. Given the historical depth and disciplinary width of the literature, there is no unambiguous choice of words, but hopefully these three adjectives will sound familiar to contemporary economists.

Frequentist approaches determine levels of probability by observation of relative frequencies. It works best when a statistically significant body of observations is available. On the contrary, when there is a low amount of evidence (a small number of observations, missing data, or correlation between experiments), the accuracy of numbers determined by relative frequencies is low.

Subjective approaches are based on the idea that the beliefs of a rational agent can be discovered by observing its choices. For example, if people buy shares in oil companies, it is generally a sign that they expect higher oil prices. This has led over the last decade to the creation of prediction markets (see Wolfers et al., 2004), that is speculative markets designed for the purpose of making predictions. Participants bet by trading assets whose final cash value is tied to a particular event or parameter. The current market prices can then be interpreted as predictions of the probability of the event or of the expected value of the parameter. Real-money prediction markets have been set up with some success to reveal market beliefs on political, financial, and technology-related questions. Regarding energy and environmental questions, there are several public play-money prediction markets but there is certainly an incentive problem with claims that are to be adjudicated in the distant future[1].

Personal approaches directly ask people to quantify their strength of opinion or level of confidence. There is a psychophysiological basis, since Sutton et al. (1965) determined that amplitude of the P300 component of the event-related brain potential increases with unpredictable, unlikely, or highly significant stimuli. In a formal expert survey, one method to elicit a probability distribution is asking the expert to dispatch a stake of 100 chips over the alternative outcomes considered. In a setting such as the IPCC writing teams, experts agree verbally.

[1] Consider for example the claim CO2LVL - CO2 Level 2030 at the foresight exchange prediction market (www.ideosphere.com) : *This claim is based on the ambient CO2 level in December of 2030. The claim pays $0.01 for each PPM by volume (PPMV) of CO2 in excess of 400 PPMV, up to 500 PPMV. For instance, 0.0 for <400.5 PPMV, 0.5 for 450 PPMV, and 1.0 for >499.5 PPMV. If available, data from the Mauna Loa Observatory will be used to judge the claim*. This claim opened in may 2002 at around $0.40 (corresponding to 440 ppmv), increased, stabilized around $0.70 between mid 2003 to mid 2005, and dropped to around $0.56 in early 2060, showing an expected value of 456 ppmv.

In contrast to the mathematical approach, for physical applications the operational procedure used to measure a variable is fundamental to the definition of what the variable is. Even if frequentist, personal and subjective probability distributions are defined by the same mathematical properties, they describe different variables. They should be viewed as having different units.

Figure 1 about here.

There are different viewpoints on the relative merits of these ways to measure probabilities. The most important division line lies between the **objective** and the **bayesian** views of probabilities[2], see Figure 1. Objective probabilities are seen as a physical propensity. They are defined using a frequentist approach or using “physical laws” models based on symmetry. Bayesian probabilities are seen as degrees of beliefs. They are defined either directly, using the personal approaches, or indirectly, using subjective probabilities. To summarize, objective probabilities are degrees of Truth, while bayesian probabilities are degrees of Certainty.

VanderMarck (2003) provides an example of the dilemma between subjective and frequentist methods in Weather risk management. Weather derivatives are contingent financial goods those value depends on the future weather, such as the number of heating degree days through the winter season. Weather is the major source of income variability in the energy sector. These financial instruments can be used to alleviate that risk. Their market has been developing rapidly since the late nineties, along with deregulation in the power industry. To evaluate a portfolio of these derivatives, one can use models based on historical weather data: that is an objective frequentist method. But there is also the possibility of valuing positions based on current market price levels. Well-known finance and econometrics techniques allow to infer the risk-neutral probability distribution of an asset from the prices of options on this asset, see for example Hull (1997) chapter 9.2. These probability distributions are in essence subjective.

VanderMarck concludes that both techniques can be used, along with hybrid approaches. The market-based approach works better when the market is sufficiently liquid, i.e. large. Financial institutions tend to be more familiar with market valuation than the frequentist model approach, since most other products they trade are solely based on supply/demand dynamics. Marking to market also ensures a more accurate reflection of a portfolio’s value should it need to be liquidated.

This example shows that the subjective methods are necessary when human beliefs and expectations are significant variables. This is a sufficient reason to allow for bayesian probabilities in an interdisciplinary assessment of the climate

[2] The same remark as above applies : The precise technical meanings of the words *subjective*, *personal* and *bayesian* have varied with time and place.

change issue, at least in the working group interested in social issues. We will argue that there are deeper reasons to use bayesian approaches even in climate sciences, but that discussion is deferred to section 5.

3. Missing, incomplete or imperfect data

The previous section presented the distinction between objective degrees of truth and bayesian degrees of certainty. The next important dimension of the debates on risk and uncertainty is the distinction between *risk* and *uncertainty*. Classically, this paper will use the word *risk* to refer to situations in which precise probabilities are well defined, while *uncertainty* refers to a broader form of ignorance.

Our point is that the two dimensions are orthogonal, so that both risk and uncertainty can be either objective or bayesian. To emphasize this uncertainty will be discussed first using a subjective approach to uncertainty, and then using an objective approach.

As discussed above, the subjective approach suggests to observe betting behavior, and use the rationality assumption to infer believed probabilities levels (Bruno de Finetti, 1937). Indeed if in a football game someone states that betting 1:1 on the home team is fair, that can be construed as a statement of equiprobability. But stating a “fair” odd is not the same as actually making a bet. If a person is observed betting at 1:1 on an event, it might be because he is certain that the event will occur, but nobody offered a better rate. The same intuition was discussed by Keynes (1921, ch. III par. 4), who explained:

> It might perhaps be held that a presumption in favor of the numerical valuation of all probabilities can be based on the practice of underwriters and the willingness of Lloyd's to insure against practically any risk. Underwriters are actually willing, it might be urged, to name a numerical measure in every case, and to back their opinion with money. But this practice shows no more than many probabilities are greater or less than some numerical measure, not that they are themselves practically definite. It is sufficient for the underwriter if the premium he names *exceeds* the probable risk.

Generally, observed betting behavior only implies upper or lower bounds on the probable risk. More precisely, observing an economic transaction on a contingent good only allows to infer that the expected value to the buyer was greater than the transaction price, and was lower for the seller[3]. If a rational actor buys 30 euros a gambling ticket giving the chance of a 100 euros prize, and further sell that ticket for 50 euros, one only learns that to the rational actor, the expected value of the

[3] Only part of the gap between the buyer and the seller's valuation come from the different beliefs about the probabilities, another part comes from the different levels of utility provided by that good. Still, given the buyer's utility function, observing the transaction provides only a lower bound on the buyer's expected value.

ticket was between 30 and 50, so that the probability of winning is between 0.3 and 0.5. This can be called a situation of uncertainty: the probability is not a well defined number, but an interval.

Uncertainty that can be represented by interval probability can also arise in a purely objective situation. Consider the Ellesberg's urn. This urn is a classical image of statistics: drawing a colored marble from a bag containing 100 such marbles. Suppose that the bag contains between 30 and 50 black marbles, and the other marbles are white. With that information, one can only say that *p*(black) is between 0.3 and 0.5.

Poorly defined probabilities are also an issue in the elicitation of expert knowledge. A practical way to elicit probabilities from an expert is to hand out a stake of 100 chips and ask the expert to distribute the chips among each alternative outcomes. The facts that experts often feel uncomfortable doing this procedure, and that when one asks an expert a certainty level for each outcome separately, numbers do not necessarily add up to unity, suggests that there may also be uncertainties about personal probabilities.

Having shown that the dimension of precision is orthogonal to the objective vs. bayesian debate, we now discuss five aspects of uncertainty, which differ by the extend to which the probabilities are not well defined. These aspects are randomness, possibility, deep uncertainty, incompleteness and fuzziness. They will be discussed using the objective example of the bag with 100 colored marbles.

Randomness: The composition of the bag is known, so there is a well founded probability distribution. For example, assuming an unchanged climate, the potential annual supply of wind, sun or hydro power in a given area is a statistically known variable. Climate is the average weather in a location over a long period of time, so climate predictions are statistical in essence. This example shows that scientific predictions are not always deterministic.

Beyond the fundamental indeterminacy in quantum theory, an important reason for randomness in science is the problem of scale and chaos. Deterministic systems can follow chaotic dynamics, when the imperfect knowledge about the present state of the world limits to the ability of science to provide predictions at the relevant timescale given. For example, the best available socio-economic description of the consequences of most mitigation measures are very likely not a deterministic model, because the global society is a complex system that may be very sensitive to initial conditions. In other words, small perturbations possibly lead to large changes in the human response to the climate issue.

Possibility: The list of outcomes is known, and there is an upper bound on the number of some colors. For example, the bag contains three colors, less than 30 black, less than 60 red and less than 100 white marbles. Stating a possibility level amounts to state an upper bound on the admissible probability of a future, knowing on the other hand that the lower bound is infinitesimal (there is an infinity of futures that could happen). Ha-Duong (2003) argued that possibility theory (Dubois et al. 1998) is more relevant than probability to quantify the plausibility of far-distant futures.

Knightian or Deep Uncertainty: Knight (1921) seminal work describes a class of situations where the list of outcomes is known, but the probabilities are imprecise. This generalizes both kinds of uncertainty above. An extreme case would be that nothing is known about the proportion of each color in the bag. However, less unspecific statements could be made that still leave deep uncertainty about the drawing's outcome. The situation of interval probability presented above, that *p*(black) is between 0.3 and 0.5 if it is known that the bag contains at least 30 black marbles and 50 white ones, is a simple example of deep uncertainty. More generally, imprecise probability theory suggests to represent such deep uncertainty using a set of equally admissible probabilities (sets being more general than intervals when there is more than two outcomes).

Ha-Duong (2003), Kriegler et al. (2003) , Borsuk et al (2004) and Hall et al. (2005) argued that the kind of ignorance about the long-term future of climate change is a situation of Knightian uncertainty that should be treated with imprecise probabilities. Kriegler (2005) made an integrated assessment of climate change using imprecise probabilities and concluded that it was very unlikely that the warming in the 21st century would remain below 2 Kelvin in the absence of policy intervention. Moreover, he found that it would require a very stringent stabilization level of around 450 ppm CO2 equivalent in the atmosphere to obtain a non-negligible value for the lower probability of limiting the warming to 2 Kelvin.

Incompleteness (absence) relates to things that can not be talked about in a given frame of reference: concepts missing from a language or variables not included in a model. There would be this kind of uncertainty in the urn example if the list of possible colors was not completely known. Probabilities distributions are normally given over a universal set Ω , which represents mutually exclusive alternative states of the world.

Transferable Belief Theory suggest to deal with absence by giving some probability weight to the empty subset {}. It is straightforward to interpret $p(\{\})$ as the probability of an event not described in Ω . Curiously, most other theories of uncertainty make the assumption that Ω is exhaustive, and rarely discuss the idea that the empty subset is after all a subset of Ω .

Climate policy assessments cannot get rid of incompleteness: it is impossible to consider any and all the technologies and physical processes potentially involved. To be precise despite this issue, IPCC guidelines stress the need to explicit as much as possible the frame of reference by asking writing teams to explain the conditions and the assumptions leading to the conclusions. There are limits to this, since no proposition can make sense without a context, but the context can never be completely explicit. In any case, it is also important to keep in mind the meaning of statements in the global context, because they will be quoted as such by the medias.

Incompleteness is acute when dealing with scenarios, since a set of scenarios do not make an exhaustive frame of reference Ω to describe the alternative futures of the energy-economy-climate system. Worst, if scenarios are given with enough precision, the probability of the scenario set itself is infinitesimal, since so many alternatives are possible. Consequently, while it could be mathematically meaningful to assign absolute probabilities level to each scenario within a set, these are probabilities conditional to a set of probability zero[4].

Fuzziness or vagueness describes the kind of uncertainty of natural language, and more generally the nature of things that don't fall sharply in one category or another. In the urn's example, given the full spectrum of colors the number of 'dark' marbles would better be represented using a fuzzy number. While fuzzy modeling could potentially be used to integrate experts' knowledge with precise quantitative informations, major integrated assessment models of energy and climate problems have not used much these techniques so far.

Informally, IPCC experts do not ignore the fact that there is vagueness in the natural language. For example, the guidance note on uncertainty is explicit that categories should be considered as having “fuzzy” boundaries. In the previous report, the « burning embers » diagram (TAR WG II fig. SPM 2) used a fuzzy graphical representation of « Reasons for concern » to assign a fuzzy quantitative meaning to the word `dangerous’ of the UNFCC article 2.

Figure 2 about here.

4. Human dimensions of uncertainty

Figure 2 shows that uncertainties are not only caused by missing information about the state of the world, but also by human volition. Global environmental change and mitigation are the outcome of social interactions. This section extends the discussion to these social and psychological aspects of uncertainty.

Strategic ignorance involves the fact that rational agents, who are aware of information can use uncertainty as a strategic tool. Strategic uncertainties are an important human dimension of the response to climate change, since this response requires coordination at the international and national level.

[4] The problem of conditioning with events of probability zero can be dealt with mathematically. Instead of defining conditional probability from the notion of unconditional probability: P(A|B) = P(A and B) / P (B), some advanced courses in Probabilities simply assume that unconditional probabilities do not exist, and consider conditional probabilities as the basic building block of the theory.

Action in the context of strategic ignorance is usually formalized with game theory using the hypothesis of information asymmetry, that is assuming that one party in a transaction has more or better information than the other party. The informed party may therefore be able to extract a rent from this advantage. The following aspects of strategic ignorance have been recognized as important in the literature:

Adverse selection is a consequence of uncertainty that degrades the quality of the participants in a market. Adverse buyers selection occurs in insurance markets : agents who know they have a higher risk will buy more insurance than those who have a below-average risk. The classical example of adverse sellers selection is the used cars market described by Akerlof (1970) : owners of good cars will be more likely to keep them for themselves. This leads to a vicious situation in which buyers presume that most used cars are bad ("lemons"), which may depress the price to the point where good car owners are not interested to sell at all.

Moral hazard occurs when the presence of a contract can affect the behavior of one or more parties (Mirrlees 1999). For example in the insurance industry, coverage of a loss may increase the risk-taking of the insured.

Free riders are actors who consume more than their fair share of a resource, or shoulder less than a fair share of the costs of its production. This issue is compounded when it is difficult to monitor the behavior of other actors. Even the possibility of free riding is likely to affect collective actions.

Information asymmetry is an important issue for the regulation of firms by governments and for international agreement. Adverse selection, free riding and moral hazard are key factors in the design of mechanisms to mitigate climate change.

However, not any strategic use of uncertainty is negative, some are generalities aimed at building agreements. Na and Shin (1998) and others suggested that generally, reaching an agreement may be easier under a "veil of uncertainty". Cooperation is more likely to emerge ex-ante, before uncertainty is resolved, than ex-post, because more agents potentially gain from the agreement before the uncertainty is resolved. In contrast, Bramoullé et al. (2004) have shown that, from an ex ante perspective, cooperation may be less likely under uncertainty. The reason is that the difference in social welfare between cooperation and non-cooperation, that is the collective gain to reach an agreement, may be lower under uncertainty. See Kolstad (2003) for a recent review.

Next we turn to social aspects of uncertainty of interest to other disciplines such as psychology or anthropology. These have a clear importance for the communication and implementation of climate policies, which require coordinated changes in people's perceptions and behaviors at all scales.

Surprise means a discrepancy between a stimulus and pre-established knowledge. Complex systems, both natural and human, exhibit behaviors that were not imagined by observers until they actually happened. Surprise is a subjective psychological state, it depends on the observer. It can occur in a situation of uncertainty, but also in a situation of randomness if a small probability event realizes.

Surprises arise because recognition of events that do not share many features with existing mental structures is difficult. Psychologists (cite Sabina Marx's paper in the Bonn or in this issue) further distinguishes between two kinds of mental structures: schemata (the plural of the greek word schema) and semantic networks[5]. `Global Warming' belongs to a schematic mental structure because it retain features of the event and relate to perception or visceral sensations. `Climatic change' is part of a semantic network, abstract and related to language and logic. Kagan (2000) argues that schematic discrepancy is a distinct from semantic discrepancy, and calls Surprise only the former while the later is termed Uncertainty.

Examples of surprise could include rapid technological breakthroughs, social upheaval affecting oil prices or GHG emissions, or abrupt change to a cooler climatic trend. IPCC guidance notes for TAR acknowledged that strictly speaking, a surprise is an unanticipated outcome, but in the IPCC SAR, “surprises” were defined as rapid, non linear response. This departed from the other subjective meaning of the word, which may be more pregnant for the lay readership. If no climate change at all occur over the next 50 years, that would be a surprise to the science community.

By allowing decision makers to get familiar in advance with a number of diverse but plausible futures, scenarios are one way of reducing surprises. Scenarios do not only allow to test existing strategies against a wide range of futures, they also facilitate stakeholders participation and allow to plant signposts allowing to recognize early which future is happening.

Metaphysical ignorance. Some things are not assigned a truth level because it is generally agreed that they can not be verified, such as the mysteries of Faith, personal tastes or belief systems. In model-based decision analysis, this kind of ignorance covers many parameters of the utility function. They include intergenerational equity parameters (discount rate), attitudes towards risk and international equity parameters such as Negishi weights. In addition, climate policy models have to consider the value of statistical life and the intrinsic value of ecosystems. While these cannot be judged to be true or false or given a mathematical distribution they can have bearing on both behavior and environmental policymaking.

Taboos matters are what people must not know or even inquire about (Smithson 1988, p. 8). These actively created areas of uncertainty exist in any social group, and go way beyond religious prescriptions covering food and sexual behavior. IPCC operates under a double set of taboos which are not only its scientific mandate, but also of a political essence. This is because its most important

[5] The difference between these two forms of knowledge is also known as the difference between Symbol and Sign in linguistics.

productions, such as the Summary for Policymakers, are approved line-by-line in plenary with government experts.

Thus, while ideally the IPCC would assess all the relevant literature for climate change mitigation, it says little on population policies, and publishes few economic scenarios where the less developing countries do not catch up fast. Informations about nuclear power, oil supply and other national security items are also impacted.

The diplomatic community also has lots of 'non negotiable' points. Indeed B. Müller [p. 68] explains the pace of climate negotiations as a stand off between two taboos that happen to be the key issues for the opposite party : the refusal of developing countries to discuss commitments and the refusal by industrialized countries to discuss anything that could remotely be interpreted as an admission of climate impact liability, such as the question of primary entitlement of emissions rights.

5. The nature of scientific knowledge

Having discussed imprecision in section 3 and the human dimensions uncertainty in section 4, this section revisits at a deeper level section 2's discussion on the difference between objective and bayesian probabilities, that is the discussion between degrees of truth versus degrees of certainty. This is about epistemology.

The IPCC guidelines on risk and uncertainty leave it to the chapter writing teams to determine what constitutes « much evidence » versus « limited evidence » in support of the findings expressed in the fourth assessment report. This is the fundamental problem of induction: how many specific cases are needed to infer a general pattern ? The problem of induction is a major source of epistemic uncertainty in situations with limited data, and it is crucial to the philosophy and the practice of science, since it is about making general rules from specific observations.

In order to understand why it is called the problem of induction, let us remind that inference is usually classified in three kinds: deductive, inductive and abductive.

Deductive inference derives a specific result from general premises (A implies B, A holds, therefore B). It is the safest way to make a conclusion. Example: Increasing the CO2 concentration increases radiative forcing, this planet's CO2 concentration has increased, therefore this planet's radiative forcing has increased. A weakness in deductive inference is that it depends on *ceteris paribus* conditions. For example, the demand curve concept for normal goods suggests that a higher price leads to a lower demand. If one forecasts a higher price of oil, can deductive inference be used to conclude that oil consumption will decline ? In fact it is quite possible that the quantity increases too, because there are other factors (i.e. the supply curve) that affect the equilibrium level.

Inductive inference learns general rules from specific cases. Induction is less powerful that deduction, as the truth of the premises make it only likely that the conclusion is also true. Example: The historical rate of decrease in energy intensity per unit of value appears to have averaged about 1 percent per year since the mid-nineteenth century (Nakicenovic 1996), therefore it is reasonable to include an autonomous rate of energy efficiency improvement in energy policy models.

Abductive inference allows one to learn a general hypothesis by observing a particular case using a general rule (A causes B, observing B, therefore suspecting A). This is also know as the « detective logic ». It is even weaker than the previous kinds of inference, as it runs contrary to deduction. Example: There is coral bleach all over the world. Global climatic change would explain that better than anything else. Therefore, there (probably) is global climatic change.

This distinction allows to stress that scientific inquiries cannot be based solely on formal logic as most people learn it, because that logic is only deductive, and science is about learning rules. Because induction and abduction are never 100% sure, there is a fundamental need to base science on a theory of risk and uncertainty.

The most influent approach today to make induction is Bayesianism. It is very valuable to society to have formal and operational scientific rules to determine, for example, the acceptability of a new drug or therapy. However, this does not means that the method is totally satisfying in practice or in theory.

For example, Ioannidis (2005) argues that due to problems with pre-study odds, insufficient statistical power of experiments and biases, false findings may be the majority of published research claims from clinical trials and traditional epidemiological studies to the most modern molecular research.

Another problem with bayesianism is that when limited to precise probabilities, it does not resolve the deeper kinds of uncertainties discussed in section 3 such as possibility and Knightian uncertainty. Imprecise probabilities would make the difference between an even chance (knowing only that $p = 0.5$) and no information (knowing only that $0 <= p <= 1$). Imprecise probabilities however still leaves open the problem of mathematical models of incompleteness, vagueness, and the human dimensions of science.

For these two reasons, the problem of induction cannot be considered as completely solved by bayesianism limited to precise probabilities. The same holds for the problem of formal abductive reasoning, related to the question of causality. Consequently, it is important that IPCC writing teams should not be limited to that single approach. The assessment should reflect the variety of risk and uncertainty analysis methods used in the climate change literature.

The questions of induction and causality are only two aspects of the more general problem of the scientific method. With respect to environmental policy, an important lesson of epistemology is that there is no guarantee that scientific uncertainties always decrease with time. This lesson justifies the precautionary principle, since there are never assurances that science will bring answers in time.

Two of the most fundamental epistemological attitudes are Rationalism and Empiricism. Rationalism holds that some ideas or concepts are independent of experience and that some truth is known by reason and logic alone. Empiricism holds that knowledge depends foremost on evidence. Empiricism is central to experimental sciences, and remains a component in most modern philosophies of science. Most of these suggest that theories are provisory at best, and argue that scientific attitude is to be ready to adjust the world view based on new empirical data. Scientific truth is not unquestionable in the sense of theology or ideology (that point of view could be called scientism).

Thus, it is expected that at times new experimental results will shed doubt on established theories. The consequence is that the progress of science sometimes increases, rather than decreases uncertainty. Schlesinger and Andronova (2005, fig. 3) suggest that the 95% confidence interval for climate sensitivity enlarged in the 60s and the 70s, apparently as the result of a temperature oscillation over the North Atlantic Ocean.

An issue with scientific empiricism is that for any set of observations, it's generally the case that several alternative theoretical explanations are possible. Tensions on the oil market, for example, could be explained equally well by long-term reserve exhaustion (the peak oil explanation) or by a conjectural underinvestment in exploration due to a cycle of low oil prices. A pragmatic answer to this is to see scientific activity as essentially a model-building activity, where the goal of models is to represent the environment without looking at perfect full knowledge. Then closure happens on the theory that explains most of the available observations « better than the others », that is the theory that makes predictions that maximally simplify problem-solving.

This working of science can be problematic for policy making. Before closure, there can not be probability distributions on the various theories. It's difficult to know when normal scientific controversies are over, since there is a qualitative human dimension to the process of finding scientific truth. And even after closure, it remains that the valid alternative explanations are still compatible with the observations and can be picked up to defend minority views. There is always room for a skeptical environmentalist to exploit the necessary scientific doubt and create areas of uncertainty for strategic purposes.

6. Conclusions

Understanding uncertainty is critical to economists because it characterizes the costs and benefits of climate policies, and under these conditions the standard decision-making criteria based on the maximization of expected utility, also called the Rational Actor Paradigm, is not so obvious. Most theories of decision making under uncertainty do not assume that it is always coherent or even possible to optimize expected utility. These include generalized expected utility by Ellesberg (2001), Knightian decision-making discussed in Bewley (2002) and Walley (2000), the rank-dependent expected utility and Prospect Theory. Some would also argue that social decision making actually follows a system of procedural rules that are determined by evolution and selection rather than forward-looking rationality.

By this paper's definition, under uncertainty a probability distribution is not well defined, so that the expected value of a contingent good is described by an interval rather than a precise number. Knightian decision making remarks that intervals are not totally ordered as real numbers are, and brings forward the intuition that under uncertainty alternative acts may sometimes be incomparable. When there are large uncertainties (meaning expected value intervals are large) about a policy, it might not be possible to conclude clearly that the expected costs are less than the expected benefits. In this situation, the concept of a globally optimal choice is replaced by a set of equally admissible but incomparable choices.

Is there reason to believe that the issues with the Rational Actor Paradigm under uncertainty count for climate policy ? When the expected value of a good is an interval, the interval's lower bound can be interpreted as the maximum price acceptable to buy that good, namely the willingness to pay (WTP). Conversely, the upper bound can be viewed as the willingness to accept (WTA). This ties the degree of uncertainty regarding to good with the WTA - WTP difference, a well studied anomaly of the Rational Actor Paradigm. Empirical research consistently finds that when people are asked to value non market goods, such as the quality of the environment, the gap between the two values can be significant. Moreover, Horowitz et al. (2002) meta-analysis found that the less the good is “like an ordinary market good”, the higher is the ratio WTA/WTP. Since climate stability and technical progress are not ordinary market goods at all, there is reason to believe that an evaluation of the climate policy would be subject indeed to the large WTA/WTP ratio effects.

This paper outlined a few philosophical dimensions of the risk and uncertainty debate in the context of climate change mitigation. It opposed not only the objective approach (viewing probabilities as degrees of truth) versus the bayesian approach (viewing them as degrees of certainty), see Figure 1, but also situations of risk (related to situations where precise probabilities are well founded) versus situations of Knightian uncertainty (a broader form of ignorance), see Figure 2.

The evolution of the IPCC guidelines on risk and uncertainties from the third to the fourth report can be read as a move away from a purely probabilistic view of risk, to include more complex aspects of uncertainty. This paper outlined additional human dimensions that were not discussed in the IPCC guidelines: they include strategic uncertainties, surprises, metaphysics and taboos. With respect to deeper epistemological issues, we argued that bayesianism is fundamental to science: scientific certainty is always provisory at best. However, purely probabilistic bayesianism does not solve the problem of induction, it needs at least to be extended to imprecise probabilities.

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Objective probabilities (degrees of Truth)
- Mathematical equiprobability / symmetry
- Frequentist

Bayesian probabilities (degrees of Certainty)
- Personal (directly stated or elicited)
- Subjective (from observed choices)

Figure 1: Kinds of probabilities

Error: ignorance that needs to be corrected
- Vagueness (Fuzzy theories)
- Incompleteness or absence (Logics, Transferable Belief Model)
- Knightian or deep uncertainty (Imprecise probability)
  - Possibility (Possibility theory)
  - Risk (Probability)

Human dimensions: actively managed ignorance
- Strategic uncertainty (Game theory)
- Surprise (Psychology)
- Taboos (Sociology, Anthropology)
- Metaphysical ignorance (Ethics)

Figure 2: An ontology of kinds of ignorance (with relevant methods).