Risk Management – Managing Risks, not Calculating Them

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Abstract

The expected utility approach to decision making advocates a probability vision of the world and labels any deviation from it 'irrational'. This paper reconsiders the rationality argument and argues that calculating risks is not a viable strategy in an uncertain world. Alternative strategies not only can save considerable cognitive and computational resources, but are more 'rational' with view to the restricted definition of rationality applied by expected utility theorists. The alternative decision making model of risk management is presented and explained.

1. Introduction

This paper proposes a model of *rational* economic behaviour. We employ the general definition of rationality. Behaviour is considered rational if the economic actors can justify it, i.e. if they can list their reasons for choices made. To clarify what we mean, economic actors have some views and theories about the world. We refer to these views and theories as knowledge. Note that this knowledge is not required to be infallible, i.e. their views and theories may be falsified. Behaviour that is supported by knowledge of economic actors can be defined as rational. To this end the proposed model will not and cannot be all embracing and explain all economic behaviour.

Therefore we do not consider *irrational* behaviour (contradicting the subjective knowledge) or *arational* behaviour (behaviour that does not directly contradict the knowledge, but which is not supported by it either). See Dequech (1997) on the classification of rationalities. We do not reject the existence of both *irrational* and *arational* behaviour and do not maintain that there are mechanisms at work (such as markets) that wipe out all behaviour that is not rational, as many rational choice theorists do (the 2002 guest speech to the AES is a good example).

Therefore when we say that (rational) economic behaviour is not possible in the face of pure uncertainty what we really mean is that one does not have sufficient knowledge to justify any given course of action. This does not mean that any action would be impossible, since in the absence of knowledge any admissible course of action would not be *irrational*, but *arational*.

The other aim of the proposed model is to obtain descriptive accuracy. Models of economic behaviour can be divided into normative and positive ones. Normative models are prescriptive in that they prescribe how people should behave in order to fit into a pre-defined notion of rationality. That is, normative models say what people should do. Positive models on the other hand aim to describe what people actually do.

The other important element of the proposed model is that it is situated in time. Time and its associated uncertainty, ignorance, novelty, surprise and errors are essentially the justification for any theory of choice.

The paper is organised as follows. First, we review some elements of existing models of choice considered inappropriate in a model seeking to explain observed patterns of economic behaviour. Then we present some elements that are necessary if a model is to provide a satisfactory descriptive accuracy. This provides us with a basis for explaining the concept of risk management. Finally the application framework of the risk management model is presented.

2. What we do not need?

2.1 Probability calculus

Probability calculus is at the heart of most economic theories of rational choice. It is often perceived as synonymous with rational choice. We aim to demonstrate that it is unnecessary in a model of rational choice. The main reason is because in most economic situations the use of probability calculus contradicts the definition of rationality. The rationality definition applied is a broad one, and if a person has a probability view of the world, (as in expected utility theory) then employing probability calculus is a rational way of behaving. This however contradicts the much narrower definition of rationality imposed by expected utility theories (EUT). For simplicity we use the term EUT to denote any theories that employ probability calculus in direct or modified form. The EUT model measures everything, including rationality with regard to the outcome of a given course of action. In this sense rationality in EUT is an outcome based concept. When one includes uncertainty in the model, this view becomes difficult to maintain. The rational choice in this context is the 'correct choice'[1]. It is therefore an ex post concept. Descriptive accuracy in a case where the future does not fully correspond to our expectations can only be achieved by an ex ante definition of rationality.

Knight (1921: 234) and Shackle(1950: 71) argue that if the individual does not have the ability to often repeat the experiment indefinitely, then since probabilities are nothing more than long-run frequency ratios, they are irrelevant to individual behaviour. This point deserves detailed explanation. For such a purpose we create a new type of economic agent and compare it to the rational economic maximiser. This comparison is aimed at demonstrating that the subject of EUT does not fit their own definition of rationality.

The main problem with probability calculus is that its use is based on a rough approximation. Let us take as an example the 'Samuleson's bet'. This often cited example about irrationality in choice is when Samuelson (1963) proposed to a colleague the following attractive bet: flip a coin; heads you win $200, tails you lose $100. The colleague declined the bet, but declared a willingness to participate in a series of 100 such bets. A vast body of literature has been dedicated to this problem and to Samuelson's claim about the irrationality of such a choice (see e.g. Benartzi and Thaler, 1999). The main problem of these studies is that they assume the probability calculus and overlook the above objection of Knight and Shackle. The apparent irrationality vanishes if one considers the problem in the following way. The

[1] "Correct foresight is then not, as it has sometimes been understood, a precondition which must exist in order that equilibrium may be arrived at. It is rather the defining character of a state of equilibrium". (Hayek 1937, p. 42). Hayek's definition is prompted by Morgensterns critique of the use of the perfect foresight assumption.

probability calculus result of $50 (0.5*200+ 0.5*(-100)) is irrelevant for a one time bet. It is an outcome whose probability of occurrence is zero. The only two possible outcomes are a loss of $100 or a win of $200 with equal probabilities. If however the experiment is repeated for a sufficiently high number of trials, then the probability calculus may become relevant. Samuelson's colleague may have reasoned in the following way:

"If I take a one time bet I am as likely to lose as win. If however the bet is repeated many times (e.g 100) then I am much more likely to win than lose and thus it is much more advantageous for me to take repeated bets".

For a risk averse person, such a choice is clearly rational. The caveat of probability calculus reasoning is that it orders the outcomes according to their 'expected' value and tries to get an 'optimal' solution. 'Optimality' is meaningless in a one time bet case, because the experience is unique and the probability calculus provides a number that is impossible to occur. 'Optimality' can only be evaluated ex-post and thus is not relevant to problems of *ex-ante* choices. Note that in this case Samuelson's colleague fits our broad definition of rationality.

Let us now provide the above case with a more formal analysis. The case of a one-off bet has only two possible outcomes: win 200 and a loss of 100. The expected value of +50 cannot happen and is not relevant to the decision. Note that the use of the expectations operator means implicit reliance on asymptotic limits. In other words if we denote the outcome distribution of a bet by X_t , (t=1, 2 … n) and where *t* **is not** a time operator), then the mathematical expectation is:

$$E(X_t) = \lim_{k \to \infty} (X_{t,k}) \qquad (1)$$

Since this is a limiting process for the random variable X_t, its finite sample realisation, (i.e. when the number of repetitions is a finite number) will be biased. Therefore, if we use CE to define a certainty equivalent, for any finite k, we can write:

$$CE(X_{t,k}) = E(X_t) + B(X_{t,k}) , \qquad (2)$$

where the last term represents the bias.

In the one-off bet case we have the bias function consisting of 150 (i.e. 200-50) and –150 (i.e. –100-50), with equal probabilities of occurrence. Note that not only is the mathematical expectation result impossible, but the bias exceeds three times the expected value. Let us further define two types of economic agents – the rational EUT utility maximiser, who uses probability calculus for making decisions whom we denote as *homo economicus*[2] *(HE)*. The other type denoted as *homo smarticus (HS)*[3] will avoid probability calculus in most situations (where this is found to be appropriate) and its behaviour will be defined in detail below.

The decision made by a 'rational' economic agent or *HE*, based on mathematical expectations assumes that the bias above (equation 2) vanishes. The latter is only true at the limit, that is when the experiment is repeated many times. With any finite number of repetitions this bias will exist. Therefore what *HE* does is simplify the problem by assuming away this bias. This simplification introduces some error into the calculation[4]. When one has a one-off experiment this error may be significantly large. In this way *HE* cannot be described as a person with a very high IQ. He is rather stupid.

Let us now examine what will happen when an 'equivalent', in the sense of probability calculus multiple repetitions bet is constructed. This bet could be for example 100 repetitions of the bet [2, (50%); -1,(50%)][5]. The expected value is again +50 units. Nevertheless it is not mathematically equivalent to the one-off bet with the same expected value. The basic logic is that while for the one-off bet, probability calculus is not relevant, in the multiple repetition experiment, subject to individual perception with a high number of repetitions, the probabilities become relevant for decision making purposes. If one maps the possible outcomes from the multiple bet case, a whole range of possible outcomes in the interval [-100,+200] at steps of 3 units emerges. In this case in two thirds of these realisations (67 realisations from +2 to +200, inclusive) the final outcome is a gain, against only one third (i.e. 33 realisations from –100 to –1) realisations of a loss. Clearly for a risk averse person this repetitive bet is more advantageous that the one-off bet in which half the realisations were losses.

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[2] Intentionally we use the term similar to but different from the widespread *homo oeconomicus*.

[3] Note that the initials are the same as for *homo sapiens*

[4] In introducing error the rationality of *HE* contradicts the correctness of the EUT definition., thus *HE* is irrational.

[5] The original paper (Samuelson, 1963) present the alternative of repetition of the same bet. Since this is not equivalent in probability sense and includes complications such as wealth effects, we use this formulation instead.

Moreover the largest loss (of 100 units) in the repetitive case is much less likely than in the one-off bet. Note that even in the repetitive bet, the probability calculus is not strictly applicable, because this is still one-off (although repeated 100 times bet). Probability calculus would have represented a probability distribution for these outcomes with a peak at +50 and an exponentially declining probability mass towards the tails. The probabilities will be calculated from the fair coin probabilities of 50:50 head to tails. Such a representation is based on an approximation. Nevertheless, as the number of repetitions increase, the realisations converge towards the limiting probability distribution. Therefore for practical reasons, *homo smarticus (HS*) may ignore the relatively small differences from this limiting distribution and consider it instead. Every individual *HS* will have different ideas about how big this number of repetitions should be. It will depend on the degree of individual risk aversion and on the perceived importance of the decision to be made. What is important however is that by doing this, unlike in the *HE* case, *HS* is aware that this is an approximation and is subject to error.

With numerous repetitions of the same experiment, the outcomes are distributed onto the interval of possible realisations. The bias function is similarly mapped onto the interval defined by the biases of the one-off bet. As an illustration the biases corresponding to the 100 times repeated bet will fill the interval [-150, +150] (at steps of 3 units). In order for *HS* to apply expected value calculations, two preconditions are necessary. First some threshold for the number of repetitions should be exceeded, so that *HS* may decide that probability reasoning applies and the resulting realisation map is weighted by these probabilities. Then since the application of this probability weighting would also apply to the bias, in order to make a decision, *HS* would have to ignore some realisations for which the probability weighted bias is very small (i.e. below some other threshold). In the above example with 100 repetitions this says that 100 is considered a sufficiently big number (the first threshold), while after ignoring some low probability weighted biases, the resulting truncated bias distribution is viewed as favourable. Let us assume that *HS* will accept bets that are viewed as (almost) risk free, subject to the above simplification mechanism. This would mean that the probability weighted biases for the left 33 realisations (i.e. the negative biases) can all be ignored due to their small values (below the second threshold). In this way the choice is viewed as a sure bet. There is still an awareness of associated risk in terms of probability of a loss, but since this probability is very low, it is ignored. Note that in this example even after the simplification *HS* is left with the middle third of the realisations. Since all these have positive biases, and are to the right of his reference point (which was assumed to be zero) then they are acceptable.

Let us now reconsider how *HE* makes the choice. He/she derives a certainty equivalent by discarding the whole bias distribution (i.e. using the mathematical expectation). Sometimes an additional term to account for risk aversion is introduced into the above scheme, and the certainty equivalent will be the difference between the expected value and this risk aversion adjustment. Note the difference to equation (2), in which due to the bias being a random variable, the certainty equivalent itself is a random variable. In the mind of *HE* however, since the bias is ignored, the certainty equivalent is a constant. Ignoring the bias is equivalent to assuming that all its non-zero values vanish. In the finite case this means that all the probability weighted biases fall below the second type of threshold, while the first threshold is zero for *HE*. It becomes clear that *HE* is an *HS*, but with an extremely low IQ. Using a very high value for the second threshold is designed to maximally simplify the problem, so that there is no room for real choice. *HE* evidently cannot be trusted to make the choice on its own. Note that the role of the adjustment for risk aversion plays the same role as the reference point (to cut off favourable from unfavourable outcomes) and this is the only place for individuality (i.e. intelligence) in *HE*. Furthermore by using a threshold of zero for the application of probability calculus, *HE* ignores the bias and thus is less intelligent than *HS* who in the one-off choice does not ignore any part of the bias (only a part of the bias is ignored and only in multiple repetitions bets). If we assume that the reference point for *HE* in the one-off bet example is zero (which means that he/she also has a risk aversion adjustment of zero) then this bet will be accepted, because of its positive expected value. In making this choice however the 50% probability of a loss of 100 units is implicitly ignored. Compared to an *HS* with the same reference point, *HE* is much less risk averse. Lets us now consider the case where they have the same risk aversion in the one-off bet case. For this comparison the reference point for *HS* is again zero and thus he will decline this bet. Then in order for *HE* to decline the bet, his/her risk aversion adjustment should be more than 100 units. Then since this is the same person and this is equivalent in terms of the probability calculus bet, in the repetitive case, the same risk aversion adjustment should apply and this bet should also be declined. This is essentially the argument Samuelson made. Let us now take the last bet and repeat it one million times and for simplicity no money exchanges hands before the last repetitions (we introduce this condition to escape the wealth effect of the Saint Petersburg paradox). For *HE* this is still the same type of bet and should be declined. For *HS* however this is a virtually risk-free way of making money and he/she will accept such an offer. What are the implications of this example? Surprisingly, it leads to another standard 'rationality' argument, the one about how *HE* will wipe out all quasi rational economic actors, via its 'superior' calculative properties. Since the world in which we live is a unique one, there is limited scope for probability calculus application. Therefore by designing appropriate repetitive gambles, *HS* can exploit the myopia of *HE* with regard to the differences between one-off and repeated bets. Then it will be *homo economicus* who will be wiped out in the market place, not the quasi rational *HS.* An interesting point is that the 'standard' argument about how *HE* can exploit non-rational economic actors does not apply to *HS.* The way in which such gambles are constructed is by exploiting some argument about consistent preferences. In the expected utility sense however the preferences of *HS* are not consistent in terms of expected utility theory. Therefore he/she cannot be fooled into participating in such gambles[6]. Only a person with consistent preferences (such as *HE*) can be involved in such machinations. Let us now consider the theorem that Samuelson proved about the irrationality of his colleague. The argument is very simple induction. Let us repeat it for *HS*. If he has played the gamble described above 99 times, and then asked for another round, he should decline, according to his elicited preferences. This condition assumes unchanging preferences and is extremely restrictive. Whether this additional bet will be accepted in the case of *HS* depends on the outcome of the previous 99, in the lines of 'mental accounting'. Nevertheless, let us assume unchanging preferences. Then, as Samuelson stated, if asked after 98 bets, his colleague, should decline and so on until realising that it is not worth beginning the sequence. Now let us look at this argument from *HS*'s perspective. What will, (assuming non changing preferences) he do after 99 bets? It depends on the view of *HS* about the threshold of repetitions above which the probability calculus applies. If this threshold is 100, he/she will only accept *ab ovo* bets which are repeated at least 100 times. Therefore before beginning the first round, he/she will be aware that the bets should be repeated at least 100 times. Then it

[6] The way these money pumping schemes are presented is usually as follows: *HE* goes to the quasi rational agent and says: "you accept gamble A and reject gamble B, then you should also accept gamble C (which I constructed), because it is constructed according to your preferences. Let's play." This does not apply if the quasi rational agent does not think in the same way and cannot be convinced by this line of reasoning.

follows that 100 is a watershed for this person. If asked after the 100 bet, he should decline an additional bet, because its marginal contribution is the same as a one-off bet. If however asked before the 100 bet, then in principle the additional bet should be accepted in order to exceed the threshold. Note however that what *HS* would normally do is to get an agreement about the number of bets beforehand and in this way refute the above type of recursive argument. The mistake Samuelson and other expected utility analysts make is that they see a 100 repetitions of the same bet simply as a collection of individual bets and not as an ensemble.

If asked after some number of repetitions about whether to stop betting here, then the answer of a typical *HS* should depend on the outcome from betting up to this point. He/she has the reassurance that betting will continue until the predetermined number of bets. The choice of whether or not to continue depends on several factors. First can the remaining number of bets be considered an ensemble (i.e. do their number exceed the threshold which he/she has set up applying probability calculus arguments?). Second what is actually proposed; an additional bet or a number of additional bets? Thirdly, what is the outcome from betting so far and how it may be altered by accepting additional number of bets? The only thing that Samuelson's argument proves is that his colleague's choice (and similarly *HS* choices) is inconsistent with expected utility theory. It would nevertheless be a mistake to generalise such a finding to that one of the two choices in irrational (as Berhartzi and Thaler (1999) and others do). It would have been the case only if these two gambles were equivalent. They are not and thus there is no contradiction in the choices *HS* makes.

Homo smarticus is a mythological creature, no more real than *homo economicus*, and the above discussion only aimed at proving the irrelevance and irrationality of ubiquitous use of probability calculus in 'explaining' economic choices.

2.2 Preferences

Preferences (like probability calculus) are another taboo in economic choice theories. They are defined in an almost tautological way: Everybody (economic agents) maximises something (utility function).[7] This assertion cannot be falsified. It has

[7] Boland (1992) argues that the above should be considered metaphysics instead of tautology.

anecdotal significance in economics, from Pareto's assertion that "the individual can disappear, provided he leaves us this photograph of his preferences (Pareto, 1971: 720) to Boulding's (1978) 'Immaculate Conception of the Indifference Curve'. It however is an ex-post concept. Preference orderings are defined over the outcomes of the decisions. It this way preferences are better though of as justification of already made decisions, rather then premises for choice (March, 1978). When there is uncertainty, then the outcomes and thus the preferences cannot be fully, but only partially, ordered (Kornai, 1971). The full ordering of preferences (together with their stability over time) is however a cornerstone in the EUT axiomatic approach to decision making.

How this becomes a problem in a descriptive model of decision making? Let us look at one of the numerous 'anomalies'[8] of decision making, the so called 'dominance effect'. It is expressed in psychological experiments as below. When people are presented with the following type of choices: (A) a holiday in London for £500, (B) a holiday in Paris for £500, (C) a holiday in London for £600, all the above options with the same duration of the holidays, most of them choose option (A). When on the other hand they are presented with the options: (D) holiday in Paris for £500, (E) holiday in London for £500, (F) holiday in Paris for £600, they chose D. It is argued that this is an inconsistent choice because according to the first choice they should prefer (A) to (B), but the second choice 'reveals the opposite preference (since (A) and (E) and also (B) and (D) are identical). This led 'dominance' effect is however perfectly rational once one takes into account the possibility for structural uncertainty and risk aversion. Let us assume that people do not know the relative cost of holidays in London and Paris (which would have allowed them to directly compare them). This assumption makes sense once one takes into account that the normal setting for such an experiment may be an American university and the subjects are students, who did not had the chance to visit both London and Paris. In this case in the first choice they would not know how exactly option (B) compares with (A) and (C). What they know for sure is that (A) clearly dominates (C). With the uncertainty where exactly (B) is to be ranked, (A) is a very attractive choice. It is at least the second best. If one chooses (B) instead, given the total uncertainty, there is two thirds of chance to choose a worse option. Therefore unless one has some additional knowledge about how these two options compare, the choice of (A) is a rational one for any risk averse person. Similarly one may consider the second choice. The mistake one may make in comparing these two choices is to state that they reveal some kind of preference. Preferences cannot be formed with regard to uncertain alternatives[9]. One may not prefer (A) to (B) without knowing something about both (A) and (B). Therefore in an uncertain setting, choices " …do not elicit pure statements of preference" (Manski, 1999). It is however clear that the world in which we live and make decisions in is an uncertain one. Hence preferences cannot explain our rational choices.

3. What do we need in a model of rational choice?

3.1 A reference point

The reference point divides perceived outcomes into favourable (gains) and detrimental ones (losses). It is now an established part of economic decision theories. It is used in the prospect theory (Kahneman and Tversky, 1979), cumulative prospect theory (Kahneman and Tversky, 1992)[10], although the earlier value function of Markowitz (1952) exhibits the same characteristics and Shackle's (1949) potential surprise curve allows for such asymmetries. It is widely accepted that there is a fundamental asymmetry in perception of advantageous (gains) and disadvantageous outcomes (losses). These are seen and acted upon in a different way. The reference point concept presents an insurmountable challenge to normative theories. As Arrow (1951) objected when commenting on Shackle's theories, this makes choice contingent on individual interpretative frameworks and thus makes a normative model of choice inapplicable. To put this explicitly we use the following extensive citation:

> "Indeed, the failures of description invariance (framing effects) and the procedure invariance (elicitation effects) pose a greater problem for rational choice models than the failure of specific axioms, such as independence or transitivity, and they demand descriptive models of much greater complexity. Violations of descriptive invariance require an explicit treatment of the framing process, which precedes the evaluation of prospects (Kahneman and Tversky, 1979). Violations of procedural invariance require context-

[8] This term is usually used since they define clear violations of EUT. This does not necessarily mean that there is something abnormal.

[9] Preferences refer to outcomes, not the alternatives.

> dependent models (for example Tversky et al., 1988) in which the weighting of attributes is contingent on the method of elicitation. These developments highlight the discrepancy between the normative and the descriptive approaches to decision making which many choice theorists (see Mark Machina, 1987) have tried to reconcile. Because invariance, unlike independence or even transitivity – is normatively unassailable and descriptively incorrect, it does not seem possible to construct a theory of choice that is both normatively acceptable and descriptively accurate" (Tversky et al. 1990: 215).

Since both the framing and the elicitation effects invoke different reference points, the above states that this concept is incompatible with normative choice theorising. It is nevertheless a useful concept for a number of reasons. First, it captures the public perception of risk. The colloquial meaning of risk invokes an idea about unfavourable consequences that one needs to try to avoid. It would be very unreasonable, on the other hand to try to avoid one's exposure to consequences perceived to be advantageous (i.e. gains). This split of consequences into two qualitative categories, provides a major tool of calculation, namely comparison. One should be aware that rational calculation may assume numerous forms and probability calculus is just one of these (Kostov and Lingard, 2003). Comparison is the easiest (in terms of application and resource requirements) form of calculation, and its application in an uncertain world should exceed the application of any other calculation tool. The reference point concept, and this is the main worry for normative choice theorists, moves us away from the 'objective' view of the decision problem. To clarify the latter point we consider the psychological literature on the 'overconfidence effect'. Suppose one is asked questions of the type:

Which of these countries has the lowest per capita GDP?

A) Malaysia, B) Kenya, C)Hungary, D)Peru,

with the additional requirement to provide a percentage figure to show how confident one is in the answer. The typical finding of such experiments is that when the answers are aggregated an 'overconfidence' effect arises in that the declared level of

[10] The prospect theory is sometimes presented as a positive decision making theory. It introduces mechanisms for translation of objective data into subjective 'facts'. Nevertheless it retains the applicability of the probability calculus to the tranformed problem.

confidence exceeds the percentage of right answers. The probability calibration psychology models present an explanation for the above effect. It can be formally proved (e.g. Juslin and Olsson,1999) then when people associate the questions with some mental ‘clues’ and use the latter to formulate their answers, the paradox of overconfidence vanishes. To clarify, let us assume that one does not know the answer to the question. Let us further assume that one knows however that Malaysia is an Asian country, Kenya is in Africa, Hungary in Eastern Europe and Peru in Latin America. Then one may reason in the following way: since the per capita GDP is a measure of wealth (poverty), Kenya as an African country is most likely to be the poorest one. The probability calibration models prove that the final results from such experiments are consistent with the probabilities associated with these mental clues, i.e. the confidence levels expressed are consistent with the objective probabilities of an African country being poorer than a country from other continents. We note that although such a model will require one to know these objective probabilities, it provides some important conclusions. Choices are made in conditions of uncertainty and ignorance (people are aware of this ignorance). In such situations one needs something to anchor one’s decision to. The reference point is one example for such orientation device.

3.2 An image of the decision problem

With a view to environmental uncertainty and the dependence of the decision on the way it is perceived, it becomes clear that this is a necessary part of any model that aims at descriptive accuracy. This perception is highly subjective and an implication of this is that there can be no universal normative model, simply because the same decision problem may be perceived differently by different people. It has been argued that “most cognitive anomalies operate through errors in perception”. (McFadden, 1999), but while some normative theorists see their mission to eliminate such errors, we maintain that not only these systematic ’errors’ need to be studied and incorporated in decision making theories (McFadden, 1999), but since their definition as errors depends on the EUT definition of rationality, they may still be rational adaptations to an uncertain environment.

Due to the important influence of the individual interpretative frameworks, it is advantageous to translate the decision problem into the subjective reality of the decision maker (Teigen and Brun, 1997; Kostov and Lingard, 2001, 2002). One can both account for perception 'errors', and map the individual knowledge relevant to the decision problem. Returning to the earlier example about *HE* and *HS*, these two decision makers have totally different word views and their different perceptions makes them act differently. Knowing the premises of their choices, i.e. their world views and the way they process the available data, can help us to determine what their choices might be. The process of translating objective into subjective reality involves extensive use of different reference points (to define what one wants to avoid) and mental comparisons. The long history of psychological experiments finding violations to basic principles of probability calculus has led to a consensus that people do not handle probabilities well. They however improve a lot their 'rationality' with regard to probabilities when they are given another comparable set of probabilities, for example when the probabilities for a chemical leak are presented alongside the probabilities of comparable events, e.g. a road accident (Kunreuther *et al*., 2001). This means that the most likely way probabilities are to be incorporated in decision making is by simple comparison. This is also the easiest and a very efficient way to use them given important restrictions on time and computational resources. The comparison provides a measure for the (perceived) significance of given probabilities and allows simple dominances to be distinguished, thus creating possibilities for problem simplification (by excluding from consideration all dominated alternatives). Note that the reference point discussed earlier is also a comparison device. It may be alternatively defined by using the no change or 'carry on' scenario. This would evaluate the likely consequences from making some decision against the status quo (i.e. the likely result if this decision is not made). This can explain the 'wealth' effects in expected utility models, because this is an additional way to incorporate part of the status quo. This leads to a conclusion that decisions should be evaluated with regard to the marginal changes they are likely to bring, not in principle. This is an important point because such a comparison allows one to use the same interpretative framework for sequences of decisions. In spite of the marginalist philosophy behind the concept, it also leads to anchoring individual choices to individual perceptions, and moving away from the normative models of choice. The role of individual knowledge is very similar to the role it has in mental accounting theories, particularly the problem of choice bracketing (Read *et al*., 1999), where individuals integrate or segregate the consequences of different decisions, and this leads to different, not beforehand determined choices.

3.3 Decisions are dynamic

Making a decision involves evaluation of its uncertain outcomes. EUT uses mathematical expectations to project this future uncertainty into the present (and thus makes an inadmissible simplifying assumption about the non-existence of uncertainty expressed by the bias term in equation (2)). Such a treatment essentially makes the problem static by excluding from it all dynamic elements It is a product of a simplistic deterministic vision, in which time has no place or role (Kostov and Lingard, 2001). Decision making however is a dynamic process. We have a 'feeling' of time and awareness of our ignorance. Therefore when making decisions one acts upon this awareness. The existence of such awareness means that we are smart enough not to engage in endless and meaningless probability calculations, but try to obtain a more tractable problem by appropriately simplifying it. This simplification is imperfect in that the tools involved may distort objective reality. Nevertheless they are workable adaptations to a highly uncertain environment. There is more to this awareness that the possibility of errors. As dynamic programming demonstrates, any deviation from the assumed optimal path changes the nature of the problem itself. When we say that decision making is dynamic, we mean that there is an awareness that the decisions are interrelated and that they change future decision problems. One should have a flexible (i.e. modifiable) view of how things function. Decision making is also a complex process in the sense that it is difficult to grasp what information the decision maker will deem important. A basic premise of much psychological research is to isolate some effect by locally purifying the decision context. This means that subjects in such experiments are assumed to use the information provided and only the information provided. As our explanation of the dominance effect shows however, decision always takes place in the context of individual knowledge (or ignorance) and experiences. Even in simplistic experiments the context emerges, it is thus necessary to concentrate our modes of explanation on the process characteristics of the decision making. In this way the decision context specific to each decision maker will find its natural place.

4. Risk management

The risk management model discussed below, fits the requirements for descriptive accuracy outlined in previous sections.

“Risk management is a process of simplifying the decision problem aimed at restructuring it in such a way that the risk (the subjective perception of the environmental uncertainty) is excluded”. (Kostov and Lingard, 2003).

It is important to stress a distinction between uncertainty and risk in the risk management framework. Uncertainty is viewed as an objective characteristic of the environment, while risk is its subjective perception. In this light both risk and uncertainty may be unstructured and radical. For more details on the above distinction and its derivation see Kostov and Lingard (2001). In this framework there many different forms of calculation which transform the decision problem. Unlike the EUT stance of universal application of probability calculus, in the risk management perspective, probability calculus is one of the less important calculation tools. Comparison is more widely used. The main device for extracting risk out of the decision problem are the risk defusing operators. The decision process in terms of risk management initially simplifies the problem by the use of such risk operators. The aim is to extract as much risk as possible. Ideally one will want a transformed problem that is (perceived as) risk free so that a straightforward decision criteria can be applied. Only when this cannot be achieved is there place for some ‘trading’ of different characteristics of the problem in the final choice. The process however does not stop there. When a decision is deemed important, it prompts post decision consolidation processes which further modify the subjective reality so that the made decision is evaluated favourably.

The risk defusing operators can be broadly classified into four main types (Huber, 1997): control, new alternatives, precautions and worst case operators. We only briefly review these with regard to the desirable decision model components outlined.

Control is the most important, though most requiring in terms of resource use, risk operator. It is expressed in an appropriate transformation of the decision problem in such a way that its characteristics are altered in an advantageous direction. In order to use control operators however, one needs a mental ‘image’ of how the environment changes. A structural and procedural knowledge about the problem is necessary. With regard to this, the use of control operators is related to the concept of associative learning[11]. Therefore the use of the control operator implies a clear 'mental image' of the problem. Furthermore since its aim is to 'improve' the characteristics of the initial problem by moving it is a more favourable direction, it also needs a reference point, i.e. some distinction between 'good' and 'bad' outcomes, i.e. gains and losses.

Unlike the conventional subjective utility story of well defined and exhaustive characterisation of the problem, we are often aware of our ignorance. The new alternatives operator transforms ignorance into knowledge. Our awareness of risk exposure is coupled with an awareness of ignorance. While new alternatives operators decrease this ignorance, it does not disappear. The new alternatives operator only exists at the edge of time. Once we step into tomorrow the novelty of today disappears and the new alternatives operator is transformed into another type of risk operator. By explicitly distinguishing it as a separate operator we pursue several aims. First this emphasises that decision makers are aware of their ignorance and are actively seeking to improve their knowledge. While the only such activity available to rational optimisers (such as the expected utility calculator *HE*) is simple information gathering (which may perversely increase their risk), the new alternatives operator requires structural learning in the sense that economic actors learn and discover the structure of the problem (which is known in EUT problems)[12]. By situating a risk operator explicitly in the present, we stress the link between individual knowledge (based in the past) and the outcomes of the decision (which will happen in the future). These however are not conflated into each other as in an EUT-like treatment of the decision problem. Another important implication of the new alternatives operator is the possibility to impact on the interpretative frameworks of the decision makers. This is actually one of the aims of this operator. One needs awareness of one's ignorance and the potential fallibility of one's knowledge in order to contemplate the use of such an operator.

Precautions operators transfer risk outside the problem by transferring them to somebody else, like insurance, or by preventing their unfavourable consequences occurring. The second type of precautions operator looks similar to the control

[11] In contrast to reinforcement learning, where the problem image does not change, associative learning allows for changes in economic actor's 'theories'.

[12] There is a vast literature on ambiguity (essentially assuming a known structure of the problem, but with unknown probability distribution). This literature and its associated quantitative tools (MaxMin criterion, Choquet integral) exclude from the outset the possibility of the structural character of the uncertainty. The learning in this context is nothing else than information gathering and probabilities discovery.

operator. The difference is that the control operator uses the interpretation of how things function in order to prevent occurrence of some unfavourable consequences, whilst the precautions operator is used without a view to altering the outcomes, but simply taking measures to offset their consequences. This represents ‘delegation’ of responsibility for some aspects of the problem to someone else, and may lead to perverse results. Nevertheless, it is a way to simplify the problem. Decision makers have limited resources and cannot cope with all perceived risks (or are unwilling to do so). The precautions operator eliminates risks (they disappear from the subjective reality).

If risks are perceived as significantly small we can ignore them, and act as if they do not exist. This thresholding of risk is a prerequisite of action, and represents a built-in mechanism of altering the subjective reality. This mechanism extends far beyond ignoring risks because of their magnitude, but also applies to ignoring information deemed to be irrelevant to the problem We consider this a feature of the subjective interpretation of the problem. Akerlof and Dickens (1982) show how one would choose to ignore certain risks, i.e. to select a belief system and ignore crucial information. This is another important difference to the normative approach where all data is equivalent and is fully processed to get an optimal decision. In psychology the value dependence of decision making is long established.

In some cases defusing all the risk, even with the use of a level of risk tolerance may not be possible. In such circumstances one would use the least risky known alternative. The worst-case plan operator is used so that risk exposure is minimised. It does not resemble a ‘risk free’ choice, but is the second best. Nevertheless the implication of the use of a worst case plans operator is similar to the use of other operators. Although there is awareness of the existence of risk in the transformed problem, decision can be made, as if it did not exist.

5. Rediscovering risk management in agriculture, food and rural development

We give some examples on this where risk management practices can be found. The purpose of this exposition of examples of use of risk management operators is to clarify the concepts discussed. The general applicability of risk management to the problems of rural development is discussed in Kostov and Lingard (2002), while a more detailed operational research agenda within this framework is presented in Kostov and Lingard (2003).

Let us consider the use of agro-chemicals in agricultural production. These are a way to increase yields, and ‘quality’ of the final product. The latter term is in quotation marks because the meaning of improved quality in this context refers mainly to improved appearance. This is achieved by reducing the influence of pests and diseases. Therefore the use of chemicals represents an control operator which has a positive impact on the ‘quality’. This effects is achieved through the knowledge of how specific chemicals will influence yields, taste and product appearance. The other side of the story is that chemical residues can accumulate in the final food product. This is nowadays perceived as a ‘bad’, and thus the ‘quality’ is reduced. Quality in the latter context is interpreted in terms of how ‘healthy’ and ‘safe’ the product is. Therefore this control operator only worked well until the categorisation of the outcomes changed.

Organic farming is also based on the use of control operators. It claims to prevent some unfavourable consequences of commercial farming by certification and other measures. Certification in itself does not make a product organic. It gives assurances to the consumer that the product is organic. In this way, certification impacts on consumers’ translation of objective into subjective reality. The knowledge element is that organic is interpreted (by these consumers who look for organic products) as a proxy for ‘healthy’, ‘safer’, ‘better quality’ and in this way less risky. The reduced risk in the minds of environmentally friendly consumers justifies a price premium. Agriculture before its commercial era was in principle organic. The control has led to two opposite tendencies. The difference is, the perception of what is good and bad, and therefore risk.

Building a waste processing plant, which is an example of a precaution operator, does not prevent the incidence of polluting waste, but takes care to reduce or eliminate the consequences, that is, the pollution itself, after they have occurred. Whilst in active risk operators (control and new alternatives) the decision makers assumes responsibility for the decision and try their best to make the best possible choice. Using a passive operator, such as precautions, transfers the responsibility for the outcome to someone else. The effects of such ‘delegation’ of responsibility may be negative. For example the effect of food safety regulations has been found (Viscusi, 1985) to be unable to restrict cases of food poisoning. The explanation of such a paradox is simple. When people rely on food safety regulations to prevent this unwanted outcome (food poisoning) they reduce their own efforts to do it (i.e. the use of control operators such as avoiding some foods or food outlets). This offsets the positive influence of the regulation. Similar arguments may be developed with regard to car safety regulations (Peltzman, 1975).

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