# Origins and Functions of Perceptions of Risk

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Presentation at NCI Workshop on

"Conceptualizing and Measuring Risk Perceptions"

February 13-14, 2003

My perspective on risk perceptions is probably very different from that of most people in this room. I started out as a mathematical psychologist, studying descriptive models of risky decision making such as prospect theory as well as normative models such as expected utility theory, and in this context started to experience the inadequacy of the ruling economic conceptualizations of risky decision making. In particular, I became concerned by the fact that they did not incorporate perceptions of attitudes towards risk in their conceptualizations of risk taking (Weber, 1997b; 2001a,b; Yates & Stone, 1992).

So, what is risk? The word has many meanings and interpretations (Slovic & Weber, 2003). Unlike preference, which can be inferred from some observable behavior (i.e., choice), judgments of risk are inconsequential. In theories of finance, however, risk has been used as a theoretical construct that is assumed to influence choice. Underlying risk—return models in finance (e.g., Markowitz, 1954) is the psychological assumption that greed and fear guiding our behavior, and that it is final balance and tradeoff between the fear of adverse consequences (risk) and the hope for gain (return) that determines our choices. How many units of risk is a person willing to tolerate for one unit of return? The acceptable ratio of risk to return is the definition of risk attitude in these models. The risk of a choice option itself is operationalized as a summary statistics of the distribution of possible outcomes, and in particular as a summary statistic that captures something about the uncertainty that prevails. In the context of pricing risky assets, the measure of risk suggested and used (e.g., in the capital asset pricing model, CAPM) is the variance of possible outcomes. The variance (i.e., the square of the standard deviation of outcomes around the mean) is, of course, a symmetric measure of variability, meaning that variation above the mean has equal impact to variation below the mean. It doesn't take anyone very long to realize that it is not a very good measure in most contexts, because we care much more about downside variability (i.e., outcomes that are worse than the average) than upside variability. Oftentimes people don't consider upward mobility risky at all, even though there might be uncertainty involved (Weber, Birnbaum, & Anderson, 1992; Klos, Weber, & Weber, 2003). Subsequently, researchers have suggested alternatives to the definition of risk as variance notion, including measures like the negative semivariance (i.e., variability just on the downside) which still assume that risk is something immutable and inherent to an alternative and thus will be perceived the same by everyone. Others have suggested measures of risk that allow for individual differences or situational differences in the perception of the risk of a disease, of an investment alternative (e.g., Luce & Weber, 1986; Keller, Sarin, & Weber, 1986). These measures, which typically capture individual, situational, or cultural differences in risk perception as interpretable parameter differences (Bontempo, Bottom, & Weber, 1997; Weber & Hsee, 1999; Weber, Blais, Betz, 2002) turn perceived risk into a psychological construct, beyond its role as an explanatory theoretical construct in finance theory and economics. The conjoint, expected risk model (Luce & Weber, 1986), for example, decomposes perceived risk into a probability side and an expected outcome side, separating both into outcomes that are equal to, better, or worse than the status quo. The model has up to seven parameters that allow us to model individual, situational, or group differences. It turns out that often the best estimate of parameters coincide with other theories about why individuals or group are different. When high school teachers vs. undergraduates judge the riskiness of lotteries, for example, you find that the undergraduates who are more concerned about winning *something* and can ill afford to lose any money put more weight on the amounts of a loss, whereas for those people who can afford to lose some money, like high school teachers, the magnitude of the loss gets less weight.

One thing that I wanted to point out is that these mathematical models subsequently have been augmented by work using other methodologies and theories. As discussed in Weber (2001b), the axiomatic measurement approach (of which the CER model is a prime example) has been supplemented by work in the psychometric tradition, in particular the pioneering research by Paul Slovic, Baruch Fischhoff, and Sarah Lichtenstein on psychological risk dimensions. Most of this audience will be familiar with controllability, dread, the other qualitative experiences associated with certain risks that are not necessarily captured by probabilities and magnitudes of outcomes (Fischhoff, Watson, & Hope, 1984; Slovic, Fischhoff, Lichtenstein, 1986). It turns out that if you really want to capture people's risk perception, you need both cognitive and affective components (see Loewenstein, Weber, Hsee, & Welch, 2001). And that's true not only for health and safety risks, which is the domain for which the psychometric model was developed, but also for financial risks. In 1993, Dave Holtgrave, a former student, and I conducted a study where we gave MBA students a variety of risks, that included financial and health and safety risks, and we measured both the objective risk dimensions, to see the probability of upside and downside loss outcomes, and the magnitude of those outcomes, but then also the psychological risk dimensions, dread, controllability, and so on. It turns out that the best model that captures both financial and health and safety risk perceptions, for this group of fairly sophisticated Chicago MBA students, was a hybrid model.  Even on the margin of objective risk dimensions, dread predicts something about people's perceptions of financial risks (Holtgrave & Weber, 1993).

This result gets us back to another theme that has emerged in this morning's sequence of talks, namely dual processing systems (see Damasio, 1994; Epstein, 1994; Sloman, 1996; Chaiken & Fiske, 1999). We really do seem to have two systems that process information, which operate pretty much in parallel and are mediated by different brain structures.  Located in the neo-cortex, which is the evolutionary accomplishment that distinguishes humans from lower animals, we have a processing system that allows us to process information in a rule based, analytic fashion. The downside of this system is that it is slow, effortful, and requires constant awareness.  Algorithmic processing that involves the manipulation of symbols and often numerical calculations requires knowledge of the correct algorithm.  To update a probability estimate in a Bayesian fashion, you need to know Bayes' theorem.  Our second processing system, on the other hand, which goes back to an older phase of evolution and is shared with lower animals, does not have some of those limitations.  It is fast and automatic.  Located in regions of the brain stem, it works on similarity and associations, with affective reactions providing a very powerful set of associations.  Many people have made the argument that "risk as feeling" serves as an early warning system (Loewenstein et al., 2001).  With attention as our ultimate scarce resource, affective reactions (e. g., fear) get us to allocate attention optimally for survival.

The two processes systems operate in parallel. Most of the time we're not aware of them, but we become aware of their separate operation when their outputs do not agree.  If someone asks you "Is a whale a fish" your associative system says "Hell yes, it's a big fish", and if you ask a three year old, the three year old will also tell you it's a fish. On the other hand, after having learned biological taxonomies in college, your analytic, rule-based system will say "No, it's not a fish". To resolve this conflict, we end up making statements like: "Technically speaking, a whale is not a fish," which translates into "My analytic system tells me so, but in the back of my minds my associative system still thinks that a whale is a big fish".

In many situations where there is a discrepancy in the outputs of the two systems, the output of the associative and affect-based system tends to win out (Loewenstein et al., 2001). There also are individual differences in how much weight the two different systems get. Formal education and expertise leads people to place more weight on their rule based analytic system, and members of the lay public will load more heavily on their associative and affective processing systems.

I am now going to show you some data that show that people make very different decisions under risk when they receive information about choice alternatives by description (e.g., a 50:50 chance of winning $100 or nothing, vs. $30 for sure) than when they acquire information about possible choice outcomes by direct experience (i.e., by sampling environments where different outcomes might occur, by repeated exposure or trial-and-error learning, the way all other creatures have to learn about risk and uncertainty in the world. You cannot tell your dog there's a fifty/fifty chance of no bone or two bones, or one bone for sure. Animals in foraging environments need to personally experience the relative variability and magnitude of the outcomes.

When we put people in these two learning information acquisition environments, their behavior is very different. We have here the following choices: either you can get one dollar for sure, or you can opt for a 90% chance of getting nothing, and a 10% chance of getting ten dollars. When people see this choice, described in exactly this way, either numerically, or in a pie chart (a condition I call description-based choice), only 40% of people choose the sure option, one dollar. Most people prefer the gamble. One way of describing that is that they overweigh, implicitly, by their choice, the probability of the rare event. The 10% chance of getting ten dollars seems to get more weight than it deserves, because based on the expected value of the two choice options, they should be indifferent. If we prefer the lottery, we are putting more weight that the probability suggests on the better outcome, thus making the lottery more attractive. Of course that is exactly what Prospect Theory (Kahneman & Tversky, 1979), which is an improvement on Expected Utility theory, tells us, namely that we overweigh small probabilities. It turns out that that is true for description-based choice. It's not true, however, for experience-based choice.

When we make decisions the way foraging animals do it, guided by personally experienced outcomes from both choice options, sampled repeatedly over time, we get the opposite choice pattern, namely that the majority of respondents now comes to prefer the sure option. In the study I am describing to you (Weber, Shafir, & Blais, 2003), undergraduates came to the lab, which was turned into a casino. They saw two decks of cards, a green deck and a blue deck, with fifty cards each. The blue deck, unbeknownst to them, all had cost of one dollar on the other side, and the other deck had 45 cards that said zero, and five cards that said ten dollars, all mixed up. Respondents were allowed to sample from the two decks. They could draw as many cards as they wanted to, in any order that they wanted to, with replacement, until they thought they knew which deck they preferred. When they knew which deck they preferred, they could then draw a card from that deck for a real monetary payoff. The money that they earned on that trial was the financial payoff for participating in the study. On average, people sampled something like 17 cards from the two decks. As I stated before, the majority of people preferred the sure thing deck in this condition, a pattern that reflects an implicit underweighting of the rare events.

[Insert Table 1 about here.]

As shown in Table 1, we observed a similar result across 5 choice pairs:

The choice pattern switched between experience-based and description-based choice, especially in those pairs where one choice option involved a rare event, i.e., an event with a probability below 20%. Across choice pairs, you basically get a negative correlation of the proportion of people picking the sure thing. People on average are doing exactly the opposite under the two conditions. If in one situation they prefer the sure thing, under description-based decision making they will actually prefer the lottery in experience-based decision making. That presents a problem if we want to predict risky choice, because we need to have two choice theories. What essentially happens under experience-based decision making is that people learn about their preferences for choice options by associations. Each time you get a new outcome you update the overall assessment of the goodness or badness of this event, and by some continuous updating process you have some weighted average model of the goodness of the choice option that is path dependent. It turns out that these models, by definition, show built-in recency, because the weight of an outcome decays over time as new impressions come in. The updating process itself results in overweighting of recent experience. Why does this have an effect especially on rare events? By definition, a rare event is less likely to have been the most recent one. The common event is more likely have been experienced more recently. That explains our observed choice pattern under experience-based conditions.

The described study is a strong caveat against applying something like Prospect Theory blindly, because in real life, there are situations where we really are making decisions based on description, and there are other situations where we make decisions based on personal experience. This difference is not just a function of expertise. It also depends on the domain of the decision. For example if you are a parent, and if you make the decision whether to vaccinate your child, chances are the doctor or nurse will give the you the information about the probability of rare side effect, and you will find out that there is a .001 chance of something really terrible happening to your child. Well, this is description-based decision making, so you will overweigh that probability and be less likely to have your child inoculated. The doctor, on the other hand, will most likely use her personal experience in inoculations, since she inoculates hundreds or thousands of children in a given year, and subsequently observes how many or few of those develop side effects. Thus the doctor will probably underweigh the occurrence of side effects. On the other hand, in something like buying insurance (say, flood insurance), the farmer will probably make the decision based on personal experience, while the actuary who is selling the insurance will make the decision based on description. So it depends on the context and the source of information that you have. Decisions depend on how the information about the uncertainty and about the outcomes is being acquired. I think it is well worth considering when we are trying to predict how someone will react in a risky choice situation *how* the person has acquired information about his or her choice options, especially when the choice options involve rare events.

I would like to make a few more comments on the function(s) of risk perception. Why do we have these feelings of worry? I will argue is that perceived risk is oftentimes a signal to take protective action, or that it raises an expectation that others will take protective actions for you, e.g., some sort of mitigation response by the public or private sector, in case of environmental risk.

Where does the hypothesis take us that perceived risk serves as a signal to take protective action? One prediction is that more a strongly experienced feeling of risk is going to drive action more than less vivid perceptions of risk. Since affective responses carry more weight and are more vivid than analytically perceived risks, such affective reactions can be expected to guide behavior more than our analytic assessments. That might explain the failure of people to take protective actions, like for example to buy flood insurance, because floods are not in the part of the psychological risk space that ranks very highly on affective reactions. Floods are not dreaded, their mechanisms are well known, and so therefore in the absence of the emotional signal there is less of an impetus for action than for other risks.

My hypothesis is also consistent with something I have called the "single action bias" (Weber, 1997). In a study of cash crop farmers in the early 1990s, I found that half of them believed that there was global warming, and half of them didn't. Those who believed there was global warming were taking some action, as they were pretty worried about it. We had open-ended interviews, which showed that there were three classes or responses: Some farmers responded by changing their production practice, e.g., using irrigation or different types (more draught resistant) of seed corn. Some farmers changed their pricing practices, e.g., taking greater advantage of futures markets or forward contracts to insure against financial risks. And some farmers strongly lobbied for government programs and government regulations. It turns out that almost no farmer engaged in more than one class of these activities. Concern and worry about climate change seemed to raise a flag of some sort, reminding them that something was "out of whack" and required action. As soon as they did *something*, however, the flag went down, even though a portfolio of responses would have been the optimal reaction. An implication of these results is that, in certain situations, it might be necessary to remind people of the need for a portfolio of reactions and responses. .

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