Goals and the Organization of Choice Under Risk

Lola L. Lopes
The University of Iowa

The discipline of experimental psychology was changed profoundly by World War II. A generation of young psychologists became engaged with the war effort and when they returned to academia, they brought back working knowledge of powerful computational tools for understanding how intelligent systems process information. Ideas from signal detection theory, cybernetics, information theory, image processing, and others provided fertile new ways to think about human information processing. Most importantly, psychologists began to seek out ways to independently confirm the existence and operation of mental processes by finding ways to measure what goes on between stimulus and response and by creating novel and interesting stimuli that would not have been envisioned except for the existence of these new theoretical ideas.

I was lucky to have entered graduate school at the right time and the right place (the early 1970s at UC San Diego) to experience the youth of what was then called the Human Information Processing movement but is now known as Cognitive Psychology or even, as the focus has moved outside psychology proper, Cognitive Science. This early cognitive movement provided the basis for how I think about psychology. In short, I try to understand what people do (i.e., their final behaviors) by understanding how they do it. In my particular case, the hows can include a variety of internal processes such as attention, perception, goal seeking, encoding, information integration, comparison, and choice.

Empirically, I focus on choice data supplemented by verbal protocols, but I also have used reaction times and judgments. My primary quantitative tool has been to write and test mathematical models whose internal structure conforms to the psychological mechanisms that I believe underlie people’s preferences when they choose among risky options, that is, options
whose outcomes are known only in terms of probabilities. These models are tested against arrays of data and evaluated according to their ability to accurately reproduce both the quantitative and qualitative aspects of the arrays.

The Exceedingly Long (and Mostly Unexamined) History of Thought on Risky Choice

I fell into the study of risky choice by accident when I chose to study how people integrate the various pieces of information available in a poker game into a decision about how much to bet against a particular set of opponents while holding a particular hand. Poker players in the audience can rest assured that nothing I studied or discovered will make them a better player, but this did get me thinking about current and past academic work on risk taking.

Academic thought on how people choose among risks can be traced back at least to the 17th century. For our purposes today, however, the critical development for risk theory was the idea of expected value first published by Christian Huygens (Daston, 1980). This is the idea that, given an uncertain prospect with two or more possible outcomes, the overall value of the prospect is a probability weighted average of its individual possible outcomes.

The expectation principle had immediate useful application to the emerging field of actuarial science, but it seemed to fail when applied to certain extreme examples. The most famous of these is called the St. Petersburg Paradox and it goes like this: A fair coin is tossed until it lands tails, at which point the player is paid \(2^n\) monetary units, say dollars, where \(n\) is the toss on which tails occurs. Tails on the first toss pays $2. Tails on the second toss pays $4. Tails on the third toss pays $8, and so forth. The question of interest is how much should a person be willing to pay for a single play of the game? Looked at through the lens of expected value, the answer is simple. The expected value of the game is infinite and, therefore, a person should be willing to exchange all he or she has for a single play.

It was obvious to scholars at the time that this was a ridiculous conclusion and there were several different proposals for how this difficulty with the expected value rule could be bypassed. The most famous of these, suggested by Daniel Bernoulli (1738/1967), continues to provide the structural basis for modern day theories about valuing risks. Bernoulli’s proposal kept the mathematical structure of the expected value rule but replaced the objective value of each outcome by its subjective counterpart or utility. He pointed out that richer men value given increments in wealth less than poorer men, suggesting that the utility of wealth is a negatively
accelerated function of actual value. Thus, if people maximize expected utility rather than value, the worth of the game becomes quite small and the paradox disappears.

Since Bernoulli, most researchers on risk have assumed that Bernoulli’s idea is essentially right, although the details and rhetoric have changed, and the utility function itself is commonly taken to provide both the cause and the mathematical description of what we call risk aversion, that is, people’s typical preference for sure things in favor of actuarially equivalent risks. But strangely, even though Bernoulli’s notion of diminishing marginal utility predicts the behavior of risk aversion, there is nothing in his formulation that can be used to define what it means for a gamble to be risky or to relate perceived riskiness to risk aversion.

**Distributional Thinking: Ruin and Safety-First**

Bernoulli’s solution for the St. Petersburg paradox underlay my personal rebellion against the expected utility framework. Although I did not doubt that some mild diminishing marginal utility might operate over very large spans of wealth, it seemed evident that this had nothing to do with the perceived low value of the St. Petersburg game. The focus was all wrong. Although the key operation of diminishing marginal utility is to shrink the incremental value of successively larger prizes to virtually nothing, it seemed to me that people evaluating the game focus almost entirely on the small prizes that are most likely to be won.

My first attack on the traditional thinking (Lopes, 1981) eschewed diminishing marginal utility altogether and directly questioned the practical value of the game. I imagined an inexhaustibly rich seller, someone like Scrooge McDuck, who was willing to sell the game at the bargain price of $100. Using hundreds of millions of trials in a Monte Carlo simulation, I confirmed the naive intuition that selling the game for $100 would be an almost certain money maker for Scrooge and no bargain at all for buyers.

As it turned out, I was not the first to take this approach to analyzing the St. Petersburg game. Some 230 years previously, Buffon (Daston, 1980) had simulated the likely outcome of the game by hiring a child to toss a coin 2000 times. On the basis of his data, Buffon estimated the value of the game to be quite small. More recently, Maurice Allais (1986) used the mathematical theory of ruin to test the importance of the size of the player’s fortune in the likely outcome of the game. He found that even if the player can buy the game cheaply, and even if the
player has a relatively large fortune, the probability is quite high that the player will be ruined if settlement must be made after every game.

These probability based solutions differ fundamentally from those that retain the expectation principle in that the locus of their psychological effect involves small payoffs that occur with large probability. They differ also in that no operations are implied that distort or modify given outcomes or probabilities. Instead the focus shifts from Bernoulli’s perceptual hypothesis to the computational mechanism that people use to evaluate the likely worth of the game.

Allais’s (1952/1979) critique of expected utility did not stop with his analysis of the St. Petersburg game. Instead, he devised new paradoxes that directly attack the principle that the impact of a given outcome in a gamble should be directly proportional to its likelihood of occurring, which is to say that preferences between pairs of gambles should be invariant to linear transformation of their probabilities. If we take a pair of gambles and reduce the probabilities of winning in both by either subtracting a constant or dividing by a constant, the relative attractiveness of the gambles should not change.

Let me illustrate with one of Allais’ choice pairs. A subject is offered a choice between Gamble A and Gamble B:

<table>
<thead>
<tr>
<th>Gamble A</th>
<th>Gamble B</th>
</tr>
</thead>
<tbody>
<tr>
<td>$1 million for sure</td>
<td>.10 to win $5 million</td>
</tr>
<tr>
<td></td>
<td>.89 to win $1 million</td>
</tr>
<tr>
<td></td>
<td>.01 to win nothing</td>
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</tbody>
</table>

Most subjects choose Gamble A. However, if the same subjects are offered two new gambles,

<table>
<thead>
<tr>
<th>Gamble C</th>
<th>Gamble D</th>
</tr>
</thead>
<tbody>
<tr>
<td>.11 to win $1 million</td>
<td>.10 to win $5 million</td>
</tr>
<tr>
<td>.89 to win nothing</td>
<td>.90 to win nothing</td>
</tr>
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most are likely to go with Gamble D. But the two gamble pairs are linearly related. Gambles C and D are just Gambles A and B with a .89 change of winning $1 million subtracted from each.

This choice pattern violates the linearity requirement of expected utility, but it is easily understood as demonstrating people’s preference for safety. In the choice between Gambles A and B, people pass up a pretty good chance at $5 million to ensure receiving at least $1 million. In this setting, safety comes first. In choosing between Gambles C and D, however, the far
likeliest outcome under either scenario is to win nothing, and so people opt to open the possibility of the $5 million outcome.

**Modeling Distributional Thinking**

My empirical research (Lopes, 1984; Schneider & Lopes, 1986; Lopes & Oden, 1999) has not studied paradoxes directly. Instead, I have focused on exploring how people think about gambles or lotteries that have different shapes or distributions. To do this, I created a variety of multioutcome lotteries that exhibit interesting distributions.

The figure below illustrates some of the lottery types. Each lottery has 100 prize tickets represented by tally marks. For ease of processing, prize amounts are spaced more or less evenly high to low. Subjects are told that each lottery has the same total amount of prize money (in other words, the lotteries have equal expected value). The labels that you see, riskless, short shot, and so forth, are just for expository convenience. Subjects were presented with unlabeled lotteries two at a time and were asked to say whether they would prefer the left or the right lottery if they were allowed to draw a ticket from either for free.
In a typical experiment subjects are presented with all possible pairs of lotteries several times each, giving us reliable data about preferences. We also typically select a subset of lottery pairs and ask subjects to tell us the reasons for their choices. These verbal protocols are highly useful for revealing the underlying dimensions and logic of subjects’ choices.

For example, here is a subject choosing between the short shot and the long shot lotteries. She says: “I choose the [short shot] because too many people got zero in the [long shot]. I would have a good chance of getting $130 in the [short shot] and this is preferable to getting 0–$98 in the [long shot].” Notice that the subject focuses on the low-value end of the distribution and chooses so as to ensure winning something. This is a pattern I have called security-mindedness.

However, when two lotteries are similar at their low ends, some subjects also consider high outcomes. Here is a subject who is normally security-minded nervously choosing the riskier long shot over the bimodal gamble. She says: “Chances of getting zero are greater in the [long shot]. On the other hand, there are better prizes in the [long shot] once you get a ticket with a prize. In fact, chances of getting a prize of less than 40 or 50 look about the same, and then the [long shot] has better prizes.” She then adds: “I’m not sure I’m making a good decision here.”

We might say that this subject becomes cautiously-hopeful when the safety differences between two gambles are small. Her decision process is lexicographic: If she can make a decision based on safety alone, she chooses the safer lottery. But if the differences seem small, she breaks the tie by bringing in potential. In other words, she is not safety-only, but truly safety-first.

Attentional processes like these can be modeled mathematically by what I have called decumulative weighting functions (Lopes, 1995). The figure below shows three such functions. The functions are decumulative rather than cumulative because they measure the probability of achieving an outcome at least as large as a focal outcome. For example, 1 refers to the probability of winning at least the smallest prize whereas 0 refers to the probability of winning more than the largest prize.
The functions map objective decumulative probabilities on the abscissa against subjective probability weights on the ordinate. The slope of the function gives the amount of attention paid to outcomes at a given point. Steep regions represent strong attention, flat regions represent scant attention. The diagonal line shows the neutral weighting of an expected value maximizer.

The left-most panel represents a security-minded pattern. The function is steep near 1 and shallow near 0 showing that the probabilities of the worst outcomes are weighted more heavily than the probabilities of the best outcomes. The function in the middle represents the opposite pattern, one I call potential-minded. Potential-mindedness is much less common than security-mindedness but no less real (Schneider & Lopes, 1986). The right-most function is a hybrid that I call cautiously-hopeful. This function is steep for both the lowest and highest outcomes but flat in the middle.

The security-minded and cautiously-hopeful patterns are particularly important because the former accounts for classical risk-aversion without relying on non-linear utility, and the latter accounts for the non-linear shifts of preference that are demonstrated by the Allais paradoxes. I should also note that I do not consider attentional processes in lottery evaluation to reflect errors in assessing probabilities. Instead, they only suppose that people’s values for security or potential can be expressed by how much attention is paid to the various regions of the lottery.

**Gambling When You Must: Aspiration and Bold Play**

Although accounting for risk aversion motivated research on risky choice for its first three centuries, recent decades have seen the focus switch to what has been called “risk seeking for losses.” For example, in the lotteries that we saw previously, suppose the various outcomes
are defined as losses rather than gains. Subjects are asked which of each pair of lotteries they would choose if they were required to draw a ticket from the lottery and pay the loss out of pocket.

Going back to the choice between the short shot and the long shot, the subject we heard from previously, who chose the short shot because it had the fewest opportunities to win nothing, now chooses the long shot. She says: “I choose the [long shot] because there is more of a chance to lose zero and a good chance of losing less than $130 which would be the likely outcome in the [short shot].

How shall we explain this switch from risk aversion to risk seeking? One popular account is that subjects have a risk averse utility function for gains and a risk seeking utility function for losses, what has been called reflection (Kahneman & Tversky, 1979). But this move begs the question. It also makes no sense. Why be risk averse in the benign environment of gains but risk seeking in the much nastier environment of losses?

Fortunately, another explanation is evident in protocols for loss choices. For illustration, here are two subjects, both of whom are reliably security-minded for gains, choosing between the rectangular and short shot lotteries for losses. The first subject chooses the riskier rectangular lottery, saying: “Another difficult one. I chose the [rectangular] lottery because the odds are equal on each dollar amount, whereas the [short shot] shows the odds in favor of a loss of $70 or more, and very good odds of losing $130. The [rectangular] seems to be a safer risk despite the potential for a higher loss, i.e., $200 max.”

The second subject goes the other way and chooses the short shot: “Chances of losing ≤ $100 are about the same for both, but [rectangular] has higher possible loss, so I picked [short shot]. I realize [short shot] gives less chance of a very low loss, which reduces my certainty about choice.”

Although both subjects willingly give up the possibility of a large gain in order to avoid winning little or nothing, when confronted with losses they are torn between accepting the almost certain loss of a non-negligible amount on the one hand, and incurring a smaller but still worrisome chance of a really large loss on the other.

People’s willingness to accept risk in the service of avoiding devastating loss is called “bold play” and it has been formalized under the rubric of stochastic control (Dubins & Savage, 1976). A particularly notable example concerns Frederick Smith, the founder of FedEx. At one
point in 1974, the company didn’t have enough money to buy the fuel to keep its planes flying. Rather than give up, Smith went to Las Vegas where he gambled his last $5,000 at blackjack, winning enough to keep the company going until other funds could be found. When asked later why he’d been willing to take such a chance, he said: “What difference does it make? Without the funds for the fuel companies, we couldn’t have flown anyway.” (Hiskey, 2011).

The key element in bold play is the operation of a specific aspiration level that lies somewhere above the status quo but typically well below the maximum. For example, Fred Smith needed less than $30,000 to stay in business; he didn’t need to break the bank. The bold player, therefore, needn’t become risk seeking. He only needs to choose whatever option offers the best probability of achieving the goal.

Our subjects tend to describe themselves as having modest aspiration levels for gains, for example, “winning at least a little something.” Modest aspiration levels are completely consistent with security-mindedness making these two factors hard to tease apart for gains. For losses, however, subjects describe themselves as hoping to lose little or nothing. This goal is inconsistent with security-mindedness and therefore produces the conflicted choices that we have seen previously in protocols.

**Demonstrating Security-Potential and Aspiration Level in the Lab**

Up to now, I have chosen particular data points to illustrate how subjects think about risky choice, but my experimental approach has been more systematic. In the final part of this paper, I want to show you how the ideas I have sketched here can be brought together quantitatively in a theory I call SP/A Theory, SP for security-potential and A for aspiration. SP/A theory can be instantiated in an algebraic model and tested against arrays of choice data generated in the lab. The experimental work and the theoretical development are too complex to be covered here, but they are explained in full in a paper that Gregg Oden and I published in the *Journal of Mathematical Psychology* in 1999 (Lopes & Oden, 1999).

For the present, let me jump in by showing you the stimulus set that we used for this work. We began with a set of lotteries similar to those you have already seen. These are the standard gain lotteries but we also had standard loss lotteries.
Then we applied a couple of transformations to the stimuli to create four additional sets of lotteries. Below we have the transformed versions of the short shot and long shot lotteries. The scaled lotteries have each outcome value multiplied by 1.14 and the shifted lotteries have $50 added to each gain outcome or subtracted from each loss outcome. The scaled lotteries are a control for outcome range and should behave just like the standard lotteries. The shifted lotteries, on the other hand, are theoretically critical because they either ensure an attractive gain or an unpleasant loss. For gains, all lotteries offer a minimum gain of $50 except for the riskless which guarantees $110. For losses, all lotteries entail a minimum loss of $50 except for the riskless which guarantees a $110 loss.
Each of the standard, scaled, and shifted lotteries was paired with the other lotteries in its set and subjects were asked to choose which lottery of each pair they would prefer if they were allowed (for gains) or forced (for losses) to draw a ticket from the chosen lottery. All together, there were 90 possible lottery pairs, 45 for gains and 45 for losses, with two replications per subject per pair.

The figure below shows the data pooled over subjects, lottery pairs, and replications. The gain data are on the left and the loss data are on the right. Lottery type (standard, scaled, shifted) is the row parameter. Each data point represents the percentage of times the lottery was preferred out of the total times it was available for choice.
The data are listed along the abscissa according to the average preference of subjects for the standard lotteries. First, note that the data for standard and scaled lotteries are virtually identical for both gains and losses. For gains, the preference functions are steeply sloped, dropping more than 60% from the riskless lottery to the long shot. This is consistent with security-mindedness or, if you prefer, with risk aversion.

For losses, however, the functions are reversed in slope and flattened. Preferences are greatest for riskier lotteries such as the long shot and least for safer lotteries such as the riskless, but the difference between high and low is just 35%. Thus, although the signs of the functions are consistent with either potential-mindedness or risk seeking, the general flattening of choice proportions suggests a lessening of consistency either between subjects or within subjects or both.

The data for the shifted lotteries also differ from their standard and scaled counterparts. For gains, the preference function is convex, being greatest for the riskless and the long shot. We believe this happens because the $50 minimum gain guarantees that the aspiration level will be met, increasing the relative importance of potential via the SP analysis.

For losses, the pattern is concave, with the riskless and long shot lotteries being least preferred. In SP/A terms, this comes about because the $50 minimum loss guarantees that the aspiration cannot be met. Without the possibility of achieving a zero loss, there is less reason to accept the possibility of very high losses. In other words, the importance of security is reasserted.
Admittedly, this is a very complex array of data that may, at first blush, suggest some souped up form of reflection. But reflection neither predicts nor explains the general flattening of the preference functions for standard and scaled loss lotteries, nor does it predict non-monotonicity in the preference functions for shifted lotteries, nor inversions in the curvature of the shifted preference functions from convex to concave.

SP/A theory, on the other hand, does predict all three phenomena, but showing this requires some model fitting. To do this, Gregg and I had to produce a mathematical model using the basic features that I have described so far. We wrote the simplest version of our model with only six free parameters. Three parameters were used for describing a generalized decumulative weighting function. We didn’t use any parameters for aspiration level since we were willing to set the aspiration level for gains to winning more than zero and for losses to losing nothing. But because the SP and A assessments were modeled separately (although not sequentially) we needed one additional parameter to combine the SP and A assessments into a single SP/A value for each lottery, and a final two parameters for describing how the SP/A evaluations of two different gain lotteries or loss lotteries are combined to produce a choice.

You can see how well we did in the figure below. In a nutshell, the predictions of the SP/A model do a good job of capturing the data for both gains and losses. In both panels, the data for the standard and the scaled lotteries are virtually identical, with the slope for the loss data being shallower than the slope for the gain data. For shifted lotteries, we were able to capture both the convexity for gains and the concavity for losses. Overall, the RMSD (root-mean-squared-deviation) between obtained and predicted is 0.0681. This is quite good for fitting 90 data points with six free parameters.
The reason we chose six, by the way, is because we wanted to compare SP/A to Cumulative Prospect Theory, CPT (Tversky & Kahneman, 1992), a theory that incorporates decumulative weighting, risk aversion for gains, risk seeking for losses, and a reference point. This required five parameters for CPT itself plus one for fitting the choice rule. Although there is no time to get into details today, I can say that the prospect theory fit was less good, \( \text{RMSD} = 0.0810 \) versus 0.0681 for SP/A, even when the prospect theory parameters were allowed to assume values that are inconsistent with the theory’s underlying psychological principles.

Gregg and I also wanted to push the SP/A model to its extremes. In one direction, we eliminated the simplifying assumptions that were necessary to bring the SP/A fit down to six parameters and fit the model with a less constrained (but still respectably few) ten parameters. This reduced the RMSD to 0.0484.

The more interesting extreme, however, pushes the number of parameters as far as possible in the other direction, in other words to zero. The zero-parameter version of SP/A replaces decumulative weighting with expected value. Since the expected value was $100 for all lotteries, this effectively leaves only aspiration level to differentiate among lotteries. That is, the model considers only the probability that the outcome will be greater than zero for gains, and exactly zero for losses.
While the zero parameter fit is visibly crude, you can see that aspiration level by itself does a pretty good job of capturing the gist of the data for all three stimulus types. Quantitatively, the RMSD is 0.1206. This reasonably good approximation on zero parameters is critically important because aspiration level has been mostly ignored in psychological theories of risky choice.

This was not always so. In the early 1980s, John Payne and his colleagues (Payne, Laughhunn, & Crum, 1980) did significant work on aspiration level effects in risky choice that has only recently been extended (Payne, 2005). Similarly, Sandra Schneider (1992) has examined the conflicts that subjects experience when choosing between losses in the context of framing and suggests how choices among gains and choices among losses can engender different aspiration levels.

Concluding Thoughts on the Importance of Application

I started on this line of research hoping to find a closer correspondence between the psychological theory of risky choice and the way that ordinary people experience and talk about risk taking. At the time I started out, most psychologists were devoted to theories derived from expected utility theory. The work tended to be highly formal and there was relatively little in the way of new data to test the usefulness of the theory for describing human choice. Indeed, the strongest challenges to the descriptive adequacy of the theory came from people like Maurice
Allais (1952/1979) and Daniel Ellsburg (1971) who devised telling counterexamples that struck straight to the heart of the expected utility axioms.

If science worked the way it is supposed to, these counterexamples would have shifted the descriptive focus of psychological research years earlier than they did. But this was not to be for several interesting reasons. One was that the rhetoric of the time tended to vacillate between treating the utility function as a descriptive device based on the psychophysics of value, as it was originally for Bernoulli, to being no more than a convenient notation for summarizing the pattern that we call risk aversion. The fact that diminishing marginal utility has nothing directly to do with riskiness was swept under the rug. Even worse, ideas to the contrary, such as Buffon’s focus on probabilities or Allais’ focus on security were treated as manifestations of error and flawed understanding.

Fortunately for me, I discovered that there are many people working in applied fields with concepts that directly relate to human risk taking. For example, one of the most significant ideas that I ran across early on had to do with the comparison of different choice options. Although there had been some work touching on variance and skewness in distributions, this was not of much use for talking about traditional two-outcome gambles. It was only after an economist friend steered me to welfare economics that I discovered that Lorenz curves offered a wonderful way to describe the salient differences between risky distributions. It was Lorenz curves that pushed me into developing my own multioutcome lotteries and, in a way, moved me toward seeing the need for decumulative weighting by foregrounding the importance of comparisons at the low and high ends of lotteries (Lopes, 1984, 1987).

In a similar way, I was lucky to discover how different agricultural economics is from theoretical economics. Learning about subsistence farming and the safety-first principle opened my eyes to alternative ways of formalizing risky choice. Likewise, it was research on stochastic choice and ruin that introduced the notion that maximization of expected utility or expected value could be approached subject to constraints such meeting an aspiration level. I owe a very great debt to these generous friends from other fields, including Dierdre McCloskey, who were so patient in talking with a psychologist who did not at all share their language. They made a big difference to me.

I am also grateful to more recent friends such as Hersh Shefrin and Meir Statman who have shown me in their own work on Behavioral Portfolio Theory, BPT (Shefrin & Statman,
2000) that ideas worked out in the domain of cognitive psychology can be brought back into an applied quantitative context. It feels good to see how threads from my own thinking can be aligned with well known ideas in finance such as value at risk, and how the two separate criteria of SP/A theory are related to multiple accounts in behavioral portfolio theory. I am also especially excited to see their interest in the evolutionary implications of different approaches to risk taking. Interest in the real-world consequences of risk attitudes has been a long time coming.

More than 20 years ago, I moved to Iowa because of my interest in a program on The “Rhetoric of Inquiry” that was founded by Deirdre McCloskey. At one of the seminars, I recall being struck by a notion from a philosopher whose name I cannot now recall. This was the idea that we scholars are engaged in what he called “the conversation of mankind,” a conversation that has spanned many centuries. The idea had great force for me personally because I have often imagined myself talking to the distant and the dead, trying to convince them of some point of my own. In time, however, I lost the sense of a quiet conversation among colleagues and found, instead, that academic life reminded me of how it feels to attend a huge conference and not know a soul. This made it relatively easy for me to move away from research and into other university endeavors.

When Leslie Shaw asked me to participate in this conference, I tried to say no since I knew it would be hard to jump back in after ten years away. But now I am glad that she was persistent since it has shown me that the conversation has continued whether or not I was there. It is not we as people who are the participants in the conversation of mankind, but rather the ideas that we have contributed in our time. These are picked up and used in new formulations much as I picked up and used ideas from Bernoulli and Buffon.

In the long run, this is what is important. All of us have been working on risk within our own disciplinary frameworks and from our own scholarly inclinations. I find it comforting to know that no matter how large the differences can seem between our views, risk itself does not belong to any one discipline. Instead, it is a central and very real aspect of human life, worthy of all our efforts to define it, measure it, control it and, one would hope, survive and even thrive in the face of it.
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