Mauboussin on STRATEGY

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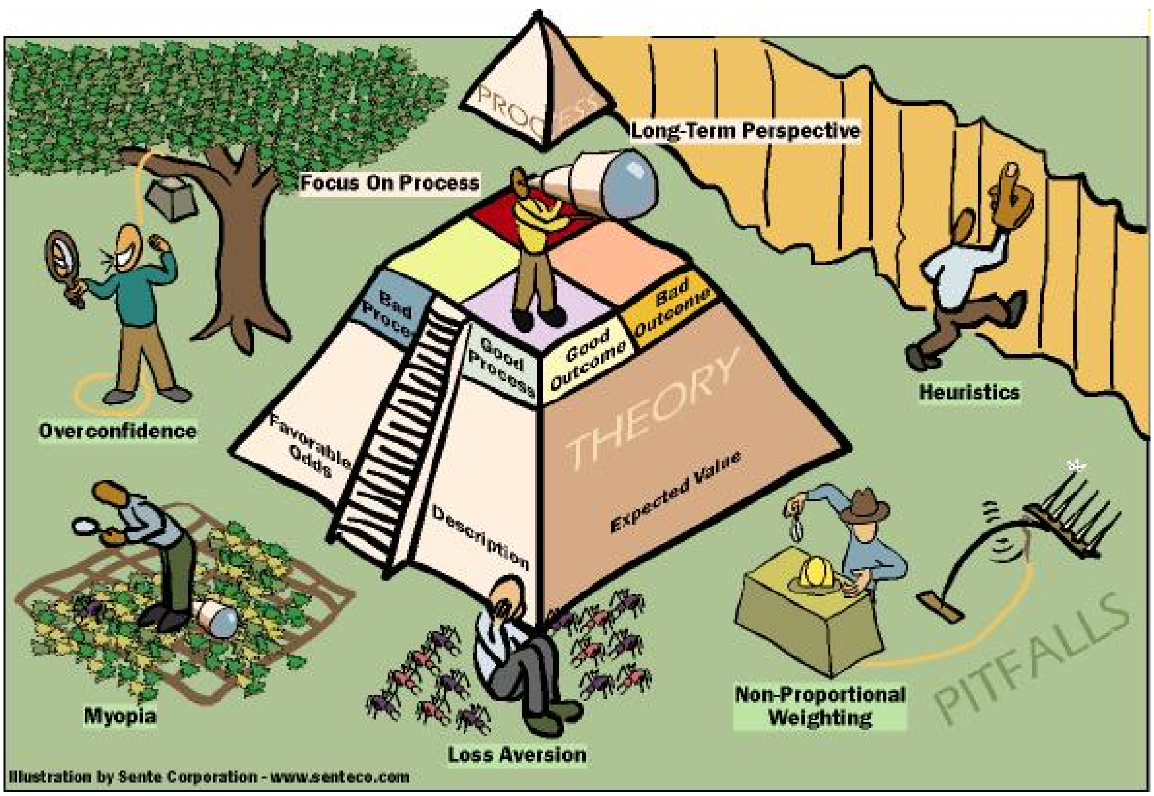
Decision-Making for Investors

Theory, Practice, and Pitfalls

The fundamental law of investing is the uncertainty of the future.

Peter Bernstein



- **Individuals who achieve the most satisfactory long-term results across various probabilistic fields tend to have more in common with *one another* than they do with the average participant *in their own field*.**

- **Distinguishing features of probabilistic players include a focus on process versus outcome, a constant search for favorable odds, and an understanding of the role of time.**

- **Success in a probabilistic field requires weighing probabilities and outcomes—that is, an expected value mindset.**

- **One key to success is a high degree of awareness of the factors that distort judgment.**

Looking Outside to Understand What's Within

Sorting skillful and lucky participants is not easy in a probabilistic field like the stock market. Markets tend to express the likelihood of various outcomes, making the financial proposition a fair game (excluding transaction costs). For example, the odds on the tote board reflect each horse's chance of winning. Research shows that handicapping accurately predicts actual results over time. [1]

The investment community values the ability to distinguish between skill and luck highly because long-term results can make the difference between meeting and falling short of future liabilities. With rare exception, the academic finance community believes that even *trying* to identify skillful investors is a futile exercise. If markets are efficient, the thinking goes, your return over time will reflect the risk you assume net of costs.

Academics generally consider investors with superior results lucky rather than skilled. If investing is a fair game like a coin toss, and you start with a sufficiently large sample, some percentage of the group will do well by virtue of chance. [2] The key notion is that it's impossible to know ahead of time which investors will end up as the lucky ones. Since you can't predict luck, academics recommend buying low-cost index funds.

Though practically sound, the academic advice ignores two critical facts. First, in almost any human endeavor, people have differential capabilities. The investing-is-a-coin-toss metaphor assumes that everyone has an equal chance of success or failure. We simply don't see this in the real world. If you go to a baseball game, you won't see all .260 hitters; you'll see a mélange of skills. The same holds true for investors. [3]

Still, differential capabilities are not enough. As we already noted, prices in probabilistic fields do make it look like a fair game, just as golf handicaps allow players of different skill to play on an equal footing. The second fact is that in each probabilistic field—including investing, poker, handicapping, and sports team management—certain individuals *do* consistently generate superior results.

The combination of differential capabilities and existence of superior performers provides a basis for judging skill versus luck. Individuals who consistently succeed in various probabilistic fields possess both superior skills and a dissimilar approach to others. In fact, these super performers appear to have more in common with *one another* than they do with the average participant *in their own field*. A great investor thinks more like a great handicapper than the average investor.

We want to study the elite performers in probabilistic fields to see what traits they have in common. These traits will provide a guideline to assess skill versus luck in the investment business. In short, we need to look *outside* the investment business to understand skill *within* it.

Same Strokes for Different Folks

We do not know what the future holds. We operate in a world where information is incomplete, facts are mingled with beliefs, and uncertainty reigns. An investor's goal is to understand how expectations for a company's future are going to change over time. This is no easy undertaking, especially since we humans are not well designed to grasp dynamic outcomes.

How should investors approach decision-making? We can begin by thinking in probability terms, because at the end of the day investing is inherently a probability exercise. Most investors acknowledge this point but very few live by it. An investor's approach to decision making might be the single most important (and least explored) facet of the investment process.

Strikingly, the best performers in all probabilistic fields tend to have a common and consistent approach that sets them apart from the average participant. This approach has a few key, related elements:

1. A focus on process versus outcome;
2. A constant search for favorable odds;
3. An understanding of the role of time.

The elite performers also stay highly aware of the factors that cause their judgment to slip.

This paper has three parts. First, we will review these three elements, drawing input from successful people in various probabilistic domains. Second, we go from theory to practice and explore the mechanics and nuances of expected value. Finally, we discuss some heuristics and their associated biases to see why we fail to properly calibrate probabilities and outcomes.

The Right Stuff

Process versus outcome. Long-term success in a probabilistic field requires a disciplined and economic *process*. Discipline does not mean inflexibility; top practitioners recognize circumstantial changes and continually adapt.

While satisfactory long-term outcomes ultimately define success in probabilistic fields, the best in their class focus on establishing a superior process with the understanding that outcomes take care of themselves. Probabilistic endeavors require a focus on process because, by definition, poor decisions will periodically result in good outcomes, and good decisions will lead to poor outcomes. Exhibit 1 is a simple two-by-two matrix that summarizes this point:

Exhibit 1: Process and Outcome Matrix

		Outcome	
		Good	*Bad*
Process Used to Make the Decision	*Good*	Deserved Success	Bad Break
	Bad	Dumb Luck	Poetic Justice

Source: J. Edward Russo and Paul J. H. Schoemaker, *Winning Decisions* (New York: Doubleday, 2002), 5.

Former Treasury Secretary and Wall Street veteran Robert Rubin emphasized process in a series of commencement addresses: [4]

> Any individual decision can be badly thought through, and yet be successful, or exceedingly well thought through, but be unsuccessful, because of the recognized possibility of failure in fact occurs. But over time, more thoughtful decision-making will lead to better overall results, and *more thoughtful decision-making can be encouraged by evaluating decisions on how well they were made rather than on outcome*. (Emphasis added.)

Rubin underscores the important point that how you *evaluate* the situation shapes your approach. A singular focus on outcomes will accommodate a lot of poor, but temporarily lucky, processes, and may even encourage dishonest behavior. In contrast, focusing on process will lead to satisfactory long-term results while allowing for inevitable, albeit unpleasant, periods of unsatisfactory outcomes.

In the introduction to his book *The Theory of Poker*, professional poker player David Sklansky has this to say: [5]

> Any time you make a bet with the *best of it*, where the odds are in your favor, you have earned something whether you actually win or lose the bet. By the same token, when you make a bet with the *worst of it*, where the odds are not in your favor, you have lost something, whether you actually win or lose the bet.

Sklansky draws out the importance of *discipline*. Note his point that "you have lost something" even on bets that work out (favorable outcome) if the odds are not favorable (poor process). This advice keeps us solidly rooted in the process and allows for some emotional detachment from short-term outcomes.

Unfortunately, the investment community currently focuses more than ever on short-term outcomes. In part, this attention to outcomes reflects a shift in emphasis between the *profession* and the *business* of investment management. [6] While the profession emphasizes long-time horizons, contrarian strategies, and outperforming an appropriate benchmark, the business dwells on short-term horizons, selling what's in vogue, and minimizing variation from a benchmark so as to facilitate asset raising.

In short, few investment firms can afford to focus on process. Not surprisingly, the firms that do focus on process deliver some of the best long-term investment results.

Always have favorable odds. Most probabilistic endeavors consist of several opportunities—whether it is pitches for a batter, stocks for the investor, or hands for the poker player. A relatively small percentage of those opportunities have favorable odds. Sifting through financial propositions to find those with favorable odds leads to success in an uncertain world.

In his classic *Beat the Dealer*, Ed Thorp describes a proper betting strategy under ideal playing conditions (head-to-head with the dealer, counting cards, single deck, etc.). He notes that even under these optimal conditions, the house has the advantage 90.2% of the time.[7] Seeking situations with favorable odds requires substantial diligence, hard work, and patience.

How do you find attractive odds in the investment business? You must locate gaps between current expectations and where expectations will likely stand in the future. While many probabilistic fields post their odds—handicapping and sports betting, for example—stock markets investors must learn to *read* the odds by deciphering the expectations built into prevailing prices.

Perhaps the single greatest error in the investment business is a failure to distinguish between knowledge of a company's fundamentals and the expectations implied by the stock price. When a company possesses strong fundamentals, investors tend to buy irrespective of expectations. Similarly weak fundamentals cause investors to avoid a stock. These tendencies lead to an inability to properly calibrate odds, producing suboptimal performance.

Consider the following from Steven Crist, chairman of the *Daily Racing Form*. Replace "horse" with "stock" and you have an excellent articulation of the challenge many investors face:[8]

> The issue is not which horse in the race is the most likely winner, but which horse or horses are offering odds that exceed their actual chances of victory . . . This may sound elementary, and many players may think that they are following this principle, but few actually do. *Under this mindset, everything but the odds fades from view. There is no such thing as "liking" a horse to win a race, only an attractive discrepancy between his chances and his price.* (Emphasis added.)

Legendary hedge fund manager Michael Steinhardt provides a similar perspective, and he emphasizes the distinction between "fundamental knowledge" and "market expectation:"[9]

> I defined variant perception as holding a well-founded view that was meaningfully different than the market consensus . . . *Understanding market expectation was at least as important as, and often different from, the fundamental knowledge.* (Emphasis added.)

Understand the role of time. Dealing with probabilities requires persistence and staying power. In the short term, results may be very unsatisfactory. Long term, an appropriate process delivers good results. You cannot judge performance in a probabilistic field over the short term—there is much too much noise.

Michael Lewis makes this point convincingly using statistics from major league baseball:[10]

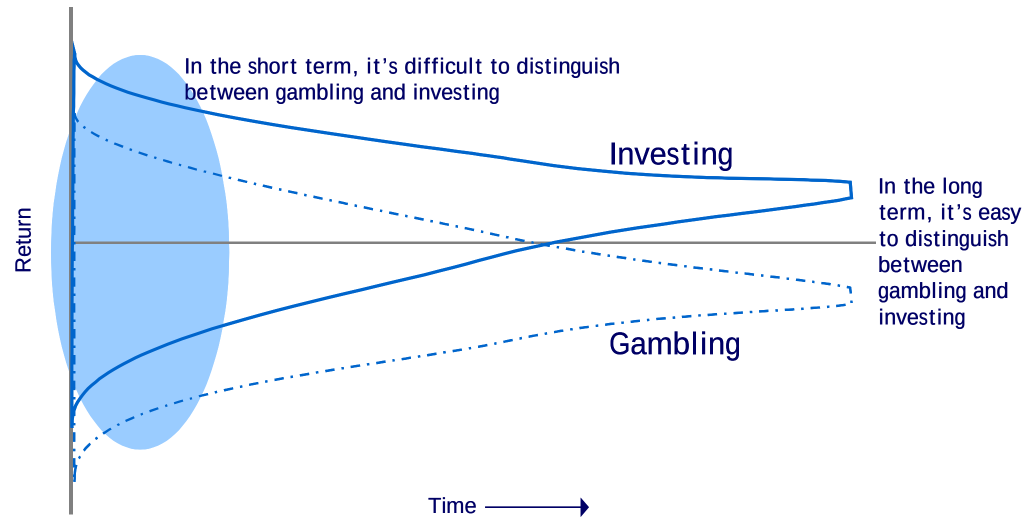
> *Over a long season the luck evens out, and skill shines through.* But in a series of three out of five, or even four out of seven, anything can happen. In a five-game series, the worst team in baseball will beat the best about 15 percent of the time. Baseball science may still give a team a slight edge, but that edge is overwhelmed by chance. (Emphasis added.)

The winner of the 1972 World Series of Poker, Amarillo Slim, delivers much the same message. His comment also underscores the important of process:[11]

> The result of one particular game doesn't mean a damn thing, and that's why one of my mantras has always been "Decisions, not results." *Do the right thing enough times and the results will take care of themselves in the long run.* (Emphasis added.)

Commentators periodically attempt to parallel investing in the stock market with gambling. This comparison remains only remotely valid in the short-term and turns disastrously false over the long term. Exhibit 2 shows that in the short-term, results vary widely for both investing and gambling. Investor Nassim Taleb argues that the ratio of noise (portfolio variability) to nonnoise (portfolio results) stays too high over short time increments to draw any sensible conclusions. Over long time horizons, though, variability and results grow more obviously distinguishable. Taleb further notes that our emotions are not well designed to understand this point. [12]

Exhibit 2: Investing and Gambling



Source: LMFM analysis.

Investing is a net present value positive activity; otherwise, savers would not forgo current consumption in the expectation of greater future consumption. Inversely, with few exceptions gamblers engage in a net present value negative pursuit. The longer your time horizon in investing, the more likely you are to generate a positive return. The longer your time horizon in gambling, the more assured you are of a loss.

In recent decades the investment community focused more and more on outcomes—and increasingly on *short-term* outcomes. This focus likely reflects incentives in the investment management business. We see evidence for this short-term focus in portfolio turnover statistics, where average annual mutual fund portfolio turnover rocketed from from about 20% in the 1960s to over 110% today, as well as investor mutual fund holding periods, which dropped from an average of roughly ten years in the early 1970s to roughly 2 ½ years now. [13]

As a result of the emphasis on short-term outcomes, most mutual fund managers do not establish an investment process that lends itself to long-term outcomes. The signatures of a quality long-term process include a focus on economic (versus accounting) value, low portfolio turnover, and relative portfolio concentration. An undue and incorrect focus on outcomes undermines the process.

In a nutshell, the best performers dwell on a process, try to capture attractive odds, and they assess their performance over the long term. This leads to a very basic question: how do you implement these ideas in practice?

The Expected Value Mindset

Unfailingly considering every financial situation in probability and outcome terms forms the core of a sound investment process. While most investment professionals acknowledge the virtue of this approach, very few internalize it. Here's a comment by Robert Rubin: [14]

> While a great many people accept the concept of probabilistic decision making and even think of themselves as practitioners, *very few have internalized the mindset*. (Emphasis added.)

A good investment process relies on three central concepts: thinking in expected value terms—combining probabilities and outcomes—considering the role of time, and appreciating the pitfalls to making quality decisions. Although no precise rules dictate how to do this in investing, the principle of expected value is fundamental. According to Warren Buffett: [15]

> Take the probability of loss times the amount of loss from the probability of gain times the amount of the possible gain. That's what we're trying to do. *It's imperfect, but that's what it's all about.* (Emphasis added.)

More formally, expected value equals the weighted average value for a distribution of possible outcomes. Here's a simple example:

Probability	Outcome	Weighted Value
40%	+20%	+8.0%
30	+5	+1.5
30	-10	-3.0
100%		+6.5% = Expected value

Calculating expected value is not conceptually difficult—especially for systems with normal distributions (weight of babies when they're born, adult female heights). However, defining sensible probabilities and outcomes is very difficult in practice, especially considering the many lurking cognitive pitfalls.

Before launching into a discussion about probabilities and outcomes, we should step back and distinguish between risk and uncertainty. While many investment professionals use these terms interchangeably, they are distinct. In his 1921 classic book *Risk, Uncertainty, and Profit*, economist Frank Knight argued that with risk, we don't know the outcome but we do know what the underlying distribution looks like. Risk also incorporates the element of harm or loss.

In contrast, with uncertainty we don't know the outcome, but we *don't* know what the underlying distribution looks like. [16] Further, uncertainty need not entail harm or loss, but often does.

Risk forms the bedrock of finance theory, including the capital asset pricing model, options pricing models, and value-at-risk calculations. Models of risk assume asset price changes follow a normal distribution. Risk is a convenient analytical assumption because it allows for tractable calculations.

For systems following a normal distribution, the mean is the expected value and the standard deviation provides a concrete sense of the risk—the likelihood of a result that differs from the mean.

Unfortunately, asset price changes do not follow a normal distribution—even at the portfolio level. This suggests at least some degree of uncertainty in capital markets. On a stock-by-stock basis, we see many cases of asymmetric distributions. For these distributions, the mean is a very poor indicator of the central tendency of value. [17] As a result, we must look beyond normal distributions to properly frame many financial propositions.

Thinking about probabilities. While conceptually straightforward, investors have difficulty applying expected value because there is substantial room for error in estimating both probabilities and outcomes. A good investment process reduces judgment errors in calculating expected value.

Let's start with probabilities. We can estimate the probability of a future outcome using one of three generally accepted ways, all useful to investors under various conditions: [18]

1. Subjective (degrees of belief)
2. Propensity
3. Frequencies

Subjective probability operates to assess unique events where investors cannot readily draw on a history of relevant results. Investors can and should use this degrees-of-belief approach as long as the process satisfies probability laws.

One vocal advocate for this approach was economist John Maynard Keynes: [19]

> By "uncertain" knowledge . . . I do not mean merely to distinguish what is known for certain from what is only probable . . . The sense in which I am using the term is that in which the prospect of a European war is uncertain, or the price of copper and the rate of interest . . . About these matters there is no scientific basis on which to form any calculable probability whatever. We simply do not know. Nevertheless, the necessity for action and for decision compels us as practical men to do our best to overlook the awkward fact and to behave exactly as we should if we had behind us good Benthamite calculation of a series of prospective advantages and disadvantages, each multiplied by its appropriate probability, waiting to be summed.

Naturally, when information reveals itself, investors need to refine their probability assessments. The formal way to do this is through Bayes's Theorem, which specifies a mathematical means to update the probability of a given situation in light of new evidence. [20]

Assessing the propensity of the system gives us a second way to estimate probabilities. Engineers often use this approach. Instead of estimating the probability of rolling a six with a fair die by evaluating lots of rolls, the propensity approach looks at the physical features of the die and concludes a one-in-six probability.

The chance of a catastrophic failure of the space shuttle is a high-profile example of the use of propensity probability. After conferring with its engineers, NASA judged the probability of failure at 1-in-145 (0.7 percent). [21] The shuttle has already seen two complete losses in 113 launches. Propensity probabilities are vulnerable when probability-setters fail to weigh all causative circumstances.

Lastly, we can estimate probabilities through a frequency assessment. In this case, an investor sets probabilities by studying a large sample of an appropriate reference class and assuming past outcomes will accurately represent of future outcomes. The finance and investment community rest largely in this camp, and with plausible reason: markets generate lots of numbers.

Investors relying on frequency probabilities must focus on the sample size (which we address below) and an *appropriate reference class*. Investors often assume a particular metric—say a price-earnings multiple—defines a reference class. For example, investment strategists routinely compare today's price-earnings multiple with multiples of the past in order to judge the relative attractiveness of the market.

Yet such comparisons are only relevant in static environments, which rarely exist in the real world. Here we encounter the problem of nonstationarity. Financial economist Brad Cornell highlights the risk to drawing conclusions from nonstationary data: [22]

> For past averages to be meaningful, the data being averaged must be drawn from the same population. If this is not the case—if the data come from populations that are different—the data are said to be nonstationary. *When data are nonstationary, projecting past averages typically produces nonsensical results.* (Emphasis added.)

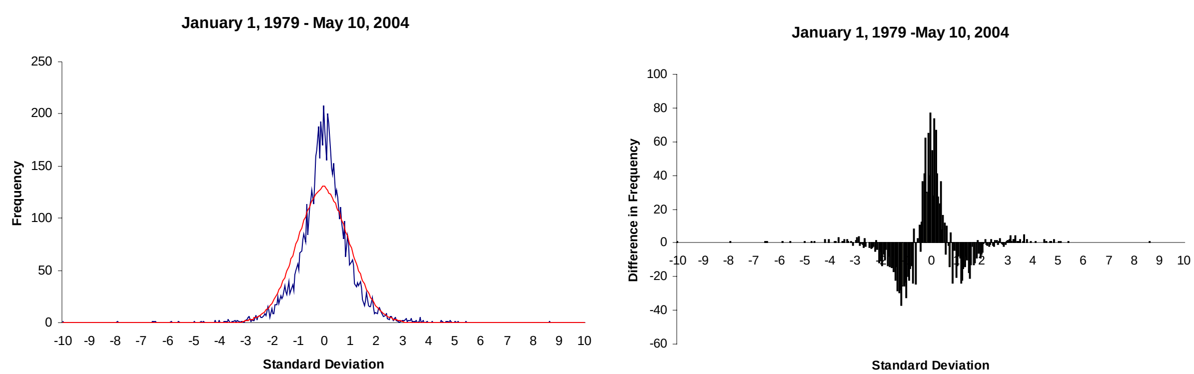
Is it proper to compare past price-earnings multiples to today's market? Tax rates, inflation rates, and the evolution from a capital-based to a service-based economy all determine price-earnings multiples. To the degree that those drivers have changed (and they have dramatically), past multiple averages may not constitute an appropriate reference class and hence say little about prevailing multiples.

Thinking about outcomes. As noted earlier, financial economists generally assume that asset price changes form a normal distribution*. For the most* part this assumption is reasonable. However, extreme changes—fat tails—happen much more frequently than the standard model assumes, and outcomes *outside* the normal distribution often have a substantial say in investment results. (Long Term Capital Management stands out as the most widely celebrated victim of fat tails. [23]) Notes Nobel-prize-winning physicist Philip Anderson: [24]

> Much of the real world is controlled as much by the "tails" of distributions as by means or averages: by the exceptional, not the mean; by the catastrophe, not the steady drip; by the very rich, not the "middle class." We need to free ourselves from "average" thinking.

To see the importance of fat tails, take a look at actual market results. The left panel of Exhibit 3 shows the actual distribution of daily S&P changes over roughly the last 25 years, as well as a normal distribution, which we derived based on the statistics from the data. Exhibit 3's right panel shows the same data a different way by taking the difference between the actual and the theoretical results. The exhibit shows more days with small changes than theory predicts, fewer medium-change days, and many more large-scale outcomes than we might expect.

Exhibit 3: Distribution of Daily S&P 500 Price Changes (1979-2004)

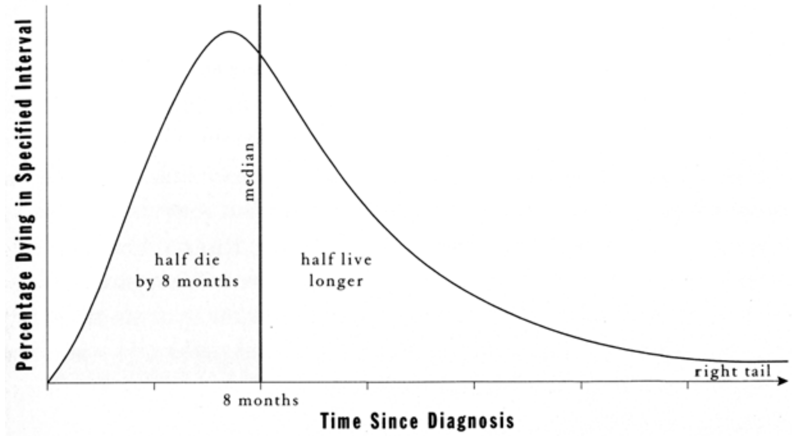


Source: LMFM analysis.

Even granting that stock price changes are not normally distributed, Exhibit 3 shows that stock price changes *at least look* fairly symmetrical. But in the real world we find asymmetries everywhere, and they are vital to proper thinking about outcomes.

In 1982, the evolutionary biologist Stephen Jay Gould was diagnosed with a rare and serious cancer. Gould bee-lined to library, only to find that sufferers of this particular cancer had a median mortality of eight months. Gould immediately recognized that the distribution around this distribution was right-skewed: while one-half of the patients died within eight months, the other half lived much longer. (See Exhibit 4.) Gould himself lived another 20 years. [25]

Exhibit 4: An Example of Asymmetric Outcomes

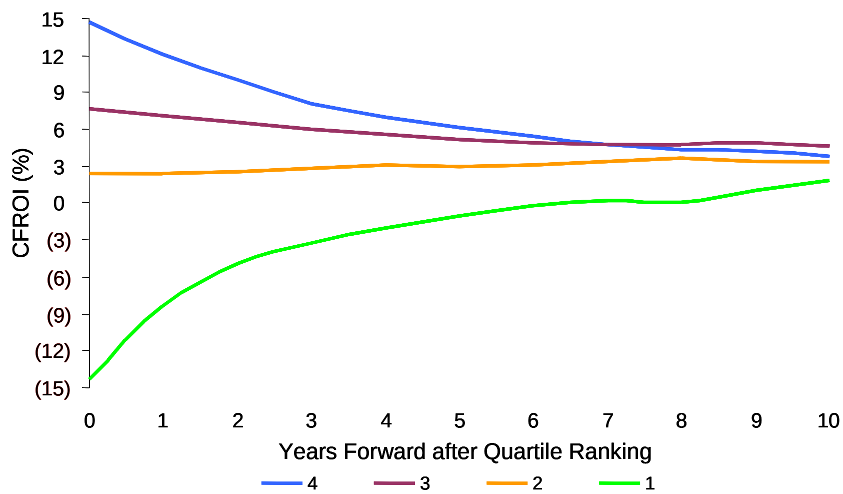


Source: Stephen Jay Gould, *Full House* (New York: Harmony Books, 1996), 51.

Investors rarely face perfectly symmetrical outcomes and should stay highly attuned to asymmetries.[26]

The concept of reversion to the mean provides one concrete example. Ample empirical data show that corporate returns on invested capital tend to revert toward the cost of capital. (See Exhibit 5.) If you select a sample of very high return businesses, you can say with reasonable assurance that in the future the distribution of returns will be asymmetric—most companies will have returns that are much lower and only a small percentage will have higher returns.

Exhibit 5: Reversion to the Mean—US Technology Companies



Source: CSFB HOLT.

The role of time (part II). One of finance's puzzles is why equity returns have been so much higher than fixed income returns over time, given the respective risk of each asset class. From 1900-2003, stocks in the U.S. earned about a 5.4% annual premium over Treasury bills.[27]

In 1995, Shlomo Benartzi and Richard Thaler proposed a solution to this puzzle based on what they called "myopic loss aversion." Their argument rests on two conceptual pillars: [28]

- *Loss aversion.* We regret losses two- to two-and-a-half times more than similar-sized gains. Since stock price is generally the frame of reference, the *probability* of gain or loss is important. The longer the holding period, the higher the probability of a positive return.
- *Myopia.* The more frequently we evaluate our portfolios, the more likely we will see losses and hence suffer from loss aversion. Inversely, the less frequently investors evaluate their portfolios, the more likely they will see gains.

Exhibit 6 provides some numbers to illustrate these concepts. The basis for this analysis is an annual geometric return of 10% and a standard deviation of 20.5% (very close to the actual return and standard deviation from 1926-2003). The table assumes stock prices follow a random walk (and imperfect but workable assumption) and a loss aversion factor of 2. (Utility = Probability of a price increase – probability of a decline x 2.)

Exhibit 6: Time, Returns, and Utilities

Time Horizon	Return	Standard Deviation	Positive Return Probability	Utility
One Hour	0.01%	0.48%	50.40%	-0.488
One Day	0.04	1.27	51.20	-0.464
One Week	0.18	2.84	53.19	-0.404
One Month	0.80	5.92	56.36	-0.309
One year	10.0	20.5	72.6	0.177
Ten years	159.0	64.8	99.9	0.997
100 years	1,377,961	205.0	100.0	1.000

Source: LMFM analysis.

A cursory glance at the exhibit shows the probability of a gain or loss in the short-term stays close to 50-50. Positive utility—essentially the avoidance of loss aversion—requires an evaluation period of nearly one year.

Using multiple simulation approaches, Benartzi and Thaler estimate an evaluation period consistent with the realized equity premium of about one year. Assuming portfolio turnover provides a reasonable proxy for the evaluation period, high turnover indicates seeking gains in the short-term, and low turnover suggests a willingness to wait to assess gains and losses.

If Benartzi and Thaler are right, the implication is critical: Long-term investors (individuals who evaluate portfolios infrequently) will pay more for the identical risk on an asset than short-term investors. *Valuation depends on your time horizon*.

Here's where agency costs kick in. If a portfolio manager—or any manager in a probabilistic field—has pressure to succeed in the short-term, they will very likely make suboptimal long-term decisions. Many portfolio managers won't buy a controversial stock, which might be attractive over a three-year horizon, because they have no idea whether or not the stock will perform well over a three-month horizon. This example shows why myopic loss aversion may be an important source of inefficiency.

Frequency and magnitude. The combination of loss aversion and asymmetric distributions shows why investors must combine probabilities (frequency) and outcomes (magnitude) to assess value. Loss aversion shows our desire to be right—the higher the percentage, the better we feel. But asymmetric distributions remind us to properly consider low probability events with extreme values. Expected value demonstrates that you can't just focus on how *often* you're right, you have to think about *how much you make* when you're right versus how much you lose when you're wrong. [29]

Consider the expected value for a stock that's "priced for perfection" just prior to an earnings release. Say there's a 70% probability that the company will meet the market's expectations leading to a 1% stock rise. Alternatively, there is a 30% chance the company will disappoint the market, resulting in a 10% stock decline. How does this investment look?

Well, this bet has a very good probability but a bad expected value. Although the odds of a favorable outcome are high, asymmetric outcomes keep the expected value negative (70% x 1% + 30% x –10% = –2.3%).

Take the inverse case of a downtrodden value stock. The probability of a poor outcome is 70%, resulting in a 1% decline, while a favorable outcome has a 30% chance and will produce a 10% gain. This scenario has a poor probability of a positive outcome but very attractive expected value (70% x –1% + 30% x 10% = 2.3%). See Exhibit 7.

Exhibit 7: Frequency versus Magnitude

Good probability, bad expected value

Probability	Outcome	Weighted Value
70%	+1 %	+0.7%
30%	-10	-3.0
100%		-2.3%

Bad probability, good expected value

Probability	Outcome	Weighted Value
70%	-1 %	-0.7%
30%	+10	+3.0
100%		+2.3%

Source: LMFM analysis.

Leon Levy, the well-known founder of the Oppenheimer Funds, related the importance of this mindset in his autobiography: [30]

> Indeed, I can be wrong more often than I am right, so long as the leverage on my correct judgments compensates for my mistakes. Al least that is how my investments have worked out thus far. A statistician might deplore this approach, but it has worked for me for a half century.

Investors must appreciate the frequency and magnitude point in a portfolio context. For example, the market might misprice a 50-to-1 odds event as a 100-to-1, but you wouldn't want to bet your net worth on such a single opportunity—as attractive as it may be. Money management addresses portfolio diversification so as to maximize long-term results while minimizing the risk of a debilitating loss.

How Do We Misspecify Probabilities and Outcomes?

Though simple in principle, the concept of expected value remains difficult to implement in practice. This discrepancy arises because we consistently fall into psychological traps that cause us to misspecify either probabilities, outcomes, or both. These traps reflect a mismatch between the kinds of problems evolution designed our brains to solve and the actual challenges we face in the investment world.

Two major sources cause these traps. First, our behavior does not conform to economic theory. This concept is formalized in Daniel Kahneman and Amos Tversky's prospect theory. A second, and related, cause of traps is heuristic biases. Investors use rules of thumb, or heuristics, to help simplify their lives. Though heuristics reduce the informational demands of decision-making, they produce biases that undermine decision quality.

Prospect theory. In the early 1960s, economist Paul Samuelson offered his lunch colleagues a bet where he would pay $200 for a correct call of coin toss and he would collect $100 for an incorrect call. But his partners didn't bite. One distinguished scholar replied, "I won't bet because I would feel the $100 loss more than the $200 gain. *But I'll take you on if you promise to let me make 100 such bets*" (emphasis added).

This response prompted Samuelson to prove a theorem showing that "no sequence is acceptable if each of its single plays in not acceptable." According to economic theory, his learned colleague behaved irrationally.[31]

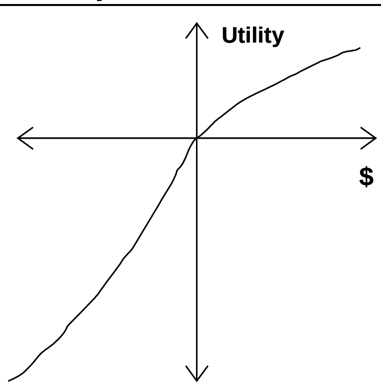
Even though the lunch bet has a positive expected value, Samuelson's proof doesn't feel quite right to most people. The concept of risk aversion explains why. One of prospect theory's main findings, risk aversion says that given a choice between risky outcomes, we are about two times as adverse to losses than to comparable gains.[32] Samuelson's proof notwithstanding, most people intuitively agree with the lunch partner: The prospective regret of losing $100 on a single toss exceeds the pleasure of winning $200.

This story shows one of the significant differences between expected utility theory (the basis for Samuelson's proof) and prospect theory—the decision frame. Expected utility considers gains and losses in the context of the investor's total wealth (broad frame), while prospect theory considers gains and losses versus isolated components of wealth, like changes in a specific stock price (narrow frame). Investors tend to make decisions based on reference points, not the big picture.

Studies confirm that investors use price, or price changes, as a reference point when they evaluate financial transactions. While expected utility theory may be normatively correct, prospect theory is descriptively accurate. Prospect theory addresses how our sense of utility and probability deviates from theory.

Loss aversion, framing, and description. Kahneman and Tversky found that most people demonstrate loss aversion in considering a gain or a loss. Prospect theory demonstrates a kink in the function describing the tradeoff between a monetary gain or loss and a measure of utility. (See Exhibit 8.) Most people implicitly base a negative answer to Samuelson's lunch offer on this function, which is not very sensitive to overall wealth.

Exhibit 8: Prospect Theory's Kinked Utility Function



Source: Jonathan Baron, *Thinking and Deciding* (Cambridge, UK: Cambridge University Press, 2000) 256.

Framing effects show a relevant and related point—how we perceive reference points strongly influences our decisions. Researchers show that when subjects see the same problem framed in alternative ways, they decide differently. Here's an example: [33]

> Imagine that the U.S. is preparing for the outbreak of an unusual Asian disease, which is expected to kill 600 people. Two alternative programs have been proposed. Assume that the exact scientific estimate of the consequences of the programs is as follows:
>
> Program A: 200 saved
> Program B: 1/3 probability that 600 are saved

Most people select A, presumably because they do not want to take the significant (2/3) risk that no one would be saved at all. Other subjects saw the same problem, presented this way:

> Program A: 400 die
> Program B: 2/3 probability that 600 die

Here, most people select Program B, clear violating the invariance principle, *which suggests people should make choices based on the situation itself, not on the description of the situation.*

In this case, the subjects perceive 400 deaths as almost as bad as 600 deaths, so they will take the chance of saving everyone. [34] Framing the problem in terms of lives saved makes people risk adverse, while framing the same problem in terms of lives lost makes people risk seeking.

Likewise, different descriptions of a financial proposition can play a very important role in shaping how people decide about the proposition's attractiveness. Investors must constantly focus on descriptions and should seek alternative descriptions if possible.

Framing and loss aversion directly produce the disposition effect. Irrespective of the stock's perceived attractiveness, investors tend to sell the stocks above the purchase price and hold onto to stocks below the purchase price. [35]

Probability. Prospect theory also shows that people do not assess probabilities according to theory. Specifically, people tend to overweight low probabilities and underweight moderate and high probabilities. Researchers identified these preferences by stating probabilities and analyzing the choices of the subjects. How we feel about a situation—affect—makes probability misspecification even more pronounced. Kahneman and Riepe write, "In general, the non-proportional weighting of probabilities makes people like both lottery tickets and insurance policies." [36]

Overconfidence. According to researchers people consistently overrate their abilities, knowledge, and skill. This holds especially true outside of their expertise. For example, scientists presented professional securities analysts and money managers with ten requests for information that the investors were unlikely to know. The scientists asked the investors to respond to each question with an answer and a "confidence range"—high and low boundaries within which they were 90% certain the true number resides. On average, the analysts choose ranges wide enough to accommodate the correct answer only 64% of the time. Money managers were even less successful at 50%. [37]

Primarily, overconfidence impedes performance by encouraging investors to consider outcome ranges that are too narrow. Studies show that people are in general poorly calibrated, and tend to be frequently surprised. Kahneman and Riepe note that if someone tells you they are 99% sure about an outcome, you would be well advised to assume the relevant probability is 85%.[38]

In tests, some professionals demonstrated very accurate calibration, including meteorologists and racetrack handicappers. Research suggests this ability stems from on three characteristics: they face similar problems every day; they make explicit probabilistic predictions; and they get swift and precise feedback.

Heuristics and biases

Evolutionary forces have shaped human cognition over hundreds of thousands of years. The use of heuristics grew of this evolution. Over the centuries heuristics served our ancestors well, allowing for quick, quality decisions—for the most part.

However, today's world presents us with decisions our mind's equipment does not necessarily deal well with. The heuristics we rely on carry associated biases, which undermine the quality of our decisions in our modern context. Here, we review four major heuristics and their biases. [39]

Availability. Individuals assess the frequency, probability, or likely causes of an event by the memory's ability to recall its instances or occurrences. Since we generally remember frequent events more easily, this heuristic often leads to accurate judgment. However, the heuristic's fallibility arises because factors beyond objective frequency shape information availability.

One bias associated with availability is ease-of-recall. You are likely to judge more recent, or easy to remember, events as more numerous than other instances of similar but harder to recall events.

What will more likely kill you if you live in the U.S., a shark attack or pieces falling from an airplane? Statisticians suggest you are 30 times more likely to die from falling airplane parts. Most people guess shark attacks because we recall sensational news, such as shark attacks, more easily.[40]

A related pair of *Wall Street Journal* articles about a Cape Cod barber illustrates this point. The first article appeared in March 2000 within weeks of the market's high. Naturally, the barbershop patrons were coming off a very lucrative period: [41]

> The conviction that the party is far from over is part of the reason . . . technology stocks soar ever higher. "I don't think anything can shake my confidence in this market," Mr. Allen says. Mr. O'Keefe adds: "Even if we go down 30%, we'll just come right back."

The follow up article came out in July 2002, near an intermediate market low. A sharp decline in mood (and market assessment) followed the market's swoon: [42]

> All they ever say is, "Buy, buy, buy," all the way down from $100 a share to bankruptcy, the burly 63-year-old barber said . . .Now, they give a stock tip and I stay as far away from it as I can. Nobody trusts anyone anymore.

Surveys of expected investor returns show similar traces of ease-of-recall bias. Researchers periodically ask investors about their expectations for market returns over subsequent 12 months. In 1998, 76% expected returns of 10% or higher, and 20% anticipated returns in excess of 20% (long term returns average around 10%). In March 2001, following a year of poor returns, about 50% anticipated returns at or above 10%, and only 8% saw the prospects for 20%-plus gains. [43]

Representativeness. Individuals assess the likelihood of an event by the similarity of the occurrence to their *stereotypes* of similar occurrences. This heuristic approximates many situations fairly well, but can lead to poor decisions in situations with insufficient information or when better information exists.

One example of a bias arising from representativeness is comparing different eras—for example, the crash of 1987 with the crash of 1929 or the US bubble in the late 1990s with the Japanese bubble in the late 1980s. Often these comparisons look interesting on a superficial level but overlook material information.

With another representativeness bias, failure to recognize reversion to the mean, individuals tend to overlook that extreme events tend to regress to the mean on subsequent trials. Excess or substandard market returns exemplify this bias. A professional baseball player hitting well above or below his average is another illustration.

Insensitivity to sample size causes a third bias. Our degree of belief in a particular hypothesis typically integrates two kinds of evidence: the strength, or extremeness, of the evidence and the weight, or predictive validity. For example, say you want to test the hypothesis that a coin is biased in favor of heads. The proportion of heads reflects the strength, while the sample size determines the weight.

Probability theory prescribes rules for how to combine strength and weight correctly. Still, research shows that the strength of evidence tends to dominate the weight of evidence in people's minds.

This bias leads to a distinctive pattern of over- and underconfidence. When the strength of evidence is high and the weight is low—a small sample size—people tend to be overconfident. In contrast, when strength is low and evidence is high, people tend to be underconfident. (See Exhibit 9.) [44]

Exhibit 9: Information Weighting

Weight (predictive validity) \ Strength (extremeness)	LOW	HIGH
LOW	*Not yet relevant*	*Overconfidence*
HIGH	*Underconfidence*	*Obvious*

Source: Dale Griffin and Amos Tversky, "The Weighting of Evidence and the Determinants of Confidence", in Gilovich, et al, eds., *Heuristics and Biases: The Psychology of Intuitive Judgment* (Cambridge, UK: Cambridge University Press, 2002), 230-249.

Anchoring and adjustment. Individuals start with an initial value and make value assessments by adjusting from that value. The initial value may reflect historical precedent, current information, or random information.

The major bias reflects people's insufficient adjustments to their initial values, as we saw in the overconfidence discussion. This problem is particularly acute if the initial value is not well grounded. One well-known example occurs in real estate, where there is some cost to price discovery. When a buyer seeks a house in an area that's unfamiliar to them, a real estate broker can first show an overpriced home, hence setting the buyer's anchor on a poor value. Subsequent homes will appear relatively more attractive, encouraging a transaction.

Affect. Affect characterizes our emotional response to a stimulus. For example, a word like treasure generates positive affect, while a word like hate is negative. Research shows that individuals tend to judge an activity based not only on what they *think* about it, but also on how they *feel* about it. [45]

The biases that emanate from the affect heuristic amplify two other pitfalls: probability miscalibration and availability.

When outcomes are not vivid (low affect), we tend to place too much weight on probabilities and not enough on outcomes. Conversely, when outcomes are vivid (high affect), we place too much weight on outcomes. How an investor feels about a financial proposition often dictates their assessment of risk and reward.

Three after-the-fact biases. So far, we focused on the sources of probability and outcome misspecification in assessing a financial opportunity. We now turn to some cognitive pitfalls that occur *after* we've already made an investment decision.

The first pitfall is the confirmation trap. Once individuals make a financial decision, they tend to seek information confirming the merit of their choice and disregard or discount disconfirming evidence. Bayes's Theorem provides a means to constantly update our assessment of probability and outcome based on the arrival of new information. Neglecting this incremental information distorts our judgment of expected value.

Hindsight and the curse of knowledge form a second cognitive pitfall. After individuals find out an event has occurred, they tend to overestimate the degree to which they would have predicted the correct outcome. On a related note, when a holding appreciates for unexpected reasons, investors tend to rewrite their own memory to reflect those reasons. An investment journal or clear notes, where an investor can record the rationale for every investment decision, acts as an effective remedy for hindsight bias.

The final pitfall is the endowment effect, the observation that people value what they possess more highly than an object of equal quality that they don't own. The challenge is to objectively value all assets, whether you own them or not.

The role of social context

Our individual cognitive foibles do not cause all decision-making errors. Some errors stem from our social interaction with others. Specifically, humans have a strong desire to be part of a group. That desire makes us susceptible to fads, fashions, and idea contagions.

Solomon Asch, a Yale psychologist, demonstrated this proclivity with a now-famous social psychology experiment. Asch's experimental group had eight members: seven knew about the experiment and the eighth was the subject. To start, Asch asked the group to solve a very simple problem: determine which of three lines is of equal length to the standard line. Going around the table, each participant named a choice. In the first few trials, all of the participants picked the right answer.

After a few trials Asch signaled the seven members to start making obvious mistakes. While many subjects expressed shock at the group's clear mistakes, a startling 35% of the subjects conformed to the group's incorrect judgments. Asch's experiment demonstrates people's preference for being an accepted part of a majority over being part of the correct minority.

The significance of Asch's experiments is readily obvious: group dynamics—often revealed as stock price performance—tempt investors to go with the majority, albeit to varying degrees. Numerous market bubbles demonstrate this point. The best way to avoid this temptation is to increase your adoption threshold by maintaining a high degree of awareness and to search constantly for diverse input. Asch's results also point to potential market opportunities—when opinion diversity breaks down. [46]

How Do We Avoid Misspecifying Probabilities and Outcomes?

Awareness of these pitfalls is the first step in mitigating their negative impact. Here are some thoughts to bear in mind:

- Try not to overestimate your abilities.
- Actively challenge your own assumptions.
- Ask disconfirming questions.
- Realize that past events or prices are signposts, not answers.
- View decisions from various perspectives.
- Seek information from a variety of sources.
- Reframe questions.
- Consider only future costs and benefits.

The point to constantly acknowledge is that we humans are not well designed to operate in probabilistic fields. While cognitive makeup makes some investors undoubtedly better suited to success than others, an appreciation of proper decision-making and its pitfalls should be of value and benefit to all investors.

Endnotes

[1] Raymond D. Sauer, “The Economics of Wagering Markets,” *Journal of Economic Literature, Vol. 36, 4*, December 1998, 2021-64. Sauer summarizes: “Wagering markets provide a natural laboratory for testing models of market prices and behavior under uncertainty. The literature on wagering, albeit contentious, has established the following. First, prices set in these markets, to a first approximation, are efficient forecasts of outcomes. Second, price changes in these markets are driven by an informed class of bettors and improve prediction.”

[2] Here’s a sample of some references (there are too many to list exhaustively): Burton G. Malkiel, *A Random Walk Down Wall Street* (New York: W.W. Norton & Company, 2003), 191; Nassim Taleb, *Fooled By Randomness, Second Edition* (New York: Thomson-Texere, 2004), 141; Gregory Baer and Gary Gensler, *The Great Mutual Fund Trap* (New York: Broadway Books, 2002), 16-17; Peter L. Bernstein, *Capital Ideas* (New York: Free Press, 1992), 141-143.

[3] Nobel-prize winning economist, Paul Samuelson, a significant contributor to the efficient market theory, said as much: “It is not ordered in heaven, or by the second law of thermodynamics, that a small group of intelligent and informed investors cannot systematically achieve higher mean portfolio gains with lower average variabilities. People differ in their heights, pulchritude, and acidity. Why not their P.Q. or performance quotient?” See Peter L. Bernstein, *Capital Ideas* (New York: Free Press, 1992), 143.

[4] See http://www.commencement.harvard.edu/2001/rubin.html.

[5] Charles D. Ellis, “Will Business Success Spoil the Investment Management Profession?” *The Journal of Portfolio Management*, Spring 2001, 11-15.

[6] David Sklansky, *The Theory of Poker, 4th ed.* (Henderson, NV: Two Plus Two Publishing, 1999), 10.

[7] Edward O. Thorp, *Beat the Dealer* (New York: Vintage Books, 1966), 56-57.

[8] Steven Crist, “Crist on Value,” in Beyer, et al., *Bet with the Best* (New York: Daily Racing Form Press, 2001), 64.

[9] Michael Steinhardt, *No Bull: My Life In and Out of Markets* (New York: John Wiley & Sons, 2001), 129.

[10] Michael Lewis, *Moneyball: The Art of Winning an Unfair Game* (New York: W.W. Norton & Company, 2003), 274.

[11] Amarillo Slim, *Amarillo Slim in a World of Fat People* (New York: Harper Collins, 2003), 101.

[12] Nassim Taleb, *Fooled By Randomness, Second Edition* (New York: Thomson-Texere, 2004), 66-67.

[13] http://www.vanguard.com/bogle_site/sp20031103.html.

[14] Robert E. Rubin, *In an Uncertain World* (New York: Random House, 2003), xi.

[15] Berkshire Hathaway Annual Meeting, 1989.

[16] Frank H. Knight, *Risk, Uncertainty, and Profit* (New York: Houghton and Mifflin, 1921). See http://www.econlib.org/library/Knight/knRUP.html.

[17] Stephen Jay Gould, *Full House: The Spread of Excellence from Plato to Darwin* (New York: Harmony Books, 1996), 48-56.

[18] Gerd Gigerenzer, *Calculated Risks* (New York: Simon & Schuster, 2002), 26-28. Also, Donald Gillies, *Philosophical Theories of Probability* (London: Routledge, 2000).

[19] John Maynard Keynes, “The General Theory of Employment,” *Quarterly Journal of Economics, 51, 2*, 213-214. See also Robert Skidelsky, *John Maynard Keynes: The Economist as Savior 1920-1937* (New York: Penguin Group, 1992), 80.

[20] For a very approachable discussion of Bayesian analysis, see Robert G. Hagstrom, *The Warren Buffett Portfolio* (New York: John Wiley & Sons, 1999), 115-117.

[21] John Rennie, “Editor’s Commentary: The Cold Odds Against Columbia,” *Scientific American*, February 7, 2003.

[22] Bradford Cornell, *The Equity Risk Premium* (New York: John Wiley & Sons, 1999), 45-46.

[23] Roger Lowenstein, When *Genius Failed: The Rise and Fall of Long-Term Capital Management* (New York: Random House, 2000).

[24] Philip W. Anderson, “Some Thoughts About Distribution in Economics,” in W. B. Arthur, S. N. Durlaf and D.A. Lane, eds., *The Economy as an Evolving Complex System II* (Reading, MA: Addison-Wesley, 1997), 566.

[25] Gould, 45-56.

[26] For multiple examples of asymmetric payoffs in financial instruments, see Nassim Nicholas Taleb, “Bleed or Blowup? Why Do We Prefer Asymmetric Payoffs?” *Journal of Behavioral Finance, Vol. 5, 1*, 2004. See http://www.fooledbyrandomness.org/bleedblowup.pdf.

[27] Elroy Dimson, Paul Marsh, and Mike Staunton, “Global Evidence on the Equity Risk Premium,” *Journal of Applied Corporate Finance, Vol. 15, 4*, Fall 2003, 27-38.
[28] Shlomo Benartzi and Richard Thaler, “Myopic Loss Aversion and the Equity Risk Premium Puzzle,” *The Quarterly Journal of Economics*, February 1995, 73-92. See http://gsbwww.uchicago.edu/fac/richard.thaler/research/myopic.pdf.
[29] A related point is that when outcome variability is high, often a stock can be attractive or unattractive even if the consensus is the scenario with the highest probability. If outcome variability is low, then you must bet against the consensus to achieve superior returns. See Alfred Rappaport and Michael J. Mauboussin, *Expectations Investing* (Boston: Harvard Business School Press, 2001), 107-108.
[30] Leon Levy, *The Mind of Wall Street* (New York: PublicAffairs, 2002), 197.
[31] Paul A. Samuelson, “Risk and Uncertainty: A Fallacy of Large Numbers,” *Scientia*, *XCVIII*, 1963, 108-113.
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[34] Jonathan Baron, *Thinking and Deciding, 3rd ed.* (Cambridge, UK: Cambridge University Press, 2000), 257-258.
[35] Hersh Shefrin and Meir Statman, “The Disposition to Sell Winners Too Early and Ride Losers Too Long: Theory and Evidence,” *Journal of Finance, 40*, 1985, 777-790. Also, Terrance Odean, "Are Investors Reluctant to Realize Their Losses?" *Journal of Finance, Vol. 53, 5*, October 1998, 1775-1798. Also, Martin Weber and Colin F. Camerer, “The disposition effect in securities trading: an experimental analysis,” *Journal of Economic Behavior & Organization, Vol. 33*, 1998, 167-184.
[36] Daniel Kahneman and Mark W. Riepe, “Aspects of Investor Psychology: Beliefs, preferences, and biases investment advisors should know about,” *Journal of Portfolio Management, Vol. 24*, 4, Summer 1998. See http://www.ibbotson.com/download/research/Aspects_of_Investor_Psychology.pdf.
[37] J. Edward Russo and Paul J. H. Schoemaker, “Managing Overconfidence,” *Sloan Management Review*, Winter 1992.
[38] Kahneman and Riepe.
[39] Max H. Bazerman, *Judgment in Managerial Decision Making, 5th ed.* (New York: Wiley Text Books, 2001).
[40] David Dreman, “Heuristics in Investor Decision Making, adopted from Contrarian Investment Strategies: The Next Generation (New York: Simon and Schuster, 1998). See http://www.psychologyandmarkets.org/research/chapter_10.html.
[41] “Tech Stock Chit-Chat Enriches Many Cape Cod Locals,” *The Wall Street Journal*, March 13, 2000.
[42] “At Cape Cod Barber Shop, Slumping Stocks Clip Buzz,” *The Wall Street Journal*, July 8, 2002.
[43] David Dreman, Stephen Johnson, Donald MacGregor and Paul Slovic “A Report on the March 2001 Investor Sentiment Survey,” *The Journal of Psychology and Financial Markets, Vol. 2, 3*, 2001, 126-134. See http://www.psychologyandmarkets.org/pdf_files/3_2001_investor_sentiment2.pdf.
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[45] Paul Slovic, Melissa Finucane, Ellen Peters, and Donald G. MacGregor, “The Affect Heuristic,” in Gilovich, Griffin, and Kahneman (eds.), *Heuristics and Biases: The Psychology of Intuitive Judgment* (Cambridge, UK: Cambridge University Press, 2002), 397-420. See also Paul Slovic, Melissa L. Finucane, Ellen Peters, and Donald G. MacGregor, “Risk as Analysis and Risk as Feelings,” *Decision Research*. www.decisionresearch.org/pdf/dr502.pdf.
[46] Michael J. Mauboussin, “Revisiting Market Efficiency: The Stock Market as a Complex Adaptive System,” *Journal of Applied Corporate Finance, Vol. 14, 4,* Winter 2002, 47-55.

For an excellent website on behavioral finance, see www.behaviouralfinance.net.

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