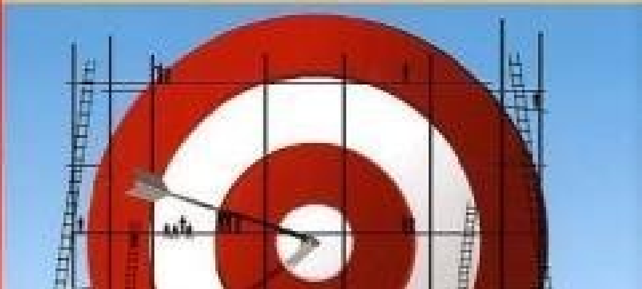
ELSEVIER FINANCE

The Sortino Framework for Constructing Portfolios

Focusing on Desired Target Return™ to Optimize Upside Potential Relative to Downside Risk



Frank Sortino

ELSEVIER

Building the Framework

Chapter 1

The Big Picture

Frank Sortino

Executive Summary

This chapter introduces the concepts of *downside risk*, *upside potential*, and *DTR*™-α, which are necessary to understand the chapters in the Applications section. In the interest of time, however, one could skip ahead to Chapter 5 without reviewing the in-depth background knowledge provided here. Most formulas and equations will be reserved for the Appendix.

Turning Points

The investment business is evolving slowly from a trade to a profession in much the same manner as the practice of medicine. The year 1876 was a turning point in medicine. Dr. Joseph Lister came to the first Centennial in America to debate the eminent Dr. Samuel Gross regarding whether surgeons should sterilize their equipment before an operation. A famous painting by Thomas Eakins shows Dr. Gross in action. The painting depicts surgical equipment lumped together in a couple of dirty trays and surgeons with bloody hands, wearing the same blood-splattered suits they had worn for many previous surgeries. Until recently, most people thought it was painted as a tribute to Dr. Gross. Many now believe Eakins was trying to point out the awful state of medicine in the United States.[1]

At the Centennial debate, Lister called upon 30 years of evidence to support his case, beginning with Dr. Ignaz Semmelweis in 1847, who found that fewer pregnant women died of puerperal fever if doctors washed their hands after leaving the morgue and before they examined pregnant women. The germ theory of disease had not yet been discovered by Louis Pasteur, so Semmelweis didn't know why this happened. He suggested it might be due to something on their hands that could not be seen with the naked eye. Unfortunately, Semmelweis was made a laughing stock by his fellow physicians, eventually had a nervous breakdown, and died in a mental institution. His observations went against the current scientific opinion of the time, which blamed diseases on an imbalance of the basic "humours" in the body. It was also argued that, even if his findings were correct, it would be too inconvenient to wash one's hands each time before treating a pregnant woman. In addition, doctors were not eager to admit that they might have caused so many deaths. Pasteur later proved that indeed there was something called *germs* that could not be seen with the naked eye, and they could jump off the hands of surgeons and into open wounds to infect the patient.

During his presentation, Lister described an antisepsis he had invented to sterilize surgical equipment. He closed by citing a study of hospitals in Europe where surgeons washed their hands, wore surgical gowns, and sterilized their equipment, and there were 50% fewer deaths due to postoperative infections. The evidence was ignored, and Lister lost the debate. This was possibly due to the fact that the debate was held in America and Dr. Gross was president of the American Medical Association. Some physicians, however, chose to believe the evidence and went to Europe to learn what was then known about the science of medicine. Innovation takes time, though. Seventeen years later, in 1893, the Johns Hopkins University School of Medicine, the first in America to offer science courses, was founded.[2]

After the debate, Lister was stuck with many gallons of antisepsis that he thought the attending physicians would want to purchase. By chance he met a promoter who suggested they water it down and sell it as a mouthwash that would make your breath "kissing sweet." You know it today as Listerine®. This sad tale (and others) is told in Thomas Kuhn's *The Structure of Scientific Revolutions* (1962, University of Chicago Press).

The year 1952 was the turning point in finance. That was the year Harry Markowitz quantified risk and presented a framework for evaluating the trade-off between risk and reward. Markowitz assumed that all investors had the same investment objective: to maximize the expected return for a given level of risk. Reward was measured as the mean from a bell-shaped (standard normal) distribution. A decade later, William Sharpe simplified the Markowitz model and presented the

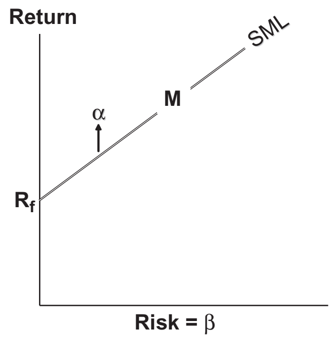


Figure 1.1 Capital asset pricing model.

capital asset pricing model (CAPM) (see Figure 1.1), which assumes there exists a risk-free asset (R_f) and a market portfolio (M) that consists of every asset in the world in the proportion in which they exist in the world. In equilibrium, all assets would lie on the security market line (SML) and no one would be able to beat the market on a risk-adjusted basis. Therefore, everyone would want some linear combination of those two assets that lie on the SML in Figure 1.1. If someone was able to beat the market on a risk-adjusted basis, they would lie above the SML and have positive alpha (α). We assume the reader is familiar with the literature describing these two theories, which earned both of these scholars the Nobel Prize in Economics. Together, these theories are often referred to as modern portfolio theory (MPT).

MPT Criticism

Just as in medicine, it took about 20 years for these theories to be put into practice. Ron Surz, the author of Chapter 2, was with one of the first firms to market a service based on MPT, and he says several partners quit his firm rather than support this innovation. In academia, MPT led to a rift between traditional economists and professors who supported MPT. The latter eventually developed MBA programs outside the department of economics that are now essential elements in every graduate school of business in the world. CAPM allowed professors to explain to students how assets should be priced so that, on a risk-adjusted basis, all returns are equal. As the saying goes on Wall Street, "There ain't no free lunch." For a greater return, you need to take more risk.

However, we and others have pointed out that the real world is more complex than the normative models hypothesized by Markowitz and Sharpe. Professor Eugene Fama[3] observed that the market portfolio described in CAPM does not exist; therefore, whatever values one gets for alpha and beta, they are theoretically wrong. Furthermore, the returns-generating mechanism is more complex than a single index model can describe. At minimum, there is a size effect (large cap stocks behave differently than small cap stocks) and a style effect (value stocks behave differently than growth stocks).

Andrew Rudd, former CEO of Barra,[4] started the company Advisor Software because he felt that many investors' investment objectives were concerned with a future payout, and "CAPM is inappropriate because it doesn't recognize the liability of future income needs."

Innovations to MPT

The purpose of this book is to present some evidence of further advancements in the young science of portfolio management. Like Lister, there is growing evidence that these advancements can improve the financial health of clients, but they have yet to become commonplace. We have a long way to go to reach the level of innovation of the medical profession. Indeed, portfolio management is still more of a trade than a profession. Figure 1.2 illustrates the work of some of the people who have made great contributions to our efforts to improve the science of portfolio management.

Peter Fishburn, while at the University of Pennsylvania, laid the foundation for a portfolio theory based on a target rate of return and offered mathematical proofs that the mean-variance model of Markowitz was a subset of his richer framework.[5] We refer to Fishburn's target return as the Desired Target Return™ (DTR™).[*] Fishburn developed the mathematical equations that we use to calculate downside risk (see the Appendix). This is the risk that returns will fall below the DTR line shown in Figure 1.2.

Bradley Efron at Stanford University developed a new statistical procedure for generating this picture of uncertainty based on what could have happened in the past, instead of relying only on what did happen.[6] This is the equivalent of taking an x-ray of the risk and reward characteristics of a portfolio. Our research indicates that this is superior to any other statistical procedure we know, and this approach is explained in Chapter 3 by Bernardo Kuan.

Atchison and Brown at Cambridge University developed the three-parameter lognormal that describes the shape of this uncertainty picture.[7] This was an important improvement over the original lognormal distribution in that it allowed for negative returns and skewness.

Finally, the field of behavioral finance developed the reward concept of upside potential.[8] The way we calculate the potential to exceed the DTR combines into

[*] Desired Target Return and DTR are trademarks of Sortino Investment Advisors.

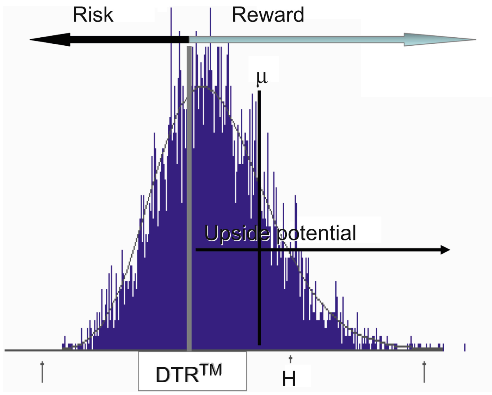


Figure 1.2 Advancements in financial quantitative methods.

	Fund 1			Fund 2		
	Return	Upside	Downside	Return	Upside	Downside
Year 1	14.0%	6%	0.000000	10%	2%	0.000000
Year 2	13.0%	5%	0.000000	13%	5%	0.000000
Year 3	11.0%	3%	0.000000	12%	4%	0.000000
Year 4	13.0%	5%	0.000000	13%	5%	0.000000
Year 5	9.0%	1%	0.000000	12%	4%	0.000000
Year 6	7.0%	0%	0.000100	8%	0%	0.000000
Year 7	7.0%	0%	0.000100	8%	0%	0.000000
Year 8	7.0%	0%	0.000100	8%	0%	0.000000
Year 9	7.0%	0%	0.000100	5%	0%	0.000900
Year 10	12.0%	4%	0.000000	11%	3%	0.000000

Return	Upside Potential	Downside Deviation	Return	Upside Potential	Downside Deviation
10.00%	2.40%	0.63%	10.00%	2.30%	0.95%
	Upside Probability			Upside Probability	
	0.6			0.6	
	Upside Potential Ratio			Upside Potential Ratio	
	3.79			2.42	

Figure 1.3 Upside potential ratio for DTR = 8%.

one number the probability of exceeding the DTR with an estimate of how far above it might be. It is a linear function that says 2% more than the DTR is twice as good as 1% excess, and 4% is twice as good as 2%. This conveys more information than the mean (μ) or the probability of exceeding the DTR. Figure 1.3 provides a highly simplified example for illustration purposes only. It omits the use of the bootstrap and other procedures shown in Figure 1.2 and explained in the Appendix that are used to actually calculate the upside potential ratio.

In Figure 1.3, both Fund 1 and Fund 2 have the same mean (10%) and the same chance of exceeding the DTR (60%). However, the potential for Fund 1 to exceed 8% is 2.4% (8%+2.4% = 12.4% potential return), as opposed to 2.3% for Fund 2. That may seem trivial until the upside potential is compared to the downside risk for an upside potential ratio. The upside potential ratio for Fund 1 is 3.8 (2.4/.63) as opposed to 2.4 for Fund 2. In other words, Fund 1 has 3.8 times more upside potential than downside risk. Fund 2 has 2.4 times more upside potential than downside risk. This highlights the importance of always considering the trade-off between risk and reward.

Sharpe [1988] then developed a returns-based style analyzer that enables us to identify the unique style of thousands of managers in a few seconds of computer time. Ron Surz will explain in Chapter 2 the importance of having the correct set of indexes to use this powerful tool in asset allocation models and manager performance measurement.

Hands-on Experience

In 2004, Sortino Investment Advisors (SIA) began managing the first model portfolio using all of the concepts mentioned in this book. In 2006, SIA began acting as a subadvisor to Fiserv Investment Services, Inc., so they could apply these concepts to five collective investment funds for 401(k) plans. In 2009, Hand Benefits & Trust (HB&T) entered into an agreement with SIA to offer this service for their 401(k) plans. David Hand will provide the background in Chapter 5 for how this service fits into the new Qualified Default Investment Alternative (QDIA) proposal of the Pension Protection Act of 2006.

If we did nothing more than describe risk and reward in terms that were more meaningful to people, that would be a valuable improvement. We plan to do more than that. We claim that this represents a substantial improvement in the way portfolios are constructed.

The essence of our approach is shown in Figure 1.4. We assume that the return needed to achieve most investment objectives can be estimated (the DTR). An example is the rate of return that discounts the future cash outflows from a retirement plan at retirement to the cash inflows prior to retirement.

The investment objective is to maximize the potential to exceed the desired target return subject to the risk of falling below it. We call this the *upside potential ratio* (see Chapter 3 and the Appendix for details). This generates an efficient frontier of portfolios of passive indexes. Each point on the frontier represents a portfolio with the highest upside potential to downside risk ratio for a given DTR portfolio. If there is some combination of passive indexes

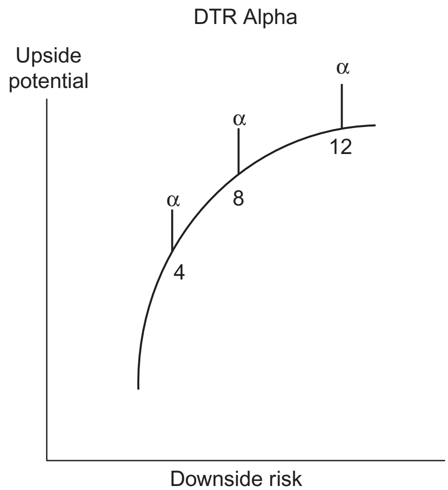


Figure 1.4 DTR-α.

and active managers that could earn a higher rate of return for a given DTR, it would have positive DTR-α and would lie above the passive efficient frontier. This is very different than the alpha of CAPM theory. The CAPM α measures a manager's ability to add value to the return on a single index such as the Standard & Poor's 500 index. Our DTR-α measures the ability of a combination of managers and passive indexes to beat a combination of passive indexes on the efficient frontier.

We believe this is simply an extension of the concepts of portfolio theory presented by Markowitz and Sharpe adjusted for the updates of Fishburn and others. The optimization routine becomes: Maximize the DTR-α for each point on the efficient frontier. This will be explained more fully in Chapter 4 by Hal Forsey.

The Risk of Investing

To return to the comparison of medicine with portfolio management, it is always risky to go to the hospital for any procedure, but we rely on the skill of the physician and the advancements in medical technology to reduce the normal risks we face in most medical situations. At times, however, a risky situation becomes dangerous and people are injured or die in spite of advancements in medical science or the skill of the physician.

The Memorial Medical Center in New Orleans is a case in point. Advancements in medical technology and the skill of the staff were overcome by Hurricane Katrina. This single event did not negate the value of advancements in medical science or suggest that physicians might just as well not sterilize their equipment before an operation.

Similarly, it is always risky to invest in securities, but we are beginning to develop a scientific approach to managing that risk. These advancements in portfolio management cannot eliminate heavy investment losses in dangerous economic times any more than good medical facilities can function when flooded. There is no question now that the financial system failed to protect us from people in government and business who were creating a dangerous environment for investors. Some dangers pass with little notice, such as the fear that Y2K would shut down all the computers in the world. Sometimes they pass without dire consequences, like Long-Term Capital Management. But, sometimes a dangerous situation spins out of control.

The portfolio construction methods explained in this book assume the financial markets are functioning, in that banks lend and investment firms invest. What we had in 2008 was a financial tsunami. But once the storm is over and the wreckage is cleared away, investors will once again benefit from technological advancements in portfolio management.

Implementation Frustration

The voice of dissent is heard in Chapter 6, where Neil Riddles points out that the world we describe in the first five chapters is not the world he lives in. In his world, a manager is not measured relative to an absolute desired target return. The manager is measured relative to the moving target of the return the competition earns or the return on an index, whichever one is higher. While the authors in the first five chapters claim both performance measurements are incorrect, the consultants for Neil's clients are still using the old approach, and if Neil's firm doesn't take the added risk of beating these moving targets they are terminated. In truth, it is the consultant not the money manager who has the major responsibility for implementing change. I am grateful to Neil for the support he has given to my ideas over the years and his courage to express his views so honestly.

This does point out the danger of clients not knowing what their goals are and what desired target return will get them there. If you don't know what your goal is, you will end up trying to accomplish someone else's goal, and that may entail taking a lot more risk than necessary. I remember the president of one of the largest consulting firms telling me, "Frank, we are not in the education business; we are in the consulting business. We give our clients what they want. When they want what you are offering we will sell it to them." In other words, give 'em what they want, not what they need. We believe this attitude is wrong. It does not put the best interests of the client first. We should no longer have to wait 50 years to find a better way to construct portfolios.

James Pupillo explains in Chapter 7 why innovation is so difficult to actually implement in a large global institution even when top management gives their approval. The changes that appear to be relatively simple to me requires layers of management to accommodate. This takes years to accomplish, and time is money during this agonizingly slow process. Nobody likes the endless flow of papers and countless phone calls necessary to actually implement the changes recommended in the first five chapters. A number of consultants have tried, but Pupillo is the first consultant I have met in Europe, Africa, the Pacific Basin, or the United States who has actually accomplished it.

Chapter 7 will help all innovators to sympathize with the hesitancy of consultants and money managers to champion their cause. The good news is that some of the changes we have been advocating for years are starting to be put into practice. A representative of J.P. Morgan was quoted in *Pensions & Investments* magazine as saying it is "tossing out the traditional mean-variance optimizer in favor of a new approach that does not assume returns are bell shaped." J.P. Morgan, along with CalPERS, is planning to use downside measures of risk instead of the MPT measures of risk mentioned above. While this is not the measure of downside risk cited in this book, it is a beginning.

In Chapter 8, David Hopelain examines the failures in the regulatory environment in which we operate and offers solutions. He provides valuable insights into the difference between risky situations and dangerous situations. Risk can be managed, but when things get dangerous the participants lose control over the outcomes of their decisions and regulators must be prepared to intervene.

Yes, But Does It Work?

Rather than reproduce the evidence to date that will be obsolete by the time this book is published, we recommend that you visit our website (www.sortinoia.com), where the performance of five model portfolios is updated quarterly. To show that I practice what I preach, the first account, established in 2004, was my own trust fund. As of this writing, we believe the results are consistent with the empirical research published in financial journals and *Pensions & Investments* magazine. Many of these articles are available on our website.

Endnotes

1. Barry, J.M. (2004). *The Great Influenza: The epic story of the deadliest plague in history.*Viking Penguin Group, New York.
2. For more on the history of medicine, see *The Great Influenza* by John M. Barry (Endnote 1).
3. Fama, E.F., and French, K.R. (2004). The capital asset pricing model: Theory and evidence. *Journal of Economic Perspectives* **18**, 25–46, Also, Fama, E. F., & French, K. R. (1996). The CAPM is wanted dead or alive. *Journal of Finance*, *51(5)*, 1947–1958.
4. Barra is one of the leading proponents of CAPM products and services in the world. It was founded by Barr Rosenberg and Andrew Rudd.
5. Fishburn, P.C. (1977). Mean risk analysis with risk associated with below target returns. *The American Economic Review* **67**, 116–126.
6. Efron, B. (1993). *An introduction to the bootstrap*. Chapman & Hall, London.
7. Atchison, J., and Brown, J.A.C. (1957). *The lognormal distribution*. Cambridge University Press, Cambridge, U.K..
8. The upside potential ratio was first introduced in *Pensions & Investments* magazine, 9/26/99, p. 22. This was followed by Sortino, F., van der Meer, R. A. H., & Plantinga, A. (1999). The Dutch triangle. *Journal of Portfolio Management*, *26(1)*, 50–58. The concept was expanded in “The U-P Ratio” on our website at www.sortino.com. Also, in Shefrin, H., & Statman, M. (2000). Behavioral portfolio theory. *Journal of Financial and Quantitative Analysis*, *35(2)*, 127–151, the authors refer to an aspiration to achieve a specific target value of wealth with the potential to reach high levels of wealth, as discussed earlier in Lopes, L. L., & Oden, G. C. (1999). The role of aspiration level in risk choice: A comparison of cumulative prospect theory and SP/A theory. *Journal of Mathematical Psychology*, *43*, 286–313. Shefrin, Statman, and Lopez measured this potential solely in terms of a probability, which led them to the conclusion that the optimal portfolio is some combination of bonds and a lottery ticket. That is enough to discredit the use of upside probability in our opinion. Our measure of upside potential also incorporates a magnitude factor (see Appendix).

Chapter 2

Getting All the Pieces of the Puzzle

Ron Surz

Executive Summary

Ron Surz, president of PPCA, Inc., explains why comparing managers to a single index like the Standard & Poor's (S&P) 500 is seriously flawed because it fails to recognize a core sector that does not behave like value or growth. Failure to recognize this piece of the puzzle distorts the final picture.

He who stops being better stops being good.

—Oliver Cromwell

A solid investment program evolves from the integration of various interrelated disciplines, or puzzle pieces. Asset allocation is paramount and involves not only the assignment to asset classes but also the make-up of asset classes, specifically the types of stocks, bonds, etc. The active–passive decision—allocating between active managers and passive indexes—is an important part of the investment program and constitutes a second level of the portfolio construction puzzle that needs to be solved.

In this chapter, we focus on solving the equity investment part of the puzzle, which entails: (1) the composition of the equity market so we can determine how we want to allocate within it, and (2) the metric we'll use to identify talent so we can make an informed active–passive decision. The first puzzle involves choosing the best family of market indexes. The second involves investment manager evaluation and requires the construction of the best benchmarks.

As you will see, indexes are not the same as benchmarks, although they are connected. We'll begin our discussion with the distinction between the two.

Equity Market Composition

An index is a barometer of how a particular market segment has performed; for example, the Dow Industrial Index tracks the performance of 30 industrial stocks. By contrast, a benchmark establishes a goal for the investment manager. A reasonable objective is to earn a return that exceeds a low-cost, passive implementation of the manager's investment approach. This may be an index, especially if the investment manager is an index hugger. But, it is best to consider customized benchmarks, which is the subject of the next section.

Solving the equity allocation puzzle requires decomposing the market into segments that behave differently, so we can be sure that we have diversified among these components. The benefits of diversification arise from allocations to assets that are uncorrelated, or move differently. The relatively recently introduced style indexes (based on market capitalization and value/growth) work well for this purpose, although you could choose another differentiator, such as economic sector. Style indexes have the desirable property of being easily applicable to many money manager disciplines, so they set up well for the second piece of the puzzle. A variety of style index families are available for consideration, including the popular Russell and S&P indexes, and the less well known Surz Style Pure^{SM} indexes.

So, how do we choose from among these candidates? We want to divide up the market into pieces small enough that they behave differently but not so many that integration is unwieldy.

The Russell and S&P families come in six pieces: large, middle, and small sizes of both value and growth. There's an inconsistency here that matters a great deal. On the size scale, defining a middle in between large and small has proven worthwhile, since there have been periods when mid-cap stocks have outperformed both large and small and periods when they have underperformed. Mid-caps behave differently than small and large, so it's important to have a separate and distinct barometer for this segment of the market.

What is missing is a similar differentiator on the style front—namely, something between value and growth. There are degrees of value and growth, so some growth stocks are more aggressive than others, and some value stocks are deeper value than others. Other stocks have characteristics that are not clearly value or growth—they're the stuff in the middle. Russell deals with this issue by allocating a percentage of each fuzzy stock into value and growth; they are classified as a specific unique mixture of value and growth. S&P ignores the problem altogether by drawing a hard line that divides half of the market's value between value and growth.

By contrast, Surz Style Pure^{SM} indexes deal with this stocks-in-the-middle issue by defining a separate category called "core," so there are nine Surz Style Pure^{SM} styles rather than the six maintained by Russell and S&P.

Surz Style Pure^{SM} indexes break out value, core, and growth stock groupings within each market cap by establishing an aggressiveness measure that combines dividend yield, price-to-earnings ratio, and price/book ratio. The top 40% (by count) of stocks in aggressiveness are designated as growth, while the bottom 40% are called value, with the 20% in the middle falling into core. The result is a family of indexes that are mutually exclusive and exhaustive, making them perfect for style analyses, including both returns-based and holdings-based style analyses, as discussed in the next section. These indexes also reveal the reasons why S&P and Russell occasionally disagree—it's because they're missing the core category. Figure 2.1 documents some recent instances of the importance of including a core index.

In the first quarter of 2005 (Figure 2.1), the S&P indicated value stocks outperformed growth while the Russell index indicated the opposite. The Surz Style Pure^{SM} indexes show that the difference is accounted for by how core was treated in both indexes. Figure 2.2 shows how the S&P 500 and two Russell indexes got it wrong by not accounting for the core element.

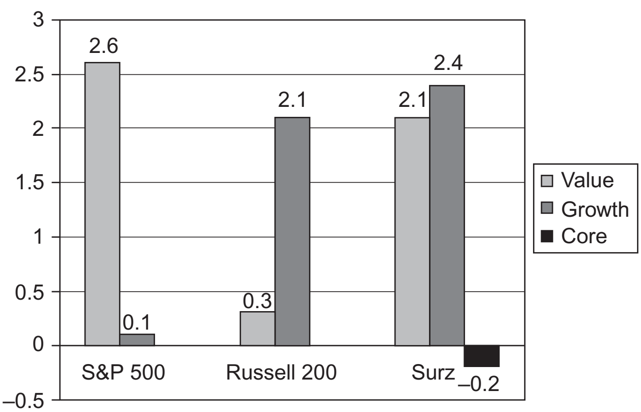


Figure 2.1 Large-cap style index returns differ in the first quarter of 2005.

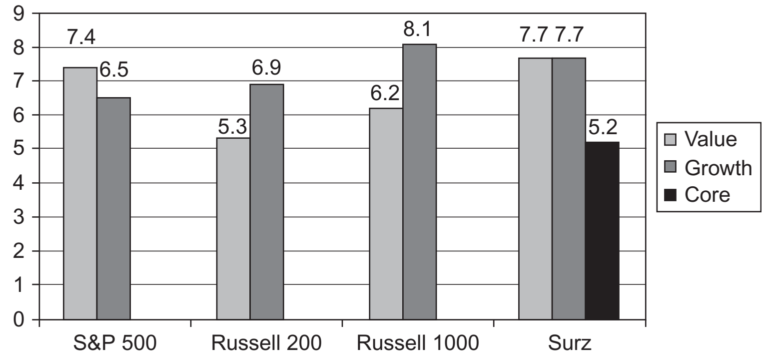


Figure 2.2 Large-cap style index returns differ in the first half of 2007.

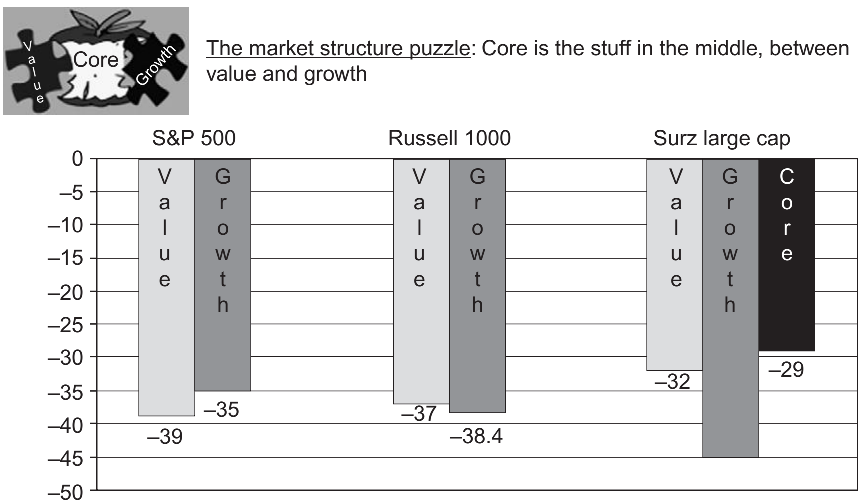


Figure 2.3 Better indexes: 2008 style quandary demonstrates the importance of core.

Core usually performs between value and growth, but about a third of the time it does not, including the periods in the exhibit. During these unusual times, the Surz Style Pure^{SM} indexes, as an alternative to Russell and S&P, provide conspicuously valuable insights. Surz Style Pure^{SM} indexes have been around for more than 20 years.

More importantly, there are times when Russell and S&P agree, but the reality is significantly different. Such was the case during the financial crisis of 2008. As shown in Figure 2.3, these two indexes measured both value and growth as losing the same amount, about 34%.

By contrast, the inclusion of core reveals that value actually outperformed growth, and core outperformed both value and growth. This is an important insight for both portfolio construction and performance evaluation, especially in these distressed times.

Ignoring core leads to poor diversification and the increased likelihood of poor performance. Homogenized core stocks, defined as the stuff in the middle as opposed to a blend of value and growth, perform differently than value and growth. Accordingly, ignoring homogenized core is like throwing away the filling in an Oreo® cookie—it's the sweet spot of diversification around which value and growth revolve.

In most portfolio construction programs, value and growth styles receive roughly market-weighted allocations, and the investor usually applies strategic bets above or below these market weights to enhance performance. But, these bets unknowingly underweight homogenized core. Research conducted by Dr. Frank Sortino of the Pension Research Institute and Sortino Investment Advisors proves this point and indicates that allocations to skillful value and growth managers systematically underweight the middle of the market. This is understandable in light of the scrutiny that most managers are under to maintain style consistency. Managers have an incentive to sell companies that drift toward the middle, away from their declared style. The result is an unintended bet in most managed portfolios away from homogenized core. This is a diversification mistake, and one that hurt performance in the economic crisis of 2008, as shown in the figure above.

The asset allocation process allocates to equity style puzzle pieces in their market proportions, or at least acknowledges that anything other than a market weight is a bet designed to add value. This leads to the second puzzle: active or passive management.

Evaluating Investment Managers: The Search for, and Use of, Skill

The professional search for investment talent is currently being conducted in the same way that the drunk looks for his keys under the light of a lamppost. When asked where the keys were lost, the drunk replies "up the street, but the light is much better here." When it comes to investment fund selection and allocation, advisors are doing what is easy rather than what makes sense. They ought to be customizing the benchmark rather than limiting their comparisons to off-the-shelf indexes, and they should allocate to talent rather than to style boxes. In other words, consultants should fish for talent with fly rods not flypaper. More thoughtful, albeit more difficult, angling for active managers will enrich investment talent harvests and their applications.

Most do not see the need for benchmark customization, primarily because it is not common practice. Ignorance is bliss. This book is called *The Sortino Framework for Constructing Portfolios*, not *A Review of Common Practices*, although in Chapter 8 of this book my co-contributor Neil Riddles disagrees with me primarily because it is common practice to use off-the-shelf indexes. Disagreement is fine, and you are the judge. Neil argues that brand indexes are well understood by all, so the mandate is clear, but there are frequently differences between what the manager actually does and the mandated index, especially for liberated non-index huggers. The mandated tail should not wag the doggone reality. Should Tiger Woods be evaluated as a bowler because it's common practice? The first-order effect of agreeing to a misspecified benchmark might be new business, but there are potential consequences. In my personal experience with an investment management firm, I witnessed the benefits and costs of benchmark misspecification. This manager is roughly 70% large cap growth, 20% large core, and 10% large value. Many billions of dollars came through the door in the late 1990s because of style rather than skill—the stipulated benchmark for this manager was typically the S&P 500, an easy bogey for a growth stock manager to beat in the 1990s. But, there is business risk in agreeing to a lie. All of that money, and more, fled out the door faster than it came in when the growth bubble burst. Do you suppose some of that money might have stuck had client expectations been set in line with what this manager actually does? Or, do you think this manager should have conformed to the S&P 500, even if it is not what the manager does well?

Fund selection criteria currently favor index funds and index huggers, because style boxes undermine the search for skill. Equity allocations are preordained to set style boxes, each with its own index, and managers are sought to track these indexes. *Risk is erroneously defined at the individual manager level as tracking error.*[1] The standard approach today begins with a decomposition of the stock market into four style segments—for example, 35% large growth, 35% large value, 15% small growth, and 15% small value. Managers are chosen for each of these four assignments, and assets are allocated to the winners at the market weights. This simplifies the process but compromises the talent search.

Because risk is defined as tracking error, index huggers have an edge in manager searches. But, recognize that alpha and R-squared are from different alphabets: low tracking error limits the alpha that can be achieved. Populating our asset allocations with index huggers makes for a mediocre but safe portfolio. The problem with this current approach is that it's hard to make a good cioppino when all the ingredients are bland, even if they are safe. Our industry has drunk the index huggers' Kool-Aid and has reversed a process that had been in place for some time.

Not too long ago, we sought skill wherever we could find it. Then, once a talent pool was filled, allocations across this pool were optimized for diversification. *Risk was defined in the aggregate as failure to achieve objectives and it was talent that mattered.* Dr. Sortino continues this tradition with his latest work. Dr. Sortino develops his talent pool using a measure he calls DTR™-α,[*] which customizes the benchmark to each manager's style profile. He then allocates to this pool to maximize total portfolio DTR-α while simultaneously minimizing style bets. Each manager comes into the solution as a blend of styles. The active–passive decision is a mix of both: Use active managers wherever you can find skill and fill in the voids with passive style indexes.

DTR-α uses custom benchmarks derived from style analysis. Before style indexes were developed, there was wide acceptance and support for the concept of a "normal portfolio," which is a customized list of stocks with their neutral weights. "Normals" were intended to capture the essence of the people, process, and philosophy behind an investment product. However, only a couple of consulting firms were any good at constructing these custom benchmarks. Today, we can approximate these designer benchmarks with style analysis. While style analysis may not be as comprehensive as the original idea of normal portfolios, it makes it possible for firms to partake in this custom blending of style indexes. Style analysis can be conducted with returns or holdings. Both approaches are designed to identify a style blend that—like normals—captures the people, process, and philosophy of the investment product.

One form of style analysis is returns-based style analysis (RBSA). RBSA regresses a manager's returns against a family of style indexes to determine the combination of indexes that best tracks the manager's performance. The interpretation of the fit is that the manager is employing this "effective" style mix, because performance could be approximately replicated with a blend of passive indexes.

Another approach, called holdings-based style analysis (HBSA), examines the stocks actually held in the investment portfolio and maps these into styles at points in time. Once a sufficient history of these holdings-based snapshots is developed, an estimate of the manager's average style profile can be developed and used as the custom benchmark. HBSA, like normal portfolios, starts at the individual security level and examines the history of holdings. The departure occurs at the blending. Normal portfolios blend stocks to create a portfolio profile that is consistent with investment philosophy, whereas HBSA makes an inference from the pattern of point-in-time style profiles and translates the investment philosophy into style.

The choice between RBSA and HBSA is complicated and involves several considerations. Although RBSA has gained popularity, this doesn't necessarily mean that it's the best choice. The major trade-off between the two approaches is ease of

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[*] DTR and Desired Target Return are trademarks of Sortino Investment Advisors.

use (RBSA) vs. accuracy and ease of understanding (HBSA). RBSA has become a commodity that is quickly available and operated with a few points-and-clicks. Some websites offer free RBSA for a wide range of investment products. Find the product, click on it, and out comes a style profile. Offsetting this ease of use is the potential for error. RBSA uses sophisticated regression analysis to do its job. As in any statistical process, data problems can go undetected and unrecognized, leading to faulty inferences. One such problem is multicollinearity, which exists when the style indexes used in the regression overlap in membership. Multicollinearity invalidates the regression and usually produces spurious results. The user of RBSA must trust the "black box," because the regression can't explain why that particular blend is the best solution. In his 1988 article entitled "Determining a Fund's Effective Asset Mix" (*Investment Management Review*, December, pp. 59–69), Nobel Laureate Dr. William Sharpe introduced RBSA and set forth recommendations for what has come to be known as the "style palette":

It is desirable that the selected asset classes be:

- Mutually exclusive (no class should overlap with another)
- Exhaustive (all securities should fit in the set of asset classes)

Surz Style Pure℠ indexes[2] are one of only two index families (the other is Morningstar) that meet these important criteria, and they are the preferred choice of Dr. Sortino in his groundbreaking work. Introduced in 1986, Surz Style Pure℠ indexes were the first on the scene. Morningstar then followed more than a decade later in 1997.

Treating all managers as index huggers is an evaluation mistake. We need to bring the best custom benchmark to each liberated manager, rather than force these square pegs into round holes; otherwise, we will miss a lot of talent. Some investment firms are simply at their best when left unfettered from indexes. This doesn't take these firms off the benchmark hook; it customizes the hook.

There is a problem with both off-the-shelf and custom benchmarks. Academics have estimated that it takes many decades to determine the statistical significance of outperforming a benchmark, even a benchmark that is customized to the individual manager. This is because the hypothesis test "performance is good" is being conducted across time. But, there is an alternative that conducts this test in the cross-section of all possible implementations of the manager's investment approach, drawing portfolios at random from the stocks in the best benchmark that can be identified. These virtual peer groups are bias free and solve the waiting time problem for statistical significance.

The investment manager research and due diligence industries have been lazy and sloppy with their benchmarks, tolerating the obfuscations of investment relationship personnel. What we allow in this high-stakes game we encourage, at the clients' expense. Flawed benchmarks lead to flawed decisions.

This manager-in-a-box approach produces flawed asset allocations. Because many managers don't belong in a box, the allocations to styles get distorted. If the intention is to allocate a percentage of assets to the large growth segment of the market and a single manager is assigned to that segment, we should be sure that the manager is 100% pure large growth.

Conclusion

The challenge in solving the portfolio construction puzzle is defining the puzzle pieces. Current practices, such as shoving every manager into a style box, amount to jamming square pegs into round holes. *Better solutions emerge when puzzle pieces fit together and utilize mutually exclusive and exhaustive style indexes that explicitly include core.* Only two style index families meet these criteria: Surz Style Pure℠ and Morningstar. Morningstar indexes are domestic only, while Surz Style Pure℠ indexes are both domestic and foreign.

ENDNOTES

1. The limitations of the information ratio are discussed by Dr. Joseph Messina in Chapter 6 of *Managing Downside Risk in Financial Markets*, by Frank Sortino and Steven Satchell (Oxford, U.K.: Butterworth-Heinemann 2001).
2. Surz indexes are available on a number of platforms, including Zephyr's StyleADVISOR®, MPI Stylist, Ibbotson Associates, Northfield, FactSet, PerTrac, PSN Informa, SunGard/Frontier Analytics, Open Finance Network, and Cainsoft.

Chapter 3

Beyond the Sortino Ratio

Frank Sortino, Robert van der Meer, Auke Plantinga, and Bernardo Kuan

Executive Summary

This chapter begins with the development of the Sortino ratio and why I discarded it for the upside potential ratio and Desired Target Return™ (DTR™).* Professors Robert van der Meer and Auke Plantinga of Groningen University then worked with me to develop the upside potential ratio. The chapter ends with Bernardo Kuan's research on the predictive power of DTR.

The Sortino Ratio

It was Brian Rom's idea at Investment Technologies to call it the Sortino ratio. I wanted to call it the "mean-lower partial moment ranking ratio," but Brian didn't think that name would catch on. I believe the popularity of this ratio is due to the fact that it made hedge funds look better than the Sharpe ratio, which led them to

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proclaim it superior to Sharpe. The Sortino ratio came out of research I did in the early 1980s. The first reference to it was in *Financial Executive Magazine* (August, 1980). The first calculation was published in a series of articles in the *Journal of Risk Management* (September, 1981). Brian suggested we simplify it and make it look more like the Sharpe ratio.

I think the Sortino ratio was an improvement at that time in that it measured risk as deviations below the investor's DTR. What we now call DTR was called MAR in the original Sortino ratio. Attorneys advised Sortino Investment Advisors (SIA) of a potential liability because referring to something as a "minimal acceptable return" could lead people to think we were promising that return at a minimum, so we changed it to DTR. Publication of an article in the *Journal of Investing* with my friend Lee Price made many people aware of the Sortino ratio (see Figure 3.1).

The numerator of the Sortino ratio measures actual returns of the manager in excess of the DTR. In the denominator, we use the bootstrap procedure on the manager's returns and calculate the deviations below the DTR. Thus, the ratio is goal oriented in that it measures performance relative to the return needed to achieve the investor's goal rather than measuring performance relative to the market. For that reason, I believe it is still more appropriate than the Sharpe ratio or the information ratio, which measure how well one is doing relative to the treasury bill rate and market index, respectively. The Sortino ratio, then, attempts to measure how the manager did relative to the investor's DTR, given the manager's downside risk.

In the 1990s, I noticed that both the Sharpe ratio and the Sortino ratio were getting smaller and smaller as the market went higher and higher because volatility was declining as the market topped out. For that reason, I began to search for an even better performance measure. That having been said, we offer the paper by Christian Pederson and Stephen Satchell in Chapter 10. Pederson and Satchell offer proof that the Sortino ratio is consistent with modern portfolio theory (MPT).

Improvements

Working with Robert van der Meer and Auke Plantinga at Groningen University in the Netherlands, we developed the upside potential ratio. For this performance measure, we generate the joint distribution of returns for the manager's style blend as shown in Figure 1.2 in Chapter 1 and explained in Chapter 2 by Ron Surz. As we

$$\frac{\text{Manager's return} - \text{DTR}}{\text{Deviations below the DTR}}$$

Figure 3.1 The Sortino ratio.

say throughout this book, the goal is what one is trying to accomplish, and the investment objective describes how to achieve it. The investment objective requires the calculation of the return needed to achieve the goal, which is the DTR. Thus, *the upside potential ratio is a measure of the inherent risk the manager is taking of not achieving the investor's DTR relative to the potential of exceeding that desired return. It is not measuring what he did but is an estimate of what he is statistically capable of achieving.*

A Pictorial Rendering

It is sometimes difficult to grasp what the equations in the numerator and denominator of Figure 3.1 look like. So, let's break it down and compare upside potential to upside probability and downside risk to downside probability. Figure 3.2 is a factual representation of the probabilities of lying above and below the DTR, and in Figure 3.3 we create a picture of the ratio of the upside probability to downside probability. This is what Neil Riddles suggests in Chapter 6.

Now one can see visually that the probability of exceeding the DTR is 3-1/2 times larger than the probability of falling below the DTR. However, this risk–return trade-off is only applicable for an investor who is risk neutral, in which case the probability ratio would be as shown in Figure 3.4 with zeros for exponents; that is, the (R – DTR) terms are reduced to zero.

But this ignores the magnitude factor. The Fishburn utility function we use assumes people like the second million dollars they make just as much as the first million. However, they feel four times as much pain from the second million dollars

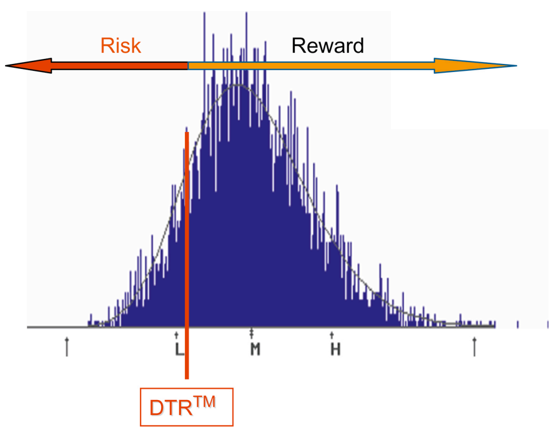


Figure 3.2 Probabilities of lying above and below the DTR.

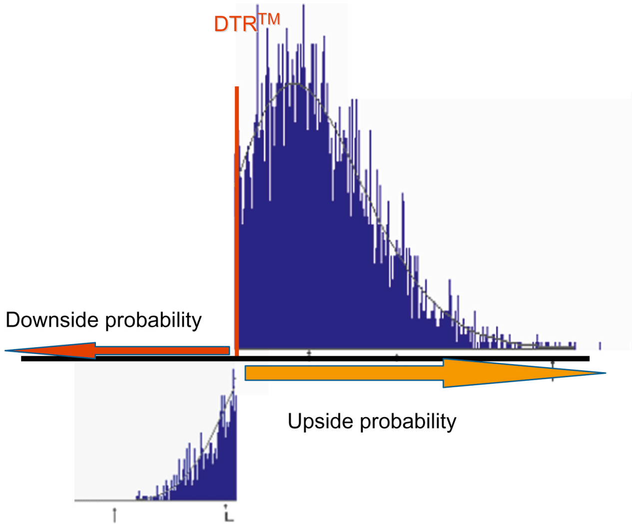


Figure 3.3 Upside probability ratio = 3.5.

$$\frac{\int_{DTR}^{+\infty} (R\text{-}DTR)^{0}\, f(R)\, dr}{\left[\int_{-\infty}^{DTR} (R\text{-}DTR)^{0}\, f(R)\, dr\,\right]^{1/2}}$$

Figure 3.4 Upside probability ratio.

they lose as they do from the first million dollars of loss. Mathematically, returns above increase linearly and returns below are squared. What would this look like? Figure 3.5 is an attempt to create this picture. The upside potential arc extends far beyond the probability but declines as the added pleasure of higher returns is overcome by the smaller probability of such returns happening.

Returns below the DTR, however, are squared; therefore, the upside potential is only 25% greater than the downside risk, whereas the probability shown in Figure 3.2 was 3-1/2 times greater than the downside probability. This risk–return trade-off is consistent with someone who is risk averse.

The exponent in the numerator of Figure 3.6 is now 1, indicating the magnitude factor; each increase in return is appreciated equally. The exponent in the denominator is 2, squaring the differences. The pain of being 2% below the DTR is 4 times greater than being 1% below, and a return of 4% below is 16 times more painful. We take the square root of the term in the denominator in order to convert it to the

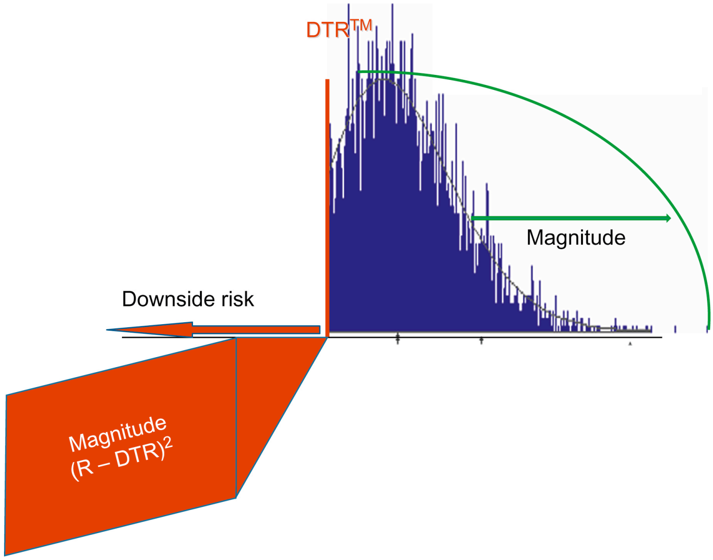


Figure 3.5 Upside potential ratio = 1.25.

$$\frac{\int_{DTR}^{+\infty} (R-DTR)^1 f(R)\, dr}{\left[\int_{-\infty}^{DTR} (R-DTR)^2 f(R)\, dr\right]^{1/2}}$$

Figure 3.6 Upside potential ratio.

same units as the numerator. Thus, an upside potential ratio of 1.25 means the manager's portfolio style has inherently 25% more upside potential than downside risk (see Chapter 1 for calculation).

Obtaining Reasonable Estimates

It is one thing to have a better concept of measuring performance. It is quite another to obtain reliable estimates of the risk and return measures. Many people are now measuring downside risk as deviations below some number other than the DTR. Also, almost all of them use the manager's returns instead of using returns from the manager's style blend. I think these are serious errors. One may only have a few years of returns for a manager, but if you know the manager's style blend you could use 20 years of returns on the indexes that account for the manager's style. This would provide much more stable estimates of risk. Using actual manager returns results in underestimating risk at the top of a market cycle and overestimating risk at the bottom of a market cycle. That is why Ron Surz's work is so valuable to SIA.

These errors could affect the upside potential ratio. For example, using the fund manager's returns in Table 3.1 for the 3 years prior to the first quarter of 2000, Manager A looks much more risky than Manager B (20% vs. 12.3%). However, if you employ Bill Sharpe's style analysis with the Surz indexes to capture each manager's style blend and then measure the downside risk of the manager's style, they are almost the same. More importantly, both would appear to have much more risk than is inherent in their style. This led people to think these funds were much more risky than they actually were. That is what is happening now in 2009. The opposite was true at the top of the market in 2000.

Failure to use style analysis to capture the inherent risk in any given portfolio leads to performance measures that encourage investors to bet the farm at the top of the market and scares them out of equities at the bottom of the market. But, isn't that what everybody does? Could that be one of the reasons why investors buy at the top and sell at the bottom?

Origins of a Utility Function for Performance Measurement

Over a pleasant lunch with Bill Fouse one day in San Francisco, I asked him what his thoughts were regarding performance measurement. He said, "Why doesn't somebody use a utility function as a measure? They use it for choosing portfolios

Table 3.1 Fund data vs. style data

1st Quarter funds data vs Style data

	Fund UP-ratio	Style UP-ratio		Fund dsDev	Style dsDev		Fund Upside	Style Potential
Large Growth								
Large Growth Mgr A	0.6	1.1		12.6%	9.3%		7.9%	10.2%
Large Growth Mgr B	0.2	1.1		20.0%	9.7%		4.1%	10.8%
Large Value								
Large Value Mgr A	0.5	1.6		11.6%	6.8%		5.6%	10.6%
Large Value Mgr B	1.4	1.5		8.2%	7.4%		11.6%	11.3%
Large Value Mgr C	0.4	1.3		13.1%	8.3%		5.3%	10.6%
Small Growth								
Small Growth Mgr A	0.4	0.9		18.9%	10.7%		6.9%	10.0%
Small Growth Mgr B	1.2	0.6		15.7%	15.1%		19.1%	8.5%
Small Value								
Small Value Mgr A	1.8	1.1		5.7%	7.2%		10.6%	7.9%

off of an efficient frontier." I thought, you're absolutely right, Bill. As soon as I got home, I looked at one of the many papers Peter Fishburn has written on this subject. That led me to include the Fouse index in the paper I wrote with Lee Price and to suggest that it was superior to the Sortino ratio.

Since then, I developed the omega excess return with my old colleague Joseph Messina. This is now called the DTR-α model, discussed in Chapter 1 and explained in detail in the Appendix. The most rigorous test of this model was performed by Bernardo Kuan and is reprinted here with his permission.

The above observations have a bearing on the bootstrap example Bernardo provides. *The Wall Street Journal* (May 2, 2009, p. B1) called attention to the "imperfections" of Monte Carlo simulations. The errors mentioned are that they tend to focus on economic scenarios, and they assume a standard normal distribution and then "spit out a success rate assuming some set market rate of return."

Monte Carlo simulation (MCS) is one of the oldest and most widely used statistical procedures for making inferences based on a small sample. The procedure was developed in 1946 by Stanislaw Ulam, who was working on the Manhattan Project, as a way of estimating the probability of winning at a game of solitaire. It is cited prominently in the marketing literature of Morningstar, Financial Engines, and T. Rowe Price, among others. MCS is part and parcel of the bootstrap procedure used by SIA. We believe that the way most practitioners use MCS creates some problems that are overcome by employing the SIA methodology.

How MCS is Used

1. Estimate the probability returns will be above or below a certain number.
2. Estimate the probability of having enough money to retire at a certain date.
3. Estimate the probability that the withdrawal rate at retirement is not excessive.

This is equivalent to using a confidence interval to assess the probability of returns falling below a certain level and equating that with risk.

Problems

This misuse of MCS confuses a procedure for generating a probability distribution with a methodology for estimating risk. It equates risk with the probability of a bad outcome. As pointed out earlier in the chapter, probability is only one component of risk. There is a magnitude component, as well. An investment strategy may only have a 10% chance of failure, but, like Long-Term Capital Management, failure could result in financial disaster. Standard deviation is a probability weighted function of returns about the mean. Downside risk is a probability weighted function of returns below the DTR an investor needs to accomplish his or her goal.

Most Monte Carlo simulations assume that the individual's DTR is irrelevant; therefore, all investors agree on the degree of risk for all assets. In terms of a Fishburn utility function, investors who make their decisions based on probabilities of a bad outcome are risk takers, and the exponent in Figure 3.4 is equal to 0. Behavioral finance shows that investors tend to ignore a very small chance of a very bad outcome; thus, they become risk takers for events such as the dot-com bubble. It would seem, then, that the way MCS is used supports a flaw in the decision-making ability of investors that leads them to buy into bubbles at the top.

At least value at risk (VAR) assumes investors are risk neutral and their utility function is linear below the DTR. Risk-neutral investors believe losing all their money is only twice as painful as losing half of it. Most firms that use Monte Carlo simulation focus on the average return and standard deviation when evaluating managers or determining the asset allocation. SIA focuses on upside potential and downside risk.

Results

1. The farther returns fall below an investor's DTR, the greater the pain. Returns above the DTR are not painful and not risky.
2. Risk of a given asset will appear different to investors with different DTRs.
3. Investors are risk averse. Losing all their money is many times more painful than losing half of it.

MCS is only the beginning for calculating risk, not the end result.

The Bernardo Kuan Study

The return earned on any portfolio must be adjusted for risk. If an investor gave a large amount of money to a money manager, and at the end of the year found the investment had increased 100%, should that be enough to praise the abilities of the manager? What if the investor discovered that the way the manager achieved this result was by going to Las Vegas and putting all the money on red at the roulette table. This illustrates not only that return alone is insufficient when looking at performance but that risk must also take into consideration what could have happened in the past, not just what did happen.

Bootstrapping

To capture this aspect of risk, I will employ the bootstrap procedure developed by Bradley Efron and Robert Tibshirani (1993). By randomly sampling the actual returns with replacement, a better estimation of the return distribution is obtained than merely assuming history will repeat itself. The following example will illustrate how this is accomplished. Figure 3.7 shows the hypothetical returns for a portfolio manager over a 4-year interval. The worst year the manager had was the first year, in which he earned +30%. The bootstrap procedure assumes this 4-year interval is a representative sample. A random draw might choose 4% as the first return that could have occurred in a given year. That 4% is replaced and another random draw is made. In this example, it is −3%. The −3% is replaced and it is again selected for the final draw in that first year. Although sequential returns have been shown to be correlated with one another, it is reasonable to assume that the returns drawn in this manner are independent. The bootstrap procedure shows that the worst return for a given year could have been −35% (see Figure 3.7).

This procedure is repeated several thousand times to generate a distribution of returns as shown in Figure 3.2. This distribution is positively skewed, and by fitting a three-parameter lognormal distribution to the data it is possible to calculate the downside risk from any point on the horizontal axis. This captures not only the mean and standard deviation but also the skewness (3rd moment) and kurtosis (4th moment). In addition, the distribution estimated is not a historical distribution but an estimation of the inherent distribution that has been brought up by its bootstraps, so to speak.

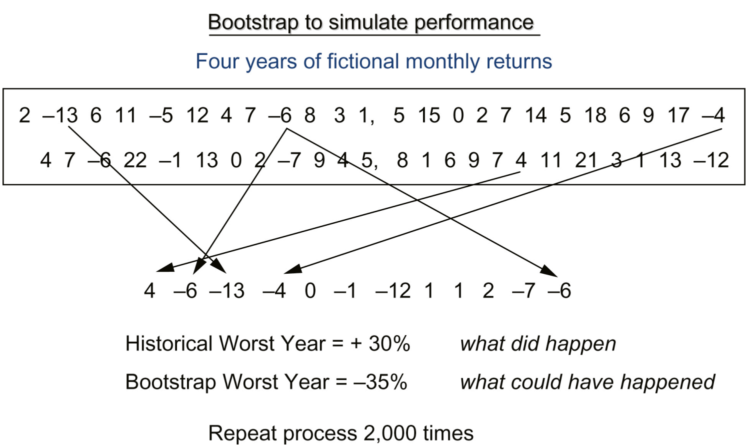


Figure 3.7 Bootstrap example.

METHODOLOGY

This study focuses on the potential value of the DTR-α return discussed in Chapter 1 and detailed in the Appendix. Because the DTR-α return has been adjusted for style, what remains is mostly the contribution of the manager's skill. To compute DTR-α returns, the SIA optimizer, which is explained in Chapter 4, was used with the following parameters and data:

- 3-year rolling time interval (1978–1993), which is short enough to capture significant style movement and at the same time long enough to avoid excessive noise in the data
- DTR = 8.3%
- Risk free rate = 5%
- Lambda (degree of risk aversion for an average investor) = 3.0
- Monthly returns from mutual funds in the *Pensions & Investment* rankings that had complete return data since 1977 (see Table 3.2)

STYLE INDEXES OF DIMENSIONAL FUND ADVISORS, SANTA MONICA, CA

These statistics generated from the SIA optimizer were transferred and consolidated into a spreadsheet program for analysis (Table 3.2). In addition, the SIA optimizer gave a style analysis result, providing the calculated mix of indices that will best match the fund's returns and how well the mix fit the returns (R^2). To gain some insight from the results calculated, the following questions were proposed:

1. How are the rankings obtained from the DTR-α returns correlated with the Sharpe and Sortino rankings?
2. How consistent are the rankings from one year to the next?
3. What are some of the statistical results of the DTR-α returns?
4. Could a simple strategy employing the DTR-α return make more money than a naive strategy?

ANALYSIS AND RESULTS

Ranking correlation

The Schwab Center for Investment Research study separated mutual funds by style and then ranked them by eight different measures: Sharpe ratio, geometric Sharpe

Table 3.2 Statistical Output

Fund	1YRet	5YRet	DS-Beta	S-Sortino	Omega1	Omega5	O-Excess	B-RAExcs	D-Dev	IDS-Risk	HDS-Risk	SAD	S-Beta	S-Sharpe
AMCap	14.10%	11.80%	1.5	0.4	9.30%	7.10%	−2.80%	−1.50%	5.40%	4.40%	10.30%	12.60%	1.10%	0.5
American Cent-20thC Growth	15.00%	6.30%	3.6	0.3	−0.10%	−8.80%	−17.10%	−8.20%	10.00%	5.30%	11.80%	22.40%	1.20%	0.4
American Cent-20thC Select	19.40%	8.00%	4	0.6	8.90%	−2.50%	−14.40%	−8.00%	7.90%	3.70%	9.30%	18.70%	1.10%	0.8
American Mutual	16.00%	13.50%	1.1	1.2	14.80%	12.30%	0.00%	0.00%	2.90%	2.80%	6.10%	6.40%	1.00%	0.9
Columbia Growth	20.90%	15.00%	1.2	1	16.60%	10.80%	0.50%	1.10%	4.90%	4.60%	11.00%	12.00%	1.10%	0.7
Dodge & Cox Stock	22.10%	17.60%	0.9	1.6	20.10%	15.50%	1.70%	1.60%	3.20%	3.30%	8.60%	8.30%	1.10%	1.0
Dreyfus	16.00%	9.00%	3.9	0.4	6.20%	−0.70%	−13.30%	−6.90%	6.40%	3.30%	9.20%	18.00%	1.00%	0.6
Fidelity Contrafund	21.90%	18.20%	1	1.5	19.40%	15.70%	4.00%	4.20%	3.80%	3.80%	9.00%	9.10%	1.20%	0.9
Fidelity Equity Income	21.10%	17.40%	0.9	2	19.90%	16.20%	2.00%	1.90%	2.60%	2.80%	6.80%	6.30%	1.00%	1.1
Fidelity Magellan	11.50%	14.80%	1.9	0.2	7.30%	10.60%	−1.30%	0.60%	5.20%	3.80%	8.70%	11.90%	1.20%	0.3
Fidelity Puritan	15.10%	14.80%	0.8	1.4	14.50%	14.10%	2.20%	2.10%	2.40%	2.70%	5.30%	4.80%	1.10%	0.9

(*Continued*)

Table 3.2 (*Continued*)

Fund	1YRet	5YRet	DS-Beta	S-Sortino	Omega1	Omega5	O-Excess	B-RAExcs	D-Dev	IDS-Risk	HDS-Risk	SAD	S-Beta	S-Sharpe
Fundamental Investors	20.20%	16.30%	1.1	1.3	17.80%	13.90%	0.80%	1.00%	3.50%	3.30%	8.50%	8.90%	1.00%	0.9
Growth Fund of America	14.80%	12.80%	1.4	0.5	9.90%	7.90%	−2.00%	−0.80%	5.40%	4.60%	10.90%	12.80%	1.10%	0.5
IDS New Dimensions A	24.50%	14.50%	1.1	1.4	20.80%	10.80%	1.50%	1.90%	4.80%	4.60%	10.40%	11.00%	1.20%	0.9
IDS Stock A	19.50%	12.70%	1.5	1.1	16.80%	9.90%	−2.50%	−1.80%	4.00%	3.30%	7.90%	9.60%	1.00%	0.9
Invesco Industrial Income	16.80%	11.00%	2.6	0.8	13.30%	7.50%	−5.00%	−3.20%	4.30%	2.70%	6.70%	10.70%	1.10%	0.8
Investment Company of America	19.40%	13.20%	1.2	1.3	17.40%	11.20%	−1.50%	−1.20%	3.80%	3.40%	7.60%	8.30%	1.00%	1.0
Janus	19.40%	12.60%	1.8	1	16.00%	9.10%	−3.10%	−1.70%	4.00%	3.00%	8.00%	10.70%	1.10%	0.9
Kemper Growth A	16.30%	7.60%	2.5	0.4	6.60%	−2.00%	−10.10%	−5.50%	8.30%	5.30%	11.40%	17.90%	1.10%	0.5
Kemper Small Cap Equity A	14.00%	11.10%	1.3	0.34	6.00%	3.00%	−1.80%	−0.10%	8.90%	7.80%	14.40%	16.30%	1.20%	0.3

Keystone Small Company Growth (S-4)	0.90%	13.60%	1.4	−0.5	−7.50%	5.20%	0.40%	2.90%	9.10%	7.80%	14.40%	16.70%	1.40%	−0.1
Lord Abbett Affiliated A	20.20%	15.90%	1	1.5	18.50%	14.20%	0.50%	0.50%	3.00%	3.00%	7.70%	7.50%	1.00%	1.0
Massachusetts Investments A	25.90%	15.50%	0.9	2.3	24.20%	13.80%	0.90%	0.70%	3.30%	3.60%	8.10%	7.60%	1.10%	1.2
Neuberger & Berman Guardian	17.80%	16.30%	1.3	0.8	14.20%	12.70%	0.20%	0.90%	4.00%	3.50%	9.60%	10.90%	1.10%	0.6
Neuberger & Berman Manhattan	9.70%	12.30%	1.3	0.1	3.30%	5.90%	−1.10%	0.40%	7.40%	6.50%	12.90%	14.60%	1.20%	0.2
Neuberger & Berman Partners	26.60%	18.10%	1.1	1.8	23.70%	15.20%	2.70%	3.00%	3.80%	3.70%	9.50%	9.80%	1.20%	1.0
New England Growth A	20.90%	9.90%	4	0.7	11.40%	0.40%	−11.80%	−6.20%	8.40%	3.60%	8.90%	17.80%	1.40%	0.7
Phoenix Growth A	14.60%	10.50%	2.1	0.5	10.70%	6.60%	−4.80%	−2.90%	4.70%	3.30%	7.80%	11.40%	1.00%	0.6

ratio, selection Sharpe ratio/information ratio, Jensen's alpha, benchmark Jensen's alpha, holding period alpha, appraisal ratio, and the Modigliani risk-adjusted performance. This study found that the rankings tend to be similar irrespective of the measure used, concluding that the investor should not be concerned about which of these measures to use.

Similarly, to see whether the DTR-α returns produce rankings similar to those obtained by using the Sharpe ratio and Sortino ratio, the Spearman rank correlation coefficient was used. The statistic takes on values between +1 and −1, where +1 indicates that they are identical and −1 indicates that the rankings are reversed. The Spearman rank correlation is computed using the following formula:

$$c = 1 - \frac{6\sum_{i-1}^{n}(x_i - y_i)^2}{n(n^2 - 1)},$$

where x_i is the rank of the ith item using a single variable, y_i is the rank of the ith item using a different variable, and n = number of items being ranked.

The results obtained by comparing the Sortino and the Sharpe rankings corroborate the Schwab findings; however, the ranking obtained by using DTR-α returns is statistically significantly different from those obtained by using the Sortino and Sharpe ratios. This suggests that the DTR-α returns may produce a different kind of ranking information than that obtained from the other two measurements (see Table 3.3).

Consistency

Another question regarding the results calculated was: How consistent were the rankings obtained from one year to the next? To study the consistency of the DTR-α returns, the following two methods were proposed.

Method 1. Quartile consistency

The mutual funds were ranked by the DTR-α returns and the Sharpe and Sortino ratios from 1981 to 1993. Then, I measured the frequency that funds moved or stayed in a given quartile from one year to the next using 3- and 5-year intervals. Tables 3.3 and 3.4 show their quartile ranking from 1981 to 1993 and Table 3.5 shows the total number and percentage of funds that remained or moved to a different quartile the following year.

The results in Table 3.4 show that DTR-α had a better quartile consistency ranking than those obtained using the Sharpe or Sortino measurements. If a fund started in the first quartile, there was a 61% chance that it would remain in the first quartile in the next-year ranking using DTR-α. Likewise, if a fund was in the lowest quartile rank, it was very likely it would have stayed in the fourth quartile in the following year (61%). Increasing the time interval from 3 to 5 years produced very

Table 3.3 Spearman rank correlation table

	Exc-omega–Sortino	Exc-omega–Sharpe	Sortino–Sharpe
96	0.857	0.718	0.945
95	0.729	0.414	0.887
94	−0.296	0.698	0.180
93	0.808	0.655	0.956
92	−0.094	−0.163	0.954
91	0.895	0.731	0.917
90	−0.111	0.323	0.873
89	0.671	0.417	0.919
88	0.093	0.008	0.976
87	0.707	0.723	0.957
86	0.826	0.657	0.938
85	0.925	0.752	0.915
84	−0.074	0.212	0.892
83	0.385	0.042	0.902
82	0.618	0.352	0.939
81	0.579	0.707	0.918
Average	0.470	0.453	0.879

Exc-omega–Sortino = Spearman rank correlation between the excess omega and the Sortino rankings.
Exc-omega–Sharpe = Spearman rank correlation between the excess omega and the Sharpe rankings.
Sortino–Sharpe = Spearman rank correlation between the Sortino and Sharpe rankings.

similar results (71% and 67%, respectively). By contrast, the Sortino and Sharpe rankings for 3 years showed a 38% and 42% chance of remaining in the first quartile and a 29% and 38% probability of staying in the fourth quartile.

Method 2. Consistency as ranking variation

A variation of Method 1 was to see how far a fund changed ranking from one year to the next. A fund is deemed consistent if its ranking did not change more than

Table 3.4 Quartile ranking using the excess omega returns

Fund	Year															
	96	**95**	**94**	**93**	**92**	**91**	**90**	**89**	**88**	**87**	**86**	**85**	**84**	**83**	**82**	**81**
AMCap	4	3	2	3	3	3	4	2	1	2	3	3	3	3	2	1
American Cent-20thC Growth	4	4	4	4	2	1	4	2	2	1	3	4	4	3	2	1
American Cent-20thC Select	4	4	4	4	4	3	3	4	3	2	2	2	1	1	1	1
American Mutual	2	2	3	2	4	3	2	3	3	2	1	1	2	3	2	2
Columbia Growth	2	3	2	4	2	2	2	1	2	2	4	3	1	1	1	3
Dodge & Cox Stock	1	1	1	3	4	4	3	2	1	1	2	2	4	4	4	3
Dreyfus	4	4	4	4	4	4	4	3	3	3	4	4	4	4	4	3
Fidelity Contrafund	1	1	1	1	1	1	1	1	4	4	4	4	4	4	4	2
Fidelity Equity Income	1	1	2	1	4	4	4	3	3	4	2	2	2	2	2	1
Fidelity Magellan	3	1	2	1	1	1	1	1	1	1	1	1	1	1	1	1
Fidelity Puritan	2	2	1	1	2	3	3	4	3	3	1	1	3	2	3	3
Fundamental Investors	1	1	2	2	3	3	3	3	1	3	1	1	1	3	3	4
Growth Fund of America	3	2	2	3	3	2	1	1	1	1	3	4	2	2	2	2
IDS New Dimensions A	3	2	3	1	1	1	2	1	1	1	1	3	2	2	1	2

IDS Stock A	3	4	3	2	3	2	2	2	1	3	3	4	3	4	4	4
Invesco Industrial Income	2	2	4	3	2	1	1	1	2	2	2	2	2	3	3	4
Investment Company of America	2	3	3	3	3	2	1	2	2	2	2	1	3	2	3	4
Janus	2	3	3	2	2	1	1	1	3	3	3	2	2	1	1	2
Kemper Growth A	4	4	4	4	1	1	2	3	4	4	4	3	3	2	3	3
Kemper Small Cap Equity A	2	2	3	2	1	2	4	4	4	4	3	3	2	1	2	2
Keystone Small Company Growth (S-4)	4	1	1	1	1	4	4	4	4	4	4	4	4	4	4	4
Lord Abbett Affiliated A	1	1	2	2	3	3	3	4	4	3	2	3	4	4	4	3
Massachusetts Investments A	1	2	3	2	—	3	2	2	4	4	3	3	4	4	4	4
Neuberger & Berman Guardian	2	3	1	1	1	4	1	2	2	4	3	2	3	3	3	3
Neuberger & Berman Manhattan	4	4	1	3	4	4	3	4	3	3	1	1	1	2	3	4
Neuberger & Berman Partners	1	3	1	3	3	4	3	3	2	2	2	2	3	3	2	1
New England Growth A	3	4	4	4	2	2	4	4	3	1	4	4	1	1	1	2
Phoenix Growth A	3	3	4	4	2	2	2	3	2	1	1	1	1	1	1	1

Table 3.5 Ranking consistency results

Ranking consistency results (quartiles) using a rolling 3-year interval

	Initial rank	Next year rank				Total	Initial rank	Next year rank			
		1	2	3	4			1	2	3	4
Excess omega	1	64	26	10	5	105	1	61.0%	24.8%	9.5%	4.8%
	2	21	43	32	9	105	2	20.0%	41.0%	30.5%	8.6%
	3	14	27	40	26	107	3	13.1%	25.2%	37.4%	24.3%
	4	6	10	24	63	103	4	5.8%	9.7%	23.3%	61.2%
		1	2	2	2			1	2	3	4
Sortino	1	43	23	23	24	113	1	38.1%	20.4%	20.4%	21.2%
	2	27	35	23	19	104	2	26.0%	33.7%	22.1%	18.3%
	3	21	33	27	25	106	3	19.8%	31.1%	25.5%	23.6%
	4	22	14	31	27	94	4	23.4%	14.9%	33.0%	28.7%
		1	2	3	4			1	2	3	4

Sharpe	1	50	30	20	19	119	1	42.0%	25.2%	16.8%	16.0%
	2	36	27	34	14	111	2	32.4%	24.3%	30.6%	12.6%
	3	19	38	25	21	103	3	18.4%	36.9%	24.3%	20.4%
	4	14	15	25	33	87	4	16.1%	17.2%	28.7%	37.9%

Excess omega ranking consistency results (quartile) using a rolling 5-year interval

	Initial Rank	Next year rank				Total	Initial rank	Next year rank			
		1	2	3	4			1	2	3	4
	1	74	22	6	2		1	71.2%	21.2%	5.8%	1.9%
	2	26	52	24	5		2	24.3%	48.6%	22.4%	4.7%
	3	5	23	51	24		3	4.9%	22.3%	49.5%	23.3%
	4	1	8	24	69		4	1.0%	7.8%	23.5%	67.6%

three ranking positions; in other words, a fund was labeled as consistent if it stayed between a three-ranking band from one year to the next. The total number of times that a DTR-α fund stayed within ± 3 ranking positions the following year was 169 in Table 3.5, which is *more than 40% of the time*. By contrast, the Sortino and Sharpe rankings had totals of 92 (21.9%) and 98 (23.3%), respectively (see Table 3.6).

Looking at individual funds with the DTR-α ranking, the Fidelity Contrafund and the Keystone Small Company Growth fund proved to be the more consistent, having a 73% and 80% consistency, respectively. By contrast, the more consistent funds under the Sortino ranking were the Kemper Small Cap Equity and the Fidelity Puritan, both with a 40% consistency. The highest rank under the Sharpe ranking was the Fidelity Contrafund, with a 30% consistency. The Sortino and Sharpe rankings produce consistencies as low as 0%. The average consistencies for the DTR-α, Sortino, and Sharpe rankings were 40.2%, 21.9%, and 23.3%, respectively (see Tables 3.6 and 3.7). These two methods showed that DTR-α returns produce a more consistent ranking from one year to the next than the rankings generated by the Sortino ratio or the Sharpe ratio.

DTR-α return statistics

The DTR-α returns from 1981 to 1993 ranged from a maximum of 31.20% for Fidelity Magellan to a minimum of −22.90% for Keystone Small Company Growth. On average, the high DTR-α return was 11% and the low was −8%. With a few exceptions, such as Fidelity Magellan (average of 9.4%) and IDS New Dimensions (4.3%), the average manager's contribution to the total return was 0.9% (as measured by DTR-α). This indicates that the average manager was able to produce a slightly higher risk-adjusted return than a set of passive indexes, which agrees with the general perception that it is very difficult to beat the market. Another interesting observation is that the average DTR-α return exhibited a downward trend, from positive DTR-α values in the early 1980s to negative ones in the later years of our study. *This indicates that DTR-α values do change over time as market conditions change* (see Table 3.8).

The descriptive statistics suggest that on average the manager's skills contribute a small percentage of the total performance return of the fund. However, there are a few funds that significantly and consistently outperform or underperform all other funds, and those are the ones that an investor should be trying to identify. The DTR-α seems to hold a greater promise for accomplishing this than the other performance measures studied. Also, looking at the top fund from 1981 to 1993, it is evident that DTR-α returns display a greater consistency than the Sortino or Sharpe rankings (see Table 3.9).

Table 3.6 Change in rankings

Number of funds that stayed within ±3 ranking positions (±10%) from previous year

	Year															
	96	**95**	**94**	**93**	**92**	**91**	**90**	**89**	**88**	**87**	**86**	**85**	**84**	**83**	**82**	**Total**
X-omega	13	12	11	10	12	8	9	7	13	7	19	9	15	15	9	169
Sortino	10	4	1	5	2	9	7	3	1	3	12	8	7	11	9	92
Sharpe	10	5	3	5	2	5	4	7	2	6	8	10	14	9	8	98

Percentage of funds that stayed within ±3 ranking positions (±10%) from previous year

	Year															
	96	**95**	**94**	**93**	**92**	**91**	**90**	**89**	**88**	**87**	**86**	**85**	**84**	**83**	**82**	**Total**
X-omega	46.4%	42.9%	39.3%	35.7%	42.9%	28.6%	32.1%	25.0%	46.4%	25.0%	67.9%	32.1%	53.6%	53.6%	32.1%	40.2%
Sortino	35.7%	14.3%	3.6%	17.9%	7.1%	32.1%	25.0%	10.7%	3.6%	110.7%	42.9%	28.6%	25.0%	39.3%	32.1%	21.9%
Sharpe	35.7%	17.9%	10.7%	17.9%	7.1%	17.9%	14.3%	25.0%	7.1%	21.4%	28.6%	35.7%	50.0%	32.1%	28.6%	23.3%

Table 3.7 10% ranking consistency table

Fund	E-omega	Sortino	Sharpe	Average return	Ex-O consistency ratio	Sortino consistency ratio	Sharpe consistency ratio
AMCap	4	1	1	15.1%	27%	7%	7%
American Cent-20thC Growth	2	3	1	15.5%	13%	20%	7%
American Cent-20thC Select	8	5	4	16.3%	53%	33%	27%
American Mutual	8	3	3	16.1%	53%	20%	20%
Columbia Growth	4	1	0	17.7%	27%	7%	0%
Dodge & Cox Stock	8	5	3	17.9%	53%	33%	20%
Dreyfus	8	0	2	12.8%	53%	0%	13%
Fidelity Contrafund	11	4	9	19.2%	73%	27%	60%
Fidelity Equity Income	7	5	5	17.4%	47%	33%	33%
Fidelity Magellan	8	3	2	21.9%	53%	20%	13%
Fidelity Puritan	6	6	6	16.3%	40%	40%	40%
Fundamental Investors	5	3	4	18.3%	33%	20%	27%
Growth Fund of America	4	2	1	16.3%	27%	13%	7%
IDS New Dimensions A	5	4	0	19.5%	33%	27%	0%
IDS Stock A	3	2	2	15.4%	20%	13%	13%

Invesco Industrial Income	9	3	4	17.8%	60%	20%	27%
Investment Company of America	5	7	4	17.3%	33%	47%	27%
Janus	5	1	3	17.8%	33%	7%	20%
Kemper Growth A	4	3	6	16.5%	27%	20%	40%
Kemper Small Cap Equity A	5	6	7	16.2%	33%	40%	47%
Keystone Small Company Growth (S-4)	12	4	7	15.1%	80%	27%	47%
Lord Abbett Affiliated A	8	4	5	16.2%	53%	27%	33%
Massachusetts Investments A	4	1	3	16.5%	27%	7%	20%
Neuberger & Berman Guardian	6	4	1	17.3%	40%	27%	7%
Neuberger & Berman Manhattan	4	2	2	16.8%	27%	13%	13%
Neuberger & Berman Partners	6	4	6	17.0%	40%	27%	40%
New England Growth A	4	1	2	19.2%	27%	7%	13%
Phoenix Growth A	6	5	5	17.9%	40%	33%	33%
			Average	17.0%	40%	22%	23%
			Maximum	21.9%			
			Minimum	12.8%			

Table 3.8 Change in DTR-α values

Fund	High	Low	Average
AMCap	11.8%	−10.1%	0.1%
American Cent-20thC Growth	18.3%	−14.6%	−1.4%
American Cent-20thC Select	16.0%	−14.1%	−0.7%
American Mutual	6.3%	−1.3%	1.7%
Columbia Growth	13.8%	−8.1%	1.9%
Dodge & Cox Stock	4.8%	−3.2%	0.9%
Dreyfus	3.4%	−13.8%	−4.0%
Fidelity Contrafund	16.4%	−15.6%	1.1%
Fidelity Equity Income	10.1%	−5.4%	1.6%
Fidelity Magellan	31.2%	−6.1%	9.4%
Fidelity Puritan	7.1%	−1.7%	2.1%
Fundamental Investors	8.2%	−4.6%	1.5%
Growth Fund of America	8.5%	−5.9%	1.8%
IDS New Dimensions A	13.4%	−4.1%	4.6%
IDS Stock A	2.4%	−7.2%	−1.2%
Invesco Industrial Income	6.3%	−6.0%	1.0%
Investment Company of America	6.5%	−2.4%	1.0%
Janus	16.0%	−3.6%	3.4%
Kemper Growth A	9.8%	−14.3%	−1.6%
Kemper Small Cap Equity A	13.9%	−8.1%	0.6%
Keystone Small Company Growth (S-4)	9.9%	−22.9%	−5.2%

Lord Abbett Affiliated A	2.8%	−4.1%	−0.4%
Massachusetts Investments A	2.4%	−5.9%	−1.3%
Neuberger & Berman Guardian	5.2%	−5.7%	1.2%
Neuberger & Berman Manhattan	9.5%	−8.1%	0.6%
Neuberger & Berman Partners	11.6%	−3.1%	2.1%
New England Growth A	25.8%	−16.2%	0.3%
Phoenix Growth A	15.3%	−8.0%	3.5%
Average	11.0%	−8.0%	0.9%
Mean	0.88%		
Median	0.80%		
Mode	1.20%		
Standard deviation	6.47%		
Sample variance	0.42%		
Kurtosis	301.71%		
Skewness	46.53%		
Range	54.10%		
Minimum	−22.90%		
Maximum	31.20%		

Year

96	95	94	93	92	91	90	89	88	87	86	85	84	83	82	81
4.2%	6.5%	7.1%	12.0%	14.5%	16.4%	10.6%	8.1%	6.2%	9.7%	5.7%	10.3%	19.9%	28.0%	31.2%	25.9%
−14.3%	−14.6%	−16.2%	−8.5%	−7.9%	−5.5%	−10.3%	−8.0%	−8.3%	−8.7%	−22.9%	−22.3%	−12.5%	−4.2%	−1.3%	−5.6%
−3.4%	−2.4%	−1.3%	−0.8%	1.9%	1.8%	−1.2%	0.3%	0.3%	0.5%	−3.2%	−1.8%	3.9%	6.9%	7.5%	5.1%

Table 3.9 Ranking consistency

Year	Top fund		
	Excess omega	**Sortino**	**Sharpe**
96	Neuberger & Berman Partners	Massachusetts Investments	Massachusetts Investments
95	Keystone Small Company Growth	Fundamental Investors	American Mutual
94	Keystone Small Company Growth	Dodge & Cox Stock	Dodge & Cox Stock
93	Fidelity Contrafund	Fidelity Puritan	Fidelity Puritan
92	Fidelity Contrafund	Fidelity Contrafund	Fidelity Puritan
91	Fidelity Contrafund	Fidelity Contrafund	Kemper Growth A
90	Fidelity Contrafund	New England Growth	Phoenix Growth A
89	Janus	Janus	Janus
88	Growth Fund of America	Neuberger & Berman Guardian	Neuberger & Berman Guardian
87	IDS New Dimensions	IDS New Dimensions	New England Growth
86	Fidelity Magellan	Fidelity Puritan	Fidelity Puritan
85	Fidelity Magellan	Fidelity Puritan	Fidelity Puritan
84	Fidelity Magellan	Fidelity Puritan	Fidelity Puritan
83	Fidelity Magellan	Fidelity Magellan	Fidelity Puritan
82	Fidelity Magellan	New England Growth	New England Growth
81	Fidelity Magellan	Fidelity Magellan	Fidelity Puritan

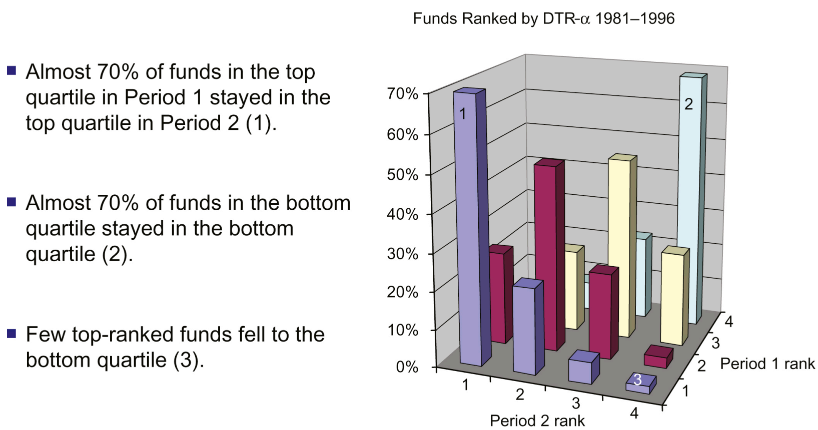
The Use of the DTR-α Return as an Investment Strategy

To see if the DTR-α returns can be used by an investor as a profitable investment strategy, a DTR-α return upgrading strategy was implemented. Each year the fund with the highest DTR-α was purchased and held for one year. This upgrading strategy was applied using the top-ranked fund and comparing it with the top quartile funds from 1981 to 1993. This DTR-α upgrading strategy was compared to a naive strategy of holding a portfolio consisting of all of the funds and to the common practice of simply buying the fund with the highest raw return.

Buying the top DTR-α fund earned a cumulative return of 1444.15% for the period 1982 to 1993, with an average annual return of 21.5%. Over this same interval, the naive strategy produced a total cumulative return of 838.8%, with an annual average of 17% (see Table 3.10). The worst performing strategy was buying the top mutual fund ranked by raw returns, which produced a cumulative total return of 793.3%, with an average yearly return of 13.3%. If one invested in the top quartile of funds based on their DTR-α instead of the single best fund, the cumulative return was 943.9%, with an average annual return of 17.8%, which was still superior to that of the naive strategy.

Conclusion

In this study, mutual funds were ranked on the basis of 3-year risk and style-adjusted returns using DTR-α. The DTR-α rankings are not correlated with the Sharpe ratio or the Sortino ratio rankings. Also, the consistency of ranking produced by the DTR-α returns is far more stable than those obtained using the Sharpe ratio or the Sortino ratio. Managers who were ranked in the first quartile tended to stay in the first quartile and very seldom dropped to the third or fourth quartile. Just as important, managers who were in the bottom quartile very seldom ever rose to the first or second quartile. This is shown graphically in Figure 3.8. This study suggests that the DTR-α returns may provide unique information about funds that would be valuable to investors.



Source: *Pensions & Investments*, November 10, 1997

Figure 3.8 The predictive power of DTR-α.

Table 3.10 Excess omega return investment strategy vs. index (all funds)

	Year														
	96	**95**	**94**	**93**	**92**	**91**	**90**	**89**	**88**	**87**	**86**	**85**	**84**	**83**	**82**
	1-year returns for the top quartile (ranked by excess omega) funds from previous year														
	22.10%	33.50%	−1.30%	21.40%	15.80%	55.10%	3.90%	34.50%	22.80%	0.80%	23.50%	43.10%	2.10%	38.60%	48.30%
	21.90%	36.20%	0.20%	25.30%	6.80%	41.10%	−4.30%	30.20%	18.50%	15.30%	19.10%	32.40%	10.20%	28.40%	42.60%
	21.10%	36.10%	1.70%	14.40%	5.30%	43.10%	−0.70%	31.70%	8.10%	11.20%	18.70%	30.40%	−7.90%	30.10%	42.20%
	20.20%	21.30%	0.60%	24.70%	−1.70%	46.30%	1.00%	29.70%	13.70%	4.50%	22.00%	37.00%	−5.60%	21.40%	34.60%
	20.20%	35.50%	0.30%	13.90%	6.70%	35.80%	−4.20%	26.70%	2.70%	3.60%	20.70%	33.90%	−6.30%	11.30%	26.70%
	11.50%	32.10%	−1.70%	16.70%	0.90%	26.40%	5.20%	27.00%	7.20%	−2.00%	16.70%	31.90%	0.00%	26.20%	29.70%
	0.90%	30.80%	−3.00%	1.60%	−4.20%	34.10%	−3.20%	28.50%	1.40%	0.00%	21.90%	35.10%	−7.40%	20.10%	9.20%
Average	16.84%	32.21%	−0.46%	16.86%	4.23%	40.27%	−0.33%	29.76%	10.63%	4.77%	20.37%	34.83%	−2.13%	25.16%	33.33%
Cumulative	943.89%	793.41%	575.73%	578.83%	480.91%	457.34%	297.33%	298.64%	207.22%	177.70%	165.06%	120.20%	63.32%	66.87%	33.33%

Average 1-year returns for all funds (index)

Average	17.66%	31.15%	−1.38%	14.14%	7.50%	38.72%	−2.28%	29.35%	13.25%	5.67%	16.55%	29.86%	0.71%	24.01%	30.81%
Cumulative	868.82%	723.41%	527.84%	536.62%	457.76%	418.84%	274.02%	282.75%	195.90%	161.28%	147.26%	112.15%	63.37%	62.22%	30.81%

Averages

Top quartile	16.84%	32.21%	−0.46%	16.86%	4.23%	40.27%	−0.33%	29.76%	10.63%	4.77%	20.37%	34.83%	−2.13%	25.16%	33.33%
Index	17.66%	31.15%	−1.38%	14.14%	7.50%	38.72%	−2.28%	29.35%	13.25%	5.67%	16.55%	29.86%	0.71%	24.01%	30.81%

Difference

	−0.82%	1.06%	0.92%	2.72%	−3.27%	1.55%	1.95%	0.41%	−2.62%	−0.90%	3.82%	4.97%	−2.84%	1.15%	2.52%

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Chapter 4

Optimization and Portfolio Selection

Hal Forsey

Executive Summary

In Part 1, Hal Forsey presents a new Forsey–Sortino optimizer that generates a mean–downside risk efficient frontier. Part 2 develops a secondary optimizer that finds the best combination of active managers (to add value) and passive indexes (to lower costs). For the latest research in this area, we recommend the book *Optimizing Optimization*, by Stephen Satchell at Cambridge University (Elsevier, 2009).

Introduction

It is important for the reader to understand the assumptions that apply to all optimizers before I discuss the development of Sortino Investment Advisors' portfolio selection routines. Utility theory[1] provides a backdrop for discussing the limitations of mathematics with respect to finding an optimal solution to portfolio selection. The underlying assumption of most people who use optimizers is that the probability distribution is known. Well, in portfolio management it is not known. It can only be estimated, which means that the portfolios on the so-called efficient frontier may or may not be reasonable (see Endnotes). Early assumptions were that distributions were bell shaped (i.e., followed a standard normal distribution). Common sense says otherwise. Because one cannot lose an infinite amount of money, even if you are a hedge fund, the distribution must be truncated on the downside and it must be positively skewed in the long run. Only to the extent that the estimate of the joint distribution of returns of a portfolio is reasonable should one put any faith in the veracity of an efficient frontier. We have expended considerable effort to obtain reasonable estimates of the joint distributions of portfolios, which leads us to the following conclusions:

- Optimal solutions to a mathematical problem are often on the boundary of possible solutions. This causes problems in applying mathematics to a real-world situation, as the mathematical model used to describe the situation is often only an approximation. The mathematical solutions to the model will often be extreme, and because the model is only approximate the solution to the model may be far from optimal. Think of the case in which the returns of the possible investments are thought to be known with certainty. The optimal solution might be a portfolio of 100% in alternative investments such as oil futures. People who behave as if they know, or their model knows, with certainty what is going to happen are unknowingly taking a dangerous amount of risk.
- Even when it is only assumed that the joint probability of returns is known, limiting solutions to some efficient frontier will give extreme portfolios that may be far from optimal if the probability model does not fit reality. For example, many probability models have thin tails that may lead to underestimating probabilities of large losses. This may, for example, lead to portfolios with too much weight in equities.
- To the extent we can accurately describe the joint distribution of returns we should get reasonably reliable estimates of efficient portfolios. If that statement is true, the pioneering work of the innovators discussed in Chapter 1 should prove beneficial. However, if the input to the optimizer is seriously flawed, so will be the output (GIGO).

Part 1. The Forsey–Sortino Optimizer

This is a model we built recently at the Pension Research Institute. It has never been marketed because we have no interest in becoming a software provider, but we don't want to keep our research efforts a secret. Therefore, we will provide an executable version and the source code for the Forsey–Sortino optimizer on the Elsevier website. Information on how to access the website can be found in the Prologue. Be advised, we have no intention of supporting the software in any way.

Our intention is to provide a starting point from which other researchers around the world can make improvements and in that way make a contribution to the state of the art.

Basic Assumptions

We begin with the assumption that the user wants to maximize the geometric average rate of return in a multi-period framework. Therefore, the three-parameter log-normal distribution suggested by Atchison and Brown[2] should provide a better estimate of the shape of the joint distribution than assuming a bell shape (standard normal distribution). We recognize that this shape should change when the market is undervalued in that it should be more positively skewed than normal and that it should be more negatively skewed when the market is overvalued.

However, when the market has been undervalued in the past, the subsequent result is seldom if ever the same. This is where we call on Bradley Efron's bootstrap procedure[3] to generate a distribution of returns that could have happened from all those periods in the past when the market was undervalued. The same is done for all those periods in the past when the market was overvalued. This saves us from saying such foolish things as "The future is going to be like 1932 or 1990, etc." What we are assuming is that the distribution of returns will be more closely approximated by bootstrapping all of the monthly returns from all past periods when the market proved to be undervalued (see Chapter 3 for more details).

Next (see Figure 4.1) we allow the user to identify which part of the world he is operating from. That will determine which currency the indexes will be denominated in and which indexes to use. We then allow the user to select one of seven scenarios drawn from three buckets of returns. The first bucket contains returns from all those times when the market was undervalued. The second contains returns from all fairly valued periods, and the third contains returns from all overvalued periods. The assumption is that all overvalued periods are different, but bootstrapping returns from all overvalued periods would be a better predictor of the next overvalued period. Different percentages of returns are drawn from the three buckets to create scenarios that provide different degrees of confidence of where the user is at this time in the market. If the user does not wish to make such a decision, the choice should be "unknown," in which case the returns from all three buckets are used.

Let us assume the choice is the United States and the user chooses "unknown" for the scenario. A distribution for each index is then presented. Figure 4.2 displays the distribution for the MSCI Japan index with a mean of 15.6%. The user now has the option to change the location point of the distribution by shifting the mean to the left or to the right. In Figure 4.3, the mean has been shifted to 6.1% and the distribution has become more positively skewed.

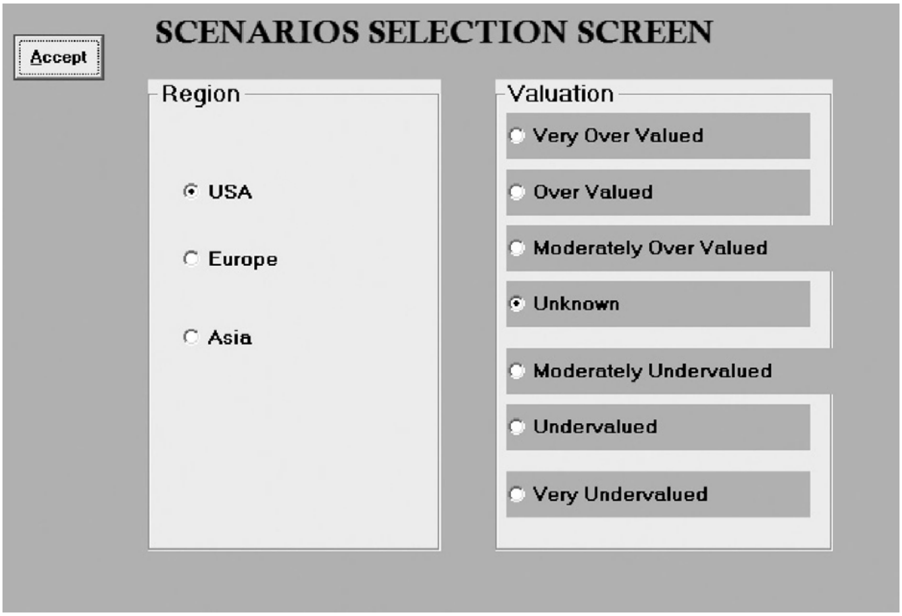

Figure 4.1 Scenario selection and manipulation.

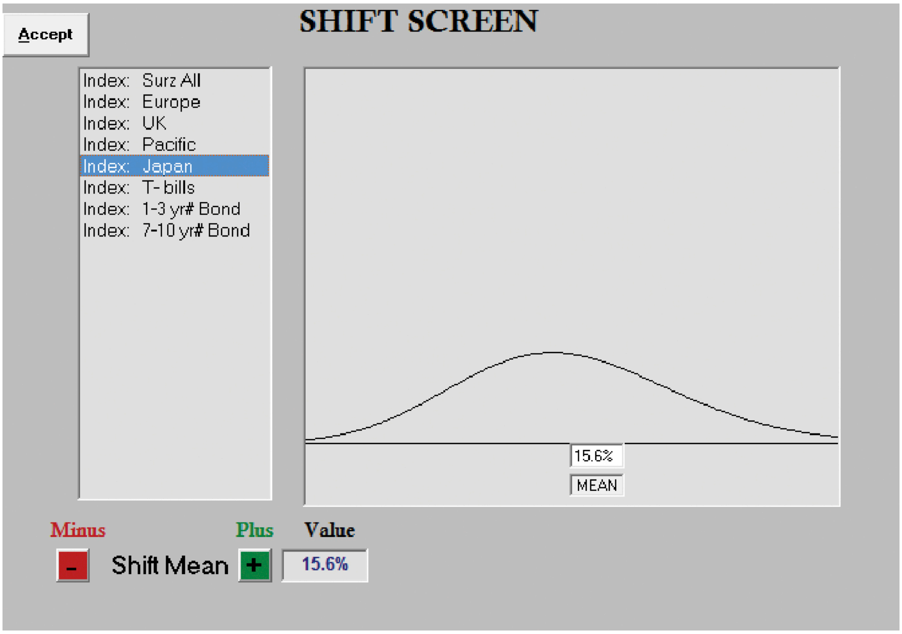

Figure 4.2 Shift screen (before).

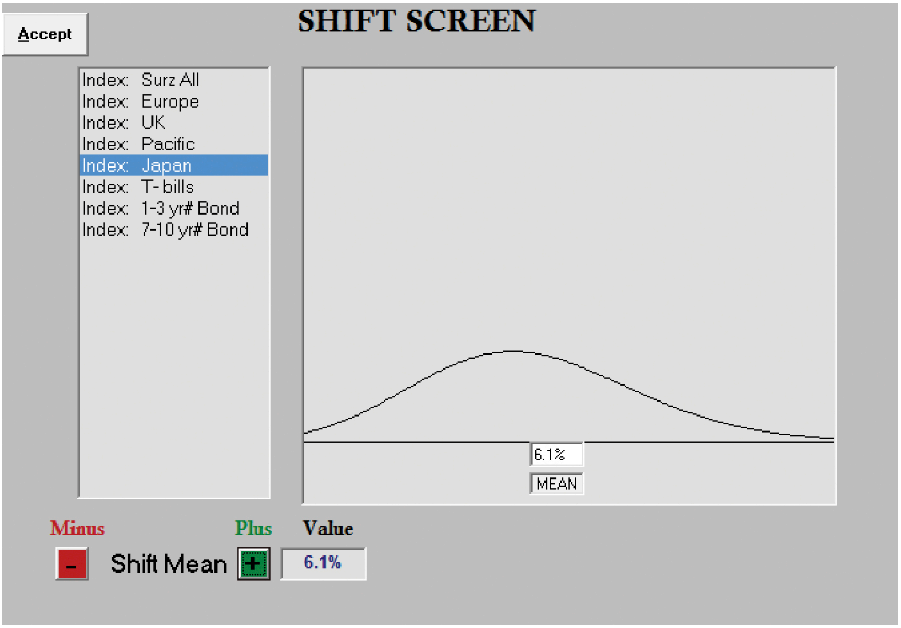

Figure 4.3 Shift screen (after).

Optimize or Measure Performance

The model now allows the user to use the optimizer in a mean–variance mode or a mean–downside risk mode, or to view performance measurement in several modes. We allow the user to run the optimizer in a mean–variance mode as well as a mean–downside risk mode because we wanted to be able to compare our mean–variance result with the output from a standard mean–variance optimizer. If we did not get very similar results, it would call into question our methodology for generating joint distributions.

Figure 4.4 shows the screen for the asset allocation choice for a defined contribution plan and an 8% DTR™* portfolio (M = moderate). The figure shows the efficient frontier in upside potential to downside risk space. The letter M is approximately where the moderate portfolio is located. The user can scroll to that approximate location and see the results to the right of the efficient frontier. The asset allocation is shown in the lower statistics table titled "Portfolio Style." 42% is allocated to the nine U.S. equity styles identified by Ron Surz in Chapter 2. Nothing is allocated to Japan because we shifted the mean down from 15.6% to 6.1%

* DTR and Desired Target Return are trademarks of Sortino Investment Advisors.

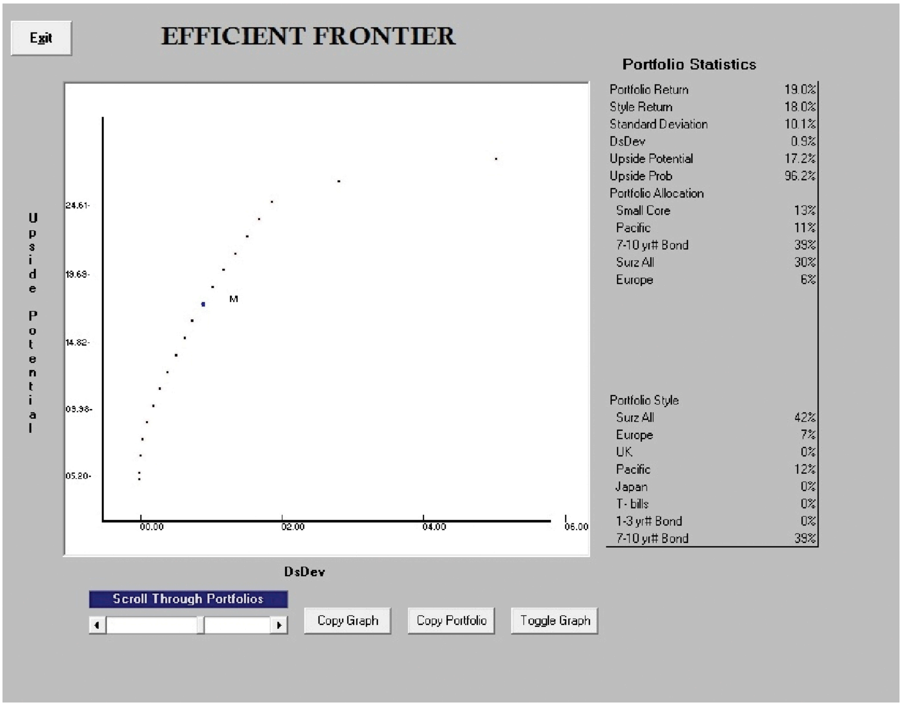

Figure 4.4 Efficient frontier for the upside potential ratio.

without making any adjustments to the other indexes. This would not prevent a mean–variance optimizer from assigning some weight to Japan if it was less than perfectly positively correlated with the other indexes.

Figure 4.5 shows two of several possible performance descriptions. The model is now operating in performance measurement mode and shows a ranking of managers as opposed to asset allocation. Notice the pattern of the risk–return framework. On the left, risk is measured as standard deviation (SAR). On the right, it is style-adjusted downside (SAD) risk. In each case it is adjusted for a term we call the style beta (see Appendix).

Part 2. The DTR Optimizer

No matter what kind of optimizer one uses to generate an efficient frontier of passive indexes, it is important to know if there may be some combination of active managers and passive indexes that would lie above the efficient frontier, as shown in Figure 4.6, which depicts a hypothetical representation of what this efficient frontier would look like. The numbers 4, 8, and 12 represent points on the efficient

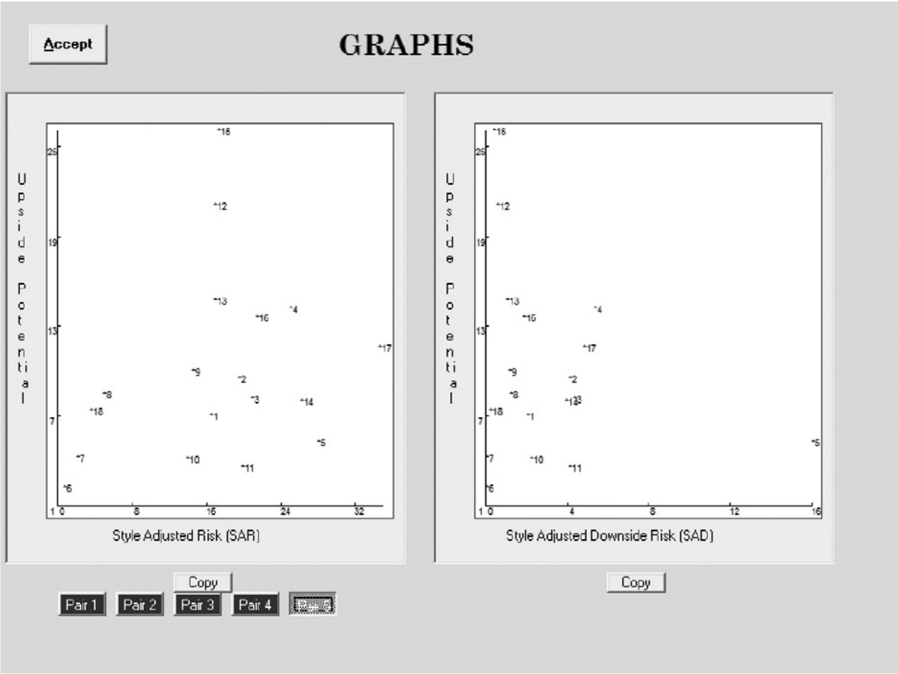

Figure 4.5 Two views of performance measurement.

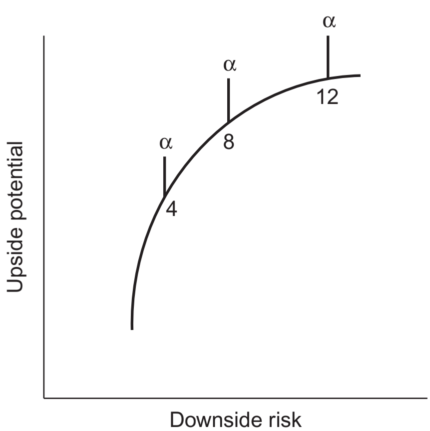

Figure 4.6 DTR-α efficient frontier representation.

frontier for portfolios of passive indexes that have the highest upside potential ratio for a given level of downside risk. The points correspond to DTRs of 4%, 8%, and 12%.

To accomplish this, we begin with a quadratic optimizer similar to the one described in Bill Sharpe's article cited in Chapter 2. Using the Surz indexes, we can quickly identify the style blend of thousands of managers. For illustrative purposes, a partial list is shown in Figure 4.7. Three years of monthly returns were used. Mellon Capital is a fund that attempts to track the S&P 500, while HW claims to be a large value manager.

The S&P 500 is often used as a surrogate for the market; for details on the error of this assumption, see Chapter 2. All a manager would have to do is change the weights to claim an enhanced index. In this case, large cap is overweighted. If an S&P 500 index is employed, it should be evaluated as an active manager competing with the passive indexes that more accurately reflect the complete market of over 6000 stocks. HW loads almost entirely on the midcap value index yet only has an R^2 of .82. In other words, 18% of the difference in the variance in returns between the midcap index plus 1% large value index is not being explained. Something is missing. We asked a friend to run the data on a standard style analyzer, and it came up with 54% large-cap value. The reason? He unknowingly was using quarterly data. There were only 12 observations for 9 variables. That is totally unreliable. When he used 5 years of quarterly data, his answer was more similar to ours. The point we wish to make is that all quantitative models that attempt to do style analysis are not the same, and even those who are the same are influenced by the periodicity of the data.

Following the style analysis, the DTR optimizer solves for that combination of active and passive managers that fulfills the desired asset allocation shown at the bottom of Figure 4.8 and provides the highest overall added value as measured by DTR-α. Portfolio 3 shown in Figure 4.8 is for the DTR 8 portfolio. 78% of the portfolio is in U.S. securities, and 48% of the portfolio is in U.S. equity. That leaves 30% in U.S. fixed income ($30 + 48 = 78$). The mean of this joint distribution is 8.5%, which is approximately equal to the DTR of 8%. If one were making decisions based on probabilities, there is about the same chance of returns being higher than the mean as there is of being lower. However, this portfolio has the potential for returning 12.7% in any given year, and the downside risk of achieving that is only 7.3%. Dividing the upside potential by the downside risk (see arrows in Figure 4.8) yields an upside potential ratio of 1.74, indicating 74% more upside potential than downside risk. Expected utility theory, explained in Endnote 1, would claim that risk-averse investors should make decisions based on the upside potential ratio instead of mere probabilities. We further claim that the proper focus is the DTR and not the mean. What is actually taking place is a shift in the joint distribution of the portfolio. Figure 4.9 depicts a shift of 500 basis points from left to right for a DTR-α of 5%.

Figure 4.10 shows the final output of the SIA optimizer. At the bottom is the asset allocation that was stipulated as input to the optimizer. At the top is the

Name	R^2	**U-P ratio**	**DTR^{TM}**α	LrgVal	LrgCor	LrgGro	MidVal	MidCor	MidGro	MinVal	MinCor	MinGro
LrgValu	1	1.25	0%	100%	0%	0%	0%	0%	0%	0%	0%	0%
LrgCore	1	0.84	0%	0%	100%	0%	0%	0%	0%	0%	0%	0%
LrgGrow	1	0.61	0%	0%	0%	100%	0%	0%	0%	0%	0%	0%
MidValu	1	**1.53**	**0%**	0%	0%	0%	100%	0%	0%	0%	0%	0%
MidCore	1	1.1	0%	0%	0%	0%	0%	100%	0%	0%	0%	0%
MidGrow	1	0.66	0%	0%	0%	0%	0%	0%	100%	0%	0%	0%
MinValu	1	1.91	0%	0%	0%	0%	0%	0%	0%	100%	0%	0%
MinCore	1	0.75	0%	0%	0%	0%	0%	0%	0%	0%	100%	0%
MinGrow	1	0.34	0%	0%	0%	0%	0%	0%	0%	0%	0%	100%
Mellon Capital	0.99	1.03	**-1%**	**43%**	**19%**	**19%**	**11%**	**8%**	0%	0%	0%	0%
HW large value	**0.82**	**1.53**	**-8%**	1%	0%	0%	**99%**	0%	0%	0%	0%	0%

Figure 4.7 Style analyzer.

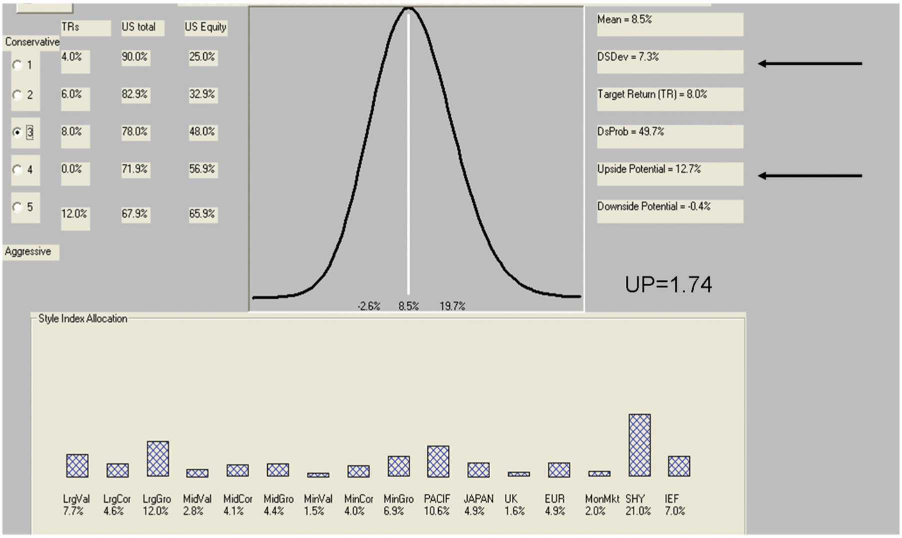

Figure 4.8 SIA optimizer.

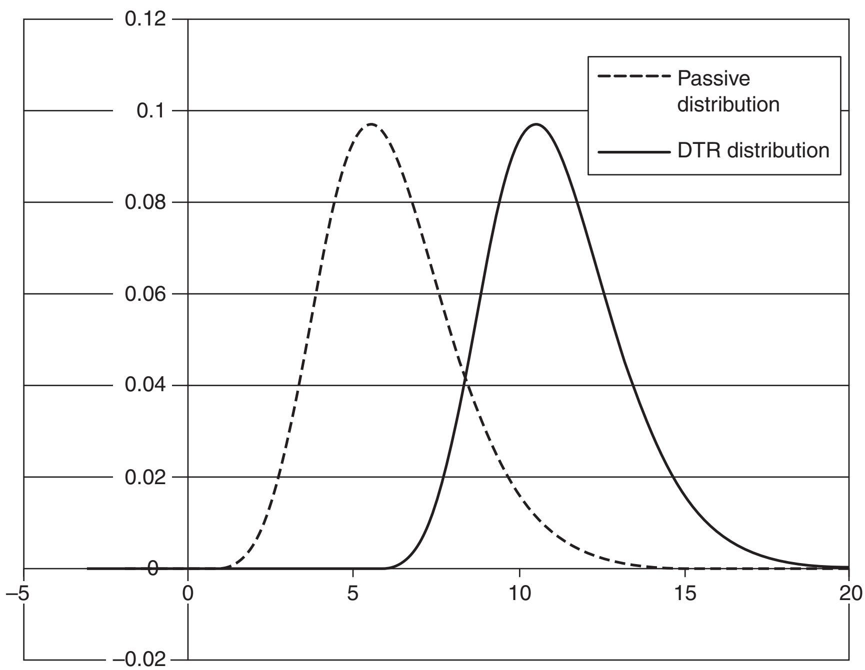

Figure 4.9 DTR-α added value representation.

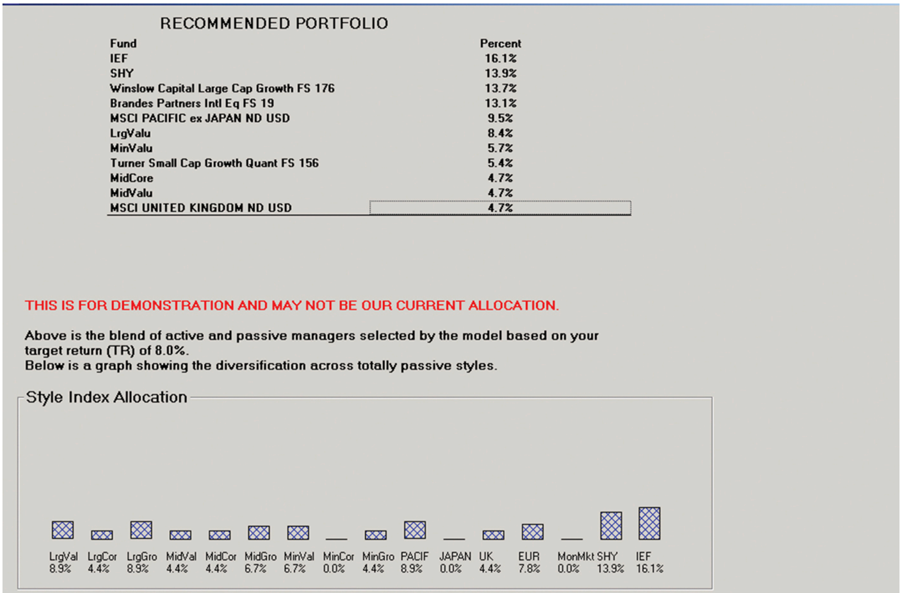

Figure 4.10 DTR-α solution.

combination of active managers and passive indexes that fulfills the asset allocation and adds value in terms of DTR-α while reducing costs by using indexes. To reiterate, the first requirement is to ensure that the asset allocation that was specified in the beginning is the asset allocation that one ends up with. This is the most important decision made in that it accounts for 80% or more of the future return of the portfolio. The second consideration is to hire those managers who can add the greatest value to the portfolio. This must take into consideration each manager's style blend in order to not corrupt the desired asset allocation (see Figure 4.7). Third, use passive indexes to fill out the asset allocation in areas where the active managers do not add value.

For a manager to come into a solution, the R^2 must be .70 or greater, the upside potential ratio must be among the highest, and the DTR-α must be in the top 3. For Portfolio 3, active managers added value to the portfolio and passive indexes were used to fulfill the asset allocation. This is a quantitative way of reducing costs while adding value as measured by a manager's ability to beat his style blend.

This represents the culmination of a quarter century of research. Just as medicine has sought to improve the equipment and techniques surgeons use to operate on bodies, we have sought ways to improve the tools and techniques investment professionals use to operate on portfolios. As pointed out in Chapter 1, the best surgeons and the most modern facilities cannot guarantee success in every operation. We both operate in a world of uncertainty.

Endnotes

1. *Utility Theory*: (a) If the outcome from a choice of action is known with certainty, then the optimal choice of action is the one with the outcome of greatest utility. (b) If the probability distribution of the outcomes from a choice of action is known, then the optimal choice of action is the one with the greatest expected utility of its outcomes. (c) If the probability distribution of the outcomes from a choice of action is only approximate, then the action with the greatest expected utility may or may not be a reasonable choice of action. *Utility Theory applied to choosing an optimal portfolio:* (a) If the return from each possible investment is known with certainty, then the optimal investment portfolio is a 100% allocation to the investment with the greatest return; this only assumes that the utility function is an increasing function of return. (b) If the joint probability of returns for the set of possible investments is known and if the utility function for portfolios with a given variance increases as the expected return increases, then the optimal portfolio is on the mean–variance efficient frontier. (c) If the joint probability of returns is only approximate, then portfolios on the efficient frontier may or may not be reasonable choices.
2. Atchison, J., & Brown, J. A. C. (1957). *The lognormal distribution*. Cambridge, U.K.: Cambridge University Press.
3. Efron, B., & Tibshirani, R. (1993). *An introduction to the bootstrap*. London: Chapman & Hall.

Applications

Chapter 5

Birth of the DTR 401(k) Plan

W. David Hand

Background

Over 30 years ago, the retirement plans of Americans were funded, administered, and managed entirely by American companies. The core plan was a defined benefit (DB) plan well designed to give the participant at retirement age a monthly pension for life. Many pension plans also granted cost-of-living increases to retiree pensions annually to keep up with inflation. Defined benefit core elements include:

1. The plan provides a monthly pension for life based on final salary.
2. The company funds this plan entirely.
3. The company bears all investment risk.
4. The plan benefits are insured by the assets in the plan.

Americans during the 1970s experienced a serious recession. Firms were laying off workers and some went bankrupt, leaving their employees (including some who had worked 40 years on the line) without any pension. It was a "perfect storm" that I remember enduring as a young man. Labor costs and all of the associated benefits, such as the cost of the pension plan (in most cases, 7 to

11% of total payroll), were too high; American labor costs were becoming non-competitive in a world market.

The solution proposed was the Pension Benefit Guarantee Corporation (PBGC). It would become the governmental agency that would *fully insure* all American company retirement plans in case a company failed. It was a political debate, with pension actuaries on one side and politics on the other. My father was president of the American Society of Pension Actuaries (ASPPA), today a large group of pension consultants and actuaries totaling over 5000 nationwide. ASPPA members saw clearly that the potential cost and liability were overwhelming. ASPPA believed each company should pay based on their unfunded pension liability; plans well funded would pay less and underfunded plans would pay more. A certain senator pushed for a $1 premium per year per participant—no calculations required! It was a fierce debate; my father and most actuaries argued that the senator's approach was overly simplistic and actuarially unsound. The battle was lost; politics and simplicity won over mathematics, and the premium was set at a flat dollar. For nearly two decades, PBGC attempted to fund the failed pension plans with a simple flat dollar computation, but today PBGC premiums can exceed $200 per person for underfunded plans. The PBGC reported $10.7 billion in unfunded liabilities in the third quarter of 2008; however, the bankruptcy of General Motors could "dump as much as $13.5 billion in unfunded pension liabilities onto the PBGC."[1]

Thirty-five years later, this mistake is again repeating itself with the 401(k) plan, except this time it will be the 401(k) participant, not the company or PBGC, paying the price. Fast forward to 2006, when I found myself preparing testimony for ASPPA to present a plan to Congress to put pension plans on a sound actuarial basis, only this time it is not only defined benefit plans but 401(k) plans that are the topic of fierce debate. 401(k) core elements include:

1. They are almost entirely funded by the employee.
2. The employee, not the company, bears all of the investment risk.
3. The employee has no insurance and can outlive the 401(k) balance.

The solutions put forward in the Pension Protection Act of 2006 and recent proposed legislation include automatic enrollment, catch-up pensions at age 50, default investment (for those employees who do not elect an investment), and full disclosure with improved 401(k) participant statements. These are all bandages for the real problem. Conventional pension plans promised 50 to 60% of pay at retirement, but neither companies nor the PBGC can now afford to honor that promise. Yet, companies currently put less than 3% of pay into 401(k) plans. *The basic problem is that too many employees are waiting too long to start investing, are investing without proper knowledge, and are putting too little aside each month to fund a decent level of retirement income.*

According to a Department of Labor report on retirement adequacy, U.S. workers retiring in the 2050s will have saved only enough in their 401(k) accounts to replace an average of 22% of their preretirement income, and 37% will have no savings at all. This historic one–two punch of poor investment judgment and lack of funding has called into question the efficacy of 401(k) plans. There has even been talk of replacing 401(k) plans with a government guarantee plan similar to Social Security. Jonathan Barry Forman[2] recommends that workers be required to contribute a mere 2% of earnings initially to receive a guaranteed 47% of retirement salary. He admits the contribution would have to increase over time, and to pay for this the government would no longer allow a tax deduction for 401(k) contributions.

We will argue that changes already enacted by Congress in 2006 under the Qualified Default Investment Alternative (QDIA) and automatic enrollment provisions of the Pension Protection Act offer a better solution. The best solution from the participant's point of view is the DB plan; however, most plan sponsors have fled DB plans mainly because they have been legislated out of business. We believe *the best solution now is a 401(k) plan that looks like a defined benefit plan at the participant level.* The QDIA option can accomplish this. The QDIA provisions set new fiduciary standards that allow plan sponsors to default participants into certain types of investment options under the safe harbor protection provided by Section 404(c). Companies may automatically enroll employees in the employer 401(k) plans, starting with a minimum of 3% of gross income and increasing to 6% after 3 years. The Department of Labor estimates that the QDIA could result in $134 billion in additional retirement savings by 2034.[3] This would only partially address the funding problem. Each participant needs to be informed every year what it is going to take to fully fund his or her retirement needs, just like a DB plan.

QDIA Options

There are three types of long-term QDIAs:

1. Target-maturity funds, sometimes called target-date funds or life cycle funds
2. Risk-based or lifestyle funds (including balanced funds)
3. Managed accounts

The preamble to the regulation states, "The Department believes that each of these qualified default investment alternatives is appropriate for participants and beneficiaries who fail to provide investment direction; accordingly, the rule does not require a plan fiduciary to undertake an evaluation as to which of the qualified default investment alternatives is the most prudent for a participant of the plan,"[4] but neither does it preclude an evaluation. Indeed, the regulation goes on to say that once a type is chosen the fiduciary must engage in a prudent process to select and monitor the QDIA. Why, then, wouldn't it be prudent to engage a consultant to evaluate the different types of QDIAs before making a selection? We will attempt to shed some light on this question.

The Government Accountability Office (GAO) report on retirement adequacy, released on December 11, 2007, noted that many economists and financial advisors only consider retirement income adequate if it replaces 65 to 85% of preretirement income. Proposed legislation such as the Harken and Kohl bill would provide a clear path to achieving that objective by requiring the plan administrator to provide a quarterly notice of "the estimated amount that the participant needs to save each month to retire at 65."[5] The Aon Consulting/Georgia State University's *income replacement ratio* is an example of the growing recognition that this is the proper investment objective for 401(k) participants.

PIMCO executives have called for plan sponsors to look beyond the asset-only-based approach of modern portfolio theory and move toward a needs-based optimization to maximize the probability of an income replacement ratio.[6] This agrees with the GAO reference above that retirement with dignity is related to replacing some percentage of preretirement income. In 1995, Andrew Rudd, cofounder of Barra, the leading proponent of capital asset pricing model (CAPM) applications, founded Advisor Software (www.advisorsoftware.com) to offer a new, goals-based software program that considers both assets and liabilities. Dr. Rudd said, "What clients really want is to know that they are able to meet a range of financial goals given their current and future assets and liabilities." He went on to say that risk budgets should be "determined by the potential impact of a shortfall on goals."[7] Sortino Investment Advisors (SIA) takes a similar approach but measures risk and reward relative to a Desired Target Return (DTR)[*] that is similar to the actuarial return for a DB plan. It is the return needed to fund a DB or 401(k) plan and provides a valuable link between the assets in a plan and the cash outflows or liabilities of the plan. All of the above discuss goals and objectives within an asset and liability framework; therefore, we make the claim that *retirement income replacement should be the main criterion for evaluation of the effectiveness of 401(k) programs.*

Goals and Objectives

Much has been written about goals, objectives, and investment policy, and there is very little agreement on what these terms mean. What some call goals, others call

[*] DTR and Desired Target Return are trademarks of Sortino Investment Advisors.

objectives, and there are some who use them interchangeably.[8] The Pension Research Institute (PRI) offers the following definitions:[9]

- The goal is the end toward which effort is directed. It is the broadest generalization of what one is trying to accomplish.
- The investment objectives translate the goal into more specific language leading to goal-oriented measures of reward and risk. The investment objective must support the goal so that if the objective is achieved the goal will be accomplished.

Given the above commentary, we believe the goal for a 401(k) participant should be to replace 65% or more of their preretirement income as recommended by the GAO. We will assume that the goal is *to replace 75% of preretirement income*. The investment objective is to maximize the potential to exceed the DTR needed to achieve the goal relative to the risk of falling below the DTR. The model that SIA uses to make this calculation is shown Figure 5.1 and explained more fully by Dr. Forsey in Chapter 4.

Figure 5.1 shows the joint distribution where the DTR = 8%. The portfolio has a mean of 8.5% and the potential to achieve 12.7%. The downside risk is 7.2%, so the upside potential ratio (upside potential/downside risk) is 1.74%. Unlike immunization strategies that try to minimize the risk of falling below 8%, the SIA model maximizes the potential to exceed 8% relative to the risk of falling below 8%.

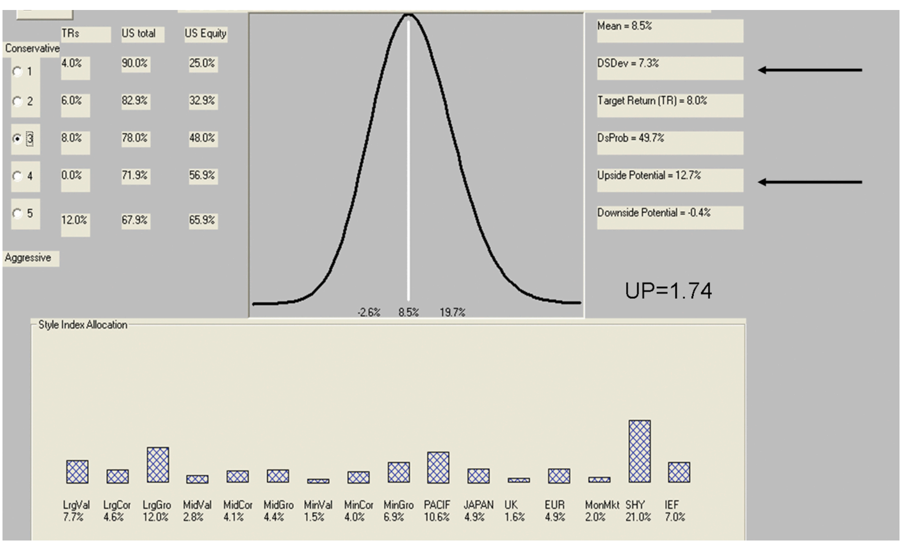

Figure 5.1 SIA optimizer output.

Immunization strategies ignore the upside potential. Immunization requires that you correctly forecast the way the yield curve is going to shift, and that is even more difficult than forecasting the level of interest rates. The result is that they seldom are able to achieve the absolute return they promise. Based on the SIA model, Hand Benefits & Trust (HB&T) has created collective investment funds (CIFs) for 4%, 6%, 8%, 10%, and 12%. *The investment objective is to maximize the upside potential ratio.*

Potential Conflicts

The goal for an individual 401(k) participant is not the same goal that portfolio theory would claim is proper for investors as a whole under certain restrictive conditions. It also may not be the same goal a money manager has; therefore, it is important to recognize potential conflicts of interests.

Portfolio theory describes how investors who make their decisions based solely on expected return (the mean or average return) and volatility (standard deviation) should make rational choices. Each investor chooses a portfolio from the efficient frontier[10] based on his or her tolerance for risk. Textbooks in finance do not discuss goals. Instead, they assume everyone has the same investment objective: to maximize expected return for an acceptable level of risk (risk is measured as volatility around the mean). The capital asset pricing model (CAPM) proposed by William Sharpe extends the theory of Harry Markowitz to say that, if there exists a risk-free asset, then everyone should want some combination of the risk-free asset and the market portfolio. Risk becomes the risk of being in the market and is called beta. In equilibrium, one should not be able to beat the market. Importantly, *neither the Markowitz nor the Sharpe model recognizes cash outflows in the future as a liability that must be dealt with. They are asset management models, not asset/liability models.*

QDIA Evaluation

The Department of Labor (DOL), by not allowing short-term, fixed-income funds to be used as a long-term QDIA, implicitly recognized that money market and stable value funds are not risk-free investments—this in spite of the fact that they are currently the most popular default option in 401(k) plans. This action on the part of the DOL also implicitly recognizes that the goal is not preservation of capital but retirement with sufficient income, because *investing everything in a money market fund or stable value fund literally guarantees an insufficient income stream at retirement for most participants.*[11]

Let us now examine each QDIA option and see how well they meet the basic criterion of future income replacement:

- *Target-date funds*—The single determinant for selecting the optimal target-date fund is the participant's age. Is that all that is needed to determine the future cash flow? Doesn't the participant need to know how much to contribute each month? Doesn't the proper contribution schedule depend on the participant's salary and how much money is currently invested? Target-date funds are a simplistic way of getting participants to invest for their future without regard to adequacy. *In short, target-date funds ignore anything to do with the replacement of preretirement income.*
- *Lifestyle funds*—Ask participants how much risk they want to take and they will probably say "as little as possible." This is why so many participants default into fixed-income or stable value funds. They don't realize that preservation of capital is not the goal. To have some chance at retiring with dignity they will have to take some loss of principle risk in order to reduce the true risk of failure to achieve the goal. How much risk they need to take depends on their financial profile, not their risk profile. *The same argument about target-date funds ignoring future cash flows applies to lifestyle funds.*
- *Managed accounts*—Many managed account services provide some type of financial planning tool that attempts to project future cash inflows to the 401(k) plan and subsequent cash outflows at retirement. This provides the opportunity to estimate short falls and or the DTR needed to provide the forecasted benefits. On that basis alone, *the managed account option holds the greatest promise of achieving a participant's goal.* It then behooves the plan sponsor to find that managed account service that best fulfills this goal of income replacement.

Given the above background, we will proceed with a proposal for constructing a DB-like plan for an individual participant under the managed account QDIA option. A quick reference to achieving the merits of a DB-like 401(k) plan is provided in Table 5.1.

Constructing a Participant-Driven Defined Benefit Plan

In simplistic terms, the actuary of a DB plan usually assumes a rate of return on assets and solves for a contribution schedule that will meet a future payout schedule to participants. This does not apply well to a single participant who, as the Department of Labor says, "has been waiting too long to start investing and putting too little aside each month to fund a decent level of retirement income." A simple quantitative model is necessary to let each participant know where they are on the

Table 5.1 Conventional 401(k) vs. DTR 401(k) plan

	Conventional 401(k)	**DTR 401(k)**
1. Bases of plan contributions	Participant decision	Actuarial calculation
2. Investments	Participant decision based on risk and return personal preference	Participant advice based on actuarial calculation
3. Type of investments	Retail mutual funds	Low-cost institutional trust (Collective Investment Funds)
4. Reports to participants	Quarterly account balance	Quarterly account balance and annual statement with estimated income at retirement
5. Monitoring of investments	Evaluation of each asset class to index	Professional evaluations of each class and absolute return relative to DTR trust target return
6. Monitoring of contributions	No monitoring for employee contribution	Employees notified and advised to increase contributions if they are not on track to meet retirement goals
7. Retirement goal	No stated goal to participant based on income at retirement	Stated goal is 70% of final years' salary at participant retirement date
8. Asset allocation	Decided by participant based on risk and personal preference or possibly by age of participant	Driven by participant's required return to meet retirement objectives

path toward their goal of adequate retirement income and how to stay on or above that path.

I will now explain the process for a DB-like 401(k) plan. The first step is to extract some basic information that will allow the QDIA provider to estimate the path in terms of information available to every record keeper. Tables 5.2 and 5.3

Table 5.2 Recordkeeper data for SIA

Plan No.	Participant No.	Age	Annual compensation	Annual contribution	Account balance
1	2345	54	$33,000	$430	$13,480
1	2346	26	$23,500	$2270	$9800
1	2348	60	$44,200	$9160	$203,191
1	2353	62	$50,200	$10,000	$303,191
1	2355	51	$35,600	$8350	$222,672
1	2357	62	$37,200	$6380	$246,331

are examples of what we use to coordinate the efforts of the recordkeeper, consultant, and trustee.

The recordkeeper may have dozens of 401(k) plans, which he can send in one file by identifying the plan by number in Column 1. The next five columns are information available to every recordkeeper about every participant. Instead of a name, an account number is used in Column 2. Column 3 is the current age of the participant. This information is sent to SIA. Assuming retirement at age 65, we can estimate the DTR necessary to retire at 75% of projected salary. The DTR has nothing to do with target-date funds. *The target for target-date funds is the participant's age*, which is insufficient for providing a link between assets and liabilities.

The data in Table 5.3 are sent from SIA to the recordkeeper, consultant, and HB&T. Column 3 is the CUSIP number of the CIF (e.g., DTR-12). Column 4 indicates that Participant 2345 should receive Alert 1. This alert would be posted on the participant's page on the recordkeeper's website and would read: "Your estimated DTR is 31%. To be placed in our moderate risk DTR-8 portfolio you would have to increase your annual contribution to $11,590. You have been placed in our DTR-12 portfolio. For more information, visit our website at www.sortinoia.com. Investing in securities entails risk and there can be no guarantee of accomplishing financial goals." The 31% and $11,590 numbers are transferred from the last two columns in Table 5.3 and electronically placed in the Alert 1 posted to the participant's web page by the recordkeeper. Column 5 tells the recordkeeper to place the participant in Portfolio 5 with the investment management company (e.g., the IMC identified by Jim Pupillo in Chapter 7). The IMC executes the trades for all of CIFs and notifies HB&T, who keeps track of the daily pricing of each IMC, pays out all fees to third-party administrators, and maintains performance records. All employee and plan sponsor reports have full fee disclosure and transparency on investments.

Table 5.3 Data from SIA to recordkeeper

Plan No.	Participant No.	CUSIP	Alert No.	Portfolio No.	Alert 1	Alert 2	Alert 3	Alert 4	DTR	To 8% contribution
1	2345	DTR-12	1	5	9	0	0	0	31.5%	$11,590
1	2346	DTR-8	0	3	1	0	0	0	6.9%	$0
1	2348	DTR-8	0	3	7	1	0	0	10.7%	$11,200
1	2353	DTR-6	1	2	5	2	1	0	9.8%	$11,900
1	2360	DTR-4	0	1	0	0	0	0	3.5%	$0
1	2384	DTR-10	0	4	1	1	1	2	8.9%	$6818

This is the typical participant who has not been contributing enough and has been warned each year for the past 9 years to increase contributions (Column 6). But, with this alert, the participant still has 10 years to make up for lost time. If the participant cannot afford to increase contributions enough to lower the DTR to 12% or less, the participant can use the calculator on the SIA website to determine how many years beyond age 65 it will take to have enough funds to expect to receive 70% of his or her salary for an actuarially determined life span and a 6% DTR portfolio thereafter. This could not happen with any other QDIA option. Of course, there are no guarantees. The participant could outlive the actuarial table or the DTR portfolio could fail to produce a return of 6%. But, if a DB plan is taken over by the PBGC, the participant will also not get the retirement income promised under the DB plan.

On the other hand, after only one Alert 1, Participant 2346 was able to increase her contributions enough to be placed in DTR-8 Portfolio 3. Participant 2347 has opted out of the QDIA option, so that number is not shown. Participant 2348 has received Alert 2, which reads: "Because you only have 5 years left before reaching age 65 you have been placed in the DTR-8 portfolio. Your DTR is 10.7%, and you will need to increase your contributions to $11,200 annually to qualify for the DTR-8 portfolio. For more information, visit our website at www.sortinoia.com. Investing in securities entails risk and there can be no guarantee of accomplishing financial goals."

Participant 2353 only has 3 years left to retirement age and therefore receives Alert 3: "Because you only have 3 years left before reaching age 65, you have been placed in the DTR-6 portfolio. Your DTR is 9.8%, and you will need to increase your contributions to $11,900 annually to qualify for the DTR-6 portfolio. For more information visit our website at www.sortinoia.com. Investing in securities entails risk and there can be no guarantee of accomplishing financial goals."

What if Things don't go as Planned?

The following example shows how DTR adjustments would tend to change the asset allocation. Figure 5.2 depicts a 30-year-old woman who had been working for 10 years without setting aside any money for her retirement. She is now beginning to set aside $5000 each year. The calculator input (see box in Figure 5.2) assigns her to the DTR-10 portfolio because participants are assigned to the portfolio closest to their actual DTR. HB&T only offers 4%, 6%, 8%, 10%, and 12% portfolios.

After 10 years, her salary has increased and her contributions are now $7500 annually. Unfortunately, the stock market has declined substantially, so her new DTR portfolio is DTR-12 (Figure 5.3), which is closest to 11.3%. Ten years later, the market has recovered (see Figure 5.4), and she is once again assigned to the

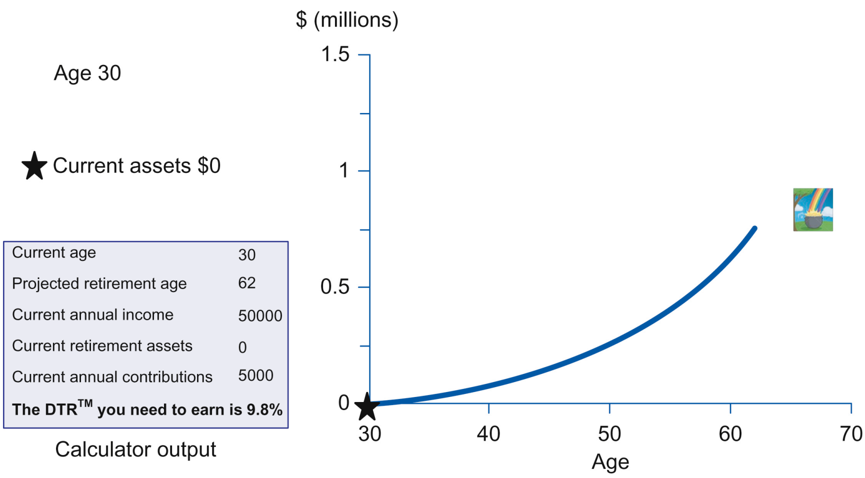

Figure 5.2 On the path (DTR-10 CIF).

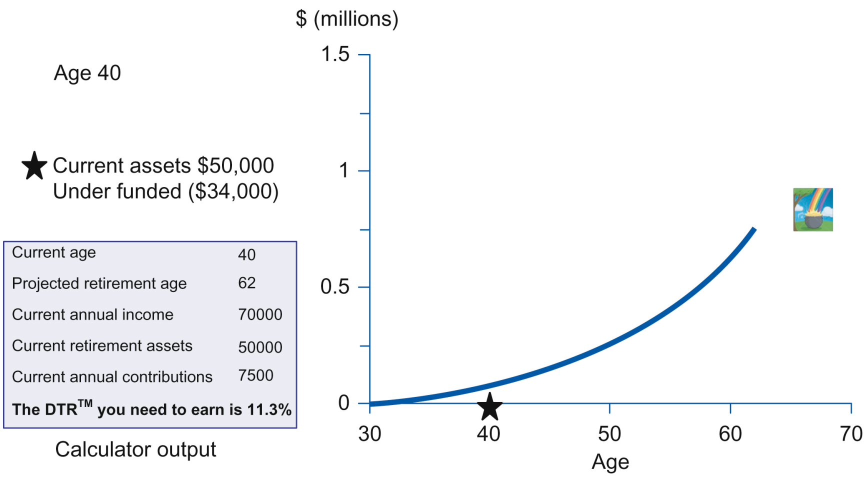

Figure 5.3 Below the path (DTR-12 CIF).

DTR-10 portfolio and is overfunded by $34,000. Finally, at age 60 (Figure 5.5), she is fully funded and the DTR portfolio is reduced to DTR-6.

This demonstrates how focusing on the return necessary to achieve the goal of replacing 75% of preretirement income increases equity exposure when market declines place the portfolio below the DTR and decreases equity when the plan is overfunded. This is the opposite of what many participants have done without professional guidance.

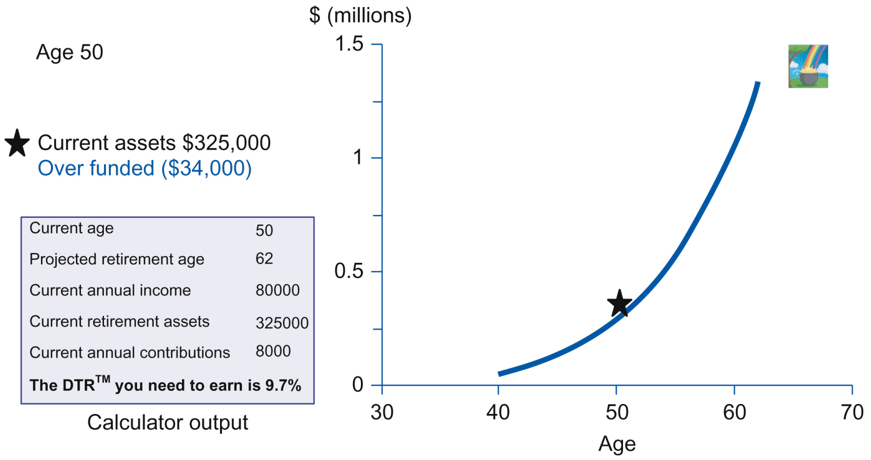

Figure 5.4 Back on the path (DTR-10 CIF).

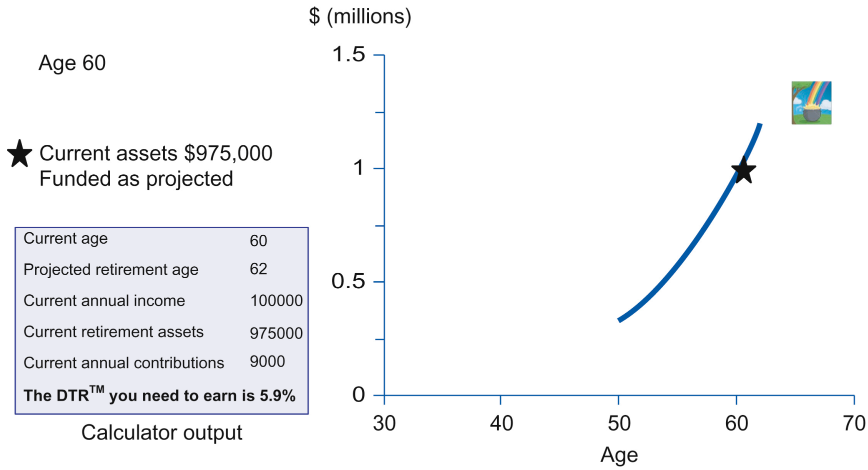

Figure 5.5 On the glide path to retirement.

Recommendations for Regulators

We believe regulators are on the right track in their efforts to improve retirement results for 401(k) participants; however, much of the proposed legislation on plan fees includes significant legislation on plan investments, index funds, benchmarking, and additional required plan administration and employee communications that need to be reviewed carefully. Another area for consideration in future revisions is to provide a new catch-up provision to participants who can show they will be less than 65% funded at age 65. The way the law currently reads, a participant 50 years old would be allowed to make catch-up contributions of $5000 per year. Unfortunately, this is right at the time that the “glide path rule” encourages the QDIA to be reducing equity exposure, resulting in lower and lower returns. Research shows that most participants are not contributing enough, and the younger they are the worse it is. If participants were aware of their current funding status and what it would take to get them back on a fully funded path, a new catch-up provision for them could allow the power of compound interest to work wonders on their behalf.

For example, most baby boomers now in their mid-50s would be defaulted under the QDIA and typical lifestyle fund into a fund earning a lower rate of return of, say, 7%. This would reduce the risk of loss of principle in 10 years but increase the risk of not achieving the desired retirement income (see Figure 5.4). True, a participant who is, say, age 55 could be allowed under the catch-up provisions to make an additional $5000 contribution per year in the 401(k) plan to offset the lower return. However, the combination of lower return, a relatively short time to invest, and only $5000 per year still yields a lower retirement income than desired.

Yet, take that same $50,000 total investment for a participant age 30 and contributions of only $2000 for 25 years with the opportunity to be defaulted into an investment product with higher returns (say, at 11%), and significant retirement income can be obtained. True, the risk of loss of principle is increased in any given year, but the true risk of not achieving a desired retirement income is actually reduced over a 35-year interval.

In the above examples (given the same $50,000 investment in a 401(k) plan), the difference is outstanding. The age 55 baby boomer has only approximately $74,000 at retirement and the age 30 participant has over $700,000, nearly 10 times the dollar amount at retirement and, adjusting for inflation, over 4 times the retirement income.

From a tax policy point of view it is less costly to allow catch-up provisions at early ages at lower amounts. Yet, this would provide the longer term retirement security so greatly needed to ensure the success of 401(k) plans.

Recommendations for Plan Sponsors

Plan sponsors should adopt a policy statement for their 401(k) plan that clearly states the goal and investment objectives in terms of income replacement. They should hire a consultant to evaluate all available QDIA options and provide this information to all participants. Plan sponsors should make participants aware of the different types of risk they must manage.

Recommendations for Consultants

Consultants should develop new performance measurement standards that specifically take into consideration the liability element of future income replacement for participants. They should consider both assets and liabilities when making asset allocation recommendations.

Performance Measurement

Performance measurement of money managers is different than measuring the performance of a 401(k) participant's portfolio. Whether the participant's portfolio beats some index or some other participant's portfolio is irrelevant. The critical question for a participant at any point in time is "Am I on the path, below the path, or above the path to my goal?" An employee who has not been putting in enough money monthly and has 25 years to go should not compare portfolio performance with an employee who has 5 years to retirement and is overfunded.

If beating an index is not the objective, then it is also not the proper benchmark to use for performance measurement of 401(k) plans. *The participant's performance should be related to the funding status of the individual participant's account.* This can be done in the traditional manner of showing the present value of the liabilities vs. the present value of the assets. We think it is helpful to view retirement as a future value problem. The question to be answered is "What rate of return do I need to earn on my contributions into the future in order to accumulate a level of assets that will provide a desired retirement income?" This DTR could be estimated and used in a manner similar to the assumed actuarial return for DB plans. The DTR could then be used as a benchmark as shown in Figures 5.2, 5.3, and 5.4.

Summary and Conclusions

We believe that a 401(k) default option should be constructed for the sole benefit of the participant and for the exclusive purpose of providing retirement benefits. This necessitates an investment strategy affecting future cash inflows in the form of contributions prior to retirement followed by cash outflows sufficient to provide a desired retirement income. The result may be thought of as a personalized defined benefit plan where the participant assumes the role of the plan sponsor. *The single most important criterion for selecting a default option is the potential to replace a designated percentage of the participant's income at retirement.*

Endnotes

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7. Rudd, A. (2005). Keynote address at the World Series of ETFs, March 30–31, Key Biscayne, FL.
8. The Pension Research Institute has published several articles on this subject.
9. These definitions are based on research carried out at the Pension Research Institute and Koontz, H., & O'Donnell, C. (1968). *Principles of management*. New York: McGraw-Hill.
10. The efficient frontier consists of those portfolios with the highest expected return for a given level of standard deviation.
11. The preamble states: "It is the view of the Department that investments made on behalf of defaulted participants ought to and often will be long-term investments and that investment of defaulted participants' contributions and earnings in money market and stable value funds will not over the long-term produce rates of return as favorable as those generated by products, portfolios, and services included as qualified default investment alternatives, thereby decreasing the likelihood that participants invested in capital preservation products will have adequate retirement savings."

Chapter 6

A Reality Check from an Institutional Investor

Neil E. Riddles

Executive Summary

Neil Riddles provides a dissenting view by pointing out the exigencies of the marketplace that prevent him from using the concepts developed in this book. This chapter will stand in contrast to that of the other authors. While I agree with much of what has been written, it is not easily applied to the world of institutional money management. In a perfect world, managers would identify the correct benchmark, the most appropriate and meaningful statistics would be employed, and everyone would operate with a time horizon sufficiently long to assess skill and achieve the clients' goals. Unfortunately, that is not the world we live in. Institutional asset managers must operate within the existing framework, or perish.

Institutional Portfolio Manager's Role is Limited

For institutional money management, the benchmark tends to be set prior to engaging the manager. In a typical situation, the plan sponsor hires a consultant to determine the ultimate asset mix. This is usually accomplished by using a number of indexes as proxies for the asset classes. The returns and correlations of these asset classes are examined in order to determine the combination of assets and weights that provides the best return for an acceptable level of risk. This is the common efficient frontier that most of us learned about in college. The entire exercise is heavily dependent on having properly constructed indexes and returns (see Chapter 2). Once the optimal asset mix has been identified, the consultant or plan sponsor staff identifies investment managers who fit a particular style category in the asset allocation.

This process leaves the plan sponsor with three main sources of risk: (1) that the asset mix is not really optimal and does not deliver their required return, (2) that the indexes do not properly represent the asset class, and (3) that the manager underperforms the assigned benchmark. The institutional investment manager is only concerned with the last of these risks—underperforming the benchmark.

So, institutional investment advisors are not and cannot be responsible for the ultimate funding of the plan; rather, they are hired to manage a small slice of the fund. In this relationship, the only risk for the client and therefore the manager is that the active portfolio underperforms the assigned benchmark, which is almost always a single benchmark.

Multiple Benchmarks

At this point, it is important to note that, while managers are typically selected to run against one published benchmark, they are typically given a second benchmark as well. Usually, a specific ranking in a peer universe is assigned. That effectively gives managers a benchmark that they may underperform as well as a group of "peers" that they also run the risk of underperforming.

I will not go into all of the many important drawbacks to peer universes. To be fair, peer universes have their uses, but suffice it to say that they are not valid benchmarks. Managers and clients cannot assess risks taken vs. the peer universes. From a portfolio structure point of view, peer universes are of little use to a portfolio manager.

It is problematic to assign multiple benchmarks to a manager. Even if both were valid benchmarks, how could you manage against both? It is an extremely difficult task to outperform one benchmark. The task becomes close to impossible when the expectation is more than one benchmark. Yet, all too often managers are held to both an index and a ranking in a peer universe. Having an index as a benchmark means that risk arises from being different from the benchmark. Having a peer universe as a benchmark means that risk arises from being different from the competition. One cannot minimize both these sources of risk. Further, it is not in the plan sponsor's best interest to have a manager concerned with what other managers are doing. After all, most managers are hired because they are expected to be different from their peers.

The benchmark that a manager is held to should be a published index with constituents and weights publicly available. Then, the manager's goal is clear and the risks taken can be easily measured. Departing from that leads to ambiguity, misunderstanding, and the possibility that the manager will not deliver what the plan sponsor wants.

Misfit Risk

As mentioned above, plan sponsors select an index to represent an asset class and then find managers who operate in that asset class. For example, the asset class may be large capitalization U.S. value style equities. A list of managers fitting that style is drawn up, and the manager who appears to best suit the needs of the plan is hired on. The idea is that if all of these managers outperform their benchmarks then the plan will outperform its target asset mix. (*Sortino note:* This totally ignores the DTR™.)

There is, however, a problem with this assumption. The benchmark may not be a complete representation of what that manager is actually doing. This can lead to unintended biases and uncovered portions of the market. The term for this problem is *misfit risk*. For example, an active manager may never research or invest in a part of his asset class—say, utilities. The manager may feel that such stocks rarely have investment candidates that are worth pursuing so no time is spent on that sector. Yet, the benchmark, which is the proxy for the asset class, contains utilities. As a result, there is an unintended active decision to short the utilities sector for both the active manager and, ultimately, the plan sponsor. Risk accepted intentionally with the goal of a commensurate reward is what active management is about. Risk accepted unintentionally with no expected reward is always bad.

A major source of misfit risk is the assumption that all managers within a particular style are doing the same thing. For example, two large capitalization equity growth managers can be doing very different things. One may be looking for absolute projected growth while another may be looking for projected growth coupled with good valuations. These managers may appear to be the same style but will at times yield very different results.

Misfit risk is a real problem for plan sponsors. No two active managers are the same. It can take a lot of analysis on the part of the sponsor to determine what the manager is actually doing and what is the most appropriate benchmark. The disadvantage is that it takes time, money, and analytical know-how to accomplish such a task. The advantage to spending such time is that it prevents unintended biases and creates the greatest likelihood for investment managers to perform well. That is a win–win scenario for the client, the consultant, and the plan sponsor.

Risk Statistics

The financial industry's relationship with statistics is a little counterintuitive. Investing is a numbers industry chock-full of statistics. The amount of data at your fingertips is truly staggering. Yet, the majority of investment experts are not comfortable with statistics. To me, that seems a bit like finding out that people at the weather service are uncomfortable making predictions.

It takes little to qualify as a "quant" in most bottom-up investment shops. Here I am not referring to shops that employ a statistical model to select investments. The professionals at these organizations are often extremely skilled statisticians, and their understanding of statistics is key to the investment process.

I refer here to the more traditional investment processes that analyze individual investments and assemble the best ideas into a portfolio. Shops like these tend to analyze a company's reported financials and look for things the rest of the market has not yet noticed. They are making a call on what the value of the company should be and comparing it to the value the market currently places on the security. This is not a statistician's job but rather an investment analyst's job. It is a difficult task requiring a specialized skill set to wade through financial information in order to make a determination about the future prospects of a company and where its stock should trade. Calculating and interpreting statistics does not typically play a role in that task. Put simply, a thorough understanding of statistics is not seen as a high priority in such a shop because it is not core to the central task of the company.

The primary statistical challenge for most traditional shops is one of communication. When they sit with clients and are asked about the risk of their portfolio, they typically respond with the standard deviation of the return series or, more often, with the tracking error. These statistics are reported because they are the industry standard.

What is wrong with this scenario? The manager is using a statistic that he does not fully understand. This can be a big problem if the statistic looks bad and the manager is left to explain why it is not such a relevant statistic after all.

Before anyone takes this as a criticism of bottom-up managers for not understanding the shortfalls of statistics such as the information ratio, I would like to point out that Dr. Joseph Messina explained the shortfalls of the information ratio in a chapter entitled "An Evaluation of Value at Risk and the Information Ratio" in *Managing Downside Risk in Financial Markets*.[1] If it takes a Ph.D. to grasp and explain the limitations of these statistics, it is not likely that financial analysts focused on selecting stocks will have a thorough understanding. Further, it is probably not in the client's or the investment advisor's best interests for the analysts to expend much time on such an understanding, as it will not increase the portfolio's return.

Downside Risk

At this point, you may be wondering what this has to do with the subject of this book—downside risk. Well, downside risk solves a number of the problems associated with the financial industry's favorite statistic, the standard deviation. Among the problems associated with the standard deviation is that it assumes that returns are evenly distributed above and below the average return. That is, a portfolio is exactly equally likely to be 20% over the average return as it is 20% below the average return. The bell-shaped curve that those returns would generate is called a *normal distribution*. In truth, much of the world is made up of truly random occurrences that do form a nice bell shape when you graph them. If that is true of investment returns, then using the standard deviation is handy because you can do a lot of neat comparative things with that statistic.

Okay, you guessed it. Investment returns are not normally distributed. I have looked at all sorts of returns for many years and have not seen them to be normally distributed. I have looked at 54 years of monthly mutual fund returns, which should be long enough for the returns to assume the bell-shaped curve if they are naturally distributed. The graph in Figure 6.1 shows the monthly returns for an actively managed mutual fund over 50 years. The dashed line shows what that dataset would look like if it were normally distributed.

As you can see from the chart, this distribution is not normal. There are significantly more observations above the mean than we would anticipate assuming a normal distribution. This distribution also seems capable of having some very bad, although unlikely, events. See the "bumps" to the far left. Noting that there are more positive events than expected but also the possibility of some large negative events is valuable information for investors. The standard deviation, with its implicit assumption of normality, will miss these insights.

Now, the number of years sufficient to be sure that you have enough data to say with confidence that you have an accurate understanding of the distribution is open to debate. However, if the manager who produced the early returns is no longer with us it is debatable whether the early returns are indicative of anything about

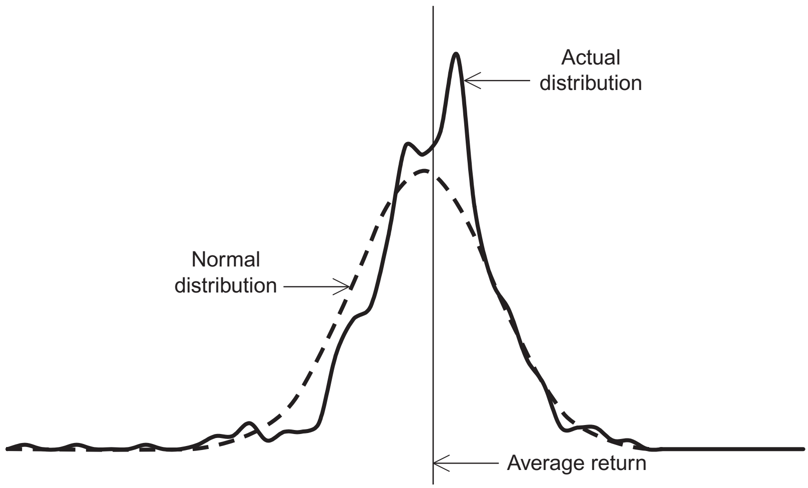

Figure 6.1 Fifty-four years of monthly portfolio returns.

the current portfolio team. How can we expect to wait for longer than 50 years to determine skill?

If returns are not evenly distributed then we need a statistic that can accommodate the actual distribution. That is where downside risk comes in. The underlying assumption of standard-deviation-based statistics is that if the average return, not the Desired Target Return™ (DTR™)*, is the proper focal point, then over a long enough period of time an investor will realize that return. That is, if there is an equal chance of being above or below the average return and it is all due to chance, then wait long enough and you will get the average return.

Downside risk does not suffer from the assumption of a uniform distribution; rather, it can accommodate distributions of different shapes. That is a vital concept but one that is rarely addressed. Even if returns were normally distributed, one cannot say that the difference between two normal distributions would itself be normally distributed. Information ratio is just that, the standard deviation of the difference between two distributions, the portfolio and the benchmark.

Identifying Bad Events is the First Step

Over the years, studies have indicated that most of a portfolio's return is dictated by the asset class weightings within the portfolio. For example, if the S&P 500 has dropped 25%, the owner of a diversified U.S. equity portfolio can be relatively

* DTR and Desired Target Return are trademarks of Sortino Investment Advisors.

certain that their active portfolio has also declined in value. This is why large institutional investors do the asset allocation studies to find the mix of asset classes that will yield the best results for that plan's particular objectives. (*Sortino note:* Contrast this view with the discussion of goals and objectives in Chapter 5.)

Once the optimal asset allocation has been defined then the plan will seek out investment advisors to manage each "slice" of the portfolio. As pointed out earlier, at this stage risk for the plan is that they have indeed selected the right asset classes and weightings but their managers underperform their respective assignments.

One way to employ downside risk is to use the benchmark return over the period as the dividing point between good and bad returns. For example, if the S&P 500 had been up an annualized 7% per year over the period studied, the downside risk analysis would compare the manager's return each year to 7%. Each time the return is below 7% it would be considered risky. (*Sortino note:* Compare this with the way downside risk is calculated in Chapters 1, 3, and 4.)

Calculating downside risk in such a manner results in a serious misstatement of risk. As we are all too aware, benchmarks tend to exhibit a great deal of variation in their annual returns. While the index may be up 7% on average over a period, it is likely that there were years when the benchmark returned significantly more than 7% and years when the benchmark returned significantly less than 7%.

For example, over the 10 years ending December 2008, the S&P 500 had a return of near zero. Many practitioners would calculate downside risk using zero as the minimum acceptable return. That would seriously misstate the risk/return of the portfolio. Over that 10-year period, the S&P 500 soared to new heights and crashed, multiple times. First we had the tech bubble, then the crash after the 9/11 terror attacks, followed later by a Fed liquidity-driven rally (the housing bubble), and then its subsequent collapse.

If a zero return is how we define risk, then any equity portfolio manager holding 100% cash would have done a terrible job during the tech bubble, a good job following 9/11, a terrible job during the housing bubble, and then a great job in the ensuing maelstrom.

The reality is much different. The way I recommend to calculate downside risk, in an environment where a portfolio is benchmarked to an index, is to compare each period's return to the index return over the same period. This is consistent with how investment advisors are asked to report to their clients. Advisors who reported five individual year returns and compared each to the index's annualized return for the 5 years would, at a minimum, embarrass themselves in front of their clients.

So, the way to measure risk for portfolios benchmarked against a specific index is to use the index's return each period as the DTR. Using an average return will seriously misstate risk experienced. (*Note:* The editor disagrees with this statement.)

A Picture is Worth a Thousand Words (or Statistics)

Albert Einstein is quoted as saying: "Things should be made as simple as possible but no simpler". As I write this, we are dealing with the aftermath of the "value at risk" method of reporting risk having blown up in the face of many practitioners. What went wrong? Well, that is the subject for another textbook. For starters, though, one can look at the aforementioned chapter by Messina. However, in my opinion, one of the chief mistakes was attempting to boil all the facets of risk exposure down to one number. Just viewing one number to determine risk exposure is woefully lacking.

The same can be said for downside risk, or any other returns-based risk statistic. Why do we insist on looking at one number, be it standard deviation, downside risk, tracking error, or any other statistic? What should be viewed is the *distribution* of returns. By viewing the graph in Figure 6.2 the user can instantly get a feel for what the numbers look like.

It has been pointed out to me that this graph does not tell the full story. Indeed, it does not. It is possible to create graphs that are even more informative. I have opted to include this graph of the distribution because, in my experience, it is easily understood. In a perfect world, we would all be comfortable using statistics such as downside risk and viewing the results in increasingly sophisticated graphs. The reality is that most of the investment industry assumes normality of distributions. In light of this, I believe simpler is better; however, I encourage the reader to consider using more sophisticated graphs that are even better at depicting the risk/reward trade-off.

Granted, viewing distributions does not lend itself to automation. On the other hand, isn't it realistic that outperforming the market will take some work? Can we really believe that plugging a formula into a computer and punching a button will allow us to beat the market? Investors viewing distributions and making informed judgments is much more likely to yield positive results. (*Note:* The editor does not believe that beating the market is the goal.)

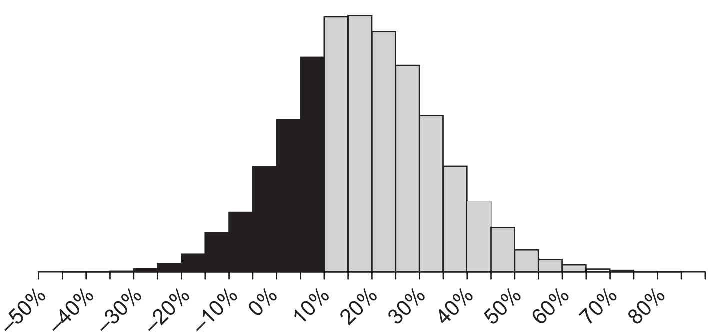

Figure 6.2 Bootstrapped data distribution.

How to Adjust for the Time Frame

I mentioned earlier that few investors, institutional or otherwise, have a long enough time frame to stick with an underperforming investment to see if it is due to luck orlack of skill. I believe this is responsible for vast amounts of wasted assets as managers are terminated, new managers hired, and entire portfolios turned over needlessly. The only people who make out well in such a scenario are the brokers who collect trading commissions.

The correct solution to this problem is for plan sponsors and consultants to expand their time horizons beyond the quarterly review that is practiced throughout the industry. This runs against reality for most in the business. Plan sponsors have boards to report to while consultants have to answer to their clients, and both have to worry about evidence of meeting fiduciary standards.

How Do Institutional Investors View Downside Risk?

My experience has been that when downside risk is explained it is typically embraced as more consistent with how investors view risk. Rare is the investor who loses sleep because his portfolio may outperform the benchmark. Yet, typical standard-deviation-based measures find outperforming the average as unacceptable as underperforming the average.

When an institutional investment manager shows a risk statistic they would do themselves and their clients a favor by reporting the statistic that they feel most accurately shows risk. In every case I can recall, industry participants have acknowledged that downside risk is more consistent with their own view of risk.

The chief reason that downside risk is not employed is usually that returns are normally distributed. I am not aware of any studies that show that. A simple examination of returns indicates the contrary.

Another reason for not using downside risk is that it is not readily available. That is a fairer point. However, if institutional investors began requesting it, then downside risk would become the standard in short order. The power of plan sponsors and their consultants is truly impressive. Calculating downside risk is fairly simple from a programming point of view, and the formulas were made public in *Managing Downside Risk in Financial Markets*.

I believe the main reason that downside risk has not gained greater acceptance is simply inertia. As most of us in the investment industry are busy, assuming that standard deviation accurately captures risk is wonderfully liberating. We can just put returns into a spreadsheet and use " = stdev" to appear to get an accurate picture of the portfolio's risk/return trade-off *vis-à-vis* the benchmark.

The wonderful thing about the times we live in is that computer processing power is inexpensive. Included with this book is a Microsoft® Excel® macro that will calculate downside risk for a set of returns. It also provides a graph of the actual distribution of returns. That downside risk statistics are not readily available is not much of a reason for not using a clearly better, more informative, and more useful measure of risk.

Why Stop There?

I have limited my remarks to the risk side of the equation. It has been pointed out, however, that there is no reason to look at just the probability of risk. The return received, after all, is also one of many possible outcomes. In an ideal world, the distribution of the risky events (downside) would be compared with the distribution of the possible good events. That would allow the user to gain the maximum insight into a set of returns.

In Summary

Institutional investment management differs significantly from other types of investing in that the role of the manager is very narrowly defined as outperforming the benchmark. If that is how the consultant and the client are going to measure performance, that will dictate the manager's investment strategy. Downside risk measurement is more consistent with the way institutional investors view risk and should replace standard deviation and beta. Finally, viewing the distribution of returns is superior to a single statistic to get an accurate idea of the portfolio's risk profile.

Endnote

1. Sortino, F. A. (2001). *Managing downside risk in financial markets*. Oxford, U.K.: Butterworth-Heinemann.

Chapter 7

Integrating the DTR™ Framework into a Complex Corporate Structure

James A. Pupillo

The views expressed herein are those of the author and do not represent the views of the broker-dealer for which he is employed, its officers, directors, or its employees.

Executive Summary

James Pupillo, senior vice president of a global investment management company, provides a case study in managerial finance. The reader will come to understand why it is so difficult for large institutions to be innovative.

Introduction

In Chapter 1, Frank Sortino and Hal Forsey presented a formal portfolio construction and monitoring framework for constructing DTR™* portfolios. Ron Surz has shown the importance of using indexes with the proper characteristics for asset allocation in Chapter 2. In Chapter 5, David Hand explained how he works with Sortino Investment Advisors (SIA) to build Collective Investment Funds that his company can offer to 401(k) plans. In this chapter, I would like to acquaint the reader with the challenges we faced when integrating these innovations into a cohesive portfolio construction service for a global investment management consulting firm (referred to here as IMC to comply with company policy). I will conclude with a case study to demonstrate how we used the concepts presented in the previous chapters for a large defined benefit plan.

As an Institutional Consulting Director of IMC, I had to seriously consider the impact on my colleagues and the firm's management when proposing to integrate these portfolio construction advances into the firm's existing organizational structure. I was mindful of this innovation being viewed as a threat rather than an enhancement to our already sophisticated portfolio construction process, active manager research, and due diligence infrastructure. Therefore, I convinced the management at SIA to relinquish control over the asset allocation decision and limit their selection of active managers to those managers who had successfully passed the rigorous due diligence of my firm's professional staff. I then presented this as an overlay process to our existing portfolio construction process.

The Integration Process

Figure 7.1 depicts the already existing portfolio construction process based on the global investment committee's strategic and tactical asset allocation modeling. It also provides a macro view of how the SIA overlay process incorporates into the corporate structure. Thus, many layers of management above and below SIA's overlay process would be affected.

If it had not been for a long-standing culture of innovation demonstrated over decades by the firm's business partnership between its seasoned practicing investment management consultants and senior management, this would not have been possible. A formal think tank association exists between the IMC's practicing investment management consultants and the IMC's senior management. This association

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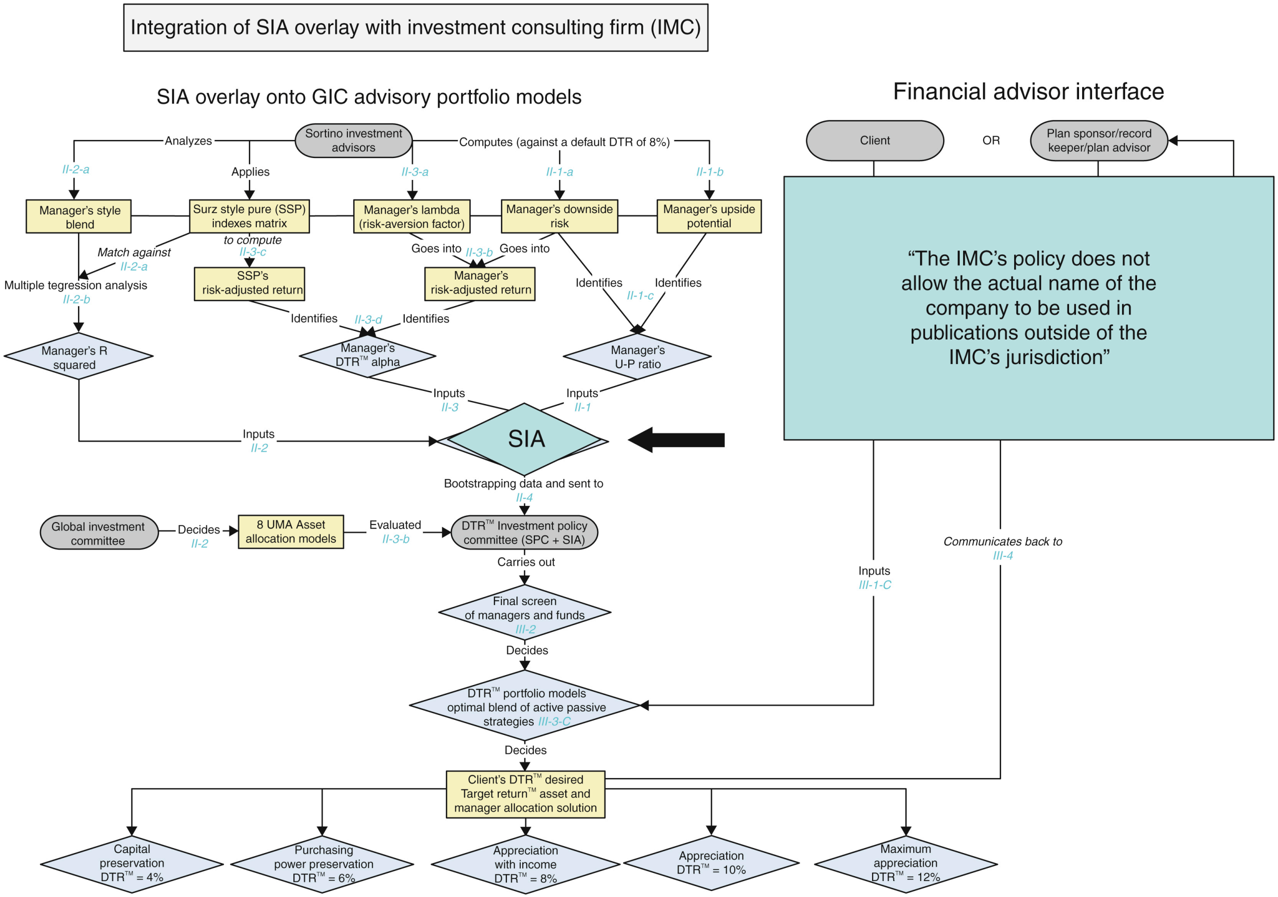

Figure 7.1 Integration of the SIA overlay methodology with the firm's structure.

has a history of linking the investment management consultants' innovative thinking with the talent of senior management to create the infrastructure to bring consultants' requests to reality.

There were very compelling reasons to push this concept forward. First, there has been a proliferation of index Exchange Traded funds (ETFs) to meet the demand for reducing costs. If we did not introduce passive investments into our consulting process or platform, clients would go elsewhere. So, I worked with my firm to integrate passive investing into our consulting portfolio construction process and integrate it onto our platforms. This could serve as an additional dimension of our consulting value proposition. I wrote a position paper to senior management to this effect and the receptiveness was unanimous. We were on our way to discovering a new frontier in portfolio construction.

Incorporating passive investing into our consulting process and onto our consulting platform was the easiest gauntlet to pass, but this led to another problem. Consultants had no formal way of combining passive indexes with active managers to fulfill management's asset allocation models. Management was being besieged with requests from consultants for guidance. I saw the SIA overlay process as a quantitative solution to this problem and was determined to present it to management as a solution to the problem faced by consultants.

The next impasse was getting through the vetting process of asset allocation committee members and active manager analysts, who inherently challenge investment ideas. Additionally, they are all governed by their corporate management supervisors and an infrastructure used to operating in a traditional mean-variance framework for doing business.

Diplomacy and perseverance were essential to conducting years of meetings with these different individuals and committees. Eventually, we successfully convinced an army of skeptics that there was merit in this optimal blending of active and passive management strategies.

The next step was to make the overlay accessible to the firm's financial advisors while also integrating it with the firm's investment advice and platforms. We began by offering the DTR™ overlay service to IMC's existing portfolio construction process shown in Figure 7.1 as follows:

1. Asset Allocation Modeling
   a. Strategic (long-term) Risk/Return Modeling
   b. Tactical (short-term) Opportunistic Allocation
2. Manager Research and Selection Process
   a. Quantitative and Qualitative Analysis
   b. Opinion and Fact-Based Manager Due Diligence
   c. Alternative Investment Expertise and Evaluation

3. **3.** DTR™ Portfolio Construction Methodology Overlay
   a. DTR™-α Upside Potential/Downside Risk Manager Overlay
   b. Client DTR™ "Balancing the Balance Sheet" Approach
   c. DTR™ Optimal Blending of Active and Passive Investment Strategies

To clarify, all DTR portfolios will follow a three step process.

Step 1

This first step is conducted by the IMC's Investment Committee. This committee's main responsibility is to design the basic portfolio DNA of eight asset allocation models based on a spectrum of different risk/return attributes (see Figure 7.2). Each of these models may have various iterations and may be subject to tactical asset allocation tilts in an effort to be opportunistic with capital market and/or economic conditions. Each model may then be subject to the Financial Advisor's tailoring to best fit a client's specific financial needs and objectives.

	SIA overlay							
	Tactical recommendations							
		Effective April 11, 2008; Reaffirmed June 10, 2008						
Model:	1	2	3	4	5	6	7	8
Cash	**30%**	**15%**	**10%**	**2%**	**2%**	**2%**	**2%**	**2%**
Bonds:								
US core	49%	35%	28%	26%	18%	10%		
High yield	7%	5%	4%	4%	4%			
Non-US governement	14%	10%	8%	8%	6%	3%		
Total fixed income	**70%**	**50%**	**40%**	**38%**	**28%**	**13%**	**0%**	**0%**
Equities:								
Large value		12%	12%	12%	16%	19%	22%	12%
Large core								
Large growth		13%	13%	13%	17%	20%	23%	13%
Mid value			4%	4%	4%	5%	7%	12%
Mid core								
Mid growth			4%	4%	4%	6%	7%	12%
Small value				4%	3%	3%	3%	8%
Small core								
Small growth				4%	4%	4%	4%	9%
Foreign								
Non-US developed		10%	17%	12%	14%	17%	20%	15%
Emerging markets				7%	8%	11%	12%	17%
Total equity	**0%**	**35%**	**50%**	**60%**	**70%**	**85%**	**98%**	**98%**
SIA selects 5 DTR Portfolios from 8 UMA portfolios based on maximizing the upside potential ratio	**DTR 4 range**							
		DTR 6 range						
			DTR 8 range					
					DTR 10 range			
						DTR 12 range		

Figure 7.2 SIA overlay on eight hypothetical tactical asset allocation models.

Step 2

The second step is conducted by IMC's Investment Manager Research Department, which evaluates both the quantitative and qualitative attributes of active managers in separate managed accounts (SMAs) and mutual funds. This group of professionals perform the research, due diligence, and analysis on thousands of mutual funds and SMA products. This huge universe is then refined into short lists of active manager universes representing both mutual funds and SMA solution sets.

The purpose of Figure 7-1 is to show the difficulty of integrating a service such as the SIA Overlay process into a complex corporate structure like my IMC firm. It requires the involvement of many people at many different levels of management. It is a major commitment of time and money.

Step 3

The next step is the integration of the SIA framework to the two previous steps. Figure 7.2 is a hypothetical example of eight tactical asset allocation models for portfolios consisting of only traditional assets. The DTR™ Portfolio Construction Committee consisted of SIA and members from my team. Collectively this DTR™ committee seeks to finalize the integration of the DTR™ overlay methodology into the investment consulting firm's two steps mentioned previously. Additionally, the DTR portfolio committee will decide which of IMC's eight tactical allocation models would be applied to the five DTR™ portfolios, which consist of DTR-4, DTR-6, DTR-8, DTR-10 and DTR-12 (the numbers 4, 6, 8, 10, and 12 represent percentages). Through a cash flow analysis, each of these DTR™ portfolios are matched to the DTR™ needed to achieve a particular client's goal. The portfolio should have the potential to meet or exceed the client's DTR™ with an acceptable level of risk, that is, the upside potential ratio according to the SIA Optimizer should be greater than 1. See Chapter 4 for an explanation of the Optimizer. Furthermore, the DTR committee determines whether it is optimistic, neutral, or defensive regarding the capital markets and economic environment. As such, the DTR committee could adjust within a predefined range (illustrated in Figure 7-2) which of IMC's eight tactical models would be applied to each of the five DTR™ portfolios. For example, as it relates to the DTR-12™ portfolio, the DTR committee choice could range between IMC's tactical models 6, 7, and 8. Similarly, models 3, 4, or 5 could be selected for the DTR-8™ portfolio. Next, these eight asset allocation models are run through the SIA Optimizer, which determines whether or not the portfolio has the potential to meet or exceed the client's DTR™ with an acceptable level of risk. In this case, the upside potential ratio according to the SIA Optimizer

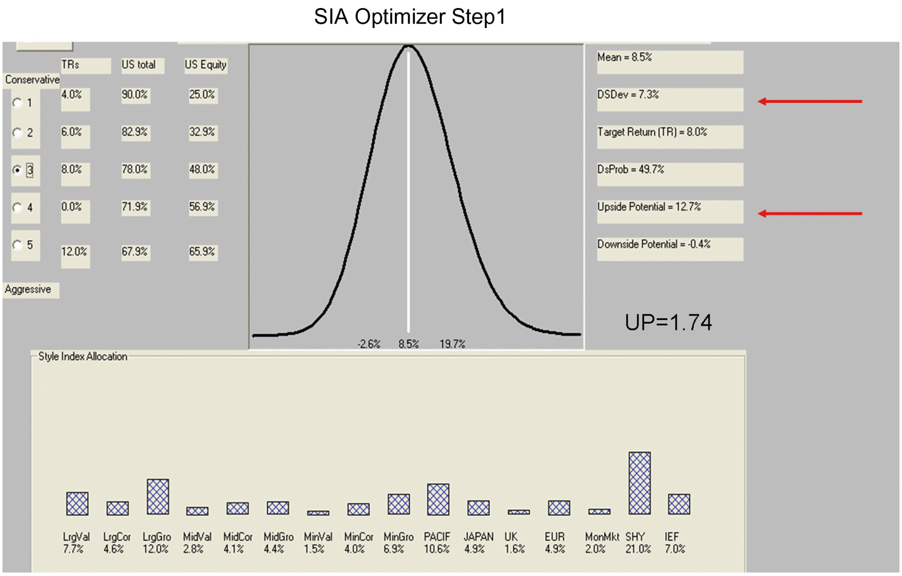

Figure 7.3 Sample output of SIA optimizer.

should be greater than 1. A sample output of the SIA Optimizer for an 8% DTR portfolio is presented for illustration in Figure 7.3.

The mean return of 8.5% in Figure 7.3 barely exceeds the DTR-8™ portfolio's return objective of an 8% return. Furthermore, the probability of falling below 8% is 49.7%. These commonly used statistics alone do not give us a lot of confidence in this choice. However, we can see that the upside potential is 12.7% and the downside risk is 7.3%. The upside potential divided by the downside risk yields an upside potential ratio of 1.74 (12.7/7.3 = 1.74). This indicates that this asset allocation has 74% more upside potential than downside risk. Sortino and Forsey give further evidence in Chapters 3 and 4 and in the Appendix as to why the upside potential ratio is much more meaningful than knowing the mean and probability of failure.

Now the question to be answered is: Which active managers who met IMC's due diligence standards can add the most value to IMC's asset allocation, shown at the bottom of Figure 7.3? A sample combination of active managers and passive indexes that fulfills the firm's asset allocation standards is shown in Figure 7.4.

This DTR™ portfolio construction methodology adds active managers where they can add value and fills in around them with passive indexes to lower costs to my clients.

There are currently two custom portfolio offerings. The first is a DTR™ mutual fund portfolio solution that constructs the portfolios by blending active mutual fund

RECOMMENDED PORTFOLIO

Fund	Percent
IEF	16.1%
SHY	13.9%
Winslow Capital Large Cap Growth FS 176	13.7%
Brandes Partners Intl Eq FS 19	13.1%
MSCI PACIFIC ex JAPAN ND USD	9.5%
LrgValu	8.4%
MinValu	5.7%
Turner Small Cap Growth Quant FS 156	5.4%
MidCore	4.7%
MidValu	4.7%
MSCI UNITED KINGDOM ND USD	4.7%

THIS IS FOR DEMONSTRATION AND MAY NOT BE OUR CURRENT ALLOCATION.

Above is the blend of active and passive managers selected by the model based on your target return (TR) of 8.0%.
Below is a graph showing the diversification across totally passive styles.

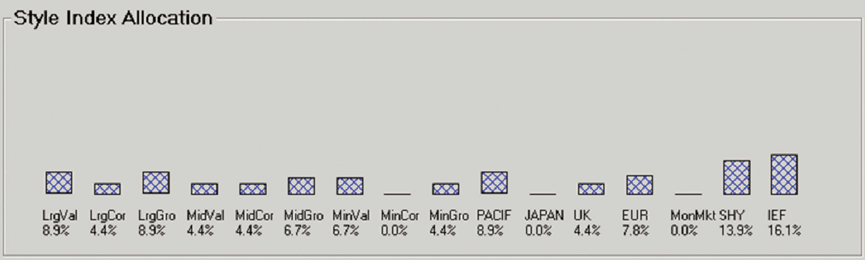

Figure 7.4 Illustration of recommended portfolio.

management with low-cost passive ETF management for portfolios $500,000 and above. The second DTR™ portfolio offering is a separate managed account (SMA) solution that constructs the portfolios blending active SMAs with passive ETF management for accounts above $5 million.

The Benefits

Now that I have explained the complex process that a global investment management consulting firm such as mine must go through to integrate the SIA Overlay and prepare to offer the DTR funds, what is the worth to the company and the clients? For some time, I have used a cash flow analysis to help my clients identify what they are trying to accomplish and what it is going to take to get there. I now have a name for the number that links the cash inflows to the cash outflows that is easily understood. Focusing on the DTR allows me to construct portfolios and measure performance in a manner that is directly related to their goals. For retirement plan sponsors and their plan participants, I can offer a totally new approach: an investment program for 401(k) plans that resembles a participant-driven defined benefit plan and is also designed to assist in meeting the QDIA standards as published by the Department of Labor. I believe this innovation will better enable many participants to accomplish their retirement goals who otherwise would fail to do so.

Now I will demonstrate how we applied this new framework to a defined benefit (DB) plan. My team received a request from a large corporate account to evaluate their current approach to managing their defined benefit plan.

This case arose due to a significant decline in portfolio value in 2008. DTR portfolios are subject to the same good, bad, and ugly capital markets as any other. However, the "balancing the balance sheet" approach offered with the DTR portfolio construction methodology is also event driven. What we mean by that is that it goes beyond structuring the portfolio based on the plan's actuarial return assumption. The DTR portfolio process monitors and dynamically manages the portfolio through client and/or market events that change the calculation of the DTR.

For example, suppose a DB plan in early 2007 had an actuarial assumption of 8% and the current asset allocation was as shown in Model 4 in Figure 7.2 a 60/40 mix of equity to fixed income. If the Bull market of 2004 to 2007 had caused the DTR calculation that discounts the cash outflows of the plan to the cash inflows to be 6%, the asset allocation recommendation would then be tilted toward Model 3, the highest range for a DTR of 6% (see DTR-6 range at the bottom of Figure 7.2). Even if the consulting firm for the DB plan was bullish in 2007, the consultant and the investment committee would have to have recognized the fact that the new DTR of 6% called for a reduction in equity exposure. That is, the market event that caused the plan to be overfunded would cause the DTR to decline regardless of forecasts and feelings of the investment professionals involved. Put another way, without the calculation of the DTR the question would not arise.

However, when my team was brought in to meet with the investment committee of the DB plan it was February of 2009. The plan was now underfunded because the portfolio had suffered a serious decline. The mood was now far from bullish in the boardroom, but the "balance the balance sheet approach" called for recalculating the DTR, which was higher than 8%. The DTR concept explained above allowed me to present the solution in a logical way that called for rejecting the old mean-variance optimizer approach that focused on maximizing expected return. Instead, we focused on the link between assets and liabilities, the DTR.

Consequently, we were invited to conduct a full DTR analysis of the portfolio's construct. This analysis consisted of the entire DTR overlay process as described above. The evaluation replaced active managers with negative DTR-α. It also reconfigured the active management component of the portfolio due to accounting for each active manager's actual style blend. This resulted in allocating more funds to those managers with positive DTR-α values and filling in around them with passive indexes where DTR-α was not available, thereby reducing expenses.

This is evidence that pension boards are ready to listen to new approaches for managing their DB plans that recognize the liabilities as well as the assets of the plan. There is nothing mystical in this DTR-event-driven approach that is difficult to understand.

The post-modern portfolio theory (PMPT) advancements incorporated in DTR portfolio construction can result in portfolios built better than those built via the mean-variance approach of treating the DB plan as an asset management problem. It is time for the financial community to recognize and integrate these PMPT attributes into practice. The evidence is mounting. This case study is only one among the many clients who are participating in the revolution of portfolio construction. *Carpe diem*!

Chapter 8

The Proper Role of Regulation in Financial Markets

David Hopelain

Executive Summary

David Hopelain explains the difference between risk and danger in financial markets by comparing investing to race car driving. Risk can be managed, but dangerous situations require government intervention.

The previous chapters in this book have advanced new concepts and methods for investment decision making and portfolio management as the next steps in the evolution of financial management. This chapter proposes a framework for understanding the *role* of the regulators of financial markets. The current financial crisis reveals that the process of regulating decision making in investment markets is essential; however, before undertaking the complex issue of adopting new rules, the role of regulation and the regulator must be defined. Not until the regulator's role is understood will financial markets function as intended. To fulfill their intended purpose financial markets must satisfy the interests of:

- Those whose funds are invested
- Those who use the funds that are invested
- Those who make the day-to-day decisions linking these two groups

Role of Regulation

It is the role of regulation to ensure that the interests of each of these market constituencies are satisfied. Heretofore, regulation has assumed that all uncertainty involves *risk*. This is not the case. Some uncertainty is *dangerous*.[1] This is an important distinction that must be made explicit in the next evolutionary cycle of financial management and regulation.

- *Risky situations* are those that can be controlled with skill, proper tools, knowledge, and experience; that is, risky situations are *self-regulating* and can be *managed*. The downside outcome of a *risky situation* is the risk for a potential loss deemed worth taking for the potential reward.
- *Dangerous situations* are those that cannot be managed. These become chaotic and spin out of control with unpredictable results. They resolve *themselves* with their own inertia or are resolved by outside influence. Resolution of a *dangerous* situation can be a calamity that proves too costly for the participants.

Role of the Regulator

This distinction brings the role of the regulator into focus. In collaboration with the decision makers described above, regulators define which circumstances are self-regulating and *risky* and which circumstances are out of control and *dangerous*. The role of the decision makers is to *take risks.* A responsibility of the regulator is to step in when a *risky* situation is no longer self-regulating and becomes *dangerous*.

Auto racing provides a model for the type of regulation proposed here.[2] In auto racing, drivers, car owners, track owners and managers, and regulators agree on rules that make a race setting attractive, competitive, and *risky* but which avoid *danger*. Once this setting is established, the role of the regulator is to observe and intervene when a situation has changed from risky to dangerous. If a driver is creating a hazard, driving recklessly, or spilling oil on the track, he is “black flagged” (taken out of the race until his equipment is fixed) or given a warning. If the auto racing framework were adopted in the regulation of financial markets, the regulator observing dangerous decisions being made would black flag the decision makers creating that danger. When the regulator is satisfied the situation is no longer dangerous, the green flag is waived. In the current financial crisis, a regulator operating under this model would have black flagged Bernard Madoff for conducting himself in a dangerous manner. This action would have prevented a significant loss of investors’ money as well as the ensuing loss of credibility for other market participants.

If a hazard, such as fire or heavy rain, is beyond a race official’s control, the race is stopped until the dangerous conditions are gone. Once the hazards are gone, it’s back to green flag racing. Likewise, regulators of financial markets who observe conditions beyond their control should be able to stop investment activity until the hazardous conditions are gone and investing can resume. The financial crisis analogy, in this case, is the subprime mortgage market. A regulator observing that portfolios containing subprime mortgages were given “AAA” ratings would have black flagged the entire field (i.e., stopped trading) until the rating system reflected the proper evaluation of the securities in its market.

If a racing official decides a condition such as an accident or debris on the track endangers the entire field or a portion of it, the yellow caution flag comes out. The entire field or the endangered portion is slowed down with no passing allowed until the dangerous condition is removed. Likewise, if an official regulating financial markets observes a situation that endangers everyone, it should be possible to slow the field down and limit it to certain safe activities. When the regulator determines the situation has returned to normal, the market equivalent of green flag racing is resumed. In this situation, the role of the regulator is to prevent one of the most common mistakes in racing and financial management—participants thinking they are making risky decisions when, in fact, their decisions are dangerous to themselves and others.

In September 2008, the Securities and Exchange Commission (SEC) identified such a dangerous situation. Hedge-fund short sellers were committing to sales of stock not in their possession or to which they did not have access. In response, the SEC waived the yellow caution flag and instituted the short sale rule for hedge funds. This rule required that a short seller have access to the instrument being sold. Other segments of financial markets responded by moving up, in the belief that a dangerous situation had been corrected. However, a number of influential hedge funds complained, and the SEC stopped enforcing the rule. Chaos followed, and Bear-Stearns went out of business. Those racing close to Bear-Stearns (i.e., those holding Bear-Stearns’ obligations) suffered costly losses as well. This is the auto racing equivalent of a serious accident and death of a driver occurring after a yellow caution flag has flown. In this case, influential drivers ignored the flag and officials withdrew the flag before the situation had been corrected. This "accident" ultimately affected the entire "racing community" (i.e., investors in other markets). Had the caution flag remained out until the dangerous situation was corrected, avoidable losses would not have occurred.

The auto racing analogy reveals the first of a regulator's roles in an enterprise based on uncertainty. The first role of a regulator is that of an active participant whose responsibility is to maintain a *risky* setting and catch errors, when that setting becomes *dangerous*. It is not to punish, unless there is a frequent and flagrant offender, nor is it to control strategy or the technology used by other participants or to control the outcome of an automobile race or an investment market. Rather, it is to maintain a self-regulating setting in which participants avoid danger and take risks they judge will provide a commensurate reward. When the situation is determined to be beyond the control of participants, it is deemed dangerous. In these circumstances, the regulator's role is to ensure that steps are taken to *restore control to the participants*.

Market regulators are as much a part of properly functioning financial markets as stewards, timers, flagmen, and other officials are part of an auto race. The current financial meltdown is the consequence of a lack of clarity regarding the role of market regulators. Markets do correct themselves; however, more often than we would like the correction brings harm to the participants (i.e., Wall St. and the larger economy). The current correction occurred *after* the situation spun out of control, became *dangerous*, and required outside intervention. In the auto racing analogy, this would be a dangerous situation in which not only drivers but also fans in the grandstand were killed or injured.

In their role of maintaining a risky setting, officials enforce rules defining the actions and relationships among drivers on the track during a race. These rules are based on historical experience and enacted with the consent of participants—drivers, owners, sponsors, and spectators who agree by paying to watch the races. Likewise, financial market officials should enforce rules regulating the relationship among those who make decisions linking those who have money requiring management and those who can, productively, put it to use. As with auto racing, the basic rules are straightforward and easy to understand—these are rules of *transparency* and *liquidity*:

- *Transparency*—There must be sufficient information available to all investors to establish market-clearing prices. That requires transparency in every transaction. This includes information about the instruments that are the object of trading decisions *and* those participants who are doing the trading. Transparency creates a common framework for understanding the objects of trading decisions and accounts for the network of traders who share that framework. Variations do not arise from the availability of information to some and not to others.

Transparency reveals the participants' underlying positions and defines their relationship to one another. It creates the ability to ascertain when an uncertain situation has become *dangerous*.

- *Liquidity*—Part of the transparency framework is the participants' understanding that there is sufficient cash to strike a price for every transaction. Without liquidity, accurate risk assessment is not possible. In an illiquid market, large price fluctuations reveal a breakdown in a commonly understood framework. It may be that a significant number of participants perceive danger and have decided to find someplace else for their money or the volume of transactions exceeds the amount of cash available to settle them. In either case, the commonly understood framework does not correspond to the underlying reality. The situation is no longer *risky*; it is *dangerous*.

There is no more poignant reflection of the failure to attend to liquidity than the following comment made by one of Wall Street's most highly regarded investors:

> *"The thing I didn't do from Day One was properly assess the severity of the liquidity crisis. …Every decision to buy anything was wrong."*[3]

Accidents Happen

Just as in racing, accidents happen in financial markets. Each accident at the race track, especially a serious one, is an opportunity for participants and officials to review what happened. They determine whether or not this was a racing accident, an incident that could not have been avoided because the circumstances were inherent in the nature of auto racing. Accidents of this nature are the downside of a *risky* enterprise. Or, they might determine that the accident could have been avoided if participants had followed the rules or officials had enforced them more effectively. This review will reveal the events and their causes that turned a *risky* situation into a *dangerous* one. Ultimately, a decision will be made whether the rules should remain the same or be changed to prevent such an accident from occurring again.

The same principles apply to financial markets. When a costly event occurs, regulators should assume their second role—that is, as conveners of meetings to evaluate whether the event was inherent in the risky nature of the market or was a dangerous situation calling for rule changes. Once again, the Bernard Madoff situation is instructive. This was serious and analogous to a racing accident in which fans were injured. A discussion of the Madoff situation would lead to a serious evaluation of whether the situation became dangerous because: (1) adequate rules were not properly enforced, or (2) the rules were inadequate and require change.

Such an evaluation would certainly find that financial markets became *dangerous*, because rules established to maintain its *risky* nature while avoiding *danger* were not adequately enforced. To the extent this is the case, avoiding a similar incident in the future is simple: Enforce the rules. *It is also certain to be found that new technologies have changed the nature of financial markets and new rules are required.*

Criteria for New Rules

The increased complexity, speed, volume, and international scope of transactions are analogous to the introduction of race cars with greater horsepower than those anticipated by existing rules. In developing new rules to accommodate more advanced race cars, officials would ask two questions: *Who* is capable of safely driving these cars (i.e., what are a safe driver's qualifications) and *what* distinguishes these cars from those that exist (i.e., what are the unique characteristics of these cars)? Likewise, for new rules adapting to changes in financial markets, the questions to be asked are *who* should participate and *what* distinguishes these new financial instruments from those already in existence?

There is no better demonstration of the need for criteria to define *who* and *what* comprise each segment of financial markets than the abandonment of the Glass–Steagell Act in November 1999. The Act defined two major types of financial activity in the same manner as the auto racing community defines two very different types of races—oval track and road course racing. In each case, the vehicles are designed and set up differently, and the skills, knowledge, and experience required to participate in each is very different.

The Glass–Steagell Act defined the banking system as institutions making decisions influencing the nation's *monetary* system. Financial instruments outside of the Fed's control were defined out of the system, in the same manner that Formula One cars are defined out of a stock car race. Institutions (i.e., the *who*) covered by the Act were defined as the nation's banks and what constituted a bank was clearly specified. The portfolios containing monetary system financial instruments were overseen by bank loan committees concerned about safety and liquidity of their institutions. These committees answered to bank shareholders, the Federal Reserve, and the U.S. Treasury Department. Decisions in this sector were evaluated in terms of their contribution to a stable money supply for the economy and their contributions to steady economic growth.

Financial instruments falling outside the definition of those regulated by the Fed were treated as *investments* tied to the equity of those using funds represented by these instruments. As such, they are subject to a different set of rules and oversight. Decisions regarding these instruments were *trading* decisions evaluated in terms of their results in relationship to performance in a particular market and the contribution of that performance to increases in wealth. Management of these portfolios was overseen by investment committees of investment banking firms, private equity firms, and hedge funds.

Abandonment of the Glass–Steagell Act had the effect of placing financial instruments, participants, and regulators from the monetary system in the same race as those in the investment market for short-term gain. Drivers with equipment designed to perform in a safe and liquid monetary system found themselves in a race against commodities and stock traders with equipment designed to perform differently. The results were predictable—a costly disaster for all participants. The great irony of the current financial calamity is that the regulator overseeing the race at the time of the accident—the SEC—is playing a limited role in the assessment of what went wrong.

The creation of collateralized debt obligations (CDOs) and similar financial instruments, and the technology to bundle and trade them in international markets is analogous to the introduction of a new higher powered car to the racing community. At the racetrack, these new higher powered cars might be placed in their own class to compete against each other, they might be put into an existing class with a rule change to ensure that racing in that class retained an acceptable level of risk, or they might be modified to conform to existing rules. In financial markets, new financial instruments and participants could result in the creation of a separate trading category with its own rules, existing rules might be changed to accommodate these transactions, or the instruments would be modified to conform to existing rules.

Had the distinction between risk and danger and the procedures that guide rule making in auto racing been applied to the introduction of derivative instruments, the following question would have been asked and answered:

> *Should we allow instruments whose objective is monetary stability to trade in the same market with highly leveraged financial instruments whose objective is high rates of return?*

Whatever the decision, everyone would know the rules for these transactions and could anticipate results with an acceptable level of uncertainty. The distinction between risk and danger together with the application of auto racing principles reveals the principle for establishing these criteria in financial markets.

One Person's Risk is Another Person's Danger

Whether a decision is risky or dangerous depends on the decision maker's skills, equipment, tools, knowledge, and experience. It's one thing for Dale Jarrett, Jr., to travel at 200 miles per hour around an oval racetrack; it's quite something else for the author to do so. It is also quite something else for Dale Jarrett, Jr., to travel 200 miles per hour in a racecar on a freeway while the author and others are traveling at 70 miles per hour. In the former case, the author would be black flagged for driving too slowly. In the latter case, Jarrett would be pulled over for speeding and recklessly driving a vehicle that was not street legal. In the first example, the author is a danger to himself and others while Jarrett is taking an acceptable risk. In the latter example, Jarrett is exposing himself and others to danger while the author and others are taking risks deemed acceptable by them and those who enforce the rules of the road. Auto racing manages the principle "one person's risk is another's danger" by creating different categories of racing, such as professional, amateur, Formula One, Indy car, NASCAR, stock car, or go-kart racing. Each fits the general concept of auto racing and is subject to the same basic rules in the same manner that transparency and liquidity are the basic rules of financial management. However, their equipment is different, the participants have different skills, and the courses are different. Different rules are created for each type of racing to prevent the contest from becoming dangerous.

The differentiation between risk and danger reveals the criteria for creating market segments subject to different regulations. Within each market segment, decisions are made with the realization that there is a trade-off between a potential reward and an acceptable level of risk. This is the upside potential/downside risk discussed in Chapter 1. When the potential loss exceeds an acceptable level, the situation is *dangerous* for its decision makers, and it is said that "the stakes are too high." The role of *stakes* in defining financial market segments is demonstrated in the distinction between risk taking for pension funds and risk taking for hedge funds.[4]

The objective of those investing in a hedge fund is to generate returns that exceed those of the market, in general, or returns in excess of a specified benchmark. Participation in a hedge fund requires a large minimum investment from wealthy participants in a position to assess how much they can afford to lose, if the worst happens. Withdrawal of funds may be restricted by the terms of their participation, even if losses exceed those anticipated by the participant. Hedge funds utilize a significant variety of financial instruments (e.g., stocks, bonds, commodities, currencies, derivatives, and options) and take long or short positions in any of these. The degree of uncertainty deemed to be risky is far greater than that of a pension plan. The skills, tools, knowledge, and experience of these participants are significantly different than those participating in a pension plan.

The objective of investing for a pension plan is to achieve the actuarially determined return necessary to meet participants' pension obligations as they come due. This is an example of the Desired Target Return™ (DTR™)[*] introduced in

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[*] DTR and Desired Target Return are trademarks of Sortino Investment Advisors.

Chapter 1. Those who invest pension funds make decisions in the face of uncertainty, believing they will produce the DTR or greater. Returns below the DTR underfund the pension plan and require additional contributions. The investment objective is to maximize the upside potential ratio.

In each case, the *stakes* are very different. In a pension fund, the stakes are the standard of living of those who have chosen to leave the work force or have been forced to do so. The level of risk associated with financial instruments eligible for pension fund investment must be restricted to avoid dangerous outcomes (i.e., those threatening the participants' future living standards). In a hedge fund, *what* is at stake is the portion of wealth sophisticated participants have chosen to put at risk. The degree of risk associated with financial instruments eligible for hedge-fund investment is substantially greater than that of a pension fund. A calamity for one group is an acceptable loss for another. The acceptable level of risk in each of these funds must be understood and acknowledged by those managing *and* regulating them.

In order for regulators to evaluate the level of risk associated with financial instruments in either market, it is essential that they know the nature and true value of assets being traded as well as *who* owns them. Once again, auto racing provides the model. Open-wheel Formula One cars do not race against covered-wheel NASCAR cars. Even in the amateur racing world of the Camero–Mustang Challenge Series, race teams are divided into two groups according to the horsepower of their cars. Investing in securities of well-established companies requires very different skills, knowledge, and experience than trading in collateralized debt obligations.

Each market requires participants with different skills, tools, knowledge, and experience. A principal element of regulating these markets is determining *who* can participate through oversight of training and licensing programs. Once again, auto racing offers a model. There is not a racing program in the country (professional or amateur) that does not qualify its participants according to their skills and equipment. That is one reason why very few serious accidents arise from racing.

The inability of regulators to understand the nature of derivatives and the inability to assess their true value resulted in a *dangerous* market being allowed to continue under the illusion that it was merely *risky*. If the distinction between risk and danger had been made and this market had been regulated in the same manner as a car race, the black flag would have flown. The entire field would have been stopped until officials understood the equipment being raced and determined whether the participants were adequately trained and prepared to take the risks associated with this equipment.

After each professional and amateur race, cars are tested to determine whether they meet the specifications for their class. Those who fail the test are disqualified and do not receive points toward their standing in the race series. Likewise, market participants and regulators must define the instruments being traded and the rules of the road in a particular market. Regulators must regularly determine that these specifications are met. Participants trading in a manner that does not meet the established standards for that market should be penalized, and those who consistently break the rules should be permanently disqualified.

Only when the stakes are well defined and participants are qualified to trade in a particular market can regulators properly identify the rules of the road for each market. Only then will *dangerous* situations that spin out of control be minimized or eliminated from financial markets.

Summary and Conclusions

The objective of financial regulation is the creation and maintenance of markets that are *self-regulating* and *risky* but avoid *danger*. Institutionalizing the distinction between risk and danger is the key to meeting this objective. Risky situations are uncertain but *manageable*. In financial markets, risky decisions are those made by individuals with the skills, tools, experience, and knowledge of the instruments being *managed*. Dangerous situations are those in which risk is *unmanageable*; they can spin out of control and are resolved by outside intervention or their own inertia. Participants in dangerous situations do not control the outcomes. This distinction defines three *roles* of regulators in financial markets:

1. Participating in the creation of rules designed to maintain a self-regulating market with appropriate level of risk for *all* participants
2. Intervening to enforce those rules when markets become *dangerous*
3. Reviewing incidents that became dangerous to determine whether new rules are required or existing rules require better enforcement

The distinction between risk and danger guides the determination of *what* financial instruments are to be covered by particular rules and determines the qualifications of those managing particular instruments—that is, *who* can participate and be subject to the rules. Application of this principle to rule making defines market segments that are self-regulating and risky but avoid becoming dangerous.

As in auto racing, the role of regulators is to intervene when a market becomes dangerous to those whose assets are being managed, those who are using funds under management, and those who provide the link between them. It is not to punish, unless there are flagrant violations; it is not to control strategies or technologies; and it certainly is not to control outcomes of risky decisions. The tools of intervening regulators resemble those of auto racing officials: black flags to stop individuals creating dangerous situations or to stop an entire market if the danger is too great; yellow flags to slow down a market or a portion of it when danger threatens; and green flags to permit full speed when the market is self-regulating.

When a financial meltdown such as the current situation occurs, the role of the financial market regulator is to investigate the incident in the same manner as a serious incident at the racetrack. The purpose of the investigation is to determine the cause—not to blame and punish, unless serious violations occurred, but to prevent such an incident from happening again. The result of such an investigation will be one of three conclusions: This was an accident inherent in the nature of managing financial markets; existing rules were not followed and require better enforcement; or circumstances have changed and new rules are required to accommodate them. If the latter is concluded, rule makers assume the first role, described above, and convene the appropriate participants to begin the process of making new rules.

The evolution of the global economy and new technology demands new forms of financial regulation. The current financial meltdown has demonstrated that Adam Smith's "unseen hand" is an ineffective regulator. Before specific regulations are written, however, the role of regulation and the regulator must be defined. Successfully defining those roles depends on a clear distinction between markets that are *risky* and markets that are *dangerous*.

Reference

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Endnotes

1. This distinction was first made, to the author's knowledge, by Gib Akin, now of the University of Virginia, in his 1977 doctoral dissertation, "The Phenomenology of Risk." It is worth noting that the subjects in Prof. Akin's study included racecar drivers and traders at the Chicago Board of Trade.
2. This model was first used by the author in an article published in the November 2, 1998, issue of *Pensions & Investments* entitled "Black or Yellow Flags on the Market's Track?" by David Hopelain.
3. Lauricella, T. (2008). Stock picker's defeat: a storied investors' big, bad bet. *The Wall Street Journal*, *December 10*, A1.
4. A similar distinction has been made, in a different context, by Frank Sortino. See Sortino, F. (1980). The pension fund: Capital investment or budgeting decision. *Financial Executive*, August, 21–23.

Chapter 9

Sharing Downside Risk in Defined Benefit Pension Funds

Auke Plantinga, Robert van der Meer, and Frank Sortino

Executive Summary

Auke Plantinga, Robert van der Meer, and Frank Sortino offer a new approach for managing downside risk in defined benefit plans that decomposes downside risk in a manner that allows the various parties to evaluate their share of the losses. This chapter is intended to add to the theoretical foundation for applications of downside risk.

Introduction

Pension funds received a lot of attention during recent turbulent stock markets. Many pension funds suffered dramatic losses. Franzoni and Marin (2006) report that defined benefit plans in the United States lost $400 billion in funding levels during the period 2000 to 2002. For 2008, we observe again large problems in the funding ratios of pension funds, mainly due to extremely bad stock markets and falling interest rates. The importance of well-funded pension plans is obvious. Franzoni and Marin (2006) found that the stocks of sponsors with severely underfunded pension plans earn lower returns for at least 5 years after the initial reports of underfunding. This suggests that sponsors have a large interest in proper management of risk for their pension funds. The beneficiaries also have a large interest in proper risk management, in particular because they may not be able to compensate unexpected lower pension benefits at retirement age.

Although exceptional market circumstances may have been the cause for these large losses, it seems also that pension funds were ill-prepared in anticipating adverse market conditions. One reason why risk management of pension funds has received little attention may be due to the fact that it is only remotely linked to the core business of its sponsor. Beneficiaries also paid too little attention to the funding status of their pension funds. Evidence from the behavior of participants in 401 (k) plans shows that employees may not care about their pension prior to receiving actual benefits.[1] However, with more pension funds entering a status of being underfunded, the quality of pensions gets the attention of those involved. Eventually, underfunding will affect all participants involved. Without a strong and sustained recovery of financial markets, the sponsor will have to pay additional premiums and the beneficiaries have to sacrifice benefits. It remains an open question to what extent each participant will suffer from potential losses. With a healthy sponsor, it seems likely that the sponsor is taking a larger share of the losses, whereas a sponsor on the brink of bankruptcy will have little room for covering losses from its pension fund. In many industries, firms have to balance between a struggle for survival and the solvency of their pension fund. For such firms, paying contributions to its pension fund is also finding a balance between the job security of the future beneficiaries (the employees) and the current beneficiaries. In finding this balance, it is important to have *ex ante* information on how future losses will affect the participants in a pension fund.

The objective of this chapter is to develop a measurement model that provides information on how risks are allocated across pension fund participants. We calculate the total risk of the portfolio, and we calculate how risk can be attributed to the individual groups of participants. In order to do this, we use a simulation model and a set of loss allocation rules. Based on the simulation results, we attribute the risk to individual groups of beneficiaries. We use downside risk as a measure of risk, and we use the decomposition of downside risk as proposed by Reed, Tiu, and Yoeli (2008). We decompose downside risk along the risky assets to see where the risk originates and over the groups of participants in the pension fund. This information is important, as it provides the input for evaluating whether the risks are shared in a responsible way.

Downside risk is of interest for investors who value losses differently than gains.[2] It is an appropriate measure for financial risks in a pension fund, because its participants usually do not see the pension fund as a source of profit generation. However, participants may be exceptionally disappointed if the fund is not able to achieve the expected pension benefits or if the fund requires considerable additional premium payments. In addition, the notion of losses and gains may be defined relative to specific targets, which may differ from standard deviation. Downside risk measures accommodate such choices by means of the minimal acceptable rate of return (MAR). Sortino, Van der Meer, and Plantinga (1999) suggested that the main threat to all stakeholders is a shortfall relative to the minimum funding requirements, either now or in future periods. Given that many pension funds currently face funding shortfalls, it is doubtful whether this would be acceptable as a MAR. The reason is that, for these funds, the MAR is well above any reasonable estimate of the expected return on equity. As a result, there may not be feasible investment strategies available. In this study, we use the return on liabilities as a natural choice for the minimal acceptable rate of return. The motivation for this is that, if the asset returns are below the liability return, the surplus of the pension fund decreases in value. With a funding shortfall this would imply a decrease in the value of the expected pension benefits, and with a funding surplus this implies a decrease in the value of the surplus benefits (e.g., premium reduction, premium holidays).

In the next section, we discuss how downside risk can be used in the context of pension funds and how it can be used to increase transparency in terms of the risks shared by its participants. Next, we introduce a stylized pension fund that serves as an example in this chapter. Finally, we construct a simulation study to generate results for the stylized pension fund.

Downside Risk and the Impact on Pension Fund Participants

The main objective of a pension fund is to provide pension payments to its beneficiaries. The main risk of a pension fund is not being able to meet its pension liabilities. Therefore, we use a measure of downside risk where the minimum acceptable return for scenario x is the liability return $r_{l,x}$:

$$DR = \sqrt{\sum_{x=1}^{n} \frac{\iota_x (r_{a,x} - r_{l,x})^2}{n}}, \tag{9.1}$$

where $r_{a,x}$ is the return on the asset portfolio in scenario x; ι_x is 1 for all $r_{a,x} < r_{l,x}$ and 0 in all other cases, and n is the number of scenarios.

The choice of the asset portfolio has a major impact on the downside risk of a pension fund. Assets that correlate well with the liabilities reduce total portfolio risk. On the other hand, assets that correlate well with the liabilities may have low returns. To help participants find an acceptable balance, we propose to use two different decompositions of downside risk. The first decomposition allocates downside risk to individual asset classes. The second decomposition allocates downside risk to the participants.

Reed et al. (2008) have shown how each asset i contributes to total downside risk. We adjust this decomposition by substituting the liability return for the minimum acceptable rate of return:

$$DR_i = \frac{1}{DR} \sum_{x=1}^{n} \frac{w_i \iota_x (r_{l,x} - r_{i,x})(r_{l,x} - r_{a,x})}{n}, \tag{9.2}$$

where w_i represents the market value of asset i as a fraction of total assets, and $r_{i,x}$ is the return of asset i in scenario x. The sum of the individual contributions is equal to total downside risk (DR). A similar decomposition can be made for each j group of participants in the mutual fund:

$$DR_j = \frac{1}{DR} \sum_{x=1}^{n} \frac{w_j \iota_x (r_{l,x} - r_{j,x})(r_{l,x} - r_{a,x})}{n}, \tag{9.3}$$

where w_j represents the value of the claims of participants as a fraction of the total claims, and $r_{j,x}$ is the return to participant group j. The sum of the individual contribution is equal to total downside risk.

A simplified example illustrates our approach. Consider a stylized representation of a pension fund with a sponsor (employer), current beneficiaries (retirees), and future beneficiaries (employees). Assume that the pension board has agreed upon a particular asset portfolio, which is assumed to serve the needs of all participants. The pension fund may invest in stocks and bonds.

In this example, the downside risk of the portfolio is 8%. Table 9.1 shows that 87.5% of this downside risk originates from the position in stocks. The important question is how downside risk is distributed over the participants in the fund. To what extent do the participants face the risk of lower returns on their stakes due to

Table 9.1 Example of asset-based risk decomposition

	Allocation	Contribution to downside risk	Relative contribution
Stocks	60%	7%	87.5%
Bonds	40%	1%	12.5%
Portfolio	—	8%	100%

Table 9.2 Example of participant-based risk decomposition

	Decomposition of downside risk over participants
Sponsor	5%
Current beneficiaries	2%
Future beneficiaries	1%
Total downside risk	8%

asset returns falling below liability returns? There are many different ways of allocating losses over the participants. To some extent these rules are determined by law and to some extent they are the outcome of negotiations between the groups of participants.

A "pure" defined benefit plan promises its beneficiaries fixed benefits. This seems to imply that the sponsor bears all the risk, which means that the reliability of a pension is determined by the ability of the sponsor to cover the losses. At the other extreme is a defined contribution plan, where the beneficiaries take all the risks. In reality, there is usually some level of risk sharing in defined benefit plans. This means that both the sponsor and the beneficiaries will increase premium payments in case of underfunding and that benefits may eventually be lowered. For example, in the Netherlands defined benefit plans face elaborate schemes of risk sharing. Within the Dutch regulatory context, pension benefits will not be updated to inflation if the funding ratio of the fund falls below the minimum requirement of 105%. This implies that the first losses will be absorbed by the retirees. Inflation indexation is only restored if the funding ratio exceeds preset levels. Increases in pension premiums because of low funding ratios are usually paid by sponsors and future beneficiaries. If it is impossible to recover from a too low funding ratio to satisfactory levels, the benefits are reduced.

As an example, Table 9.2 presents a possible outcome of calculating the downside risk for each group of participants. In order to do such a decomposition, we have to create a mathematical representation of the formal and informal rules in reallocating losses across participants. In this example, the sponsor has the largest share in the total downside risk of the pension fund. If the sponsor is not willing or able to bear this share of losses, the analysis could be redone with new allocation rules more in favor of the sponsor.

A Simplified Model of a Pension Fund

To illustrate the use of downside risk attribution in managing a pension fund, we use a stylized model of a pension fund, with a plan sponsor and current and future beneficiaries. The value of the pension fund benefits is calculated as the present value of the future nominal cash flows based on the accrued pension rights of the beneficiaries. The discount rate is based on a market-based interest rate on government bonds. For reasons of convenience, we assume that the term structure of interest rates is flat. We make a distinction between current and future beneficiaries. Current beneficiaries are the retirees, and they are already receiving benefits. The sponsor does not pay premiums for current beneficiaries. Future beneficiaries are the current employees of the sponsor. They receive no benefits yet, but they do pay a premium. The sponsor also pays an annual premium. We use the following variables in defining the balance sheet:

	Assets		**Liabilities**
A	Market value of assets	S	Surplus
		L_r	Present value of cash flows to current beneficiaries
		L_n	Present value of cash flows to future beneficiaries

The value of assets is calculated based on the market value of the underlying securities. The value of the liabilities is calculated as the present value of the future benefits indexed against inflation.

In the first step, we calculate the returns and the balance sheet before reallocating losses. This analysis is focused on the impact of returns of assets and liabilities on the funding ratio. The return on assets is the value-weighted average total rate of return on the asset portfolio:

$$r_a = \sum_{i=1}^{n} w_i r_{a,i}. \tag{9.4}$$

The return on liabilities is defined as the relative change in fair value of the liabilities that existed at the beginning of the period. The return on surplus is:

$$r_s = r_a + (L/S)(r_l - r_a). \tag{9.5}$$

Analyzing the asset returns before reallocating losses provides information on the return and risks as far as investment decisions are considered in isolation; however, the risks in the asset portfolio interact with the distribution of risk over its participants, since high asset risk may result in a high risk for one of the participant groups. Therefore, we also perform a decomposition of risk over the value changes excluding and including the redistribution of losses. Because the mechanism for redistribution is triggered by the funding ratio, we first calculate the funding ratio before reallocating losses:

$$FR_{t+1} = \frac{A(1+r_{a,t}) + P_{t+1} - C_{t+1}}{L_t(1+r_{l,t}) + P_{t+1} - C_{t+1}}, \tag{9.6}$$

where P_t represents the premiums paid to the pension fund and, and C_t is the pension benefits paid to the beneficiaries at time t. At the end of the year, a group of future beneficiaries reaches the retirement age and therefore migrate to the group of current beneficiaries. The present value of their accrued pension benefits equals M_t. The value of the liabilities attributed to the two groups of beneficiaries at time $t+1$ is:

$$L_{r,t+1} = L_{r,t}(1+r_{lr}) - C_{t+1} + M_{t+1} \tag{9.7}$$

$$L_{n,t+1} = L_{n,t}(1+r_{\mathrm{ln},t}) + P_{t+1} - M_{t+1}, \tag{9.8}$$

where r_{ln} is the return to the future beneficiaries and r_{lr} is the return to the current beneficiaries.

Although a low funding ratio usually triggers the process that results in the reallocation of losses, the threshold level that triggers this differs widely among countries and pension funds. In addition, particular types of reallocation may also be triggered by different threshold levels within one pension fund. The reallocation rules used in this example are inspired by those prevalent in the Netherlands.

A unique institutional feature of pension funds in the Netherlands is the shared responsibility of the participants for the financial health of the pension fund. Dutch pension funds are governed jointly by representatives of the employers and the employees. With sufficient surplus in the pension fund, the benefits of the retirees are updated to compensate for inflation. With excess surplus, premium payments can be lowered, and the sponsor is sometimes exempted from paying premiums (the so-called premium holiday). When the funding ratio of a pension fund falls below a critical threshold level, a process is triggered that will allocate the losses directly over the participants in the fund. This may limit the benefits of the different groups of beneficiaries and increase the premiums. The exact allocation of losses over retirees, active members, and sponsors depends on the legal environment, rules specific for the pension fund, and the outcomes of bargaining. For reasons of simplicity, we assume that the surplus is owned by the sponsor. In reality, this is not representative for the Dutch institutional setting, as the pension fund is an independent entity. Both the sponsor and the beneficiaries can benefit from the surplus.

In compliance with legal requirements, the fund has to cease inflation indexation for the current beneficiaries if the funding ratio is below 105%. Given that we have modeled the liabilities as real cash flows, this means that the liabilities are reduced by the level of realized inflation π_t over the period t to $t+1$. The reduction of the liabilities by $(1-\pi)L_{r,t}(1+r_{lr})$ may be sufficient to cover the pension fund's losses, and no further action is necessary. However, if losses turn out to be larger than those covered by the value of the indexation of retired beneficiaries, further action is necessary. We assume that when this happens, the future beneficiaries and the sponsor will increase the pension premiums a sufficient amount to regain a funding ratio of 105% in five years' time. In the simulation study, we have assumed that the increase in premium is equally shared between the future beneficiaries and the sponsor. Although the exact course of action depends on the outcome of negotiations between the sponsor and the beneficiaries, we believe that this is a reasonable way to model this process. The redistribution of losses Δ_s (surplus), Δ_n (future beneficiaries), and Δ_r (current beneficiaries) is the difference in the value of each group of participants' claims after and before the redistribution. Because this involves a value neutral redistribution, these components add up to zero:

$$\Delta_s + \Delta_n + \Delta_r = 0. \tag{9.9}$$

To analyze the impact of the redistribution of losses on performance of the fund's participants, we adjust the returns by including these redistributions. The return on surplus becomes:

$$r_s' = \frac{S_{t+1} + \Delta_s}{S_t}. \tag{9.10}$$

The return on the value of the claim of future beneficiaries becomes:

$$r_{ln}' = \frac{L_{n,t}(1+r_{ln}) + \Delta_n}{L_{n,t}}. \tag{9.11}$$

And the return on the value of the claims of current beneficiaries becomes:

$$r'_{lr} = \frac{L_{r,t}(1+r_{lr}) + \Delta_r}{L_{r,t}}. \tag{9.12}$$

A Simulation Experiment

To illustrate the proposed model for managing downside risk in a pension fund, we discuss the outcomes of a simulation study involving a stylized pension fund. The assets and liabilities of the fund are presented in the following balance sheet:

	Assets		**Liabilities**
3700	Market value of assets (mln)	336	Surplus (million)
		1151	Liabilities of current beneficiaries (mln)
		2212	Liabilities of future beneficiaries (mln)

The fund invests in stocks, nominal bonds, and real (inflation-linked) bonds. For reasons of simplicity, we assume that the maturities of the bonds are matched with the liabilities. Given that the liabilities are linked to inflation, inflation-linked bonds are the least risky assets. Currently, the portfolio has an allocation of 55% to stocks, 20% to nominal bonds, and 25% to real bonds. To assess the risks of this portfolio, we have designed a simulation study. We generate 1000 simulation runs, where each run represents an economic scenario with inflation levels, interest rates, bonds, and returns. In calculating the returns of beneficiaries and the surplus, we have ignored the impact of bankruptcy. The descriptive statistics of the assets and the liabilities for these simulation runs are provided in Table 9.3.

Based on the outcomes of the simulation study, we are able to calculate downside risk measures for the pension fund. In Table 9.4, we present the statistics on the asset portfolio. The portfolio has a downside risk of 11.87%, which is mainly attributed to stocks, which has a contribution of 11.12% to the total portfolio downside risk.

The contribution of inflation-linked bonds to total downside risk is zero, due to its ability to match with the inflation-index liabilities and the low weight in the portfolio. The nominal bonds contribute 0.75% to the portfolio's downside risk, which is 6.32% of the total downside risk. Stocks generate the bulk of the risk by contributing 11.12%. Notice that the risk contribution is not linearly related to the portfolio weights. Stocks represent 55% of the portfolio in terms of market value but 93.68% in terms of downside risk.

Table 9.3 Risk and return characteristics of assets and liabilities

	Stocks	Bonds	Inflation-linked bonds	Liabilities (current beneficiary)	Liabilities (future beneficiary)
E[r]	7.41%	5.28%	3.98%	7.41%	6.56%
σ	32.38%	16.64%	7.35%	32.38%	22.61%
			Correlation coefficients		
Stocks	1.000	0.314	0.289	0.270	0.270
Bonds	0.314	1.000	0.506	0.489	0.489
Inflation-linked bonds	0.289	0.506	1.000	0.966	0.968

Table 9.4 Risk characteristics of the asset portfolio

Summary stats	Stocks	Bonds	Inflation-linked bonds	Portfolio
Weights	55.0%	20.0%	25.0%	100.0%
E[r]	7.41%	5.28%	3.98%	6.13%
σ	32.38%	16.64%	7.35%	19.82%
Downside variance	1.32%	0.09%	0.00%	1.41%
Downside risk	11.12%	0.75%	0.00%	11.87%
Relative contribution	93.68%	6.32%	0.00%	100.00%

In Table 9.5, we present the decomposition of risk over the participants before and after redistributing losses. Panel A shows the return and risk for all participants before any redistribution of losses. First, we observe that the claims of the sponsor and the current and future beneficiaries are risky in terms of standard deviation; however, in terms of downside risk, the claims of the beneficiaries have almost no risk at all. In other words, the choice of the risk measure also changes the perception of risk. Without redistribution of losses, the sponsor bears all the risk. It is obvious that this is not desirable for the sponsor, although it may not be desirable for the participants, as well. By allocating all the risk to the sponsor, it is also more

Table 9.5 Decomposition of risk over participants

	Surplus	Future beneficiaries	Current beneficiaries	Portfolio
Weights of participant's claim	9.1%	59.8%	31.1%	100%

Panel A. Decomposition of downside risk before redistribution

	Surplus	Future beneficiaries	Current beneficiaries	Portfolio
E[r]	27.62%	4.24%	3.48%	6.13%
σ	202.59%	9.80%	2.65%	19.82%
Downside variance	1.41%	−0.01%	0.01%	1.41%
Downside risk	11.87%	−0.08%	0.08%	11.87%
Downside share	100.00%	−0.65%	0.65%	100.00%

Panel B. Decomposition of downside risk after redistribution

	Surplus	Future beneficiaries	Current beneficiaries	Portfolio
E[r]	50.58%	1.88%	1.89%	7.03%
σ	170.18%	12.42%	4.37%	20.87%
Downside variance	0.87%	0.40%	0.14%	1.41%
Downside risk	7.33%	3.36%	1.17%	11.87%
Downside share	61.77%	28.34%	9.89%	100.00%

likely that the sponsor faces bankruptcy. This would result in future beneficiaries losing their jobs and both groups of beneficiaries losing the backup of the sponsor in cases where the pension fund has a low funding ratio but the sponsor is in good financial health. In other words, the pension fund aligns the interests of the sponsor and the beneficiaries in such a way that they may be willing to share losses.

In panel B, we present the analysis after redistributing the losses, based on the rules specified above. The redistribution of losses results in lower downside risk for the sponsor and some downside risk for the beneficiaries. The sponsor bears 62%

of the downside risk and the beneficiaries 38%. From the perspective of the sponsor, this is an improvement. Nevertheless, the risk may still be too high for the sponsor, and this may create the need for different loss distribution rules. These rules can be evaluated using the same simulation model. The actual choice for a particular model should be the outcome of balancing the interests of sponsor and beneficiaries.

In addition to the direct allocation of losses over participants, risk sharing will also be affected by the level of risk in the portfolio. In Table 9.6 we present the impact of different asset allocations for the risk sharing among participants given

Table 9.6 Asset allocation and risk sharing

Asset allocation			Down side risk	Risk allocation over participants		
Stocks	Bonds	Inflation-linked bonds		Sponsor	Future beneficiaries	Current beneficiaries
0	0.2	0.8	1.98%	1.89% (95.8%)	0.00% (0.0%)	0.09% (4.2%)
0.1	0.2	0.7	3.17%	2.72% (86.0%)	0.16% (5.3%)	0.28% (8.7%)
0.2	0.2	0.6	4.94%	3.76% (76.0%)	0.72% (14.5%)	0.47% (9.5%)
0.3	0.2	0.5	6.87%	4.78% (69.6%)	1.42% (20.6%)	0.67% (9.7%)
0.4	0.2	0.4	8.86%	5.80% (65.6%)	2.18% (24.6%)	0.87% (9.8%)
0.5	0.2	0.3	10.86%	6.82% (62.8%)	2.97% (27.3%)	1.07% (9.9%)
0.6	0.2	0.2	12.89%	7.84% (60.9%)	3.76% (29.2%)	1.28% (9.9%)
0.7	0.2	0.1	14.92%	8.87% (59.4%)	4.57% (30.6%)	1.48% (9.9%)
0.8	0.2	0	16.95%	9.89% (58.3%)	5.38% (31.2%)	1.68% (9.9%)

the rule for distributing losses. Portfolios without stocks have little downside risk, and most of it is allocated to the sponsor. Increasing the risk level of the portfolio means that a larger share of the risk is allocated to the beneficiaries; however, this does not imply that the sponsor has an interest in increasing the risk. The risk contribution of the sponsor is also increasing in downside risk terms, so more stocks means more risk for the sponsor as well, despite the fact that the sponsor's relative share in total downside risk is decreasing.

Table 9.6 suggests that a portfolio without stocks is the least risky for all participants involved. This does not mean that this portfolio is optimal for all groups of participants. The ultimate choice will also depend on the upside potential. Usually, the rules for sharing the upside potential are very favorable for the sponsor, who can often claim the entire surplus above some maximum funding ratio. As a result, the sponsor may be willing to take more risk.

Conclusion

In this study, we have developed an attribution framework for evaluating the downside risk for groups of participants in a pension fund. This presentation format is based on decomposing downside risk over the participants involved in a pension fund. To do this, it is necessary to develop a simulation model for creating different economic scenarios of asset and liability returns. In addition, it is necessary to specify rules for distributing losses over participants. These rules can be derived from the legal environment, including bankruptcy laws, pension law, and the pension charter. Next to the formal rules, there are informal rules that are dictated by negotiations and the willingness of participants to share losses. The decomposition of downside risk allows the group of participants to evaluate their relative share in the losses. This may facilitate the discussion between sponsor and beneficiaries on strategies in times of underfunding.

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Endnotes

1. See, for example, Madrian & Shea (2001) or Benartzi & Thaler (2002).
2. See Sortino & van der Meer (1991).

Chapter 10

On the Foundation of Performance Measures Under Asymmetric Returns

Christian S. Pedersen and Stephen E. Satchell

Executive Summary

We examine two performance measures advocated for asymmetric return distributions: the Sortino ratio—originally introduced by Sortino and Price (1994)—and a measure based on power utility introduced in Leland (1999). In particular, we investigate the role of the Maximum Principle in this context, and assess the

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conditions under which the measures satisfy it. Our results add further motivation for the use of a modified Sortino Ratio, by placing it on a sound theoretical foundation. In this light, we discuss its relative merits compared with alternative approaches.

JEL Classification: G00, G11, G12

Keywords: Asymmetry, Maximum Principle, Performance Measurement

Introduction

When distributions are symmetric and the classical mean-variance Capital Asset Pricing Model (CAPM)—most often attributed to Sharpe (1964), Lintner (1965) and Mossin (1969)—valid, performance measures can be extracted directly from the model. In particular, from the empirical representation, three classical statistics are most commonly employed: the Sharpe ratio, introduced in Sharpe (1966); the Treynor Index, derived in Treynor (1965); and Jensen's Alpha, which was developed by Jensen (1972). However, when returns are asymmetric and mean-variance rules no longer efficient, these measures cease to capture the essential features of the distribution. Whilst this has been a widely recognised problem in Finance, not least due to the presence of skewness in much financial data, only recently have remedies for this been advanced.

Sortino and Van der Meer (1991) advance the square root of the second lower partial moment, i.e.

$$\theta_{r_p}(t) = \left(\int_{-\infty}^{t} (t - r_p^{\%})^2 pdf(r_p^{\%}) dr_p^{\%} \right)^{\frac{1}{2}} \tag{10.1}$$

as a measure of risk, rather than standard deviation. In (1), t can be a fixed, observable or random target, or a combination of these categories. It is often defined as the rate of return on a long-dated bond or Treasury Bill. Also, $r_p^{\%}$ denotes return on portfolio p with density function pdf $(r_p^{\%})$. We shall follow the popular literature and define the above as the *semi-standard deviation* and its square as the *semi-variance*, although strictly speaking such terminology is correct only when $t = E(r_p^{\%})$ The semi-variance only takes positive values for returns below t and is therefore sensitive to both skewness in the data and the probability of shortfalls, unlike variance, which weighs extreme positive and negative outcomes equally. Based on this measure of risk, Sortino and Price (1994) introduce the Sortino Ratio,

$$\frac{\bar{r}_p - t}{\theta_{r_p}(t)} \tag{10.2}$$

where θ_{r_p} is the semi-standard deviation and $\bar{r}_p$ denotes average returns. A modified version of this, namely

$$\frac{\bar{r}_p - r}{\theta_{r_p}(t)} \tag{10.3}$$

where r denotes the risk-free asset, is put forward as a competing performance measure in this article. This is equivalent to the Sharpe Ratio except standard deviation has been replaced by the semi-standard deviation (1) in the denominator.[1] We note that, although the earlier performance measure (2) implies that the riskless asset would have infinite performance when $t \leq r$, this is not the case with (3), when the performance of the riskless asset becomes undefined (as it does with the Sharpe ratio). In this article, we shall add support for the use of (1) as risk measure by drawing on theoretical risk work and equilibrium arguments, essentially showing it relies upon assumptions no more obscure than the Sharpe ratio itself.

Very recently, Leland (1999) has used options strategies and equilibrium theory to illustrate the shortcomings of CAPM-based performance measures, and argued for alternative approaches. In particular, he uses results from Rubinstein (1976), Brennan (1979) and He and Leland (1993) to argue the case for a representative agent "CAPM" based on power utility. The power utility model implies the empirical equation

$$E[r_p^{\%} - r] = \left[\frac{cov\left[r_p^{\%}(1+r_m^{\%})^{-b}\right]}{cov\left[r_m^{\%}(1+r_m^{\%})^{-b}\right]} \right] E[r_m^{\%} - r] \tag{10.4}$$

where b is a constant such that $b > 0$, $r_m^{\%}$ is the return on the market and r is the risk-free rate of return. This model can capture skewness in data, since expanding expected utility gives an expression in the higher moments of returns. Also, Leland shows that under certain market conditions, the risk measure

$$B_p = \frac{cov\left[r_p^{\%}(1+r_m^{\%})^{-b}\right]}{cov\left[r_m^{\%}(1+r_m^{\%})^{-b}\right]} \tag{10.5}$$

determines the risk of any fairly priced asset, even those exhibiting highly asymmetric returns. The performance measure Leland favours is the analogue of Jensen's Alpha (see Jensen (1972) for details) in this setting, namely

$$A_p = E[r_p^{\%}] - r - B_p(E[r_m^{\%} - r]) \tag{10.6}$$

This measures excess return after correcting for risk using a general equilibrium risk measure derived from a representative agent with power utility.

Although both Sortino's and Leland's work are motivated by the need for skewness to be captured by equilibrium risk measures, there might appear to be sharp differences between their approaches, not least because Leland's aim is to look at excess performance in a fashion similar to Jensen's Alpha, whilst the Sortino ratio extends the Sharpe ratio. It is our contention that one can motivate both these classical performance measures by similar arguments, and we shall use such methods to provide support for the original and modified Sortino ratios, which hitherto have not been formally placed in a theoretical framework. This thus also addresses an assertion by Leland, who refers to Sortino and Price's extension (2) as an "*ad hoc*" measure which is "*not grounded in capital market equilibrium theory*" (see Leland (1999), page 34, endnote 4), and will hopefully help dispel possible doubts amongst practitioners considering its use.

The paper is organised as follows: In the next section, we present the Maximum Principle, which is commonly deemed a necessary property of a good performance measure, and discuss its relevance for the modified Sortino ratio (3): in particular, Section 2.1 looks at the nature of the mean-semi standard deviation efficient frontier, whilst Section 2.2 considers the possibility of deriving a representative agent with mean-semi standard deviation preferences using support from both risk theory and economic equilibrium arguments. Section 3 is reserved for our conclusions.

The Maximum Principle and the Modified Sortino Ratio

We shall put forward a view of a performance measure as a measure that ranks portfolios both for individual investors and for the representative investor, who holds the market portfolio. Such a measure should be maximised by the representative investor, so that if one exceeds that maximum, the presence of special information or skills can be inferred. This maximality of the market is what we refer to as the Maximum Principle. The idea behind this already exists in the literature. Most notably, Grinblatt and Titman (1989) propose a measure referred to as the "positive period measure", which is zero for the market, but positive in the presence of good market timing and/or stock selection abilities. The next Proposition presents two conditions under which a performance measure in general satisfies the Maximum Principle.

Proposition 1

The Maximum Principle is satisfied if either of the following two conditions is satisfied:

1. The performance measure is based on the maximised expected utility of the representative agent.
2. The performance measure is the ratio of the excess expected return to the risk measure, the efficient frontier is linear and the market portfolio is efficient.

Proof

In case 1, the proof is immediate. In case 2, since the efficient frontier is linear, the ratio of expected excess return to the risk measure along it is constant. Thus, since the market portfolio is efficient and lies on the frontier, it maximises the performance measure ■

Whilst there may be other conditions that guarantee the Maximum Principle, Proposition 1 implies that Leland's performance measure (6) satisfies the Maximum Principle by the first condition, whilst the Sharpe ratio satisfies the Maximum Principle by the second condition. The question that now arises, is whether the modified Sortino ratio (3) will satisfy the Maximum Principle. In accordance with Proposition 1, such an analysis can be approached in at least two ways. We shall first investigate the nature of the mean-semi standard deviation efficient frontier; in Section 2.2, we then examine the conditions in which one gets a representative agent with mean-standard deviation decision characteristics.

The Mean-Semi Standard Deviation Frontier

In this section, we examine the nature of the efficient frontier when investors have mean-semi standard deviation preferences, where we make the assumption that two-fund money separation (TFMS)—i.e. that all investors choose a mixture of the riskfree asset and the same risky portfolio, though not necessarily the same mixture—is attained. We let μ_p denote the mean return of a portfolio p with return $\tilde{r}_p w$, is the weight in the risky portfolio with return $\tilde{r}_k$, and r is the riskfree return. Then, by definition, for w assumed positive,

$$r_p^{\%} = w_k^{\%} + (-w)r \tag{10.7}$$

Furthermore, if the target, t, is a given constant, the semi-variance can be written as

$$\theta_{r_p}^2(t) = \int_{-\infty}^{t} (t - r_p^{\%})^2 pdf(r_p^{\%}) dr_p^{\%} \tag{10.8}$$

where $pdf\ (r_p^{\%})$ denotes the probability density function of $\tilde{r}_p$. To illustrate our inferences about the (μ_p, θ_{r_p}) frontier, we find working with $pdf\ (r_k^{\%})$ more informative.

By changing variables, we get

$$\theta_{r_p}^2(t) = \int_{-\infty}^{\frac{1}{w}(t-(1-w)r)} (w(r_k^{\%} - r) + r - t)^2 pdf(r_k^{\%}) dr_k^{\%} \tag{10.9}$$

By differentiating (9) w.r.t. w, substituting for $\frac{\partial \mu_p}{\partial w} = \mu_k - r$, and for w by rearranging the expectation of (7)-i.e. $w = \frac{\mu_p - r}{\mu_k - r}$ - we derive the $\left(\mu_p, \theta_{r_p}\right)$ frontier given by

$$\theta_{r_p}(t) = \frac{(\mu_p - r)^{\frac{1}{2}}}{\mu_k - r} \left[\int_{-\infty}^{\frac{(\mu_k - r)t - (\mu_k - \mu_p)r}{\mu_p - r}} [(\mu_p - r)(r_k^{\%} - r) + (r - t)(\mu_k - r)]^2 pdf(r_k^{\%}) dr_k^{\%} \right]^{\frac{1}{2}} \tag{10.10}$$

This is clearly non-linear, which has implications for the concavity/convexity of the efficient frontier, and thus also for equilibrium arguments and the Maximum Principle. Harlow and Rao (1989) show that the frontier of $\left(\mu_p, \theta_{r_p}^2\right)$ is concave; however, this has no implication for the concavity/convexity of $\left(\mu_p, \theta_{rp}\right)$ The following theorem resolves this issue; the proof is in the Appendix.

Theorem 1

In the TFMS case, for $t < r$, the $\left(\mu_p, \theta_{rp}\right)$ -frontier is concave if $0 < w < 1$ and convex for $w > 1$. At $w = 1$ it has a point of inflection. If $t = r$, the frontier is linear.

It follows from the above theorem that when $t < r$, in order to maximise the Sortino ratio one should increase w when $w > 1$, and decrease w when $w < 1$. Hence, if short sales (and borrowing) are disallowed, the Sortino ratio is maximised at the point where one holds zero equity. A representative agent who follows the Maximum Principle would thus hold only bonds, which is not consistent with an equilibrium in any economy with a positive supply of stocks. Indeed, these are the arguments that have raised doubts about the Sortino ratio. The question then arises as to whether there are other conditions in which the Maximum Principle may be true. The following Proposition establishes such a condition.

Theorem 2

If $w > 0$, so the representative agent holds some equity, and the representative agent has a mean-semivariance utility function-to be defined in (13)-with target

$$t = r + wt^* \tag{10.11}$$

for some $t^* \leq 0$ then the mean-semi standard deviation frontier is linear and the modified Sortino ratio (3) satisfies the Maximum Principle.

Proof

Under this parameterisation, by substituting (11) into (9), one observes that $\theta_{r_p}^2$ (t) simplifies to

$$\theta_{r_p}^2(t) = w^2 \int_{-\infty}^{r+t^*} [(r_k^{\%} - r) - t^*]^2 pdf(r_p^{\%}) dr_p^{\%}$$

$$= w^2 \int_{-\infty}^{r+t^*} [r_k^{\%} - (r+t^*)]^2 pdf(r_p^{\%}) dr_p^{\%}$$

$$= w^2 \theta_{r_p}^2 (r+t^*) \qquad (10.12)$$

Hence, from (10) and (12), it is apparent that both θ_{r_p} and $\mu_p - r$ are linear in w; thus, the (μ_p, θ_{r_p}) - frontier is linear.

We have thus established conditions in which the modified Sortino ratio satisfied the Maximum Principle. One feature of this result is that the condition (11) would imply targets changing with the optimal allocation w; i.e. the target would be endogenous and so the axioms of expected utility may not hold. (In the conventional case, the target would have been exogenous to the process.) Without digressing into a discussion of the merits or failings of Expected Utility Theory, we mention that there is a large literature which deals with examining how target-based preference may be applied in Finance without necessarily satisfying the expected utility axioms (e.g. see Francke and Weber (1997) or Ang, Bekeart et al (2000) where a large bibliography can be found) precisely by making targets endogenous or functions of initial wealth. This is furthermore related to the standard practice that a portfolio composed of different asset classes (e.g. cash, bond, equity), would need different benchmarks for each class.

Thus, there are plausible criteria under which the Sortino ratio might satisfy the Maximum Principle. We next explore this further by considering a utility representation of the mean-semi standard deviation preferences and examine when a representative agent exists in such conditions.

Representative Agent and Equilibrium

The Leland (1999) approach to performance measurement involves showing the existence of a representative agent (in his case with power utility) whose optimal portfolio is that of the market as a whole. In this section, we shall investigate the representative agent in the case where individual investors have mean-semi standard deviation preference, discussing the assumptions necessary to ensure existence. We further include some motivation on the use of mean-standard deviation preferences to address Leland's criticisms of the Sortino ratio, as outlined in the Introduction.

The link between mean-semi standard deviation preferences and expected utility was formally established by Fishburn (1977), who showed that a decision rule based on expected returns and semi-variance (and thus also semi-standard deviation (1)) is congruent with Expected Utility Theory only if the utility function[2] takes the form

$$U(r_p^{\%}) = \begin{cases} r_p^{\%} & r_p^{\%} \geq t \\ r_p^{\%} - c(t - r_p^{\%})^2 & r_p^{\%} > t \end{cases} \tag{10.13}$$

where t and c are constants, where c satisfies $c > 0$. Note that by taking expectations of (13), one gets

$$E[U(r_p^{\%})] = E(r_p^{\%}) - cE\left[(t - r_p^{\%})^2 (r_p^{\%} < t)\right] \tag{10.14}$$

$$= E(r_p^{\%}) - c \int_{-\infty}^{t} (t - r_p^{\%})^2 pdf(r_p^{\%}) dr_p^{\%}$$

$$= \mu_p - c\theta_{r_p}^2(t)$$

Thus, expected utility is a trade-off between mean and semi-variance. Essentially, this is analogous to quadratic utility in conventional mean-variance analysis except the risk measure is now (1) rather than conventional standard deviation. This can be contrasted with the Leland (1999) utility function which, despite following from his assumptions, does not explicitly transform to comparable risk and return measures.

The choice of (1) as risk measure and consequently (13) as utility function is far from random. In Fishburn (1980 and 1981), the author gives an elegant justification for the use of formal asymmetric risk measures including the semi-standard deviation (1), by imposing a series of plausible restrictions on the underlying preference relations. His general approach was to split the return distribution into a loss probability, a gain probability and conditional measures of return levels *given* a loss or gain, where loss/gain was measured relative to an arbitrary target, t. Such a structure has since been adapted by financial econometricians (see for instance Knight et al. (1995)) as an appropriate way to statistically model asymmetric financial time series. More recently, the use of the Sortino ratio as a performance measure in practice has also been evident by its application on a large number of Web-based performance rating companies (see, for instance http://www.cta-online.com/, http://www.cradv.com/ or http://www.worthtrading.com/).

The use of downside risk measures has been advocated by numerous academics and practitioners in Finance, and serve a broad range of functions. As early as the original mean-variance text of Markowitz (1952), the author points to the semi-variance as an attractive risk measure, but is dissuaded from examining it further at the time due to it's computational and algebraic unfriendliness. Later authors have linked downside risk to stochastic dominance and popular risk-ranking literature (see, for instance, Bawa (1975) or Menezes, Geiss et al. (1980)). Several other advance asset pricing models based on numerous different downside risk measures (see Roy (1952), Bawa and Lindenberg (1977), Harlow and Rao (1989) or Salomon Brothers (1989)). Empirically, these models were shown to be favourable to CAPM at explaining small company returns (see Pedersen (1998)). For an extensive bibliography of relevant works, we refer the reader to Pedersen (1999b). Very recently downside risk was taken in a new direction and linked with derivatives portfolio optimisation (see Huang et al. (2001) and Pedersen (2001)). Finally, we mention that the large amount of interest in loss aversion utility functions, which can be extracted from Prospect Theory (see Kahnemann and Tversky (1979)) and were illustrated in Fishburn and Kochenberger (1979), is yet another reason why semi-variance and other downside risk measures have received renewed interest. We hence claim that there is nothing *ad hoc* at all about the choice of risk measure in the denominator of the Sortino ratio (2). However, the question of whether this, or the modified Sortino ratio (3), can be justified as a performance measure in an equilibrium setting, still needs to be addressed.

In this regard, we shall compare the underlying assumptions needed to establish the required conditions with the standard assumptions made in traditional and comparable models. The Leland (1999) performance measure (6) and the three classical performance measures (the Sharpe ratio, Treynor's Index and Jensen's Alpha) are all rooted in versions of the Capital Asset Pricing Model, originally presented by Sharpe (1964), Lintner (1965) and Mossin (1969) but where, rather than quadratic utility, Leland uses a representative agent who has power utility with an exponent less than one. Bawa and Lindenberg (1977) and Harlow and Rao (1989) derived equilibrium pricing models which were identical to CAPM, except investors minimise the semi-standard deviation (1). However, as was pointed out by Chow and Denning (1994), neither set of authors proves the existence of equilibrium without making assumptions that automatically validate the original mean-variance CAPM. Hence, they argued, there were still no conditions presented in the literature proving the existence of such downside risk asset-pricing models in a world where CAPM was not equally suitable. The Sharpe ratio remained the appropriate, best theoretically supported, performance measure.

We will draw upon a result in Satchell (1996)—which was later generalised in Pedersen (1999a) to include more general asymmetric preferences—and consider an equilibrium model obtained under certain parameter restrictions, but without restrictive distributional assumptions. To do this, we assume that individual investors have piece-wise utility functions as given by (13), but otherwise maintain all the standard assumptions of CAPM. The crucial step is to prove that two-fund money separation (TFMS)—i.e. the property that all investors choose to invest in a mixture of the riskless asset and a fixed risky portfolio—obtains, which enables aggregation and thus allows one to characterise the utility function of the representative agent. We thus state two theorems, which are the main results in Satchell (1996); their proofs, and further details and discussion, can be found in the original text. The first theorem addresses TFMS, making trivial non-restrictive distributional assumptions.

Theorem 3 (Satchell, 1996)

Suppose that there are K individuals indexed $k = 1,2,\dots K$. Individual k has positive initial wealth W_{0k}, wealth target $h^k = W_{0k}(1+t^k)$, where $t^k < r$, and utility function

$$U_k(W) = \begin{cases} W & W \geq h^k \\ W - \lambda^k (h^k - W)^2 & W < h^k \end{cases} \tag{10.15}$$

where $\lambda^k > 0$ and h^k is a real number. In addition, we assume that

$$\lambda^k = (W_{0k} f^k)^{-2} \tag{10.16}$$

for all k, where

$$f^k = 1 - \frac{t^k}{r} > 0 \tag{10.17}$$

and that the joint distribution of returns assigns positive probability to the events $W < h^{\mathrm{k}}$ and $W \geq h^{\mathrm{k}}$ Then, if all investors hold the risky portfolio long, TFMS obtains and fk is the fraction invested by agent k in the risky portfolio.

We reiterate that the expected utility given (15) was shown earlier to be of the form "expected return minus risk", where risk is denied as (1), as discussed earlier. This result hence gives conditions under which the Maximum Principle may be satisfied for the modified Sortino ratio through the second part of Proposition 1. The following theorem establishes the existence of a representative agent in an economy full of agents with such preferences.

Theorem 4 (Satchell, 1996)

When all individuals satisfy the conditions of the last theorem, aggregate demand is identical with that of a single representative consumer whose initial wealth is $W_m = \sum_k W_{0k}$, target $h^m = W_m(1+t^m) = \sum_k h^k$, where $t^m = \frac{\sum_k W_{0k} t^k}{W_m} < r$, and utility function given by

$$U(W) = \begin{cases} W & W \geq h^m \\ W - \lambda (h^m - W)^2 & W < h^m \end{cases} \tag{10.18}$$

where $\lambda = (W_m f_m)^{-2}$ and $f_m = 1 - \frac{t^m}{r} > 0$.

Hence, there are conditions under which TMFS and aggregation hold for an economy, in which people have mean-downside risk preferences. We note that the above results are not in conflict with the necessity results on TFMS in Cass and Stiglitz (1970) since our wealth targets, h^k, which are part of the specification of investor's utility functions, depend on initial wealth W_{0k}, a similar restriction to that of having optimal allocations affecting targets, as in Theorem 2. Having showed the existence of a representative agent, we state the following corollary without proof, which describes the representative agent in the case of a linear frontier, which thus formally links the analysis with that conducted in the previous section.

COROLLARY

If $t^m = r + f_m t_m^* < 0$, as in Theorem 2, the (μ_p, θ_{r_p}) - frontier is linear so that the modified Sortino ratio (3) satisfies the Maximum Principle.

This argument can be taken one step further. When a representative agent with utility function $U(W)$ exists, the first order conditions of his optimisation problem can be rearranged (see, for instance, Huang and Litzenberger (1988), Chapter 6) to give

$$E[r_p^{\%} - r] = \left[\frac{cov\left[r_p^{\%} U'(W)\right]}{cov\left[r_m^{\%} U'(W)\right]} \right] E[r_m^{\%} - r] \tag{10.19}$$

This relationship holds for all utility functions which are strictly increasing and concave. With power utility, this yields the Leland model (4). For our representative agent's utility function (18), which satisfies the sufficient conditions to apply (19), one gets the equilibrium risk measure

$$\beta = \frac{cov\left[r_p^{\%} \Delta (t - r_m)^2\right]}{cov\left[r_m^{\%} \Delta (t - r_m)^2\right]} \tag{10.20}$$

where $\Delta = 1$ if $W < h$ and 0 otherwise. Hence, purely by choosing alternative utility functions and making no market assumptions other than those in the traditional CAPM, an alternative capital markets equilibrium characterisation may be established. This result should be compared with the results of Bawa and Lindenberg (1977) and Harlow and Rao (1989), where similar beta's were derived, albeit without a representative agent.

The results we have demonstrated in this section were derived on the grounds of Proposition 1(1), namely that performance is based on the maximised expected utility of the representative agent. In doing so, we have also demonstrated Proposition 1 (2), i.e. that the frontier can be linear. Together, these arguments show that the models which lead to the use of more general performance measures such as the Sortino ratio are based on theoretical foundations comparable to those underpinning the

Sharpe ratio and, what is more, use similar representative agent and equilibrium techniques to those applied in the power-utility CAPM advocated by Leland (1999).

Conclusions

A sensible measure of an economic or financial relationship customarily follows as the consequence of an equilibrium in a model that is consistent with known characteristics of observable data. Our arguments for the use of the semi-variance are to correct the belief that the semi-variance has no theoretical foundations and to advance the modified Sortino ratio as a performance measure, whose origins are as sound as alternative measures. To support this, we have referred to existing axiomatic approaches to downside and asymmetric risk from Mathematical Psychology, which derive the semi-variance from first principles, and have listed further advocates of the use of downside risk. Also, we have shown that there exists a utility-based one-period capital market equilibrium model which is akin to replacing the standard deviation by semi-standard deviation as risk measure in CAPM, and thus provides motivation for the Sortino ratio exactly like the CAPM promotes use of the Sharpe ratio. This model does not rest on assumptions about the distributional properties of the market portfolio, but requires the existence of a representative agent; we have given results which prove that, under certain conditions, such a representative agent exists.

Practitioners today already use semi-variance as a risk measure and mean-semi variance optimization methods have been used sporadically since their introduction by Markowitz (1952). We hope our results go some way to remove potential doubt about the appropriateness of using measures derived from downside risk considerations (and the Sortino ratio in particular) amongst practitioners, and encouraged further development in this field.

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ENDNOTES

1. We have to exclude the case $t > r$, as this implies that, at $\bar{r}_p = r, \theta_{r_p}(t) \neq 0$, and a riskless asset is not regarded as riskless.
2. In fact, Fishburn's result holds for (13) where the exponent of $(t - r_p^{\%})$ is $b \geq 2$. Hence, there are other risk measures for which the congruency can be established. For the purposes of this paper, we restrict ourselves to the relevant case $b = 2$.

Appendix. Proof of Theorem 1

The case for $t = r$ is proved in Harlow and Rao (1989). Recalling (7)

$$r_p^{\%} = wr_k^{\%} + (-w)r \tag{10.21}$$

for $t < r$, it suffices to show that, when $0 < w < 1$,

$$(1-w)\theta_r(t) + w\theta_{r_k}(t) \leq \theta_{r_p}(t) \tag{10.22}$$

and when $w > 1$,

$$(1-w)\theta_r(t) + w\theta_{r_k}(t) \geq \theta_{r_p}(t) \tag{10.23}$$

Now, since $t < r, \theta_r(t) = 0$, it suffices to show that

$$w\theta_{r_k}(t) \geq \theta_{r_p}(t) \Leftrightarrow w \geq 1 \tag{10.24}$$

To see this is true, note that $w\theta_{r_k}(t) \geq \theta_{r_p}(t) \Leftrightarrow w^2\theta^2_{r_k}(t) \geq \theta^2_{r_p}(t)$. Hence, using (9),

$$\begin{aligned}\theta^2_{r_p}(t) &= w^2 \int_{-\infty}^{\frac{1}{w}(t-(1-w)r)} \left(r_k^{\%} - \left[\frac{t-(1-w)r}{w}\right]\right)^2 pdf(r_k^{\%})d_k^{\%} \\ &= w^2\theta^2_{r_k}\left[\frac{t-(1-w)r}{w}\right]\end{aligned} \tag{10.25}$$

Now, by definition, $\theta^2_{r_f}(t)$ is an increasing function of t (since, if the target increases, a larger part of the distribution contributes to risk). Thus,

$$\begin{aligned}\theta^2_{r_p}(t) = w^2\theta^2_{r_k}\left[\frac{t-(1-w)r}{w}\right] &\geq w^2\theta^2_{r_k}(t) \\ \Leftrightarrow \frac{t-(1-w)r}{w} & \\ \Leftrightarrow t(1-w) &> r(1-w)\end{aligned} \tag{10.26}$$

Now, since $t < r$, $t\,(1-w) > r(1-w) \Leftrightarrow w > 1$ and the result holds ■

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This book is dedicated to:

Dean James Reinmuth, without whose support and guidance I never would have completed the Ph.D. program

Jim Kaffen, who co-founded SIA, named the firm, and sacrificed much to make these advancements in portfolio construction available to investors

My long time colleague Hal Forsey, who breathed life into my ideas

My wife, Karen, who puts a song in my heart and a smile on my lips

Prologue

This book is not about making money. It is about helping clients accomplish goals. Making money is how they accomplish the goal; it is not the goal itself. It is also not about how to time the market or pick winners in the stock market. *As the book cover suggests, it is a framework for constructing portfolios based on other people's theories that we tested at the Pension Research Institute*. The focal point of the construction process is the Desired Target Return™ (DTR™),[1] which links the cash inflows (assets) to the cash outflows (liabilities). The basic framework is to maximize the potential to exceed the DTR subject to the risk of falling below the DTR.

Again, the theories presented here are not mine. What I have done for over 25 years is to test theories that I thought might make an improvement in portfolio construction. What I present here are those few theories that passed years of testing. Of course, there is no guarantee it will work in the future, and nothing can be expected to work all of the time in the world of finance.

While I was the architect of this framework for constructing portfolios, the co-authors performed tasks necessary to actually build it and implement it.

Dr. Hal Forsey played the most important role. I learned enough math in 8 years of graduate school to explain to Hal what I was trying to do. Hal had the amazing quantitative skills to make my vision become a reality. For 5 years, every professor I talked to told me it was impossible to adapt Peter Fishburn's theory to an asset allocation model. Hal proved them wrong by utilizing an obscure optimizer he learned about at a University of California–Berkeley colloquium. This optimizer, called the *Forsey–Sortino optimizer*, will be available at no charge to anyone who purchases this book. To access the optimizer, go to http://booksite.elsevier.com/Sortino, password SOR3QA73QB72. No royalties of any kind apply. It is our hope that others will use the source code to build improved versions. To distinguish such improved versions from optimizers that are not based on our work we ask that a reference be made on the opening screen (e.g., "based on the original Forsey–Sortino optimizer").

Ron Surz was among the first to apply capital asset pricing model (CAPM) theory in the late 1970s when he was an executive with A.G. Becker. It took several years for me to convince Ron that downside risk was a superior way to look at risk compared to standard deviation or beta, but then it took several years for Ron to convince

[1] DTR and Desired Target Return are trademarks of Sortino Investment Advisors.

me that I should use his style indexes instead of the Russell indexes. I had tested a number of different indexes and always got very similar results. I came to believe all indexes were basically the same. When I finally gave in and tested Ron's indexes, I was very surprised to find it made a dramatic difference in determining which managers came into solution and improved the performance of my models.

Herr Dr. Professor Robert van der Meer was a senior executive with the Shell Oil pension fund management team in the late 1980s when I first met him. He invited me to spend the summer teaching a class with him at Erasmus University in Rotterdam and do some testing of the asset allocation model we had developed at the Pension Research Institute. That is where I first heard the term "Herr Doctor Professor," which is the highest sign of respect a student can show. The result was the first of many papers we wrote together about the application of downside risk and upside potential (see www.sortino.com for a partial list of publications). As Robert moved to top-level executive positions at Aegon and Fortis, he pioneered the wider use of these new concepts in Europe. Now he is writing a new textbook that will, for the first time, include chapters on downside risk and upside potential.

David Hopelain's first teaching job, after receiving his Ph.D. in organizational theory at UCLA, was at the University of Oregon, where I was in the Ph.D. program in finance. His classes were among the most enlightening I attended. Dave was one of the founding members of the Pension Research Institute in 1980. In the first research project at PRI he helped develop the relationship between goals and objectives expressed in this book. Dave is a very creative thinker, as you will see in the final chapter.

Jim Pupillo is described in *The Tipping Point* as the one who makes things happen. Even great innovations in finance are worthless until somebody uses them to benefit clients. After years of heroic effort, Jim was able to convince his firm's top management that the overlay process developed by Sortino Investment Advisors (SIA) would be a valuable service for his clients. It is no wonder that *Barron's* (February 9, 2009) referred to Jim as an innovator when they named him the "Top Advisor" in his state.

David Hand is following in the footsteps of his father and grandfather by developing an innovative service for 401(k) participants. David's father offered one of the first prototypes of the 401(k) plan to receive IRS approval in 1971. David and I wrote an article for the *ASPPA Journal* (Summer, 2008) that touches on some of the issues developed in Chapter 5.

Neil Riddles' expertise is in performance measurement. Neil first became interested in downside risk and upside potential to measure performance when he was senior vice president and director of performance measurement at Templeton. Neil contributed a chapter to *Managing Downside Risk in Financial Markets* (2001, Butterworth–Heinemann) and provided a spreadsheet that would enable consultants to calculate downside risk. This contributed to the widespread use of the Sortino ratio. Neil will point out the difficulties portfolio managers face when trying to implement the ideas presented in this book. Neil has to deal with the exigencies of the marketplace—the way the world is, as opposed to the way it ought to be. I have great respect for Neil, although I disagree with some of his points of view. I think dissenting views should be heard and welcome Neil's contribution to this book.

All of the co-authors in this book are people I worked closely with in the development of the material in their chapter. They were chosen for their expertise in specific aspects of this new approach, and I am deeply grateful to each of them for their contribution to this book and to this portfolio construction methodology.

A number of people have asked me to start a blog where those who are interested in post-modern portfolio theory (PMPT) can meet and exchange ideas. Interested parties may now go to http://pmpt.wordpress.com.

Appendix

Formal Definitions and Procedures

Overview

Our portfolio selection is mostly based on an analysis of return data. Each fund has a *style blend* described by a portfolio of passive indexes obtained by a quadratic fit of return data. As a result we are able to compare the fund with its style blend. We summarize this comparison with a difference in risk-adjusted returns called the Desired Target Return™-alpha (DTR™-α).* The DTR-α is a measure of added value and is key to our final selection process; however, before making this calculation possible, funds are carefully screened. One part of the screening process is based on an analysis of risk and return statistics defined in terms of a DTR. The purpose of this Appendix is to give formal definitions to these statistics and explain how they are estimated.

The Desired Target Return™

The Desired Target Return is the annualized rate of return required from investments to be able to support expenditures during retirement. This rate of return depends on many factors, including life expectancy, retirement contributions, and retirement income from sources other than investments. As many of these factors are not

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known, this rate can only be approximated. This is especially true if retirement is many years in the future. We have developed a calculator to help an investor to determine a reasonable combination of retirement contribution level, retirement age, and DTR. This calculator is available on the Sortino Investment Advisors' website (www.sortinoia.com). (*Note*: The calculations for Example 3 in the discussion below are based on assuming a discrete probability function of returns determined by the sample of returns.) Following are formal definitions for the case presented here.

THE BASIC STATISTICS, DISCRETE VERSION

Let $p(x)$ be the discrete probability function of returns and $T =$ DTR:

$$\text{Upside probability} = \sum\nolimits_{x>T} p(x)$$

$$\text{Upside potential} = \sum\nolimits_{x>T} (x-T) \cdot p(x)$$

$$\text{Downside deviation} = \sqrt{\sum\nolimits_{x \leq T} (T-x)^2 p(x)}$$

$$\text{Upside potential ratio} = \text{Upside potential}/\text{Downside deviation}$$

$$= \frac{\sum_{x>T} (x-T) \cdot p(x)}{\sqrt{\sum_{x \leq T} (T-x)^2 p(x)}}$$

THE BASIC STATISTICS, CONTINUOUS VERSION

Rather than using a discrete probability function and following a procedure similar to that of Example 3 to estimate our statistics, we fit a 3+-parameter lognormal distribution by using a bootstrap procedure on historical data. First, we give the general formulas for a probability density function and then we will consider the special case of the lognormal. A more expansive justification and further details for using the lognormal are given in Chapter 4 of *Managing Downside Risk in Financial Markets.*

Let $f(x)$ be the probability density function of returns and $T =$ DTR. As explained in the next section, we use a 3+-parameter lognormal density function, and in that case there are analytic expressions for each of the following integrals:

$$\text{Upside probability} = \int_{x>T} f(x)dx$$

$$\text{Upside potential} = \int_{x>T} (x-T)f(x)dx$$

$$\text{Downside deviation} = \sqrt{\int_{x<T} (T-x)^2 f(x)dx}$$

$$\text{Upside potential ratio} = \text{Upside potential}/\text{Downside deviation}$$

Estimating the Probability of Returns with a 3+-parameter Lognormal Distribution

The formulas for the lognormal are not pretty. They are generally described in terms of the parameters for the underlying normal, so, with the logarithmic translations, they can get a bit involved. The resulting basic formulas are collected together below. For now, we will not concern ourselves with these technical details. What we will do is describe the essentials.

First, what are the three parameters? There is some choice in selecting the parameters. We made these selections so the meanings of the parameters would be easily understood in terms of the annual returns. The parameters are the mean, the standard deviation, and the extreme value of annual returns. You are probably already familiar with the mean and standard deviation. The mean is a measure of the central tendency, and the standard deviation is a measure of the spread of the curve. These two parameters are enough to describe a normal and the standard lognormal. But, the three-parameter version of the lognormal uses another parameter. A lognormal curve has either a largest value or a smallest value. This third parameter, the extreme value, allows us to shift and flip the distribution.

Now, we must find a way of estimating these parameters from a sample. We choose to solve this problem by using the sample mean and sample standard deviation to estimate the mean and standard deviation of the underlying lognormal. Our estimate of the extreme value was selected on the basis of simulations. These simulations showed that only a rough estimate of the extreme value is required to obtain a reasonable lognormal fit. We estimate it as follows: First, calculate the minimum and the maximum of the sample and take the one closest to the mean. The extreme value is obtained from this value by moving it four standard deviations further from the mean. For example, if the mean, standard deviation, minimum, and maximum of a sample are 12%, 8%, −15%, and 70%, respectively, then the extreme value is (−15%) − (4)(8%) = −47%, as the minimum is closer to the mean than the maximum.

Consider the following table with statistics computed from a lognormal fit:

Parameters and Statistics	Example 1	Example 2	Example 3
Mean	12%	12%	12%
Standard deviation	22%	22%	22%
Extreme value	−50%	74%	−50%
DTR	7.5%	7.5%	13.5%

(*Continued*)

Parameters and Statistics	Example 1	Example 2	Example 3
Upside probability	51.9%	74%	40.4%
Downside deviation	10.5%	15.5%	14.3%
Upside potential	10.6%	11.2%	7.8%
Upside potential ratio	1.01	0.73	0.55

The first two examples differ only in extreme values. One is a maximum and the other a minimum. Please notice how different these two examples are *even though they have the same mean and standard deviation*. These differences cannot be captured by the normal curve. The third example is similar to the first but with a higher DTR.

The three basic parameters are estimated from a sample obtained from a bootstrap procedure on historical returns:

Mean = sample mean.

Standard deviation = sample standard deviation.

Tau (τ^{τ}) = extreme value, computed as described above.

Some Auxiliary Parameters

$$Dif = |\text{Mean}-\tau|^{|\text{Mean}-Tau|}$$

$$\sigma = \ln\left(\left(\frac{SD}{Dif}\right)^2 + 1\right)$$

$$\mu = \ln(Dif) - \frac{\sigma}{2}$$

$$\alpha = \frac{1}{(\sqrt{2\pi} \cdot \sigma)}$$

$$\beta = -\frac{1}{(2\sigma^2)}$$

Formula for The Lognormal Curve *f*(*x*)

If the extreme value is a minimum and x is greater than the extreme value, then:

$$f(x) = \frac{\alpha}{x-\tau} \cdot \exp(\beta \cdot (\ln(x-\tau)-\mu)^2).$$

If the extreme value is a maximum and x is less than the extreme value, then:

$$f(x) = \frac{\alpha}{\tau - x} \cdot \exp(\beta \cdot (\ln(\tau - x) - \mu)^2).$$

Formula for the Lognormal Cumulative Distribution Function *F(x)*

If the extreme value is a minimum and x is greater than the extreme value, then:

$$F(x) = 1 - \frac{\text{erfc}(\ln(x - \tau) - \mu)}{2\sqrt{2} \cdot \sigma}.$$

If the extreme value is a maximum and x is less than the extreme value, then:

$$F(x) = 1 - \frac{\text{erfc}(\ln(\tau - x) - \mu)}{2\sqrt{2} \cdot \sigma}.$$

Note: erfc is the complementary error function (Press, Flannery, Teukolsky, & Vetterling, 1992, p. 220).

Analytic Expressions for the Downside and Upside Statistics

Using the above formula for the lognormal density function, it is possible to obtain analytic expressions for the integrals defining the basic statistics. Following are fragments of Visual Basic code in the case τ is a minimum for analytic expressions of the basic statistics for a lognormal distribution. (As above, T is the DTR.) The upside probability (U) can be written in terms of $F(x)$, the distribution function, as $U = 1 - F(x)$.

Upside potential (UP)

```
If T > tau then

b = T - tau

c = sqrt2 * sigma

UP = 0.5 * Exp(mu + 0.5 * sigma ^ 2) * (2 - erfc((mu+sigma ^ 2 - log
(b))/c))

Else

    UP = tau+exp(mu+sigma * sigma/2)

End If
```

Downside variance (DV) (the square of the downside deviation)

```
If T > tau then

b = T - tau

c = sqrt2 * sigma

a = (Log(b) - mu)/c

DV = 0.5 * Exp(2 * mu+2 * sigma ^ 2) * (2 - erfc(a - c))

- b * (2 - erfc(a - c/2)) *Exp(mu+(sigma ^ 2)/2)+0.5 * b ^ 2
* (2 - erfc(a))

Else

    DV = 0

End If
```

And, of course:

$$\text{Upside potential ratio} = \text{Upside potential}/\text{Downside deviation}$$

Style Analysis: Determining the Style Blend of a Fund

The costs of investing in an actively managed fund are often much higher than owning a portfolio of index funds, so how can we determine if these extra costs are warranted? One approach is through returns-based style analysis (Sharpe, 1988) to determine a portfolio of index funds that most closely matches the investment style of the fund. Here, briefly, are the procedures for determining this portfolio, called the style blend.

A small set (less than 20) of indexes is chosen to divide, without overlap, the space of potential investments. This selection should be made so as to reduce the problem of colinearity but still allow a good fit as measured by R^2. The selection of the time interval of data to fit is also important. The interval must be long enough for a good fit but short enough to capture just the current style of the management of the fund. We call this interval the *style interval*. Weights to form a passive portfolio of indexes are chosen so the variance of the difference between the fund's returns and the passive portfolio's returns over the style interval is minimized. This choice is accomplished with a quadratic optimizer.

A Style Statistic

Now that we have our comparison portfolio—the style blend of passive indexes—how do we make the comparison? First, we don't even try unless the style fit, as measured by R^2, is high enough (say, 0.75 or higher). Then, the obvious thing is to look at the difference of annual returns over the style interval. This is not bad, but an improvement would be to adjust for difference in risk. One way to do this is to use a Fishburn utility function. Here's the definition for the statistic we use, called DTR-α:

$$\text{DTR-}\alpha = \text{Risk-adjusted return of the fund} - \text{risk-adjusted return of the style blend}$$

$$\text{Risk-adjusted return} = \text{Annual return} - \lambda * (\text{downside variance} * \text{style beta})$$

Downside variance is the square of the downside deviation, and λ is a constant we usually take to be 3. The style beta is the downside variance of the manager divided by the downside variance of the style benchmark.

We will consider using a fund in our portfolio only if it has a positive DTR-α. There is more about this selection process in Chapter 4.

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