1
INTRODUCTION

BRAINWASHED

For the past 40 years, a total of approximately one million unsuspecting MBA students have been thoroughly indoctrinated by business schools with the belief that stock markets are efficient.

An efficient market always prices every stock correctly. That is, the price of each stock accurately reflects the very best estimate of all the dividends to be received over the life of the company. Given those projected dividends and the price established by the efficient market, you can expect to earn a return on the stock that is perfectly fair, given the stock's relative risk and the returns that are available elsewhere in the financial markets.

True advocates of efficient markets believe this is the case at *all* times and for *every* stock.

If it *is* true, you can pick stocks by throwing darts. But forget darts! Your best investment is really a simple index fund—a fund that invests in a broad market index like the S&P 500.

Think stocks are too risky? Then lower your risk by putting a sufficient amount of your money in the bank instead of in the index fund. You see, risk management is really easy in an efficient market.

Trying to smooth the earnings of your company through accounting adjustments? You're simply wasting your time! The efficient market sees right through the numbers you report—it *knows* the real numbers, so you might as well report them in the first place.

Delaying making a business investment because you think interest rates are too high? Another mistake! Interest rates are *never* too high. They always reflect the best possible estimate of future inflation as well as a fair level of compensation to bondholders for consuming later so that *you* can invest now.

By the way, it makes no difference whether you finance that investment by selling bonds or stock. The efficient market prices both fairly. In fact, if you raise money by selling any type of financial claim on the profits of your firm, given its best estimate of your firm's future profits and given its sound analysis of the nature of the claim, the efficient market will price it fairly. So go ahead. Issue a few AA debentures—or a lot of junk bonds. Make them convertible, callable, zero coupon, etc. The efficient market will assign any or all a price that is correct and fair. The total value of your firm will be unaffected no matter what you do.[1]

Pretty heady stuff.

If the market is efficient, the world turns into a pretty simple place—at least for the people in academic finance.

However, don't throw away all those investment and business books you've collected over the years.

Because it's *not.*

Efficient, that is.

Although efficient markets people *still* go around saying there is a "mountain" of evidence supporting their hypothesis, the truth of the matter is that it's a very old mountain that's eroding rapidly into the sea.

A new and growing mountain of evidence is completely contradictory to the notion of efficient markets.

And contradictory in a big way. It's now very clear that the market makes BIG mistakes in pricing stocks. It *doesn't* see through reported accounting numbers. It's typically overly optimistic about to-be-reported earnings.[2] It projects that successful firms will continue their success for far too long into the future.[3]

And the list goes on and on.

And what about the one million MBAs who went to business school to *learn* about investing and running a business?

They should ask for their money back.

THE EVOLUTION OF ACADEMIC FINANCE

As a rather ancient ex-academic, I like to distinguish between The Old Finance, Modern Finance, and The New Finance.

Figure 1–1 summarizes their basic features. The top of the figure shows the time frame over which each existed.

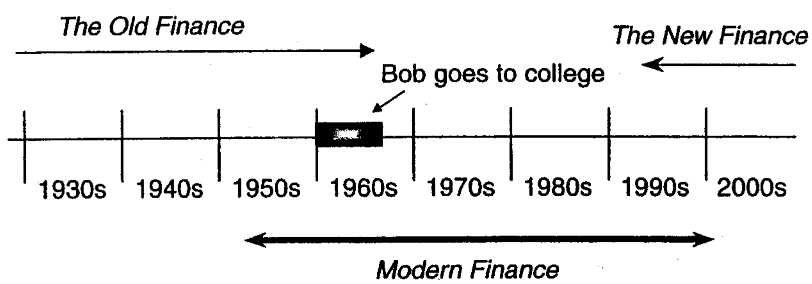
See the blocked-off period during the 1960s? This is when I received my formal education in finance. Note that I went to school when Modern Finance was relatively young and when The Old Finance was dying.

An interesting time indeed.

My professors, groomed in The Old Finance, were mostly expert in the fields of accounting and law. In fact, accounting and law are the basic foundations of The Old Finance.

Of all the books I was asked to master, two stand out clearly in my mind.

The first was called *Security Analysis.*[4] It was written by Benjamin Graham and David Dodd, and we used it to study investments. Graham and Dodd spent most of their book showing us the painful process of adjusting accounting statements so that the earnings and assets of different companies could be directly compared.



The Old Finance

Theme:	Analysis of Financial Statements and the Nature of Financial Claims	
Paradigms:	*Analysis of Financial Statements* (Graham & Dodd)	*Uses and Rights of Financial Claims* (Dewing)
Foundation:	Accounting and Law	

Modern Finance

Theme:	Valuation Based on Rational Economic Behavior			
Paradigms:	*Optimization* (Markowitz)	*Irrelevance* (Modigliani & Miller)	*CAPM* (Sharpe, Lintner & Mossen)	*EMH* (Fama)
Foundation:	Financial Economics			

The New Finance

Theme:	Inefficient Markets		
Paradigms:	Inductive *ad hoc* Factor Models		
	Expected Return (Haugen)	*Risk* (Chen, Roll & Ross)	*Behavioral Models* (Kahneman & Tversky)
Foundation:	Statistics, Econometrics, and Psychology		

This was mostly very *dry* stuff and not too interesting.

But, to their credit, our professors taught us a craft. We learned what to watch out for in accounting statements and how to make the proper adjustments. *Useful* stuff.

The second book was called *The Financial Policy of Corporations.*[5] It was written in two great volumes by Arthur Stone Dewing. *This* book made *Security Analysis* look like a Stephen King thriller. In *Policy,* we learned the legal rights of financial claims—*in great detail.* We learned the laws relating to merger and acquisition as well as those governing bankruptcy and reorganization.

Once again, our professors were teaching us a craft. We were preparing for our future. As possible future financial executives, we needed to know the rules of the game if we had to merge or go bust, as well as the legal impediments on our firm's behavior created by the financial claims that were there today or might be there tomorrow.

Unbeknownst to me at the time, the birth of Modern Finance occurred when, early in the 1950s, a Ph.D. student named Harry Markowitz created a dazzling new tool for building stock portfolios called *portfolio optimization.*

Suppose you have a population of stocks, each having a different expected future return and a different level of risk.[6] You want to construct a portfolio of these stocks that has a 10% expected return. Harry showed how much to invest in each stock so as to have the lowest possible variability in periodic return, given our 10% expected return objective.

Although portfolio optimization would ultimately prove to be of great value to the world, Harry's new tool would lie almost unnoticed for more than a decade.

In the middle of that decade, two economists named Modigliani and Miller introduced the second major paradigm of Modern Finance—*the M&M Irrelevance Theorems.*

What was irrelevant?

Apparently all the rules and laws we had been studying in Dewing's *Policy.* M&M claimed that the nature and composition of the right side of a firm's balance sheet—its financial claims—didn't matter. What did matter was the nature and composition of the left side—its assets and investments. How you packaged, for delivery to the claimants, the fruits of those investments had no impact whatsoever on the total value of the firm.

Although M&M didn't say so at the time, the Irrelevance Theorems assumed an efficient market. Only if all possible claims are fairly priced will their nature have no impact on firm value.[7] If you know that your stock is being priced at half its fair value by an inefficient market, issuing more of it to *new* stockholders will not be in the interests of your *existing* stockholders.

The third and fourth paradigms of Modern Finance appeared at approximately the same time in the early 1960s.

The *Capital Asset Pricing Model* (CAPM) assumed *universal*[8] and *unrestricted*[9] use of Harry Markowitz's optimization tool. If *everyone* built their stock portfolio by optimizing, how would this affect pricing in the securities market?

The answer:

Under these conditions, a *single* factor would make one stock different from another in its expected return. In the world of CAPM, investors hold widely diversified portfolios. In fact, in the simple form of the model, we all invest in the market index. Risk is then variability in return to that index. The risk of an individual stock is measured by its contribution to that variability.

They called this contribution *beta*—the sensitivity of a security's periodic return to changes in the periodic return to the market index.

The ascension of Modern Finance was complete with the introduction of the fourth paradigm. Interestingly, it came from the same campus as Harry's tool.

Again, a Ph.D. student.

Eugene F. Fama dreamed of the *efficient market* and wrote of it in his dissertation.

Not much in the way of rigorous theory here. Just a contention consistent with some initial empirical evidence. Stock prices appeared to change randomly from one period to the next. If stocks were always responding instantly and accurately to the appearance of new and unanticipated information (which must come in randomly if it truly can't be anticipated), prices would move randomly as well.

All in all, this looked like an impressive set of paradigms at the time.

Impressive, but *threatening* to my old professors.

Given these paradigms, what good would come from standardizing accounting statements? The statements had already been "standardized" in the minds of countless investors looking for bargains. These investors had acted. Prices had been set.

To reflect the *true* level of earnings.

Standardizing accounting statements was now seen as a colossal waste of time. Learning how to do it as well.

And the nature of financial claims was also irrelevant.

The craft of finance and the teachings of my old professors had been rendered *obsolete.*

It's not nice to be obsolete.

The professors of The Old Finance fought very hard to retain their relevance. The battles of this intellectual war are still recorded in the pages of ancient issues of the *Journal of Finance* and the *American Economic Review.*

But the professors of The Old lost most of these battles, and eventually they lost the war itself.

New professors came to the university. With very different skills. Many came from economics departments, and they had been trained to theorize under the assumption of *rational economic behavior.*

How would the market behave if emotions or biases never came into play? How would the market behave if everyone thought through the implications of every decision to the finest detail?

With initial empirical support for their paradigms and the *true* triumphs that came with the introduction of models for the pricing of options, Modern Finance took off, seeming to possess the characteristics of a true paradigm shift. It became the dominant discipline in business schools, and it carried great influence in the real world.

Those who would dare to question the validity of the paradigms—especially that of efficient markets—were summarily dismissed as *gauche.*

Those who dared to publish papers contradicting the paradigms were ridiculed. Their studies were supposedly replete with bias. And their methods, of course, were presumed naïve.

Their studies included only firms that survived the study period—survival bias. They used earnings numbers that may not have been publicly available at the time they bought the stocks—look-ahead bias. They probably spun the computer countless times until they got an interesting result—data mining. They didn't take transactions costs into account. They didn't risk-adjust their returns. They didn't test for statistical significance. Their results weren't robust in different time periods.

On and on . . .

However, we *now* know these initial results were *on the mark.*[10]

But summarily *dismissed.*

Fortunately, even when the mud is thick, truth always makes its way to the surface.

Modern Finance received a real punch in the nose in 1976 in the form of a study out of the University of Iowa.[11] Roseff and Kinney discovered that January was a very unusual month for the stock market. The returns to an equally weighted stock index were remarkably high in the first month of the year.

Then the results came pouring in.

Most of the premium return came in the first two weeks,[12] normally to the smaller stocks.[13] The effect was prevalent in most of the stock markets throughout the world.[14] Stocks that paid no dividends were particularly affected,[15] as were stocks that had been poor performers in the past.[16]

Modern Finance now faced a myriad of *anomalies* coming from every direction.

Anomaly: evidence of behavior that contradicts accepted theoretical prediction.

Anomalies: stocks with relatively high current-earnings yields produce relatively high future returns.[17] Stocks with relatively high book-to-price ratios also.[18] Short-term reversals in stock price movements. Intermediate-term momentum and longer-term reversals.[19] Underreaction to financing through sales of stock[20] and to announcements of stock repurchase programs.[21]

And this is but a short list.

Anomalies: statistically significant, risk-adjusted results, net of transaction costs, which can't be explained on the basis of the bias problems discussed above.

But that's okay. After all, they're only *anomalies.* Fair warning. Anyone who takes them seriously can expect to be dismissed as gauche.

But alas! There are *too many* to be dismissed.

And now Modern Finance begins to teeter.

And a New Finance appears.

Discard those theories that obviously have *no* predictive power. Discard the requirement that all explanations must be based on rational economic behavior. Look carefully at the data and measure accurately without preconception. Discard the tradition that you must *first* model without looking and *then* verify. Carefully measure behavior first, and then find *reasonable* and *plausible* explanations for what you see. Ascension of the *ad hoc,* expected return, factor model. The measure of any model's relative merit: the *unmined, out-of-sample, relative accuracy of its predictions.*

Go back to teaching students a *craft* rather than a *religion.*

The drummers sound, the cannons roar, and a second war begins.

The side that *predicts best* must ultimately win this war, for the simple reason that the world places great value on accurate prediction.

Students will want to claim that value.

And business school *deans* will want to satisfy their demands.

The war is long and bitterly fought. Obsolescence is, once again, on the line. The students are coming to the university, once again, to learn the craft of finance.

Unfortunately, many of the "modern" professors haven't learned the craft themselves.

So they must be retooled.

WHY YOU NEED TO READ THIS BOOK

The inefficient market makes many mistakes in pricing stocks. These mistakes result in *tendencies.* Stocks with particular characteristics *tend* to produce premium returns.

The market has a map with topography measured in expected return. There are places to go on that map that are *evil.* If you go there, you will underperform badly in the long run. There are *good* places, too. Go there and you will be rewarded.

In this book, you will learn how to measure the payoffs to stock characteristics (factors). My book *The New Finance: The Case for an Overreactive Stock Market*[22] is about the positive payoff to cheapness. In this book, we will reconfirm the critical importance of cheapness. However, we will also discuss, among other things, the payoffs to risk, liquidity, profitability, and a stock's performance in past periods.

And, in the tradition of The New Finance, we shall seek reasonable explanations for these payoffs. Some of these explanations *are* consistent with rational behavior. However, the contractual environment in which this behavior takes place is, itself, irrational, creating agency problems that induce the behavior. Some payoffs are rooted in purely irrational human behavior. For these, we look toward the field of psychology.

You will also discover a new kind of stock.

You've probably heard of growth stocks and value stocks. Both reside at different places on the market's map. But there are other places on the map where few have ever gone.

Such as the land of Super Stocks.

A Super Stock portfolio has the following characteristics: The companies in the portfolio are, *on average,* big, liquid, and well-known. They have low risk, and they are financially sound. They are highly profitable in all dimensions. And while they have had strong relative performance over the past year, they are still selling at dirt-cheap prices relative to their cash flow, earnings, and dividends.

This is a dream profile. It is the profile of a portfolio that can be expected to produce the best returns in the future.

No individual stock has the complete profile. If a stock were complete, the inefficient market would price it up until it was expensive rather than cheap.

Nevertheless, it is easy to construct a complete portfolio by assembling incomplete stocks that have components of the complete profile.

Want to learn how to build such a portfolio?

Want to learn what pays off and why?

Keep reading.

Notes

1. Technically, even if the market is efficient, your choice between debt and equity may affect your tax bill because interest payments are deductible while dividend payments are not. Also, the presence of debt may make you, as manager, do things you wouldn't ordinarily do—like try harder to make enough money to meet the interest charges.
2. See P. Dechaow and R. Sloan, "Returns to Contrarian Investment Strategies: Tests of Naïve Expectations Hypotheses," *Journal of Financial Economics,* 43 (1997).
3. See R. La Porta, J. Lakonishok, A. Shleifer, and R. Vishny, "Good News for Value Stocks: Further Evidence on Market Efficiency," *Journal of Finance,* June 1997.
4. B. Graham, D. Dodd, and C. Tatham, *Security Analysis,* New York, McGraw-Hill, 1951.
5. A. Dewing, *The Financial Policy of Corporations,* New York, The Ronald Press, 1953.
6. Define risk as the contribution that an individual stock makes to the variability of return to a portfolio of which it is a member.
7. If securities are priced fairly, they have zero net present value. Net present value is computed by subtracting the cost of acquiring the investment from the best estimate of the present value of future cash flows to be derived from the investment. For marketable securities, the cost of acquisition is their market price. If the market price is fair and reflects the best estimate, etc., then the net present value is zero. Just as investing in a project with zero net present value has no impact on firm value, so will selling a zero net present value bond to raise capital.

8. This means that every investor in the world uses it.
9. This means that the percentage of your wealth that you can invest in *any* stock can range from minus infinity to plus infinity.
10. For example, early evidence of market overreaction can be found in W. Breen, "Low Price-Earnings Ratios and Industry Relatives," *Financial Analysts Journal,* July–August, 1968; S. Huang, "Study of the Performance of Rapid Growth Stocks," *Financial Analysts Journal,* Jan.–Feb., 1965; F. K. Flugel, "The Rate of Return on High and Low P/E Ratio Stocks," *Financial Analysts Journal,* Nov.–Dec., 1968.
11. M. Roseff and W. Kinney, "Capital Market Seasonality: The Case of Stock Returns," *Journal of Financial Economics,* November 1976.
12. D. Keim, "Size-Related Anomalies and Stock Return Seasonality: Further Empirical Evidence," *Journal of Financial Economics,* June 1983.
13. M. Reinganum, "The Anomalous Behavior of Small Firms in January," *Journal of Financial Economics,* June 1983.
14. M. Gulteken and B. Gulteken, "Stock Market Seasonality: International Evidence," *Journal of Financial Economics,* December 1983.
15. D. Keim, "Dividend Yields and Stock Returns: Implications of Abnormal January Returns," *Journal of Financial Economics,* September 1985.
16. W. DeBondt and R. Thaler, "Does the Stock Market Over-react?" *Journal of Finance,* July 1985.
17. S. Basu, "The Relationship Between Earnings Yield, Market Value and Return for NYSE Common Stocks," *Journal of Financial Economics,* June 1983.
18. J. Lakonishok, A. Shleifer, and R. Vishny, "Contrarian Investment, Extrapolation and Risk," *Journal of Finance,* December 1994.
19. N. Jegadeesh and S. Titman, "Returns to Buying Winners and Selling Losers: Implications for Stock Market Efficiency," *Journal of Finance,* March 1993.
20. T. Loughran and J. Ritter, "The New Issues Puzzle," *Journal of Finance,* March 1995.
21. D. Ikenberry, J. Lakonishok, and T. Vermaelen, "Market Under-reaction to Open Market Share Repurchases," *Journal of Financial Economics,* October/November 1985.
22. R. Haugen, *The New Finance: The Case for an Over-reactive Stock Market,* Prentice Hall, 1998.

5

PREDICTING FUTURE STOCK RETURNS WITH THE EXPECTED-RETURN FACTOR MODEL

HOW WE ESTIMATE EXPECTED RETURN

Please go back and take another look at Table 3–3.

This is an example of the spreadsheet used to compute the relative expected rate of return to a single stock. Relative, because the bottom-line number is the difference between the particular stock's rate of return and the expected return to an average stock.

As indicated in Table 3–3, for each of the factors in the model, you multiply the stock's factor exposure by the projected payoff to the factor. This gives you the component of total expected return coming from the particular factor:

Factor Exposure × Projected Factor Payoff =
Factor Component of Exposure Return

After doing this for each factor, you add up all the components to get the total relative expected return for the stock.

To test the predictive accuracy of our factor model, compute for all months, beginning with January 1979 and ending with December 1999, the expected return for each of the roughly 3,500 largest stocks in the U.S. population.[1] Factor exposures are based on information that would presumably have been available at the beginning of the month.[2] The projected factor payoffs are the simple moving averages of the trailing 12 estimated monthly payoffs.

HOW WE DID

Going into each month, we rank stocks by our estimates of total relative expected return. The 3,500 stocks are formed into (equally weighted) deciles of 350 stocks each. At the end of the month, we observe the returns actually produced. At the end of the month, we also update the estimates of expected return and reform the deciles for the next month. This completes the monthly cycle. At the end of each year, we compute the cumulative monthly realized rates of return over each year. Table 5–1 shows the accuracy of our predictions.

Decile 1 is the lowest expected-return decile. Decile 10 is highest. The ten numbers under the deciles are the realized rates of return by year and then across all the years.

Let's graph the results across all the years. Figure 5–1 plots the realized rates of return on the vertical axis against the decile numbers on the horizontal axis. The line of best fit going through the plot points has a slope of 3.2%. This is the expected increase in realized rates of return in going from one decile to the next. To get the spread in realized return between one end of the line and the other, you multiply the slope by 10 to get 32%.

32%!!

Not bad, I'd say.

To see the slopes for the other years, look at the second-to-last column of Table 5–1.

Note that the slopes are positive in *every year.*

The model is consistent from year to year because it employs so many factors. Growth stocks and value stocks tend to move in and out of favor. Over long periods, value tends to outperform, but when value is out of favor, growth tends to do well. The expected-return factor model does well in every year because its predictions are based partly on measures of cheapness (value) and partly on measures of profitability (growth).

A comprehensive list of factors brings predictive stability and predictive power.

The numbers in the last column of Table 5–1 show the fraction of the differences between the returns to the deciles explained by decile ranking. Note how large these numbers are. In several years, the fraction approaches 100%.

In Figure 5–2, we cumulate the rates of return and plot them on a log scale. Note how quickly the deciles order themselves in their relative performance.

Recall that in Chapter 3 we compared the predictive power of risk-factor models with naïve estimates of portfolio risk made over a trailing 60-month period. With the naïve estimates, we compute what the variance of the portfolio would have been in some past period and project that into the future. Risk-factor models *do* provide more accurate estimates than the naïve estimates, but the difference isn't profound.

Expected-return factor models may be another matter entirely. For expected return, the analogue to the naïve risk estimate is to calculate the average return to the portfolio over the past period and project *that* forward.

How would the accuracy of the naïve projection compare with the accuracy of the expected-return factor model?

Table 5-1 U.S. Realized Deciles Formed by Ranking on Expected Return

Deciles	*1*	*2*	*3*	*4*	*5*
Annual return					
1979	33.5%	32.6%	33.9%	43.1%	35.2%
1980	17.4	26.2	25.4	27.2	25.8
1981	–15.6	–14.2	–7.9	–4.6	2.1
1982	3.2	15.5	21.8	24.6	24.0
1983	11.8	18.0	23.4	29.5	28.8
1984	–30.9	–20.7	–13.4	–9.1	–6.5
1985	4.3	18.4	26.6	37.8	34.9
1986	–15.2	–7.1	1.9	9.2	12.1
1987	–23.8	–12.3	–5.0	–6.8	0.0
1988	1.5	10.4	18.5	24.0	22.2
1989	–3.0	8.2	9.7	16.8	18.7
1990	–46.9	–36.2	–27.5	–21.7	–15.5
1991	23.9	29.3	36.5	42.0	45.2
1992	2.5	7.5	16.3	20.3	17.8
1993	6.4	9.2	18.2	18.5	19.9
1994	–15.51	–8.20	–7.28	–4.10	–1.2
1995	15.01	15.10	29.34	28.34	26.1
1996	5.96	25.07	22.80	21.74	20.6
1997	8.75	23.32	23.38	27.06	32.7
1998	–26.73	–12.68	–7.49	–8.81	–10.0
1999	22.31	–0.73	0.27	4.64	4.5
Overall	–1.45%	5.37%	9.57%	12.42%	13.7%

Source: Reprinted from *Journal of Financial Economics*, 41, Robert Haugen and Nardin Baker, "Commonality in the Determinents of Expected Stock Returns," p. 414, Copyright 1996, with permission from Elsevier Science.

FIGURE 5-1 Expected Return Factor Model Decile Scatter Plot 1980–1999

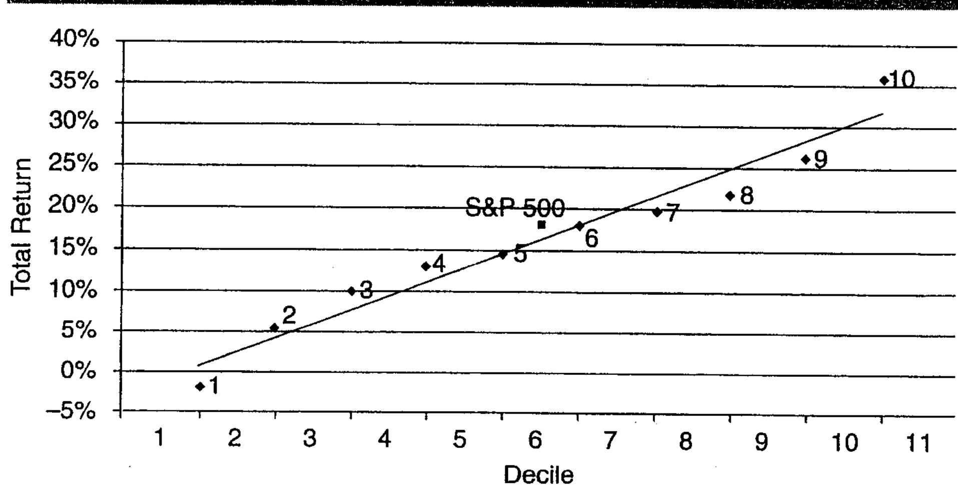


Table 5-1 continued

6	*7*	*8*	*9*	*10*	*Slope*	*R-Squared*
36.3%	47.3%	40.1%	39.3%	43.4%	1.1%	0.446
41.3	42.6	45.3	55.6	68.4	5.0	0.897
5.6	0.4	6.3	9.7	16.2	3.3	0.931
25.9	32.1	34.6	39.5	49.7	4.1	0.929
39.3	37.8	46.1	45.1	54.5	4.4	0.962
1.0	2.8	12.8	15.4	22.4	5.5	0.986
37.8	34.9	41.2	43.4	45.7	3.7	0.776
15.1	19.9	23.2	23.0	30.9	4.7	0.925
1.6	–3.4	–2.0	1.2	–5.1	1.8	0.486
28.8	26.9	25.9	29.7	27.0	2.5	0.714
21.5	28.5	29.8	32.4	28.7	3.6	0.893
–12.7	–10.2	–9.9	–2.9	1.3	4.8	0.937
45.7	51.1	46.6	46.9	57.4	3.1	0.817
15.7	17.1	18.9	21.1	24.5	1.8	0.619
20.1	20.0	20.7	24.2	22.2	1.6	0.738
22.3	21.6	24.0	27.1	30.9	3.5	0.932
–2.14	–0.24	8.96	7.28	10.01	2.6	0.931
37.56	31.99	33.58	42.15	53.55	3.5	0.832
24.85	17.30	21.91	15.93	25.47	0.6	0.093
26.74	35.91	37.95	45.15	51.75	3.8	0.899
1.09	–4.26	2.06	6.86	11.57	3.4	0.862
15.40	15.99	10.56	17.83	29.31	1.7	0.288
17.27%	18.56%	20.61%	24.69%	33.62%	3.2%	0.950%

[illegible]

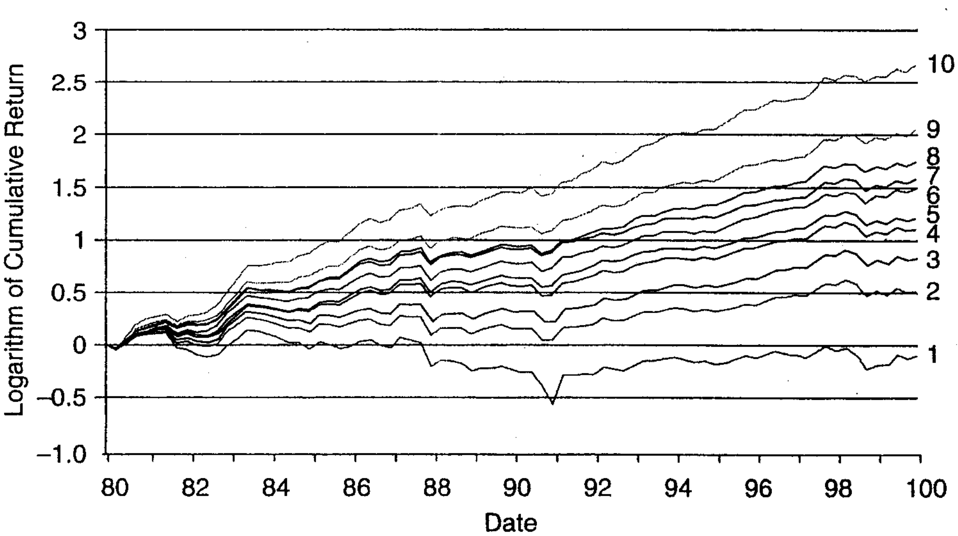


FIGURE 5–3 Naïve Model Logarithm of Cumulative Decile Performance

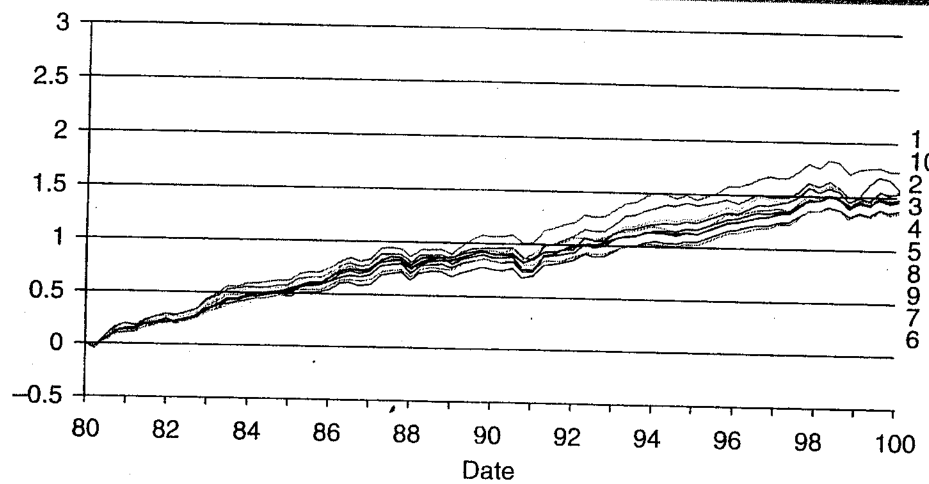
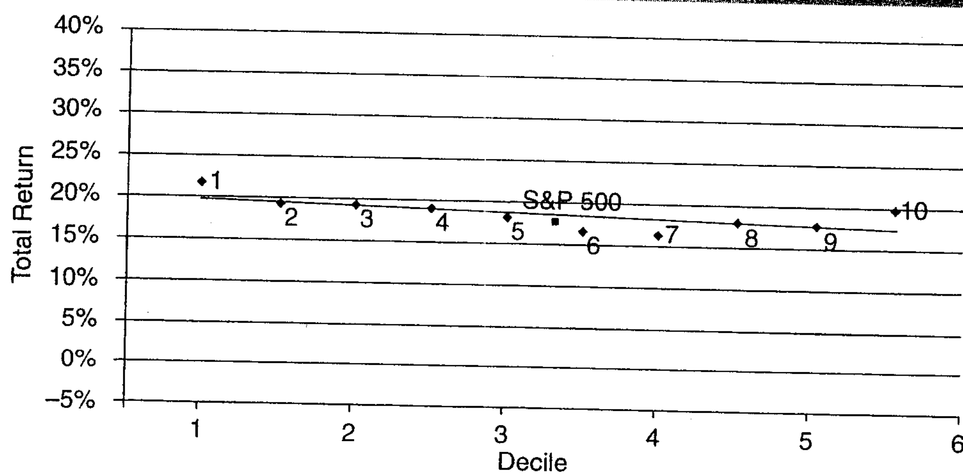


FIGURE 5–4 Naïve Model Decile Scatter Plot 1980–1999



To find out, we project forward, as the expected return for the next month, the average return for each of the 3,500 stocks over the trailing 60 months. Once again we form deciles based on the naïve projections.

The results of the experiment are presented in Figure 5–3. Note that the naïve models are actually perverted in terms of their predictions. The deciles predicted to do relatively well actually tended to *underperform*. A performance scatter plot is provided in Figure 5–4.

Remarkably, in spite of the relative strength of *expected-return* factor models, it is the *risk* models that have gained great popularity among practitioners and captured the attention of academics.

THE PROBLEM OF TURNOVER AND TRADING COSTS

Unfortunately, you can get the returns of decile 10 only if you can trade for *free.* Remember, the deciles are re-formed every month, and the expected returns projected by the factor model have a tendency to mean-revert. Moreover, this tendency is strongest in the extreme deciles 1 and 10.

Consequently, a great many of the stocks in these deciles will be leaving each month, probably to be replaced by stocks from deciles 2 through 9.

To see what fraction of the performance spread is "eaten" by trading costs, we will simulate the performance of a trading strategy in which we employ the Markowitz optimization tool to find portfolios in the efficient set.

We're going to make several changes in methodology, all of which will serve to narrow the spreads of Table 5–1.

First, we shift from the Russell 3000 stock population to the Russell 1000—roughly the 1,000 largest stocks in the U.S. market. These are the focus of institutional investors, and it will be interesting to gauge the predictive power of the model in the big stocks. *Second,* we move from monthly to quarterly rebalancing. *Third,* we will control portfolio turnover. *Fourth,* we will account for the cost of trading. We will assume a 2% total cost associated with the roundtrip of buying and selling. This is as much as ten times the actual cost of trading in stocks this large. *Finally,* these results will be restricted to the 1979-93 period covered in our original paper.

We will attempt to build portfolios on an efficient set similar to that of Figure 2–1A.

The constraints imposed in finding the portfolios are stated in Exhibit 5–1. These constraints are merely designed to limit the "bets"[3] we take in individual stocks and industries. The constraints prevent the optimization process from "plunging" or over-investing in particular stocks or industries. The results of the test aren't very sensitive to reasonable modifications in these constraints.

First, we will attempt to go for the nose of the efficient set—the stock portfolio with the lowest possible risk *period.* We'll use a naïve approach in finding this portfolio. At the beginning of each quarter, we look back to the preceding 24 months, and we find the portfolio with the lowest trailing volatility of return.[4] We hold this portfolio for one quarter, and then rebalance into the new portfolio with trailing 24-month volatility. This continues for the total period 1979 to 1993. Call this portfolio *G.*

Next, we try to build a portfolio with a higher expected return. We are armed, from the factor model, with estimates of expected return for each stock. At the beginning of each quarter, we try to build (with Harry's portfolio optimization tool) a portfolio with a level of risk between *G* and the risk of the Russell 1000 Index. We hold the portfolio for a quarter, and then we rebalance under the same objective, at the beginning of the next quarter. Call this portfolio *I.*

Now we go for a portfolio with even higher return. Our objective is to aim for the risk level of the Index. Call this portfolio *H.*[5]

EXHIBIT 5–1

OPTIMIZATION CONSTRAINTS

1. The maximum weight in a portfolio that can be assigned to a single stock is limited to 5%. The minimum is 0%. (Short selling is not permitted.)
2. No more than three times its percentage of the Russell 1000 total market capitalization can be invested in any one stock in the portfolio.
3. The portfolio industry weight is restricted to within 3% of the market capitalization weight of that industry.[9]
4. Turnover in the portfolio is constrained from 20% to 40% annually, depending on the emphasis in the optimization toward higher expected return.

Finally, we turn Harry's tool in reverse and try to build a portfolio with a low expected return. This portfolio is constructed under the same constraints as the first three. The level of aggressiveness in pursuing low expected return is approximately the same as *H* in its pursuit of high return. Call this one *L*.

The performance of these four portfolios relative to the Russell 1000 Index is presented in Figure 5–5.

Note that the *G* portfolio actually outperforms the index. Recall that *G* was dedicated only to risk minimization. Its outperformance is further evidence that the payoff to risk is *negative* during the period of the test.

As anticipated, climbing the efficient set with the factor model produces additional returns. Portfolio *I*, which emphasizes low risk over high return, outperforms by more than the *G* portfolio. In aiming for market-level risk, the *H* portfolio, which turns out to actually have similar volatility to the market, outperforms the market by nearly 4% (400 basis points).

Portfolio turnover increases, as attempts to capture extra return become more aggressive. Turnover runs from as low as 20% per year for Portfolio *G* to 40% per year for *H*.

The *L* portfolio lies to the southeast. In building *L*, we were looking for stocks with low expected return. The optimizer that built *L* emphasized low return over minimizing risk.

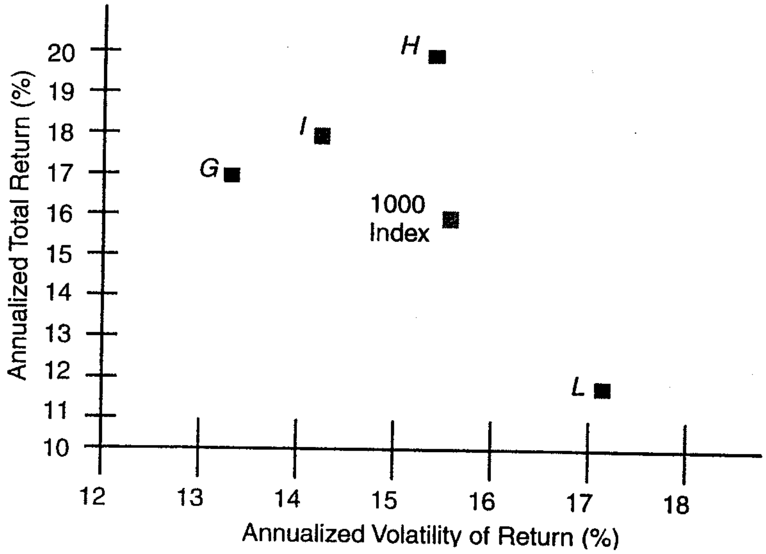
It didn't do a very good job at minimizing risk, did it?

Why?

Because in building L, the optimizer searched for stocks with low expected return. Peculiar as it may seem, these stocks, as well as the portfolios built with them, tend to have *high* volatility. The relationship between risk and return is upside down within the stock market.

In terms of its realized return, the highly volatile *L* portfolio underperforms *H*, its high-return counterpart, by approximately 9%.

FIGURE 5-[illegible]



Even though L is more volatile, an efficient-markets professor would likely argue that, for some reason, H is the more risky of the two, and the difference in their returns is really a risk premium.

For example, Fama and French (F&F)[7] might claim that the 900 basis-point differential is really a risk premium that was expected to be received by investors all along. When they see such differentials, they like to "risk-adjust" them.

They have chosen to believe that the risk of a stock is accounted for by three factors:

- The monthly difference between the return to the market and the risk-free rate (*market*)
- The monthly difference between the return to small stocks and large stocks (*size*)[8]
- The monthly difference between the return to value stocks and growth stocks (*value/growth*)[9]

F&F also use a multiple-regression approach. With our factor model, we try to explain why different stocks have different returns *within a single month.* F&F, on the other hand, try to explain why a single portfolio of stocks has different returns *from month to month.*

What they do is similar to what we discussed under the Arbitrage Pricing Theory. With APT, the factors are usually numbers from the macroeconomy. F&F have chosen to risk-adjust returns by taking numbers mostly from the stock market. With APT, you obtain things like inflation beta—the sensitivity of stock return to inflation. F&F also obtain betas, but these tell of the portfolio's sensitivity to things like the relative performance of value and growth stocks.

As a result of their process, F&F obtain an estimate[10] of the portfolio's expected return in a market environment where:

- The market produces a return equal to Treasury bills
- The performance of small and large stocks is the same
- The performance of value and growth stocks is the same

F&F firmly believe that this estimate provides a very good measure of risk-adjusted performance.[11]

Let's use their procedure to risk-adjust the returns to portfolio H and L:

Risk-adjusted Annualized Return: $H = 5.03\%$; $L = -7.44\%$

Risk adjustment actually widens the spread from 900 to 1,247 basis points.

The return reduction for risk is actually much bigger for L than it is for H.

This must mean that, by F&F's own measure, the risk of L is greater than that of H.

Getting interesting?[12]

AFTERTHOUGHTS

Interestingly, the predictive power of the factor model improves as you move from groups of large companies to groups of small companies. That is, decile slopes, such as those presented in Table 5–1, are decidedly greater for a small stock population like the Russell 2000 than they are for a large stock population such as the S&P 500. Why might we expect this to be the case? Large stocks can be thought of as portfolios of individual enterprises. As such, the individual characteristics, which collectively represent their profiles, will be blended across the components. In contrast, small stocks are likely to be more individualistic and heterogeneous with respect to their nature. If their profiles are more heterogeneous, their expected returns, as predicted by the model, will be as well. That is, the spread in expected return between decile 1 and 10 will be larger if the deciles are constructed over small stocks than they will be if they are constructed over large ones. As might be expected, the spread in the realized returns, and the slopes, turn out to be larger as well.

Notes

1. Prior to 1993, the population roughly consisted of the Russell 3000 stock population. After 1993 it roughly consisted of the largest 3500 U. S. stocks, where required data was available.
2. Prior to 1988, we assume a three-month reporting lag. During and after 1988, we use the actual data files that would have been available to someone trying to use the model.

3. Over- or under-weighting relative to the weights in the Russell 1000 Index.
4. Even though there are 24 months and 1,000 stocks, given our constraints, there is a unique solution to the problem. We find that solution through a numerical search procedure. Thus, we need not invert the covariance matrix.
5. Here and elsewhere, I have argued for a negative payoff to risk. One might ask, "If the relationship between risk and return is negative, how can there be a positively sloped efficient set?" If we plot expected return vertically and risk horizontally, think of an egg-shaped plot of the positions of individual stocks. The egg is tilted to the northwest, reflecting the negative payoff to risk. The egg still has an efficient set (albeit a small one) running from near the most westerly position of the egg to near the most northerly.
6. Based on the two-digit SIC code.
7. See E. Fama and K. French, "Multifactor Explanations of Asset Pricing Anomalies," *Journal of Finance,* March 1996, pp. 55–84.
8. In our tests, *size* is found by monthly ranking the stocks in the Russell 3000 by total market capitalization (market price times number of shares). Equally weighting the returns to the largest 20% gives us the return to large stocks. Doing the same for the bottom 20% gives the return to small stocks.
9. The 3,000 stocks are ranked monthly on the book-to-price ratio. Equally weighting the returns to the highest 20% gives the return to value stocks and weighting to the lowest 20%, the return to growth stocks.
10. The estimate is the constant term for a regression in which the dependent variable is the portfolio's return, and the independent variables are *market, size,* and *value/growth.*
11. I have no idea why they believe this to be true.
12. In a recent University of Chicago working paper, "Profitability in the Cross-section of Stock Returns" by J. Douglass Hanna and Mark Ready, the authors successfully replicate the results of the Haugen and Baker study. They examine the results of trading strategies that go long in decile 10 and short in decile 1. They find that, assuming a one-day delay between model estimation and trading, the net results of a highly active strategy of holding only decile 1 stocks during each month and shorting only decile 1 stocks each month indicates a positive but insignificant performance after trading costs. A less active strategy whereby the stocks held long are held until they fall below decile 7 results in a positive and highly significant net performance after trading costs. However, in practice, one would be foolish in following either of these strategies. Rather, it is best to employ the expected returns in conjunction with a risk model in a process of portfolio optimization and rebalancing. As discussed in this chapter, we employed such a process in our original tests and concluded that the net results were economically significant even after allowing for trading costs that were, in general, *higher* than those assumed by Hanna and Ready. It is also the case that actual users of the model estimate after the close of trading on a given day and then trade at the open of the next day. Thus, we do not see the rationale for their one-day delay.

6

COUNTERATTACK—THE FIRST WAVE

When they're not screaming "*Risk premium!*" the professors from the College of Cardinals like to cry "*Bias!*"

You see, results inconsistent with their religion *must* be biased.

So if you're going to offer evidence against what's taught in the catechism, you had better be prepared for a series of ferocious attacks.

We're prepared for battle.

SURVIVAL BIAS

The ground under our feet shakes. Here comes the first wave of cavalry thundering over the hill, and, by George, they're screaming "*Survival Bias!*"

What's that?

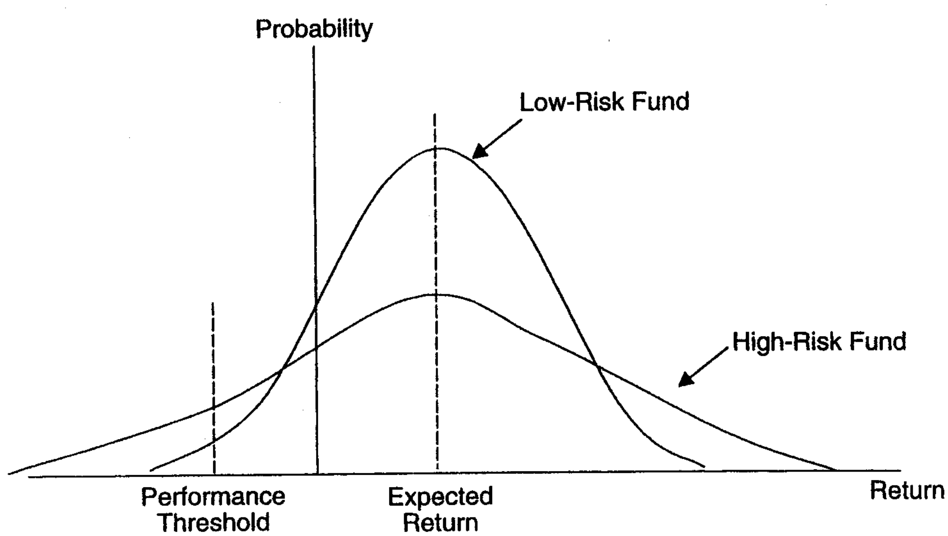
Survival Bias occurs if individual firms that go inactive during the test period are systematically excluded from the test population.

Consider studies of the performance of mutual funds, for example.

Suppose all mutual funds have *identical expected rates of return* (equal to that of the market), but different volatilities, as in the probability distributions of Figure 6–1. Assume also that, if performance falls below the threshold indicated in the figure, they go out of business. Then the probability of reaching that threshold *increases* with the *risk* of the fund.

If we observe the performance of only those funds that remain active, we will tend to find that the average performance of the surviving funds exceeds that of the market. To see why, consider Figure 6–2 on page 62. Each point in the figure represents one of our hypothetical mutual funds. We plot realized return on the vertical scale, and monthly volatility on the horizontal. Note that the range of possible outcomes is wider for the more risky funds.

We will also tend to find that performance increases with the level of variability in return, as with the x's of Figure 6–2. The o's in the figure represent the funds that fell below the threshold, didn't survive, and were not included in the test. The line drawn through the scatter of x's is the line of best fit. It has a positive slope.



Thus, it will appear to us that we can predict performance on the basis of fund risk. We detect a positive payoff to risk and we predict that the more risky the fund, the higher its expected return.[1]

In the case of our model, if the factors used in prediction are somehow related to the probability of going inactive, failure to include inactive firms in the database will result in misleading estimates of predictive power.[2]

Does our test suffer from Survival Bias?

No.

In the original 1996 study, our population of firms included the firms that were actually in the Russell 1000 and 2000 Stock Indexes at the beginning of each quarter.[3] We weren't able to find all the firms that were ever in the index, but after years of searching we came pretty close.

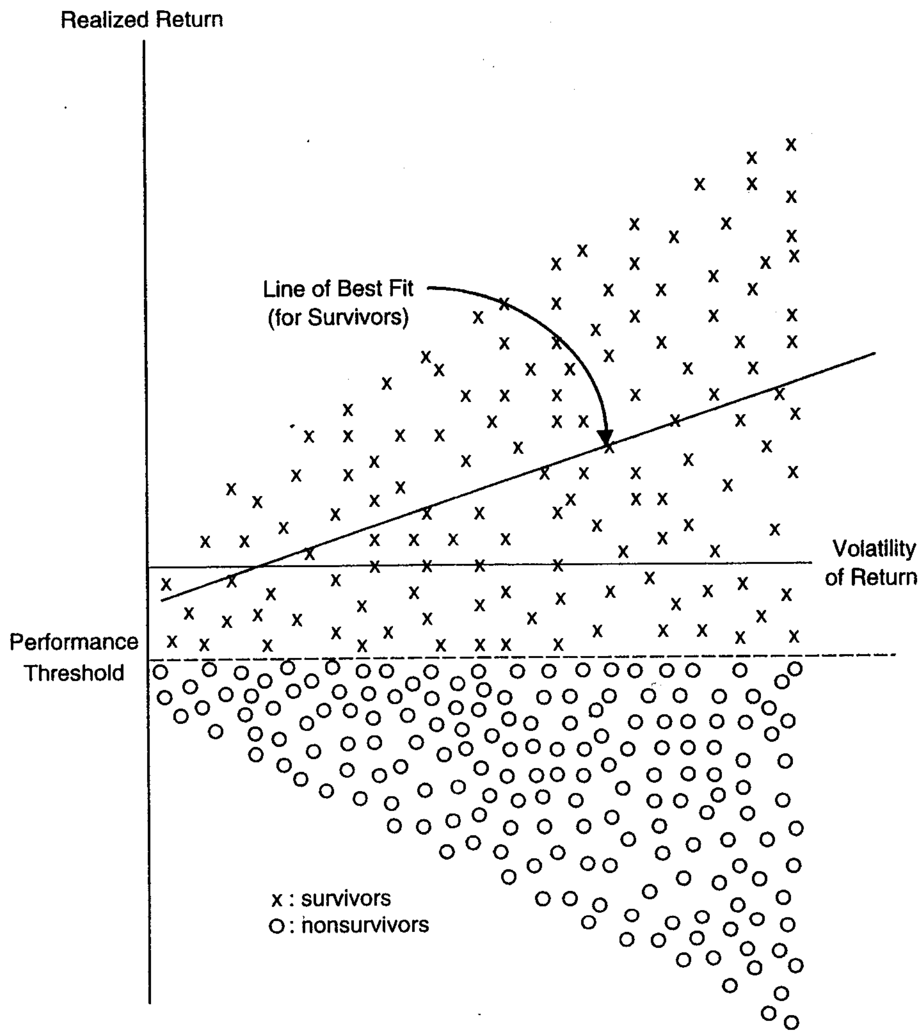
In addition, given the nature of our results described in the next chapter, Survival Bias, even if it were present, would work against us rather than in our favor. We find that the stocks with the highest return are bigger and more profitable. One can hardly argue that this is the product of Survival Bias.

Sorry. No Survival Bias here.

LOOK-AHEAD BIAS

And now, from the direction of our left flank, spitfire, black smoke, and the crack of rifle shots. The Temple's ground infantry is shouting, "*Look-Ahead Bias!*"

[redacted]



Look-Ahead Bias occurs when you calculate factor exposures using data items that wouldn't have been known when the predictions were made.

Please refer back to Table 3–3. Suppose you are forecasting expected returns for March 1988. Your forecasts are the product of projected factor payoffs and contemporary factor exposures. The question is, "Did you use information that wasn't released until after February 28th to compute the exposures?"

If you did, you're *cheating*. We'd all like to know information before it's announced, wouldn't we?

Here's an example of how Look-Ahead Bias can mislead us.

Suppose that the earnings-to-price ratio is used as a predictive factor. If the ratio is calculated with an earnings number that was unreported as of the date of prediction, the factor's predictive power will be exaggerated. This is because the set of firms with relatively high-earnings yields will include those with *unexpectedly high (but unreported)* earnings for the fourth quarter. Market reactions to these numbers are likely to be positive. Thus, high earnings-to-price ratios will be associated with high subsequent returns, even though there may be no *true* predictive information in the number whatsoever.

Does our test suffer from Look-Ahead Bias?

Not likely.

For the period prior to 1987, we assumed a three-month lag between the end of each quarter and the reporting of the accounting numbers. If that's not long enough to satisfy the Cardinals, after 1987 we began saving our files. After 1987, we used the actual files that would have been available to an analyst at the time the exposures were calculated.

If you look back at Table 5–1, there's not much of a difference in the results before and after 1987.

No Look-Ahead Bias here.

BID-ASKED BOUNCE

What now? A blast of artillery from the ridge over our *right* flank. As the cannonballs hit the ground around us, they seem to do the *Bid-Asked Bounce.*

Bid-Asked Bounce?

Another insidious bias.

Stocks trade at bid or asked prices, depending on whether the trade was a buy or a sell. Returns are measured close-to-close, irrespective of whether the closing price was at the bid or the asked price.

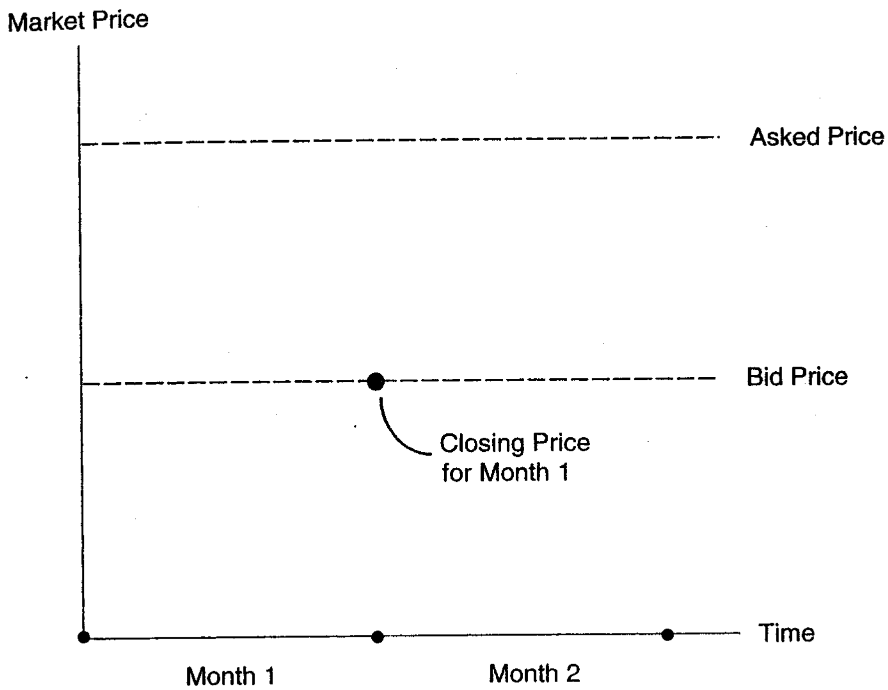
Suppose that the underlying market value of a stock does not change during months 1 and 2 of Figure 6–3. As you can see, the last trade of month 1 was at the bid. There is roughly an even chance that the stock traded at the asked price at the *beginning* of month 1 and at the end of month 2.

This being the case, the measured return will either be zero or negative for the first month and either zero or positive for the next.

Therefore, we may seem to observe short-term reversal patterns in stock returns, even when there are none. Thus, the existence of Bid-Asked Bounce can lead a researcher to falsely conclude that last month's return has predictive power, even when it is completely unrelated to the next month's return.

Are our results a product of the Bid-Asked Bounce?

Assuredly not.



To determine the extent to which Bid-Asked Bounce influences our results, we leave a month out between the time the expected returns are calculated and the time the trades are to be made.

It's as though we make our calculations and then go on a month's vacation before we bother to trade.

The effect of this is to slightly reduce the slopes of Figure 5–1 and slightly increase the percentages of the differences in decile realized returns we are able to explain by decile ranking (the R-squares).

Sorry, but the Bounce is not on us.

DATA SNOOPING

And now, on horseback, atop the hill to our rear, five men peer at us through powerful binoculars. They are the scouts of the Army of Modern Finance. They carry a flag. It bears the fearsome words "*Data Snooping.*"

A Data Snooper reads papers written by others that report that unusual stock returns seem to be associated with things like short-[4], intermediate-[5], and long-term[6] past returns, book-to-price ratios,[7] earnings-to-price ratios,[8] and measures of liquidity.[9] These papers give them good ideas about factors that should be included in an expected-return model. *Then they test their model using the same data as the other studies.*

Not fair.

I would now like to stand and humbly confess to being a Data Snooper.

I did read the papers. So what can I say?

Three things.

First, all the studies that I read before doing the original tests ended, at the latest, in the year 1990. In spite of this, our results still persist through 1999. Second, in Chapter 8, we take the model international and find similar results in countries that haven't been snooped. Finally, I will shortly show you results for a real portfolio, constructed with the expected-return factor model, that couldn't *possibly* be the result of snooping.

DATA MINING

Now, from our left rear, a brigade of coal-dirty men wearing yellow helmets adorned with little lanterns charges down toward us. Their banner bears the *fighting* words "*Data Mining.*"

Data Mining is an inflammatory charge.

A Data Miner spins the computer thousands of times. Tries a thousand ways to beat the market.

You'll always find one way in a thousand.

That's the one that looks interesting. That's the one you publish.

Unethical, Data Mining is.

Problem with Data Mining, however, is that the "lucky" list of factors is bound to look pretty *fluky.*

On the other hand, our list looks very *basic.*

That's because it's the *first* list we tried.

COUNTERFEIT

But, good Lord! Look who followed the miners over the hill. It's the Temple Choir, marching and singing "It's Only a *Paper* Moon."

What kind of a battlefield is this, anyway?

The rest of the first bar goes, "Sure you can beat the market on *paper,* but just try it for *real.*"

True, there's a big difference between paper money and real money, but, fortunately, we can prove that this factor model works "on the front lines."

On December 16th 1996, *Business Week* published an article about the expected-return factor model discussed in this book. The article featured an investment management firm called Analytic Investors, which was among the first to adopt the technology. Analytic continues to use the technology to this date. They use the expected-return model in conjunction with a risk factor model to manage a neutral, core investment strategy in which there is no tilt toward either value or growth. Analytic restricts their stock population to those included in the S&P 500 stock index, and they rebalance their positions on a monthly basis. They began their strategy in 1996 and currently manage more than $1 billion in the core composite. Since then, they have been steadfast in their implementation.

Figure 6–4 shows their AMIR compliant performance across their composite. Annualized average return is plotted vertically and annualized monthly standard deviation of return is plotted horizontally. The time period covered extends from October 1996 through December 2000. The S&P 500 is also plotted in the graph. Note that Analytic has approximately the same risk with an annualized average premium in their return of 4.30%.

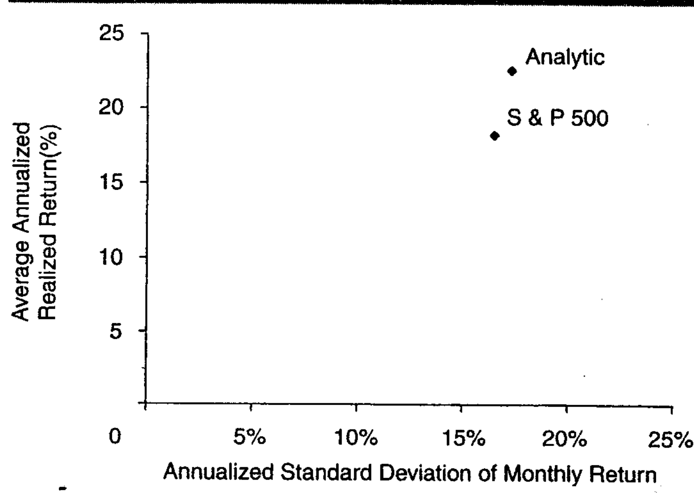
The results presented in this book are *not* based on Survival Bias, Look-Ahead Bias, Bid-Asked Bounce, Data Snooping, or Data Mining.

They are *real.*

AFTERTHOUGHTS

For the past few years I have provided monthly estimates of expected return, based on a factor model similar in form to the one discussed in this book, to a wide variety of institutional investors, including pension funds, endowments, and professional money managers. Based on electronic feeds of information about corporate accounting data, macroeconomic numbers, and stock returns, factor values are computed, based on the closing prices on the last day of the month. Within hours, the payoffs to each factor are computed, and, based on the trailing history of these payoffs, the payoffs for the next month are projected forward. Expected returns for the month are then computed and electronically mailed to each client. Clients then use optimizers to rebalance their portfolios at the open on the next trading day.

FIGURE 6–4 [illegible]



We have developed a history of the numbers mailed to clients that are subject to audit. These numbers are obviously completely free of any of the biases discussed in this chapter. Stocks are ranked by our predictions and formed into deciles. The realized returns to the deciles are presented in the following table. The returns for 2000 are through August.

Decile	*1*	*2*	*3*	*4*	*5*	*6*	*7*	*8*	*9*	*10*
1997	9.6%	19.7%	20.1%	19.7%	32.8%	32.15%	37.3%	39.2%	52.5%	61.55%
1998	-27.0%	-11.7%	-11.4%	-5.3%	-1.6%	-1.7%	1.0%	3.6%	8.2%	7.6%
1999	12.5%	9.5%	5.0%	6.8%	10.2%	12.4%	11.3%	18.0%	34.9%	40.6%
2000	-5.8%	3.0%	4.2%	7.3%	13.4%	14.5%	17.8%	21.4%	32.4%	36.6%

These results are not back-tests, and the predictive power of the factor model speaks for itself.

Notes

1. For studies of portfolios of individual firms, the nature of the bias is less clear because many firms can disappear because of merger as well as failure. In either case, it is likely that the overall returns to nonsurvivors will be abnormal.
2. Survival Bias is exacerbated by the nature of firms that tend to be back-filled in commercial databases. Providers tend to add companies that have significant market positions when the records are back-filled. Thus, given two firms of identical size five years prior to the back-fill, the larger (and more successful) firm at the time of the back-fill is more likely to be added to the database.
3. We wish to thank the Frank Russell Company for providing us with a history of the list.
4. See N. Jegadeesh, "Evidence of Predictable Behavior of Security Returns," *Journal of Finance,* 1990.
5. See N. Jegadeesh and S. Titman, "Returns to Buying Winners and Selling Losers," *Journal of Finance,* 1993.
6. See W. DeBondt and R. Thaler, "Does the Stock Market Overreact?" *Journal of Finance,* 1985.
7. See E. Fama and K. French, "The Cross-section of Expected Stock Returns," *Journal of Finance,* 1992.
8. See S. Basu, "Investment Performance of Common Stocks in Relation to Their Price-earnings Ratios—A Test of the Efficient Market Hypothesis," *Journal of Finance,* June 1977.
9. Y. Amihud and H. Mendelson, "Asset Pricing and the Bid-Ask Spread," *Journal of Financial Economics,* 1986.
10. Therefore, they are always *fully* invested in Japan.