Quantitative Investing Is Fundamental

Gina Marie N. Moore, CFA
Principal and Portfolio Manager
AJO
Philadelphia, PA

The quant manager has the same set of tools that any active manager has: Quants simply apply them using the ever-increasing power of computers. These tools allow the manager to pursue reward and deal with risk, costs, fees, and buying themselves the time necessary to distinguish investment skill from luck.

Quants are known for numbers, and I'm going to start with a couple of important ones: 500,000,000 and 1. These two numbers represent the fundamental relationship underpinning the evolution of quantitative investing. In 1955, $500 million was the price of a megabyte of RAM (random-access memory). Today, the price is $0.01.

Computers matter in quantitative investing, and the drop in computing costs is critical to understanding the quant revolution. In 1974, my partner, Ted Aronson, was working at Drexel Burnham Lambert in the quantitative equities group in Philadelphia. It was not a large group, and it was not the firm's specialty. When he ran the quant model, he had to submit information every time the firm rebalanced its portfolios, and they rebalanced quarterly. If he got a ticker symbol wrong when he submitted the information, the cost of rerunning the model was $10,000. Can you imagine the pressure for a person straight out of graduate school?

Fast-forward to 1998: I was new at AJO, and we did what we called our "model run," our weekly portfolio rebalancing. We waited until the 4:00 p.m. close. We started up the computers, let them roll, and waited to vet the output—the trades for the next day. If I got a ticker symbol wrong, if I missed a semicolon in the code that we were using to drive our model, three hours was needed for a restart. Starting at the 4:00 p.m. close, with three hours for a normal run time, if I made a mistake, everybody would be there until 11:00 p.m.

The cost of computing has real consequences and not just in dollars or time; it has consequences for all the tools we use to achieve our investment goals.

The Business of Quantitative Investing

My academic background is in accounting, and I began my career as a certified public accountant. When I think about investing, I naturally think of financial statements. And when I think about financial statements, I think back to Benjamin Graham and David Dodd's (2009) *Security Analysis*, written in 1934 and now in its sixth edition. Graham and Dodd provided us with the notion that through the "disciplined analysis" of financial statements, we could derive an intrinsic value for a company. We could then compare that intrinsic value with the market's price for the company. The concept of value investing was born.

From Graham, we have quotes such as "disciplined analysis" and "buy not on optimism, but on arithmetic." Advocating for a systematic, math-based approach to investing drives the image of Graham as the first true quant practitioner in Steven Greiner's (2011) *Ben Graham Was a Quant: Raising the IQ of the Intelligent Investor*.

At AJO, we, too, are in the business of quant investing. As modern-day practitioners of the quant trade, we describe our differentiating characteristics as independent and focused, value driven and disciplined, cost conscious and communicative, and more David than Goliath. It's no accident that many of these words call to mind Graham and Dodd and attempt to frame our style of quantitative investing as a clear, plastic box with clear, lucid goals.

Goals and Tools for Achieving Them

Before we proceed, let's talk about goals—personal goals, professional goals, and your goals as an investor. To make this a conversation, I am going to lean on a question that was asked of me at the outset of my AJO career: If you divide your goals into three categories, what weights do you assign to the categories of fame, fortune, and fun? The one condition is that the weights must equal 100%.

Now that you've established what's important to you, we can discuss the tools you might use to achieve your goals. We'll first focus on tools that fall

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into three key categories: return, risk, and cost. We'll add a few other categories later.

Return may be an obvious support: positive returns will help you achieve fame, fortune, *and* fun! Risk? Where you fall along the spectrum from risk averse to risk seeking can clearly define whether others perceive you as fun, but as investors, we'll need to dig deeper to understand the influence. And cost is the obvious drag on your fortune. Costs might be a necessary evil, but they can also be the low-hanging fruit. Either way, they, too, must be considered.

Let's explore these categories of tools in light of two important concepts in investing—modern portfolio theory (MPT), introduced by Harry Markowitz in 1952, and the capital asset pricing model (CAPM), which is associated most prominently with the work of Bill Sharpe in 1964. These theories are foundational theories of quantitative investing, but they can be associated with the goals of fundamental and quant investors alike. In fact, we can play a word association game to home in on the various investment tools brought to us by MPT and CAPM:

- *Diversification*: the concept that you shouldn't put all your eggs in one basket.
- *Standard deviation*: a way to measure investment uncertainty, to quantify the probability of loss (and gain).
- *Beta*: the quantification of systematic risk or how a security moves with the market.
- *Efficient portfolios*: portfolios that achieve the highest level of return for a given level of risk.
- *Mean–variance frontier*: the range of efficient portfolios across the risk spectrum.

MPT and CAPM help us to identify and quantify the trade-off between risk and return; they started us on the path of factors and optimizers. And none of it would be possible if the price of a megabyte of RAM had stayed at $500 million. In the 1970s, the price of RAM was dropping (one megabyte cost approximately $2.5 million in 1966), and quantitative investing was on the rise.

Risk

Leveraging the work of Markowitz and Sharpe, Barr Rosenberg (1974) gave us a tool to improve our prediction of a security's systematic risk beyond the past movement of its price. In 1975 (when the price of one megabyte of RAM was $50,000), he brought us the Barra US Equity 1 Model. Using quarterly data and a handful of factors, the most prominent of which was industry membership, the so-called Barra USE1 provided a robust, commercially available way to estimate a covariance matrix for US equity securities. In the 1990s, as the cost of computing fell to $50 per megabyte of RAM, risk models moved to monthly data and included the notion of "recency weighting," whereby the freshest data spoke the loudest in the forecast. A shock to our perception of risk—the volatility introduced by the bursting of the TMT (technology, media, and telecom) bubble—put "fresher is better" in vogue. As we entered the twenty-first century, monthly data moved to daily data. Today, many off-the-shelf risk models are available. In addition to Barra, we have Wilshire, Axioma, Northfield, and MSCI, to name a few.

The one thing these risk models have in common is that they are all good at predicting risk! Risk, defined as the future variability of returns, is a fairly stable, serially correlated property. One might even argue that the prediction of risk is easy. However, as we think back to our goals, it is hard to relate risk directly to fame, fortune, or fun. Indirectly, perhaps. But let's look further. . . .

Return

Exploiting anomalies to generate return brings fame, fortune, and fun back into the picture in obvious ways. When thinking of anomalies, keep in mind that we are moving from the use of factors to predict risk to the use of factors to generate profits.

Let's start with my favorite anomaly of all, the "value" anomaly. We have many ways to identify value stocks—price to book, price to cash flow, price to sales, and good old price to earnings (P/E).

The earnings yield, or P/E, phenomenon was first published by Sanjay Basu (1977). A powerful example of this phenomenon can be demonstrated with a very simple exercise. Starting with a 2,000-stock universe of institutionally appropriate investments, we create a value strategy by going long the highest-yielding companies (those with low P/Es) and short the lowest-yielding companies (those with high P/Es) in equal-weighted amounts within each sector. We rebalance the portfolio on a monthly basis and calculate the excess (theoretical) return. From 1977 to May 1998, the average annualized (paper) return to this simple P/E strategy was 8.9%. That sounds pretty good, right?

Then along comes the TMT bubble in May 1998. Of course, investors did not *know* it was a bubble at the time. For value investors, TMT might as well have been TNT, because it was a ride of terror for the next 21 months. The value strategy that had provided an average annualized return of 8.9% was returning *negative* 53% over the 21 months beginning May 1998.

If you had held on to your values (pun intended), however, and stuck with your value strategy through the era of stocks being priced relative to the number of "eyeball hits per page," you got a 357% snapback in the subsequent 32 months, starting February 2000. This lesson is one that quantitative investors and their models learned well. It is why value investing has such sticking power in the quantitative world of investing.

Thinking back to the CAPM and the risk-to-reward relationship it exploits, we find another anomaly that may better explain the relationship—or may simply be a byproduct of it. Identified by Rolf Banz in 1981, the size anomaly recognizes the following: The smaller the company, the more variable its returns; the more variable the returns, the more returns needed to justify investment. How does the size effect relate to a quant like me? It hits me directly in the center of my institutionally oriented universe of stocks, right where those midcap stocks fall. The annualized return on the Russell Midcap Index over the 35 years ending 30 June 2016 is 12.2%. Good luck beating that return or finding another index that does. The size effect is why so many large-cap managers are accused of "cheating down" in their capitalization—that is, they want to capture as much of that size effect as they can.

Another anomaly that may explain the performance of midcap stocks is momentum, described by Narasimhan Jegadeesh and Sheridan Titman (1993). Momentum strategies embody the idea of that which goes up will continue to go up. Consider the following demonstration of the momentum phenomenon, published in *Barron's* as an advertisement in 2004: As **Figure 1** shows, for the 60 months, or five years, ending 30 June 2004, the Value Line Group One, the choices of a largely momentum-based stock-picking service, was up 62.8%. For the same period, the S&P 500 Index was down 13% and the NASDAQ was down 20%. If even half of the record of the Value Line Group One picks were achievable, momentum must be a fabulous strategy!

And speaking of fabulous strategies, low-volatility investing is another interesting phenomenon. It was first presented by Robert Haugen and A. James Heins (1972).[1] What is behind this obviously popular topic? If we start with the CAPM and a market that is appreciating, a security with a higher sensitivity to market variance (high beta) will go up in a wilder way than a security with a low beta. The stock with low market sensitivity (low beta) will move around with a lot less volatility.

The CAPM says that there is a risk–return relationship whereby for a higher risk, an investor should achieve a *higher* return. Thus, people started to question whether that risk–return relationship was true almost as soon as the CAPM work was published, as evidenced by the first date on the research I just mentioned. The CAPM was a great foundational theory, but should we actually be investing in this manner? Maybe we don't have the risk-free rate correct; maybe there are different risk premiums. The low-volatility anomaly suggests that those low-volatility stocks may, in fact, be the ones that deserve to outperform. Low-volatility investing turns the CAPM on its head!

[1]And then again by Haugen and Baker (1991); by Chan, Karceski, and Lakonishok (1999); and by Clarke, de Silva, and Thorley (2006).

Cost

Up until this point, I have been talking about the tools of return and risk in relation to outcomes described in research papers—that is, paper portfolios. To implement any one of these strategies, to apply them to a real portfolio, you have to go to the NYSE or some other exchange. And there you will face costs.

The history of the NYSE begins with the Buttonwood Agreement on 17 May 1792. The NYSE board was formed by 24 members. Two important agreements supported its creation. First, the members agreed to trade *only* with each other. They were going to drop the auctioneers out of the process. Second, they fixed commissions, establishing the commission price of $0.24 per share.

Fast-forward to modern times.

- 1 May 1975: May Day. Commissions are no longer fixed. The trading world is now open to competition, and the notion of discount brokerage is born.
- 2001: Decimalization. Trading in eighths stops. NYSE trading joins the rest of the world and begins trading in increments of pennies.
- 2007: Regulation National Market System (Reg NMS) is launched. A trader must route a trade to the most competitive bid. Reg NMS introduces competition and fairness. Even for small retail investors, traders have to get the best quote, the best bid. (Detractors of Reg NMS would argue that it also introduced a lot of market complexity.)
- 2014: High-frequency trading arrives. Some argue it is an improvement of the trading environment; others argue it is a deterioration.

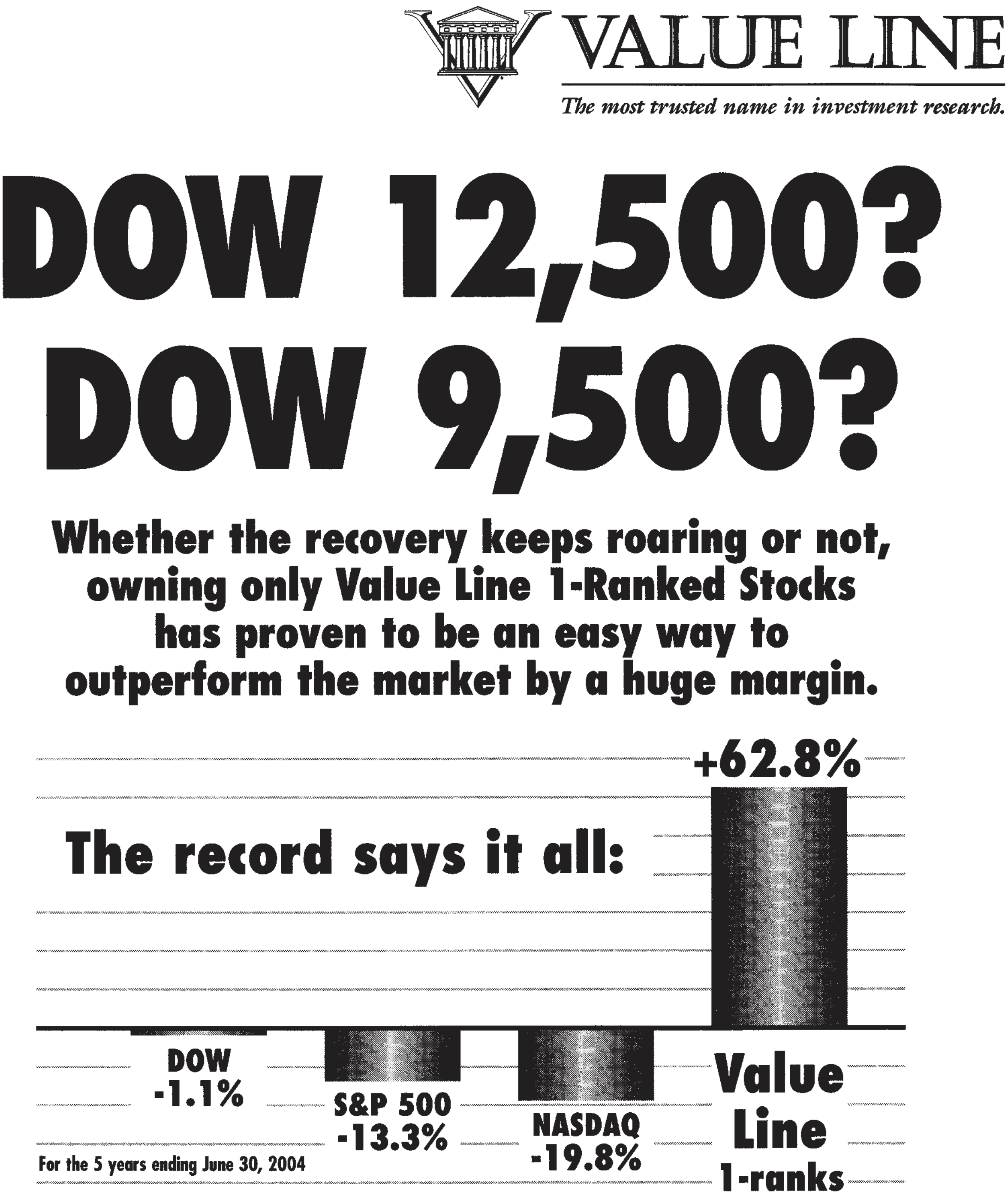
An underlying theme in our ability to make these changes harkens back to our timeline of computing power. How did we get from the Buttonwood Agreement on fixed commissions to high-frequency trading? Computing power. By 2014, the cost of a megabyte of RAM had dropped to $0.01.

What do those changes mean for investors?

Implementation Shortfall

André Perold (1988), a professor at Harvard University at the time, suggested implementation shortfall as a measurement for trading costs. It is, arguably, one of the toughest standards for measurement, but it is also an important method for

Figure 1. Advertisement for Value Line Group One



Source: Barron's (2004).

measurement when you are thinking about investing. Implementation shortfall is simply the difference between your target investment price and your final execution price.

Implementation shortfall can be dissected into a combination of obvious and insidious components: commission, bid–ask spread, market impact, and opportunity cost. Two are obvious to most investors, namely, commission and bid–ask spread. Through decimalization, Reg NMS, and the increase in computing power, commissions and bid–ask spreads have become a trivial part of the equation. Commissions have dropped from \$0.24 to \$0.01 and bid–ask spreads from \$0.125 to \$0.011.

The two components that are insidious but less obvious are market impact and opportunity cost. What are they, and how have they evolved? Market impact, which is the extent to which a trade moves the price of a security against the market participant, has shifted from having close to zero "impact" to having an infinite amount of influence on the cost of trading. Fixed commissions facilitated all manner of ugly, illiquid trades. Today, we consider market impact a square root function related to change in the size and liquidity of a trade; that is, those costs increase more steeply at first and theoretically extend on infinitely. At AJO, executing a buy in our large-cap US equity strategy with $23 billion in assets under management almost guarantees that we *will* move the price. It's hard to hide our intentions and still get trades done.

Which brings us to opportunity cost. Opportunity cost is perhaps the trickiest to measure, because it is the measurement of the path not taken. It is the cost of not being able to complete a trade. Today, depending on the ugliness and illiquidity of a trade, a stock could possibly reach zero before we have the opportunity to close our position. We call this phenomenon "the one that got away." When commissions were fixed, none got away.

So, after the precipitous drop in commissions, we can measure the effect on the components of implementation shortfall. But what about the effect on our favorite brokers? Is trading no longer a valid path to fame, fortune, and fun? Before we take up a collection for these brokers, consider this: In 1974, the average daily share volume on the NYSE was 14 million, but today, the composite of daily shares traded is closer to 7.7 billion. That increase in volume more than covers the loss of cents per share in commission, even after adjusting for inflation. If fortune is your goal, you can *still* skip all the risk-and-return stuff and head directly to the trading desk to collect your share.

How do these components of cost relate to the risk-and-return categories of tools we've been considering? The components relate differently to the various types of strategies we implement. For example, consider the momentum-driven Value Line Group One strategy. As outlined in Perold's seminal work (1987), the difference between a theoretical Value Line Group One strategy, the paper portfolio, and an actual implementable version is an average 6.9%! Why? Because a momentum-driven strategy pushes heavily on the impact and opportunity components of cost. Recognizing these costs and their interplay with the anomaly you are trying to exploit will help you nudge just a bit closer to realizing your return goals.

The Information Ratio

As an accountant, I learned well the adage "you can't manage what you don't measure." If return, risk, and cost are the categories of tools we have to achieve fame, fortune, and fun, we need a tool to measure our effectiveness that efficiently relates these tools to one another. How can we determine how efficient or effective we are in applying these tools toward our goal? One measure is the information ratio (IR). The IR is a derivation of the Sharpe ratio, in which we take our realized return, subtract the target return (the benchmark return), and adjust this amount on the basis of the excess risk we took above the benchmark (the tracking error). The result is a measure of investment efficiency.

Table 1 shows a sample of IRs based on today's top-quartile managers in their respective strategy universes. One could argue that top-quartile managers are *very* good at what they do. Their information ratios give us a perspective on the type of investment efficiency we, as investors, could expect from a manager who is *very* good.

Fees

Beyond risk, return, and cost, another lever we can pull to help us achieve our goals is fees. In fact, let me share with you some fee arrangements I think you'll find *very* attractive:

- 0% + 50% (no benchmark)
- 5% + 36% (no benchmark)
- (2% + 20%) + (1% + 10%) + (0.5% + 5%)

In the first example, there is no fee. If the strategy provides a return, the firm shares it at a level of 50%. Sound appealing? How about 5% and 36%? After a 5% base fee, the firm gets 36% of the upside.

Investment managers are probably saying to themselves, "I would like to have those fees." But what would it take to get those fees? You have to put up solid returns to earn those fees—solid, consistent returns. The first case was the setup for SAC Capital Advisors, providing consistent returns in the mid-30% range. The second case, Renaissance Technologies, took that number up to 70%—results so attractive that investors would willingly pay!

Now consider the last example. A fund aggregator firm came in and asked if AJO would want to be

Table 1. Information Ratios for Strategies as of 30 June 2016

	Excess Return (%)	Tracking Error (%)	IR
Large cap	1.0	4.4	0.28
Small cap	2.7	6.6	0.52
International	1.7	4.4	0.47
Emerging	2.4	4.9	0.50
Minimum volatility	2.9	7.6	0.45

Note: Average annualized 10-year excess returns and tracking errors at the 25th percentile of the strategy's universe.

Source: eVestment database.

a founding participant in a strategy for which the fee arrangement would ultimately be 3.5% and 35%. It's actually not far off from the 5% and 36% already described, but this fee arrangement was for AJO's plain-vanilla, long-only, US equity large-cap work, hoping to generate 2% of added value per year. The aggregator was suggesting that AJO charge 2% and 20%. The first fund pool aggregator would charge an additional 1% and 10%, and the final aggregator would take another 0.5% as a base fee, with 5% of the profits. What would the investor get? Absolutely nothing.

Jack Bogle has a great way of describing such arrangements: "hyper helpers." Hyper helpers in the investing industry are people who all want a thumb in the pie. They want a piece of the action. They want a direct path to fortune.

The moral of the story is that returns need to justify fees. People are willing to pay high fees if the returns justify them. How, then, can we as investment managers use fees as a tool to achieve fame, fortune, and fun?

We can actually improve our standing as investment managers with the right fees. **Table 2** presents the IRs we saw in Table 1, except this time, we see those IRs from the client's perspective—the investment efficiency of the top-quartile managers *after* fees. In Table 1, small-cap managers were winning, based on their average top-quartile IR of 0.52. That said, those top-quartile small-cap managers also set top-quartile fees, averaging 75 bps.

After fees, top-quartile managers no longer beat the other strategies, at least not from the client's perspective. Setting the fee at the right level is another tool for improving on investment efficiency from the perspective that matters most—that of our clients.

Time

Our last tool is time. How can we use time to achieve our goals? Time gives us investment managers a chance to prove we are worthy of our fees.

Many investment managers can put up good numbers. Our challenge is to prove to our clients that the numbers we put up—those returns, adjusted for risk, net of costs—are achieved via skill, not luck. And for this assurance, we need the right amount of time. If a client believes you are skillful, you have found a "sticky" client. You have a chance of earning that client's fee stream over a long period of time.

But how much time is needed to prove our skill? Richard Brignoli (1989) provides us with a framework for determining the number of years required to establish true "outperformance" at a pre-specified level of confidence. Taking his approach, we will use the IR together with a common measure of confidence, a *t*-statistic. Let's assume that our clients will find us skillful if we achieve our outperformance within a confidence interval of 95%. We can translate that into a *t*-statistic of 2.0. It is a common measure and a common level to use to ascertain whether a factor is worthy of inclusion in our alpha models. So, we can use it here at the strategy level.

On the other side of the equation, instead of setting up the factor's rate of return adjusted for risk, we can set our strategy's return stream adjusted for risk (our strategy IR) and solve for time:

$$\text{Skill} = \left(\frac{\text{Excess return}}{\text{Tracking error}}\right)\left(\sqrt{\text{Time}}\right).$$

Table 3 indicates how much time is required to confirm skill at various levels of IR, with 95% confidence.

This information is intended to shock you a bit. If your IR is a little bit less than that of today's average top-quartile international equity manager, 0.25, you need 64 years to convince your clients with a 95% level of confidence that you are a skillful investor! The bottom line is that clients will pay for skill, and proving skill requires time.

Conclusion

The final equation we reviewed brings all the concepts—our collection of tools—together. To stay competitive, to achieve our own mix of fame, fortune, and fun, we have five levers to pull. We can work to improve our *returns*—hard to do, but with faster computers and more access to data, we're bound to find a new anomaly to exploit. We can work to

Table 2. Information Ratios for Clients as of 30 June 2016

	Excess Return (%)	Fees (bps)	Tracking Error (%)	Client's IR
Large cap	1.0	40	4.4	0.13
Small cap	2.7	75	6.6	0.30
International	1.7	47	4.4	0.28
Emerging	2.4	84	4.9	0.32
Minimum volatility	2.9	22	7.6	0.35

Note: Average annualized 10-year excess returns, tracking errors, and fees at the 25th percentile of the strategy's universe.

Source: eVestment database.

Table 3. Time Required to Establish Skill for Various IRs

Information Ratio (net of fees)	Years to Confirm Skill vs. Luck
0.25	64
0.50	16
0.65	10
0.75	7
1.00	4

reduce our *risk*—maybe the easiest lever we can pull in a theoretical way but not the most powerful tool we have in practice. We can minimize our *costs*—but some costs are insidious, so we can only work to reduce what we first reveal. We can reduce our *fees*—a lever or part of the equation that is truly ours to control. And we can recognize our window of *time*—keeping it open to ensure that our clients see the skill behind our craft.

Whether we pull these levers in a quantitative or fundamental way, improvements in the power of computing have played a significant role in the collection of tools we can use to ply our trade of active management. I hope I have inspired you to think deeply about how you use and improve your collection of tools in the future. Let's continue to make active management an attractive alternative—attractive for ourselves and our clients alike.

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Question and Answer Session

Gina Marie N. Moore, CFA

Question: As more and more investment managers embrace factors, are some anomalies being arbitraged away?

Moore: Yes, anomalies can absolutely be arbitraged away. In fact, I have a great example of such a development. When we started our model, data on insider holdings were not available. These data were not available because people were hand-filing insider information. One company had an exclusive contract with the US SEC to keypunch the data, and in return, the company was able to receive and use the data it was keypunching. The company turned it into a model, and when it sold the model, we bought it. That was in the 1980s. Fast-forward to the 1990s, and some 600 investors were using that insider-holdings model. The returns diminished significantly.

The good news is that there is often a way to dig a little bit deeper, particularly where the information is messy. Eventually, when insiders filed electronically, we were able to grab the detailed data ourselves. Whittling it down to a signal that we considered representative purely of insider sentiment allowed us to get additional power out of the information.

Fast-forward again to the Sarbanes–Oxley Act of 2002. We thought our model was going to be dead in the water because we weren't sure what was going to happen with insider-holdings data. But in fact, the model is more powerful today than it was before 2002.

Of course, the more people are using a strategy, the more it will be squeezed. You may have to move on to a new anomaly, a new factor. You may not be able to use it in its exact format, but if you have a lot of data on a factor, dig deeper and keep looking.

Question: What are your thoughts about managers, even passive smart-beta managers, using extensive backtesting? Could that be construed as data mining?

Moore: Data mining is easy to do. It's really hard not to fall in love with the backtesting because if you find something that's got a positive stream to it, you can suddenly justify it for a bunch of reasons. You don't have to have an investment thesis at the beginning; you can always fit one to the results coming out. The best defense against a strategy that is simply based on data mining is to begin with and understand the investment thesis.

If you're the investor in the smart-beta strategy, you need to understand it. It needs to make sense to you, and it needs to make sense over the long run. If you're a manager trying to craft a smart-beta strategy, don't let yourself start with the numbers until you have a good idea of why you're doing it.

