Blending Quantitative and Traditional Equity Analysis: An Overview

H. Russell Fogler
Partner
Aronson+Fogler

A colleague once pondered, "If everyone has the algorithms, will they not get the same answers?" This question reflects an important observation and is one of the reasons for this conference—*Blending Quantitative and Traditional Equity Analysis*—at this time. Consider three advances in quantitative modeling that have emerged recently: nonlinear estimation, conditional forecasting, and improved holdout sampling. Neural nets, classification trees, and pattern recognition are nonlinear estimation procedures. Chaos theory highlights nonstationarity, in which conditional forecasting works. Data mining (i.e., searching a data base repeatedly until you uncover some pattern from the past) focuses attention on holdout sampling.

The increasing use of the new quantitative techniques introduces the dilemma posed in my colleague's question: As nonlinear and conditional forecasting algorithms are used more and more, will not everyone obtain the same answers from the same data samples? Because of the dilemma brought about by the quantitative advances, traditional investment analysis assumes a monumental role and the need for blending the two approaches becomes clear. Profitable research requires three additions that traditional analysis can provide quantitative analysis: (1) isolation of homogeneous groups of companies (value versus growth, large versus small, utilities versus high-technology firms), (2) isolation of different market environments (1988 for value, 1989 for growth), and (3) assessment of whether empirical findings coincide with both theory and "Street smarts." This last effect is especially important when statistical significance cannot be achieved because of either small sample size or data mining.

Summarizing the State of the Art

Russell Fogler begins by stressing that modelers need to focus on information theory rather than statistical significance, particularly the information content of surprise events, and on the *process* of research. The presentation goes on to clarify specific nonlinear models and how they produce profitable research. Strengths and weaknesses are noted for each major nonlinear or nonstationary model (i.e., neural nets, trees, chaos theory, fuzzy logic, and genetic algorithms). This presentation warns modelers to beware of data mining and "combinatorial complexity" in backtesting. Superior active management is discussed, with recent research citations, and the presentation ends by offering guidance for managers on communicating unanticipated over- and underperformance.

David Leinweber's original oral presentation, containing nearly 200 slides and several video segments, was a true visual and oral delight that was difficult to translate onto the printed page. Nevertheless, readers will note that the presentation extends Fogler's points by focusing on the awesome implications of computing power. For example, a high-end workstation today exhibits a price/performance improvement factor of 400 million times that in 1960! (If cars had evolved this fast, they would have a speed of 10,000 miles per hour, get 1,200 miles per gallon of gas, and cost 12 cents.) Leinweber goes on to show how technology continuously transforms the securities business. The transformation did not start with computers, but it certainly has been accelerated by them, particularly when the computing power is combined with quantitative methods. Leinweber shows how yesterday's "impractical" ideas find their way onto analysts' desks and into firms' trading rooms. This presentation looks at some of today's most promising impractical ideas—visualization, artificial intelligence, genetic algorithms, and trading robots—to project the future of finance technology.

Introducing Neural Nets and Classification Trees

Neural networks have the potential to become an important tool in modeling complex nonlinear relationships among financial instruments. Despite the simplicity of their fundamental components, they can capture a wide range of nonlinearities through sophisticated network configurations, and they are easily adapted for efficient computation.

Andrew Lo's introduction provides a basic description of neural networks and discusses their key

features. The strengths and weaknesses of neural network applications are reviewed through the use of economic and financial examples. Both of the standard back-propagation nets, multilayer perceptrons and radial basis function nets, outperform linear models and often outperform the Black–Scholes model when estimating option prices on historical data. This presentation is required reading for all serious investors.

Dean Barr provides a practical example of using a neural net to analyze a stock. He also shows that, in using neural networks for picking stocks, both top-down and bottom-up (using security-specific information) approaches can be used for training the network.

One primary challenge for stock pickers is to create neural nets that will rapidly determine not only what but also when to buy and sell. Additionally, the nets must identify opportunities in which the modeler can have high confidence that a pattern has indeed been found. Barr shows how sensitivity analysis can put analysts in familiar territory and help them understand how a neural network works.

Christopher Murphy, Gary Koehler, and Fogler then ask, "If neural networks can outthink humans, why are quants not rich?" This presentation illustrates the problems novice modelers should expect to encounter as they venture into neural nets—together with some solutions. A simple example shows the impact on a net of the number of nodes, the number of layers, activation functions, learning rate, training tolerance, and noise. Understanding this example is a research necessity before using a neural net. Most importantly, Murphy, Koehler, and Fogler present guidelines for avoiding "artificial stupidity"—such as overfitting of sample data. Also discussed is how the new quant models are likely to mature in the future.

Finally, Koehler turns attention to classification trees. These algorithms help provide rules, such as: "Profitable stocks exhibit low P/Es, solid growth, and reasonable debt levels." The output arrives in the form of a decision tree. The presentation illustrates the application of two popular classification algorithms (ID3 and ITrule) using backtest data. Koehler uses these examples to clarify problems practitioners can expect to encounter in using these methods and nuances they should be aware of before applying such algorithms.

Data Mining ("Snooping") and Sampling Problems

Measurement problems afflict both linear and nonlinear techniques and are compounded by the probability of data mining and statistical insignificance.

Practitioners need to understand these problems: What if, as Fogler's presentation discusses, 80 years are needed to measure whether a money manager's strategy can produce a positive alpha? Practitioners need to understand why statistical significance cannot be known for many profitable strategies and what can be done in such situations.

The human predilection toward the interesting and unusual can have dramatic effects on statistical inference—if such events are not taken into account properly. Quantitative models for stock selection, asset allocation, and other investment decision making are all prone to data-snooping biases, particularly when their performance is assessed exclusively with historical data.

In his second presentation, Lo discusses the origins of such biases, gives examples of their effect on quantitative analytical approaches, and presents some partial solutions to this unavoidable aspect of statistical analysis. In an amusing and revealing example, he shows the need for applying theory and financial savvy to any quantitative stock selection model. He also discusses Peter Lynch's superb outperformance in 11 of 13 years among thousands of money managers and draws an interesting conclusion.

Stephen Ross tackles the other major problem of backtesting—survivorship bias. Survivorship bias distorts results of virtually all current performance studies based on time series. Thus, researchers need to recognize and adjust for this bias. Not only does the bias affect the absolute performance measures, it also affects the relative rankings of managers over time. This presentation illustrates how high-risk managers are likely to show outstanding performance but also demonstrates that this performance may be caused by the elimination of underperforming high-risk managers from the data bases.

Blending Approaches

Traditional equity analysis plays a critical role in quantitative analysis. Statistical significance becomes less reliable in the presence of data mining, survivorship bias, and nonstationarity. When reliability drops, selecting the "right" variables and their transformation are crucial.

A number of the presentations illustrate the importance of combining quantitative and traditional approaches and, at the same time, give some idea of the range of applications found for neural nets and other nonlinear techniques. Ralph Goldsticker provides a practitioner's experience with blending quantitative modeling into a traditional research team. For traditional portfolio managers to trust and use a quant model, the model must make sense and

the rankings must be understandable. One way to persuade managers that a model is trustworthy is to exclude from it companies that do not fit the model's assumptions. This approach enhances the model's ability to separate attractive from unattractive stocks, and the process can be carried out with simple screens and little cost.

Philip Erlanger turns from fundamental equity analysis to technical analysis, showing how stock price patterns can be captured by a neural network. Results presented for stocks and other assets provide evidence of actual successes and failures.

Finally, Douglas Case illustrates how a traditionally oriented plan sponsor uses quantitative analysis for risk control and selecting investment managers. Based on previous experience with managing equity size and style exposures within an aggregate portfolio, the State Board of Administration of Florida adopted a new investment management concept in 1993. The approach recognizes the power and importance of style/size management, uses an equity target with a relatively style-neutral profile that excludes very-small-capitalization stocks, minimizes and manages risks associated with structural sources of risk, optimizes aggregate risk relative to return expectations, and carefully manages the balance between active and passive managers.

Value versus Growth Modeling

Some of the first applications of computer-assisted valuation techniques to traditional equity analysis focused on value-versus-growth investing. While undoubtedly attracted by the opportunity for timing gains, this choice was also influenced by the differences between the underlying valuation methods of these two approaches. This distinction is still crucial.

Claudia Mott presents the results of studies determining the usefulness of seven factors commonly used in stock selection. The study concentrated on the small-cap universe and analyzed factor behavior in growth and value subsets, in up and down markets. In addition to differing by sector, factor effects differed for the growth and value universes. The most powerful factor found by the study was revisions of earnings estimates. The time-dependent effects of each factor are also shown.

Murali Ramaswami focuses on four issues related to the construction of return-enhancing investment strategies: (1) probabilistic definition of the size and style categories (large, medium, and small; growth and value stocks), (2) development of an econometric forecasting model capable of exploiting discernible patterns in the return series of the preceding categories of stocks, (3) design of the investment strategies to capitalize on the output of the size and style return-forecasting model, and (4) out-of-sample tests of investment strategies based on the forecasting model. The growth-versus-value indexes are shown to be importantly different from the indexes supplied by BARRA, the Frank Russell Company, and Wilshire Associates. Practical examples, such as Amgen switching its trading pattern from growth to value and back, make this a very interesting paper.

Finally, James Hall brings the seminar together by discussing how one company uses neural networks to select value-versus-growth stocks, what the company's model does, and how it has performed. He discusses five pitfalls the company learned to avoid if neural networks are to work well for forecasting.

Bottom Line

Quantitative investing is something of an art. Nonlinearities imply an infinite number of possibly productive approaches, and statistical significance is rare. Just as traditionalists cannot escape from computer-driven investing and trading, no market professional can escape from the dilemmas of data mining, nonstationarity, and nonlinearity. Future investment success will truly require the blending of traditional and quantitative approaches. This seminar provided examples of the opportunities and problems to be encountered in the marriage of the two approaches.