From the Board

Demystifying Multiple Valuation Models

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"Multiple valuation," a popular stock selection technique, is defined as a weighted average of stock selection "models" or "factors." It forms the fundamental basis of many modern approaches to active equity management. Multiple valuation is an automated and more sophisticated version of the stock "screens" performed by traditional investment managers.

A multiple valuation may consist, for example, of an equally weighted average of a stock's earnings growth rate, a measure of earnings momentum and a dividend discount model (DDM) alpha.[1] Each factor may be on a different scale.[2] A simple approach for dealing with this scaling issue is to compute factor value rankings and apply weightings in accordance with each factor's presumed relative importance. The end result is a set of values that may serve as a multiple valuation of the security's attractiveness.

Reasons for Using Multiple Valuation

Probably the single most important reason for the development of multiple valuation models was dissatisfaction with various single-factor stock valuation models. To illustrate, in many time periods a low price/earnings (P/E) model does not work—i.e., is not positively correlated with subsequent (risk-adjusted) return. As a result, more models were added to the valuation process. Intuitively, in time periods when one model is less useful, others may be able to pick up the slack.

One of the earliest and most influential papers demonstrating the potential power of the multiple valuation approach was by Ambachtsheer and Farrell.[3] They examined the performance of a composite based on a standard DDM alpha and a Value Line timeliness ranking. They showed that, over the test period, the combination of the two models had less variability and greater ability to select stocks than either of the two models separately.

Unfortunately, the Ambachtsheer and Farrell results have often been misinterpreted and used to justify two erroneous conclusions—(1) that multiple valuation models always perform better than the individual factors and (2) that the more factors included in the composite, the better the performance. Consequently, some investment managers use composite models with a large number of factors.

If these misinterpretations were valid, multiple valuation models would represent a "free lunch" and a means for mechanically creating enormous wealth. But, in fact, adding factors will often *reduce* forecasting ability. Also, multiple valuation models may not only perform less well than some of the factors they include, they may perform less well than *any* of the factors. Such events are not only theoretical possibilities, but have been experienced by users of multiple valuation models. It is therefore of substantial interest to understand better the benefits and limitations of the technique.

Fundamentals of Composite Valuation

A natural statistical measure of the level of information, or predictive power, in a model is the "IC" or "information" correlation between the forecast and subsequent (risk-adjusted) return. Perfect forecasting ability has an IC value equal to 1; 0 indicates no forecasting ability; −1 indicates a perfect negative relationship.

Consider a situation where factor a has positive predictive power and an IC of 0.2 ($IC_a = 0.2$). We consider adding a second factor, b, with an IC of 0.1. Figure A illustrates this case.[4] The curves trace the composite IC as a function of the relative weight in factor b. The IC value at $x = 0.80$ is the forecasting power of a composite model weighted 0.80 in factor b and 0.20 in factor a.

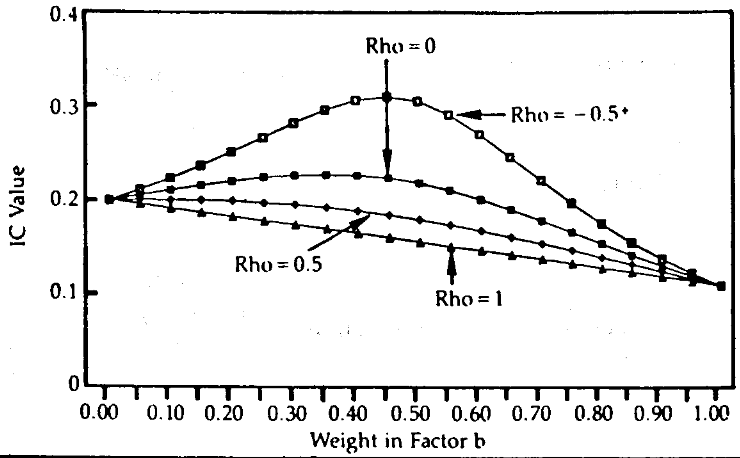
The composite IC also depends on the relation or correlation between the two factors, indicated by the value of "rho." At a rho of 1, the bottom curve or line, the factors are perfectly correlated and the composite IC is a weighted average of the factor ICs. If rho equals 0, the factors are uncorrelated and the composite IC is larger than the weighted average. When rho is negative, represented by the rho equals −0.5 curve, the factors are inversely related and the composite IC is very favorable. The height of the curves above the bottom line indicates the multiple valuation enhancement with respect to a weighted average.

Forecasting Properties

It is useful to think of the performance of a multiple valuation model as roughly equal to the weighted average of the performances of the individual factors. Consequently, like all averaging processes, multiple valuation will tend to be less volatile than its individual components. The critical issue, however, is whether, and when, performance can be enhanced. In general, our discussion will assume that the factors are not perfectly correlated (rho < 1).

1. Footnotes appear at end of article.

Figure A Two-Factor Multiple Valuation when Both Factors Have Positive Predictive Power*



*Factor a information correlation (IC) = 0.2; factor b IC = 0.1.
+Rho = correlation between factor a and factor b.

Case 1: *Both factors have positive predictive power.* Figure A shows that multiple valuation can enhance performance as well as reduce volatility. If (as in Ambachtsheer and Farrell) both factors have similar ICs, then the curves in Figure A shift so that the bottom line is horizontal. This implies that, regardless of the factor weights, the composite always has a higher IC value than the individual models. As Figure A also shows, however, if one model has more predictive power than the other, the benefits of using a multiple valuation model over the best performing model are less clear. They depend on the value of reduced volatility, factor weights and the assumed relation between the factors. A multiple valuation can often perform less favorably than the best available model.

Case 2: *Both factors have negative predictive power.* This situation can be illustrated by rotating the curves in Figure A about the horizontal axis. By symmetry the results for Case 1 are reversed. A multiple valuation will perform worse than the weighted average of the factors and can perform worse than any of the factors.

Case 3: *Neither factor has predictive power.* In this case, all the curves in Figure A would collapse to a single horizontal line with a zero IC value. Multiple valuation does not enhance performance if there is no information in the factors.

Case 4: Figure B illustrates the consequences of *adding a model without predictive power,* assuming the second factor has an IC of zero. The interesting result is that the performance of the composite can be better than the weighted average. The results show, however, that unless the factors have an inverse relationship (rho < 0), adding a model without predictive power will reduce performance.

The Key to Making Multiple Valuation Work

Multiple valuation is essentially a framework for using information. Our results demonstrate that the benefits depend critically on the availability of less than perfectly correlated factors with statistically significant ICs.

The heart of the issue is to find reliable factors and relationships. This is not a simple task. From an efficient-market point of view, the proof of the existence of even one, never mind several, such factors is a remarkable fact.

Constructing a Multiple Valuation Model

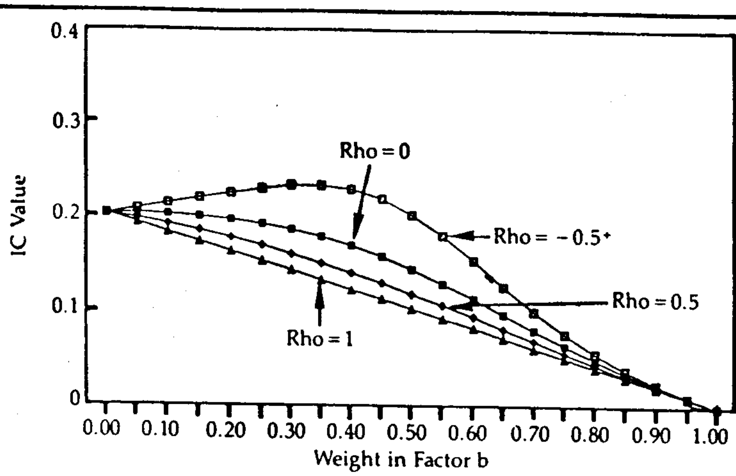
The following example, derived from Ambachtsheer and Farrell, illustrates multiple valuation model construction guidelines that may be useful.

Stocks may be priced, at least in part, on their "value"—i.e., whether they are cheap or expensive with respect to firm fundamentals. Such models are typically inversely related to price. A stock selection model such as a DDM alpha or low P/E may be useful in characterizing value pricing.

Stocks may be priced, at least in part, on whether the firm is "fashionable" and is of wide interest in the investment community. This concept is similar to the "beauty contest" view of Keynes. A model based on earnings revision or momentum may be useful in characterizing fashion pricing or investor interest.

Investor interest and value are unlikely to be strongly correlated over a market cycle. Investor sentiment may dominate pricing in a bull market, while value may dominate in times of economic uncertainty and in bear markets. Consequently, on an *a priori* basis, each component of a multiple valu-

Figure B Two-Factor Multiple Valuation when One Factor Has No Predictive Power*



*$IC_a = 0.2$; $IC_b = 0$.
+Rho = correlation between factor a and factor b.

ation model such as the one above has an economic rationale for being part of a stock selection model and a relationship with other factors that is expected to benefit performance.

The purpose of this discussion is not to recommend a particular set of components for multiple valuation or provide a complete description of the process. The purpose is simply to illustrate the application of principles of stock valuation as a guide for multiple valuation construction.

It should be noted that individual components of a multiple valuation model may validly consist of a number of factors. Multiple factors may be necessary to capture information of a given kind, which can then be aggregated into a single factor in a multiple valuation context. No prescriptions for constructing each component of the composite model are intended. However, the probable negative effects of adding factors without care remain.

Some Conclusions

Used properly, multiple valuation can be a valuable tool for stock selection and investment management. The critical conditions underlying its value depend on the reliability of the forecasting power of the factors and their interaction over time. The benefits of the technique can be great, even if the composite consists of only two factors. However, simply adding factors to a multiple valuation without careful consideration of predictive power and relationships is likely to be counterproductive.

Footnotes

1. For a description and a discussion of some of the properties of the standard DDM see R. Michaud and P. Davis, "Valuation Model Bias and the Scale Structure of Dividend Discount Returns," *Journal of Finance*, May 1982.
2. Scale issues are of importance in defining factor weightings and the performance of composite models. Some scale issues are discussed in R. Michaud, "The Markowitz Optimization Enigma: Is Optimized Optimal?" *Financial Analysts Journal*, January/February 1989, appendix.
3. K. Ambachtsheer and J. Farrell, "Can Active Management Add Value?" *Financial Analysts Journal*, November/December 1979.
4. The curves are derived assuming that the standard deviations of the two factors are equal. If this simplifying assumption is not correct, the analysis and implementation of the procedure can change substantively.