by Robert D. Arnott and William A. Copeland

The Business Cycle and Security Selection

Many investors use security selection models to evaluate a broad spectrum of investment information. But individual models often prove vulnerable to the dynamics of the business cycle. A model that performs well in one economic environment is likely to perform poorly in a different one. To the extent that model weakness or strength can be forecast, investors can employ models with greater effectiveness.

Correlations between various models and measures of interest rates and inflation indicate that growth models are more effective during periods of high inflation and less effective in a strong economy. Value-oriented models, however, perform well in periods of low inflation and in poor economic climates. Most of the models tested perform better in periods of low real interest rates. Past model performance is a generally good indicator of future performance.

ALL SYSTEMATIC investment strategies are vulnerable to the dynamics of the marketplace. The market may reward a value-oriented strategy one year, a growth strategy the next. The investment practitioner who focuses on a single strategy is unlikely to achieve consistent results. The low-P/E strategy, for example, has a demonstrated and significant long-term track record. Yet some practitioners failed to survive the long dry spell from 1969 through mid-1973.

In our industry, consistency is as important as performance. That is why multiple valuation models have been gaining acceptance. Two or more security selection disciplines, used in combination, can be both more effective and more consistent than a single discipline—*if* the individual models add value and provide independent information.

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This article reviews the limitations and strengths of multiple security selection disciplines and shows how their application can be improved by forecasting model effectiveness. Objective measures of inflation, the business cycle, and past model performance are all important indicators of which strategies are likely to be rewarded in the current market environment.

Forecasting Model Effectiveness

Many investment practitioners systematically apply multiple valuation models to meet the combined objectives of superior performance and consistency. Some investors simply seek issues that pass several screens. Others rate stocks on the basis of several criteria, weight these criteria, and generate a combined score. Indeed, all money managers use a composite stock selection framework: Even the manager who claims to use no models takes in information from many sources, weighs it subjectively and *combines* the information to assess stock attractiveness.

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The use of a multiple valuation approach is founded on the fact that a composite of several security selection disciplines can be simultaneously more effective and more consistent than any single component.[1] This can hold true *if* each discipline works independently and contributes independent information. The approach is not without limitations. For example, a combination of two essentially identical strategies will *not* be better than either approach alone. Also, inclusion of a discipline that does not generate favorable results will not normally result in a superior composite.

The value of a disciplined multiple valuation strategy is often diluted by the subjective review of recommendations for safety or prudence. The market demands superior returns for "unsafe" issues; hence discarding such issues can hamper performance. Including undisciplined subjectivity in a disciplined framework tends to contradict the multiple model's very purpose—its imposition of discipline. The problem does not lie with the multiple valuation approach, but with the *implicit* inclusion of a discipline that does *not* add value.

In order to demonstrate the advantages of integrating single selection disciplines into a multiple valuation framework, it is necessary to have an objective measure of model effectiveness. The most widely accepted measure of model effectiveness is the information coefficient (IC)—the correlation between the predicted stock return and the realized return.[2] (The appendix details the derivation of ICs.) A quarterly IC of 0.10 implies that the most favored decile of stocks will outperform the least favored decile by roughly 4 per cent per quarter.[3]

Consider two independent security selection models; assume each has an information coefficient (IC) of 0.10, and that each "works" (i.e., exhibits a positive IC) 75 per cent of the time.[4] We can construct an equally weighted composite of the two models by simply averaging their estimates of stock attractiveness. The combined model would work approximately 82 per cent of the time and have an average IC of 0.14 (see the appendix for the mathematics).

If we know that the multiple model approach will be superior to the single model, why bother to forecast model effectiveness? The value of forecasting is best demonstrated by assuming perfect prescience. If we knew exactly how well two models would work in a certain market environment, we could choose to use only the more effective, which would work 94 per cent of the time and provide an average IC of 0.18.[5]

Alternatively, we could weight the two models according to their expected ICs. Our variable-weighted multiple valuation model would have an IC of over 0.24 and would *never* fail.[6] Any failure on the part of one model would be anticipated, and a negative weight would be assigned to that model. Thus, with perfectly anticipated ICs, one can construct a combined model that will provide results superior to those of an equally weighted composite (which is, in turn, superior to any single component of the composite).

Of course, model effectiveness cannot be anticipated with certainty. Therein lies the risk. An imperfect forecast of model effectiveness may overemphasize the less effective models and underemphasize the more effective ones. This can result in a variable-weighted composite that is less effective than a simple equally weighted composite. Obviously, use of a composite based on a variable-weighting approach is only as good as the forecast ICs it is based on. ICs must be estimated carefully. Ill-conceived IC estimates may impair, rather than enhance, security selection.

Indicators of Model Effectiveness

We tested the popular security selection models listed in Table I over 15 years of quarterly data from 1968 to 1982.[7] We measured the IC of each model by calculating the correlation between the model's ranking of stocks in a 700-plus universe and subsequent three-month total returns.[8]

To determine which objective measures of the economic environment are useful in predicting the effectiveness of each sample model, we performed regression tests. In each regression, the dependent variable was the effectiveness (IC) of some model in quarter t, and the independent variable was some economic variable that would have been available in quarter t-1. Thus we regressed *ex post* observations of model effectiveness against *ex ante* economic variables.[9]

Table II lists the variables found to be most significant for predicting the effectiveness of the security selection models. When tests are based on relatively few observations (in our case, 60 quarters for each stock), statistical tools may fail to detect relations that are, in fact, present. We

1. Footnotes appear at end of article.

Table I Security Selection Models

Value-Oriented Models

Dividend Discount Model Rate of Return (ROR): Internal rate of return (ROR) is calculated from a three-stage extrapolation-based dividend discount model. High dividend discount RORs are favored.

Earnings Retention Yield ((EPS-Dividend)/Price): Earnings retention yield is based on earnings and dividends over the latest four quarters. Above-average retained earnings yield is preferred.

Earnings Yield (latest 12-month EPS/Price): Earnings yield is the reciprocal of P/E. This model favors low P/E stocks.

Dividend Yield (Dividends per Share/Price): This dividend yield model excludes zero yield stocks. The model favors high-yield stocks over low-yield stocks.[a]

Book-to-Price Ratio (Book Value per Share/Price): This ratio is determined from the book value at the end of the last fiscal year. Stocks with high book-to-price ratios are preferred.

Growth-Oriented Models

ROE Change (five-year): ROE change is based on the slope of an ordinary least squares regression line through the last five years of return on equity. Growing ROE is favored.

Sales Growth Rate (five-year): Sales growth is the slope of an ordinary least squares regression line through the last five annual sales per share on a logarithmic basis. This model focuses on above-average growth in sales.

EPS Momentum: EPS momentum is the percentage change from the latest fiscal year EPS to the I/B/E/S consensus EPS estimate for the current fiscal year.[b] Firms with positive momentum (which are expected to earn more in the current year than last year) are favored.

Other Models

Capitalization: Academic research suggests that small capitalization stocks have outperformed large stocks. This is often called the "small stock effect."

EPS Variability (σ_{EPS}/Price): EPS variability is based on the volatility of EPS over the prior seven years. High earnings variability is favored.[c]

a. We find that low yield stocks generally offer inferior risk-adjusted returns, but that zero yield stocks generally offer substantially above-average risk adjusted returns.
b. I/B/E/S is the Institutional Brokers Estimation System produced by Lynch, Jones & Ryan.
c. R. D. Arnott, "What Hath MPT Wrought: What Risks Reap Rewards?" *Journal of Portfolio Management*, Fall 1983.

Table II Variables Tested for IC Forecasts

Inflation and Interest Rates

CPI: Prior 12-month percentage change in the Consumer Price Index.

INFC: The Boston Company's Inflation Pressure Composite, a proprietary model used to forecast inflation over the next 12 to 18 months.

REAL: Real rates of interest, or commercial paper rates less consensus expected inflation.

Business Cycle Descriptors

IP: 12-month percentage change in industrial production.

COIN: 12-month percentage change in the Bureau of Labor Statistics (BLS) Coincident Indicators.

LEAD: 12-month percentage change in the BLS Leading Indicators.

Measures of Recent Performance

QTR1: A dummy variable, set to 1.0 for the first calendar quarter, and set to zero for other quarters.

PRIORIC: Latest quarterly IC.

YEARIC: Average of latest four quarterly ICs.

were, then, pleasantly surprised to find that many of the relations we tested turned out to be statistically significant. Even the insignificant results were generally in the "right" direction, consistent with common sense. The findings lend credence to the possibility of forecasting model effectiveness.

Seasonality and Prior Performance

By far the most powerful relation we found is a "first quarter" effect. The "small stock effect" has been shown to be enormously powerful in the first month (or quarter) of the calendar year and rather weak for the balance of the year.[10] Our findings support this: A first quarter dummy variable (which equals one for the first quarter and zero otherwise) exhibits a highly significant correlation of 0.37 with the quarterly IC of the Capitalization model.

While much attention has focused on the strength of a first quarter (or January) effect for small capitalization issues, surprisingly little attention has focused on calendar effects for other security selection disciplines. Interestingly, a first quarter effect is a powerful factor for virtually every model. Curiously, this effect is even more pronounced in several models other than the Capitalization model. All but one relation is significant (only the EPS Momentum model fails to show significance), with half the correlations exceeding ±0.5. The data suggest that all three growth-oriented models are substantially less effective in the first quarter than in the balance of the year. All other models, particularly those based on risk (e.g., EPS Variability) tend to be dramatically better in the first quarter than in the balance of the year.

Contrary to our expectations, the relation between past and future model effectiveness is quite strong. We had expected that a recent slump would increase the likelihood of subsequent success. The evidence in Table III clearly contradicts this hypothesis. Indeed, 18 of 20 correlations are positive, and six are statistically significant. Placing extra bets on recent winners clearly helps in the case of most models.

For example, Table III shows that if the Dividend Yield model has been working well over either the last quarter or the last year, we can have confidence that it will continue to add value. If it has been experiencing a slump, the slump is likely to persist.

An automatic focus on recent performance is not always warranted, however. A few models (including the Capitalization model, Sales Growth, EPS Momentum and EPS Variability) exhibit no strong relation between past and future performance. Finally, the relation between one quarter and the next for ROE Growth is not strong.

Table III Seasonality and Prior Performance, 1968–1982 (t-statistics in parentheses)

Security Selection Model	*Descriptors:* *First Quarter*	*Latest 4-Quarter Average IC*	*Latest Quarter IC*
ROR	+0.38	+0.14	+0.31
	(+4.9)*	(+0.9)	(+3.1)*
EPS Retention	+0.33	+0.10	+0.31
	(+2.6)*	(+0.8)	(+2.4)*
EPS Yield	+0.29	+0.22	+0.20
	(+2.2)*	(+1.7)	(+1.5)
Dividend Yield	+0.72	+0.44	+0.37
	(+7.6)*	(+3.7)*	(+3.0)*
Book to Price	+0.51	+0.30	+0.18
	(+4.3)*	(+2.3)*	(+1.4)
ROE Change	−0.47	+0.36	−0.01
	(−3.8)*	(+2.9)*	(−0.0)
Sales Growth	−0.59	+0.07	+0.21
	(−5.3)*	(+0.5)	(+1.7)
EPS Momentum**	−0.10	+0.10	+0.25
	(−0.4)	(+0.5)	(+1.2)
Capitalization	+0.37	+0.24	−0.17
	(+3.0)*	(+1.8)	(−1.3)
EPS Variability	+0.61	+0.10	+0.08
	(+5.6)*	(+0.7)	(+0.6)

* Significant at the 95 per cent confidence level.
** Results cover 1976–82 period.

The Business Cycle

Table IV shows the relations between measures of the business cycle and model effectiveness. The 12-month change in the Department of Commerce (DOC) Coincident Indicators Index was used as a measure of current economic health. The correlations suggest that a focus on past growth, profitability or low P/E (as evidenced by the correlations for Sales Growth, ROE Growth, Retained EPS Yield and EPS Yield) is rewarded in a strong economy, whereas focus on strong EPS Momentum is not rewarded.

The strongest relation is found for the ROE Change model. In a robust economy, a focus on companies with improving profitability is desirable. These are often companies recovering from depressed earnings.

Another business indicator—the DOC Index of Leading Economic Indicators—exhibits an interesting dichotomy. We expected that this index would be significant in several models. However, it proved insignificant for most models but exhibited surprisingly strong significance for EPS Momentum (in light of the limited data on this model).

The results suggest that the market pays too high a premium for strong expected EPS Momentum in a healthy economy. In an improving economy a contrarian bet on weak companies appears to be profitable, whereas in a weakening economy, bets on the stronger companies with favorable earnings prospects are warranted. This use of EPS Momentum is unconventional, but it is not surprising.

ROE Growth and Retained EPS Yield appear to become more effective as the Leading Indicators rise. These results fall short of statistical significance, but they mesh with the findings for the Coincident Indicators. There is a key difference: The Leading Indicators test suggests a relation based on economic *outlook*, whereas the other test suggests coincident relations.

Inflation and Interest Rates

Table V gives the correlations between the

Table IV Business Cycle and Model Effectiveness, 1968–1982 (t-statistics in parentheses)

Security Selection Model	Descriptors: 12-Month Change in Coincident Indicators	12-Month Change in Leading Indicators
ROR	−0.08	+0.07
	(−0.6)	(+0.5)
EPS Retention	+0.21	+0.13
	(+1.6)	(+1.0)
EPS Yield	+0.09	+0.07
	(+0.7)	(+0.5)
Dividend Yield	−0.10	−0.01
	(−0.7)	(−0.1)
Book to Price	−0.06	−0.03
	(−0.4)	(−0.2)
ROE Change	+0.38	+0.23
	(+3.0)*	(+1.7)
Sales Growth	+0.38	+0.09
	(+1.6)	(+0.7)
EPS Momentum**	−0.19	−0.55
	(−0.9)	(−2.9)*
Capitalization	−0.06	0.00
	(−0.5)	(0.0)
EPS Variability	−0.05	0.00
	(−0.4)	(0.0)

* Significant at the 95 per cent confidence level.
** Results cover 1976–82 period.

Table V Inflation, Interest Rates and Model Effectiveness, 1968–1982 (t-statistics in parentheses)

Security Selection Model	Descriptors: 12-Month Change in CPI	Inflation Composite	Real Interest Rate
ROR	−0.00	−0.28	+0.16
	(−0.0)	(−2.1)*	(+1.2)
EPS Retention	+0.01	−0.07	−0.21
	(+0.1)	(−0.5)	(−1.6)
EPS Yield	+0.07	−0.15	−0.13
	(+0.5)	(−1.1)	(−1.0)
Dividend Yield	+0.01	−0.18	+0.16
	(+0.1)	(−1.4)	(+1.2)
Book to Price	+0.10	−0.16	−0.06
	(+0.7)	(−1.2)	(−0.4)
ROE Change	−0.03	+0.31	−0.24
	(−0.2)	(+2.4)*	(−1.8)
Sales Growth	+0.01	+0.16	−0.13
	(+0.1)	(+1.2)	(−0.9)
EPS Momentum**	+0.31	+0.34	−0.24
	(+1.5)	(+1.6)	(−1.1)
Capitalization	+0.06	−0.21	−0.30
	(+0.4)	(−1.6)	(−2.3)*
EPS Variability	+0.02	−0.17	−0.18
	(+0.2)	(−1.2)	(−1.3)

* Significant at the 95 per cent confidence level.
** Results cover 1976–82 period.

effectiveness of forecasting models and various measures of inflation and interest rates. Inflation, as measured by the 12-month rate of change in the CPI, is not significantly related to model performance. We were surprised by the complete insignificance of the CPI in forecasting model effectiveness. It had been our expectation that models such as the Dividend Yield model would be significantly affected by inflation.

To gain a clearer perspective of the impact of inflation, we also tested a proprietary model (the Boston Company's "Inflation Pressure Composite") designed to detect inflation pressures as they are building, hence to anticipate acceleration in the inflation rate. Whereas inflation, as measured by the CPI, is "backward-looking," based on observed history, the Inflation Pressure Composite is "forward-looking," although limited to the near-term (six to 12 months).

Given the forward orientation of the Inflation Pressure Composite, we anticipated that it would exhibit stronger relations with the 10 security selection models than historical inflation. The results appear to support our expectations. The breakdown by model category is interesting, however.

- Growth-oriented models (ROE, Sales Growth and EPS Momentum) all performed better in periods of inflationary pressures. If economic conditions portend accelerating inflation, these models merit particular attention.
- All other models are adversely affected by inflation pressures.

We also examined the impact of real interest rates on model effectiveness. All but two of the models were adversely affected by high real interest rates (only the Dividend Discount ROR and Dividend Yield correlations were slightly positive). Low real rates appear significantly favorable for companies with above-average retained earnings. This last correlation may reflect a relation between high real interest rates and the economy. High real interest rates adversely affect most economic sectors, but mature companies with large capitalization are relatively less affected than other companies.

Model Stability

Do these techniques for predicting model effectiveness continue to work after the fact? To test the persistence, hence the merit, of IC forecast-

Table VI Model Forecast Stability: Actual IC vs. Forecast IC, 1978–1982

Security Selection Model	Correlation $IC, \widehat{IC}$	t-Statistic $IC, \widehat{IC}$
ROR	+0.63	+3.5*
EPS Retention	+0.25	+1.1
EPS Yield	+0.16	+0.7
Dividend Yield	+0.65	+3.6*
Book to Price	+0.53	+2.6*
ROE Change	+0.38	+1.8
Sales Growth	+0.55	+2.8*
EPS Momentum**	−0.19	−0.6
Capitalization	+0.19	+0.8
EPS Variability	+0.46	+2.2*

* Significant at the 95 per cent confidence level.
** Model tested in the same fashion as other models. However, IC data were available only from 1976–82, so the *ex ante* IC forecasts were constructed only for 1980–82.

ing models, we used the following process.

(1) Using data from 1968–77, we created multiple regression models (using only those economic variables with t-statistics of at least ±1.0) to predict ICs for each of the security selection models. (The modeling was adjusted to correct for serial correlation.)

(2) We used these regression models to generate IC forecasts for each model for the four quarters of 1978.

(3) Using 1968–78 data, we created regression models to predict ICs for 1979.

(4) We repeated this process for each year until we had 1982 IC forecasts based on 1968–81 data, so that we generated *ex ante* IC forecasts for five years (1978–82) for each security selection model.

We compared these *ex ante* predicted ICs with the true ICs for the five years for each of the models. We did not expect the results to be statistically significant, given the relatively few observations. A positive correlation between the predicted ICs and the actual ICs would suggest, however, that forecasting ICs is a productive exercise.

Once again, we were pleasantly surprised. Statistical significance cropped up where none was expected. Table VI gives the correlations between *ex ante* projections of ICs and actual ICs, along with the t-statistics for the correlations. Of the 10 models, only one exhibits a negative correlation between forecast and actual IC; EPS Momentum shows an insignificant negative correlation. Five exhibit positive correlations of at least 40 per cent, all of which are statistically significant. The evidence clearly suggests that *ex ante* prediction of ICs is feasible.

Conclusion

Our findings have passed statistical tests with surprising levels of confidence. ICs *can be forecast* without great difficulty. What's more, properly anticipated ICs can tell us a great deal about future market trends. This can allow the construction of superior multiple valuation strategies for security selection. In other words, it is possible to determine *in advance* the strategies that are likely to reap rewards in the near future. ■

Appendix

The Information Coefficient (IC)

The concept of the Information Coefficient (IC) has become the most widely used standard for measuring the effectiveness of security selection disciplines. An IC is nothing more than the correlation, across some universe of securities, between the estimated attractiveness of a security, as measured by some model, and the subsequent return on that security. It is often measured as a rank correlation, although we prefer a pure correlation, which attaches more significance to the "tails" of the distribution of anticipated returns.

Given two or more models, it is not difficult to estimate the value of a composite model.[11] Suppose model i has an average IC of IC_i, and is weighted in a composite with weight W_i. The IC of the composite (IC_c) can be estimated as:

$$IC_c \cong \frac{\underline{W}'_\sigma \, \underline{IC}}{(\underline{W}'_\sigma \, \underline{\underline{\rho}}_{\hat{R}} \, \underline{W}_\sigma)^{0.5}} \qquad \text{(A1)}$$

where

$\underline{W}_\sigma$ = a column vector with ith entry of $W_i \sigma_{\hat{R}_i}$,
$\underline{IC}$ = a column vector with ith entry IC_i,
$\underline{\underline{\rho}}_{\hat{R}}$ = a matrix whose ijth entry is the correlation between the return forecasts of methods i and j,
$\sigma_{\hat{R}_i}$ = the standard deviation of the return forecast of method i, and
W_i = the weight on method i.

Furthermore, if IC_i varies over time with a standard deviation of σ_i, the standard deviation of IC_c (the composite IC) can be estimated as

$$\sigma_c \cong \frac{\underline{W}'_\sigma \, \underline{\underline{\Sigma}}_{IC} \, \underline{W}_\sigma}{\underline{W}'_\sigma \, \underline{\underline{\rho}}_{\hat{R}} \, \underline{W}_\sigma}, \qquad \text{(A2)}$$

where

$\underline{\underline{\Sigma}}_{IC}$ = a matrix of covariances between the IC_i.

This holds true if $\sigma_{\hat{R}_i}$ and $\rho_{\hat{R}}$ are relatively stable over time.

In constructing a variable-weighted composite, one may choose to maximize IC. This is accomplished by solving the j simultaneous equations:

$$\underline{W}_\sigma \cong \underline{\underline{\rho}}_{\hat{R}}^{-1}\ \underline{IC} \qquad \text{(A3)}$$

for the optimal weights (W_σ).

If the user chooses to maximize consistency (or to minimize the likelihood of adverse performance), the relationship IC_c/σ_c should be maximized. An approximation of the optimal weights can be found by solving:

$$W_\sigma \cong \underline{\underline{\Sigma}}_{IC}^{-1}\ \underline{IC}. \qquad \text{(A4)}$$

Footnotes

1. See Keith P. Ambachtsheer and James L. Farrell, "Can Active Management Add Value?" *Financial Analysts Journal*, November/December 1979.
2. Different practitioners may use a pure correlation, a rank correlation or a correlation of decile categorizations of forecast and outcome. Some practitioners use total returns as a measure of subsequent outcome, while others employ a measure of alpha. These various measures are essentially the same. We use a pure correlation and subsequent total returns, for simplicity, but have no strong reservations about other measures. The results presented in this article are not meaningfully affected by this choice.
3. The return on stocks at the 95th percentile (the median of the top decile), ranked by quarterly return, is typically about 40 to 50 per cent above the return on stocks at the fifth percentile (the median of the bottom decile). A stock selection model with a quarterly IC of 0.10 should capture 10 percent of this. Thus, for a model with an IC of 0.10, the median performance of the most favored decile should be 4 to 5 per cent better than the median performance of the least favored decile. This result does not include transaction costs. Nonetheless, such results should be ample to record substantially above-average results net of transaction costs, except in the case of a very high turnover strategy.
4. If two security selection disciplines are independent, there is no correlation between a stock's attractiveness as measured by one discipline *vis-a-vis* the other. A stock is equally likely to be viewed as attractive on one discipline whether or not it is attractive on the other discipline.
5. The combined IC if we use only the better of the two models is defined by:

   $$\max(IC_1, IC_2).$$

   If IC_1 and IC_2 exceed zero 75 per cent of the time, then $\sigma_{IC} \cong 1.5\ \overline{IC}$. We can solve the IC of the better of the two models as:

   $$\begin{aligned} &\iint P_{IC_1} P_{IC_2} \max(IC_1, IC_2)\, dIC_1\, dIC_2 \\ &= \overline{IC} + (1/\sqrt{\pi})\, \sigma_{IC} \\ &= 0.18 \cdot \overline{IC} \end{aligned}$$

   if

   $$IC_1, IC_2 \sim N(IC, \sigma_{IC}).$$

   If two independent models work some 75 per cent of the time each, then they will *both* fail only 25 per cent times 25 per cent of the time, or 6.25 per cent of the time.
6. If $IC_1, IC_2 \sim N(IC, 1.5 \cdot IC)$, and IC_1 and IC_2 are independent, then the combined IC for a properly weighted composite is defined by

   $$\begin{aligned} &\iint P_{IC_1} P_{IC_2} (IC_1^2 + IC_2^2)\, dIC_1\, dIC_2 \\ &= 2\,(IC, \sigma_{IC}^2) \\ &= 2.45\ IC. \end{aligned}$$

7. It should be noted that market experience in recent years has an unavoidable influence on our choice of stock selection strategies. Some of these strategies have attracted attention because of recent performance, which may not be achieved in the future. However, this does not affect our premise that ICs for these (and perhaps other) models can, indeed, be predicted to some extent.
8. The test universe included the current stocks in the S&P 500 and The Boston Company Stock Monitor. Selection bias (particularly survival bias) may affect our results somewhat. Certain models were tested on a larger universe, including non-survivors, with comparable results; we are thus confident that this is not a significant issue.

   The sample is large enough to ensure that the IC estimates have a standard deviation of only ±0.04. The standard error in an estimate of IC is

   $$(1 + IC)(1 - IC)/\sqrt{n - 1}$$

   where n is the number of issues.
9. A Hildreth-Lu adjustment was used to correct for any autocorrelation in the residuals.
10. See R. Banz, "The Relationship Between Return and Market Value of Common Stocks," *Journal of Financial Economics*, March 1981; or Mark Reinganum, "Abnormal Returns in Small Firm Portfolios," *Financial Analysts Journal*, March/April 1981. Stoll and Whaley of Vanderbilt University have constructed a bibliography of over 40 related articles.
11. We are indebted to Bob Ferguson, of Leland, O'Brien, for suggesting revisions in the mathematics, which broaden the applicability of the formulas.