Forecasting factor returns: An intriguing possibility

Feasible forecasts of factor returns disclose intriguing patterns in the rewards for various investment styles.

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Investment style matters. At times, a focus on high-yield stocks may be generously rewarded. At other times, such issues are outpaced by others with rapid earnings growth. Some investment styles have a record of producing respectable long-term results. Even the most successful styles and strategies, however, sometimes experience extended dry spells. Indeed, styles that pay off in one economic environment frequently fail in a different one. Obviously, any technique that can predict the performance of various styles would be of considerable practical value.

This article describes the results of our research on predictors for the performance of various investment styles. It builds on earlier research (Arnott and Copeland [1985]) that suggested a direct linkage between measures of the business cycle and the power of several stock selection disciplines. The stocks most favored under the disciplines presented here outperform the average stock by over 100 basis points per month. The stocks least favored under these disciplines lag by nearly 100 basis points per month.

Of course, the full power of such disciplines cannot be realized in actual stock selection. Implementation would generate high portfolio turnover and correspondingly high transaction costs. Nevertheless, selection styles merit considerable attention as a guide to the timing of transactions.

INVESTMENT STYLE

The style of an investment portfolio shapes the pattern of returns more significantly than virtually any other element in the investment process. We cannot know whether this will be a year that rewards growth or value investors. But, in a year that rewards value managers, almost all growth managers will suffer. Conversely, in a year that rewards growth investors, those who favor value will generally suffer.

Table 1 summarizes the median performance of value and growth managers tracked by EAI for a full decade. At some times value managers beat

TABLE 1

Returns to Alternative Management Styles (%)

Time Period	S&P 500 Index	Growth Managers	Value Managers	Best Performing	Worst Performing
			Cumulative Returns		
1975 I–1976 I	57.6	41.0	53.7	53.7	41.0
1976 II–1978 I	− 4.8	− 1.9	12.6	12.6	− 1.9
1978 II–1980 IV	75.9	99.9	67.4	99.9	67.4
1981 I–1982 II	−12.4	−11.4	1.8	1.8	−11.4
1982 III–1983 II	61.1	68.4	62.4	68.4	62.4
1983 III–1984 IV	6.6	− 5.3	9.3	9.3	− 5.3
			Annual Returns		
1975 I–1984 IV	14.8	14.6	18.0	20.5	12.2

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growth managers, while at others the reverse occurred (see Bailey and Arnott [1986]). Certainly, if we could anticipate which would be rewarded, we would have a valuable tool for investment management. Indeed, the more accurately we could forecast sources of return, the more valuable a tool we would have.

How do we quantify style? One widely used tool is the BARRA "E2" risk model, which scores every stock on the market according to twelve factors detailed in Table 2. For example, stocks favored by value managers typically have high exposure to the book to price, earnings to price, and dividend yield factors. They also frequently exhibit low exposure to the trading activity and market variability factors. Stocks selected by growth managers generally have the opposite exposure. With either growth or value management, exposure to the other factors, such as size and foreign income, may be either low or high.

TABLE 2

BARRA Risk Factors

Factor	Description
Market Variability	A measure of volatility in stock price and options prices.
Success	A measure of relative stock price performance.
Size	A measure of company assets and market capitalization.
Trading Activity	A measure based on various indexes of share turnover.
Growth Orientation	A measure designed to predict subsequent growth in earnings per share.
Book to Price	A measure of book value per share relative to price per share.
Earnings to Price	A measure of earnings per share relative to price per share.
Earnings Variability	A measure of volatility in earnings and cash flow per share.
Financial Leverage	A measure of balance sheet and operating leverage.
Foreign Income	A measure of the proportion of earnings derived from foreign sources.
Labor Intensity	A measure of the relationship between labor cost and capital cost.
Dividend Yield	A measure of the predicted dividend yield on common stock.

Table 3 shows the relative importance of the various factors. Persistence in the factor returns is measured by their mean return. The factors with statistically significant mean returns, as indicated by their t-statistics, are book to price, earnings to price, foreign income, success, and size. A style that maintains exposure to one or more of these factors can thus expect to produce respectable long-term results, assuming past patterns persist. Indeed, some of the most successful investment managers use precisely such an approach.

TABLE 3

Summary Statistics on Factor Returns[a]
(1/73 – 12/88)

Factor	Mean Return	t-Statistic	Standard Deviation	Relative Power[b]
Market Variability	−0.10	−0.89	1.42	15.6
Success	0.29	3.04[e]	1.21	11.3
Size	−0.17	−2.70[e]	0.80	4.9
Trading Activity	−0.10	−1.61[c]	0.79	4.8
Growth Orientation	0.07	0.73	1.22	11.5
Book to Price	0.33	5.66[e]	0.74	4.2
Earnings to Price	0.24	4.12[e]	0.74	4.2
Earnings Variability	−0.01	−0.18	0.70	3.8
Financial Leverage	−0.05	−1.35[c]	0.47	1.7
Foreign Income	−0.09	−3.18[e]	0.36	1.0
Labor Intensity	0.05	1.08	0.59	2.7
Dividend Yield	0.07	1.05	0.85	5.6

[a] Monthly returns in percent.
[b] Computed by squaring the standard deviation and expressed as a multiple of the lowest such value.
[c] Significant at 10% level.
[d] Significant at 5% level.
[e] Significant at 1% level.

Variability in the factor returns is measured by their standard deviation. All the factors have a standard deviation that is large relative to the mean return. This suggests that a discipline that alters factor exposures can hope to produce spectacular investment results, *provided* some of this variability can be explained. This prospect motivates our research.

The importance of the factor returns in explaining security price behavior is measured by their relative power. Factors of the greatest importance are market variability, growth orientation, and success. The market variability factor is a more powerful factor in stock returns than the five least powerful factors combined! This is not surprising, because market variability is analogous to beta, which is clearly the strongest single determinant of stock price behavior. The growth orientation and success factors are almost as powerful.

If some of this variability can be explained for the most powerful factors, the results could be particularly valuable.

RESEARCH METHODOLOGY

We conducted our research in two parts. First we explored individual variables that are thought to have an important influence on factor returns. We examined three classes of variables — calendar, market, and economic relationships — using a simple ex post regression framework.[1] We then examined the

combined merit of these three classes of variables for forecasting factor returns.

In the second stage of our analysis we applied multivariate statistical techniques within a rigorous ex ante regression framework. The resulting ex ante factor return forecasts were then used to simulate simple stock selection disciplines.

The sample data employed in our research consist of 192 monthly observations from January 1973 through December 1988. Our ex ante testing was carried out as follows. First, sample data consisting of 70 monthly observations from January 1973 through October 1978 were used to estimate regression equations for each BARRA factor. The equations were applied to predict factor returns for November 1978.

Next, sample data from February 1973 through November 1978 were used to estimate another set of regression equations with the same explanatory variables. This equation was applied to predict factor returns for December 1978. This process was repeated to predict factor returns for every remaining month through December 1988.

The biases found in ex post modeling, with full benefit of twenty-twenty hindsight, are not the only problems to avoid. There are several other potential sources of error. For example, the independent variables are not always available immediately at month-end. Therefore every effort was made to insure that the data tested would be available at the beginning of the month for which the next ex ante test would be run. Consequently, all explanatory variables were lagged at least one month from the time the data were announced.

Care must be taken not only in choosing which variables we use but also in how we use them. For example, capacity utilization can be used directly as a raw variable. It usually lies in a range from 70% to 100% and exhibits no secular trend. On the other hand, money supply and price indexes should probably be measured in terms of either growth or acceleration rates.

RESULTS

Calendar Effects

Our tests for calendar effects in factor returns focus on both seasonalities and serial correlation. The tests originated from the belief that there exist patterns in factor returns that are related exclusively to the passage of time. The results of this analysis suggest that seasonal effects, but not serial correlation effects, have statistically significant value as predictors of factor return.

We explored the seasonal effects using dummy variables, one for each month.[2] Table 4 presents the statistically significant results for the month effects. These results corroborate previous findings that indicate significant January effects. There are significant effects for eight factors: market variability, success, size, trading activity, book to price, earnings variability, foreign income, and dividend yield factors. To put it casually, the dogs jump in January and nap the rest of the year.

The January effect for the size factor is perhaps the most famous but clearly among the less significant. The effect for the book to price factor is the most

TABLE 4

Significant Ex Post Results for Calendar Variables
(1/73 – 12/88)

	January Effect		Other Effects		
Factor	Correlation Coefficient	t-Statistic	Month	Correlation Coefficient	t-Statistic
Market Variability	−0.180	2.516[c]			
Success	−0.261	−3.717[c]			
Size	−0.130	−1.803[b]	October	0.238	3.369[c]
Trading Activity	−0.236	−3.339[c]			
Growth Orientation					
Book to Price	0.366	5.407[c,d]	October	−0.218	−3.071[c]
Earnings to Price			June	−0.207	−2.908[c]
Earnings Variability	0.264	3.763[c]			
Financial Leverage					
Foreign Income	−0.121	−1.676[b,d]			
Labor Intensity					
Dividend Yield	0.198	2.777[c]			

[a] Significant at 10% level.
[b] Significant at 5% level.
[c] Significant at 1% level.
[d] Exhibits a statistically significant reversal between December and January.

significant at three times the magnitude of the January size effect. Next in importance are the effects for earnings variability and success.

Intriguingly, there also exists a strong October effect for the book to price and size factors. This effect is opposite in sign to the January effect for these factors. The October effect for size actually has a t-statistic more than twice that for the corresponding January effect.

Finally, there exists a significant June effect for the earnings to price factor. While the January and October effects are evident for many of the factors, only earnings to price shows a significant June effect. This is not likely to be a statistical fluke, as the t-statistic of −2.908 implies significance at the 1% level. Moreover, it is a far stronger effect than the well-accepted January small-stock effect.

We studied the serial correlation effects using standard statistical techniques. If there were either momentum or reversal effects for factor returns, statistically significant serial correlations would be evident. Unfortunately, these relationships proved fickle. There was essentially no evidence of momentum effects. If a particular factor had been generating persistent positive or negative factor returns, it was at best a mediocre predictor of subsequent factor returns.

Market Conditions

Our tests for the effects of market conditions on factor returns concentrate on three market variables: the equity risk premium, market volatility, and yield change. The capital markets themselves seem to tell us something about which factors are likely to be rewarded. Table 5 shows that all three variables have statistical significance as predictors of several factor returns.

The risk premium is measured by S&P 500 earnings yield[3] minus the Treasury bill yield. This variable has been demonstrated to be useful in forecasting market return (Arnott and Sorensen [1988]). Our hypothesis was that it should be useful likewise in forecasting factor returns.

The risk premium variable demonstrates a statistically significant impact on several factors. Notably, it produces an impressive t-statistic of 4.1 for the market variability factor. This is not surprising because this variable also shows impressive significance in forecasting the direction of the stock market. So, a factor that is analogous to beta should also respond to the risk premium. If the risk premium is high, stocks with high betas should do well. If the risk premium is low, stocks with low betas should do well. The risk premium also has a significant impact on the success, growth orientation, and financial leverage factors.

Market volatility is defined as the six-month variance of returns on the S&P 500. Volatility plays a strong role in shaping market sentiment (Arnott [1987]). Periods of high volatility lead to investor unease, which may encourage a flight to safety. Periods of market stability engender complacency, which may encourage investors to extend their investment horizons.

The market volatility variability shows a statistically significant effect on fully seven factors. Most notably, issues with high market variability, growth-oriented issues, issues with strong recent success, and

TABLE 5

Significant Ex Post Results for Market Variables
(1/73 – 12/88)

Factor	Risk Premium		Market Volatility		Yield Change	
	Correlation Coefficient	t-Statistic	Correlation Coefficient	t-Statistic	Correlation Coefficient	t-Statistic
Market Variability	0.287	4.119[c]	0.162	2.257[b]		
Success	−0.145	−2.015[b]	0.158	2.200[b]		
Size			0.103	1.424		
Trading Activity			0.132	1.831[b]		
Growth Orientation	0.177	2.472[c]	0.167	2.329[c]	−0.146	−2.028[b]
Book to Price						
Earnings to Price			−0.102	−1.410		
Earnings Variability			0.125	1.732[b]		
Financial Leverage	0.145	2.014[b]	0.124	1.718[b]	0.110	1.521
Foreign Income						
Labor Intensity	0.101	1.396	0.169	2.357[c]		
Dividend Yield					−0.171	−2.386[c]

[a] Significant at 10% level.
[b] Significant at 5% level.
[c] Significant at 1% level.

issues with high labor intensity tend to perform well following periods of high stock market volatility.

The yield change variable is simply the one-month change in the Treasury bill yield. It often indicates tightness in the money supply. It also shapes sentiment in the investment community. Rising short-term interest rates create unease.

The yield change variable demonstrates a statistically significant relationship with only two factors. These factors are growth orientation and dividend yield. Not surprisingly, stocks with high dividend yield do poorly as interest rates rise. The intriguing thing about this relationship is that it occurs *after* the interest rate increase is already evident. Issues with high growth orientation also tend to do badly as interest rates rise. This is likely attributable to the higher discount rate applied to future earnings.

Clearly, market conditions do have a bearing upon the types of issues that can be expected to perform. Interestingly, such relationships appear to be predictable, contrary to conventional wisdom.

Economic Conditions

Our tests for the effects of economic conditions on factor returns center on three economic variables: price inflation, economic health, and financial liquidity. We were curious as to whether economic conditions have effects on factor returns that occur with a lag after the relevant data become public. The results indicate that economic conditions do influence the markets in ways that we can predict.

Table 6 details the significant results for these economic effects. The price inflation variable is measured by the percentage change in the Producer Price Index. This variable provides perhaps the earliest indicator of domestic price inflation pressures. We felt that increases in inflation would have a negative impact on companies whose financial condition would be most adversely affected. Accordingly, the price inflation variable displays a statistically significant effect on three factors. These factors are earnings to price, foreign income, and dividend yield. The direction of these effects is intuitively appealing: An increase in price inflation could be expected particularly to hurt companies with high exposures to these factors.

The economic health variable is measured by the percentage change in the Leading Indicators, a useful predictor of change in the level of economic activity. Here again, we see a statistically significant effect on three factors: market variability, earnings to price, and financial leverage. The sign of these effects is likewise intuitively appealing. An improvement in economic health could be expected to have a greater benefit for weaker companies, with high exposure to the earnings to price and financial leverage factors.

The financial liquidity variable is measured by the percentage change in M1, which is a useful indicator of the most liquid part of the money supply. It is M1 that finds its way most quickly into the economy. Our hypothesis was that increases in financial liquidity have a positive effect on stocks of companies that would benefit most from future economic health and suffer at least from future price inflation.

The financial liquidity variable likewise demonstrates a statistically significant effect on three different factors: size, book to price, and foreign income. The benefits from improved financial liquidity appear

TABLE 6

Significant Ex Post Results for Economic Variables
(1/73 – 12/88)

	Price Inflation		Economic Health		Financial Liquidity	
Factor	Correlation Coefficient	t-Statistic	Correlation Coefficient	t-Statistic	Correlation Coefficient	t-Statistic
Market Variability			−0.145	−1.911[b]		
Success						
Size					0.127	1.699[b]
Trading Activity						
Growth Orientation						
Book to Price					−0.226	−3.034[c]
Earnings to Price	−0.197	−2.620[c]	0.172	2.277[b]		
Earnings Variability						
Financial Leverage			0.177	2.419[c]		
Foreign Income	−0.272	−3.685[c]			−0.243	−3.266[c]
Labor Intensity						
Dividend Yield	−0.151	−2.055[b]				

[a] Significant at 10% level.
[b] Significant at 5% level.
[c] Significant at 1% level.

to flow to stocks of companies — such as the nifty fifty — with high exposure to the size factor and low exposure to the book to price factor, possibly in anticipation of future economic health. They also appear to flow to stocks with low exposure to the foreign income factor, perhaps in anticipation of future increases in price inflation.

Combined Effects

Table 7 summarizes the combined effects of the variables in predicting factor returns. It appears that most of the factor returns can be predicted with some degree of accuracy. This result is surprising, particularly in light of the ex ante nature of these multivariate tests. These results are much stronger than those reported in the 1985 predecessor to this research (Arnott and Copeland [1985]). Only the returns to the growth orientation and labor intensity factors cannot be predicted with statistical significance. In contrast, the returns to the earnings to price and book to price factors can be predicted with a high degree of statistical significance.

TABLE 7

Ex Ante Results Summary
(1/78 – 12/88)

Factor	Multiple Correlation	Adjusted R^2	t-Statistic
Market Variability	0.205	0.034	2.294[b]
Success	0.269	0.065	3.067[c]
Size	0.279	0.070	3.185[c]
Trading Activity	0.340	0.108	3.962[c]
Growth Orientation	0.183	0.025	1.542[a]
Book to Price	0.381	0.138	4.518[c]
Earnings to Price	0.450	0.196	5.527[c]
Earnings Variability	0.227	0.044	2.557[c]
Financial Leverage	0.283	0.072	3.234[c]
Foreign Income	0.274	0.067	3.123[c]
Labor Intensity	0.093	0.000	−1.019
Dividend Yield	0.312	0.090	3.601[c]

[a] Significant at 10% level.
[b] Significant at 5% level.
[c] Significant at 1% level.

The proof of the pudding is in the performance. To evaluate the investment implications of our analysis, we constructed a very simple simulation test. We used the models just described to calculate monthly forecast returns for the 1,000 largest stocks in the market. This was accomplished by multiplying the company factor exposures by the ex ante forecasts of factor returns, for each month from December 1978 to December 1988. The stock with the highest forecast return in each of fifty-five industry groups was placed in a long portfolio, while the stock with the lowest forecast return was placed in a short portfolio. This arbitrage portfolio was based solely on forecast factor returns. It was rebalanced at each month-end when new forecast factor returns were produced.

This simulation test does not represent a usable investment strategy because it ignores transaction costs. Typical turnover would be over 100% per month: over 50% both for the long portfolio *and* for the short portfolio. Our results should not be taken with a grain of salt but with a whole shakerfull. They illustrate nevertheless the power of factor return forecasts.

The long portfolio exhibited an average monthly return of 2.37%, while the short portfolio returned only 0.16%. Equivalently, the arbitrage portfolio offered a monthly return of 2.21%. These are startling numbers. If factor return forecasts can capture even a fraction of this spread by improving the timing of our trades, much will have been achieved.

CONCLUSION

Forecasting factor returns seems feasible. Indeed, such forecasts have the potential to refine the timing of trading and perhaps even to permit a style rotation strategy for investment management.

None of the work summarized in this paper will necessarily prove useful for stock selection, however. Following the forecast factor returns would result in tremendous turnover. The October and January effects, for example, are typically in opposite directions. A strategy of buying large stocks in late September and then trading them for small stocks in December would be absurd because of tremendous transaction costs.

Such tools could be extremely valuable, however, in refining the timing of trades. Specifically, suppose we wish to sell a stock because of whatever disciplines drive our investment process. Furthermore, suppose that this stock has factor exposures that appear likely to be rewarded near-term. We are probably better off waiting a few weeks for an opportunity to sell at a still higher price. Similarly, suppose we wish to buy a stock for whatever reason. Moreover, suppose this stock likewise has attributes that also are likely to be rewarded near-term. Then we can pounce on the opportunity. If it does not have this exposure, we may want to wait for a more opportune price and time.

To reiterate, investment style matters. Indeed, it matters so much that any disciplines that can forecast the performance of an investment style offer the potential of impressive incremental returns. Such forecasting seems feasible — so does style management itself.

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[1] In a simple historical regression, we might use past data to develop a forecasting model, and then test that forecasting model on the same data. This kind of test is often called an ex post test. The correlation coefficients and t-statistics from the regressions are crude measures of the power of these forecasts. Although such an approach is appealingly simple, it is fraught with obvious biases and errors and is appropriate only for exploratory analysis. An ex ante test constructs a sequence of forecasts, based on regression equations estimated exclusively from data available prior to the period being forecast. The correlation coefficients and t-statistics from these regressions can be used as rigorous measures of predictive power.

[2] A dummy variable for a particular month has a value of one if the observation corresponds to that month and zero otherwise.

[3] We define earnings yield as S&P 500 earnings divided by price, expressed as a percentage yield.