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Performance Evaluation Using Conditional Alphas and Betas

A better job at predicting returns.

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Pension fund sponsors have long sought to find active portfolio managers able to deliver abnormal excess performance — expected returns in excess of suitable benchmarks. Yet evidence that a subset of active managers can deliver *consistently* superior returns remains controversial. While some studies have found that the past performance of open-ended mutual funds provides some predictive value for future performance, sparse evidence of this exists for pension funds.[1]

In estimating abnormal excess performance for a sample of pension fund portfolio managers, Christopherson and Turner [1991] conclude that past performance of a manager's portfolio provides little or no useful information about expected future performance. This study, however, relies upon *unconditional* performance measures, those whose estimates of future performance ignore information about the changing nature of the economy. Thus, unconditional measures can incorrectly measure expected excess returns when portfolio managers react to market information or engage in dynamic trading strategies. These well-known biases make it difficult to accurately measure alpha and beta.

Ferson and Schadt [1996] and Ferson and Warther [1996] advocate *conditional* performance evaluation (CPE) to more accurately form expectations about excess return and risk. CPE presupposes that portfolio managers can change both their alphas and betas over time depending on the influence of publicly available information about the economy. The methodology implicitly assumes that a portfolio's alphas and betas change dynamically with changing market conditions.[2] To the extent that we are better able to measure beta, we are also better able to measure alpha, and vice versa.

In an actively managed portfolio, time variation in the beta may occur for a variety of reasons. First, the betas of the underlying securities may change over time. Obviously, a portfolio composed of stocks with changing betas can experience a change in beta even with no turnover at all. Second, managers may change the beta of their portfolios through their pursuit of alpha. Third, a manager may experience large cash flows into the portfolio, and those cash holdings may cause the beta of the fund to fluctuate. Changing beta may or may not be an active decision by managers.

The first study applying CPE to institutional portfolios, Christopherson, Ferson, and Glassman [1998], finds that institutional portfolio betas on market- and style-based benchmarks change with public information about the state of the economy. In measuring alpha after taking into account effects such as interest rates and dividend yields, they show that the resulting *conditional alphas* are superior predictors of the portfolio's returns.

Our article expands the analysis of CFG [1998] in several ways:

- *Broader sample.* We apply CPE to a larger sample of equity pension advisors — 261 versus 185.
- *Longer time period.* We extend the time period to include December 1990 through May 1996, providing an out-of-sample analysis of the usefulness of CPE.
- *Different market cycles.* We study the performance of CPE measures over different market cycles.
- *Style analysis.* We analyze performance within the style groups.
- *Simpler instruments.* We rely on a simpler set of instruments for public information.
- *More realistic portfolio formation.* We form portfolios based on solid investment principles rather than simple averages.

Overall, we find that managers' excess abnormal returns are partially predictable using some predetermined information variables. Our results confirm that the conditional measures are more informative about future performance than are unconditional measures. Thus, the use of conditional measures can improve upon the current practice of performance measurement.

MODELS FOR PERFORMANCE MEASUREMENT

First we lay out the mathematics behind the traditional performance measure — the capital asset pricing model (CAPM) — and CPE performance evaluation to show the difference between the two. An example then illustrates the logic of the CPE model.

Unconditional Alphas

Jensen [1969] creates an unconditional measure of abnormal performance by estimating a regression using historical data:

$$r_{pt} = \alpha_p + \beta_p r_{bt} + v_{pt} \tag{1}$$

where for portfolio p over time t = 1, ..., T:

r_{pt} = the return of the manager net of the one-month Treasury bill return R_{ft}, or $r_{pt} = R_{pt} - R_{ft}$ with R_{pt} as the return of the managed portfolio;
r_{bt} = the return of the benchmark portfolio net of the one-month Treasury bill return, or $r_{pt} = R_{pt} - R_{ft}$ with R_{bt} as the return of a benchmark;
α_p = the unconditional alpha;
β_p = the unconditional beta; and
v_{pt} = the regression error or residual.

Jensen's alpha has become one of the standards for measuring performance. Unconditional alphas, however, are also commonly estimated using various customized benchmark portfolios such as style indexes. They can also be estimated using multiple-benchmark models, in which β_p and r_{bt} are vectors of factor exposures and factor returns. The average value of the *excess return*, $\alpha_p = R_{pt} - R_{bt}$, is sometimes used as a simple alternative performance measure, when the beta in Equation (1) is equal to 1.0. We use both a market index and the four style indexes described below as benchmarks.

Conditional Betas

If expected market returns and managers' betas change over time and are correlated, the regression Equation (1) is misspecified, and alpha and beta will be incorrectly estimated. Ferson and Schadt [1996] propose a modification of Equation (1) to address these concerns. They assume that the market prices of securities fully reflect readily available and public information. This information is measured by a vector of market information variables, Z.[3] The betas of stocks and managed portfolios are allowed to change with market conditions.

Ferson and Schadt assume a linear functional form for the changing conditional beta of a managed portfolio, given the market information variables, Z_t:

$$\beta_p(z_t) = b_{0p} + B_p' z_t \tag{2}$$

where $z_t = Z_t - E(Z)$ is a normalized vector of the deviations of Z_t, from the unconditional means, and B_p is a vector with the same dimension as Z_t.[4] The coefficient b_{0p} can be interpreted as the "average beta" or the beta when all information variables are at their means. The elements of B_p measure the sensitivity of the conditional beta to the deviations of the Z_t from their means.

A modification of Equation (1) follows from the model of changing betas:

$$r_{pt+1} = \alpha_p + b_{0p} r_{bt+1} + B_p'[z_t r_{bt+1}] + \mu_{pt+1} \tag{3}$$

Under the null hypothesis of no abnormal performance, Equation (3) implies that the *conditional alpha*, α_p, is zero; α_p in Equation (3) may differ from Equation (1) if the vector B_p is non-zero.

In the case of a single benchmark return, r_{bt+1} and L information variables in Z_t, Equation (3) can be viewed as a regression of the manager's return on a constant and L + 1 explanatory variables. The products of the future benchmark return and the information variables ($z_t r_{bt+1}$) capture the covariance between the conditional beta and the conditional expected market return, given Z_t. Ferson and Schadt [1996] find that this covariance is a major source of measurement error in unconditional alphas of mutual funds. By controlling for this covariance, the model of Equation (3) produces more reliable estimates of alpha.

Time-Varying Conditional Alphas

In the same way that beta can be dynamic and change with market conditions, alphas may also be dynamic. Using a single coefficient α_p in Equation (3) presumes that expected abnormal performance is constant over time. If managers' abnormal returns vary over time, however, a constant alpha may not provide much power to detect abnormal performance.

Christopherson, Ferson, and Glassman [1998] propose modifying Equation (3) to include *time-varying* conditional alpha, allowing the alpha to be a function of Z_t in the same manner as beta is a function of Z_t:

$$\alpha_{pt} = a_p(z_t) = a_{0p} + A_p' z_t \tag{4}$$

Equation (4) approximates the conditional alpha by a linear function.[5]

The modified regression is therefore

$$r_{pt+1} = a_{0p} + A_p' z_t + b_{0p} r_{bt+1} + B_p'[z_t r_{bt+1}] + \mu_{pt+1} \tag{5}$$

Equation (5) allows us to estimate conditional alphas and track their variation over time as a function of the conditioning information.

Logic of Conditional Performance Evaluation

How does the conditional approach work? An example will illustrate the central idea. In this example, we assume that "bull" and "bear" market conditions serve as a metaphor for commonly understood economic conditions for the class of investors to which the model is being applied. The commonly understood economic conditions include the current levels of interest rates, market prices, and various other measures of economic activity.

Let us suppose the equity market can take on two equally likely states that represent widely held expectations based on publicly available information. In a "bull state," suppose the expected return for holding the broad equity market is 20%. In a "bear state," the expected market return is -20%; high-quality stocks return -5% and have a beta of 0.25.

Suppose further that the expected future return is widely known among skilled professionals. Of course, the actual return is unknown — only the *expected* return, given the state of the market, is common knowledge. An investment strategy using only this information will not on average yield abnormal returns, and so should have a measured alpha of zero.

This example assumes, of course, that some classes of investors use the publicly available information and adjust their portfolio beta in bear states, while others remain to ride the bear market out. Not everyone can adjust their beta to 0.25 or get out of the market completely. Someone is holding the equities that constitute the market when the expected return is -20%.[6]

Consider a portfolio managed to hold the Russell 3000 index in a bull market and quality stocks in a bear market. The portfolio manager's stock-picking ability is zero. In this (admittedly simplistic) world, the only ability required is the ability to read the newspaper, monitor what is widely known, and act upon this information.

Conditional on an expected bull market, the beta of the fund is 1.0, the fund's expected return is 20%, and the alpha is zero. Conditional on an expected bear market, the fund's equity beta is 0.25, also with an alpha of zero. The conditional approach correctly reports an alpha of zero in each state of the market. An unconditional measurement approach that does not adjust beta or take into account the widely known information about expected bull or bear markets incorrectly reports an alpha of 7.5% and a beta of 0.625.

The situation is illustrated in Exhibit 1, where the expected returns for the benchmark Russell 3000 index fund plot at –20% and +20%. The manager acting on common knowledge has expected returns of –5% and +20%.[7] A line between the two points crosses the vertical axis at 7.5% and has a slope of 0.625. Using the conditional approach to evaluation, we have a beta of 1.0 in a bull market and a beta of 0.25 in a bear market — implying that the more precise alpha is zero.

In other words, there are two types of skill: the ability to exploit widely available macroeconomic information, and the ability to pick stocks. The unconditional approach confuses the manager's use of simple market dynamics models with superior security selection ability. The conditional approach tries to separate this naive market-timing ability from superior stock-picking ability. We will show that using alpha estimates that adjust for common knowledge can provide superior results. The analysis of dynamic betas has not been explored.[8]

Example of Dynamic Alpha and Beta Estimation Equations

To illustrate the model's estimation, let us formulate a simple example. We will choose only two information variables — dividend yield (dividend/price or DP), and the detrended level of short-term Treasury yields (TB). Both variables are readily available at low cost and widely understood to be relevant to future returns. We could choose lagged z_t to represent whatever level we feel constitutes "common knowledge" or superior knowledge.

The original model is

$$r_{pt+1} = a_{0_p} + A'_p z_t + [b_{0pb} + B'_{pb} z_t] + \mu_{pt+1} \qquad (6)$$

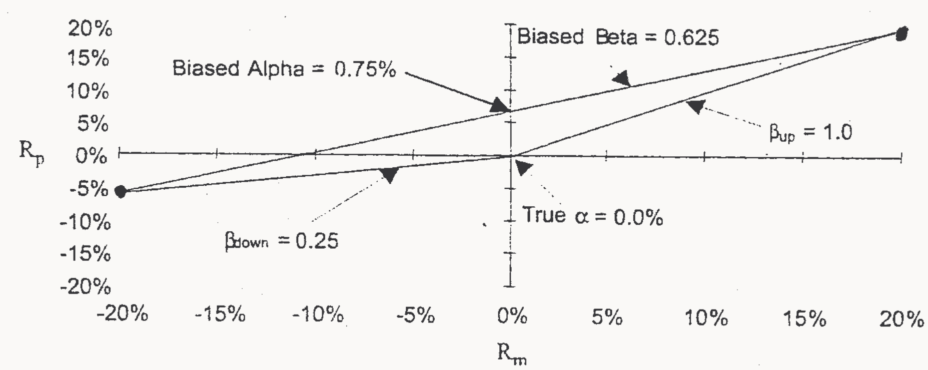
with time-varying alpha component as $a_{0p} + A'_p z_t$ and the time-varying beta multiplied by the excess return on the market as $[b_{0pb} + B'_{pb} z_t] r_{bt+1}$. In our example, the beta component is replaced with:

$$b_0 r_{bt} + b_1[r_{bt} DP_{t-1}] + b_2[r_{bt} TB_{t-1}] \qquad (7)$$

Therefore, the sensitivity of the portfolio due to the market (or beta of the portfolio) is an average sensitivity to the market excess return, b_0, plus a conditional sensitivity of the portfolio to predictable market changes. These time-varying sensitivities are captured by the terms $b_1[DP_{t-1}]$ and $b_2[TB_{t-1}]$.

The alpha of the portfolio is analogously determined. The alpha component, α_p, of the CAPM is replaced with a time-subscripted α_{pt}, which is defined

EXHIBIT 1
MANAGER WITH TIME-VARYING BETA



as an average alpha plus an alpha increment/decrement due to the lagged levels of dividend yield and T-bill yields:

$$a_0 + a_1 DP_{t-1} + a_2 TB_{t-1} \tag{8}$$

The risk-adjusted excess return of the portfolio is thus a conditional linear function of the lagged information variables at the beginning of the time period, $a_1 DP_{t-1}$ and $a_2 TB_{t-1}$, plus an average risk-adjusted excess return, a_0. Therefore, the total estimated regression is:

$$r_{pt} = a_0 + a_1 DP_{t-1} + a_2 TB_{t-1} + b_0 r_{bt} + b_1[r_{bt} DP_{t-1}] + b_2[r_{bt} TB_{t-1}] + \varepsilon_t \tag{9}$$

A variety of different models are tested; all are constructed analogously to this equation.

DATA

Managed Portfolio Returns

Our sample comprises monthly returns for 261 institutional equity managers over the period January 1980 through June 1996. The data come from the Russell Mellon Analytical Services Company (RMAS) data base, which includes returns for large accounts of domestic U.S. equity investment advisors of pension funds. Over the sample period, over 416 managers show some returns data, and 261 managers have more than sixty months of data. Of these, fifty-two are large growth managers, sixty-three are large value managers, seventy-four are large cap market-oriented managers, and seventy-two are small-cap managers. Tactical asset allocators and market timers are excluded. The style classifications for the managers are determined on the basis of the managers' investment philosophies and portfolio characteristics.[9]

Total portfolio returns are measured to include any cash holdings. The cash holdings are typically less than 10%, but vary considerably over time. The returns include the reinvestment of all distributions (e.g., dividends). The returns are net of trading commissions but not management fees. Except where indicated, our analysis examines the returns net of the monthly return to investing in a one-month Treasury bill. The one-month Treasury bill return data are from Ibbotson and Associates.

Although a given money management firm may have a number of portfolios and accounts, our data base includes only one "representative" account per firm. Representative accounts usually have existed for some time, and are subject to fewer investment restrictions than many individual-client accounts. We may therefore expect representative accounts to perform better than a more restricted client account.

Our sample is likely to have a selection bias, because managers will have entered the data base after they attract attention from equity manager research and/or clients. Usually, this will have coincided with positive performance. When managers enter the data base, records typically start from that date forward. Occasionally, however, some back-history is entered with a new portfolio.

When we measure performance persistence, however, we use the first sixty months to estimate the model parameters, and evaluate the future performance with subsequent data. Since it is unlikely that more than sixty months would ever be backfilled, there should be no selection bias in the future performance figures.

In addition to the selection bias, our data set is likely to have a survivorship bias, as it includes only surviving managers. When a manager is dropped, the entire return history for that manager is removed from the data base. To mitigate some bias, we use cross-sectional analysis to study persistence. A cross-sectional analysis focuses on relative, not absolute, performance. As we explain below, the patterns in our results on persistence suggest that they may be conservative in the face of some types of survivorship bias.

Benchmark Portfolios

There are four investment styles represented among the managers: growth, value, market-oriented, and small-capitalization, and four associated indexes that constitute appropriate benchmarks for each style. The market-oriented benchmark is the Russell 1000, a value-weighted index of the stocks of large-capitalization firms. The small-capitalization benchmark is the value-weighted Russell 2000 index. These are non-overlapping subsets of the Russell 3000 index universe. The Russell 1000 is divided into two groups of stocks forming the Russell growth and value indexes.[10] These two indexes are the benchmarks for the growth and value styles.

In the growth and value indexes, the stocks are divided on the basis of the relationship of their ratio of market price to the book value of equity (value-weighted) as compared to the Russell 1000 median ratios. Weights in the value and growth indexes increase as the portfolio value moves away from the median to either the high-or low-quartile values. Stocks with high ratios have high weights in the growth index, and those with low ratios have high weights in the value index.[11] We also use the Russell 3000 as an overall market benchmark.

Predetermined Information Variables

The conditional performance models (3) and (5) include a vector of lagged information variables, Z_t. We use the same variables used by Ferson and Warther [1996], which have been found to explain stock returns in previous research. These are not the only variables known to be related to stock returns — other macroeconomic variables might produce different results — but they provide a useful place to begin.

The variables are 1) the lagged level of the one-month Treasury bill yield (TB), and 2) the lagged dividend yield of the CRSP value-weighted NYSE and AMEX stock index (DP). Both are computed as deviations around their exponentially smoothed means. This avoids the look-ahead bias implicit in deviations around long-term means that use total sample means.[12]

EMPIRICAL RESULTS

Our work refines the research of CFG [1998]. They demonstrate that a CPE methodology works well in estimating the alpha and beta of manager portfolios. They report that managers' returns and excess returns are partially predictable using public information variables. Conditional betas, measuring exposure to market risk and to investment style factors, change over time. The CFG findings are reconfirmed here except as noted.

We examine first whether CPE provides additional precision in estimating alpha, then compare its effectiveness relative to unconditional measures in predicting performance persistence in our sample. We then look at how each measure performs in different market conditions, when portfolios are weighted using the information ratio, and when relevant style indexes replace a broad market index as the benchmark.

Statistical Significance of Alphas

CFG [1998] find a striking persistence in the relative performance of the managers, and the conditional measures allow them to better detect persistence in performance. Such persistence in institutionally managed portfolios had not been found before in manager performance measures.

One interesting finding is that poor performance is followed by poor future returns. While it may not be surprising to find that some managers can generate consistently poor returns, the survival of such managers suggests that plan sponsors do not take action to terminate managers with poor performance. Perhaps this is because they do not have the benefit of conditional evaluation models to help them identify poorly performing managers. Conditional models seem to provide a more powerful signal than has previously been available to measure risk-adjusted investment performance.

Our first empirical investigation confirms the alpha estimates from CPE are positively associated with future returns. Exhibit 2 shows the average t-ratios for CPE alpha and CAPM alpha.[13]

We find in Exhibit 2 that average t-statistics for CAPM alphas are generally insignificant at the 0.05 level, with hardly any t-ratios approaching 1. The t-statistics for CPE alpha estimates, on the other hand, are much closer to significance overall, with an average of 1.53 (critical value of about 2.0), and are significant for small-cap managers when the alphas are grouped by style.

These results refine the evidence of CFG [1998],

EXHIBIT 2
T-STATISTICS FOR NULL HYPOTHESIS THAT AVERAGE ALPHA EQUALS ZERO

	CAPM Alpha T-Statistic	CPE Alpha T-Statistic
Overall T-Ratio	0.54	1.53*
(standard error of t-ratio)	0.07	0.08
T-Statistics for Styles		
Large-Cap Broad Market	0.63	1.04
(standard error of t-ratio)	0.07	0.05
Large-Cap Growth	0.31	1.29
(standard error of t-ratio)	0.07	0.07
Large-Cap Value	0.64	1.35
(standard error of t-ratio)	0.07	0.06
Small-Cap Broad Market	0.54	2.45
(standard error of t-ratio)	0.06	0.13
Small-Cap Growth	0.23	2.25
(standard error of t-ratio)	0.06	0.12
Small-Cap Value	0.68	1.55
(standard error of t-ratio)	0.10	0.07

*The value of 1.53 is the average t-statistic for the null hypothesis — that the CPE alpha is zero over the entire sample with each t-statistic computed over a sixty-month time period. Results are based on January 1980 through June 1996.

who find similar results in the aggregate, but do not examine the evidence within the style groups.

Conditional Performance Evaluation

Having established that there is some additional precision in estimating alphas using CPE, we shift our focus to methods for exploiting the new CPE estimates. A natural question is how well the conditional alpha and beta model works on the expanded data set. We also examine the performance of portfolios of managers formed using the results of the CPE analysis.

We perform several different analyses. The first set of analyses fits the conditional performance measures to each manager in our sample using as the benchmark the Russell 3000 broad market and as the market condition variables the thirty-day T-bill yield and the S&P 500 dividend yield. The second set of analyses uses the same market condition variables, but an appropriate style index as the benchmark.

To determine whether economic information is generated by the CPE methodology, we create portfolios based on quintiles of forecasted alpha. In doing so, we use two portfolio management techniques. Most of the tables use equal-weighted portfolios of managers in each quintile. We also produce ranks of alpha that include the quality of fit information to refine the ranks, and we weight the managers in each quintile portfolio by the information ratio.[14]

In CFG [1998], high-alpha quintiles outperform the low-quintile portfolio by 4.09% annualized. Exhibit 3 provides a baseline for comparison with this previous work. In the first panel, equal-weighted portfolios are formed at the end of each month based on the CAPM analysis of the manager's returns in excess of the risk-free rate. The estimation window is sixty months. For each time period, the oldest month is dropped, and the most recent month is added. The alpha estimates are formed by multiplying the alpha coefficients α_1 and α_2 by the macroeconomic variable observed at $t - 2$ and adding α_0. The benchmark used for the market is the Russell 3000. The estimated alphas are rank-ordered into quintiles from highest to lowest. The quintiles are formed into portfolios in which each manager has equal weight. The first portfolio is formed in March 1986, and the last portfolio is formed in May 1996.

This strategy implies that we are hiring and firing managers on a monthly basis according to their estimated alphas. We find turnover for this strategy is in the range of 20% to 50% per year, although that evidence is not presented here. Pursuing such a strategy is cost-prohibitive because the cost of hiring and firing managers is greater than buying or selling stocks. Moreover, it may take up to six months to complete the necessary transactions such as liquidation of portfolios and signing contracts. The strategy does, however, provide a method for comparing the information content in the alpha evaluation methods.

Unlike the results in CFG [1998], Exhibit 3 reveals that CAPM alpha appears to have some predictive power over the time period investigated here. In the earlier work, the performance of CAPM quintiles is roughly the same across the quintiles, with the middle quintile actually outperforming the top and bottom quintiles. Quintile 1 of CAPM alpha returns 10.40% and outperforms quintile 5 by 145 basis points annualized and by 11 bp on average each month. All previous work has found these alphas to perform less well; the difference we find here may be simply sampling error. (The last column in Exhibit 2 displays the results for portfolios formed in the same way as the CAPM results, except that the CPE alpha estimates are used instead of the CAPM estimates.)

The managers as a group outperform the Russell 3000 9.43% to 8.71%, or 72 basis points annualized, about 9 bp per month. The spread between the top and bottom quintiles is 400 bp for CPE alphas, very close to the figure reported in CFG [1998]. Portfolios based on the top quintiles of CPE alpha estimates outperform portfolios based on top quintiles of CAPM alpha estimates 11.22% to 10.40% or 82 bp, while portfolios based on the bottom quintiles underperform 7.22% to 8.94%, or −172 bp.

The CPE alphas are able to differentiate top-performing managers from bottom-performing managers more effectively than CAPM alphas. In fact, the bottom quintile of CPE alpha estimates underperforms the Russell 3000 by 149 bp.

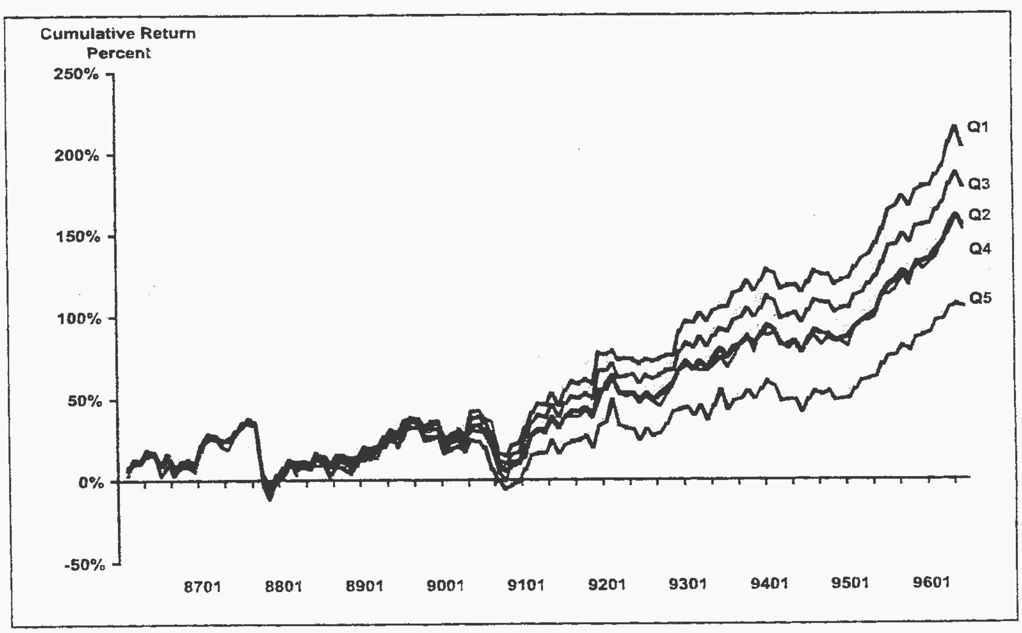
Exhibit 4 shows the cumulative returns of portfolios based on the quintiles of CPE alpha estimates. The cumulative return of the top quintile of CPE alpha estimate is 202%, while the bottom is 106%, for a spread of 96 percentage points over 125 months. Quintile 1 of CPE estimates outperforms quintile 1 of CAPM estimates by 22 percentage points and the Russell 3000 by 46 percentage points. An investor would have to have the return to the Russell 3000 plus another asset that returns 2.30% to equal the return to the top quintile of CPE estimates.

EXHIBIT 3
PERFORMANCE OF QUINTILES BASED ON RANKS OF CAPM AND CPE ALPHA ESTIMATES

	Average Monthly Log Return	Cumulative Return	Annualized Return
CAPM Alpha Estimates:			
Alpha Quintile 1	0.83%	180.24%	10.40%
Alpha Quintile 2	0.76	157.07	9.49
Alpha Quintile 3	0.77	160.78	9.64
Alpha Quintile 4	0.69	137.61	8.66
Alpha Quintile 5	0.72	143.99	8.94
Q1-Q5 Percentage Point Difference	0.11	36.25	1.45
CPE Alpha Estimates:			
Alpha Quintile 1	0.89%	202.71%	11.22%
Alpha Quintile 2	0.74	151.13	9.24
Alpha Quintile 3	0.82	176.62	10.26
Alpha Quintile 4	0.74	150.59	9.22
Alpha Quintile 5	0.58	106.75	7.22
Q1-Q5 Percentage Point Difference	0.31	95.96	4.00
Benchmarks:			
Russell 3000	0.70%	138.67%	8.71%
Avg. Mgr. in Sample	0.75	155.94	9.43

Note: Macroeconomic variables: S&P 500 dividend yield and T-bill yields.

EXHIBIT 4
CUMULATIVE RETURNS TO QUINTILES OF CPE ALPHA COMPARED WITH RUSSELL 3000



Consistency of Performance over Market Cycles

The next logical question is to ask whether these patterns of performance are consistent or whether they vary over market environments. A bull market, one of the strongest of all time, dominates the sample period. The early period, however, covers the 1987 stock market crash and the mild recession of 1989 to 1990.

Exhibit 5 focuses on the returns to the top and bottom quintiles of CAPM and CPE estimates. It is clear from this graph that neither alpha estimate proves a consistently superior predictor of future returns over this period of instability.

We would conclude from these cumulative return patterns that the differences between the performances of the CAPM and the CPE alpha estimates are small over the 1986-1990 subperiod. From the bottom in 1987 to the recovery peak in 1989, high CAPM alpha portfolios actually did slightly better.

In the 1990s, however, the CPE alphas have proved more informative. As Exhibit 6 illustrates, during the bull market from October 1990 onward, the top quintile of CPE alpha consistently outperforms the top quintile of CAPM alpha by a substantial amount. The bottom quintile of CPE alpha estimates performs on a par with the Russell 3000 over this time period. This superior performance over the bull market time period accounts for the overall superior performance of the CPE alphas over the sample period.

Perversely, the bottom quintile of CAPM alpha estimates outperforms the top quintile of CAPM alphas over the bull market period. This is hardly what we would expect, and is counter-intuitive, given that the high CAPM alpha managers outperformed the bottom quintile managers during the unstable market conditions surrounding the crash of 1987. The performance of quintiles based on CAPM alphas is inconsistent; they seem to behave perversely in stable or trending markets.

Exhibit 6 shows the spread between quintiles 5 and 1 for both the CAPM alpha estimates and the CPE alpha estimates. The differences between cumulative returns to the top and bottom quintiles of CAPM alpha are small, with the difference close to zero at the end of the investigated time series. The differences between cumulative returns for quintile 1 and 5 for CPE alpha

EXHIBIT 5
RETURNS TO QUINTILES 1 AND 5 OF CAPM AND CPE ALPHAS COMPARED WITH RUSSELL 3000 FROM JANUARY 1986

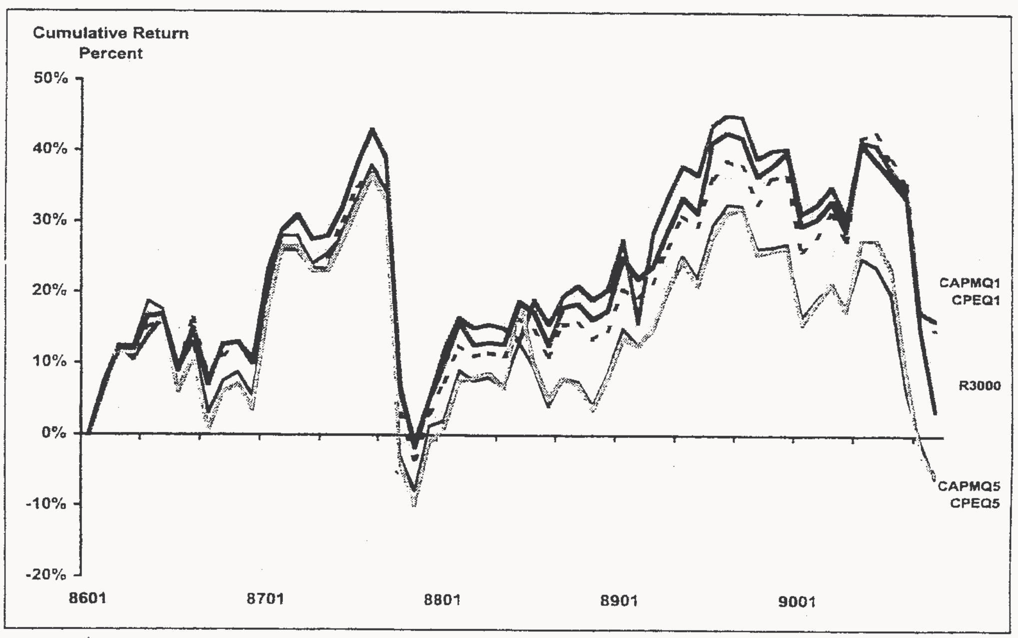
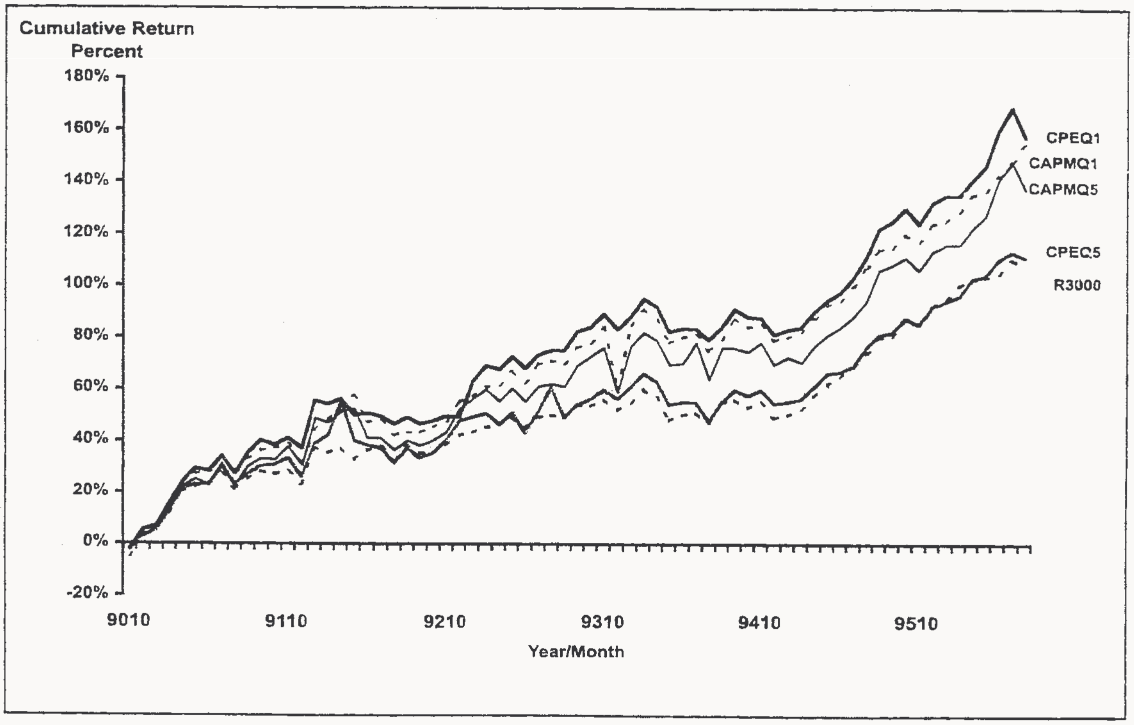


EXHIBIT 6
CUMULATIVE RETURNS TO QUINTILES 1 AND 5 OF CAPM AND CPE ALPHAS COMPARED WITH RUSSELL 3000



estimates are always positive and grow over time. This indicates that CPE alpha estimates discriminate between top- and bottom-performing managers better than CAPM alpha estimates

Information Ratio Weighting of Quintile Portfolios

Our next analysis follows the work of Elton, Gruber, and Blake [1996], who investigate the behavior of mutual fund portfolios using information on the quality of CAPM estimates of alpha to form portfolios. They argue that one can achieve better-performing portfolios by exploiting modern portfolio theory principles (MPT). Their method is to generate portfolio weights for each manager based on the information ratio. The information ratio, a form of the return-to-risk ratio, is the size of risk-adjusted excess return relative to the tracking error of the portfolio around the index. The idea is that a manager with high alpha who tracks the index well should be accorded more weight in the portfolio than a manager with the same alpha but greater tracking error.

In Exhibit 7, the CAPM alpha estimates are compared with CPE alpha estimates using MPT portfolio formation principles, again using the Russell 3000 as the benchmark for all managers. The variable used to rank each manager is α_{CAPM} or α_{CPE}, with each manager weighted by the absolute value of α/σ_e, the appraisal ratio. The value of σ_e is the standard deviation of the residuals obtained from the regressions that produce α_{CPE} and α_{CAPM}.

CFG [1998] find that the extreme CAPM alpha portfolios in their sample produce large standard errors of return, so weighting the returns by the α/σ_e might be expected to reduce the spread in the portfolio formation period. We find that it also reduces the spread in the future returns. The portfolios based on quintiles of CAPM alpha have narrower spreads than equal-weighted portfolios.

When portfolios are based on quintiles of CPE alpha, the spread drops from 400 bp for equal-weighted

EXHIBIT 7
PERFORMANCE OF QUINTILES BASED ON RANKS OF CAPM AND CPE ALPHA ESTIMATES WEIGHTED BY INFORMATION RATIO

	Average Monthly Log Return	Cumulative Return	Annualized Return
Unconditional CAPM Alpha Estimates:			
Alpha Quintile 1	0.77%	161.22%	9.66%
Alpha Quintile 2	0.77	161.49	9.67
Alpha Quintile 3	0.70	138.66	8.71
Alpha Quintile 4	0.69	135.84	8.59
Alpha Quintile 5	0.75	153.55	9.34
Q1-Q5 Difference	0.02%	7.67%	0.31%
CPE Alpha Estimates:			
Alpha Quintile 1	0.78%	163.95%	9.77%
Alpha Quintile 2	0.71	142.03	8.86
Alpha Quintile 3	0.73	147.08	9.07
Alpha Quintile 4	0.67	131.16	8.38
Alpha Quintile 5	0.66	127.64	8.22
Q1-Q5 Difference	0.12%	36.31%	1.55%

Note: Rank Variable = CAPMALFA × CAPM R^2, Case Weight = abs(CAPMALFA)/CAPM MSE. Macroeconomic variables: S&P 500 div. yield and T-bill yields.

portfolios to 155 bp for appraisal-weighted portfolios. The relative superiority of CPE-based portfolios over CAPM-based portfolios remains, but is reduced.

Effects of Style Indexes as Benchmarks

The next question is to what extent the information content of various alpha estimates can be enhanced by using benchmarks closer to the market areas in which managers choose securities. In the analyses presented in Exhibit 8, unconditional style and CPE alpha measures are created in a similar manner to those of Exhibit 3. The benchmark used to evaluate each portfolio, however, is based on the Russell universe from which each manager is drawn. The Russell 1000 value index is used for large-cap value portfolios. The Russell 1000 growth index is used for large-cap growth portfolios, the Russell 2000 index for small-cap portfolios, and the Russell 1000 index for large-cap market-oriented portfolios.

The portfolios are formed on the basis of quintiles of unconditional and CPE style alpha estimates. The estimates are pooled, without regard to the individual style of the manager. The quintile portfolios are equal-weighted according to ranks of alpha, with no adjustment to weights for the quality of fit.

In this analysis, the higher return to high unconditional CAPM alpha managers that we see in Exhibit 3 not only disappears, but also in fact becomes negative. The spread between the top and bottom quintile of portfolios based on unconditional style is 895 basis points versus 1,136 bp or –2.41 percentage points annualized. Higher alpha estimates produce a portfolio that underperforms lower alpha estimates.

This would indicate that whatever information about superior future returns that is incorporated in unconditional CAPM alphas computed against the broad market benchmark is completely subsumed in style. It suggests that managers with high alphas versus the broad benchmark tend to fall into styles that are generally outperforming. The subsequent future superior returns we observe for these managers occur because the style continues to outperform, not because of any particular skill of the manager. For this sample, when manager performance is controlled for style, unconditional alphas convey negative information about manager future returns.

Comparing the performance of the top-quintile

EXHIBIT 8
PERFORMANCE OF QUINTILES BASED ON RANKS OF CAPM AND CPE ALPHA ESTIMATES USING STYLE INDEX AS THE BENCHMARK FOR EACH MANAGER

	Average Monthly Log Return	Cumulative Return	Annualized Return
CAPM Style Alpha Estimates:			
Alpha Quintile 1	0.72%	144.11%	8.95%
Alpha Quintile 2	0.73	148.36	9.13
Alpha Quintile 3	0.67	131.31	8.38
Alpha Quintile 4	0.75	155.87	9.44
Alpha Quintile 5	0.90	206.67	11.36
Q1-Q5 Difference	(0.18%)	(62.56%)	(2.41%)
CPE Style Alpha Estimates:			
Alpha Quintile 1	0.88%	200.07%	11.13%
Alpha Quintile 2	0.70	139.10	8.73
Alpha Quintile 3	0.75	154.89	9.40
Alpha Quintile 4	0.75	154.79	9.39
Alpha Quintile 5	0.68	134.34	8.52
Q1-Q5 Difference	0.20%	65.72%	2.61%

portfolios based on CPE alphas presents a different story. The annualized return for the top quintile of style-based CPE alpha estimates is 11.13%, not much different from 11.22% in Exhibit 3, the Russell 3000-based CPE alpha estimates. The major difference is in the bottom quintiles. The bottom quintile portfolio formed on style-based CPE alphas yields 8.52% annualized versus 7.22% using the R3000. The top quintile of CPE alpha outperforms the bottom quintile of CPE alpha by 261 bp even after we have controlled for style. Furthermore, the top quintile of CPE alpha estimates outperforms the average manager by 170 bp and the Russell 3000 by 242 bp annualized.

Of the 400-bp spread between the top and bottom quintiles of CPE alpha in Exhibit 3, 139 bp is removed using a style benchmark, yet 261 bp additional return can still be achieved by selecting high-alpha managers using the macroeconomic variables to estimate alpha.

At the same time, the top-performing quintile loses only 9 bp of return when alpha is estimated relative to the proper style benchmark. In this sense, high CPE alpha estimates are independent of style. Low CPE alpha estimates are less independent.

It appears that using the proper benchmark to estimate CPE alphas picks up some of the same alpha information that the conditioning macroeconomic variables do within the CAPM. At the same time, the better benchmark does little to identify future poor-performing managers. Nevertheless, CPE alpha estimates using style benchmarks seem to pick out the worst-performing managers. In this sample, avoiding these managers would improve returns about 114 bp annualized.

SUMMARY

Conditional performance evaluation or CPE alpha estimates do a better job than traditional CAPM alpha estimates of predicting future returns in the 1980-1996 time period. The CAPM with a broad market benchmark produces unstable results that vary with market conditions and are unreliable in strong markets. When style indexes are used to compute unconditional alphas, the ability to forecast return disappears. The CPE alpha estimates continue to work even when style is included, but the ability to identify managers likely to be unsuccessful deteriorates slightly when style effects are extracted.

Following the work of Elton, Gruber, and Blake [1996], we also use information ratios to form portfolios of quintiles of alpha. Appraisal ratio-weighted portfolios based on quintiles of CAPM and CPE alpha do not perform better than equally weighted portfolios.

Our research suggests that the investor should evaluate the manager's return series using public information. While higher CPE alphas do not guarantee superior returns, they are more likely to successfully forecast alphas than previously available measures.

Further development of conditioning models may be promising. We could expand the number and kinds of macroeconomic variables to be used in estimating CPE alphas. Further research into the most effective way to exploit the CPE alphas is also warranted. How well do the CPE alpha estimates perform when used in a normal pension plan equity portfolio formulation?

Using the CPE beta estimates to manage portfolio risk is clearly another interesting path of investigation. To the extent that betas can be predicted, we may better predict portfolio beta and therefore add a new dimension to risk management. To the extent that these initial findings bear fruit in the portfolio formulation process, the CPE alpha and beta measurements portend new horizons in plan management.

ENDNOTES

[1]See Jensen [1969], Carlson [1970], and, more recently, Carhart [1997] for evidence of persistence in mutual fund performance. Lakonishok, Shleifer, and Vishny [1992] find some persistence of the relative returns of pension fund managers for two- to three-year investment horizons, but not at shorter horizons. Coggin, Fabozzi, and Rahman [1993] study market-timing ability using unconditional models, while Christopherson, Ferson, and Glassman [1998] study persistence of institutional portfolio performance using conditional models.

[2]Of course, this assertion calls out for examination. The nature and change of alpha and beta is research in and of itself. In this article, we take one approach to attacking the problem, but our attempt is by no means exhaustive.

[3]In other words, they assume that markets are informationally efficient in a version of the "semistrong form" efficiency of Fama [1970].

[4]It is important to de-mean the information variables, using only past data, to avoid biases in the regressions. See Ferson, Sarkissian, and Simin [1999] for an analysis of bias in regressions like Equation (3).

[5]Obviously, the alpha of a portfolio can be dynamic for a variety of reasons besides changes in the macroeconomic environment. CFG [1998] show that alpha generally depends on the covariance between managers' portfolio weights and future asset returns. Conditional on z_t, this covariance and the conditional alpha should be a function of z_t.

[6]The point of this example does not depend on the particular numbers. These are chosen to make the calculations easy to comprehend.

[7]These numbers are the expected returns, given public information. The actual returns would appear as a random cloud centered at these two points.

[8]Recent studies of conditional market timing include Becker et al. [1999], a study of mutual funds, and Goodwin et al. [1999], a study of pension funds.

[9]See Haughton and Christopherson [1990] and Christopherson and Trittin [1995].

[10]Our style benchmarks differ in construction from the ones used by CFG [1998]. This different construction provides information on the robustness to index design of the main results.

[11]Since 1995 the Russell style indexes have also used IBES forecasted growth as a second variable to help determine the growth/value weight. A non-linear methodology has also been introduced that allows stocks to be in both growth and value indexes when their P/B and forecasted growth are close to the medians.

[12]Detrending the series in this way, in the presence of continuing underlying trend data, can produce biases in alpha and beta estimates. We do not think this is a serious problem in our data.

[13]The CPE alphas reported in Exhibit 2 and those following are a_0 in Equations (4) through (8) because the alpha in any single time period will be a function of the conditioning information at that time. Since we do not have a particular time in mind, we evaluate each conditioning variable at its expected value, i.e., its mean, and since the variables we use are formulated as deviations from their long-term mean, they have a mean of zero. Hence, their expected effects are zero, and the alpha terms in Equations (4) through (8) reduce to a_0.

The t-ratio averages and standard errors are intended to serve as a comparative indicator between techniques. The alpha t-ratio averages are grand means from rolling sixty-month sample windows for each manager in the style universe. Note that because overlapping data are used, the alpha t-ratio averages are not calculated from independent draws.

[14]The information ratio is the ratio of alpha to standard error. The higher the alpha and the lower the unexplained variance, the greater the weight of the manager in the portfolio.

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