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# CONDITIONING MANAGER ALPHAS ON ECONOMIC INFORMATION: ANOTHER LOOK AT THE PERSISTENCE OF PERFORMANCE

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## ABSTRACT

This paper evaluates persistence in the performance of institutional equity managers. We build on recent work on *conditional performance evaluation*, using time-varying conditional expected returns and risk measures. We find evidence that the investment performance of pension fund managers persists over time. A conditional approach is better able to detect this persistence and to predict the future performance of the funds than are traditional methods. The performance persistence is especially concentrated in the managers with negative prior-period conditional alphas.

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The question of whether professional portfolio managers can deliver expected returns in excess of naive benchmarks has long been important, both for academic research and for practical decision making. However, the evidence on the ability of managers to deliver consistently superior returns, or positive *alphas*, remains controversial. Some studies find that particular open-ended mutual funds which have performed relatively well or poorly in the past tend also to do so in the future. Jensen (1969), Carlson (1970) and a number of more recent studies find evidence of such *persistence* in mutual fund performance.[1]

While a large number of studies examine the persistence of mutual fund performance over time, the evidence for institutional equity managers is sparse. Christopherson and Turner (1991) estimate alphas for a sample of pension managers and conclude (page 10) that "alpha at one time is not predictable from alpha at a previous time." Lakonishok, Shleifer and Vishny (1992) find some persistence of the relative returns of pension fund managers for 2-3 year investment horizons, but not at shorter horizons. Coggin, Fabozzi and Rahman (1993) study market timing and stock picking ability, and provide references to the few additional academic studies of institutional equity manager performance.

It is important to further study the performance of institutional fund managers, for at least three reasons. First, institutional managers control a larger portion of the aggregate wealth than mutual funds [see Coggin et al. (1993)]. Second, as institutional equity managers and mutual fund managers operate in different environments, their performance may differ. For example, pension fund managers are reviewed periodically by their clients and pension consultants, who presumably are more sophisticated than the typical individual investor. However, mutual fund investors can simply withdraw their money or invest in a "hot" fund at any time. Thus, it is interesting to compare the persistence properties of performance for the two types of managers. Third, fund sponsors and other institutional investors must decide which managers to retain, and predicting the future performance of a manager is a critical part of that decision-making process. If abnormal investment performance, or alpha, of pension managers is randomly distributed over time -- consistent with the findings of Christopherson and Turner (1991) -- the past performance of a manager provides no useful information about future performance. While this is consistent with some versions of the efficient market hypothesis, it suggests that investment firms are wasting money trying to measure alphas.

It has been traditional to measure performance by the average portfolio returns, net of a fixed benchmark return, over some historical period. Such an approach uses *unconditional* expected returns as the performance baseline. It assumes that the consumer of the performance evaluation uses no information about the state of the economy to form expectations. However, such unconditional measures of performance are known to be biased when managers react to market indicators or engage in dynamic trading strategies. These well-known biases make it difficult to accurately measure even the average performance. Furthermore, if biases in alpha persist over time, they can distort inferences about the persistence of investment performance. In this paper we therefore move beyond the traditional, unconditional measures of performance.

In recent papers, Chen and Knez (1996) and Ferson and Schadt (1996) advocate *conditional performance evaluation*. The idea is to use time-varying conditional expected returns and conditional betas instead of the usual, unconditional moments. The expected returns and risks are conditional on a set of predetermined, publicly available information variables. One appeal of a conditional approach is that it can control for biases that are induced in the traditional measures when managers trade on public information. Ferson and Schadt find that incorporating public information variables, such as dividend yields and interest rates, affects the inferences about the average performance in a sample of open-ended mutual funds.

In this paper we apply conditional performance evaluation to a sample of 185 U.S. equity pension managers from Russell Data Services over the 1979-90 period. We extend the approach of Ferson and Schadt (1996) to estimate time-varying *conditional alphas*. We find that the managers' returns and excess returns are partially predictable using standard predetermined information variables. We also find evidence of time-varying conditional betas, investment style-factor exposures, and time-varying conditional alphas.

The primary focus of the paper is on the question of persistence in performance. Ours is the first study of the persistence of performance to use the conditional measures and the first study of pension manager performance to use conditional measures. We find evidence that the investment performance of the managers persists over time. Low conditional-alpha managers in the past tend to be low-return managers in the future. Our results show that the conditional measures are more informative about future performance than are traditional, unconditional measures. Therefore, the use of conditional measures may improve upon the current practice of performance measurement.

The paper is organized as follows. Section 1 describes the models and section 2 describes the data, including some of the unique features of our sample of equity pension fund managers. Section 3 presents preliminary results which establish the relevance of the conditional performance measures. Section 4 addresses the issue of persistence in performance and the economic significance of that persistence. Section 5 offers concluding remarks.

## 1. Models for Performance Measurement

### 1.1 Unconditional Alphas

The traditional, or *unconditional alpha*, $\alpha_p$, is estimated by the following regression:

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

Both the return of the manager, $r_{pt}$, and the return of the benchmark portfolio, $r_{bt}$, are measured net of the one-month Treasury bill rate, $R_{ft}$. That is, $r_{pt}=R_{pt} - R_{ft}$ and $r_{bt} = R_{bt} - R_{ft}$, where $R_{pt}$ is the return of the managed portfolio and $R_{bt}$ is the return of a benchmark. $\beta_p$ is the unconditional beta and $v_{pt}$ is the regression error. Jensen (1968) proposed the unconditional alpha as a measure of abnormal performance, using a proxy for the "market portfolio" as the benchmark, $R_{bt}$. Jensen was thinking about the Capital Asset Pricing Model [CAPM, see Sharpe (1964)], but unconditional alphas are commonly estimated using various benchmark portfolios. They can also be estimated using multiple-benchmark models, in which $\beta_p$ and $r_{bt}$ are vectors.

The average value of the *excess return*, $R_{pt}$-$R_{bt}$ is sometimes used as a simple alternative performance measure. The past average excess return is a special case of an unconditional alpha, where the beta in equation (1) is assumed to be equal to 1.0.

Christopherson and Turner (1991) choose manager style indexes as the benchmarks; i.e., a manager is classified according to style and a single index which reflects that style is used in the regression. The implicit assumption is that the style index is an efficient combination of the assets held by managers who follow the investment style [see Grinblatt and Titman (1989)]. In this paper we use both a market index and four style indexes, described below, as benchmarks.

### 1.2 Conditional Models

If expected market returns and managers' betas change over time and are correlated, the regression equation (1) is misspecified. Ferson and Schadt (1996) propose a modification of equation (1) to address such concerns. They assume that market prices fully reflect readily available, public information, which is measured by a vector of predetermined variables, $Z_t$. In other words, they assume that markets are informationally efficient in a version of the "semi-strong form" efficiency of Fama (1970). Ferson and Schadt also assume a linear functional form for the conditional beta, given $Z_t$, of a managed portfolio:[2]

$$\beta_{pb}(Z_t) = b_{0pb} + B_{pb}' z_t, \tag{2}$$

where $z_t = Z_t - E(Z)$ is a vector of the deviations of $Z_t$ from the unconditional means, and $B_{pb}$ is a vector with dimension equal to the dimension of $Z_t$. The coefficient $b_{0pb}$ is an "average beta." The elements of $B_{pb}$ measure the response of the conditional beta to the information variables $Z_t$. The beta of a managed portfolio can change as a function of $Z_t$ because the portfolio weights change, or because the betas of the assets available to managers change over time. Equation (2) models the combined effect on the risk exposures.

The following modification of regression (1) follows from the model of changing betas:

$$r_{pt+1} = \alpha_p + b_{0pb}\, r_{bt+1} + B_{pb}'\,[z_t\, r_{bt+1}] + u_{pt+1}. \tag{3}$$

Under the null hypothesis of no abnormal performance, the model implies that the average *conditional alpha*, $\alpha_p$, is zero (the $\alpha_p$ in equation (3) will differ from equation (1) if $B_{pb}$ is nonzero). In the case of a single benchmark $r_{bt+1}$ and L information variables in the vector $Z_t$, equation (3) is a regression of the manager's return on a constant and L+1 variables. The products of the future benchmark return and the predetermined variables 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 bias in the traditional, unconditional alphas of mutual funds. The specification in (3) can easily be extended to the case of a multiple-benchmark model, and we will estimate a four-factor model below.[3]

Using a single coefficient $\alpha_p$ in equation (3) captures a particular alternative to the null hypothesis of no abnormal performance. The alternative is that the expected abnormal performance is constant over time. But if managers' abnormal returns vary over time and can change signs, this may not provide much power to detect any abnormal performance of managed portfolios.

### 1.3 Extending the Models: Time-varying, Conditional Alphas

In a conditional performance evaluation model, the conditional alpha should be zero when managers' portfolio weights are no more informative about future returns than the public information variables, $Z_t$. However, if a manager uses more information than $Z_t$, causing the portfolio weights to be conditionally correlated with future returns given $Z_t$, then the conditional alpha is a function of the covariance between the manager's weights and the future returns, conditional on $Z_t$.[4] This conditional covariance, and therefore the expected abnormal performance, is an unobserved function of $Z_t$. We therefore modify the regression (3) to include an explicit *time-varying conditional alpha*, allowing the alpha to be a function of $Z_t$:

$$\alpha_p(Z_t)=\alpha_{0p} + A_p' z_t. \tag{4}$$

In equation (4) we assume that the conditional alpha is a linear function. The modified regression is therefore:

$$r_{pt+1} = \alpha_{0p} + A_p' z_t + b_{0pb}\, r_{bt+1} + B_{pb}' [z_t\, r_{bt+1}] + u_{pt+1}. \tag{5}$$

Regression (5) allows us to estimate conditional alphas, and to track their variation over time as a function of the conditioning information, $Z_t$.[5]

We estimate the standard errors, t-ratios and Wald tests for all of our models using the heteroskedasticity-consistent estimation techniques of White (1980), Hansen (1982) and Newey and West (1987), because our evidence of time-varying betas implies conditional heteroskedasticity in the data. Lee and Rahman (1990) and Ferson and Schadt (1996) also find evidence of heteroskedasticity effects in mutual fund returns.

## 2. The Data

### 2.1 The Managed Portfolio Returns

We obtained monthly returns for 273 institutional equity managers from the Frank Russell Company's Russell Data Services (RDS) data base. The returns are for large accounts of domestic, U.S. equity pension fund managers who have been allocated funds by Frank Russell Company clients. We present most of our results for the January, 1979 to December, 1990 period. Over this period, there are 232 managers with some returns data and 185 managers with more than 12 months of data. Managers enter the data base at different points in time, but all are present at the end of the sample period. Our sample of 185 managers includes 41 growth managers, 40 value managers, 55 large cap managers and 49 small cap managers. Explicit asset allocators and market timers are not in this data base. The style classifications for the managers are determined by RDS, based on the managers' investment philosophies and portfolio characteristics [see Haughton and Christopherson (1990) and Christopherson and Trittin (1995)].

A given money management firm may have a number of portfolios and accounts, but our data base includes only one "representative" account per firm. We do not have data on the values of the accounts, but we were told by RDS that most are over $100 million in size. On average, the small cap portfolios tend to be smaller sized accounts. The firm chooses which account to designate as its representative account. Representative accounts usually have been in existence 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 typically restricted client account.

The data measure the total portfolio returns, including any cash holdings. We were told by RDS that cash holding are typically less than 10%. The returns include the reinvestment of all distributions (e.g., dividends) and are net of trading commissions but not of management fees. Except where indicated, our analysis is performed on the returns net of the monthly return to investing in a one-month Treasury bill. The Treasury bill data are from the Center for Research in Security Prices at the University of Chicago (CRSP).

Several features of the data will be important in the analysis that follows. In order to understand these features, it is useful to briefly review some aspects of the management of pension fund monies.

Pension fund management involves (1) plan sponsors, specifically, the administrators or trustees of pension funds, (2) pension fund consultants, and (3) investment management firms. Typically, the plan sponsor divides the funds among a number of managers with various investment styles. In addition to investment returns, money managers provide certain services to their clients. These include education, research and reports that the responsible officers at the plan sponsor organization can use in reporting to their superiors. Plan sponsors periodically review their managers, commonly at quarterly to annual frequencies. Consultants such as the Frank Russell Company, advise plan sponsors on manager review and selection and also on the allocation of funds among different asset classes and investment styles. In order to perform this function, the consultant tracks the performance of a large number of money managers.

Given these differences between the institutional structures surrounding pension fund and mutual fund management, a number of prior conjectures about the persistence of performance can be made. On the one hand, the relative sophistication of institutional investors and the large amounts of money at stake suggest that lackluster performance may be detected and responded to more quickly with pension funds than with mutual funds. On the other hand, there are reasons to expect that poor performance can persist. Pension managers deliver services in addition to investment returns and they develop relationships with their clients that mutual fund investors typically do not enjoy. Agency problems may also allow persistence. For example, firing a manager may be seen as evidence that the previous investment decision was a poor one.[6]

## 2.2 Survivorship and Selection Biases

Our data base almost certainly has a survivorship bias, as it contains only surviving managers. When a manager is dropped by RDS, the entire returns history for that manager is removed from the data base (and is unavailable to us). One obvious reason for dropping a manager is poor performance. To the extent that managers are dropped because of poor performance, the measured performance of the surviving managers is biased upwards.[7] However, a manager is unlikely to be dropped in response to only a few periods of poor returns, because of the relationships that develop between managers and clients, because the managers provide services other than investment returns and because of the agency issues discussed above.

Managers are dropped from the data base not only when the Frank Russell Company and its clients lose interest in the manager. They are also dropped when the firm undertakes a change in strategy or has an important change in management personnel, such as when a star performer leaves for another firm. In these cases, a new data series may be introduced to pick up the changed firm. To the extent that managers are dropped from the data base because they were star performers, and the new firm is not included, the measured performance of the surviving managers is biased downwards.

In general, the effects of survivorship depend on the selection, or birth, process and on the death processes, and they can be quite complex [Brown, Goetzmann and Ross (1995) provide a recent general analysis]. Most of the literature on survivorship biases focus on a death process by which the low return funds leave the sample. However, high return managers can also leave the sample, as the star performers move on to manage larger accounts or form new firms. We believe that a similar affect occurs with mutual funds, as the successful managers may leave to manage pension funds, for example. Since we are uncertain how to model the birth and death processes in our data base, it is not possible to control for survivorship biases. We therefore leave this as a topic for future research.

Our sample is also likely to have a selection bias, because managers enter the data base after they attract attention from the Frank Russell Company and its clients. When a manager is added to the data base, some previous history of the manager's returns may be back-filled. There is evidence consistent with selection bias for the average returns in our sample. The average annual return on an equally-weighted portfolio of all managers is 16.11% over 1981-90. If we exclude the first five years of data for each manager, the average annual return over 1981-90 drops to 15.45%. In the analysis of performance persistence we use the returns following the first five years of data for a given manager. This should reduce the effects of selection bias.

### 2.3 Money Management Fees

We do not have specific fee data associated with the individual managers, as the managers are not identified to us by name. Halpern and Fowler (1991) find that, for accounts of $100 million, posted management fees average about 50 basis points at the end of our sample period. Internal RDS research shows that average quoted fees vary by investment style. For example, the median (interquartile range) of the quoted fees for $100 million accounts in 1988 varies from 44 (35-58) basis points for the large cap managers to 78 (56-100) basis points for the small cap managers. The figures for growth and value managers are 49 (40-59) and 53 (43-59) basis points, respectively. Fees vary according to account size, and smaller accounts would pay more. There has been a secular decline in management fees over our sample period. According to RDS, the median quoted fees of value managers fell from 53 basis points in 1988 to 47 in 1994.

It would be difficult to determine the actual fees paid by plan sponsors, even if posted fee data were available for each manager. "Banner" sponsors are likely to be offered a discount from the posted fees and they prefer not to disclose the details of these discount arrangements [Halpern and Fowler (1991)]. In addition, there may be some substitution between fees and other types of costs, such as brokerage commissions. For example, a plan sponsor might pay lower fees and, in exchange, buy research or direct trading to designated brokers, who then rebate a portion of the trading commissions (known as "soft dollars").

## 2.4 Benchmark Portfolios

The RDS data base includes passive benchmarks for four investment styles. These are the Russell Growth, Value, Market-oriented, and Small-capitalization indexes. The Russell Market-oriented style index is the Russell 1000, a value-weighted index of the stocks of large capitalization firms. The Russell Small-capitalization index is the value-weighted Russell 2000 index. These are nonoverlapping subsets of the Russell 3000 index universe. The Growth and Value indexes are formed by further dividing the stocks in the Russell 1000 into two groups of stocks. The stocks are divided at the median market value-weighted ratios of market price to the book value of equity. Stocks with high ratios go into the growth index, and those with low ratios are in the value index. We also use the CRSP value-weighted NYSE and AMEX index as an overall market benchmark. This allows us to compare our results with previous studies based on the CAPM, which used similar market portfolios as their benchmarks.

## 2.3 The 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 Schadt (1996). They are (1) the lagged level of the one-month Treasury bill yield (TBILL), (2) the lagged dividend yield of the CRSP value-weighted NYSE and AMEX stock index (DY), (3) a lagged measure of the slope of the term structure (TERM), (4) a lagged quality spread in the corporate bond market (QUAL), and (5) a dummy variable for the month of January.

TBILL is the discount yield of a bill that is the closest to one month to maturity at the end of the previous month. It is drawn from the CRSP RISKFREE files. The bill yield is calculated from the average of bid and ask prices on the last trading day of each month. The dividend yield is the price level at the end of the previous month on the CRSP value-weighted index divided into the previous twelve months of dividend payments for the index. TERM is a constant-maturity 10-year Treasury bond yield less the 3-month Treasury Bill yield; both are annualized weekly averages from Citibase. QUAL is Moody's BAA rated corporate bond yield less the AAA rated corporate bond yield, using the weekly average yields for the previous month, as reported by Citibase.

## 3. Empirical Results

### 3.1 Predictability of Pension Fund Excess Returns

Table 1 summarizes time series regressions which attempt to predict the managers' future monthly returns over the 1979-90 period. The dependent variables are the managers' returns, in excess of either the one-month Treasury bill, the Russell style index or the CRSP value-weighted index. The independent variables are the predetermined information variables. The purpose of these regressions is to determine whether managers' returns are related to public information. If so, this provides one motivation for a conditional performance analysis.

When the dependent variables are the returns net of the Treasury bill return, the regressions for equally-weighted portfolios of the managers (panel B) and the averages of the individual manager regressions (panel A) produce adjusted R-squares in excess of 12% for each of the four style groups. For small-cap managers, the R-squares are about 17%.

These adjusted R-squares are high by conventional standards for monthly predictive regressions [for passive size and industry-grouped portfolios, see Ferson and Harvey, (1991b) and Ferson and Korajczyk (1995)]. Most of the regressions for the individual managers' returns in excess of the bill are strongly significant at conventional levels. The residual autocorrelations typically are not large; for the equally-weighted portfolios they are between .07 and .13, which is within two standard errors of zero.

The excess returns of the value managers produce slightly higher R-squares in Table 1 than those of the growth managers, and the small-cap funds produce higher R-squares than large-cap funds. To check whether these patterns reflect differences in the predictability of the assets held by the funds, panel C reports regressions where the dependent variables are the passive style indexes. The R-squares in panel C follow the same pattern as those in panels A and B: they are higher for value than growth indexes, and they are higher for small-cap than for large-cap indexes.

Table 1 also presents regressions for the managers' returns measured in excess of the CRSP value-weighted index and the Russell index for the manager's style group. The excess returns relative to these benchmarks may be interpreted as measures of ex post abnormal performance, under the assumptions that the benchmark is efficient and that the conditional beta of each manager on the benchmark is identically equal to 1.0. Under this interpretation, the return in excess of the benchmark should not differ predictably from zero.

Using the returns in excess of the value-weighted index, the regressions produce adjusted R-squares which average between six and ten percent for the individual managers and vary between 2.6% and 10% for the equally-weighted portfolios. The regressions are statistically significant for each of the equally-weighted portfolios, excepting the portfolio of the large-cap managers. The equally-weighted portfolios mask significant variation across the funds in the degree of predictability. For example, in the case of the large-cap managers, while the average right-tail p-value for the significance of the R-square is 0.34, more than half of the individual fund regressions produce p-values less than 0.05.

The regressions for the returns net of the CRSP index show that the hypothesis that there is no predictable abnormal performance can be rejected, if one assumes that the CRSP index is an efficient benchmark and that all funds have unit betas. The rejection of this joint hypothesis may be due to either time-varying betas or abnormal returns; either reason motivates a conditional performance analysis. Alternatively, the rejection could simply be driven by inefficiency of the CRSP index. The middle columns of Table 1 therefore report regressions for the returns net of the alternative benchmarks provided by the Russell style indexes.

The regressions for the returns in excess of the style indexes deliver typically lower R-squares than the other regressions. At the equally-weighted portfolio level, the regressions are statistically significant only for the small-cap managers. The style indexes are more closely correlated with the fund returns than a typical market index, which reflects a practical appeal of style indexes as performance benchmarks. (High correlation should reduce the estimation error associated with measures of abnormal performance.) The predictable excess returns of the small-cap managers may indicate that small-cap fund returns are more difficult to capture with a style index than are the other groups.[8] Similar to other regressions in Table 1, the equally-weighted portfolios mask cross-sectional variation. The individual-fund regressions net of the style indexes are significant at the 5%

level for about half of the managers, and the average adjusted R-square for a small-cap manager is over 10%.

To summarize, the regressions show that the expected excess returns of the managers vary over time with the public information variables. The evidence of predictable returns in excess of a benchmark is not attributed to the use of the CRSP index as the benchmark. This motivates the use of conditional models to study the performance of pension managers.

### 3.2 Estimates of Pension Fund Alphas

Section 1 described models for estimating the average performance measure, alpha. We estimate unconditional and conditional versions of the CAPM, using the CRSP value-weighted index as the benchmark in equations (1) and (3), respectively. The unconditional CAPM assumes that both the betas and the alphas are constant over time but that they may differ across funds. The conditional model (3) allows time-varying betas, but assumes that any abnormal performance which may exist under the alternative hypothesis is captured by the fixed alpha coefficients. We also estimate alphas using equations (1) and (3), where the Russell style index for a manager replaces the CRSP index as the benchmark. The results are summarized in Table 2.

The two right-hand columns of Table 2 report right-tail p-values of F-tests and of heteroskedasticity-consistent Wald tests for the hypothesis that the conditional market betas are constant over time. This is an exclusion test for the additional terms in the conditional models, which are the interaction terms between the benchmark index and the lagged conditioning variables in regression (3). At the level of the equally-weighted portfolios of funds, the incremental explanatory power of the interaction terms is significant for value and large-cap funds, but not for the other two fund groups. The R-squares of the equally-weighted portfolios do not go up much when the conditioning variables are included. However, the averages conceal significant evidence of time-varying betas for some individual funds.

Table 2 also includes the average R-squares, taken across the individual funds in a group, which may be compared to the results for the equally-weighted portfolios. The R-squares go up more, on average, for an individual fund than for the portfolio when the conditioning variables are brought into the model. This pattern suggests that there is time-variation in the individual fund betas that washes out at the aggregate level. The regressions for the individual funds reveal wide variation across funds in the statistical importance of the lagged variables. Using a 5% significance level, the CAPM benchmark and the F (Wald) statistic, the hypothesis of a constant conditional beta is rejected for 23 (23) of 41 growth managers, 25 (26) of 40 Value managers, 46 (41) of 55 large-cap managers, and 27 (27) of 49 small-cap managers. Similar results are found using the style index benchmarks.[9]

These results reflect heterogeneity in the month-to-month market risk dynamics of the individual funds within a style group. Some of the managers reduce their betas at the same time that others increase their betas. Therefore, we would expect that conditional models, which allow for fund-specific risk exposure dynamics, should be able to model returns across managers better than models which assume that the betas are constant.[10] [11]

Table 2 reports a joint test for the hypothesis that the individual betas are constant, for each fund in each style group. These are based on the Bonferroni inequality.[12] The joint test rejects the hypothesis that all managers have constant conditional betas.

We also estimated four-factor models in which the Russell Style Indexes are used in multibeta generalizations of the models of equations (1) and (3). The factors are the four style indexes, measured net of the Treasury bill return. The results (not reported here) are qualitatively similar to those in Table 2.[13]

Figure 1 presents the distribution of the alphas from the six models -- unconditional and conditional versions of the CAPM, the single style index models and the four-factor models. As described above, the returns in the RDS data base do not subtract off management fees, which differ across the style groups. Therefore, we adjust the alphas by subtracting the median 1988 fees reported in section 2. A striking feature of figure 1 is a similarity in the distributions. While the style-index models generally make the managers look better than does the CAPM, the unconditional and conditional alphas appear similar for each model. This is an interesting result, in view of the finding of Ferson and Schadt (1996) that conditional alphas for mutual funds are on average larger than the unconditional alphas. Ferson and Warther (1996) show that these differences reflect correlation between expected market returns and the flow of new money into mutual funds, combined with a negative relation between new money flows and mutual fund betas.

While we also find time-varying betas for pension funds, it is likely that the flow of pension monies behaves differently in relation to expected market returns, given the different institutional structures. Our results therefore reveal interesting differences in the dynamics of mutual fund and pension fund performance. We believe that further analysis of these dynamic patterns represents fertile ground for future research.

### 3.2 Time-varying Conditional Alphas

Table 3 summarizes the results of estimating equation (5) with time-varying conditional alphas. This model approximates the conditional alpha as a linear function of the predetermined information, allowing the function to be different for each manager.[14]

Panel A of Table 3 uses the CRSP value-weighted index as the benchmark portfolio. The two far right-hand columns report right-tail p-values for the F test and for a heteroskedasticity-consistent Wald test of the hypothesis that the conditional alphas are constant over time, against the alternative that they are time-varying. If management fees are relatively stable over time, these tests should be relatively robust to the level of fees. The tests in panel A provide strong evidence that some managers have time-varying conditional alphas relative to the CAPM. A 5% F-test (Wald test) rejects the constant-alpha hypothesis for 27% (24%) of the growth managers, and for 43% (48%) of the value managers. The fractions for the large-cap and small-cap managers are in between these figures. The joint Bonferroni tests reject the constant-alpha hypothesis at the 0.024 level or less. A similar result is found in panel B, where the style index benchmarks are used. The tests therefore provide evidence that the conditional alphas in these models are time-varying.

Table 3 summarizes, using equally-weighted portfolios, the estimates of the $A_p$ coefficients and their heteroskedasticity-consistent t-ratios, which measure the sensitivity of the conditional alphas to the public information variables. The results at the group levels, as reported in the table, show that the dividend yield and the Treasury bill yield are the more important variables. We also examine the coefficients for the individual managers. Judging by the frequency of t-ratios larger than two, the most important variables in panel A are, again, the Treasury bill yield (41 cases), and the dividend yield (37 cases). The term spread is the least important, with 19 cases. The signs of the significant $A_p$ coefficients for individual funds are mixed, but there is a tendency for more positive coefficients on the dividend yield and negative coefficients on the Treasury bill. Among the small cap managers, 15 of the 16 significant coefficients on the dividend yield are positive, and all 13 of the significant coefficients on the Treasury bill are negative.

The finding that the coefficients on the Treasury bill tend to be negative, while those on the dividend yield tend to be positive, says that the managers deliver higher risk-adjusted abnormal performance relative to the CAPM when dividend yields are high and short term interest rates are low, even after allowing for time-varying risk exposures. Since high dividend yields and low short term interest rates both predict high stock returns, the coefficients indicate that the conditional alphas of the funds tend to be positively correlated with expected stock market returns. While consistent with the conventional wisdom that it is easier for a fund manager to look good in an up market, this result may also reflect a misspecification in the CAPM.

Panel B of table 3 summarizes the results of estimating conditional alphas when the Russell style index is the benchmark portfolio for a manager, and different managers therefore have different benchmarks. A 5% test using the F (Wald statistic), rejects the hypothesis that the alphas are constant for 53 (77) of the 185 managers. The Bonferroni joint p-values are 0.003 or less for each manager group. The significant time-variation in the alphas is spread fairly evenly across the groups, which is similar to the results for the

CAPM. There is a tendency for more positive coefficients on the dividend yield and negative coefficients on the Treasury bill, also similar to what we found using the CAPM.

## 4. The Persistence of Investment Performance

### 4.1 Methods for Measuring Persistence

Our approach to measuring persistence is based on cross-sectional regressions of future excess returns on a measure of past performance, or alpha:

$$r_i(t,t+\tau) = \gamma_{0,t,\tau} + \gamma_{1,t,\tau}\,\alpha_{it} + u_i(t,t+\tau), \quad i=1,\ldots n \tag{6}$$

where $r_i(t,t+\tau)$ is the compounded return from month $t$ to month $t+\tau$ for manager *i*, measured net of the return to rolling over one-month Treasury bills. The symbol $\tau$ denotes the return horizon, for $\tau=1,3,6,12,18,24$, and 36 months. The regressor, $\alpha_{it}$, is a measure of past abnormal performance, estimated using time-series data up to month t. The term $u_i(t,t+\tau)$ is the regression error. The cross-sectional regression is estimated for a number of months, resulting in a time series of the slope coefficients, $\gamma_{1,t,\tau}$, $t=1,\ldots T-\tau$. The hypothesis that the alpha cannot be used to predict the future return (i.e., no persistence) implies that the expected value of the coefficient $\gamma_{1,t,\tau}$ is zero.

The regression (6) is a predictive cross-sectional regression, since the alpha is based on past data only. Similar regressions are used in asset pricing studies [e.g., Fama and MacBeth (1973), Ferson and Harvey, (1991a)], where a risk measure like beta is the independent variable. Given the work of Roll and Ross (1994) and Kandel and Stambaugh (1995), which suggests that generalized least squares (GLS) is preferable to ordinary least squares (OLS) in cross-sectional regressions, regression (6) is estimated by GLS methods. We use a computationally-feasible weighted least squares (WLS) approach. The weight for each observation is the inverse of the standard deviation of the residuals for the time-series model that was used to estimate the alpha, $\alpha_{it}$. Note that, in the WLS regression, the deflated alpha is similar to an appraisal ratio. Brown, et al. (1992) suggest the appraisal ratio as a partial adjustment for survivorship bias.

The cross-sectional regression methodology is attractive for a number of additional reasons. Because the slopes of the cross-sectional regressions are invariant to any (additive) factors the results are robust to any additive bias in returns that is common across the funds at a given date, even if that bias is time-varying (for example, a misspecified risk-free rate). In other words, the regressions examine relative but not absolute performance at each date. By using the future return as the dependent variable in (6), the regressions focus directly on the question of the most practical interest: to what extent can the past alpha be used to predict future relative returns? The alternative approach of using the alpha for a future subperiod as the dependent variable, as in some previous studies, is problematic if there are biases in the alphas that persist over time. Most of the likely sources of bias in alphas (e.g. missing priced factors, size effects, book-to-market or earnings yield effects, etc.) are likely to be correlated over time. If future alphas were used as the dependent variable, such biases in alpha can generate spurious evidence of persistent performance.

While the cross-sectional regression approach has some attractive features, it also implies some complications. The regression errors are likely to be cross-sectionally correlated, making the usual regression statistics, such as R-squares and standard errors, unreliable. Therefore, we use the methodology of Fama and MacBeth (1973) to test the hypothesis that the expected value of $\gamma_{1,t,\tau}$ is zero against the alternative hypothesis that the mean value of the coefficient is not zero. A t-statistic is formed, where the sample mean of the time series of the $\gamma_{1,t,\tau}$ estimates is the numerator and the standard error for the mean is the denominator. This approach has good sampling properties even when the cross-sectional regression errors are correlated [see Shanken (1992)].

When the future return horizon is longer than one month ($\tau > 1$), the time series of the $\gamma_{1,t,\tau}$ estimates will be autocorrelated due to the overlapping data. We adjust the standard errors in the t-statistics to account for this autocorrelation, using the approach of Newey and West (1987) with $\tau$-1 moving average terms.

## 4.2 Measures of Past Performance

The various unconditional and conditional models provide estimates for past abnormal performance or alpha. We wish to compare the evidence of persistence for different performance measures. The simplest measures are the past average returns and the returns in excess of the manager's passive style index, based on the most recent 36 or 60 months. We also measure the performance of a manager as the past average return net of the return for an equally-weighted portfolio of the actual managers in the same Russell style group (denoted in the tables as "net of group mean").

In addition to the past average returns, we use various estimates of alpha from the regression models. The "60-month unconditional (conditional) CAPM" alphas use equation (1) (or 3), the previous 60 months of data, and the market index as the benchmark. The "60-month unconditional (conditional) style alphas" are similar, but use the passive style indexes as the benchmarks. The "time-varying conditional CAPM" alphas use equation (5) and the previous 60 months of data to estimate the parameters. The most recently-available values of the information variables $Z_t$ are then used to determine the conditional alpha. The "time-varying conditional style" alphas are similar, but they use the style indexes as the benchmark.

A final set of alphas are the "timing-adjusted" conditional and unconditional alphas. The unconditional models are based on the classic market timing regressions of Treynor and Mazuy (1966):

$$r_{pt+1} = a_p + b_p r_{bt+1} + \gamma_{tmu} [r_{b,t+1}]^2 + v_{pt+1}, \tag{7}$$

where the coefficient $\gamma_{tmu}$ measures market timing ability. Admati, et al. (1986) describe a model in which this coefficient is positive if the manager increases beta when he or she receives a positive signal about the benchmark. Alternatively, the coefficient may capture nonlinearities which arise due to the use of derivative securities or dynamic trading strategies [see Jagannathan and Korajczyk (1986) or Glosten and Jagannathan (1994)]. The intercept coefficient, $a_p$, is the *timing-adjusted unconditional alpha.*

Ferson and Schadt (1996) propose a conditional version of the Treynor-Mazuy regression:

$$r_{pt+1} = a_p + b_p r_{bt+1} + C_p'(z_t r_{bt+1}) + \gamma_{tmc} [r_{b,t+1}]^2 + v_{pt+1}, \tag{8}$$

where the coefficient vector $C_p$ captures the response of the manger's beta to the public information, $Z_t$, and the term $C_p'(z_t\ r_{bt+1})$ controls for the public information effect. The coefficient $\gamma_{tmc}$ measures the sensitivity of the manager's beta to any private market timing signal, conditional on the public information $Z_t$. The intercept, $a_p$, is the *timing-adjusted conditional alpha*. In this model, the conditional alpha is assumed to be a fixed parameter over time. We estimate the model using a 60-month moving window, which allows ad hoc time-variation. We also estimate conditional and unconditional versions of market timing regressions in which the Russell style indexes are used in place of the CRSP index as the benchmark portfolio. These models imagine that managers attempt to time their moments between cash and a portfolio of stocks which is well approximated by their Russell style index.

### 4.3 Evidence that Performance Persists

Table 4 summarizes the results of the cross-sectional regressions, using the past performance to predict the future returns. Each row presents the results for a different alpha. In panel A, unconditional measures of past average return and alpha are used. In panel B, conditional measures of alpha are used. The middle columns of the table show the Fama-MacBeth t-ratios, adjusted for autocorrelation if the future return horizon $\tau$ is longer than one month.

As a number of comparisons are made, and the results are likely to be correlated across the horizons, joint tests across the horizons are appropriate. The right-hand columns of Table 4 report the results of joint tests. The first is the Bonferroni p-value, based on the collection of the individual p-values for the seven horizons, using the t-distribution. The far right-hand columns report right-tail p-values for Wald tests of the hypothesis that the vector of the slope coefficients for all of the horizons is zero. The Wald test statistic is a quadratic form in the vector of the sample means of the cross-sectional regression slopes, where the matrix is the inverse of the covariance matrix for the mean values of the slopes. The covariance matrix is formed using the standard errors of the means, as described above, and the correlations are estimated from the time-series of the cross-sectional regression slopes. The Wald test is asymptotically distributed as a Chi-square variable, with degrees-of-freedom equal to the number of horizons examined.

The results of Table 4 are interesting in a number of respects. Focussing first on panel A, the unconditional models provide little evidence of predictive ability at the short horizons. The unconditional alphas relative to the CAPM and the past average returns seem to have little information about the future returns. However, as the future return horizon is increased, evidence of persistence appears, and five of nine models produce t-ratios larger than 2.0 at the 36-month horizon. Unconditional alphas relative to the passive style indexes and past returns net of the style group means produce the strongest evidence of persistence among the unconditional models. All but one of the significant coefficients are positive, which says that good (bad) performance tends to predict high (low) future returns. Based on the Bonferroni tests, three of the nine models produce jointly significantly positive coefficients across the horizons.

Panel B summarizes the results when using the conditional models to estimate the alphas. Three of six models produce significantly positive coefficients, based on the Bonferroni tests, and all of the significant coefficients are positive. The t-ratios of the coefficients are typically larger at the longer horizons. The exceptions are the time-varying conditional CAPM and style models, which also produce large t-ratios at the one-month and three-month horizons. Overall, the regression evidence of persistence is stronger when the conditional models are used.

Table 4 is based on the full sample of managers with enough data to estimate alpha over the previous 60 (or 36) months. Studies of open-end mutual funds find that persistence is concentrated in the poorly-performing funds [ e.g. Brown and Goetzmann (1994), Shukla and Trzcinka (1994), Carhart (1995)]. Table 5 therefore repeats the persistence analysis using only the pension funds whose prior alphas are negative each month. Panel A of Table 5 shows the results for the past average returns and unconditional models of alpha. The lagged average returns have little predictive ability, unless they are measured relative to the style group fund average, but the regressions are significant (jointly across the horizons) for five of the nine unconditional models. The evidence of persistence is similar to, but stronger than in panel A of Table 4, where all the managers were used. The significant coefficients are almost always positive, and they are concentrated at the longer horizons. This says that, among the negative-alpha funds, those with relatively low prior alphas in a given month tend to have relatively low returns for many months into the future.

Panel B of Table 5 reports results using the conditional alphas, and only those managers with negative conditional alphas. The evidence of persistence is even more impressive than for the conditional models in Table 4. The regression coefficients are jointly significant across the horizons for five of the six conditional models. The conditional models have somewhat more explanatory power at the shorter horizons than the unconditional models. All of the significant coefficients are positive for the conditional models, indicating positive persistence in the relative performance of the negative-alpha managers. We conclude that, among those managers that have performed poorly by the conditional measures, the worst are likely to deliver significantly lower returns in the future.

### 4.4 Robustness of the Evidence

We investigate the robustness of our evidence of persistent performance in a number of ways. First, we investigate whether it is a statistical artifact. Then we assess its economic significance.

Hendricks, Patel and Zeckhauser (1992) consider the effects of survivorship bias under the simplifying assumptions that the expected returns of all managers are the same, but that there are differences in variances. They argue that past poor performers in a sample with survivorship bias are likely to reverse their performance in the future, because a poor performer that is not culled from the data base is one that is more likely to have performed better in the future. However, in Table 5, the cross-sectional correlation between past and future performance of the poor performers is not negative, but is positive and significant. This suggests that our estimates of the persistence in the performance of the low-alpha managers may be conservative relative to an uncensored sample.[15]

The t-ratios in Tables 4 and 5 suggest that persistence becomes stronger as the future return horizon increases out to three years. This pattern could be an artifact of more precision in the estimates for the longer horizons, or of finite sample biases in the estimators. The Newey-West estimator places declining weights on the autocovariances at longer lags. While the estimator is consistent, it could place too little weight on the longer lags in finite samples. We therefore re-estimated a number of the cases using Hansen's (1982) covariance matrix, which gives equal weights to all of the lags. We find that this produces slightly smaller t-ratios for the shorter horizons, similar numbers in the one to two-year range, and larger t-ratios at the longest horizons. These patterns are consistent with the negative sample autocorrelations that are typically found in longer-horizon portfolio return data, and the weak or positive autocorrelation in shorter-horizon returns [e.g., Fama and French (1988)].

It is conceivable that the weaker relation of alphas to future returns in the full sample of managers and the stronger positive relation in the subsample of negative-alpha managers masks a significant pattern among the high-alpha managers. To explore this possibility, we repeated the analysis using the subset of managers with alphas in the top third each month (results available by request). We find no strong evidence of persistence in the performance of the high-alpha managers. Most of the coefficients are negative at the shorter horizons, which suggests some mean reversion in the performance of the top managers, but the negative coefficients are generally not significant. Only eleven of the 91 t-ratios are larger than two, and all but one of these are positive coefficients at longer horizons. These results therefore confirm the impression that the evidence of persistence in the performance of these managers is concentrated in the poorly-performing group.

We examined the point estimates of the cross-sectional regression coefficients, in order to see how much of the pattern across the horizons is attributed to larger coefficients, as opposed to smaller standard errors at the longer horizons. The magnitudes of the coefficients also have an interesting economic interpretation [Fama (1976)], under the simplifying assumption that the managers' returns can be sold short. The coefficient in a given month is the return of a portfolio with short and long positions, such that the net investment is zero. The position is constructed to have an historical alpha equal to 1 (percent per month). The average coefficient is the time-series average return to such a strategy. We compute the average values of the cross-sectional coefficients, taken across the models which produce significant coefficients, and express the result as a return per month (the coefficient is divided by the number of months in the return horizon). The average coefficients range from over 0.2% per month to more than 0.6% per month. The larger t-ratios for the longer horizons are not simply a result of more precise estimates. The magnitudes of the coefficients are also larger (on a per-month basis) for the longer horizons. The magnitudes of the coefficients are also larger in the sample of negative-alpha managers, which suggests that the economic significance of the persistence is larger for this group of managers.

### 4.5 The Economic Significance of Persistence

The economic interpretation of the cross-sectional regression coefficients as the premiums on portfolio strategies is hypothetical because it is not possible to sell short these portfolios. The evidence of Tables 4 and 5 therefore suggests that the alphas may be useful for avoiding poorly-performing managers, but not for picking winners. However, the regressions do not account for differences in the risk of the future returns. If the alphas are related to the future risks because of some systematic bias, then some of the evidence of persistence may reflect persistence in the expected compensation for these risks. Adjusting the cross-sectional regressions for risk is problematic, because errors in the risk adjustment are likely to be correlated over time, which could actually produce -- instead of control -- for spurious persistence.

To address these issues, we construct simple trading strategies, designed to facilitate risk adjustments and to provide an economic interpretation for the magnitudes of the persistence effects. Each trading strategy uses an estimate of alpha based on the past 60 months of data for each eligible manager. The alpha estimates are ranked, grouped according to quintiles and an equally-weighted portfolio is formed from each quintile group. This portfolio is held for one month, and the procedure is repeated. Both the monthly returns and the cumulative investment values are tracked. If there is persistence in performance, then high-alpha portfolios should generate higher returns than low-alpha portfolios. To adjust for risk, the performance of each quintile portfolio is evaluated using both conditional and unconditional models. The first date of the trading strategy returns is January 1984, and there are 84 monthly returns for each trading strategy.

Table 6 shows the results of the simple trading strategies, formed from three alpha estimates. The alphas use a time-varying conditional CAPM, an unconditional CAPM and past average returns. For each trading strategy Table 6 reports unconditional and conditional betas, the alphas of the strategy measured relative to four risk models (unconditional and conditional CAPM and three-factor models),[16] the cumulative return after 84 months, and the fraction of positive returns. For comparison purposes, the first two rows present results for the CRSP value-weighted index and an equally-weighted portfolio of all managers.

Using the unconditional CAPM alphas to drive the strategies, the mean returns and cumulative investment values are not monotonic across the quintiles. The lowest-alpha quintiles have the largest standard deviations of return and the largest betas. Although low-alpha quintiles have the highest risk measures, they do not have the highest returns. The high-alpha quintile actually has the lowest average return. However, the difference between the high-alpha and the low-alpha quintile average return is only 0.2% per year. Estimates of the alphas for the unconditional-alpha-quintile strategies are not statistically different from zero. Thus, unconditional CAPM alphas appear to provide little information about future performance.

Similar results hold when we use the past average returns to form quintiles. The extreme quintiles have slightly larger standard deviations and betas, but insignificant alphas. Overall, like the unconditional CAPM alphas, past average returns seem to have little information about future manager performance.

Focussing on the alphas generated using the time-varying conditional CAPM, the results of the trading strategies are striking. The average returns are monotonic across the alpha-quintiles, and the difference between the high-alpha and low-alpha quintile is 4.9% per year. The cumulative value of a one-dollar investment made in 1984 and held until the end of 1990, ranges from $2.73 for the high-alpha to $1.93 for the low-alpha quintile.

Table 6 also provides evidence that risk differences do not account for the predictability of the future returns based on the conditional alphas. Simple measures of risk for the quintiles are not monotonic across the conditional-alpha quintiles. The standard deviations of the excess returns, the unconditional betas, and the time-series averages of the conditional CAPM betas for the quintile strategies, are all lower in the middle quintiles and higher at the extreme quintiles. The high-return quintile does not appear to be the highest-risk quintile. In fact, all three of these risk measures are the largest for the low-alpha, low return quintile strategy.

The fraction of the 84 excess returns that are positive is also monotonic across the conditional-alpha quintiles, ranging from 60.7% for the high-alpha to 54.8% for the low-alpha quintile. Estimates of CAPM alphas (unconditional and conditional versions) for the quintile-strategy returns are positive for the highest quintile, significantly negative for the lowest, and ordered nearly monotonically across the quintiles.

### 4.5 Do Pension Managers Have Poor Performance?

Our evidence on the average performance of the pension funds differs from the conclusions of Lakonishok, Shleifer and Vishny (LSV, 1992), who find that pension managers underperformed the S&P 500 by an average of over one percent per year, for 1983 to 1989. Since our universe of managers, sample period, benchmarks, and methodology all differ from LSV, we address the reasons for the differing conclusions in this section. In the appendix Table A1 we present results using LSV's methodology: a simple comparison of annual returns (without subtracting fees) for equally-weighted portfolios of the managers to the S&P 500. We also report, for comparison purposes, some of the figures from their tables.

We find positive average performance in our sample of managers, measured relative to the S&P 500. Over our sample period of 1979-1990, the average return on the equally-weighted portfolio of all managers is 18.95%, as compared to an average annual S&P return of 16.45%. By contrast, LSV find an average return of 17.73% for their managers over 1983-1989, compared to an S&P average return of 18.96%. Over the 1983-89 period, they find that 54.1% of the managers in their sample earned lower returns than the S&P, whereas we find 50.0% over the same period. Over the 1979-90 sample period, 40.6% of the managers in our universe earned returns below that of the S&P. Clearly, the different results of the two studies reflect both differences in the sample period and differences in the samples of pension managers.[17]

To determine to what extent the differing results are a function of the sample period and the universe of managers studied, we decompose the difference between the average returns in the two studies. Let $r_{\text{study, sample period}}$ denote the average returns, measured in excess of the S&P 500 return, in a study (CFG or LSV) over a particular sample period (83-89 or 79-90). The decomposition is:

$$
\begin{aligned}
r_{LSV,83\text{-}89} - r_{CFG,\,79\text{-}90} &= (r_{CFG,83\text{-}89} - r_{CFG,\,79\text{-}90}) + (r_{LSV,83\text{-}89} - r_{CFG,\,83\text{-}89}) \\
-3.73 &= (-2.64) + (-1.09)
\end{aligned}
$$

The first term on the right-hand side captures the average *sample period effect*, and the second term captures the *manager universe effect*. While the managers in our sample have excess returns 3.73% higher than those in the LSV sample, over 70% of this difference, or 2.64 percentage points, is attributed to the sample period effect. For the years in our sample but not in the LSV sample (1979-1982 and 1990), our managers earned an average annual return of 24.9%.

The remaining difference between the excess returns in our sample and the LSV sample is 1.09 percentage points. As this is measured over a common subperiod, we attribute it to differences in the population of managers in the two studies. There are a number of differences in the samples that could explain our higher returns. One is that the RDS data base includes only representative accounts -- one per management firm -- while the SEI data base used by LSV includes multiple accounts per firm. As noted above, representative accounts are relatively unrestricted and may therefore have higher expected returns. A second difference is the larger account sizes in our sample. As described previously, the average account size for the managers in our sample is in the range of $100 million. The LSV data base has more accounts in the $25-$50 million range. Possibly, managers with larger accounts are better performers. A third potential difference is a differential effect of selection bias. As noted above, if we delete the first five years of data for each of our managers, the average return is 56 basis points lower, which is consistent with a selection bias.[18]

While these differences between the two samples are consistent with larger returns in our sample of managers, other differences appear to work in the opposite direction. LSV exclude cash holdings when calculating manager returns, while our returns data include any cash holdings. Since average cash returns are lower than equity returns, this means that the returns in our data base would be even higher if based on equity-only data. Second, the returns in our data base and in the LSV study do not subtract management fees. It is likely that the managers in our sample charged lower fees than those in the LSV sample, because fees are typically lower for larger accounts.

It is also likely that the pension managers in both LSV and our study hold portfolios which are more heavily concentrated in small stocks than the S&P500. This calls into question the use of the S&P500 as a benchmark. Indeed, the average manager in our sample beat the S&P500 in precisely the same years in which small stocks as a group return more than the S&P500.[19] Still, it is possible that our sample of large equity accounts is more concentrated in large-cap stocks than are the accounts examined by LSV. If this is the case, then the poor performance recorded by LSV may be partly explained by the fact that small firms did not perform well, relative to the S&P 500, over their sample period. We provide an additional decomposition of the differences in average returns to investigate this possibility. Using our sample of small-cap managers instead of our overall sample, we compare the results to the LSV universe (LSV do not report results for small-cap managers separately). The results of the decomposition are as follows:

$$r_{LSV,83\text{-}89} - r_{small,\,79\text{-}90} = (r_{small,83\text{-}89} - r_{small,\,79\text{-}90}) + (r_{LSV,83\text{-}89} - r_{small,\,83\text{-}89})$$
$$-\,4.81 \qquad = \qquad (-4.66) \qquad + \quad (-0.15)$$

The small-cap managers in our sample earn 4.81 percent more per year, in excess of the S&P 500, than the managers in LSV's sample. Using our small-cap universe, almost all of the difference in average returns between the two studies is attributed to the sample period effect. The average returns of the LSV managers are very close to those of our small-cap managers in the same time period. This supports the idea that LSV's sample of managers held relatively more small-cap stocks than our sample of RDS managers.

In summary, the results using average returns show that the evidence on the average performance of pension managers is sensitive to the sample period. The 1983-89 period studied by LSV was a period in which small stocks performed poorly relative to the S&P 500 benchmark, and LSV managers probably held relatively more small-cap stocks. Using a longer sample period and larger accounts than LSV, we find no evidence that the pension managers as a group perform poorly. Indeed, we find essentially the opposite result. We therefore believe that LSV's conclusions about the poor performance of the industry are premature.

## 5. Concluding Remarks

This paper provides the first analysis of the performance of institutional equity managers using conditional performance evaluation techniques. We use time-varying conditional alphas as well as betas in our models. We find 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 with lagged economic information. The conditional measures provide more power to predict future performance than unconditional measures.

Our analysis documents a striking persistence in the relative performance of the managers, which appears to be of economic significance. Poor conditional performance tends to be followed by low future returns. The finding that persistence is concentrated among the poorly-performing managers is similar to the evidence of previous studies for mutual funds. However, in contrast to studies of mutual funds, we do not find that unconditional alphas are good predictors of future returns. The additional information used by a conditional measure allows us to better detect the persistence in performance.

Finding that a conditional measure can detect persistence in pension fund performance is consistent with the view that more sophisticated techniques are used to evaluate pension fund managers than are used by a typical investor to evaluate mutual funds. This could indicate that the market for pension fund monies is more informationally efficient than the market for mutual fund monies.

However, the finding that poor conditional performance is followed by poor future returns is puzzling. 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 remove their money from a manager with poor performance. This raises a number of interesting questions for future research. What strategies for trading and trade execution characterize these persistently poor performers? Why do the poorly performing managers survive? Is this an inefficiency in the market for pension manager services, as Lakonishok, et al. (1992) suggest? Possibly, the poorly-performing managers deliver valuable services to their sponsors which offsets their poor investment returns. Conditional models seem to provide a more powerful signal than has previously been available to measure risk-adjusted investment performance. Future research is needed, using conditional methods, to address these issues.

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## Footnotes:

1. See, for example the studies by Grinblatt and Titman (1994), Hendricks, Patel and Zeckhauser (1993), Brown and Goetzmann (1994), Ippolito (1992), Goetzmann and Ibbotson (1994), Shukla and Trzcinka (1994), Malkiel (1995), and Carhart (1995).

2. Many previous studies in the asset pricing literature have used linear functional forms to model time-varying betas and second moments. Examples include Ferson (1985), Shanken (1990), Ferson and Harvey (1993), Cochrane (1996) and Jagannathan and Wang (1996). The approach is especially attractive for fund performance for two reasons. First, linear betas can be motivated by theoretical models of manager behavior such as Admati, Ross and Pfliederer (1986). Second, the linear regression models which result from this assumption are easy to interpret, as illustrated by Ferson and Schadt (1996).

3. The regression (3) may also be interpreted as an unconditional multiple factor model, where $r_b$ is the first factor and the product of $r_b$ and the lagged information variables are additional factors. The additional factors may be interpreted as the returns to dynamic strategies, which hold $z_t$ units of the index $r_b$, financed by borrowing or selling $z_t$ in Treasury bills. This interpretation is similar to Hansen and Jagannathan (1991) and Cochrane (1996). The model may also be interpreted as a special case of a general asset pricing framework based on the expression $E(m_{t+1} R_{t+1} |Z_t) = 1$, where $m_{t+1}$ is a stochastic discount factor and $R_{t+1}$ is the vector of the gross returns of the primitive assets available to portfolio managers. This interpretation implies that the stochastic discount factor is a linear function of the excess return $r_b$, where the coefficients may depend linearly on $Z_t$.

4. To see this, assume that the underlying assets follow

$$r_{t+1} = \beta(Z_t)\, r_{bt+1} + u_{t+1},$$

where $E(u_{t+1}|Z_t)=E(u_{t+1}\, r_{bt+1}|Z_t)=0$, $r_{t+1}$ is a vector of the underlying asset returns and $\beta(Z_t)$ is the vector of their conditional betas. The underlying assets' alphas are equal to zero. Let the manager's portfolio weight vector be x, so that the portfolio excess return is $x'r_{t+1}$. Taking the conditional expectation of the portfolio return given $Z_t$, and allowing that x may be a random variable given $Z_t$, it is easy to see that the manager's alpha in the conditional model is a function of $Cov(x; u_{t+1}|Z_t)$ and $Cov(x; r_{bt+1}|Z_t)$. The first term may be considered as conditional "security selection" and the second term as conditional "market timing." Both terms should be functions of $Z_t$.

5. The approach of modelling alphas by a linear function goes back in the asset pricing literature at least to Rosenberg and Marathe (1979), but our paper is the first to use economy-wide conditioning variables for conditional alphas to measure portfolio manager performance. Ferson and Harvey (1994) use a similar approach in a study of international equity market returns. They show that the regression (5) imposes the same moment conditions which define Generalized Method-of-Moments conditional betas.

6. While it has been argued that individual investors may stick with a "loser" fund due to a cognitive dissonance, an individual investor is unlikely to lose his job over the issue.

7. Magnitudes for this upward bias are estimated for mutual funds by Grinblatt and Titman (1988) -- 0.1% to 0.4% per year -- by Brown and Goetzmann (1995) -- about 0.8% per year, and by Malkiel (1995) -- about 1.4% per year. Of course, we do not know how these estimates for mutual funds compare to the survivorship bias in our sample of institutional managers.

8. Consistent with this view, we learned shortly after beginning this study that RDS was experimenting with using the Russell 2500 instead of the Russell 2000 as a small-cap index.

9. Since the time-variation can occur in the alphas and the betas, we conduct tests of the hypothesis that the betas are constant, allowing for time-varying alphas. Using and F (Wald) test, the average p-value is 0.09 (0.12) and there are 122 (114) funds with individual p-values below 0.05. We conclude that time-varying alphas alone are not sufficient to capture the role of the lagged variables.

10. Recent studies show that conditional versions of the CAPM do a better job at capturing cross-sectional differences in passive portfolio expected returns than unconditional versions of the CAPM [e.g. Jagannathan and Wang (1996) and Carhart, et. al. (1996)].

11. Note that the alphas of the equally-weighted portfolios are larger that the averages of the individual managers' alphas. The equally weighted portfolios combine the data for every manager that exists in the data base for a given month. Therefore, a manager with a longer data history gets more weight in these results, and each date in the sample period gets equal weight. The averages for the individual manager regressions give unit weight to each manager, provided there are more than 12 observations of the manager's returns. Since there are more managers at the end of the sample period, dates at the end of the sample period get more weight. Finding that the alphas of the equally-weighted portfolios are larger is consistent with the view that managers with longer data series are the better performing managers. It may also reflect better performance for the managers in general in the latter part of the sample.

12. Consider the event that any of N statistics for a test of size p rejects the hypothesis. Given dependent events, the joint probability is less than or equal to the sum of the individual probabilities. The Bonferroni p-value places an upper bound on the p-value of a joint test across the equations. It is computed as the smallest of the N p-values for the individual tests, multiplied by N, which is the number of funds in a group. The Bonferroni p-values are one-tailed tests of the hypothesis that all of the slope coefficients are zero against the alternative that at least one is positive (maximum value) or negative (minimum value).

13. For parsimony and to reduce collinearity of the regressors, we reduce the number of instruments in these models to a constant and the two most important variables, based on the previous analysis, which are the Treasury bill yield and the stock market dividend yield. In the conditional four-factor models, the regression equation has twelve regressors: a constant, the four style indexes, and the products of the two information variables with the four style indexes.

14. To keep the number of coefficients manageable, we use a subset of the original instruments in these models, deleting the January dummy variable and the quality-related bond yield spread. These two variables were typically the least important in the predictive regressions.

15. On the other hand, to the extent that the sample of surviving managers excludes star performers, who may move on to better positions or to form new firms, there may

be a bias in the sample against finding persistence in the performance of better-performing managers. As we discussed above, this remains an issue for future research.

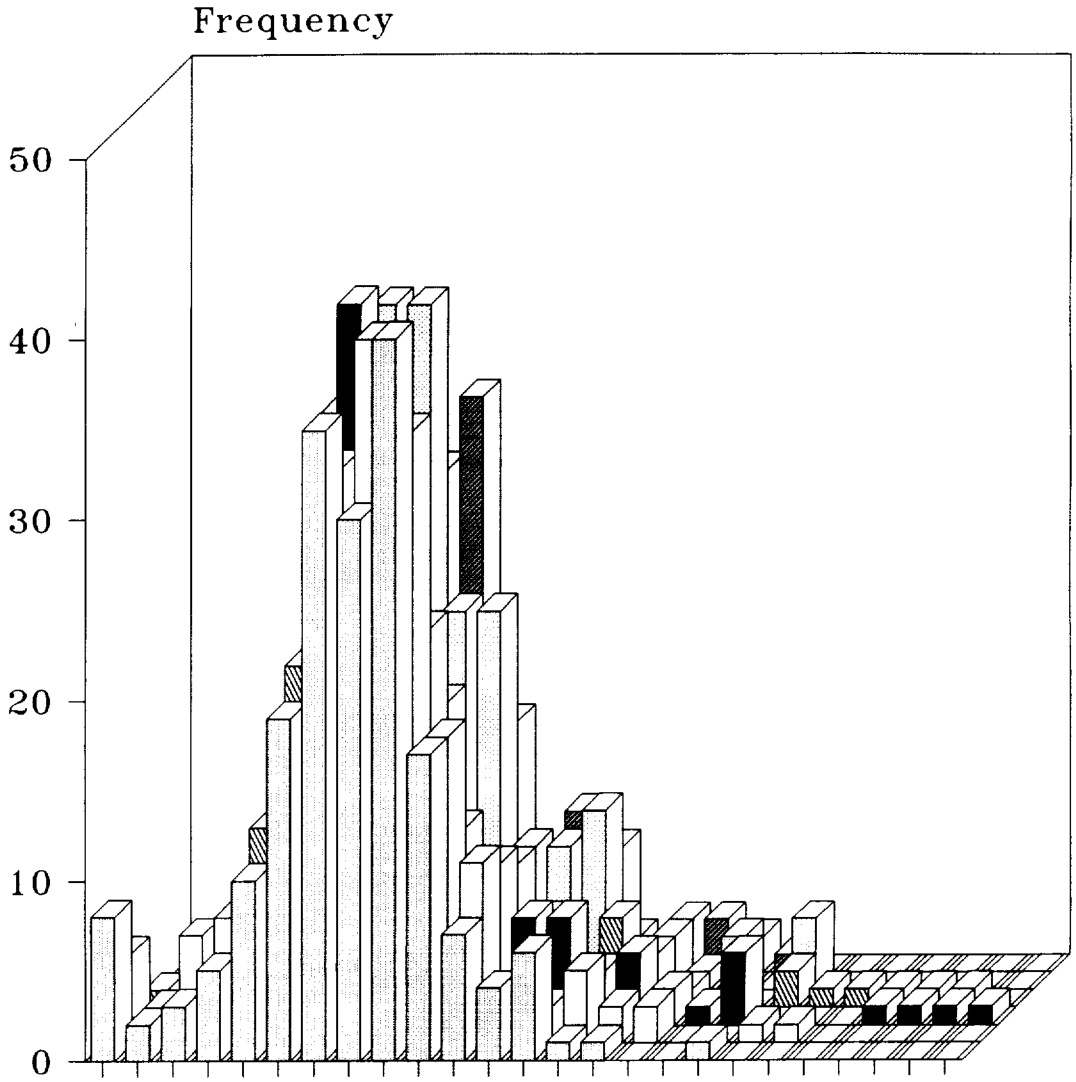
16. The conditional three factor alphas are the intercepts in regressions of the quintile portfolio returns on three factors and their products with three lagged instruments. (We do not use the yield spread QUAL or the January dummy as instruments in the three factor models.) The three factors roughly follow Fama and French (1993). They are: (1) the Standard and Poors 500 excess return, (2) the difference between the small-cap and the large-cap style index returns, and (3) the difference between the value and the growth style index returns.

17. Coggin, et al. (1993) examine pension manager performance using Frank Russell data for 1983-1990, but they only report separate results for timing and selectivity measures, using unconditional models. Their results are therefore not directly comparable to ours or to LSV's.

18. LSV consider a second data base (the "search" data base), which tracks returns by money management firm rather than by individual manager. Using this data base, LSV report average returns higher than those for their first data base over 1983-1989, and even higher than ours. They argue that their search data base is likely to have a greater selection bias.

19. We are grateful to Diane Del Guercio for bringing this to our attention.

# Figure 1: Distributions of Alphas Adjusted for Median 1988 Fees




| | <-.05 | -0.4 | -0.3 | -0.2 | -0.1 | 0 | 0.1 | 0.2 | 0.3 | 0.4 | 0.5 | 0.6 | 0.7 | 0.8 | 0.9 | 1 | 1.1 | 1.2 | 1.3 | 1.4 | 1.5 | 1.6 | 1.7 | 1.8 | >1.9 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| C-Four fac | 2 | 0 | 1 | 7 | 16 | 33 | 24 | 26 | 32 | 14 | 4 | 9 | 7 | 1 | 3 | 3 | 2 | 1 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| U-Four fac | 0 | 0 | 1 | 3 | 11 | 16 | 38 | 36 | 21 | 21 | 6 | 8 | 10 | 3 | 3 | 1 | 3 | 0 | 4 | 0 | 0 | 0 | 0 | 0 | 0 |
| C-Style | 1 | 3 | 2 | 10 | 19 | 33 | 36 | 31 | 17 | 7 | 6 | 5 | 1 | 5 | 3 | 1 | 0 | 0 | 2 | 1 | 1 | 1 | 1 | 1 | 0 |
| U-Style | 0 | 1 | 3 | 7 | 10 | 29 | 40 | 27 | 22 | 11 | 9 | 6 | 6 | 3 | 4 | 2 | 1 | 4 | 0 | 0 | 0 | 1 | 1 | 1 | 1 |
| C-Capm | 5 | 2 | 6 | 7 | 8 | 15 | 32 | 39 | 34 | 17 | 10 | 2 | 2 | 4 | 2 | 2 | 0 | 0 | 1 | 1 | 0 | 0 | 0 | 0 | 0 |
| U-Capm | 8 | 2 | 3 | 5 | 10 | 19 | 35 | 30 | 40 | 17 | 7 | 4 | 6 | 1 | 1 | 0 | 0 | 1 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |

Alpha Values

## Table 1
Predictability of Returns and Excess Returns of Institutional Equity Manager Portfolios

The returns on the managed portfolios in excess of a one-month Treasury bill and in excess of alternative benchmarks are regressed on a vector of predetermined information variables. These variables are the dividend yield of the CRSP index, a yield spread of long versus short term bonds, the yield on a short term Treasury bill, a corporate bond yield spread of low versus high grade bonds, and a dummy variable for Januaries. The adjRsq are the adjusted R-squares of the regressions and the pval(F) are the right-tail probability values of the F tests for the significance of the regression. The auto are the first order sample autocorrelations of the regression residuals. Panel A reports the average results, taken across the regressions for the individual managers. Panel B reports regressions for an equally-weighted portfolio of the funds in each group. The equally-weighted portfolios for each group are formed using every manager whose return is available in a given month. Panel C reports regression results when the dependent variables are the passive style indexes. The data are monthly from 1979:1-1990:12, or the shorter subsample available for an individual manager. Cases with fewer than 13 observations are not included.

| | returns excess of bill | | | returns excess of style | | | returns excess of CRSP index | | |
|---|---|---|---|---|---|---|---|---|---|
| | auto | adjRsq | pval(F) | auto | adjRsq | pval(F) | auto | adjRsq | pval(F) |
| PANEL A: AVERAGES FOR THE INIVIDUAL MANAGERS | | | | | | | | | |
| Growth | 0.132 | 0.129 | 0.095 | -0.052 | 0.0387 | 0.465 | 0.0031 | 0.0608 | 0.369 |
| Value | 0.127 | 0.158 | 0.064 | -0.064 | 0.0562 | 0.437 | -0.0479 | 0.0891 | 0.288 |
| Large | 0.127 | 0.148 | 0.048 | -0.062 | 0.0729 | 0.339 | -0.0609 | 0.0656 | 0.344 |
| Small | 0.199 | 0.175 | 0.074 | -0.047 | 0.1090 | 0.227 | 0.0586 | 0.0971 | 0.244 |
| PANEL B: RESULTS FOR EQUALLY WEIGHTED PORTFOLIOS | | | | | | | | | |
| Growth | 0.077 | 0.132 | 0.0004 | -0.015 | 0.0366 | 0.148 | 0.0620 | 0.0656 | 0.029 |
| Value | 0.075 | 0.136 | 0.0003 | -0.256 | 0.0238 | 0.277 | 0.0288 | 0.0908 | 0.006 |
| Large | 0.078 | 0.135 | 0.003 | -0.147 | 0.0410 | 0.117 | -0.1530 | 0.0226 | 0.292 |
| Small | 0.123 | 0.170 | 0.000 | 0.056 | 0.0188 | 0.001 | 0.0808 | 0.0999 | 0.003 |
| PANEL C: RESULTS FOR THE INDEXES | | | | | | | | | |
| Growth | 0.0679 | 0.130 | 0.0004 | | | | 0.113 | 0.090 | 0.006 |
| Value | 0.0037 | 0.131 | 0.0004 | | | | 0.094 | 0.055 | 0.054 |
| Large | 0.0385 | 0.133 | 0.0004 | | | | 0.0147 | 0.056 | 0.050 |
| Small | 0.138 | 0.188 | 0.0000 | | | | 0.0349 | 0.123 | 0.001 |

## Table 2
## Estimates of Pension Fund Alphas

Alpha and beta are the intercept and slope coefficients in market model regressions for the managed portfolio returns net of a one-month Treasury bill. In the unconditional CAPM, the regressor is the excess return of the CRSP Value-weighted market index. In the style index models, the excess return of the Russell Style index is used as the benchmark return. For the conditional models, the portfolios are regressed over time on the excess return of the relevant benchmark index and its product with a vector of predetermined instruments. The instruments are the dividend yield of the CRSP index, a yield spread of long versus short term bonds, the yield on a short term Treasury bill, a corporate bond yield spread of low versus high grade bonds, and a dummy variable for Januaries. Alpha and beta are the intercept and the slope coefficient on the market index. Heteroskedasticity-consistent t-ratios are reported for all coefficients. The Rsq are the R-squares of the regressions. pval(F) is the right-tail probability value of the F test for the marginal significance of the additional lagged variables in the conditional model regression. pval(W) is the right-tail probability value of a heteroskedasticity-consistent Wald test. The Bonferroni P-values are the minimum of the individual p-values in a group multiplied by the number of managers in the group. The data are monthly from 1979:1-1990:12, or the subsample available for a particular manager. The units are percent per month. Panel A presents averages taken across the regressions for each manager, which may refer to different subperiods. Panel B reports equally-weighted portfolios for each group, formed using every manager whose return is available in a given month. Cases with fewer than 13 observations are not included.

| | Unconditional Models | | | | | Conditional Models | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | alpha | t(alpha) | beta | t(beta) | Rsq | alpha | t(alpha) | beta | t(beta) | Rsq | pval(F) | pval(W) |
| PANEL A: AVERAGES FOR THE INIVIDUAL MANAGERS, CAPM BENCHMARK | | | | | | | | | | | | |
| Growth | 0.100 | 0.438 | 1.11 | 25.1 | 0.888 | 0.087 | 0.314 | 1.22 | 13.7 | 0.902 | 0.376 | 0.184 |
| Fraction of p-values < 0.05 | | | | | | | | | | | 0.56 | 0.56 |
| Bonferroni P-values | | | | | | | | | | | 0.011 | 0.000 |
| Value | -0.034 | -0.026 | 0.91 | 24.3 | 0.880 | -0.033 | -0.038 | 1.00 | 13.5 | 0.899 | 0.344 | 0.181 |
| Fraction of p-values < 0.05 | | | | | | | | | | | 0.63 | 0.63 |
| Bonferroni P-values | | | | | | | | | | | 0.007 | 0.000 |
| Large | 0.104 | 0.675 | 0.95 | 33.5 | 0.899 | 0.099 | 0.570 | 0.96 | 20.9 | 0.920 | 0.236 | 0.066 |
| Fraction of p-values < 0.05 | | | | | | | | | | | 0.84 | 0.75 |
| Bonferroni P-values | | | | | | | | | | | 0.000 | 0.000 |
| Small | -0.105 | -0.309 | 1.15 | 14.5 | 0.791 | 0.031 | 0.084 | 1.47 | 7.88 | 0.820 | 0.387 | 0.186 |
| Fraction of p-values < 0.05 | | | | | | | | | | | 0.55 | 0.55 |
| Bonferroni P-values | | | | | | | | | | | 0.103 | 0.000 |
| PANEL B: RESULTS FOR EQUALLY WEIGHTED PORTFOLIOS OF MANAGERS, CAPM BENCHMARK | | | | | | | | | | | | |
| Growth | 0.173 | 1.54 | 1.09 | 49.8 | 0.932 | 0.162 | 1.43 | 1.10 | 45.3 | 0.933 | 0.927 | 0.878 |
| Value | 0.164 | 2.25 | 0.87 | 49.6 | 0.960 | 0.130 | 1.79 | 0.88 | 55.0 | 0.966 | 0.004 | 0.032 |
| Large | 0.126 | 2.04 | 0.91 | 48.5 | 0.972 | 0.113 | 2.11 | 0.91 | 79.0 | 0.980 | 0.000 | 0.000 |
| Small | 0.159 | 0.89 | 1.12 | 23.8 | 0.859 | 0.251 | 1.37 | 1.11 | 27.5 | 0.863 | 0.540 | 0.311 |

TABLE 2, PAGE 2

| | Unconditional Models | | | | | Conditional Models | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | alpha | t(alpha) | beta | t(beta) | Rsq | alpha | t(alpha) | beta | t(beta) | Rsq | pval(F) | pval(W) |
| PANEL C: AVERAGES FOR THE INIVIDUAL MANAGERS, STYLE INDEX BENCHMARKS | | | | | | | | | | | | |
| Growth | 0.074 | 0.521 | 1.01 | 30.5 | 0.918 | -0.010 | -0.005 | 0.98 | 16.2 | 0.930 | 0.106 | 0.101 |
| Fraction of p-values < 0.05 | | | | | | | | | | | 0.68 | 0.68 |
| Bonferroni P-values | | | | | | | | | | | 0.000 | 0.000 |
| Value | 0.018 | 0.109 | 0.95 | 24.4 | 0.884 | 0.003 | -0.010 | 1.12 | 14.3 | 0.901 | 0.110 | 0.163 |
| Fraction of p-values < 0.05 | | | | | | | | | | | 0.68 | 0.55 |
| Bonferroni P-values | | | | | | | | | | | 0.000 | 0.000 |
| Large | 0.107 | 0.708 | 0.930 | 33.6 | 0.902 | 0.064 | 0.331 | 0.92 | 21.3 | 0.923 | 0.084 | 0.084 |
| Fraction of p-values < 0.05 | | | | | | | | | | | 0.80 | 0.80 |
| Bonferroni P-values | | | | | | | | | | | 0.000 | 0.000 |
| Small | 0.597 | 2.11 | 0.974 | 23.3 | 0.887 | 0.493 | 1.79 | 1.14 | 11.0 | 0.907 | 0.075 | 0.121 |
| Fraction of p-values < 0.05 | | | | | | | | | | | 0.80 | 0.69 |
| Bonferroni P-values | | | | | | | | | | | 0.000 | 0.000 |
| PANEL D: RESULTS FOR EQUALLY WEIGHTED PORTFOLIOS OF MANAGERS, STYLE INDEX BENCHMARKS | | | | | | | | | | | | |
| Growth | 0.268 | 3.34 | 0.99 | 63.8 | 0.968 | 0.143 | 1.80 | 0.99 | 70.6 | 0.971 | 0.014 | 0.000 |
| Value | 0.128 | 1.92 | 0.92 | 49.4 | 0.964 | 0.106 | 1.56 | 0.92 | 59.3 | 0.965 | 0.206 | 0.307 |
| Large | 0.142 | 2.30 | 0.89 | 47.0 | 0.973 | 0.086 | 1.59 | 0.89 | 81.9 | 0.980 | 0.000 | 0.000 |
| Small | 0.357 | 3.50 | 0.91 | 45.3 | 0.954 | 0.265 | 2.78 | 0.91 | 50.0 | 0.960 | 0.004 | 0.000 |

# Table 3
## Evidence of Time-varying Conditional Alphas

In Panel A, coefficients and heteroskedasticity-consistent t-ratios are shown for the conditional alphas in the following regression model, for equally-weighted portfolios of the managers:

$$r_{p,t+1} = \alpha_{0p} + A_p'z_t + b_{0pb}\, r_{bt+1} + B_{pb}'\,[z_t\, r_{bt+1}] + u_{pt+1}$$

where the conditional alpha is a linear function of the information: $\alpha_p(Z_t)=\alpha_{0p} + A_p'z_t$. $r_{p,t+1}$ is the excess return of the fund and $r_{b,t+1}$ is the return of a benchmark index, in excess of a one-month Treasury bill. In panel A, the benchmark is the CRSP value-weighted stock index. In panel B, $r_{b,t+1}$ is the Russell Style index for the manager. The instruments $z_t$ are a constant (denoted by const), the dividend yield of the CRSP index (dy), a yield spread of long versus short term bonds (term), and the yield on a short term Treasury bill (tbill). The Rsq are the R-squares of the regressions. pval(F) is the right-tail probability value of the F test for the hypothesis that the $A_p$ coefficients in the conditional alphas are jointly zero and pval(W) is the right-tail probability value of a heteroskedasticity-consistent Wald test for the hypothesis that the $A_p$ coefficients of the conditional alphas are jointly zero. The second line reports the Bonferroni P-values, which are the minimum p-value in a group multiplied by the number of managers in a group. The data are monthly from 1979:1-1990:12, or the subsample available for a particular manager. The units are percent per month. The equally-weighted portfolios for each group are formed using every manager whose return is available in a given month. Cases with fewer than 13 observations are not included.

PANEL A: Coefficients of the conditional CAPM alphas:

| manager | const | t(const) | dy | t(dy) | term | t(term) | tbill | t(tbill) | Rsq | pval(F)/ Bonferroni | pval(W)/ Bonferroni |
|---|---|---|---|---|---|---|---|---|---|---|---|
| Growth | 0.218 | 2.00 | 0.284 | 1.18 | -0.145 | -1.69 | -0.047 | -0.598 | 0.934 | 0.656 | 0.064 |
| | | | | | | | | | | 0.000 | 0.000 |
| Value | 0.186 | 2.47 | 0.196 | 1.25 | 0.057 | 0.864 | 0.030 | 0.594 | 0.964 | 0.291 | 0.002 |
| | | | | | | | | | | 0.000 | 0.000 |
| Large | 0.168 | 2.96 | 0.184 | 1.45 | 0.009 | 0.192 | -0.028 | -0.755 | 0.978 | 0.719 | 0.016 |
| | | | | | | | | | | 0.000 | 0.000 |
| Small | 0.353 | 2.02 | 1.22 | 3.72 | -0.207 | -1.850 | -0.210 | -2.01 | 0.872 | 0.134 | 0.000 |
| | | | | | | | | | | 0.024 | 0.000 |

PANEL B: Coefficients of the conditional style model alphas:

| manager | const | t(const) | dy | t(dy) | term | t(term) | tbill | t(tbill) | Rsq | pval(F)/ Bonferroni | pval(W)/ Bonferroni |
|---|---|---|---|---|---|---|---|---|---|---|---|
| Growth | 0.248 | 3.16 | 0.236 | 1.37 | -0.0906 | -1.68 | -0.0125 | -0.220 | 0.971 | 0.299 | 0.003 |
| | | | | | | | | | | 0.003 | 0.000 |
| Value | 0.206 | 3.06 | 0.310 | 2.25 | 0.0185 | 0.345 | -0.007 | -0.206 | 0.967 | 0.215 | 0.004 |
| | | | | | | | | | | 0.000 | 0.000 |
| Large | 0.179 | 3.13 | 0.184 | 1.44 | 0.017 | 0.325 | -0.022 | -0.578 | 0.979 | 0.648 | 0.006 |
| | | | | | | | | | | 0.000 | 0.000 |
| Small | 0.404 | 4.10 | -0.049 | -0.207 | 0.003 | 0.030 | -0.005 | -0.071 | 0.959 | 0.881 | 0.001 |
| | | | | | | | | | | 0.000 | 0.000 |

**Table 4**

Measures of the Persistence of Institutional Equity Manager Performance

T-ratios for time-series averages of the slope coefficients in monthly cross-sectional regressions of the future excess returns of the funds on predetermined measures of the funds' alphas. The t-statistic for the average coefficient is calculated similar to Fama and MacBeth (1973), using the time-series standard error of the mean. The standard error of the mean is adjusted for autocorrelation induced by overlapping data for horizons $\tau$ longer than one month, using $\tau$-1 Newey-West lags. The "Bonferrroni pvals" are the individual right-tail p-value from a normal distribution, for the minimum (or maximum) t-ratio across the investment horizons, and multiplied by the number of horizons, which is seven. (Values larger than 1.0 are shown as 1.0.) The joint Wald Test is a heteroskedasticity-consistent test of the hypothesis that the regression coefficients for all seven horizons are zero. The different models for alpha, one for each row of the table, are described in the text. The excess returns are in excess of a one-month Treasury bill. The group means refer to the arithmetic average of all managers in the same Russell style group. The data are monthly from 1979:1-1990:12. The cross-sectional regression for each month and horizon, $\tau$, uses all managers with 60 past (36 in the case of the 36-month average return alphas) returns available.

PANEL A: UNCONDITIONAL MODELS

| MEASURE OF PRIOR PERFORMANCE | T-RATIOS FOR FUTURE RETURNS, BY HORIZON | | | | | | | Bonferroni pval | | Wald |
|---|---|---|---|---|---|---|---|---|---|---|
| | 1 mo. | 3 mo. | 6 mo. | 12 mo. | 18 mo. | 24 mo. | 36 mo. | Minimum t-ratio | Maximum t-ratio | Joint pvalue |
| 36-month past average return | -0.353 | -0.148 | 0.419 | 0.616 | 0.211 | 0.211 | 0.009 | 1.00 | 1.00 | 0.998 |
| 36-month average excess return | 0.076 | 0.141 | 0.669 | 0.962 | 1.31 | 1.52 | 2.10 | 1.00 | 0.128 | 0.741 |
| 60-month average excess return | -0.717 | -0.633 | -0.700 | -1.05 | -2.05 | -1.24 | -1.13 | 0.145 | 1.00 | 0.999 |
| 36-month net of group mean | 1.84 | 2.39 | 2.19 | 2.55 | 2.99 | 4.03 | 3.79 | 0.231 | 0.000 | * |
| 60-month net of group mean | 1.40 | 1.59 | 1.72 | 2.78 | 3.57 | 3.38 | 3.54 | 0.566 | 0.001 | * |
| 60-month unconditional CAPM | -0.005 | 0.025 | 0.095 | 0.328 | 0.072 | 0.195 | 0.579 | 1.00 | 1.00 | 1.00 |
| 60-month unconditional style | -0.285 | 0.067 | 0.531 | 1.27 | 2.23 | 3.21 | 2.77 | 1.00 | 0.005 | 0.0289 |
| Timing-adjusted unconditional CAPM | -0.629 | -0.971 | -0.996 | -0.717 | -0.958 | -1.36 | -1.06 | 0.608 | 1.00 | * |
| Timing-adjusted unconditional style | -0.094 | 0.081 | 0.244 | 0.741 | 1.49 | 2.55 | 2.48 | 1.00 | 0.39 | 0.147 |

PANEL B: CONDITIONAL MODELS

| MEASURE OF PRIOR PERFORMANCE | T-RATIOS FOR FUTURE RETURNS, BY HORIZON | | | | | | | Bonferroni pval | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | 1 mo. | 3 mo. | 6 mo. | 12 mo. | 18 mo. | 24 mo. | 36 mo. | Minimum t-ratio | Maximum t-ratio | Joint pvalue |
| 60-month conditional CAPM | -0.449 | -0.665 | -0.848 | -0.581 | -0.586 | -0.564 | -0.113 | 1.00 | 1.00 | * |
| 60-month conditional style | -0.487 | -0.149 | 0.142 | 0.760 | 1.81 | 3.50 | 3.16 | 1.00 | 0.0018 | 0.00 |
| Timing-adjusted conditional CAPM | -0.0678 | -0.262 | -0.397 | -0.263 | -0.306 | -0.230 | 0.195 | 1.00 | 1.00 | 1.00 |
| Timing-adjusted conditional style | 0.456 | 0.559 | 0.664 | 1.26 | 2.27 | 3.89 | 3.66 | 1.00 | 0.0004 | 0.00051 |
| Time-varying conditional CAPM | 2.20 | 2.11 | 1.39 | 2.69 | 0.958 | 0.729 | 2.67 | 1.00 | 0.026 | * |
| Time-varying conditional style | 2.14 | 1.66 | 1.31 | 1.77 | 2.22 | 2.19 | 1.88 | 0.664 | 0.095 | * |

Notes: * indicates that the covariance matrix was not positive definite.

## Table 5
### Measures of the Persistence of Institutional Equity Manager Performance: Using Only Negative Prior Period Alphas

T-ratios for time-series averages of the slope coefficients in monthly cross-sectional regressions of the future excess returns of the funds on predetermined measures of the funds' alphas. Only the managers with negative prior period alphas are used. The t-statistic for the average coefficient is calculated similar to Fama and MacBeth (1973), using the time-series standard error of the mean. When the horizon of the future return, $\tau$, exceeds one month, the standard error of the mean is adjusted for the autocorrelation induced by the overlapping future returns data using $\tau$-1 Newey-West lags. The "Bonferroni pvals" are the individual right-tail p-value from a normal distribution, using the minimum (or maximum) t-ratio across the investment horizons, and multiplied by the number of horizons, which is seven. (Values larger than 1.0 are shown as 1.0.) The joint Wald Test is a heteroskedasticity-consistent and autocorrelation-adjusted test of the hypothesis that the regression coefficients for all seven horizons are zero. The different models for alpha, one for each row of the table, are described in the text. The excess returns are in excess of a one-month Treasury bill. The group means refer to the arithmetic average of all managers in the same Russell style group. The data are monthly from 1979:1-1990:12. The cross-sectional regression for each month and horizon $\tau$, uses all managers with 60 past (36 past, in the case of 36-month past return alphas) returns available.

### PANEL A: UNCONDITIONAL MODELS

| MEASURE OF PRIOR PERFORMANCE | T-RATIOS FOR FUTURE RETURNS, BY HORIZON | | | | | | | Bonferroni pval | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | 1 mo. | 3 mo. | 6 mo. | 12 mo. | 18 mo. | 24 mo. | 36 mo. | Minimum t-ratio | Maximum t-ratio | Joint pvalue* |
| 36-month past average return | -1.05 | -0.81 | -1.20 | -1.30 | -1.11 | -1.89 | -1.70 | 0.21 | 1.00 | * |
| 36-month average excess return | -1.04 | -0.50 | -0.39 | -0.20 | -0.48 | -0.62 | -0.52 | 1.00 | 1.00 | * |
| 60-month average excess return | -3.02 | -0.29 | 0.466 | 0.845 | 1.17 | 1.90 | 2.31 | 1.00 | 0.074 | 0.980 |
| 36-month net of group mean | 1.17 | 1.13 | 1.16 | 2.56 | 2.69 | 3.17 | 4.01 | 0.913 | 0.000 | 0.999 |
| 60-month net of group mean | 1.32 | 1.89 | 2.19 | 3.26 | 3.41 | 3.73 | 5.04 | 0.657 | 0.000 | 0.076 |
| 60-month unconditional CAPM | 1.58 | 1.01 | 0.50 | 1.31 | 2.39 | 3.09 | 2.74 | 1.00 | 0.008 | 0.039 |
| 60-month unconditional style | 0.55 | 0.768 | 0.571 | 0.62 | 1.14 | 1.54 | 2.75 | 1.00 | 0.022 | 0.108 |
| Timing-adjusted unconditional CAPM | 0.07 | 0.11 | 0.66 | 1.68 | 1.99 | 2.12 | 4.04 | 1.00 | 0.000 | 0.007 |
| Timing-adjusted unconditional style | -0.60 | 0.06 | 0.98 | 1.84 | 1.71 | 1.44 | 1.08 | 1.00 | 0.233 | * |

### PANEL B: CONDITIONAL MODELS

| MEASURE OF PRIOR PERFORMANCE | T-RATIOS FOR FUTURE RETURNS, BY HORIZON | | | | | | | Bonferroni pval | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | 1 mo. | 3 mo. | 6 mo. | 12 mo. | 18 mo. | 24 mo. | 36 mo. | Minimum t-ratio | Maximum t-ratio | Joint pvalue |
| 60-month conditional CAPM | 0.38 | 0.54 | 1.21 | 2.03 | 2.14 | 2.36 | 4.73 | 1.00 | 0.00 | * |
| 60-month conditional style | 0.745 | 0.886 | 0.907 | 1.53 | 1.93 | 2.22 | 4.10 | 1.00 | 0.00175 | 0.0311 |
| Timing-adjusted conditional CAPM | 1.72 | 1.07 | 1.33 | 2.85 | 3.36 | 2.96 | 2.14 | 1.00 | 0.003 | * |
| Timing-adjusted conditional style | 1.12 | 1.54 | 2.47 | 2.43 | 3.20 | 2.86 | 2.80 | 0.929 | 0.002 | * |
| Time-varying conditional CAPM | 1.57 | 2.02 | 1.21 | 1.77 | 1.36 | 1.55 | 2.52 | 0.79 | 0.04 | * |
| Time-varying conditional style | 1.62 | 1.55 | 0.711 | 1.06 | 1.31 | 1.43 | 1.82 | 1.00 | 0.244 | * |

Notes: * indicates that the covariance matrix was not positive definite.

## Table 6
Simple Trading Strategies using Past Alphas

Each trading strategy uses an estimate of performance, or alpha, based on the past 60 months of data for each eligible manager. The alpha estimates are ranked, grouped according to quintiles and an equally-weighted portfolio is formed from each quintile group. This portfolio is held for 1 month, and the procedure is repeated. The different models for alpha are described in the text. The data are monthly from 1979:1-1990:12, and the first date of the trading strategy returns is 1984:1. There are 84 monthly returns for each trading strategy measured net of a one-month Treasury bill return. The first two rows show results for the CRSP value-weighted index and an equally-weighted portfolio of all managers, for comparison purposes. Uncond. beta is the unconditional beta against the CRSP value-weighted index, and Condit. beta is the time series average of the time-varying conditional beta. All of the beta have t-ratios in excess of 25.0. The unconditional alpha for the CAPM is the intercept in a regression of the excess return of the strategy on the CRSP value-weighted excess return over the 84 month period. The unconditional 3FAC alpha is the intercept in a regression on the Standard and Poors 500 excess return, the Russell value index less the growth style index, and the small stock less the large stock index. The conditional alpha is the intercept when the regression also includes the product of the factor(s) and a vector of predetermined variables. These variables are the dividend yield of the CRSP index, a yield spread of long versus short term bonds, the yield on a short term Treasury bill, a corporate bond yield spread of low versus high grade bonds, and a dummy variable for Januaries. In the three-factor models, the corporate bond yield spread and the January dummy are excluded. The alpha coefficients have a * when their heteroskedasticity-consistent t-ratios are larger than 1.94.

| STRATEGY | MEAN | STD | UNCOND. BETA | CONDIT. BETA | UNCONDITIONAL ALPHAS | | CONDITIONAL ALPHAS | | CUM. VALUE | FRACTION POSITIVE | Min-Max RETURNS |
|---|---|---|---|---|---|---|---|---|---|---|---|
| | | | | | 3FAC | CAPM | 3FAC | CAPM | | | |
| CRSP VW-index | 0.599 | 4.89 | 1.00 | 1.00 | 0.56 | 0.00 | 0.81 | 0.00 | 2.45 | | -22.2+12.4 |
| Hold all managers | 0.553 | 5.05 | 1.02 | 1.03 | 0.51 | -0.06 | 0.73 | -0.07 | 2.34 | | -22.8+11.8 |
| Time-varying conditional CAPM: | | | | | | | | | | | |
| Q1 - high alphas | 0.744 | 5.17 | 1.03 | 1.00 | 0.68 | 0.126 | 0.93 | 0.221 | 2.73 | 60.7% | -25.4+11.7 |
| Q2 | 0.638 | 4.83 | 0.97 | 0.99 | 0.59 | 0.057 | 0.81 | -0.016 | 2.54 | 57.1% | -20.1+11.3 |
| Q3 | 0.578 | 4.78 | 0.96 | 0.98 | 0.53 | 0.001 | 0.77 | -0.012 | 2.42 | 57.1% | -20.8+10.7 |
| Q4 | 0.467 | 5.34 | 1.07 | 1.07 | 0.42 | -0.175 | 0.65 | -0.182* | 2.15 | 56.0% | -25.3+12.9 |
| Q5 - low alphas | 0.333 | 5.33 | 1.05 | 1.09 | 0.28 | -0.297* | 0.46 | -0.397* | 1.93 | 54.8% | -22.5+12.6 |
| Unconditional CAPM: | | | | | | | | | | | |
| Q1 - high alphas | 0.443 | 4.81 | 0.96 | 0.99 | 0.40 | -0.132 | 0.58 | -0.190 | 2.16 | 56.0% | -20.8+11.1 |
| Q2 | 0.650 | 4.74 | 0.96 | 0.98 | 0.59 | 0.076 | 0.79 | 0.063 | 2.58 | 58.3% | -20.9+10.5 |
| Q3 | 0.627 | 4.85 | 0.97 | 1.00 | 0.58 | 0.044 | 0.81 | -0.010 | 2.52 | 58.3% | -20.1+11.2 |
| Q4 | 0.599 | 5.23 | 1.05 | 1.05 | 0.55 | -0.030 | 0.82 | -0.028 | 2.41 | 56.0% | -24.2+12.9 |
| Q5 - low alphas | 0.461 | 5.87 | 1.15 | 1.12 | 0.40 | -0.228 | 0.65 | -0.165 | 2.08 | 58.3% | -28.6+13.7 |
| Past average returns: | | | | | | | | | | | |
| Q1 - high past returns | 0.454 | 5.37 | 1.07 | 1.07 | 0.39 | -0.189 | 0.61 | -0.154 | 2.12 | 57.1% | -25.3+12.0 |
| Q2 | 0.594 | 4.86 | 0.97 | 1.01 | 0.55 | 0.010 | 0.75 | -0.025 | 2.45 | 58.3% | -20.5+11.4 |
| Q3 | 0.596 | 4.89 | 0.98 | 0.99 | 0.54 | 0.006 | 0.76 | 0.001 | 2.45 | 60.7% | -22.4+11.3 |
| Q4 | 0.589 | 4.93 | 0.99 | 0.98 | 0.55 | -0.004 | 0.80 | -0.002 | 2.43 | 56.0% | -22.7+12.6 |
| Q5 - low past returns | 0.548 | 5.38 | 1.06 | 1.08 | 0.50 | -0.087 | 0.73 | -0.156 | 2.30 | 58.3% | -23.2+12.5 |

**Appendix Table 1**
**Annual Returns of Equally-Weighted Portfolios of Funds and Percentage of Funds with Returns less than the S&P 500**

| Year | CFG number of managers[a] | S&P 500 return (percent) | CFG equal-weighted return (percent) | CFG % less than S&P 500[b] | LSV equal-weighted return (percent)[c] | LSV % less than S&P 500 |
|---|---|---|---|---|---|---|
| 79 | 26 | 18.62 | 32.04 | 11.5 | | |
| 80 | 31 | 32.63 | 34.23 | 54.8 | | |
| 81 | 41 | -4.96 | 5.50 | 2.4 | | |
| 82 | 47 | 21.65 | 27.89 | 19.1 | | |
| 83 | 71 | 22.57 | 25.53 | 36.6 | 17.8 | 59 |
| 84 | 84 | 6.18 | 3.93 | 54.8 | 3.8 | 63 |
| 85 | 100 | 31.88 | 32.74 | 44.0 | 33.3 | 38 |
| 86 | 120 | 18.69 | 17.76 | 52.5 | 18.1 | 50 |
| 87 | 140 | 5.21 | 3.60 | 60.0 | 4.0 | 61 |
| 88 | 155 | 16.50 | 19.49 | 38.7 | 17.9 | 47 |
| 89 | 174 | 31.67 | 28.71 | 63.2 | 29.2 | 61 |
| 90 | 189 | -3.13 | -4.03 | 49.7 | | |
| Mean 79-90 | | 16.45 | 18.95 | 40.6 | | |
| Mean 83-89 | | 18.96 | 18.82 | 50.0 | 17.73 | 54.1 |

Notes:

[a] The number of managers out of 273 with return data for all months in a given year. All CFG return data are from the Russell Data Services data base, in percent per year.

[b] The fraction of the managers whose return over the period was less than the return of the Standard and Poors 500 stock index.

[c] LSV figures are based on Lakonishok, Shliefer and Vishny, 1992, Table 2 (the performance data base).