Conditioning Manager Alphas on Economic Information: Another Look at the Persistence of Performance

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This article presents evidence on persistence in the relative investment performance of large, institutional equity managers. Similar to existing evidence for mutual funds, we find persistent performance concentrated in the managers with poor prior-period performance measures. A conditional approach, using time-varying measures of risk and abnormal performance, is better able to detect this persistence and to predict the future performance of the funds than are traditional methods.

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, performing relatively well or poorly in the past, tend 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 [see, for example the studies by Ippolito (1992), Goetzmann and Ibbotson (1994), Grinblatt and Titman (1994), Shukla and Trzcinka (1994), Hendricks, Patel, and Zeckhauser (1993, 1996), Brown and Goetzmann (1995), Malkiel (1995), Elton, Gruber and Blake (1996a), Gruber (1996), and Carhart (1997)].

A large number of studies examine the persistence of mutual fund performance over time, but the evidence for institutional equity managers is sparse. Christopherson and Turner (1991) study pension managers and conclude 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 funds for 2–3 year investment 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 funds for several reasons. First, institutional managers control a larger portion of the aggregate wealth than do mutual funds [Coggin, Fabozzi, and Rahman (1993)]. Second, institutional equity managers and mutual fund managers operate in different environments. For example, pension fund managers are reviewed periodically by their clients and pension consultants, who presumably are more sophisticated than the typical individual investor. Mutual fund investors may not monitor a fund manager's behavior as closely, but they can simply withdraw their money or invest in a "hot" fund at any time. The process by which some funds survive and others disappear is thus likely to be different for pension and mutual funds. Mutual funds and pension funds are also taxed differently. Given these differences, it is interesting to compare the persistence in performance for the two types of managers.

Our study is also motivated by an important practical problem. Institutional investors must decide which managers to retain, and attempting to predict the future performance of a manager is a critical part of that decision-making process. If the 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. This approach uses *unconditional* expected returns as the performance baseline, assuming that the consumer of the performance evaluation uses no information about the state of the economy to form expectations. Such as assumption is even less tenable for sophisticated institutional investors than for individual investors evaluating mutual funds. Furthermore, 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 measure even the average performance; if these biases persist over time they can also distort inferences about the persistence of investment performance.

To address these concerns about unconditional measures, 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 conditioned on predetermined, publicly available information. A conditional approach can control for biases in the traditional measures when managers trade on public information. Ferson and Schadt (1996) find that incorporating public information, such as dividend yields and interest rates, affects inferences about the average performance in a sample of open-ended mutual funds.[1]

In this article we study persistence in the performance of a sample of 185 U.S. pension fund equity managers over the 1979–1990 period. We extend the approach of Ferson and Schadt (1996) to estimate time-varying *conditional alphas* as well as betas. Tests on these models support the assumption that pension funds have time-varying conditional betas, investment style-factor exposures, and time-varying conditional alphas.

We find evidence that the investment performance of the pension managers persists over time. In particular, low conditional alpha managers in the past tend to be abnormally low-return managers in the future. Our results show that the conditional measures are more infor-

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[1] An alternative approach, directed at capturing nonlinearities in managed portfolio returns, is to include option payoffs as additional "factors" when calculating alphas [see Glosten and Jagannathan (1994)].

mative about future performance than are traditional, unconditional measures.

This article is organized as follows. Section 1 draws the main distinctions between pension and mutual funds that motivate our analysis of the persistence in pension fund returns. Section 2 describes the data. Section 3 describes the empirical methods. Section 4 presents preliminary results which establish the relevance of the conditional measures. Section 5 addresses the issue of persistence in performance and the economic significance of the persistence. Section 6 offers concluding remarks.

1. Pension Funds Versus Mutual Funds

There are differences between the institutional details surrounding pension fund and mutual fund management, and these differences suggest a number of prior conjectures about the persistence of performance. Pension fund management involves (i) plan sponsors (specifically, the administrators or trustees of pension plans), (ii) pension fund consultants, and (iii) investment management firms. Typically a plan sponsor divides funds among a number of managers with various investment styles. 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.

There are a number of reasons to think that performance should be more highly persistent in pension funds than in mutual funds. It is useful to distinguish between the persistence of good and bad performance. Superior performance presumes that fund managers have the ability to pick undervalued investments or time market returns. The literature on market timing finds few cases of consistently superior market timers; our sample of pension funds excludes market-timing funds in any case. If some managers are good at picking stocks, then it is reasonable to think that such talents persist over time. Consistently superior managers should gravitate to larger pools of cash, such as in pension funds, where the compensation is higher.

With the specialization that is common among pension fund managers, it is likely to be hard to maintain continued superior performance as the size of the pension fund expands. Such considerations may lead to mean reversion in the relative performance of superior fund mangers.

It is not difficult to imagine that there are inferior fund managers, but there are reasons to think that abnormally poor performance is less likely to persist among pension funds than among mutual funds. The

relative sophistication of institutional investors and the large amounts of money involved suggest that lackluster performance should not be tolerated for long in pension funds. Large institutional investors have enough money at stake to provide incentives to monitor their managers, whereas it is more difficult for individual mutual fund investors to justify these monitoring costs. Some mutual fund investors may be reluctant to sell a fund if they are "locked in" by a previous capital gain. However, pension funds have no such concerns, as pension fund returns are not taxed at the firm level.

There are, however, reasons to expect that low returns can persist among pension fund managers. Like mutual funds, pension fund managers deliver services to their clients in addition to investment returns. These include education, research, and reports that the responsible officers at the plan sponsor organization can use in reporting to their superiors. Fund managers develop relationships with their clients that mutual fund investors typically do not enjoy. Agency problems may also allow poor performance to persist. For example, firing a manager may be seen as evidence that the pension plan administrator's previous decision to hire the manager was a poor one.[2] Finally, while no-load mutual funds make switching between funds inexpensive, there are significant transactions costs associated with firing one manager and hiring another. Consistent with the importance of these costs, pension plan sponsors periodically review their managers, commonly at quarterly to annual frequencies. Flows of money in response to measured performance typically occur episodically and in large amounts. This is in contrast to mutual fund flows, which occur virtually continuously in response to short-term performance [e.g., Ippolito (1992), Gruber (1996)].

2. The Data

2.1 Pension fund returns

We obtained monthly returns for 273 institutional equity managers from the Frank Russell Company's Russell Data Services (RDS) database. 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 database at different points in time, but

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[2] While it has been argued that individual investors may stick with a "loser" fund due to a cognitive dissonance [e.g., Goetzmann and Peles (1993)], an individual investor is unlikely to lose his job over the issue.

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. The style classifications for the managers are determined by RDS, based on the managers' investment philosophies and portfolio characteristics [see Christopherson and Trittin (1995)].

A given money management firm may have a number of portfolios and accounts, but our database 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 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 holdings 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 1-month Treasury bill. The Treasury bill data are from the Center for Research in Security Prices (CRSP) at the University of Chicago.

2.2 Survivorship issues

Our database almost certainly has survivorship biases, as it contains only surviving managers. When a manager goes out of business or is dropped by RDS, the entire return history for that manager is removed from the database (and is unavailable to us). Managers also fall out of the database when their firms stop sending data to the Frank Russell Company, often because Russell has not recommended the manager to its clients. Survivorship creates a number of potential problems affecting both the average levels of performance and the apparent persistence in performance.

One obvious reason for a manager to leave the database is poor performance. To the extent that managers are dropped because of poor performance, the measured performance of the surviving managers is biased upward. For example, Elton, Gruber, and Blake (1996b) find an average bias of 0.7–0.9% per year in mutual fund data [see also Brown and Goetzmann (1995), Malkiel (1995), Gruber (1996), Carhart (1997), and others cited in the references].

Brown et al. (1992), Goetzmann et al. (1995), and Hendricks, Patel, and Zeckhauser (1996) consider the effects of survivorship on

performance persistence under the simplifying assumptions that the expected returns of all managers are the same, but there are differences in variances, and that managers leave the database when their returns are relatively low. Under these assumptions survivorship is likely to induce a spurious "J-shaped" relation between future and past relative returns. In particular, past poor performers in a sample with survivorship bias are likely to reverse their performance in the future.[3]

The empirical evidence on performance persistence for mutual funds suggests a positive relation between the future and past performance, concentrated in the poorly performing funds. This is not as expected if persistence is a spurious result in a simple model of survivorship bias. Brown and Goetzmann (1995), Elton, Gruber, and Blake (1996a), and Carhart (1997) find similar patterns in samples of mutual funds designed to avoid survivorship bias.

Our evidence for pension funds also reveals positive persistence, concentrated in the poorly performing funds. This is interesting, as the evidence for pension funds appears generally consistent with that for mutual funds. However, the "death process" for pension funds is likely to differ from that for mutual funds. Managers are dropped from pension fund databases for reasons other than poor performance. For example, funds are dropped from our database when the firm has an important change in management personnel, such as when a star performer leaves for another firm. To the extent that managers are dropped from the database because they were star performers, the average measured performance of the surviving managers is biased downward. From the analyses of Goetzmann et al. (1995) and Hendricks, Patel, and Zeckhauser (1996), one would also expect a more complex pattern than the J-shaped relation between past and future relative returns, if the sample is truncated in both tails. Since the data that would allow us to model the birth and death processes are not available to us, it is not possible to measure the effects of survivorship on the pension fund evidence. We leave this as a topic for future research, and we remind the reader: caveat emptor.

2.3 Selection biases
Our sample is likely to have a selection bias because managers enter the database after they attract attention from the Frank Russell Company and its clients. When a manager is added to the database, some

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[3] Goetzmanan et al. (1995) show that a J-shape can fail to occur with nontrivial probability in a sample satisfying the assumptions of Hendricks, Patel, and Zeckhauser (1996) when there is correlation across the funds.

previous history of the manager's returns may be backfilled. 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 1981–1990. If we exclude the first 5 years of data for each manager, the average annual return over 1981–1990 drops to 15.45%. In the analysis of performance persistence we use the returns following the first 5 years of data for a given manager. This should reduce the effects of selection bias.

2.4 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 posted 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 as "soft dollars."

2.5 Benchmark portfolios

Performance measurement compares a fund's return to the return of some benchmark. We 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. Christopherson and Turner (1991) choose manager style indexes as the benchmarks; that is, a

manager is classified according to style and a single index reflecting that style is used.

The RDS database 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. Over the period covered in this study 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.[4]

2.6 Predetermined information variables

The conditional performance models include a vector of lagged information variables. We use the same variables used by Ferson and Schadt (1996). We use the same variables for comparability with their results for mutual funds and to avoid our own data snooping on this "new" dataset. The lagged instruments are (i) the lagged level of the 1-month Treasury bill yield (TBILL), (ii) the lagged dividend yield of the CRSP value-weighted NYSE and AMEX stock index (DY), (iii) a lagged measure of the slope of the term structure (TERM), (iv) a lagged quality spread in the corporate bond market (QUAL), and (v) a dummy variable for the month of January.

TBILL is the discount yield of a bill that is the closest to 1 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 12 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.

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[4] Newer versions of these indexes provided by RDS use a nonlinear weighting scheme and allow stocks near the median to be in both the value and growth indexes.

3. Empirical Methods

3.1 Unconditional models

The traditional, or *unconditional alpha*, α_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 1-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. β_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 β_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.

3.2 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. Ferson and Schadt also assume a linear functional form for the conditional beta, given Z_t, of a managed portfolio:[5]

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

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

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[5] 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 in Admati, Bhattacharya, 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).

information variables, Z_t. A modification of Equation (1) follows:

$$r_{pt+1} = \alpha_p + b_{0pb}r_{bt+1} + B'_{pb}[z_t r_{bt+1}] + u_{pt+1}. \qquad (3)$$

Under the null hypothesis of no abnormal performance, the model implies that the average conditional alpha, α_p, is zero [the α_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 Equation (3) can easily be extended to the case of a multiple-benchmark model, and we will estimate a four-factor model below.

Using a single coefficient α_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.

3.3 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 conditional covariance between the manager's weights and the future returns, given Z_t.[6] This conditional covariance, and therefore the expected abnormal performance, is an unobserved function of Z_t. We therefore modify Equation (3) to include an explicit time-varying conditional

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[6] 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 $\text{cov}(x; u_{t+1}|Z_t)$ and $\text{cov}(x; r_{bt+t}|Z_t)$. 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.

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

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

Equation (5) allows us to estimate conditional alphas, and to track their variation over time as a function of the conditioning information, Z_t.[7]

We estimate standard errors and *t*-ratios and construct Wald tests for 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.

4. Empirical Results

4.1 Predictability of pension fund excess returns

We first estimate time-series regressions which attempt to predict the managers' future monthly returns in excess of either the 1-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. We summarize the results of these regressions briefly in this section; tables of the results are available by request.

When the dependent variables are the returns net of the Treasury bill the regression R^2 varies between 12 and 18% for groups of the funds. These are higher than would be found for passive portfolios [see Ferson and Harvey (1991a) and Ferson and Korajczyk (1995)]. The excess returns of the value managers produce slightly higher R^2 than those of the growth managers, and the small-cap funds produce higher R^2 than large-cap funds. These patterns partly reflect differences in the predictability of the assets held by the funds. However, when the managers' returns are measured in excess of the CRSP value-

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[7] 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 article 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.

weighted index or the Russell index for the manager's style group, the regressions are still significant at the 5% level for about half of the managers, and the average adjusted R^2 for a small-cap manager is over 10%. The regressions show that the expected excess returns of the managers vary over time with the public information variables, which motivates the use of conditional models to study the performance.

4.2 Estimates of pension fund alphas

Section 3 described various models for alpha. We estimate unconditional and conditional versions of the CAPM, using the CRSP value-weighted index as the benchmark, as given in Equations (1) and (3). 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 [Equation (3)] allows time-varying betas, but assumes that any abnormal performance is captured by the fixed alpha coefficients. We also estimate models where the Russell style index for a manager replaces the CRSP index as the benchmark. The results are summarized in Table 1, where panels A and B report results using the CAPM benchmark and panels C and D give the results for the style indexes.

The two right-hand columns of Table 1 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. These are exclusion tests for the additional terms in the conditional models, which are the interaction terms between the benchmark index and the lagged conditioning variables in Equation (3). In panel B we see that the incremental explanatory power of the interaction terms is significant for equally weighted portfolios of the value and large-cap funds.

Table 1 includes the average R^2, taken across the individual funds in a group. The R^2 goes up more for a typical individual fund than for the portfolio when the conditioning variables are brought into the model. This suggests that there is time variation in the individual fund betas that washes out at the aggregate level. The regressions for the individual funds show this to be the case. 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.

Table 1 also reports a joint test for the hypothesis that the individual betas are constant for each fund in each style group. These are based

Table 1
Estimates of pension fund alphas

	Unconditional models					Conditional Models						
	alpha	t(alpha)	beta	t(beta)	R^2	alpha	t(alpha)	beta	t(beta)	R^2	pval(F)	pval(W)
Panel A: Averages for the Individual 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
Panel C: Averages for the Individual 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

Table 1
(continued)

	Unconditional models					Conditional Models						
	alpha	t(alpha)	beta	t(beta)	R^2	alpha	t(alpha)	beta	t(beta)	R^2	pval(F)	pval(W)
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

Alpha and beta are the intercept and slope coefficients in market model regressions for the managed portfolio returns net of a 1-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 R^2 are the R^2 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 January 1979–December 1990, or the subsample available for a particular manager. The excess returns 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.

on the Bonferroni inequality.[8] The joint test rejects the hypothesis that all managers have constant conditional betas.

The above results imply 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 capture returns across managers better than models that assume that the betas are constant.[9,10]

We 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 1.[11]

Figure 1 presents the distribution of the alphas from 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 database do not reflect the cost of management fees, which differ across the style groups. Therefore we adjust the alphas by subtracting the median 1988 fees reported in Section 2.4 for each style group.

While the style index models generally make the managers look better than does the CAPM, the unconditional and conditional versions of the alphas appear similar in Figure 1. This similarity in the

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[8] 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).

[9] 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., Carhart et al. (1996) and Jagannathan and Wang (1996)].

[10] 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 database 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.

[11] 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—the Treasury bill yield and the stock market dividend yield. In the conditional four-factor models, the regression equation has 12 regressors: a constant, the four style indexes, and the products of the two information variables with the four style indexes.
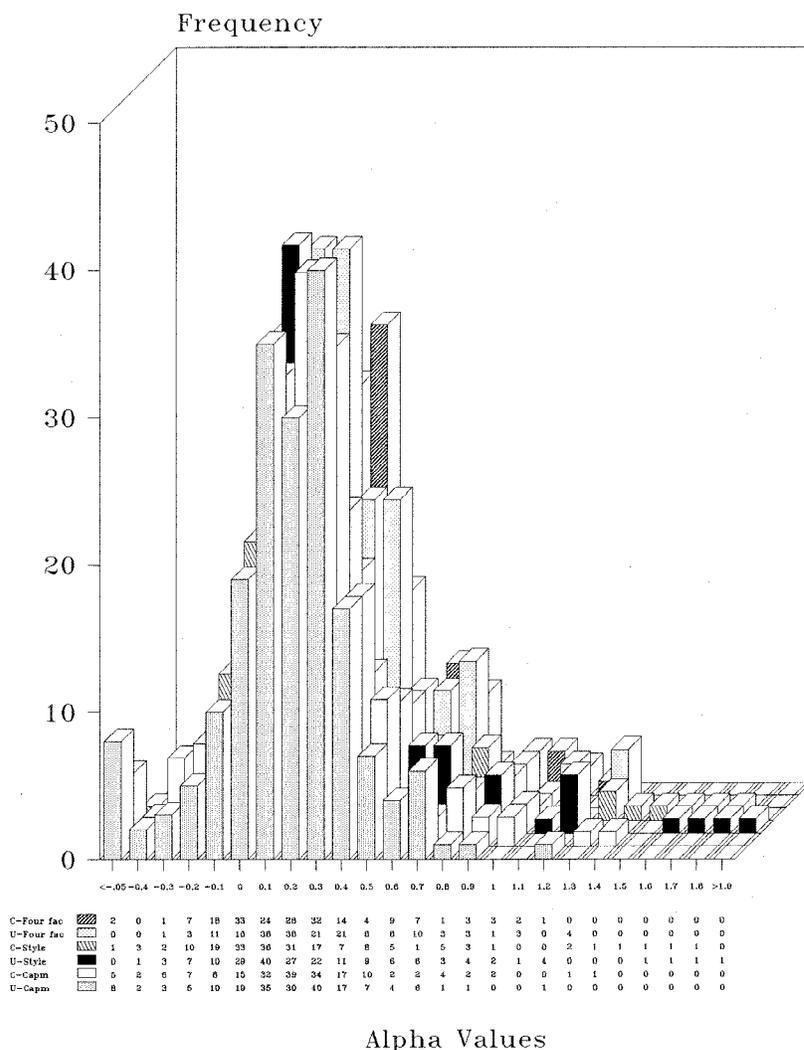
Figure 1
Frequency distributions of alphas
Estimates of alpha are net of median posted fees, by fund type, for 1988. Starting from the back row moving forward, the frequency distributions of the alphas are shown for the following models: C-Four fac = conditional, four-factor model, U-Four fac = unconditional four-factor model, C-Style = conditional single style-factor model, U-Style = unconditional single style-factor model, C-Capm = conditional capital asset pricing model, and U-Capm = unconditional capital asset pricing model. The models are described in more detail in the text.

distributions is an interesting result, in view of the finding by Ferson and Schadt (1996) that conditional alphas for mutual funds are on average larger than unconditional alphas. Ferson and Warther (1996) show that these differences reflect a positive correlation between expected market returns and the flow of new money into mutual funds over time, 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 and the cash holdings of these funds do not respond as much in the short run to expected market returns as is the case for mutual funds. This may explain the difference between our results in Figure 1 and the findings of Ferson and Schadt (1996). Such differences motivate further analysis of the performance dynamics.

4.3 Evidence of time-varying conditional alphas
Table 2 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.[12]

Panel A of Table 2 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. The tests in panel A provide 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 lie 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.[13]

Table 2 summarizes, using equally weighted portfolios, the estimates of the A_p coefficients and their heteroskedasticity-consistent

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[12] 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.

[13] Since the time variation can occur in the alphas and the betas, we tested the hypothesis that the betas are constant, allowing for time-varying alphas. Using an 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. Bonferroni joint tests produce p-values of 0.000 based on either the F- or the Wald statistics. We conclude that time-varying alphas alone are not sufficient to capture the role of the lagged variables.

Table 2
Evidence of time-varying conditional alphas

Manager	const	t(const)	dy	t(dy)	term	t(term)	tbill	t(tbill)	R^2	pval(F) Bonferroni	pval(W) Bonferroni
Panel A: Coefficients of the Conditional CAPM Alphas											
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											
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

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 1-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 R^2 are the R^2 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*-values in a group multiplied by the number of managers in a group. The data are monthly from January 1979–December 1990, or the subsample available for a particular manager. The excess returns 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.

t-ratios, which measure the sensitivity of the conditional alphas to the public information variables. At the group level, 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 are, again, the Treasury bill yield (41 cases) and the dividend yield (37 cases).

Among the small-cap managers, 15 of the 16 significant coefficients for alpha on the dividend yield are positive, and all 13 of the significant coefficients on the Treasury bill are negative. This says that the small-cap 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 conditional alphas 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 reflect a misspecification in the conditional CAPM.

Panel B of Table 2 summarizes the results of estimating conditional alphas using the Russell style index for the manager as the benchmark portfolio. Different managers with different style classifications therefore have different benchmarks. The results are similar to what we found using the CAPM, including the tendency for positive coefficients on the dividend yield and negative coefficients on the Treasury bill. 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 also similar to the results for the conditional CAPM. Our conclusion is that some pension fund managers have time-varying conditional alphas, and these are not an artifact of using the conditional CAPM as the benchmark model.

5. The Persistence of Investment Performance

5.1 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:

$$r_p(t, t + \tau) = \gamma_{0,t,\tau} + \gamma_{1,t,\tau}\alpha_{pt} + u_p(t, t + \tau), \quad p = 1, \ldots, n \quad (6)$$

where $r_p(t, t + \tau)$ is the compounded return from month t to month $t + \tau$ for manager p, measured net of the return to rolling over 1-month Treasury bills. The symbol τ denotes the return horizon, for $\tau = 1, 3, 6, 12, 18, 24,$ and 36 months. The regressor, α_{pt}, is a measure of past abnormal performance, estimated using time-series data up to month t. The term $u_p(t, t + \tau)$ 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.

Equation (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 (1991b)], where a risk measure like beta is the independent variable. Equation (6) is estimated by generalized least squares (GLS), using a computationally feasible weighted least squares (WLS) approach. The weight for each observation is the inverse of the standard deviation of the residuals from the time-series model that was used to estimate the alpha. This has two advantages. Note that the deflated alpha is essentially an appraisal ratio. Because deflating by the standard error reduces cross-sectional differences related to variance, Brown et al. (1992) suggest using the appraisal ratio as a partial adjustment for survivorship bias. Roll and Ross (1994) and Kandel and Stambaugh (1995) also show that GLS is preferable to ordinary least squares (OLS) in cross-sectional stock return regressions.

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 (for example, a misspecified risk-free rate). By using the future return as the dependent variable in Equation (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 for the following reason. 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 correlated over time. If future alphas were used as the dependent variable, such biases in alpha are likely to be correlated over time, which 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 cross-sectionally correlated, making the usual regression statistics, such as R^2 and OLS 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.

When the future return horizon is longer than 1 month ($\tau > 1$), the time series of the $\gamma_{1,t,\tau}$ estimates will be autocorrelated because of 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.

5.2 Evidence that performance persists

Table 3 summarizes the results of the cross-sectional regressions, using various measures of the past performance to predict the future returns. Each row of the table uses a different measure of alpha. The simplest measures are the past average returns and the returns in excess of the manager's style index, based on the most recent 60 months.[14] We also measure the past average return net of the return for an equally weighted portfolio of the other managers in the same Russell style group (denoted in the tables as "net of group mean"). The "60-month unconditional CAPM" alphas use Equation (1), the previous 60 months of data, and the market index as the benchmark to estimate an alpha. The "60-month unconditional 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.[15]

The middle columns of Table 3 show the Fama–MacBeth t-ratios, adjusted for autocorrelation if the future return horizon, τ, is longer than 1 month. Since 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 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

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[14] We also examine the past 36 month average returns, and the results are similar.

[15] We also examine "timing-adjusted" conditional and unconditional alphas. The unconditional models are based on the classic market timing regressions of Treynor and Mazuy (1966), and the conditional version follows Ferson and Schadt (1996). 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. The results for these models lead to similar conclusions.

Table 3
Measures of the persistence of institutional equity manager performance

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
Panel A: Unconditional Models, All Managers										
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
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
Panel B: Conditional Models, All Managers										
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	*
Panel C: Unconditional Models, Only Negative Prior Alphas										
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
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
Panel D: Conditional Models, Only Negative Prior Alphas										
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	*

t-Ratios for time-series averages of the slope coefficients in monthly cross-sectional regressions of 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, and adjusted for autocorrelation induced by overlapping data for horizons τ longer than 1 month, by using $\tau - 1$ Newey–West lags. The "Bonferroni pvals" are the individual right-tail *p*-values 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 1-month Treasury bill, expressed as percent per month. The group means refer to the arithmetic average of all managers in the same Russell style group. The data are monthly from January 1979–December 1990. The cross-sectional regression for each month and horizon, τ, uses all managers with 60 past returns available. * indicates that the covariance matrix was not positive definite.

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Wald tests of the hypothesis that the vector of the slope coefficients for all of the horizons is zero.[16]

Focusing first on panel A, the unconditional models provide little evidence of predictive ability at the short horizons. However, as the future return horizon is increased, evidence of persistence appears, and two of four models produce *t*-ratios larger than 2.0 at the 36-month horizon. The unconditional alphas relative to the style indexes and past returns net of the style group means produce the strongest evidence of persistence, and the only evidence in this panel that is significant across the horizons, based on the Bonferroni tests.

Panel B summarizes the results for the time-varying conditional models. All of the coefficients are positive and half of the *t*-ratios are larger than 2.0. The conditional models present evidence of persistence at all of the horizons. The positive coefficients say that good (bad) performance predicts high (low) future returns. Overall, the regression evidence of persistence is stronger when the conditional models are used.

Studies of open-end mutual funds find that persistence is concentrated in the poorly performing funds [e.g., Hendricks, Patel, and Zeckhauser (1993), Shukla and Trzcinka (1994), Brown and Goetzmann (1995), Carhart et al. (1996)]. Therefore panels C and D repeat the persistence regressions using only the pension funds whose prior alphas are negative each month. Panel C shows the results for unconditional models of alpha and panel D presents the conditional models. Now the regressions are significant jointly across the horizons for five of the six models. The significant coefficients are almost always positive, which says that among the negative-alpha funds, those with relatively low prior alphas in a given month tend to have relatively low future returns.

5.3 The economic significance of persistence
The patterns of the *t*-ratios in Table 3 suggest that persistence becomes stronger as the future return horizon increases out to 3 years. The point estimates of the cross-sectional regression coefficients have an 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 an arbitrage portfolio (zero net

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[16] 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.

investment) constructed to have an historical alpha equal to 1% per month. The average coefficient is the time-series average of the actual return to such a strategy. The average values of the cross-sectional co-efficients are taken for each horizon, over time and across the models which produce significant coefficients, and expressed 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 magnitudes of the coeffi-cients are larger (on a per-month basis) for the longer horizons. The larger *t*-ratios for the longer horizons are therefore not simply a result of more precise estimates.

The interpretation of the cross-sectional regression coefficients as portfolio strategies is hypothetical because, unlike mutual funds, it is not possible to sell short pension funds. Furthermore, the regressions do not account for differences in the risk of the future returns. If the alphas are related to risk because of some systematic bias, then the evidence of persistence may reflect persistence in the expected compensation for this risk. Adjusting the cross-sectional regressions for risk is problematic, as discussed above, 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 de-signed to facilitate risk adjustments and to provide a further economic interpretation for the persistence effects. Each trading strategy uses an estimate of alpha based on the past 60 months of data for each el-igible 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 monthly returns and the cumulative investment values are tracked. If there is persistence in performance, then the high-alpha portfolios will generate higher future returns than low-alpha portfolios.

To adjust for risk, the performance of each quintile portfolio is evaluated using both unconditional and conditional models. The con-ditional models allow for time-varying risk exposures of the quintile strategies. The first date of the trading strategy returns is January 1984, and there are 84 monthly returns for each trading strategy.

Table 4 shows results when the quintiles are formed using three alternative measures of past performance. These are based on a time-varying conditional CAPM, an unconditional CAPM, and on past aver-age returns with no risk adjustment. For each trading strategy Table 4 reports the alphas of the strategy's future returns, measured relative to four risk models (unconditional and conditional CAPM and three-

factor models),[17] unconditional and conditional betas, and other performance statistics. The first two rows present comparable figures for the CRSP value-weighted index and an equally weighted portfolio of all managers.

When past average returns are used to form quintiles, the extreme high and low quintiles produce the riskiest future returns measured by standard deviation, unconditional beta, or conditional beta. This is consistent with persistence in the volatility of funds, as assumed in the model of survivorship used by Goetzmann et al. (1995) and Hendricks, Patel, and Zeckhauser (1996). However, the expected J-shaped relation between future and past returns or between future returns and volatility, is not evident. If anything the means present an inverted U-shaped pattern, with the extreme past return quintiles delivering the lowest future returns. However, any patterns in the means are not statistically significant.

Using the unconditional CAPM alphas to drive the strategies, the lowest-alpha quintiles have the largest standard deviations of their future returns and the largest betas. These patterns are consistent with a systematic bias in the unconditional CAPM. An inverse relation between alphas and betas is also observed in the early classic studies of the CAPM [e.g., Black, Jensen, and Scholes (1972), Fama and MacBeth (1973)]. The relation of the future returns to the past unconditional alphas again resembles an inverted U. The difference between the future returns of the high-alpha and the low-alpha quintile is only 0.2% per year, and the alphas of the future returns are not statistically different from zero. Thus unconditional CAPM alphas appear to provide little reliable information about future abnormal performance.

Focusing on the time-varying conditional CAPM, the results of the trading strategies are strikingly different. The average future returns are now monotonically decreasing 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 $1 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. The fraction of the 84 excess returns that are positive is monotonic across the conditional alpha quintiles, ranging from 60.7% for the high-alpha to 54.8% for the low-alpha quintile.

Table 4 also provides risk-adjusted returns for the trading strategies. Simple measures of risk are not monotonic across the conditional al-

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[17] 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 (i) the Standard and Poors 500 excess return, (ii) the difference between the small-cap and the large-cap style index returns, and (iii) the difference between the value and the growth style index returns.

Table 4
Simple trading strategies using past alphas

Strategy	Mean	Std	Uncond. beta	Average condit. beta	Unconditional alphas 3FAC	Unconditional alphas CAPM	Conditional alphas 3FAC	Conditional alphas CAPM	Cumulative value	Fraction positive	Min-max returns
CRSP VW-index	0.599	4.89	1.00	1.00	0.56	0.00	0.81	0.00	2.45	56.9%	−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	59.5%	−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

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 January 1979–December 1990, and the first date of the trading strategy returns is January 1984. There are 84 monthly returns for each trading strategy measured net of a 1-month Treasury bill return. The excess returns are percent per month. The first two rows show comparable results for the CRSP value-weighted index and an equally weighted portfolio of all managers. Uncond. beta is the unconditional beta against the CRSP value-weighted index; 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 an * when their heteroskedasticity-consistent *t*-ratios are larger than 1.94.

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pha quintiles. The standard deviations of the future excess returns, their unconditional betas, and the time-series averages of the conditional CAPM betas are all lower in the middle quintiles and higher at the extreme quintiles. All of the risk measures are the largest for the low-alpha quintile.

Estimates of CAPM alphas (unconditional and conditional versions) for the conditional quintile-strategy returns are positive for the highest-return quintile and ordered nearly monotonically across the quintiles. The return differences generated by the conditional alpha strategies do not appear to be explained by these measures of risk. Significantly negative alphas are found for some of the low conditional performance quintiles. This is consistent with our previous observation that persistence is concentrated in the poorly performing managers. In summary, these are not the patterns that would be expected under a simple survivorship bias or a bias related to risk measurement. We conclude that the persistence in pension fund performance is most likely to be an economically meaningful phenomenon.

5.4 Robustness of the evidence

As we discussed above, it is difficult to evaluate the extent to which survivorship biases may be responsible for our results. There are other statistical issues that we can partially address.

The patterns of the *t*-ratios in Table 3 suggest that the statistical significance of persistence becomes stronger as the future return horizon increases out to 3 years. 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 reestimated a number of the cases using Hansen's (1982) covariance matrix, which gives equal weights to all of the lags. This produces slightly smaller *t*-ratios for the shorter horizons, similar numbers in the 1- to 2-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)]. We conclude that the results are not driven by our use of the Newey–West estimator.

It is conceivable that the strong positive relation of alphas to future returns in the subsample of negative-alpha managers masks a significant pattern among the high-alpha managers. Possibly, mean reversion in the high-alpha managers could combine with persistence in the low-alpha managers to generate an insignificant relation in the full sample. Mean reversion of the top managers may reflect actual performance or an "up and out" form of survivorship bias, as was discussed above. To explore this possibility, we repeated the analysis

using the subset of managers with alphas in the top third each month. We find no strong evidence of persistence. Most of the point estimates of the coefficients are negative at the shorter horizons. However, the negative coefficients are generally not significant. We compare the magnitudes of the persistence regression coefficients in the full samples and the subsamples. The largest coefficients are found in the subsample of negative-alpha managers, which suggests that the economic significance of the persistence is larger for the poorly performing managers. These results confirm the impression that the evidence of persistence in performance is especially concentrated in the poorly performing managers.

6. Concluding Remarks

This article 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. Our analysis documents a striking persistence in the relative performance of the managers, which appears to be of economic significance. The additional information used by a conditional measure allows us to better detect persistence in the performance of pension funds. Similar to the previous evidence for mutual funds, we find that poor performance tends to be followed by low future returns, and that persistence is concentrated in the poorly performing managers.

Finding that a conditional measure can detect persistence in pension fund performance is consistent with the view that more sophisticated techniques are used to successfully evaluate pension fund managers than a typical investor uses to evaluate mutual funds. 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 fund with predictably poor performance. This raises a number of interesting questions for future research. Why do the poorly performing managers survive? Is this an inefficiency in the market for pension manager services, as Lakonishok, Shleifer, and Vishny (1992) suggest? Are the costs of firing low-return managers high enough to justify this persistence? Do the poorly performing managers deliver valuable services to their sponsors which offset their poor investment returns? What strategies for trading and trade execution characterize these persistently poor performers? Conditional models seem to provide a more powerful signal than has previously been available to measure risk-adjusted investment performance. Fu-

ture research is needed, using conditional methods, to address these issues.

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