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ABSTRACT

The use of predetermined variables to represent public information and time-variation has produced new insights about asset pricing models, but the literature on mutual fund performance has not exploited these insights. This paper advocates conditional performance evaluation in which the relevant expectations are conditioned on public information variables. We modify several classical performance measures to this end and find that the predetermined variables are both statistically and economically significant. Conditioning on public information controls for biases in traditional market timing models and makes the average performance of the mutual funds in our sample look better.

THE PROBLEM OF ACCURATELY measuring the performance of managed portfolios remains largely unsolved after more than 30 years of work by academics and practitioners. Standard measures of performance, designed to detect security selection or market timing ability, are known to suffer from a number of biases. Traditional measures use unconditional expected returns as the baseline. For example, an "alpha" may be calculated as the past average return of a fund in excess of a risk-free rate, minus a fixed beta times the average excess return of a benchmark portfolio. However, if expected returns and risks vary over time, such an unconditional approach is likely to be unreliable. Common time variation in risks and risk premiums will be confused with average performance.

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The problem of confounding variation in mutual fund risks and risk premia has long been recognized (e.g. Jensen (1972), Grant, (1977)), but previous studies interpreted it as reflecting superior information or market timing ability. We emphasize a different interpretation. This paper takes the view that a managed portfolio strategy that can be replicated using readily available public information should not be judged as having superior performance. Traditional, unconditional models can ascribe abnormal performance to an investment strategy that is based only on public information. (See Breen, Glosten, and Jagannathan (1989) for an example.) Using instruments for the time-varying expectations, it is possible to control common variation caused by public information and reduce this source of bias.

Recent studies have documented that the returns and risks of stocks and bonds are predictable over time, using dividend yields, interest rates, and other variables. If this predictability reflects changing required returns in equilibrium, then measures of investment performance should accommodate the time variation.

There is reason to think that predictability using predetermined instruments represents changing required returns. For example, standard beta pricing models of expected returns can capture a substantial fraction of the predictability in passive portfolios (Ferson and Harvey (1991), Evans (1994), Ferson and Korajczyk (1995)). Also, conditional versions of simple asset pricing models may be able to explain the cross-section of returns better than unconditional models (e.g. Chan and Chen (1988), Cochrane (1992), Jagannathan and Wang, (1996)).

We advocate *conditional performance evaluation,* using measures that are consistent with a version of market efficiency in the semi-strong form sense of Fama (1970). We believe that a conditional approach is especially attractive in fund performance evaluation for two reasons. First, many of the problems with traditional measures reflect their inability to handle the dynamic behavior of returns.[1] Second, it is possible that the trading behavior of managers results in more complex and interesting dynamics than even those of the underlying assets they trade. Our results suggest that this indeed is the case.

We modify Jensen's alpha and two simple market timing models to incorporate conditioning information. We use these models to illustrate the intuitive appeal and the empirical importance of conditional methods for performance evaluation. We examine monthly data for 67 mutual funds over the 1968–1990 period, and find that conditioning information is both statistically and economically significant.

[1] A few previous studies partially address this issue. Grinblatt and Titman (1989a) use predetermined information on the attributes of firms to develop performance benchmarks, but they use unconditional expected returns as the baseline for measuring performance. Glosten and Jagannathan (1994) use a contingent claims approach to address nonlinearities that may arise when managers engage in dynamic strategies, but they also use unconditional expected returns. Sirri and Tufano (1992) use rolling regressions for Jensen's alpha, an approach that may approximate conditional betas. Chen and Knez (1992, 1994) develop general measures of performance using the framework of Hansen and Richard (1987).

Introducing the information variables changes the estimated performance of many funds. We also find two striking empirical results at the aggregate level. First, the unconditional Jensen's alphas of the mutual funds are negative more often than positive, which is similar to the evidence that Jensen (1968) and Elton *et al.* (1992) interpret as indicating poor average performance. Using the conditional models, the distribution of the mutual fund alphas is consistent with neutral performance for the group.

A second result involves the market timing models of Treynor and Mazuy (1966) and Merton and Henriksson (1981). The evidence of these models suggests that the market timing ability of the typical mutual fund manager in our sample is perverse in the sense that funds on average have higher market exposure when subsequent market returns are low. Chang and Lewellen (1984), Henriksson (1984), and Grinblatt and Titman (1988) found similar results. We modify the approaches of Treynor-Mazuy and Merton-Henriksson to condition on public information and find that the evidence of negative timing performance for the group of mutual funds is removed.

The conditional models allow us to estimate time-varying conditional betas, and we find evidence that mutual fund betas are correlated with the public information variables. The more pessimistic results of the unconditional models are attributed to the common variation in mutual fund betas and expected market returns that is captured by these variables.

Further preliminary analysis suggests that the negative correlation between mutual fund conditional betas and expected market returns may be related to the flows of net new money into mutual funds. Changes in the conditional betas of the funds are negatively related to changes in net new money flows, and cash holdings are positively correlated with net new money flows. These relations present intriguing opportunities for future research.

The paper is organized as follows. Section I describes the basic models. Section II discusses market timing. Section III describes the data. Section IV presents the main empirical results. Section V examines the robustness of the results. Section VI offers concluding remarks.

I. The Models

The appeal of a conditional model for performance evaluation can be illustrated with the following hypothetical scenario. Suppose that the expected market excess return and its volatility move together proportionately over time with economic conditions, as in the model of Merton (1980). Consider a mutual fund that wishes to keep its volatility relatively stable over time. Based on economic conditions, the fund will lower its beta when the market is more volatile and raise it in less volatile markets. The beta of the fund will be negatively correlated with the market return, so the average excess return of the fund will be less than the average beta of the fund applied to the average market premium. The use of an unconditional model would lead to the conclusion that the fund has a negative alpha. However, this does not reflect performance, but the fact that the fund takes more risk when the premium for beta risk is low. A conditional model that controls for the time-varying betas and market premium shows that the fund has neutral performance.

The rest of this section describes our basic assumptions and develops a simple model for conditional performance evaluation. We also discuss how our models are related to the traditional, unconditional approach.

A. The Basic Assumptions

The first assumption is the form of an asset pricing model that describes the conditional expected returns of the assets available to portfolio managers. We use a conditional version of Sharpe's (1964) Capital Asset Pricing Model (CAPM) to illustrate the approach. Of course, studies have rejected the CAPM for conditional returns (e.g. Ferson, Kandel, and Stambaugh (1987), Bollerslev, Engle, and Wooldridge (1988), and Harvey (1989)), and Roll (1978) shows that the inferences about performance can be sensitive to the specification of an inefficient benchmark. We therefore extend the analysis to a multiple-factor asset pricing model, and find that the results are robust.

The second important assumption is a notion of market efficiency. The traditional performance evaluation literature assumes that the user of a performance measure holds unconditional expectations. With this assumption the use of any information by managers, including public information, may lead to measured abnormal performance. In contrast, we assume that market prices fully reflect readily available, public information. We hypothesize that managers may use this information to determine their portfolio strategies. The use of public information should not imply abnormal performance, under semi-strong form market efficiency, because investors can replicate on their own any strategy which depends on public information.[2]

The third assumption required for our approach is a functional form for the betas, or factor sensitivities of a managed portfolio. Time-variation in a managed portfolio beta may come from three distinct sources. First, the betas of the underlying assets may change over time. Second, the weights of a passive strategy such as buy-and-hold, will vary as relative values change. Third, a manager can actively manipulate the portfolio weights by departing from a buy-and-hold strategy.

We model the combined effect of these factors on the risk exposures indirectly, as a "reduced form." We use a linear function, which is a natural extension of traditional approaches. For example, Admati and Ross (1985), and Admati, *et al.* (1986) assume that managers act as if they maximize a constant absolute risk aversion expected utility function, defined over normally distributed variables. In this case the portfolio weights are linear functions of the information, and if the betas of the underlying assets are fixed over time, the

[2] Of course, the argument that investors can replicate or undo managers' trades that are based on public information assumes that investors can infer the trades. It also ignores any cost advantages in trading that funds may have over investors and assumes that managers do not waste resources by "churning" their clients' portfolios at cost.

managed portfolio beta would also be a linear function of the information. A linear function for beta is also attractive because it results in simple regression models that are easy to interpret. While we use simple, linear functions to illustrate the conditional approach, the correct specification is an empirical issue. The general approach can accommodate many choices for the functional form.

B. A Model Based on the CAPM

The conditional CAPM implies that equation (1) is satisfied for the assets available to portfolio managers:

$$r_{it+1} = \beta_{im}(Z_t)\, r_{mt+1} + u_{i,t+1}, \qquad \begin{array}{l} i = 0, \ldots, N, \\ t = 0, \ldots, T-1, \end{array} \tag{1a}$$

$$\mathrm{E}(u_{i,t+1}|Z_t) = 0, \tag{1b}$$

$$\mathrm{E}(u_{i,t+1} r_{mt+1}|Z_t) = 0, \tag{1c}$$

where R_{it+1} is the rate of return on the investment asset i between times t and $t+1$, $r_{it} = R_{it} - R_{ft}$ is the *excess return,* R_{ft} is the return of a one-month Treasury bill, Z_t is a vector of instruments for the information available at time t, and r_{mt+1} is the excess return of the market factor. The $\beta_{im}(Z_t)$ are the time t conditional market betas of the excess return of asset i. Equation (1b) follows from the market efficiency assumption and equation (1c) says that the $\beta_{im}(Z_t)$ are conditional regression coefficients.

Equation (1) implies that any unbiased forecast of the difference between the return of a security and the product of its beta and the excess return on the market factor which differs from zero must be based on an information set that is more informative than Z_t. Using only the information Z_t the forecast of this difference is zero. A portfolio strategy that depends only on the public information Z_t will satisfy a similar regression. The intercept, or "alpha" of the regression should be zero, and the error term should not be related to the public information variables.[3]

Because we hypothesize that the manager uses no more information than Z_t, the portfolio beta, $\beta_{pm}(Z_t)$, is a function only of Z_t. Using a Taylor series

[3] That is, if $R_{p,t+1} = x(Z_t)'\mathrm{R}_{t+1}$, where $x(\cdot)$ is an N-vector of weights and R_{t+1} is the N-vector of the available risky security returns, then the portfolio excess return will satisfy equation (1), with $\beta_{pm}(Z_t) = x(Z_t)'\beta_m(Z_t)$, where $\beta_m(Z_t)$ is the vector of the securities' conditional betas. The error term in the regression for the portfolio strategy is $u_{p,t+1} = x(Z_t)'\mathrm{u}_{t+1}$, where u_{t+1} is the vector of the $u_{i,t+1}$'s, and therefore

$$\mathrm{E}(u_{p,t+1}|Z_t) = \mathrm{E}(x(Z_t)'u_{t+1}|Z_t) = x(Z_t)'\mathrm{E}(u_{t+1}|Z_t) = 0.$$

we approximate this function linearly, following Shanken (1990) and others:

$$\beta_{pm}(Z_t) = b_{0p} + B'_p z_t, \tag{2}$$

where $z_t = Z_t - \mathrm{E}(Z)$ is a vector of the deviations of Z_t from the unconditional means, and B_p is a vector with dimension equal to the dimension of Z_t. The coefficient b_{0p} may be interpreted as an "average beta," i.e., the unconditional mean of the conditional beta: $\mathrm{E}(\beta_{pm}(Z_t))$.[4] The elements of B_p are the response coefficients of the conditional beta with respect to the information variables Z_t.

Equations (1) and (2) imply the following generating process for the managed portfolio return:

$$r_{pt+1} = b_{0p} r_{mt+1} + B'_p[z_t\, r_{mt+1}] + u_{p,t+1}, \tag{3}$$

where $\mathrm{E}(u_{p,t+1}|Z_t) = \mathrm{E}(u_{p,t+1}\, r_{mt+1}|Z_t) = 0$. Now consider a regression of a managed portfolio excess return on the market factor and the product of the market factor with the lagged information:

$$r_{pt+1} = \alpha_p + \delta_{1p}\, r_{mt+1} + \delta'_{2p}(z_t r_{mt+1}) + \varepsilon_{pt+1}. \tag{4}$$

Taking the relevant expected values in (4) and comparing the result with (3) shows that the model implies $\alpha_p = 0$, $\delta_{1p} = b_{0p}$, and $\delta_{2p} = B_p$.[5]

C. Interpreting the Conditional Model

Our approach may be interpreted as a special case of a general asset pricing framework based on the expression $\mathrm{E}(m_{t+1}\, R_{t+1}|Z_t) = 1$, 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. Our version of the conditional CAPM implies that the stochastic discount factor is a linear function of the market excess return, where the coefficients may depend linearly on Z_t.

The regression (4) may also be interpreted as an unconditional multiple factor model, where the market index is the first factor and the product of the market 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 market index, financed by borrowing or selling z_t in Trea-

[4] This interpretation is an approximation, as it ignores the higher order terms in the Taylor expansion. The information variables are demeaned for ease of exposition.

[5] OLS estimation of the regression model imposes the same moment conditions as does Hansen's (1982) GMM estimator. Consider a linear conditional beta $\beta_{t-1} = b + B'z_{t-1}$ in a linear regression model $y_t = x'_t\beta_{t-1} + \epsilon_t$. The moment conditions:

$$u_t = x_t y_t - (x_t x'_t)(b + Bz_{t-1}),\ \mathrm{E}(u_t|z_{t-1}) = 0$$

would be the basis of the GMM estimation. Typically, the implementation of the GMM would use the implication: $\mathrm{E}(u_t \otimes z_{t-1}) = 0$. Consider the OLS regression estimator of the linear model which results from substituting the beta equation into the regression and note that the error terms are related as $\epsilon_t x_t = u_t$. It is easy to verify that the two sets of moment conditions are the same.

sury bills. This interpretation is similar to Hansen and Jagannathan (1991) and Cochrane (1992). The coefficient α_p in (4) is the average difference between the managed portfolio excess return and the excess return to the dynamic strategies which replicate its time-varying risk exposure. A manager with a positive conditional alpha is one whose average return is higher than the average return of the dynamic strategies.

Our approach may be contrasted with Chen and Knez (1994), who construct m_{t+1} as a time-varying combination of the primitive assets available to fund managers. Theirs is a conditional version of the method of Grinblatt and Titman (1989b). The idea is to construct a minimum-variance-efficient portfolio to use as a benchmark in the place of a market index. By constructing an efficient benchmark portfolio, the problem of benchmark inefficiency is avoided, at least in theory. However, it requires that the set of primitive assets available to managers is correctly specified, a difficult empirical task indeed!

Specifying m_{t+1} using an asset pricing model does not require measuring the returns of all the assets that are available to portfolio managers. Also, using familiar asset pricing models is convenient for relating our results to the traditional literature. However, since the asset pricing model is likely to be misspecified, the results may be sensitive to an inefficient benchmark. Therefore, it is important to investigate the sensitivity of the results to alternative benchmarks.

Investors who wish to make optimal portfolio decisions need to avoid the errors that an unconditional model is likely to make in classifying portfolio performance. A conditional alpha should be a more reliable guide for mean-variance improving portfolio adjustments. Simple portfolio theory shows that alpha is zero if the benchmark portfolio is mean-variance efficient. A positive alpha for a particular investment means that the ratio of expected excess return to variance, for the benchmark, is increased by shifting funds into the positive-alpha investment. If investors form expectations of future returns and risks using public information, the conditional expectations should determine the relevant alphas. Our results show that conditional alphas and unconditional alphas are significantly different, so relying on unconditional alphas is likely to produce inferior investment decisions.

While conditional alphas are an improvement, the fact that conditioning information is important raises deeper issues about optimal investment decisions. Time-varying risks and expected returns require a dynamic investment model. In a dynamic model, investors may not optimally choose conditional mean-variance efficient portfolios (e.g., Merton (1973)), and multiple-factor benchmarks may be appropriate. Also, in a dynamic model the investment horizon of the investor becomes a complex issue. In general, the form of the model is not invariant to the return measurement interval (see Longstaff (1989) and Ferson and Korajczyk (1995)), and the optimal investment horizon is an endogenous variable. These issues are complex, but they are important for applying conditional performance measures in practice.

D. Multiple-Factor Models

It is easy to extend the analysis to use a conditional multiple-beta or exact arbitrage pricing (APT) model for the expected returns on the assets available to managers:[6]

$$E(R_{it+1}|Z_t) = \lambda_0(Z_t) + \sum_{j=1}^{K} b_{ij}(Z_t)\lambda_j(Z_t), \qquad \begin{array}{l} i = 0, \ldots, N, \\ t = 0, \ldots, T-1, \end{array} \tag{5}$$

where the $b_{i1}(Z_t), \ldots, b_{iK}(Z_t)$ are the time t conditional betas or factor loadings, which measure the systematic risk of asset i relative to the K risk factors. The $\lambda_j(Z_t)$, $j = 1, \ldots, K$ are the market prices of systematic risk or the expected risk premiums.

In our multiple factor models, we replace equation (2) with a similar equation for each of the K factor-betas of a managed portfolio. That is, we model each of the conditional betas as a linear function of the information. Our unconditional K-factor model regression is a multiple regression of the excess returns on a constant and the K factor-portfolios, and the intercept is the unconditional alpha. In our conditional K-factor model, the regression equation has $(L + 1)K + 1$ regressors. The regressors are a constant, the K factor-portfolios, and the products of the L information variables in Z_t with the K factor-portfolios.

E. Traditional Measures Revisited: Jensen's (Unconditional) Alpha

A traditional approach to measuring performance is to regress the excess return of a portfolio on the market factor. Assuming that the market beta is constant, the slope coefficient is the market beta and the intercept, a_p, is the *unconditional alpha* coefficient, which measures the average performance (e.g. Jensen (1968)):

$$r_{pt+1} = a_p + b_p\, r_{mt+1} + v_{pt+1}. \tag{6}$$

It is well known that Jensen's original methodology presents problems when risk and return are not constant over time. We can use our model to correct alpha for bias caused by common variation in betas and expected market returns. Assume that equation (3) is the true model for a managed portfolio return, but the analyst uses the unconditional regression of equation (6). Under standard assumptions, the OLS regression estimates satisfy:

$$\text{plim}(b_p) = b_{0p} + B_p'\text{Cov}(r_m; z\ r_m)/\text{Var}(r_m) \tag{7}$$

$$\text{plim}(a_p) = E(r_m)[b_{0p} - \text{plim}(b_p)] + \text{Cov}(r_m; B_p'Z)$$

[6] The multiple-beta model was developed by Merton (1973). The APT was developed by Ross (1976) and extended for conditioning information by Stambaugh (1983).

where E(·), Cov(·), and Var(·) denote the unconditional mean, covariance and variance, respectively. The notation $z\, r_m$ refers to the vector of the products of the lagged information variables with the market excess return.

The first term in the expression for plim(a_p) reflects the fact that the OLS slope coefficient in equation (6) is not a consistent estimate of even the average conditional beta, b_{0p}. The second term reflects the covariance between the conditional beta of the fund and the future market return. Equation (7) may be interpreted as a missing-variable bias in equation (6). The effect depends on the regression coefficients of the omitted variables, zr_m, on the included variable, r_m. When $B_p = 0$, the managed portfolio beta is not a function of the public information, the conditional and unconditional betas are the same, and the probability limit of the intercept is zero.

Evaluating equation (7) at the sample moments and using the OLS estimates from (4), we can obtain bias-adjusted estimates of alpha. The adjusted alpha is numerically identical to the OLS estimate of α_p in equation (4). We can also use our conditional K-factor models to adjust for bias in the alphas that results from omitting the conditioning information in those models. The adjustment is a straightforward extension of the adjustment to alpha in the CAPM.[7]

Equation (7) is similar to expressions derived by Jensen (1972), Grant (1977), and Grinblatt and Titman (1989b) in an unconditional setting. However, the interpretation is different. Traditional studies view the covariance between beta and the future market return as a result of portfolio managers' superior information. Equation (7) is developed under the hypothesis that managers do not have superior information. In our model the hypothesis of no abnormal performance allows a covariance between beta and the future market return, because of their common dependence on the public information variables.

[7] Standard analysis shows that the slope coefficient in the unconditional factor model regression for asset i converges in probability to:

$$b_{0i} - B'_{pi}\mathrm{E}(Z) + \mathrm{Cov}(F)^{-1}\,\mathrm{Cov}(F;\, Z'B_{pi}\,F),$$

where b_{0i} is the vector of the expected values of the K conditional betas for asset i, and B_{pi} is the $L \times K$ matrix of the beta response coefficients for asset i, and F is the vector of the K factors. When the true alpha is zero, the intercept in the unconditional factor model regressions converges to:

$$\mathrm{E}\{Z'B_{pi}F\} - \mathrm{E}(F)'\mathrm{Cov}(F)^{-1}\,\mathrm{Cov}(F;\, ZB_{pi}\,F).$$

We can subtract this expression from the unconditional alphas to adjust them, using our estimates of B_{pi} from the conditional factor models. Alternatively, estimating an intercept in the conditional model produces the same result.

II. Market Timing

A. General Issues

When we depart from the hypothesis that managers simply form portfolios using public information, it raises a number of issues. Some of these issues are the same as in the traditional approaches to measuring performance. For example, the trading of managers with truly superior information must be "small" in some appropriate sense, so it will not affect equilibrium prices (e.g. Mayers and Rice (1979)). If managers generate patterns of payoffs which can not be otherwise obtained in the market, even if at a different cost, then evaluating the performance is problematic (Dybvig and Ross (1985), Glosten and Jagannathan (1994), Chen and Knez (1994)). Of course, benchmark inefficiency, as emphasized by Roll (1978), remains a problem.

The traditional performance measurement literature has attempted to distinguish security selection, or stock-picking ability, from market timing, or the ability to predict overall market returns. However, the literature finds that it is not easy to separate ability into two such dichotomous categories (see Glosten and Jagannathan (1994) for a recent discussion). Furthermore, if managers trade options, spurious timing and selectivity may be recorded (e.g. Jagannathan and Korajczyk (1986)). Similar problems arise with dynamic strategies, such as portfolio insurance, if trading takes place more frequently than our return measurement interval, which is monthly. Conditional versions of the simple market timing models do not resolve these problems.

Market timing ability can only be accurately measured under the assumptions of highly stylized models. Traditional models, in addition to their strong assumptions about how managers use their abilities, have taken the view that any information correlated with future market returns is superior information. In other words, they are unconditional models. Our approach is to use basically the same simplifying assumptions as the traditional models, but to assume semi-strong-form market efficiency. The idea is to distinguish "market timing" based on public information from market timing information that is superior to the lagged information variables.

B. The Treynor-Mazuy Model

A classic market timing regression is the quadratic regression of Treynor and Mazuy (1966):

$$r_{pt+1} = a_p + b_p r_{mt+1} + \gamma_{tmu}[r_{m,t+1}]^2 + v_{pt+1}, \tag{8}$$

where the coefficient γ_{tmu} measures market timing ability. Admati *et al.* (1986) describe a model in which a manager with constant absolute-risk aversion in a normally distributed world observes at time t the private signal, $r_{mt+1} + \eta$, equal to the future market return plus noise. The manager's response is to change the portfolio beta as a linear function of the signal. They show that the γ_{tmu} coefficient in regression (8) is positive if the manager increases beta when the signal about the market is positive. The hypothesis of no abnormal performance implies that γ_{tmu} is zero.

Using essentially the same analysis as Admati *et al.* (1986), we propose a conditional version of the Treynor-Mazuy regression. Assume that the manager observes the vector $(z_t, r_{mt+1} + \eta)$ at time *t*, and the question is how to allocate funds between the market portfolio and a risk-free asset. With exponential utility and normal distributions, the demand for the risky asset is a linear function of the information. In a two-asset model, the portfolio weight on the market index is the portfolio beta, and it is a linear function of z_t and $(r_{mt+1} + \eta)$. Replacing equation (2) with this linear function and letting η join the regression error term, we have a conditional version of the Treynor-Mazuy regression:

$$r_{pt+1} = a_p + b_p r_{mt+1} + C_p'(z_t\, r_{mt+1}) + \gamma_{tmc}[r_{m,t+1}]^2 + v_{pt+1}, \qquad (9)$$

where the coefficient vector C_p captures the response of the manager's beta to the public information, Z_t. The coefficient γ_{tmc} measures the sensitivity of the manager's beta to the private market timing signal. The term $C_p'(z_t r_{mt+1})$ in equation (9) controls for the public information effect, which would bias the coefficients in the original Treynor-Mazuy model of equation (8). The new term in our model captures the part of the quadratic term in the Treynor-Mazuy model that is attributed to the public information variables. In the conditional model, the correlation of mutual fund betas with the future market return, which can be attributed to the public information, is not considered to reflect market timing ability.

C. The Merton-Henriksson Model

Merton and Henriksson (1981) and Henriksson (1984) describe an alternative model of market timing. In their model a manager attempts to forecast when the market portfolio return will exceed the risk-free rate. When the forecast is for an up market, the manager adjusts the portfolio to a higher target beta. When the market forecast is pessimistic, a lower target beta is used. Given this model, Merton and Henriksson show that if the manager can time the market, the coefficient γ_u in the following regression is positive:

$$r_{pt+1} = a_p + b_p r_{mt+1} + \gamma_u[r_{m,t+1}]^+ + v_{pt+1}, \qquad (10)$$

where $[r_{m,t+1}]^+$ is defined as Max(0, $r_{m,t+1}$). Merton and Henriksson interpret Max(0, $r_{m,t+1}$) as the payoff to an option on the market portfolio with exercise price equal to the risk free asset.[8]

[8] Merton and Henriksson proposed the regression (10) to separate market timing from security selection ability. However, just as with the Treynor-Mazuy model, this separation is problematic, as illustrated by Jagannathan and Korajczyk (1986). Glosten and Jagannathan (1994) provide conditions under which the sum of the timing and selectivity components of performance can correctly estimate the average (unconditional) value added by a manager. Their arguments can be

To extend the Merton-Henriksson analysis to a conditional setting, suppose that the manager attempts to forecast $u_{m,t+1} = r_{m,t+1} - \mathrm{E}(r_{m,t+1}|Z_t)$, the deviation from the expected excess return, conditional on the public information. If the forecast is positive, the manager chooses a portfolio conditional beta of $\beta_{up}(Z_t) = b_{up} + B'_{up}z_t$. If the forecast is negative, the manager chooses $\beta_d(Z_t) = b_d + B'_d z_t$. Using this model for the portfolio betas and equation (1) for the individual assets, we derive:

$$r_{pt+1} = b_d r_{mt+1} + B'_d[z_t\, r_{mt+1}] + \gamma_c r^*_{mt+1} + \Delta'[z_t\, r^*_{mt+1}] + u_{p,t+1}, \tag{11}$$

where

$$r^*_{mt+1} = r_{m,t+1}\mathrm{I}\{r_{m,t+1} - \mathrm{E}(r_{m,t+1}|Z_t) > 0\}, \quad \gamma_c = b_{up} - b_d, \quad \text{and} \quad \Delta = B_{up} - B_d.$$

$\mathrm{I}\{\cdot\}$ is the indicator function. The null hypothesis of no market timing ability implies that γ_c and Δ are zero. The alternative hypothesis of positive market timing ability is that $\gamma_c + \Delta' z_t > 0$, which says that the conditional beta is higher when the market is above its conditional mean, given public information, than when it is below the conditional mean. This implies that $\mathrm{E}(\gamma_c + \Delta' z_t) = \gamma_c > 0$, which says that market timing is on average positive.[9]

III. The Data

A. The Fund Returns

We study monthly returns for 67 open-end mutual funds from January 1968 to December 1990, a total of 276 observations. As in previous studies that use monthly data, we implicitly assume that investors evaluate risk and return, and that mutual fund managers trade using a one-month horizon. The returns include reinvestment of all distributions (e.g. dividends) and are net of expenses but disregard load charges and exit fees. For the period from 1968 to 1982 the fund data are from Lehmann and Modest (1987). The returns are calculated from month-end bid prices and monthly dividends obtained from Standard and Poor's *Over-the-Counter Daily Stock Price Records*. Dividend records were checked using Wiesenberger's *Investment Companies Annual* compendium and Moody's *Annual Dividend Record* (Lehmann and Modest (1987), p. 243). For 67 of the 130 funds from Lehmann and Modest the return

extended to a conditional setting. Of course, the problem of survivorship bias in a sample of funds such as ours would be likely to make the measure of value added appear too large.

[9] The derivation assumes that if x_i, $i = 1, \ldots, N$ are the manager's portfolio weights, then $\mathrm{E}(x_i u_{i,t+1}|Z_t) = 0$, where $u_{i,t+1}$ is the error term in equation (1). This says that the manager may have market timing ability, but has no security selection ability given Z_t. The description also assumes that the managers' forecasts are correct under the alternative hypothesis of market timing ability. Following Merton and Henriksson (1981), if managers forecasts and beta adjustments can be correct or incorrect with some fixed probabilities, then it can be shown that:

$$\operatorname{plim}(\gamma_c + \Delta)' z_t = \mathrm{E}\{\beta_{up}(Z_t)\,|\,r_m > \mathrm{E}(r_m|Z_t), Z_t\} - E\{\beta_d(Z_t)\,|\,r_m < \mathrm{E}(r_m|Z_t), Z_t\}.$$

series could be updated through December 1990 using total returns from Morningstar, Inc. Funds were matched using the overlapping time series.[10]

Table I records the names of the funds, along with summary statistics for the 1968–1990 period. The funds are grouped by their Wiesenberger type as of 1982, which is roughly the middle of our sample period.[11] The funds are primarily equity funds, with objectives as classified by Wiesenberger varying from "maximum capital gains" to "income." The excess returns are net of the monthly return of investing in a Treasury bill with maturity greater than or equal to one month. The bill data are from Ibbotson & Associates. We place four of the funds in a "special" category. In two cases (Scudder International and Templeton Growth) the funds had sizable holdings in foreign equity markets. Century Shares Trust holds primarily securities issued by financial firms. Fidelity Capital Trust merged into Fidelity Trend in 1982, so the two series differ only before that date. One fund, Scudder Income, is a bond fund that we assign to the income fund group.

Our sample of funds has the potential for survivorship bias, as it contains only surviving funds. Survivorship may be expected to bias the relative performance measures upwards (e.g. Grinblatt and Titman (1988), Brown, Goetzmann, Ibbotson and Ross (1992), Brown and Goetzmann (1995), Malkiel (1995)). If survivorship bias is important, our estimates of the overall performance of the mutual funds is too optimistic. However, we find that the traditional measures suggest poor performance for the funds in our sample and that the poor performance is removed when we control for public information variables. It seems unlikely that survivorship bias can explain these results.

B. The Predetermined Information Variables

We use a collection of public information variables that previous studies have shown are useful for predicting security returns and risks over time. The variables are (1) the lagged level of the one-month Treasury bill yield, (2) the lagged dividend yield of the CRSP value-weighted New York Stock Exchange (NYSE) and American Stock Exchange (AMEX) stock index, (3) a lagged measure of the slope of the term structure, (4) a lagged quality spread in the corporate bond market, and (5) a dummy variable for the month of January.

We use the 30-day annualized Treasury bill yield from the CRSP RISKFREE files to predict the future returns. This is based on the bill that is the closest to one month to maturity at the end of the previous month, using 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 of NYSE firms, divided into the previous 12 months of dividend pay-

[10] We are grateful to David Modest for making these data available and to Peter Knez for help with matching and updating the data.

[11] Elton *et al.* (1992) evaluate the effects of classification errors that may arise from grouping a sample of funds at the beginning versus at the end of the period used by Ippolito (1989), and they found that only 12 of 143 funds changed categories. We conduct an analysis of the information in the categories below.

Table I

Summary Statistics for Excess Returns from 1968:01 to 1990:12

The statistics are calculated from monthly returns in excess of one-month T-bill rates for 67 open-end mutual funds. The data cover 23 years. Fund names are taken from Wiesenberger's 1983 annual "Investment Companies" compilation. The fund groupings are derived from the two classifications assigned by Wiesenberger at the end of 1982, which are reproduced here under their names: Primary Objective and Investment Policy. The abbreviations are explained at the bottom of the table. We assigned "balanced" and "flexible" funds to the Income group, conservative stock funds to the Growth-Income category, funds with a growth objective to the Growth fund group and aggressive funds are named after their objective Maximum Capital Gain. The Special group collects those funds that don't fit in either category: Century Shares Trust invests primarily in securities issued by financial firms, Fidelity Capital merged into Fidelity Trend in 1982, while the other two funds, Templeton and Scudder International, had sizable foreign positions.
Panel B reports return statistics for relevant benchmark portfolios. The T-bill returns are from Ibbotson & Associates and are the return from investing in a T-bill with maturity greater or equal to one month. We use this rate to compute excess returns for the funds and the other benchmarks. The value-weighted CRSP index represents the excess return for all stocks listed on the NYSE, our CAPM market proxy. The next four benchmarks are the factor returns for our four-factor model. The S&P 500 return (incl. dividends), the small cap return, which represents the ninth and tenth deciles of market values on the NYSE, and the Long Government Bond, which is the excess return on a long-term (approx. 20 year) U.S. Government bond, are all from Ibbotson Associates, while the Junk Bond series representing low-grade corporate bonds is from Blume, Keim, and Patel (1991), updated using the Merrill Lynch High Yield Composite index.

Mutual Funds by 1982 Name	Wiesenberger Classification: Primary objective	Wiesenberger Classification: Investment policy	Mean	Standard Deviation	Minimum	Maximum
		Panel A				
Boston Foundation F.	sgi	bal	0.19	3.98	−22.20	11.15
Financial Industrial In. F.	ig	flex	0.49	4.16	−18.60	14.17
Franklin Custodian F.-In. Series	i	flex	0.20	3.41	−11.51	14.17
Keystone Income F. (K1)	i	flex	0.15	3.04	−14.10	9.03
Nation-Wide Securities	isg	bal	0.29	3.80	−22.40	11.62
Northeast Invest. Trust	i	flex	0.04	2.12	−6.01	9.09
Provident F. for In.	i	flex	0.27	4.49	−25.00	13.22
Putnam Income Fund	i	flex	0.06	2.63	−8.81	10.19
Scudder Income Fund	is	bonds	0.00	3.08	−11.11	11.69
Security Investment F.	i	flex	0.26	4.13	−18.04	11.41
Sentinel Balanced Fund	igs	bal	0.24	2.85	−12.10	9.46
United Income Fund	i	flex	0.27	4.43	−13.10	15.26
Value Line Income Fund	i	flex	0.31	4.20	−16.96	15.24
Wellington Fund	sig	bal	0.19	3.50	−13.80	11.89
Income Group Average			0.21	3.56	−15.27	11.97

Table 1—*Continued*

Mutual Funds by 1982 Name	Wiesenberger Classification: Primary objective	Wiesenberger Classification: Investment policy	Mean	Standard Deviation	Minimum	Maximum
Panel A:—*Continued*						
Colonial Fund	gi	cs	0.11	3.71	−16.60	9.32
Composite Fund	gis	cs	0.16	4.37	−14.50	12.96
Delaware Fund	gis	cs	0.31	4.67	−18.60	14.42
Eaton and Howard Stock	gi	cs	0.08	4.54	−17.60	20.70
Fidelity Fund	gi	cs	0.32	4.57	−25.30	15.27
Financial Industrial Fund	gi	cs	0.23	4.79	−25.00	16.03
Founders Mutual Fund	gi	cs	0.09	4.20	−15.10	15.15
Guardian Mutual Fund	gi	cs	0.49	4.99	−24.70	14.20
Investment Company of America	gi	cs	0.41	4.44	−18.00	13.25
Investment Trust of Boston	gi	cs	0.13	4.63	−20.20	13.23
Keystone High-Grade Common Stock Fund (S1)	gi	cs	0.08	4.80	−24.70	22.80
National Industries Fund	gi	cs	0.03	4.99	−20.80	15.49
Philadelphia Fund	gi	cs	0.27	5.01	−21.20	17.58
Pine Street Fund	gi	cs	0.26	4.37	−21.70	15.27
Pioneer Fund	gi	cs	0.38	4.71	−25.00	15.17
Safeco Equity Fund	gi	cs	0.21	5.00	−21.90	15.37
Selected American Shares	gi	cs	0.10	4.30	−17.90	13.93
Sentinel Common Stock Fund	gi	cs	0.38	4.09	−19.10	12.24
Wall Street Fund	gis	cs	−0.03	5.32	−29.90	15.78
Washington Mutual Investors	gi	cs	0.46	4.49	−18.50	15.53
Growth-Income Average			0.22	4.60	−20.82	15.18
Axe-Houghton Stock Fund	g	cs	0.13	5.70	−34.90	20.48
David L. Babson Investment	g	cs	0.20	4.80	−23.60	19.26
Boston Company Capital Appreciation Fund	g	cs	0.19	4.77	−22.20	18.45
Colonial Growth Shares	g	cs	0.09	5.36	−25.30	17.07
Country Capital Growth	g	cs	0.18	4.86	−18.80	14.88
The Dreyfus Fund Inc.	g	cs	0.20	4.42	−17.20	16.62
Fidelity Trend Fund	g	cs	0.09	5.71	−30.20	20.48
Keystone Growth Fund (K2)	g	cs	0.04	5.32	−25.20	18.42
Keystone Growth Common Stock Fund (S3)	g	cs	0.21	6.69	−27.80	24.40
Lexington Research Fund	g	flex	0.20	5.08	−22.60	13.87
Penn Square Mutual Fund	g	cs	0.31	4.78	−19.00	15.55

Table 1—*Continued*

Mutual Funds by 1982 Name	Wiesenberger Classification: Primary objective	Wiesenberger Classification: Investment policy	Mean	Standard Deviation	Minimum	Maximum
		Panel A:—*Continued*				
Pilgrim Fund	g	cs	0.22	5.36	−20.60	17.55
Price (T. Rowe) Growth	g	cs	0.08	5.23	−24.20	19.69
Putnam Investors Fund	g	cs	0.37	5.22	−22.70	17.09
Security Equity Fund	g	cs	0.28	5.91	−25.50	18.07
Stein, Roe and F. Capital Opportunities Fund	g	cs	0.30	6.56	−27.80	19.07
Stein, Roe and Farnham Stock Fund	g	cs	0.22	5.61	−27.30	19.24
United Accumulative Fund	g	cs	0.20	4.73	−17.70	19.24
United Science and Energy	g	cs	0.09	5.36	−22.80	20.46
Value Line Fund	g	cs	0.34	6.49	−25.50	22.21
Windsor Fund	g	cs	0.49	4.76	−17.20	18.09
Growth Average			0.21	5.37	−23.72	18.58
Financial Dynamics Fund	mcg	cs	0.12	6.34	−31.60	19.17
Founders Growth Fund	mcg	cs	0.19	5.18	−22.50	11.98
Keystone Speculative	mcg	cs	0.09	7.96	−34.47	21.43
Mutual Shares Corporation	mcg	flex	0.66	4.17	−19.40	13.26
Oppenheimer Fund	mcg	cs	0.03	5.70	−27.30	15.33
Scudder Special Fund	mcg	cs	0.25	5.75	−28.80	16.97
Twentieth Century Growth Investors	mcg	cs	0.75	8.05	−28.80	25.30
Value Line Special Situations Fund	mcg	cs	−0.01	7.76	−31.60	30.40
Maximum Capital Gain Average			0.26	6.36	−28.06	19.23
Century Shares Trust	g	spec	0.45	5.89	−15.50	26.25
Fidelity Capital Fund	g	cs	0.07	4.93	−18.58	22.49
Scudder International	g	c&i	0.40	4.64	−26.50	14.04
Templeton Growth Fund (inc. in Canada)	g	cs	0.82	4.29	−23.90	11.62
Special Group Average			0.43	4.94	−21.12	18.60
Overall Average			0.25	5.26	−23.78	18.24

Table 1—*Continued*

Mutual Funds by 1982 Name	Wiesenberger Classification: Primary objective	Wiesenberger Classification: Investment policy	Mean	Standard Deviation	Minimum	Maximum
Panel B						
Benchmark Excess Returns						
1-Month T-bill (Gross)			0.60	0.22	0.25	1.35
Value-Weighted CRSP index			0.29	4.74	−22.23	16.29
S&P 500			0.30	4.65	−22.12	16.06
Government Bonds			0.08	3.26	−9.28	13.97
Junk Bonds			0.11	2.59	−8.97	11.74
Small cap			0.47	6.68	−29.79	27.09

Wiesenberger Classifications

Primary Objective		Investment Policy	
mcg	maximum capital gain	cs	holdings are predominantly common stock
g	growth	bal	balanced; both senior securities and cs are held at all times
i	income	bonds	investments concentrated in bonds
s	stability	c&i	holdings are primarily Canadian and/or international issues
tf	tax-free municipal bond	flex	flexibly diversified; usually, but not necessarily, balanced
		spec	specialized; holdings are concentrated in one or more specified industry groups or types of securities

ments for the index. The term spread is a constant-maturity 10-year Treasury bond yield less the 3-month Treasury bill yield. The corporate bond default-related yield spread is Moody's BAA-rated corporate bond yield less the AAA-rated corporate bond yield. The bond yields are the weekly average yields for the previous month, as reported by Citibase.

The issue of data mining arises in connection with the information variables. Data mining refers to the fact that many researchers in finance use the same data, and a chance correlation of future returns with a predictor variable is likely to be discovered as an "interesting" phenomenon. (See Lo and MacKinlay (1990) and Foster and Smith (1992) for analyses of data mining biases in asset pricing studies.) Extending the study of predictability to mutual funds is interesting, as the fund returns represent a new data set. However, to the extent that the assets held by funds are similar to those used in previous studies of predictability, the correlation implies that a data mining bias may be inherited by the funds. Also, the market index and factor returns that we use have been prominent in the predictability literature.

We assume that the lagged variables are readily available, public information over our entire sample period, which starts in 1968. Most of the academic studies of these variables appeared in the literature after 1968. Using our approach, a manager who knew in 1968 that dividend yields, interest rate levels, and yield spreads could be used to predict stock returns gets no credit for using this knowledge before it was promoted in the academic literature. However, similar variables were discussed as stock market indicators as early as Dow (1920) and Graham (1965), which suggests that investors knew about them long before they became prominent in the academic literature. Pesaran and Timmermann (1995) cite a number of additional studies from the 1930s to the early 1960s that emphasize stock market predictability based on interest rates, dividend yields, and other cyclical indicators. In a model-selection experiment designed to avoid hindsight, they confirm the importance of predictable components in stock returns.

C. The Risk Factors

We use the value-weighted CRSP index for all stocks listed on the NYSE as the market factor. We also examine a four-factor model. This model uses large stocks, small stocks, government bonds, and low-grade corporate bonds. Related factor models are examined by Elton *et al.* (1992), who use three factors; Sharpe (1988, 1991), who uses 10 to 12 factors; and the investment firm BARRA, which uses as many as 68 factors in their model. We chose a relatively parsimonious factor model because our application is mutual funds, as opposed to individual common stocks. Also, our conditional model requires that we estimate more parameters than an unconditional model, so parsimony becomes important.

In the four-factor model, the S&P 500 total return is used to represent large market capitalization (cap) equities. The small cap index from Ibbotson Associates represents stocks whose market values correspond to the ninth and tenth decile of market values on the NYSE. Starting in 1982, this small cap index corresponds to the performance of Dimensional Fund Advisors' nine-ten portfolio. The third factor is the return to a long-term (approximately 20-year) U.S. Government bond from Ibbotson Associates. Finally, low-grade corporate bond returns are based on the return series in Blume, Keim, and Patel (1991), updated using the Merrill Lynch High Yield Composite Index return.[12]

D. Naive Strategies

If naive strategies appear to have abnormal performance, it implies that our benchmarks are inefficient. This would call into question the measures of performance for the managed portfolios. We therefore construct three strategies to provide a basis of comparison. Each naive strategy enters 1968 with an initial set of weights: 65 percent large stocks, 13 percent small stocks, 20

[12] The Blume, Keim, and Patel series is used for 1968:01–1990:01, and the Merrill Lynch series is used for the last eleven months of 1990.

percent government bonds, and 2 percent low-grade bonds. The first strategy is a monthly rebalancing strategy, for which these weights are held fixed over the sample. The second is a buy-and-hold strategy, whose weights change over time as the relative values of the four asset classes evolve. A buy-and-hold strategy is passive, but its weights depend on relative values over time.[13] Third is an annual rebalancing strategy, which evolves as buy-and-hold unless the month is a January, in which case the weights are reset to the initial weights.

IV. Empirical Results

A. *The Statistical Significance of Conditioning Information*

In Table II, we regress each fund's excess return on the excess return of the market factor. The slopes and intercepts are estimates of the unconditional alpha and beta coefficients, as in equation (6). We also run the regressions for an equally-weighted portfolio of the funds within each fund group. The results are summarized in the left-hand columns, and labeled as the *unconditional* CAPM. Additional columns record the intercepts, α_p, the coefficients, δ_{1p}, and the R-squares of the regression model (4). These are denoted as the *conditional* CAPM.

Table II shows that the betas increase, moving down the table from the income funds to the maximum capital gain funds. The R-squares are slightly higher for the conditional model. The right-most column reports right-tail probability values for the F-test of the marginal explanatory power of conditioning information in the CAPM. The additional variables are significant at conventional levels for the equally-weighted portfolios of the fund groups, excepting the income fund group. The F-tests can reject the hypothesis that the additional variables do not matter, at the 5 percent level, for 50 of the 67 individual funds, and the average of the individual p-values is 0.06.

Heteroskedasticity-consistent Wald tests produce similar results: the p-values are below 0.05 for 43 of the 67 funds. We also compute heteroskedasticity- and autocorrelation-consistent Wald tests, using the Newey and West (1987) covariance matrix with an MA(1) term, and the results are similar. This is evidence of statistically significant movements in the conditional market betas, which are related to the public information variables.

[13] The weight vector of the buy-and-hold strategy evolves as:

$$x_{jt} = x_{j,t-1}(1 + R_{j,t}) \Big/ \left[\sum x_{j,t-1}(1 + R_{j,t}) \right].$$

We do not include a monthly rebalancing strategy for the four-factor model, because with constant weights a regression of this strategy's returns on the factors produces a perfect fit by construction.

Table II

Measures of Performance Using Conditional and Unconditional CAPMs

The coefficients a_p and b_p are the intercept and slope coefficients in the following regression:

$$r_{pt+1} = a_p + b_p r_{mt+1} + v_{pt+1}, \tag{6}$$

where r_{pt+1} is the excess return of a fund and r_{mt+1} is the excess return of the CRSP value-weighted market index. Heteroskedasticity-consistent t-ratios are shown as $t(.)$. For the conditional CAPM models, the regressions are:

$$r_{pt+1} = \alpha_p + \delta_{1p} r_{mt+1} + \delta'_{2p}(z_t r_{mt+1}) + \epsilon_{pt+1}, \tag{4}$$

where z_t is the vector of predetermined instruments, consisting of the dividend yield of the CRSP index, a Treasury yield spread (long- minus short-term bonds), the yield on a short-term Treasury bill, a corporate bond yield spread (low- minus high-grade bonds), and a dummy variable for Januarys. *Rsq* are the R-squares of the regressions and pval(F) is the right-tail probability value of the F-test for the marginal significance of the term including the predetermined variables. The funds are grouped by their Wiesenberger type as of 1982. Our "Special" category includes Scudder International and Templeton Growth, which have sizable holdings in foreign equity markets, Century Shares Trust, which holds primarily securities issued by financial firms, and Fidelity Capital Trust, which merged into Fidelity Trend in 1982. The data are monthly from 1968–1990, a total of 276 observations. The units are percentage per month.

Fund Types	Unconditional CAPM					Conditional CAPM					
	a_p	$t(a_p)$	b_p	$t(b_p)$	*Rsq*	α_p	$t(\alpha_p)$	δ_{1p}	$t(\delta_{1p})$	*Rsq*	pval(F)
Panel A: Averages of Individual Fund Regressions											
Income	0.0275	0.283	0.64	22.7	0.702	0.0601	0.604	0.64	26.6	0.727	0.078
Gro-Inc	−0.0572	−0.537	0.93	37.6	0.887	−0.0261	−0.244	0.93	42.4	0.895	0.066
Growth	−0.0766	−0.649	1.03	34.2	0.852	−0.0388	−0.340	1.04	39.6	0.863	0.058
Max. gain	−0.0804	−0.433	1.18	25.5	0.769	0.0842	0.539	1.19	30.5	0.784	0.070
Special	0.1980	0.928	0.81	15.6	0.619	0.2670	1.300	0.82	22.2	0.651	0.005
Overall	−0.0307	−0.304	0.92	33.4	0.817	0.0220	0.124	0.93	38.4	0.831	0.060
Panel B: Results for Equally-Weighted Portfolios of Funds											
Income	0.0275	0.43	0.64	41.5	0.892	0.0601	0.913	0.64	41.5	0.895	0.151
Gro-Inc	−0.0572	−1.66	0.93	118.	0.983	−0.0261	−0.766	0.93	127.0	0.984	0.008
Growth	−0.0766	−1.35	1.03	76.5	0.964	−0.0388	−0.715	1.04	86.4	0.966	0.004
Max. gain	−0.0804	−0.65	1.18	35.4	0.877	0.0842	0.683	1.19	42.9	0.888	0.001
Special	0.1980	1.93	0.81	29.7	0.837	0.2670	2.530	0.82	33.0	0.845	0.027
Overall	−0.0331	−0.73	0.92	80.5	0.971	0.0186	0.421	0.93	90.5	0.974	0.001

Tests for the significance of the individual information variables in the regressions produce little evidence that the January dummy or the default-related yield spread are important predictors, but the other instruments are important. This is interesting, as it suggests that our results are not driven by

January seasonals or the default spread resolving CAPM-related biases, such as the small firm effect.[14]

B. Performance Measured by Alpha

The evidence on the unconditional alphas of managed portfolios remains controversial. Jensen (1968) found that mutual funds had negative alphas on average, adjusting for fees. Ippolito (1989) found positive alphas in a more recent sample. Elton *et al.* (1992) argue that the positive alphas in Ippolito's sample may be explained by funds' holdings of asset classes that have positive alphas. Using a multiple-factor benchmark, they confirm Jensen's result that mutual funds' unconditional alphas tend to be negative.

Table III focuses on the cross-sectional distributions of the t-ratios for the alphas. The table shows the minimum and maximum of the t-statistics for each model, together with their "Bonferroni p-values." These are based on the Bonferroni inequality. 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, pN. The Bonferroni p-value places a conservative upper bound on the p-value of a joint test. It is computed as the smallest of the N p-values for the individual tests, multiplied by N, which is the number of funds. The Bonferroni p-values are one-tailed tests of the hypothesis that all of the alphas are zero against the alternative that at least one is positive (maximum value) or negative (minimum value).

All of the extreme t-ratios are significant by the Bonferroni test, excepting the minimum ones in the CAPM models, rejecting the joint hypothesis of zero alphas. However, the tabulation shows more observations in the tails than would be expected, given a t-distribution (which, with more than 200 degrees of freedom, is close to a normal distribution). The left tails are thicker than the right tails in both of the unconditional models. The distribution of the t-ratios shifts to the right when the conditioning information is introduced into the models. (We replicate this analysis, excluding the special fund group, and the results are similar.)

Overall, Jensen's measure would lead to the inference that the funds have more negative than positive alphas. In the unconditional CAPM, about two-thirds of the point estimates of the alphas are negative, including all but three of the growth funds. Of the 13 "significant" (absolute t-ratio larger than 2.0) alphas, eight are negative. (The t-statistics are heteroskedasticity consistent. The results are the same when they are also adjusted for autocorrelation using the Newey-West covariance matrix.) Based on a simple binomial test, the

[14] We also construct Bayesian odds ratios to examine the importance of the lagged variables. Using an uninformed prior, the odds ratios confirm that the January dummy and default spread variables are not important predictors, and that the other variables are jointly and individually important.

Table III

Cross-sectional Distribution of *t*-statistics for the Alphas in Conditional and Unconditional Models

For the CAPM, the unconditional alphas are the intercepts in regressions for the excess returns of the funds on the excess return of the CRSP value-weighted market index. The conditional alphas are the intercepts in regressions of fund excess returns on the CRSP index and the product of the index with a vector of predetermined instruments. The unconditional alphas in the four-factor models are the intercepts in regressions of the excess returns of the funds on the four factors, which are the S&P 500 index, the small stock index, the government bond index and the low-grade corporate bond index. The factor returns are measured in excess of the one-month Treasury bill. The conditional alphas in the four-factor models are the intercepts when fund excess returns are regressed over time on the factors and the products of the factors with the vector of predetermined instruments. The distributions of the heteroskedasticity-consistent t-ratios for the alphas are summarized. The numbers in each of the four right-hand columns in the body of the table are the number of mutual funds for which the t-statistics for the alphas fell within the range of values indicated in the far left hand column. The Bonferroni p-value is the maximum or minimum one-tailed p-value from the t-distribution, across all of the funds, multiplied by the number of funds, which is 67. The instruments are the dividend yield of the CRSP index, a yield spread (long- minus short-term bonds), the yield on a short-term Treasury bill, a corporate bond yield spread (low- minus high-grade bonds), and a dummy variable for Januarys. The data are monthly from 1968–1990, a total of 276 observations.

	CAPM		Four-Factor Models	
	Unconditional	Conditional	Unconditional	Conditional
Minimum t-statistic	−2.78	−2.71	−4.08	−3.80
Bonferroni p-value	0.194	0.238	0.002	0.006
$t < -2.326$	5	5	8	3
$-2.326 < t < -1.960$	4	1	4	3
$-1.960 < t < -1.645$	4	3	5	4
$-1.645 < t < -1.282$	4	5	4	3
$-1.282 < t < 0.0$	26	20	25	25
$0.0 < t < 1.282$	15	18	13	19
$1.282 < t < 1.645$	1	5	0	0
$1.645 < t < 1.960$	3	4	4	3
$1.960 < t < 2.326$	1	2	2	2
$t > 2.326$	4	4	2	2
Maximum t-statistic	3.89	4.90	3.80	6.40
Bonferroni p-value	0.004	0.000	0.006	0.000

t-statistic for the hypothesis that 50 percent of the alphas are positive is −2.32.[15]

Previous studies finding negative unconditional alphas interpreted them as indicating poor performance. However, it is difficult to know where the distri-

[15] The t-statistic is $(0.5\text{-}x)/[(0.5)(0.5)/67]^{1/2}$, where x is the fraction of the 67 alpha estimates that are negative. This calculation ignores the correlation across the funds. We present joint tests below which account for cross-equation correlation.

bution of the alphas should be centered under the hypothesis of no abnormal performance. For example, the presence of transactions costs, some of which are deducted from the funds' returns but not from the benchmark returns, suggests that the alphas should be centered to the left of zero. The presence of survivorship bias, on the other hand, shifts the distribution of alphas to the right.

The negative unconditional alphas may reflect a bias caused by omitting public information that is correlated with the portfolio betas, as is suggested by our hypothetical example in Section I and the evidence that the predetermined variables are significant. The "conditional alphas" are the intercepts from equation (4). About half (34 of 67) of these estimates are negative, and half are positive. The binomial test produces a t-statistic of -0.12. There are 12 funds whose conditional alphas have t-statistics larger than two in absolute magnitude. Of these, exactly half (6) are negative, and half are positive. (The results for autocorrelation-consistent t-statistics are the same.) Thus, a simple adjustment to condition on public information has removed the inference of the traditional approach that mutual fund alphas tend to be negative.

We repeat our analysis of alphas, using the four-factor asset pricing model. The four-factor model is motivated by previous evidence that the value-weighted index is not an efficient portfolio. Roll (1978) shows that, given an inefficient benchmark, seemingly small variations in the benchmark can have a large impact on alphas. Grinblatt and Titman (1994) also find that measures of (unconditional) performance can be sensitive to the choice of the benchmark.

Moving from a simple CAPM to the four-factor model does not change the result that the unconditional alphas tend to be negative more often than would be attributed to chance. For example, of the 67 point estimates of the unconditional alphas, 46 are negative. The t-statistic for the alpha of an equally-weighted portfolio of the funds is -1.71. Using the conditional four-factor model, only 38 of the 67 point estimates of α_p are negative, and the t-statistic for the alpha of an equally-weighted portfolio of the funds is 0.14. Overall, introducing the conditioning information seems to have a greater impact on the measures of performance than does moving from the single-factor to the four-factor model.

C. Joint Tests

The summary statistics used above to describe the overall effects of conditioning information on the alphas do not discriminate between funds with different investment objectives and do not account for dependence of the regressions across funds. To account for these effects, we conduct joint tests across the equations. We pool the funds according to their Wiesenberger types, form five equally-weighted portfolios of the funds, and stack the regressions for the portfolios into a system of five equations. We restrict the alphas to be zero in each equation and estimate the systems using Hansen's (1982) generalized method of moments (GMM). The GMM is robust to nonnormality and allows for time-varying conditional heteroskedasticity. Such an approach is appropriate in view of the fat tails of the distributions and the assumption that betas may vary with information in the conditional models. The restrictions are tested using the standard GMM chi-square goodness-of-fit statistic.

The tests reject the hypothesis that the unconditional alphas are jointly zero in the CAPM (and four-factor model), the test producing a right-tail probability value equal to 0.07 (0.02). This confirms our previous observation that there are more negative unconditional alphas than would be attributed to chance. The tests for zero conditional alphas also reject the joint hypothesis, producing right-tail probability values of 0.01 (0.04). However, inspecting the coefficients for the equally-weighted portfolios suggests that the rejection of zero alphas for the conditional model is driven by the large positive alpha of the special group, which includes the international funds. When we repeat the tests with only four portfolios, excluding the special group, we find that no test can reject the hypothesis that the alphas are jointly zero.

D. Market Timing: Results for the Naive Strategies

Table IV presents an initial analysis of the market timing models, using the naive strategies. If the models are well-specified, the naive strategies should not show evidence of abnormal performance. In the unconditional version of the Treynor-Mazuy model, the table shows that the buy-and-hold strategy has a negative timing coefficient, with a t-statistic of -3.76, and a positive alpha, with a t-statistic of 2.01. In the unconditional Merton-Henriksson model, the buy-and-hold strategy has a negative timing coefficient, with a t-statistic of -1.84, and a positive alpha, with a t-statistic of 1.86. These results are similar to those of Jagannathan and Korajczyk (1986), who show that naive strategies may exhibit option-like characteristics and hence have timing coefficients and alphas with opposite signs. These results indicate a clear misspecification of the unconditional market timing models.

In the conditional version of the Treynor-Mazuy model, none of the naive strategies have significant alphas or timing coefficients, and the same is true in the conditional Merton-Henriksson model. This is interesting, as it suggests that conditional timing models can control misspecification in the unconditional models. The conditional models may therefore be more informative about the performance of fund managers than the unconditional models.

E. Market Timing: Results for Mutual Funds Using the Treynor-Mazuy Model

Table V reports the Treynor-Mazuy (1966) regressions for mutual funds. For the unconditional model (8), we find 44 of the 67 estimates of the timing coefficient are negative, and all of the estimates for the maximum gain funds are negative. Of the 11 individual timing coefficients larger than two standard errors, eight are negative. The timing coefficient for an equally-weighted portfolio of all of the funds has a t-statistic of -2.47. Each of the equally-weighted portfolios by fund group, except the income funds, has a t-statistic

Table IV

Market Timing Models: Results for Naive Strategies

The three naive strategies are portfolios of four broad indexes: large stocks, small stocks, government bonds, and low-grade corporate bonds. The portfolio weights of the strategies differ as described in the text. For the unconditional Treynor-Mazuy models, the timing coefficient is the regression coefficient on the squared excess market return in a regression for the excess return of the strategy on the excess return of the CRSP value-weighted market index and its square, and α is the intercept. In the conditional Treynor-Mazuy models, the regressions include the products of the lagged instrumental variables with the excess return of the market index. For the unconditional Merton-Henriksson models, α is the intercept coefficient in regressions for the excess strategy returns on the excess return of the CRSP value-weighted market index and a variable equal to the maximum of the index excess return or zero. The timing coefficient is the slope coefficient on the maximum of the index or zero. For the conditional Merton-Henriksson models, fund excess returns are regressed over time on the CRSP index, the product of the index with a vector of predetermined instruments, the variable r_m^* and the product of r_m^* and the instruments, where r_m^* is the product of the index excess return and an indicator dummy for positive values of the difference between the index excess return and the conditional mean of the excess return, which is estimated by a linear regression on the instruments. The coefficient α is the intercept. Heteroskedasticity-consistent t-ratios are reported for all coefficients. The instruments are the dividend yield of the CRSP index, a Treasury yield spread (long- minus short-term bonds), the yield on a short term Treasury bill, a corporate bond yield spread (low- minus high-grade bonds), and a dummy variable for Januarys. The data are monthly from 1968–1990, a total of 276 observations. The units for the alphas are percentage per month.

Models	α	$t(\alpha)$	Timing Coefficient	t-Statistic
		Panel A: Treynor-Mazuy Models		
Unconditional models				
Buy-and-hold	0.082	2.01	−0.004	−3.76
Annual rebalance	0.047	1.09	−0.001	−0.82
Fixed weights	0.004	0.08	0.001	0.74
Conditional models				
Buy-and-hold	0.057	1.39	−0.001	−0.93
Annual rebalance	0.037	0.82	0.000	0.12
Fixed weights	0.001	0.02	0.001	1.10
		Panel B: Merton-Henriksson Models		
Unconditional models				
Buy-and-hold	0.121	1.86	−0.065	−1.84
Annual rebalance	0.045	0.72	−0.010	−0.33
Fixed weights	−0.021	−0.32	0.026	0.77
Conditional models				
Buy-and-hold	0.055	1.03	−0.010	−0.33
Annual rebalance	0.028	0.50	0.009	0.29
Fixed weights	−0.011	−0.20	0.028	0.94

smaller than −1.90. A chi-square test across the five groups strongly rejects the hypothesis that the coefficients are jointly zero (p-value less than 0.001). Thus, the evidence is consistent with Grinblatt and Titman (1988) and Cumby

Table V

Conditional and Unconditional Measures of Timing and Selectivity: The Treynor-Mazuy Model

The unconditional timing coefficient is the regression coefficient on the squared excess market return in a regression for the excess return of the fund on the excess return of the CRSP value-weighted market index and its square. For the conditional timing coefficients, the regressions also include the products of the lagged instrumental variables with the excess return of the market index. The alphas are the intercepts of the regressions. Heteroskedasticity-consistent t-ratios are reported for all coefficients, and denoted as t-stat. The instruments are the dividend yield of the CRSP index, a Treasury yield spread (long- minus short-term bonds), the yield on a short-term Treasury bill, a corporate bond yield spread (low- minus high-grade bonds), and a dummy variable for Januarys. The funds are grouped by their Wiesenberger type as of 1982. Our "special" category includes Scudder International and Templeton Growth, which have sizable holdings in foreign equity markets, Century Shares Trust, which holds primarily securities issued by financial firms, and Fidelity Capital Trust, which merged into Fidelity Trend in 1982. The data are monthly from 1968–1990, a total of 276 observations. The units for the alphas are percentage per month.

	Unconditional Timing		Conditional Timing		Unconditional Alphas		Conditional Alphas	
	Coefficient	t-stat	Coefficient	t-stat	Coefficient	t-stat	Coefficient	t-stat
Panel A: Averages of Individual Fund Regressions								
Income	0.0005	0.086	0.0039	1.16	0.015	0.216	−0.000	−0.019
Gro-Inc	−0.0014	−0.452	0.0010	0.54	−0.026	−0.198	−0.041	−0.434
Growth	−0.0023	−0.496	0.0009	0.40	−0.025	−0.291	−0.052	−0.545
MaxGain	−0.0096	−2.180	−0.0018	−0.36	0.137	0.848	0.112	0.726
Special	−0.0103	−2.160	−0.0121	−2.23	0.432	2.090	0.454	2.310
Overall	−0.0028	−0.810	0.0003	0.31	0.036	0.211	0.018	0.002
Panel B: Results for Equally-Weighted Portfolios of Funds								
Income	0.0005	0.38	0.0039	1.72	0.015	0.230	−0.000	−0.005
Gro-Inc	−0.0014	−2.33	0.0010	1.07	−0.026	−0.703	−0.041	−1.140
Growth	−0.0023	−1.90	0.0009	0.57	−0.025	−0.408	−0.052	−0.870
MaxGain	−0.0096	−2.70	−0.0018	−0.44	0.137	1.030	0.112	0.870
Special	−0.0103	−4.37	−0.0121	−3.52	0.432	4.020	0.454	4.170
Overall	−0.0028	−2.47	0.0004	0.31	0.030	0.618	0.012	0.247

and Glen (1990), who found negative timing coefficients in unconditional Treynor-Mazuy regressions.

A negative timing coefficient may arise if the manager has the perverse ability to predict market moves, but systematically in the wrong direction. This makes little sense, because an investor could profit by trading against such a manager. Negative timing coefficients may also reflect the use of options and related strategies, but there is no evidence of significant positive alphas to offset the negative unconditional timing coefficients in Table V, excepting for the special group of funds. We do not believe the results of the unconditional models to be reliable. The evidence in the preceding section shows that a negative timing coefficient may arise in an unconditional model, even if the manager follows a buy-and-hold strategy, as the unconditional model is misspecified.

Using our conditional version of the Treynor-Mazuy regressions, we find very different results. Of the 67 point estimates of the conditional timing coefficients for the individual funds, only 27 are negative. There are 13 with t-ratios larger than two in absolute magnitude, of which only two are negative. The t-statistic for the timing coefficient of an equally-weighted portfolio of the funds is +0.31. There is no evidence of systematic nonzero alphas in these models, excepting the special fund group. Overall, except for the special group, incorporating conditioning information has essentially removed the findings of negative timing coefficients in the unconditional model.

The special funds stand out as being different. This group has a strong positive alpha and a significant negative timing coefficient, even in the conditional Treynor-Mazuy model. This may not be surprising in view of the fact that the results for the special group are driven largely by the Templeton Growth Fund and the Scudder International Fund. Glosten and Jagannathan (1994) also find positive (unconditional) alphas for the Templeton Growth Fund. The pattern of the coefficients is consistent with a portfolio strategy similar to writing covered call options. However, these funds concentrate in international investments, and studies such as Ferson and Harvey (1993) and Schadt (1995) show that different factors are needed to explain international equity returns. These results suggest that even the conditional Treynor-Mazuy model is probably not appropriate for evaluating the special group.

F. Market Timing: Results for Mutual Funds Using the Merton-Henriksson Model

Table VI summarizes results for the Merton-Henriksson (1981) model, using equations (10) and (11). In the unconditional model, 46 of the 67 estimates of the timing coefficients are negative, including all of the estimates for the maximum gain funds. The binomial test of the hypothesis that 50 percent of the coefficients are positive produces a t-statistic of −3.05. Of the seven coefficients larger than two standard errors, six are negative. The coefficient for an equally-weighted portfolio of the funds has a t-statistic of −2.38. The chi-square test strongly rejects the hypothesis that the coefficients are jointly zero (p-value = 0.008). Based on the unconditional model, the mutual funds' market timing again appears to be of the "wrong" sign. This evidence is consistent with the results of Chang and Lewellen (1984), Henriksson (1984), and Glosten and Jagannathan (1994), and similar to our results for the Treynor-Mazuy regressions.

The results for the conditional model are quite different. There are 25 negative point estimates for the 67 funds, which produces a t-statistic for the hypothesis that 50 percent are negative, equal to +2.08. The chi-square test of

Table VI

Conditional and Unconditional Measures of Timing and Selectivity: The Merton-Henriksson Model

For the unconditional models, alpha is the intercept in regressions for the excess returns of the funds on the excess return of the CRSP value-weighted market index and a variable equal to the maximum of the index excess return or zero, and $t(\alpha)$ is the heteroskedasticity-consistent t-statistic. In the unconditional models, the timing coefficient gamma is the slope coefficient on the maximum of the index or zero, and $t(\gamma)$ is the heteroskedasticity-consistent t-statistic. For the conditional models, fund excess returns are regressed over time on the CRSP index, the product of the index with a vector of predetermined instruments, the variable r_m^* and the product of r_m^* and the instruments, where r_m^* is the product of the index excess return and an indicator dummy for positive values of the difference between the index excess return and the conditional mean of the excess return, where the conditional mean is estimated by a linear regression on the instruments. In the conditional models alpha is the intercept in this regression and gamma is the slope coefficient on the product of r_m^* and the instruments, and $t(\alpha)$ and $t(\gamma)$ are the heteroskedasticity-consistent t-statistics. The instruments are the dividend yield of the CRSP index, a Treasury yield spread (long- minus short-term bonds), the yield on a short-term Treasury bill, a corporate bond yield spread (low- minus high-grade bonds), and a dummy variable for Januarys. The funds are grouped by their Wiesenberger type as of 1982. Our "special" category includes Scudder International and Templeton Growth, which have sizable holdings in foreign equity markets, Century Shares Trust, which holds primarily securities issued by financial firms, and Fidelity Capital Trust, which merged into Fidelity Trend in 1982. The data are monthly from 1968–1990, a total of 276 observations. The units for the alphas are percentage per month.

	Unconditional Model				Conditional Model			
Fund	α	$t(\alpha)$	γ	$t(\gamma)$	α	$t(\alpha)$	γ	$t(\gamma)$
Panel A: Averages of Individual Fund Regressions								
Income	0.009	0.114	0.0099	0.11	−0.006	−0.114	0.0587	0.894
Gro-Inc	−0.001	0.003	−0.0308	−0.32	−0.057	−0.508	0.0261	0.500
Growth	0.031	0.010	−0.0594	−0.46	−0.053	−0.550	0.0119	0.344
MaxGain	0.391	1.560	−0.2590	−1.97	0.179	0.880	−0.0576	−0.496
Special	0.742	2.290	−0.2990	−1.77	0.641	2.780	−0.2610	−2.200
Overall	0.109	0.465	−0.0758	−0.68	0.033	0.008	−0.0014	0.216
Panel B: Results for Equally-Weighted Portfolios of Funds								
Income	0.009	0.106	0.0099	0.22	−0.006	−0.065	0.0587	1.200
Gro-Inc	−0.001	−0.030	−0.0308	−1.43	−0.057	−1.230	0.0261	1.110
Growth	0.031	0.389	−0.0594	−1.59	−0.053	−0.669	0.0119	0.293
MaxGain	0.391	2.100	−0.2590	−2.84	0.179	1.050	−0.0576	−0.626
Special	0.742	5.470	−0.2990	−4.86	0.641	4.910	−0.2610	−3.450
Overall	0.102	1.560	−0.0746	−2.38	0.025	0.397	0.0013	0.039

the hypothesis that the coefficients are jointly zero produces a right-tail p-value of 0.004. Of the seven coefficients more than two standard errors from zero, only three are negative. The t-statistic for the equally-weighted portfolio of the funds is +0.04. Based on the conditional model, and excepting the special group, we no longer find the mutual funds' market timing to be of the "wrong" sign. If anything, the timing coefficients reveal some weak evidence of positive market timing ability, once we control for the predetermined information variables.

G. Conclusions About the Market-Timing Models

Table VII summarizes the cross-sectional distributions of the t-ratios associated with the key timing coefficients in the four market timing models. The Bonferroni p-values indicate that the extreme t-ratios are significantly different from zero, except for the maximum values in the unconditional timing models, but the tails of the distributions are thicker than the normal. In both of the timing models the distribution of the t-ratios shifts to the right when the conditioning information is introduced. The right tails of the distributions are thicker and the left tails are thinner than in the unconditional models. It is clear that introducing the conditioning information makes a dramatic impact on the results of the timing models.

Both the Treynor-Mazuy and the Merton-Henriksson models are motivated using strong assumptions about how mutual fund managers use any superior information that they might have. When these strong assumptions fail, the models will not separate timing and selectivity. As the assumptions are unlikely to be true, the models may be viewed as approximations to a more complicated relation between the portfolio weights of the managers and the future market return. In the unconditional versions of the models, the underlying asset betas are assumed to be constant. The Treynor-Mazuy model approximates the relation between managers' weights and the future market return by a linear function, while the Merton-Henriksson model uses an indicator function (the weight is either zero or one, depending on the forecast of the market return). In our conditional versions of the models, the assumptions are simple extensions of the assumptions in the original models.

While our extensions of these models are adequate to illustrate that the use of conditioning information is important, we do not advocate using them to evaluate managers in practice. For example, even the conditional timing models are likely to be misspecified when applied to funds with sizable holdings of non-U.S. stocks. We believe that the development of more sophisticated and realistic market timing models in the presence of conditioning information is an important problem for future research.

H. Interpreting the Empirical Results

The evidence shows that the use of conditioning information makes the performance of the funds in our sample look better. We can interpret these results using a simple specification analysis. In Table II we found that the unconditional betas are typically slightly smaller than the average conditional betas. From equation (7), if the conditional alphas are larger than the unconditional alphas for a typical fund, it implies that the term $B_p'\text{Cov}(z; r_m)$ is negative for the typical fund. (We examine the sample values of this term and

Table VII

The Cross-sectional Distribution of t-statistics for the Key Timing Coefficients in Conditional and Unconditional Market Timing Models

For the Treynor-Mazuy model, the unconditional timing coefficient is the regression coefficient on the squared excess market return in a regression for the excess return of the fund on the excess return of the CRSP value-weighted market index and its square. In the conditional Treynor-Mazuy models, the regressions include the products of the lagged instrumental variables with the excess return of the market index, and the timing coefficient is the regression coefficient on the squared excess market return. For the unconditional Merton-Henriksson models, the regression is the excess return of the fund on the excess return of the CRSP value-weighted market index and a variable equal to the maximum of the index excess return or zero. The unconditional timing coefficient is the slope coefficient on the variable defined as the maximum of the index or zero. For the conditional Merton-Henriksson models, fund excess returns are regressed over time on the CRSP index, the product of the index with a vector of predetermined instruments, the variable r_m^* and the product of r_m^* and the instruments, where r_m^* is the product of the index excess return with an indicator dummy for positive values of the difference between the index excess return and the conditional mean of the excess return, estimated by a linear regression on the instruments. The instruments are the dividend yield of the CRSP index, a yield spread (long- minus short-term bonds), the yield on a short-term Treasury bill, a corporate bond yield spread (low- minus high-grade bonds), and a dummy variable for Januarys. The distributions of the heteroskedasticity-consistent t-ratios for the coefficients are summarized. The numbers in each of the four right-hand columns in the body of the table are the number of mutual funds for which the t-statistics for the alphas fell within the range of values indicated in the far-left-hand column. The Bonferroni p-value is the maximum or minimum one-tailed p-value from the t-distribution, across all of the funds, multiplied by the number of funds, which is 67. The data are monthly from 1968–1990, a total of 276 observations.

	Treynor-Mazuy		Merton-Henriksson	
	Unconditional	Conditional	Unconditional	Conditional
Minimum t-statistic	−5.98	−4.01	−4.15	−3.74
Bonferroni p-value	0.000	0.003	0.002	0.008
$t < -2.326$	6	2	5	2
$-2.326 < t < -1.960$	2	1	2	2
$-1.960 < t < -1.645$	4	3	4	1
$-1.645 < t < -1.282$	12	5	2	1
$-1.282 < t < 0.0$	20	16	33	19
$0.0 < t < 1.282$	16	25	15	31
$1.282 < t < 1.645$	2	4	5	4
$1.645 < t < 1.960$	2	0	0	3
$1.960 < t < 2.326$	2	3	1	2
$t > 2.326$	1	8	0	2
Maximum t-statistic	2.43	4.16	2.05	3.33
Bonferroni p-value	0.524	0.001	1.38	0.033

confirm that this is the case.) In other words, the component of the correlation of mutual fund betas with the future market return that can be attributed to the predetermined information tends to be negative. Since the future market return can be written as $r_m = E(r_m|Z) + \epsilon$, and ϵ is uncorrelated with Z, we can replace r_m in the above term with $E(r_m|Z)$. A similar interpretation is implied by the results of the market timing models.[16]

Why would fund managers tend to reduce their market betas when public information implies relatively high expected market returns, and/or raise them when expected returns are relatively low? Managed portfolio betas can change because the portfolio weights are managed or because the underlying asset betas change. The phenomenon could arise, therefore, from the underlying assets held by mutual fund managers. There is some weak evidence in favor of this interpretation. The buy-and-hold strategy produces negative timing coefficients in the unconditional timing models, and the coefficient is close to zero in the conditional models. If fund portfolios are concentrated in large stocks, the patterns of beta variation suggested by these results are consistent with the time-variation in large stock betas (negative correlation with expected market returns), as suggested by Chan and Chen (1988) and documented by Ferson and Harvey (1991) and Jagannathan and Wang (1996).

Movements in the underlying asset betas, however, are unlikely to fully explain our results. The response coefficients for the funds' betas are significantly different from those of the buy-and-hold strategy. Also, we find negative alphas for the funds, but not for the buy-and-hold strategy, in the unconditional Jensen model. Deviations in mutual fund portfolio weights from the buy-and-hold strategy are probably important.

One hypothesis is that the movements in beta are driven by the flow of money into mutual funds. If more new money flows into the funds when the public perceives expected stock returns to be high, and if managers take some time to allocate new money according to their usual investment styles, then the funds would have larger cash holdings at such times. Larger cash holdings imply lower betas. Of course, the effects of new money flows on the fund's betas will depend on the magnitudes of the flows, relative to the size of the asset holdings. To investigate this *new money-flow hypothesis,* it is necessary to use data on the flow of money, fund distributions, and redemptions.[17]

Warther (1995) studies aggregate money flows for classes of mutual funds. In private communication he provided a separate analysis of our time-varying

[16] For example, if the conditional version of the Treynor-Mazuy model, equation (9), is assumed to be the "true" model, then the unconditional model (8) has a left-out-variables bias. The OLS estimate of the unconditional timing coefficient will converge, under standard assumptions, to $\gamma_{tmc} + \mathrm{Cov}(C_p'zr_m;\, r_m^2)$, where the time subscripts have been suppressed. The covariance term arises when funds' betas are related to the future market return through the public information. Our results indicate that this covariance is negative for the average fund. We can simplify the covariance term by considering a regression of the vector of information variables on the future market return. Let A be the vector of the slopes of this regression and assume that the error terms are independent of r_m. Then, the probability limit of the unconditional timing coefficient is $\gamma_{tmc} + (C_p'A)\mathrm{Var}(r_m^2)$. Our results suggest that $C_p'A = \Sigma_j C_{pj} A_j$ is negative for the average fund, where C_{pj} measures the response of the fund's beta to the public information variable Z_j, and A_j measures the relation of Z_j to the future market return.

[17] Since the new money-flow hypothesis relies on unspecified market "frictions," it may be theoretically inconsistent with the CAPM. Future research into the determinants of mutual fund risk-taking behavior may require theoretical models which accommodate market frictions.

conditional betas. The net new money for a group of mutual funds is defined by Warther as the net sales (the dollar value of new shares sold, excluding automatically-reinvested dividends), normalized by the lagged aggregate stock market value. Warther finds that changes in net new money are negatively related to changes in our estimated mutual fund betas. In monthly regressions for 1976:03 to 1990:12, of beta changes on new money changes, the t-statistics for the slope coefficients are between -2.8 and -3.9, depending on the fund group. This is consistent with our conjecture that funds' betas are lower when more new money flows into the funds.

Warther finds that, on average, funds invest about 62 cents of each new dollar in the concurrent month, while 38 cents goes into cash. He also analyzes the relation between new money inflows and the portfolio weight in cash, and he finds a significant positive relation between the two. When inflows are large, cash balances tend to increase. While Warther's analysis of our conditional betas is preliminary, the results are consistent with our conjecture that fund betas change in response to larger cash positions associated with net inflows of new money. A more comprehensive analysis of these relations should be interesting. (We are grateful to Professor Warther for contributing this analysis.)

I. Conditional Betas and Fund Strategy

This section summarizes the main observations from our examination of the conditional beta functions. Since the funds' beta functions are significantly different from the passive strategies, they may provide additional insights into active management behavior.

Wiesenberger uses an internal approach to fund classification, which means that funds are grouped using data on their asset holdings. Our approach measures fund strategy by the response of the exposures to public information, without the need for asset holdings data. It is interesting to compare the two approaches. We conduct a simple analysis of variance in which we regress the cross-section of the average risk exposures to each factor on dummy variables indicating the group to which the fund is assigned. We exclude the funds in our special category from this analysis. These regressions indicate that the fund groupings capture 25 to 49 percent of the variance of the average sensitivities of the funds. Thus, the groupings are related to the average risk exposures, but there is still significant variation of the exposures within a fund category.

We conduct a similar analysis of variance for the beta response coefficients, B_p. The results show that the Wiesenberger fund groupings are also related to the dynamic behavior of the risk exposures. For example, the sensitivity of the conditional market betas to the dividend yield increases, moving from the income funds to the maximum capital gain funds. The income fund betas are generally more sensitive to shifts in the term structure and the quality-related yield spread than are the growth funds.[18] In the four-factor models, the coefficients measuring the sensitivity of the factor betas to the slope of the term structure are significant for half of the income funds. However, the signs of the coefficients differ across the funds, which suggests that different income funds may adopt different strategies in response to changes in the term structure. There is more variation of the beta response coefficients than of the average exposures, within a fund group. This makes sense if managers within a fund group adopt similar long run investment policies, but may use different short run strategies. We believe that a more in-depth analysis of mutual funds' conditional betas should be interesting.

V. Robustness of the Results

A. Subperiod and Out-of-Sample Analyses

We split the sample into two equal subperiods with 138 observations each. Estimating the Jensen's alphas on the subperiods produces results similar to the full sample. The unconditional alphas are negative more often than positive, and the distribution of the alphas and of their t-ratios shifts to the right when the conditioning information is introduced.[19]

The timing coefficients from the Treynor-Mazuy models present a similar picture in the first subperiod as in the full sample, and moving from the unconditional to the conditional model shifts the distribution of the coefficients to the right. We find more negative timing coefficients in the second subperiod than in the full sample. The estimates of the alphas present similar impressions in the subperiods as in the full sample period. In the Merton-Henriksson timing models, we find that the distribution of the timing coefficients and the alphas are similar in both subperiods to the results for the full sample.

We conduct out-of-sample experiments in which we estimate the CAPM and four-factor models using the data to 1985. We call these coefficients the *historical* alphas and betas. Then, using the last 60 months of data (1986–1990), we estimate alphas for both the conditional and unconditional models. The *out-of-sample alphas* use the sample means for the last 60 months and the historical regression betas or beta-response function coefficients. The *last-*

[18] Many of the response coefficients for the dividend yield (and 23 of the 25 significant ones) are negative, which suggests that managers reduce their market exposure when equity yields are high. The passive, buy-and-hold strategy has a t-statistic of -2.4. Since the dividend yield goes up when stock prices go down, the buy-and-hold strategy may automatically reduce its stock market exposure. Such a "price effect" can induce a negative response coefficient. The monthly rebalancing strategy does not display a dividend yield effect.

[19] We find that 40 of the 67 unconditional CAPM alphas are negative in the second subperiod and all seven with absolute t-ratios larger than two are negative. Thirty-eight of the conditional alphas are negative, but only five t-ratios are significant, and only two of these are negative. The Bonferroni p-values for the hypothesis of a negative alpha are less than 0.10 for all of the unconditional models, with the single exception of the unconditional CAPM in the second subperiod (p-value = 0.102). Only 28 of the conditional CAPM alphas in the first subperiod are negative, five t-ratios are smaller than -2.0, and ten t-ratios are larger than $+2.0$.

period alphas use coefficients estimated with only the last 60 months of data. We find that the mass of the distributions of both of these estimated alphas shifts to the right when the conditioning information is introduced.

B. The Persistence of Performance

We calculate the cross-sectional correlations of the individual alphas in the first and second halves of the sample. The correlation of the unconditional CAPM alphas is 0.26 and the correlation of the alphas in the conditional CAPM is 0.29, so this evidence of persistence in the alphas is similar in both models. However, previous studies have found that persistence in performance may be concentrated in the extreme-performance funds. We delete roughly the top and bottom 10 percent (seven each) of the alphas in the first subperiod and calculate the correlations on the remaining sample. The correlation of the alphas in the conditional CAPM is only 0.14 when the tails are removed, while using the unconditional CAPM the correlation on the subsample is 0.32. This suggests that persistence concentrated in the extreme performers may be more easily detected using conditional methods. We believe that future research should use conditional models to further study the persistence in mutual fund performance.[20]

VI. Concluding Remarks

This paper explores the effects of incorporating lagged information variables in the analysis of investment performance, an approach that we call *conditional performance evaluation.* In contrast to traditional methods based on unconditional returns, we take the view that a managed portfolio strategy that uses only readily available public information does not imply abnormal performance. Using monthly data for 67 mutual funds over the 1968–1990 period, we find evidence that their risk exposures change in response to public information on the economy. The use of conditioning information in performance measurement is both statistically and economically significant.

Traditional measures of average performance (Jensen's alpha) are negative more often than positive, which has been interpreted as inferior performance. Both a simple CAPM and a four-factor model produce this result in our sample. However, using conditional models, the distribution of alphas shifts to the right and is centered near zero.

Traditional measures of market timing suggest that the typical mutual fund takes more market exposure when stock returns are low. This has been interpreted as perverse market timing ability. Alternatively, the negative timing coefficients can reflect the importance of written call or put options, or other derivative strategies. We find that unconditional versions of the Treynor-Mazuy (1966) and Merton-Henriksson (1981) market timing models are misspecified when applied to naive strategies, and that conditional versions of

[20] See Christopherson *et al.* (1994) for a study of persistence in pension manager performance using conditional models.

these models are an improvement. Using the conditional market timing models for U.S. equity funds, the evidence of perverse market timing for the typical fund is removed.

The relatively pessimistic results of the traditional measures is attributed to common time-variation in the conditional betas and the expected market return. When this predictability is ignored, fund managers as a group show spurious inferior performance. This "inferior" performance is primarily due to a negative covariance between mutual fund betas and the conditional expected market return. When the common variation is controlled using lagged instruments, the conditional models make the performance of the funds in our sample look better. Our results suggest that there is much more interesting work to be done. Incorporating public information variables into the analysis of investment performance is an important area for future research.

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