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Conditional Performance Evaluation, Revisited

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PRELIMINARY

ABSTRACT

This monograph revisits and extends major empirical findings of the literature on *conditional performance evaluation (CPE)* for U.S. equity mutual funds. This approach allows expected performance and fund risk to vary over time with the state of the economy. We use an improved and expanded data set, a more extensive list of variables reflecting the state of the economy than in previous work, and some refinements in methodology. Among various proxies for the state of the economy, we find that the states of the term structure of interest rates are informative about fund performance and risk exposures relative to a broad equity index. States of the macroeconomy are informative about performance relative to fund style benchmarks. Balanced and asset-allocation style funds respond most strongly to the states of the financial markets. We confirm that conditional models make the average performance of U.S. equity funds look better than traditional methods. Overall, US Equity style funds deliver neutral risk adjusted performance, which implies that fund managers have just enough investment ability to cover trading costs and expenses. There is some evidence that conditional performance and timing ability is concentrated in certain fund types and in certain states of the economy. Our findings have a variety of implications for practicing financial analysts.

Biographies

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Contents

Preface

This monograph revisits and extends the central empirical findings of the literature on *conditional performance evaluation (CPE)* for U.S. equity mutual funds. CPE compares a fund's return with the return of a dynamic strategy that attempts to match the fund's risk exposure. The risk exposures are matched as they vary through time, by mechanically trading based on easily-measured, predetermined variables. A fund's risk exposures and the related market premiums are said to be "conditioned," or allowed to vary over time with the state of the economy. The performance measures that result are the *conditional alphas*.

The early conditional performance evaluation studies found that controlling for time-variation associated with the state of the economy makes the average performance and also the market timing ability of mutual funds look better, compared with traditional performance measures (e.g. Ferson and Schadt, 1996). Performance net of expenses was mildly negative under traditional models that ignore conditioning, but neutral under the conditional models. Ferson and Warther (1996) attribute the difference to predictable patterns of new money flows in and out of mutual funds at the aggregate level. These studies used small samples of mutual funds, subject to survival selection, and ending in 1990.

The present study revisits conditional performance evaluation using a large, updated sample of mutual funds. We assess the robustness of the conditional performance of mutual funds to fresh data that controls for survival bias. This is important because survival bias in earlier data sets may make performance look better than it is. We expand and refine the treatment of conditioning information, and expand the list of measures of the state of the economy. Expanding the state variables is interesting because the early studies' results are mainly driven by the relation of returns to an overall market dividend yield and the level of short term interest rates. We wish to know if fund performance responds to other measures of the economic state. We also use the predetermined variables to define discrete states, which helps to avoid statistical problems associated with persistent, lagged regressors. In addition to a standard market benchmark, we also measure conditional performance relative to style-specific benchmarks, using an approach similar to that of Sharpe (1988, 1992). This allows us to assess the sensitivity of the conditional performance results to the choice of benchmark.

We confirm that conditional alphas tend to make funds look better than traditional performance measures, in a broader sample of funds, and using fresh data constructed to control survivor selection bias. Conditional performance, measured at the fund style-group level, is essentially neutral. On a subsample of balanced and tactical asset allocation funds, we find that conditional timing ability is more likely to be found among the funds with the largest total net assets, the longest track records and the lowest expense ratios.

Our list of lagged instruments is more inclusive than previous studies, thus establishing the robustness of these results to the choice of lagged instruments. The conditional performance analysis reveals patterns in expected performance across states of the economy that traditional measures would miss. With our expanded list of instruments we explore the question of which economic variables are the most informative. We find that in a list of eleven proxies for the state of the economy, the states of the yield curve are the most informative about fund performance relative to a broad market index. At the level of fund style groups, we find the strongest evidence for time-varying market betas among the income funds. The variables representing the states of the macro economy are also found to be informative about shifts in the risk exposure and performance of fund groups, relative to static style-specific benchmarks.

We analyze the performance of individual funds relative to the funds' characteristics. We wish to know to what extent the conditional performance can be predicted using objective characteristics such as fund size, turnover, fee structure, and new-money flows. For example, do low-expense-ratio funds have better conditional timing ability than high expense ratio funds? (We find that they do.) We also examine the relative performance of individual funds, using cross-sectional regressions. We find that extremely good and bad performance is concentrated in particular types of funds and in particular economic states.

We find that older Growth funds typically have larger alphas than younger funds. Growth funds with relatively high capital gains and total returns over the last year are expected to have higher alphas over the next year. Growth funds tend to follow momentum trading strategies and this feeds through to their alphas. However, among Income funds past returns are not positively related to future performance. We find that funds with higher load charges are expected to have higher alphas than those with lower load charges.

When dividend yields are high, large fractions of Growth, Small Company Growth, Sector and Growth and Income funds generate positive performance. None of these funds appear to outperform in low dividend yield states. Many Growth and Income funds generate positive performance when inflation is high, but not when inflation is low. We find that almost 20% of the Sector funds generate high t-ratios for their alphas when the short term corporate debt markets are illiquid, but not when short term liquidity is high.

Chapter 1 reviews and motivates conditional performance evaluation and places our study in context. Chapter 2 discusses how we condition on the state of the economy. Chapter 3 introduces the empirical methods. Chapter 4 describes the data. Chapter 5 presents empirical results on the performance of broad fund groups. Chapter 6 summarizes the cross-sectional distribution of individual fund performance. Chapter 7 studies individual fund performance in relation to fund characteristics. Chapter 8 studies market timing. Chapter 9 reviews the implications of our findings for practicing investment managers. Chapter 10 offers a summary and conclusions.

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1. Conditional Performance Evaluation: A Review

Traditional measures of risk-adjusted performance for mutual funds compare the average return of a fund with a benchmark designed to control for the fund's average risk. For example, Jensen's (1968) alpha is the difference between the return of a fund and a portfolio constructed from a market index and cash, where the portfolio has the same average market exposure, or "beta" risk as the fund. The returns and beta risks are typically measured as averages over the evaluation period, and these averages are taken "unconditionally," or without regard to variations in the state of financial markets or the broader economy. One weakness of this approach relates to the likelihood of changes in the state of the economy. For example, if the evaluation period covers a bear market, but the period going forward is a bull market, the unconditional performance evaluation may not have much forward-looking value.

In the CPE approach, fund managers' risk exposures and the related market premiums are allowed to vary over time with the state of the economy. The state of the economy is measured using predetermined, public information variables. Provided that the estimation period covers both bull and bear markets, we can estimate expected risk and performance in each type of market. This way, knowing that we are now in a bull state of the market for example, we can estimate the fund's expected performance given a bull state.

The conditional performance measure, the *conditional alpha*, is the difference between a fund's excess return and that of a strategy that attempts to match the fund's risk dynamics over time by mechanically trading, based on the predetermined variables. The idea is a natural generalization of the classical performance measures, which compare a fund's return with a benchmark that carries the same average exposure to risk. In the CPE approach, for example, the risk adjustment for a bull market state may be different from that for a bear market state, if the fund's strategy implies different risk exposures in the different states. The conditional alpha can also be estimated conditional on the state, as we will explain below.

Conditional Performance Evaluation is consistent with a version of semi-strong-form market efficiency as described by Fama (1970). The idea is that if the market is efficient, a fund manager whose performance can be replicated by mechanically trading on the public information is not adding value. In order to add value and generate a positive conditional alpha, a manager should offer a higher return than the mechanical-trading strategy. While market efficiency motivates the null hypothesis of our tests—that conditional alphas are zero—one need not ascribe to market efficiency to use CPE. By choosing the lagged variables, it is possible to set the hurdle for superior ability at any desired level of information. Our results show that the choice of lagged variables should matter in practice, and provides some practical guidance on the variables to use.

In addition to the lagged state variables, CPE like any performance evaluation requires a choice of benchmark portfolios. Traditional measures used a broad equity index, motivated by the Capital Asset Pricing Model (CAPM, Sharpe, 1964). Current practice is more likely to use a benchmark representing the fund manager's investment style. We use both types of benchmarks in this monograph. The idea, in any event, is that the portfolio formed from the benchmark should capture an alternative to employing the manager's services. If alpha is positive the manager adds value, relative to the alternative of holding the benchmark portfolio strategy. It is important to recognize the role of costs in this comparison. In most academic studies using the traditional measures and in our analysis using CPE, the benchmark strategy does not pay trading costs. Mutual fund returns, in contrast, are measured net of all expenses and trading costs. Therefore, the measure of value added should be interpreted as an increment to these costs. Roughly speaking, a manager with a zero alpha has enough ability to cover his or her costs and fees.

A Stylized Example

The theoretical appeal of CPE can be illustrated with the following highly stylized numerical example. Assume that there are two equally-likely states of the market as reflected in investors' expectations; say, a "Bull" state and a "Bear" state. In a Bull market, assume that the expected return of the S&P500 is 20%, and in a Bear[1] market, it is 10%. The risk-free return to cash is 5%. Assume that all investors share these views—the current state of expected market returns is common knowledge. In this case, assuming an efficient market, an investment strategy using as its only information the current state, will not yield abnormal returns.

Now, imagine a mutual fund which holds the S&P500 in a Bull market and holds cash in a Bear market. Consider the performance of this fund based on CPE and Sharpe's (1964) CAPM. Conditional on a Bull market, the beta of the fund is 1.0, the fund's expected return is 20%, equal to the S&P500, and the fund's conditional alpha is zero.[2] Conditional on a Bear market, the fund's beta is 0.0, the expected return of the fund is the risk-free return, 5%, and the conditional alpha is, again, zero. A conditional approach to performance evaluation correctly reports an alpha of zero in each state.

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[1] This, of course, differs from the conventional definition of a bear market, which some consider to be a 20% decline off of a previous high.

[2] The conditional alpha given a bull state, according to the CAPM, is the fund's excess return over cash minus its conditional beta multiplied by the market excess return over cash, which is equal to (.20-.05) - 1(.20-.05) = 0.

This is essentially the null hypothesis of a CPE analysis.

By contrast, an unconditional approach to performance evaluation incorrectly reports a nonzero alpha for our hypothetical mutual fund. Without conditioning on the state, the returns of this fund would seem to be highly sensitive to the market return, and the unconditional beta of the fund[3] is 1.5. The unconditional expected return of the fund is .5(.20) + .5(.05) = 0.125. The unconditional expected return of the S&P500 is .5(.20) + .5(.10) = .15, and the unconditional alpha of the fund is therefore: (.125 -.05) - 1.5(.15-.05) = **-7.5%**. The unconditional approach leads to the mistaken conclusion that the manager has negative abnormal performance. But the manager's performance does not reflect poor investment choices or wasted resources, it merely reflects common variation over time in the fund's conditional risk exposure and the market premium. In this example the correlation between the two is positive, meaning that the manager takes more risk when the market premium is higher, and this makes the unconditional risk exposure look high. The traditional model therefore

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[3] The calculation is as follows. The unconditional beta is Cov(F,M)/Var(M), where F is the fund return and M is the market return. The numerator is:

$$\begin{aligned} \text{Cov}(F,M) &= E\{ (F-E(F))(M-E(M)) \mid \text{Bull}\} \times \text{Prob(Bull)} + \\ &\quad E\{ (F-E(F))(M-E(M)) \mid \text{Bear}\} \times \text{Prob(Bear)} \\ &= \{ (.20-.125)(.20-.15) \} \times .5 + \{ (.05-.125)(.10-.15) \} \times .5 \\ &= 0.00375. \end{aligned}$$

The denominator is:

$$\begin{aligned} \text{Var}(M) &= E\{ (M-E(M))^2 \mid \text{Bull}\} \times \text{Prob(Bull)} + \\ &\quad E\{ (M-E(M))^2 \mid \text{Bear}\} \times \text{Prob(Bear)} \\ &= \{ (.20-.15)^2 \} \times .5 + \{ (.10-.15)^2 \} \times .5 \\ &= 0.0025. \end{aligned}$$

The beta is therefore .00375/.0025 = 1.5. Note that the unconditional beta is not the same as the average conditional beta, because the latter is 0.5 in this example.

overadjusts for market risk and assigns the manager a negative alpha. However, investors who have access to information about the economic state would not use the inflated risk exposure and would therefore not ascribe negative performance to the manager.

Previous Empirical Evidence

The first conditional performance evaluation studies, by Chen and Knez (1996), Ferson and Schadt (1996) and Ferson and Warther (1996) found that conditioning on the state of the economy is both statistically and economically significant for measuring investment performance. Conditioning also helps control biases in traditional market timing models. Jagannathan and Korajczyk (1986) and Ferson and Schadt (1996) show that traditional measures of market timing can assign "negative" timing ability to a passive portfolio strategy, and earlier studies had found that measures of timing ability for mutual funds were typically close to zero or negative. Negative timing coefficients make no sense because if funds could time the market but got the direction systematically wrong, investors could profit by taking the opposite position. Ferson and Schadt show how such a result arises as a statistical bias, when funds' betas vary over time with the state of the economy. Using a conditional approach to control for time-varying betas, the bias is removed.

The original studies found that conditioning makes the average performance of mutual funds look better. This may seem puzzling, given that CPE sets a higher information standard for abnormal performance than traditional methods. However, this can occur, as the stylized example in the previous section suggests. CPE does not penalize a fund for patterns in its risk exposures that are predictable based on the public information, even if that predictability may hurt average returns. Early studies suggested that this is the case for US Equity funds. Ferson and Warther (1996) attributed the higher alphas in the conditional approach to predictable patterns of new money flows in and out of mutual funds. They argued that managers respond passively to new money flows, so their market exposures are lower when more new money flows in. Ferson and Warther also show that more new money comes in for a typical equity fund, when market indicators predict high expected returns. The combined effect lowers the unconditional performance, but not the conditional performance. Such results illustrate the refinements in performance attribution that CPE makes possible, in combination with traditional methods.

The original CPE studies used small samples of mutual funds, subject to survival selection, and ending in 1990. We use a much larger sample, ending in 2001. Samples limited to survivors are likely to produce biased estimates of performance, as explained by Brown et. al (1992, 1995) and others. If funds that survive have higher new money flows, survival screening of the data set may also affect the relation between unconditional and conditional performance measures. This motivates our use of mutual fund data that avoids survivor selection bias.

Edelen (1999) considers the effects of new money flows on unconditional measures of performance at the fund level. He argues that flows beyond the manager's control require disadvantageous trades that hurt performance, while discretionary trades should produce better performance. He finds that unconditional alphas and timing measures are negatively related to the part of fund turnover that is explained by flows, and performance is positively related to the part of fund turnover that is uncorrelated with flows. He does not examine conditional measures of performance directly. Rakowski (2003) finds evidence that the volatility of flows hurts fund performance. We use a measure of "discretionary turnover," following Edelen, in our

CPE analysis.

Zheng (1999) and Becker et al. (1999) also find that conditional alphas make mutual funds look better than unconditional alphas, and that conditional timing models remove spurious negative timing. Christopherson, et al. (1998) find that the overall distribution of conditional alphas for pension funds is similar to the unconditional alphas, unlike the case for mutual funds as found by Ferson and Schadt (1996). Pension funds present a setting where high frequency flows of new public money are not at issue, and Christopherson et al. suggest that these results are consistent with the interpretation of Ferson and Warther (1996). These studies also used limited samples of funds and conditioning variables. No systematic re-examination of these major results has appeared in a large, current data base that controls for survival bias. In addition, there has been little analysis of how sensitive conditional performance measures are to the choice of conditioning variables. We provide a detailed analysis of this issue.

Christopherson et al. (1998, 99) found that conditional alphas are informative predictors about the cross-section of future performance in samples of pension funds. High-conditional alpha funds deliver high future returns, and conditional alphas predict future returns better than the traditional, or unconditional alphas. Del Guercio and Tkac (2000) find that new money flows into pension funds are more responsive than in mutual funds to more "sophisticated" measures of performance such as Jensen's alpha, but report no evidence of fund flows in response to conditional measures of performance.

Most of the conditional performance evaluation of mutual funds has used standard market-wide benchmarks for capturing risk exposure. We refine the approach by also using style-based benchmarks in the performance measurement. Myers (1999) studies the role of investment style and survivorship bias in the evidence for persistence of performance in pension funds. He suggested that much of the persistence in pension fund performance, such as found in Christopherson, et al. (1998) is related to fund style. These results for pension funds suggest that it should be useful to examine the conditional performance of mutual funds, controlling for style. Since performance relative to a peer group receives so much attention in practice, and has been found to be a determinant of new money flows into mutual funds (e.g. Sirri and Tufano, 1998), it should be interesting to compare and evaluate these alternative approaches.

2. Measuring the States of the Economy

Previous studies have used a standard set of lagged variables, such as the level of interest rates, yield spreads and aggregate market dividend/price or similar ratios to measure the state of the economy. For example, Ferson and Warther (1996) use a short term interest rate and a dividend yield, and these are the most important instruments in Ferson and Schadt (1996). Previous studies have modelled the time-variation in the CPE measures as linear functions of these variables. For the purposes of checking the robustness and validity of the previous results, we include similar lagged variables. We also expand the list of instruments beyond those of the earlier studies.

We use a list of eleven instruments for the economic state. The first is the level of short-term interest rates, measured as the bid yield to maturity on a 90-day Treasury bill. The second is the term structure slope, measured as the difference between a five-year and a one-month discount Treasury yield. Term structure concavity is $y_3 - (y_1 + y_5)/2$, where y_j is a j-year fixed-maturity yield. Interest rate volatility is the monthly standard deviation of three-month Treasury rates, computed from the days within the month.[4] All of the interest rate data are from the US Federal

[4] One complication is that the daily three-month spot rates are highly autocorrelated. Since the interest rates refer to overlapping periods longer than one month, the data should follow a moving average process with more terms than the number of days in the month. This causes a bias in the sample variance. We approximately control this bias by modelling the autocorrelation as a first-order autoregressive, or AR(1) process. Let the AR(1) coefficient be ρ, let the number of daily observations in the month be T, and let $s^2(r)$ be the maximum likelihood estimator of the variance, ignoring the autocorrelation. It is easy to show that the expected value of $s^2(r)$ differs from $\sigma^2(r)$, the true variance. An unbiased estimator, in the sense that its expected value under the AR(1) assumption is $\sigma^2(r)$, may be constructed as:

$$s_*^2 = s^2(r)/ [1-(1/T)-(2/T^2)\{\rho/(1-\rho)\}\{T(1-\rho^{T-1})-(1-\rho^{T-1})/(1-\rho) + (T-1)\rho^{T-1}\}].$$

We use s_*^2 as our estimate of the monthly variance, where T is the number of daily observations in the month and ρ=0.99, the value estimated using all of the daily

Reserve database. Stock market volatility is constructed similarly using daily returns for the Standard and Poors 500 index. Dividend yield is the annual dividend yield of the CRSP value-weighted stock index. Inflation is the percentage change in the consumer price index, CPI-U. Industrial production growth is the monthly growth rate of the seasonally-adjusted industrial production index. Short-term Corporate Illiquidity is the percentage spread of three-month high-grade commercial paper rates over three-month Treasury rates, which follows Gatev and Strahan (2003). Stock market liquidity is the measure from Lubos and Stambaugh (2003), based on price reversals.

A Discrete State Approach

In addition to using the lagged variables themselves, we also measure the state of the economy using discrete state variables. These discrete measures may help to resolve some of the potential econometric problems associated with the continuous measures. Using the dummy variables to condition performance we also avoid the linear functional forms assumed by previous studies.

For each state variable we measure the average abnormal performance, conditional on the state variable being "higher than normal," lower than normal, or normal. This follows Ferson, Henry and Kisgen (2003) who use a similar approach to study fixed income funds in a stochastic discount factor framework. Consider the example where the lagged instrument is the level of a short term interest rate, r_t. We first convert the rate into a deviation from its recent level, measured as the average value over the last 60 months: $x_t = r_t - (1/60)\Sigma_{j=1,\ldots 60}\, r_{t-j}$. We then use the last 60 months of data to estimate the standard deviation of r_t, $\sigma(r_t)$. The dummy variable $D_{t,hi}$ for a "higher than normal" level of the interest rate is defined as the indicator function:

observations in the sample.

$I\{[x_t/\sigma(x_t)] > 1\}$. Thus, higher than normal is defined as being greater than one standard deviation above the trailing mean. Similarly, the dummy variable $D_{t,lo}$ for a "lower than normal" level of the rate is defined as the indicator function: $I\{[x_t/\sigma(x_t)] < -1\}$. If the data are approximately normally distributed, we should get about 2/3 of the observations in the "normal" category, and 1/6 of the observations each in the "high" and "low" categories.

Dummy variables for the other state variables are similarly defined. For example, we measure performance conditional on high versus low market volatility. To construct this series we use the daily CRSP market index returns within each month to compute a monthly standard deviation. The time-series of the monthly standard deviations replaces r_t above and the dummy variables for high and low volatility are computed in the same fashion.

Summary Statistics

Panel B of Table 1 presents summary statistics for the instruments that are used in constructing the state variable dummies. Many of the instruments are highly persistent series, as can be seen from their high first order autocorrelations. For example, the short term interest rate, credit spread and dividend yield have autocorrelations in excess of 95%. High persistence can create econometric problems, as reviewed by Ferson, Sarkissian and Simin (2003a,b). With persistent variables, it is easy to find "spurious" predictability in a given sample. The predictability is spurious because standard statistical analysis suggests the predictability is there, but it really isn't there when you need it, outside of the given sample. Our expanded list of instruments includes variables without so much persistence. For example, six of the instruments we introduce in Table 1 have first order autocorrelations less than 0.80. Ferson, Sarkissian and Simin show that spurious regression is not a significant issue at these levels of persistence.

In the Appendix A, Tables 1A and 2A report summary statistics for the dummy variable indicators for the various states. The dummy variables are less persistent than the underlying continuous variables from which they are constructed, which reduces concerns about spurious regression biases. For the dummy variables, the largest first order autocorrelation is 85%, and most are much smaller. The lower persistence of the dummy variables is one of their attractive features.

The Table 2A shows that the state variable dummies are mutually correlated. The highest correlation among the low-state dummies is 82% (short rate level and its volatility). The highest correlation among the high-state dummies is 72% (again, short rate level and its volatility). The other correlations are typically much smaller. For example, the next highest correlations among the dummies are 64%, then 58%, and the rest are below 50%.

In the Appendix B, Figure B1 presents plots of the lagged state variables and their associated discrete dummy variables. The dummies are shown as positive for a higher than normal state, negative for a low state and zero for a normal state. The graph for the 90-day Treasury bill shows an overall declining trend in the levels since 1981, but with enough cyclicality that the dummy variables are not simply subperiod indicators for early and late in the sample. There are brief periods of high-rate states at the end of 1989 and in much of 2000, and long periods of "normal" rate levels since 1991 as well. The graph for the slope of the term structure reveals a more uniform distribution of shorter duration high, low and normal episodes over the sample period. High slopes occur in 1976, 1983-85, mid-1988 and 1992-93, interspersed with normal slopes during those periods. Low slopes occur in 1979-81, 1989-91 and 1995-99, also interspersed with normal periods. The graph for concavity appears similar to the slope graph. When the slope of the term structure is high it tends to be concave (the two high-state dummies have a correlation of 58%), and low slopes tend to be associated with less concavity (the low state dummies having a correlation of 64%). Interest rate volatility displays a decreasing trend since 1982, like the interest rate levels. (The dummies for low rates and low volatility have a correlation of 77%.) Periods of high interest rate volatility are evident during the 1979-82 monetary experiment, and periods of low volatility occur during 1985-88 and 1992-94.

The first state of the financial market variables in Figure B1 is stock market volatility. The spike in volatility corresponding to October of 1987 is the most prominent feature of the series. Volatility was mostly normal over the 1988-92 period. The dummies oscillate between low and normal periods during 1985-86 and 1993-95 and they oscillate between high and normal during 1973-75, 1980-83, and 1996-99. Credit spreads show a downward drift since 1982, like the interest rate level and volatility. There are brief high spread periods in 1975-76, 1981-83 and since 1999. Much of the period since 1982 is characterized by oscillation between normal and low spreads. The dividend yield is the series that appears most likely to be nonstationary. It displays a smooth downward trend since 1982. The dummies indicate mostly high or normal yields during 1973-82, and mostly low or normal after that. The commercial paper - Treasury spread, our measure of short term corporate illiquidity, displays sharp peaks during 1974, 1980, 1983 and 1988. The dummy variables indicate primarily normal or low spreads during 1973-75 and 1983-93, with seemingly random patterns over other periods. The stock market liquidity variable is the most random-looking of the financial market indicators, except for a brief period of frequently-low liquidity during 1973-75, and a negative liquidity spike in October of 1987.

Finally Figure B1 includes graphs of the state variables for the macroeconomy. The inflation rate series looks like a noisier version of the short term interest rate, with high, low and normal states scattered throughout the sample. This makes sense if variation in the short term rate largely tracks variation in expected inflation, as suggested by Fama (1975). Under this interpretation the short rate would appear as a smoothed version of the inflation rate. The dummy variables indicate a concentration of low inflation states during 1982-83, normal interspersed with low during 1991-99 and a concentration of high inflation states during 1973-80. Finally, the industrial output growth rate series appears stationary and largely random. However, the dummy variables can pick out business cycle patterns in the growth rate. There are frequent high growth states, although interspersed with normal, during 1983-84 and 1994-95. There are frequent low growth states, again interspersed with normal, during 1975, 1981-82 and 1989-91. Overall, the state variables track interesting variation in interest rates, financial markets and the macroeconomy.

3. Empirical Models

We focus on two versions of conditional performance regressions and two conditional market timing models, and we compare these with the classical performance measures that they generalize. Three of these conditional models are developed by Ferson and Schadt (1996) and one by Christopherson, et al. (1998). Let $r_{m,t+1}$ be the excess return on a market or benchmark index. For example, this could be the S&P 500, a "style" index such as "small cap growth," or a vector of excess returns if a multi-factor model is used.

Our first model is proposed by Ferson and Schadt:

$$r_{p,t+1} = \alpha_p + \beta_o \, r_{m,t+1} + \beta' \, [r_{m,t+1} \otimes Z_t] + u_{pt+1} \qquad (1)$$

where $r_{p,t+1}$ is the return of the fund in excess of a short term "cash" instrument, and Z_t is the vector of lagged conditioning variables, in demeaned form. The symbol $\otimes$ denotes the kronecker product, or element-by-element multiplication when $r_{m,t+1}$ is a single market index. A special case of Equation (1) in the classical CAPM regression, where the terms involving Z_t are omitted. In this case, α_p is Jensen's (1968) alpha.

When $r_{m,t+1}$ is the excess return on a broad market index, then Equation (1) is a version of the *Conditional CAPM*, which says that $E(r_{t+1} | Z_t) = \beta(Z_t) \, E(r_{m,t+1} | Z_t)$, where $\beta(Z_t)$ is the conditional beta, and α_p=0 is there is no abnormal performance. The conditional CAPM is examined empirically by Harvey (1989), Shanken (1990), Ferson and Harvey (1991) and Jagannathan and Wang (1996), among others. These authors apply the model to hypothetical, passive portfolios of common stocks. Jagannathan and Wang emphasize that the conditional CAPM can be boiled down to an *unconditional* model; that is, a model for average expected returns with more than one "beta." This interpretation can also be seen in Equation (1), where (β_0,β) is a vector of regression coefficients or betas, on the multiple factors defined by ($r_{m,t+1}$, $r_{m,t+1}\otimes Z_t$).

To see more explicitly how the model in Equation (1) arises, consider a "market model" regression allowing for a time-varying fund beta, $\beta(Z_t)$, that may depend on the public information, Z_t:

$$r_{p,t+1} = \alpha_p + \beta(Z_t)\, r_{m,t+1} + u_{pt+1}. \tag{2}$$

Now assume that the time-varying beta can be modelled as a linear function: $\beta(Z_t) = \beta_o + \beta' Z_t$. The coefficient β_o is the average beta of the fund (as Z is normalized to mean zero), and the term $\beta' Z_t$ captures the time-varying conditional beta. Substituting this expression into Equation (2), the result is Equation (1). Note that since $E(Z_t)=0$, it follows that:

$$E\{\beta'[r_{m,t+1}\otimes Z_t]\} = Cov\{\beta(Z_t), r_{m,t+1}\} = Cov\{\beta(Z_t), E(r_{m,t+1} \mid Z_t)\}, \tag{3}$$

where the second equality follows from representing $r_{m,t+1} = E(r_{m,t+1} \mid Z_t) + u_{m,t+1}$, with $Cov\{u_{m,t+1}, \beta(Z_t)\}=0$. Thus, the additional factors defined by the interaction term $\beta'[r_{m,t+1}\otimes Z_t]$ in the regression (1) arise as a control for common movements in the fund's conditional beta and the conditional expected benchmark return. The conditional alpha, α_p, is measured net of the effects of these risk dynamics.

Christopherson et al (1998) propose a refinement of (1) to allow for a time-varying conditional alpha. This is our second model:

$$r_{p,t+1} = \alpha_{p0} + \alpha_p' Z_t + \beta_o\, r_{m,t+1} + \beta' [r_{m,t+1}\otimes Z_t] + u_{pt+1}. \tag{4}$$

In this model, $\alpha_{p0} + \alpha_p'Zt$ measures the time-varying, conditional alpha. This refinement of the model may have more power to detect abnormal performance if performance varies with the state of the economy. For example, if a manager generates positive alpha when the yield curve is steep, but negative alpha when it is shallow, the average abnormal performance may be close to zero so that it can not be detected using regression (1). In such a case regression (4) would track the time-variation in alpha and record this as a nonzero coefficient α_p on the instrument for the term structure slope.

4. Data

Our study involves several data sets. This chapter describes these data, including our sample of mutual funds' returns and characteristics.

Benchmark Returns

We use a number of "passive" index returns as benchmarks for the mutual funds' performance. Summary statistics for the eight standard indexes are in Table 1, and their conditional mean returns are presented in Table 2. The benchmark indexes cover a range of asset classes with different risks and returns. They include the monthly returns on a "cash" instrument, measured by the 90-day U.S. Treasury bill; a government bond return, measured by the 20-year bond from Ibbotson Associates; a BAA corporate bond index return; a broad equity market index, measured by the Center for Research in Security Prices (CRSP) value-weighted market index; a small capitalization stock index; and two indexes of stocks grouped according to their lagged book-to-market ratios. The Growth index consists of stocks with low book-to-market ratios and the Value index has high book-to-market ratios.[5]

The summary statistics of the benchmark returns, reported in Table 1, show the expected result that average return and volatility go together, as we move from cash to government bonds, to corporate bonds to equities. The cash market returns have significant autocorrelation, at 77%, but none of the other autocorrelations is larger than 29%.

Over the 1973-2000 period the value stock index slightly outperformed the small stock index, which in turn slightly beat the broad equity index. The growth stock

[5] The broad market, small cap, value and growth indexes are courtesy of Kenneth French, via his web site at Dartmouth College, and are formed from data on CRSP and Compustat.

index delivered the lowest equity returns. Growth stocks and small cap stocks were the most volatile. Previous studies, including Basu (1977), Fama and French (1992), and Lakonishok, Shleifer and Vishny (1994) claim that value strategies, which choose stocks with high book/market or earnings/price ratios, outperform growth strategies.

Benchmark Returns Conditioned on Economic States

Table 2 shows the average return and standard deviation of return for the eight benchmark indexes conditional on the high, low and normal values of the economic state dummies. The columns are the various asset returns, from low to high risk as we move from left to right across the table; the rows correspond to the state variables. The state variables are organized into three groups, with one panel for each group. The first group measures the state of the term structure, the second group measures the state of general financial markets and the third measures the state of the macro economy. In each case the state variable dummy is used to predict the future returns in real time. For example, the state is defined at the end of January using data prior to the last day of the month, and this is used to predict the return over the month of February.

Starting with the term structure state variables in Panel A, we find that the states of the term structure are powerful predictors, not just for fixed income but also for equity returns. Campbell (1987) and other authors have observed that term structure variables could be used to model time-variation in expected bond and stock returns. The evidence in Table 2 both confirms these claims on more recent data and refines the descriptive relations using our discrete states. High levels of short term interest rates predict relatively high and volatile short term bond returns and low stock returns. There is a gradual transition between the two cases across the columns, as we move to the longer term, riskier asset classes. The difference in the Broad Equity stock return, predicted by low versus high spot rates, is 1.7% per month (1.65% given low rates and -0.06% given high rates) and strongly statistically significant. These results are generally consistent with previous evidence such as Fama and Schwert (1977) and Ferson (1989), but appear striking in the discrete-state design.

A steeply sloped term structure predicts high long-term bond returns and stock returns. The former reflects a failure of the constant-premium version of the expectations hypothesis of the term structure (e.g. Campbell and Shiller, 1991). The latter result is consistent with consumption-based model predictions such as Breeden (1986), which emphasize a positive relation between the slope of the term structure and expected economic growth and stock returns. Harvey (1989) also finds that a steep slope predicts high economic growth.

The level and the slope seem to be the most informative indicators from the term structure about future investment returns, with concavity being less important. This is not surprising as far as predicting fixed income returns is concerned, given the evidence in studies such as Litterman and Sheinkman (1988). Table 2 shows that higher term structure concavity predicts higher returns on the longer term Government and BAA Corporate bonds, but has little predictive power for equity returns. High interest rate volatility states are highly correlated with high interest rate levels; Table A1 shows the conditioning dummy variables have correlations between 77 and 80%. It is therefore not surprising to find that high interest rate volatility is associated with higher and more volatile short term bond returns, and with lower returns on stocks and bonds exposed to default risks.

The variables associated with the state of general financial markets in Panel B of Table 2 are also associated with interesting return differences. High credit spreads predict high returns on stocks, consistent with Keim and Stambaugh (1986).

High dividend yields predict high returns on stocks and bonds, consistent with Fama and French (1989), but the effect is not statistically significant for the broad equity index or the Value Stock index. Goyal and Welch (2002) and others have found that the predictive ability of dividend yields is weak in post-1990 data, and the dominant downward trend in yields displayed in Figure B1 could be an explanatory factor. The most economically significant predictor among the financial market instruments, judging from the magnitudes of the expected returns differences, is the commercial paper - Treasury spread, measuring short term corporate illiquidity. When the spread is high all of the long term bonds and stock indexes earn high returns over the next month. For example, the difference in monthly expected returns in high versus low spread states is about 70 basis points per month for the long term government bond, 2.1% for the broad equity index and an impressive 3% per month for the small stock index. Finally, the stock market liquidity measure predicts no reliable differences in the returns.

The last set of variables measure the state of the macro economy. The table shows that high inflation is bad news for stocks and corporate bonds. When output growth is abnormally low, it predicts high returns, especially for the riskier assets. In the case of the Broad Equity Index, the difference between the low output state and the high output state is an average return of 1.7% per month, while for growth stocks the difference is 2.3% per month. The patterns are consistent with the positive relation between expected economic growth and risky asset returns, that most asset pricing models would predict if economic growth is mean reverting. The intuition is that when the real economy is performing poorly we expect it to get better, so expected growth and stock returns are high at such times. (See Chen, 1991, for related empirical evidence.)

In summary, this section shows that by conditioning on the state of the term structure, general financial markets and the macro economy, it is possible to predict differences in the expected returns and volatilities of benchmark asset-class returns. Our discrete state approach reveals a number of interesting patterns that have not been exploited by previous studies of conditional fund performance. The discrete variables should also avoid problems with persistent lagged instruments that previous studies are subject to, and allow us to check the robustness of CPE results to the choice of state variables.

Mutual Funds

We use the CRSP Mutual Fund Data base, 2001 version. This allows us to expand the coverage of funds to the 1973-2000 period. Ferson and Schadt (1996) and Ferson and Warther (1996) studied the 1968-1990 time period, and the data in Christopherson et al (1998) also ended in 1990. Thus, the last ten years of our study represent an "out of sample" check on the robustness of these earlier findings. The total sample of funds, from which we select a subset, includes all funds for which monthly returns data exists in a given month. The number ranges from a low of 146 in January of 1962 to a high of 27,289 in June of 2001, much larger than the sample of 67 large funds studied by Ferson and Schadt and Ferson and Warther. By including funds that do not survive until the end of the sample period, we provide some control of sample selection bias related to fund survival. We exclude fund-years for which the current year is earlier than the reported year in which the fund was organized. This is done to reduce biases associated with back-filled data. Data may be back-filled when incubator funds with good track records enter the sample, resulting in a selection bias.[6]

[6] However, Elton Gruber and Blake (2001) argue that the CRSP data base may have other selection biases, so the control for sample selection bias is not perfect.

We build two samples of US equity mutual funds. The first is a general sample, which we group by fund style. Styles are defined by their Wiesenberger objective codes, which are available for 1962-2001. These are matched with ICDI fund objective codes, available for 1993-2001, and Strategic Insight codes, available starting in 1992. The main style groups are growth, growth and income, income, maximum capital gain, small cap growth, sector, other aggressive growth funds and timing funds. We use the first four groups for comparability with Ferson and Schadt (1996) and Ferson and Warther (1996), who used the same fund groupings.[7]

The main reason we classify funds by style using the self-reported groups indicated on the CRSP database is for comparability with the earlier CPE studies of mutual funds. There are, of course, a variety of alternative classification schemes. Brown and Goetzmann (1997) develop a returns-based style classification scheme, minimizing the mean within-group sum-of-squares. Like a conditional performance analysis, their approach allows time-variation in funds' conditional betas. They compare their classification scheme with seven other approaches to style classification, including self-reported categories, principal components analysis, and various types of loadings on prespecified factors. They find that their returns-based approach performs relatively well at predicting future fund returns. They also find considerable overlap

[7] The CRSP codes that define each style group are the same as in Pastor and Stambaugh (2002), and are as follows. The objective codes from Wiesenberger are denoted by OBJ, those from ICDI are denoted ICDI and those from Strategic Insight are denoted SI. Small company growth funds are coded OBJ SCG or SI SCG. Other aggressive growth funds are coded OBJ AGG, ICDI AG or AGG, or SI AGG. Growth funds are coded OBJ G, G-S, S-G, GRO or LTG; or ICDI LG or GRO. Income funds are coded OBJ I, I-S, IEQ, or ING; or ICDI IN or ING. Growth and Income funds are coded OBJ GCI, G-I, G-I-S, G-S-I, I-G, I-G-S, I-S-G, S-G-I, S-I-G or GRI; ICDI GI or GRI. Maximum capital gains funds are coded OBJ MCG. Sector funds are coded OBJ ENR, FIN, HLT, TCH, UTL; ICDI SF, UT, ENV, FIN, HLT, TEC, UTI, RLE, NTR or SEC. Timing funds include those whose OBJ code is BAL or AAL, whose POLICY is Bal or Flex, whose ICDI_OBJ code is BL, or whose SI_OBJ code is BAL.

between the interpretation of their style classifications and the self-reported style groups.[8]

Alternative approaches to fund classification and performance analysis use the reported holdings of the funds. There are two versions of this approach in the literature. In the first version, the portfolio weights are directly examined to see if they contain information about the future returns of the securities held by the fund. This approach to performance measurement is developed by Grinblatt and Titman (1989). Ferson and Khang (2002) further develop a conditional version of this measure and show that it has several advantages. In the second version of weight-based approaches, various characteristics of the stocks held by a fund are measured, and using the fund's reported holdings and characteristics-based style benchmark is constructed. Average performance can be measured as the difference between the fund and benchmark returns. An example of this approach is the "style box" provided by Morningstar, based on the market capitalization, book/market and earnings/price ratios of the stocks held by the fund. Daniel, Grinblatt, Titman and Wermers (1997) and Wermers (2000), refine and further develop this approach.

Weight-based approaches have advantages and disadvantages, compared with the methods used in this monograph. By using more information, weight-based methods may provide more precise performance measures. As Ferson and Khang (2002) emphasize, conditional weight-based approaches can avoid biases that arise in returns-based measures as a result of frequent trading by fund managers. However, portfolio weights for mutual funds are only required to be publicly reported every six months, while returns are available more frequently. Portfolio weights are subject to

[8] Brown and Goetzmann (1997) identify eight style categories which they interpret as Growth and Income, Growth, Income, Global Timing, International, Value, Glamour and Metal funds.

"window dressing," whereby end-of-period holdings may not accurately reflect a fund's strategy. Since reported weights are a snapshot, they obviously will not capture dynamic trading strategies that do affect returns. Finally, weight-based approaches do not capture actual trading costs as reflected in fund returns.

Funds Grouped by Style

Summary statistics are shown in Table 3 for equally weighted portfolios of the mutual funds in each style group. The three largest categories are the Growth, Growth-and-income and Income funds. The number of growth funds ranges from 42 funds in January of 1962 to a high of 6995 in October of 2000. The growth-and-income funds start with 62 and end with 3806 over the same period. Income funds start with 20 and end with 850 over the same period. Data for the other fund groups are available over more limited periods. The maximum capital gain style is discontinued in 1992, while the Small Company Growth and Sector series are not usable until 1990 because there are only a few funds prior to that date. For the same reason, the Other Aggressive Growth group is not used until 1992.[9]

The summary statistics in Table 3 show that, among the groups available beginning in 1961 or 1962, the growth funds earned the highest average return, while income funds returned the least. The relative volatilities are as expected, with Maximum Gain and Growth funds the most volatile, income funds the least volatile, and growth-and-income funds in between the two. Over the latter part of the sample period, Small Company growth funds earned more than Sector funds and the Other Aggressive Growth category, and also had the highest volatility among those fund

[9] For example, the other aggressive growth group has 1-3 funds in 1989 but no data during the May, 1990-November, 1991 period. Panel A of Table 3 uses all of the available data on these funds.

groups. The autocorrelations of the equally-weighted portfolios of funds vary from less than one percent to almost 18%. This is similar to the passive benchmarks summarized in Table 1, except for the higher autocorrelation of the short term cash return.

We study fund performance in relation to various fund characteristics available on the CRSP database. For example, the characteristics observed at the end of a given calendar year are used to predict relative performance over the next three years in subsequent analysis. Each year the funds are grouped into thirds on the basis of a characteristic at the end of the previous year, and equally-weighted portfolios of the funds are formed for the next calendar year. The characteristics include: (1) the new cash flow over the past year, defined as TNA_t - $(1+R_t)TNA_{t-1}]/TNA_{t-1}$, where TNA is the total net assets of the fund and R_t is the annual return; (2) the age of the fund; (3) the income passed through to investors in the previous year; (4) the capital gains distributions over the past year; (5) the reported turnover for the past year; (6) the reported total load charges; (7) fund size, measured by total net assets; and (8) the expense ratio; and (9) the lagged annual return over the previous year.

Market-Timing Funds

A broad sample of U.S. equity funds is unlikely to contain many funds that attempt to aggressively time the market. We therefore concentrate our study of conditional market timing on the subsample of funds that are relatively likely to be engaged in market timing activities as indicated by their declared style.[10] Our group of market-timing funds is dominated by balanced funds, but also includes all the funds identified as asset allocation-style funds. The initial number of fund-years in this sample is 9626. The

[10] We do not study market "timing," taken to mean allowing fraudulent trading after the close of the market, or trading on stale prices in net asset values, which practices are currently under legal investigation at some mutual fund companies.

number of funds in any given month ranges from a low of 34 in January of 1962 to a high of 2510 in April of 2000. As for the broader sample, we exclude fund-years for which the current year is earlier than the reported year in which the fund was organized. We find seven such cases.

Summary statistics for an equally-weighted portfolio of our market-timing funds are reported in Table 3. The average returns and volatility of timing funds are below those of any other group except the income funds. This makes sense if the timing funds are out of the market, or holding reduced market exposure, in a substantial fraction of the months.

We form subgroups of the market-timing funds based on the various fund characteristics described above. In the Appendix B, Figure B2 plots the annual time-series of the cutoff values for the fund characteristics that define the upper and lower thirds of the distributions. These figures present a nice illustration of some trends in the mutual fund industry. Since the sample of timing funds is dominated by balanced funds, the figures present a microcosm of how these fund characteristics have evolved over time, while abstracting from variation across the fund styles in our broader sample. (We produced similar figures for the Growth, Income and Sector style groups, and the overall impressions were similar.)

The graph of the fund age breakpoints over time illustrates how the large number of new funds entering the sample, starting in the mid-1980s, has driven down the age distribution. The cutoff for the oldest third of the funds peaked at 38 years in 1983-85, then subsequently fell to a low of only three years in 1994-95. The total net assets per fund has trended up mildly during the sample, with a peak in 1987, then falling to less than half the peak values by 1994, before resuming a slow upward trend through 1999.

The income return passed through by funds to their shareholders displays an inverted U-shape during the sample period. The upper-third cutoff for income rose from about 0.4% per month in 1961-62 to just under one percent per month in the high-interest rate period ending in 1982-83, then fell back to under 0.4% by 1999 as interest rates fell. The capital gains distributions present a different pattern. The lower-third cutoff was zero for most of the years between 1970 and 1985. The upper third-cutoff shows peaks in 1968, 1986 and again in 1996-97. The bull market of the 1990s is clearly evident.

Figure B2 shows that most funds charged load fees in the 7.5-8.5% range during 1961-67, and funds clustered even more tightly on the maximum 8.5% load charge during 1970-74. Starting in 1975 the lower-third cutoff began to fall, followed by the higher-third cutoff in 1984. By 1978 the lower-third charged no load fees at all, and by the end of the sample the upper-third cutoff had fallen to 4.75%. It is well known that during this period funds began to substitute load charges with 12-b1 fees, and expense ratios have risen. The graph of the expense ratios shows a clear upward trend over the sample. The upper-third cutoff was 0.65% at the beginning of the sample, rising to 1.6% by the end. Fund turnover has risen as well, and the spread between low-turnover and high-turnover funds has widened. Until 1979 the upper third cutoff for turnover hovered near 50% per year then it began to rise, finishing the sample period at more than 100% per year.

The final characteristics relate to the flows of new money and the lagged return performance over the preceding year. Figure B2 shows that the year-to-year fluctuations in these are greater than for the other characteristics. New money flows were low during 1975-1980 and relatively high during 1988-1998.

5. The Performance of Broad Fund Groups

In this chapter we present an analysis of conditional performance at the level of the fund style groups. We first examine the funds' returns without any risk adjustment, focusing on the conditional behavior across states of the economy. We then use the CAPM for risk adjustment, and examine both the unconditional and conditional alphas, which extends the evidence in studies such as Ferson and Schadt (1996). To evaluate the sensitivity of these results to the model for risk, we then replace the market index benchmark of the CAPM with a fund style-specific benchmark, constructed from the indexes that were described in Table 3. The style-specific benchmarks are constructed using a methodology similar to that of Sharpe (1988, 1992). We then provide a CPE analysis based on the discrete dummy versions of the state variables. Using the discrete state variables, in comparison with the continuous versions of the state variables, we conclude this chapter with an analysis of the time-variation in risk exposures at the fund style-group level.

Table 3 presents the conditional expected returns of the funds, grouped by style, across the various discrete economic states. For each state variable there are three rows, showing the expected returns given high and low values of a state variable, then a t-statistic for the difference in the conditional means in the high versus low state. The columns are the fund style groups. The calculations for each group of funds are based on the data for every month in which a return is available for the fund group, starting in January of 1973. Like in Table 2, the state variables are predetermined, so they could be used to predict the subsequent monthly returns in real time. In many respects the conditional returns of the funds mirror those of the benchmarks in Table 2. However, with the shorter sample period available for some of the fund groups, the conditional mean effects do not as often attain statistical significance.

The term structure state variables seem to be the most powerful predictors of the future fund returns. Low short-term interest rates predict high fund returns and high interest rates predict low returns. The differences in the conditional mean returns given high versus low short-term interest rates are significant, with t-ratios larger than 2.0 for five of the eight fund groups. The expected returns given low interest rates are more than 2% per month greater than given high interest rates for the Maximum Capital Gains funds and almost that large for the Growth funds. A steep term structure slope also predicts high subsequent returns for most groups, statistically significant for three of the eight based on the t-ratios. The differences are often economically large, at 3.2% per month for the maximum capital gains funds and just under 2% for the growth funds. High interest rate volatility is bad news for most fund groups, but the differences are not significant, except perhaps for the timing funds.[11] Finally, term structure concavity has little predictive ability for the funds' returns.

The second group of variables captures the general state of financial markets. Here we find fewer instances where the conditional expected returns differ significantly across the states. The credit spread indicator produces t-ratios larger than 2.0 in three of the eight fund groups, with high spreads predicting high fund returns. The differences exceed 2% per month in three cases. Dividend yield, equity market volatility and market liquidity measures produce no statistically significant effects. However, the point estimates under the short-term corporate liquidity variable suggest economic significance, where the high-liquidity states predict higher fund returns for every fund group, with the magnitudes ranging from 0.5% to almost 3.5% per month across the fund groups.

[11] Recall that the level and volatility of interest rates are the two most highly correlated state variable dummies, so we are conditioning on periods with significant overlap in these two cases.

The final set of state variables reflects the state of the macroeconomy. We find few statistically significant differences in the fund returns across these states. In the case of inflation, the point estimates suggest that low inflation is good news for subsequent fund returns, similar to the long-maturity bonds and passive equity benchmark returns described earlier. However, the high volatility of fund returns in high inflation states results in small values of the t-ratios that measure the statistical significance of the difference across states. One exception is the case of the timing funds, where the t-ratio is 2.1. In the case of output growth, the point estimates suggest that low current growth is good news for subsequent fund returns, again similar to the passive benchmarks, but the t-ratio is larger than two only in the case of the Maximum Capital Gains funds.

Overall, the conditional mean returns of the funds suggest significant differences, predicted by the state of the term structure of interest rates and credit spreads, but only statistically weak evidence of conditional mean return differences related to the other state variables. The single state variable with the most predictive ability seems to be the level of the short term interest rate. Ferson and Schadt (1996) found the short term interest rate to be the most important conditioning variable, among the more limited set of variables that they examined, so our evidence supports this finding in fresh data. The next question is whether the differences in conditional returns reflect abnormal performance, or if these return differences can be explained by fund risk exposures that vary over time.

Conditional and Unconditional Alphas

Our first set of risk-adjusted performance results, summarized in Table 4, uses the equally-weighted fund portfolios to examine average performance at the level of the fund-style groups. While it would be unusual to find significant abnormal performance for entire groups of funds, this section allows us to explore the robustness of the results of previous studies, where unconditional and conditional performance is compared for broad fund groups.

We first compare fund performance in conditional and unconditional versions of the CAPM. Panel A of Table 4 starts with the unconditional CAPM regression, which is Equation (1) without the $[r_{m,t+1} \otimes Z_t]$ term. All of the point estimates of alpha are negative, excepting the Sector funds, but they are small—10 basis points per month or less—and are not statistically significant based on the t-ratios, which are denoted t(alpha) in the table. Thus, our sample of funds reproduces the findings of previous studies, which found that the unconditional performance of mutual funds tends to be slightly negative. The negative unconditional alphas are of the same order of magnitude as funds' expense ratios, which average about 1.2% per year over this period according to Figure B2. The CAPM betas, as expected, are strongly significant. The betas are sensibly ordered across the fund groups, with Small company growth funds having the largest beta, equal to 1.13, and Income funds the smallest beta, equal to 0.37. The regression model R-squares indicate how much of the volatility of fund returns is associated with fluctuations in the market index. These also present reasonable patterns across the fund groups. For example, the largest regression R-squared is for growth funds, at 92%, and the smallest is 58%, for the income funds.

Panel B of Table 4 presents the Ferson and Schadt (1996) regression for the conditional CAPM, as given by Equation (1). In this panel we run the lagged instruments one at a time. The lagged instruments are used in this model to track variation through time in the funds' market betas. We conduct F-tests for the null hypothesis that the additional terms implied by the conditional models may be excluded from the regression. That is, the null hypothesis is that beta is constant over time while the alternative hypothesis is that beta moves as a linear function of the state variable. Only the results for those instruments whose F-tests reject the null hypothesis by producing p-values less than 0.10 are shown. This is a conservative inclusion criterion, and even if no instrument is individually useful, we would expect to find 10% of the cases, or 8-9 examples, that meet the inclusion criterion. We find that only 13 out of the 88 cases examined meet the criterion.[12] However, the cases are not randomly distributed across fund groups, as half of them are the income funds. Thus, Table 4 suggests that among the various fund groups, income funds are the most likely to shift their stock market betas in response to state of the economy.

Another pattern that does not appear to be random in Table 4 is the frequent presence of the stock market liquidity variable in the regressions with small p-values for the F-statistic. Stock liquidity appears three times, for three fund groups. This is interesting because no previous study of funds has used a liquidity instrument to condition performance, and we did not find the stock market liquidity variable to be a significant predictor of either the passive benchmark returns or the fund returns. Nevertheless, Panel B suggests that some of the more aggressive fund styles may shift their market betas in response to the state of liquidity in the stock market.

Ferson and Schadt (1996), using data that ends in 1990, found that conditional alphas tended to make funds look better than unconditional alphas and that conditional alphas were centered around zero. This is consistent with a market where the typical fund manager has enough ability to cover trading costs and expense ratios,

[12] It is necessary to account for the multiple comparisons in order to conduct meaningful inference about this finding. Under the null hypothesis of no predictability in fund betas using the lagged instruments, and assuming independent Bernoulli trials, the t-ratio for the significance of finding 13 cases is $[13/88 - 8.8/88]/[(.10)(.90)/88]^{1/2} = 1.5$.

once you remove biases by conditioning on the public information about the state of the economy. A comparison of panels A with panels B and C of Table 4 is consistent with this result. While none of the estimates of alpha is statistically significant, seven of the eight in Panel A are negative, while in the conditional models about half are positive and half are negative. Thus, the conditional performance is roughly centered at zero.

The original CPE studies used multiple lagged instruments in their regressions, whereas Panel B of Table 4 uses only one instrument at a time. In panel C of Table 4 we therefore use multiple lagged instruments in the models, where the instruments are grouped as in Table 2. The results tend to confirm the impressions from Panel B. (The table only reports cases where the p-values are less than 10%.) Overall, of the 24 cases, nine of the conditional alpha point estimates are positive and 15 are negative. However, in some of these cases the additional regressors in the conditional models are not significant, and we would expect to get results similar to the unconditional model when the coefficients on the conditional terms are zero. In other words, some of these cases are essentially unconditional alphas. If we restrict our attention to the subset of cases where the p-value of the F statistics for the conditional terms is less than 0.10, we find six of the 24 cases, which is statistically significant.[13] Three of these alphas are positive and three are negative. This confirms two of the main results of the earlier CPE studies. First, the conditioning variables are jointly statistically significant. Second, the conditional alphas are centered around zero.

Since our sample of funds is much broader than in Ferson and Schadt (1996), Table 4 shows that the general flavor of their results on conditional alphas hold in a broader sample of funds, constructed to control survivor selection bias. Our list of

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[13] Under the null hypothesis of no predictability and assuming independent Bernoulli trials, the t-ratio for the significance of finding 6 of 24 p-values less than 0.10 is $[6/24 - .10]/[(.10)(.90)/24]^{1/2} = 2.45$.

lagged instruments is more inclusive, which shows that the central results are robust to the choice of instruments. Finally, table 4 shows that the main results are robust to including a decade of new data.

Performance Against Style-based Benchmarks

Given the cumulative empirical evidence against the accuracy of the CAPM in describing risk-adjusted required returns, it is increasingly common to evaluate funds relative to benchmark indexes that control for the manager's investment style. This can be done using multiple risk-factor indexes in place of the market portfolio of the CAPM, as in the Arbitrage Pricing Model (APT, Ross, 1976) or the Merton (1973) multifactor asset pricing model. This approach is developed for unconditional fund performance measures by Lehmann and Modest (1987) and Connor and Korajczyk (1986), and applied to style indexes by Carhart (1997). Alternatively, a single index can be constructed from a set of primitive asset-class returns, with fund style-specific weights, and the single index can replace the market return in the CAPM. We use the latter approach. The asset-class returns are the passive benchmark returns described in Table 1, and whose conditional returns were studied in Table 2.

We construct style-matched benchmarks using an approach similar to Sharpe (1988, 1992). The problem is to combine the asset class index returns, denoted by R_i, using a set of portfolio weights, denoted by $\{w_i\}$, so as to minimize the "tracking error" between the return of the fund or fund style group in question, denoted by R_p, and the style-match benchmark portfolio, denoted by $\Sigma_i w_i R_i$. The portfolio weights are required to sum to 1.0 and must be non-negative, which effectively rules out short positions.[14] We formally state the problem to be solved as:

[14] Dor, Jagannathan and Meier (2003) argue that when returns-based style analysis is applied to hedge funds, the restriction against short sales may be relaxed.

$$\text{Min}_{\{wi\}} \text{Var}[R_p - \Sigma_i w_i R_i], \quad (5)$$

$$\text{subject to:} \quad \Sigma_i w_i = 1, \; w_i \geq 0 \text{ for all i},$$

where Var[.] denotes the variance. We solve the problem numerically for each of the fund style groups and derive a set of weights for each group.

In the returns-based style analysis as conducted by Sharpe (1988, 1992) and others, and as reviewed recently by Dor, Jagannathan and Meier (2003), it is common to use the return difference, $R_p - \Sigma_i w_i R_i$ to measure performance. The average difference over an evaluation period is a measure of alpha. The variance of the difference is a measure of tracking error, or active management. However, these interpretations are only correct if the style of the fund does not change over the estimation period, as emphasized by Christopherson (1995).[15] Furthermore, this approach assumes that the "beta" of the fund on the style-matched benchmark is constant over time and equal to 1.0. Our approach relaxes the restriction that the beta of the fund on the style-matched benchmark is exactly 1.0. In addition, our conditional models allow the betas to vary over time with the state of the economy.

In Appendix A, Table 3A presents the style-index weights for each asset class and summary statistics for the style-matched benchmark returns that result from applying these weights to the asset class returns. Panel A presents the weights. (The weights reported in the table do not sum exactly to 1.0 due to rounding errors, but we carry many more digits of precision in the actual calculations.) There are a fair number of cases where the assigned weight is zero (twenty six out of sixty four weights), which indicates that the no-short-selling constraint is binding. The largest weights are for

[15] Sharpe (1992) and Dor, et al (2003) use a rolling, 60-month estimation period.

sector funds in growth stocks (78%) and small company growth funds in growth stocks (72%), which both make intuitive sense. Other large weights include the weight of Growth and Income funds on the broad equity index (67%) and of Timing funds on the one-year government bond return (60%). The most concentrated weights are assigned to the Sector funds, where the benchmark comprises 78% growth stocks and 11% each value stocks and long-term government debt. The most disperse set of weights is applied to the Maximum Capital Gains funds, where the benchmark holds six of the eight asset classes and sports five weights in the 4%-15% range.

The weights applied to the fixed-income asset classes are nontrivial. Timing funds have the highest total fixed income weight, at 82% (60% in government and 22% in corporate bonds), followed somewhat paradoxically by the Maximum Capital Gains funds, at 60% total fixed income. This cold indicates a misspecification of the style analysis for Maximum Capital Gains funds. Other cases with large fixed income weights include Income funds (37%), Other Aggressive Growth funds (34%), Growth and Income (22%) and Small Company Growth funds (28%). These large fixed income weights no doubt reflect the fact that mutual funds hold cash balances in reserve against investor withdrawals.

Panel B of Table 3A presents summary statistics for the returns that result when the weights in Panel A are applied to the asset class benchmark returns to construct the style-based benchmark for each fund group. The highest mean return, over 1% per month, is associated with the benchmark for Sector funds. This style-based benchmark also has the largest standard deviation of return, over 5% per month. The high mean and high standard deviation reflect the concentration of the Sector fund benchmark in growth stocks, and its small fixed income exposure. The lowest mean return and the lowest standard deviation are both associated with the Timing fund benchmark, which earns 0.8% per month with a standard deviation of only 1.4%. This reflects the fact that 82% of this benchmark consists of fixed income securities.

In Appendix A, Table 4A repeats the performance analysis of Table 4, where the style-based benchmarks replace the market index of the CAPM. Otherwise, the analysis conducted is identical to that in Table 4. The first panel, which reports the unconditional regressions, reveals the higher precision that becomes available using style-matched benchmarks. The regression R-squares are higher for seven of the eight fund groups, and they exceed 79% in each case. Using the market index of the CAPM we had R-squares as low as 58%. Many of the betas are significantly different from 1.0, which supports our approach of not constraining the betas to equal one. The estimated alphas, however, are similar to what we found using the CAPM in their overall magnitudes. Five of the eight are negative. This is weak evidence that the funds look better against their style benchmarks than against the market, where seven of the eight alphas were negative. Due to the greater precision using style benchmarks, we have smaller standard errors, and the absolute values of the t-ratios attached to the alphas is larger than in Table 4. Still, no t-ratio for the unconditional alpha of any fund group is larger than two.

Panel B of Table 4A presents the regressions estimating the conditional alphas, one instrument at a time. Compared to the model with the market index we find a larger number of cases where the F-test can reject the hypothesis that the lagged state variables may be excluded from the regression. Using a 10% significance level, this null is rejected for 26 of the 88 cases examined, while using a 5% level there are 17 cases. The multiple-comparisons t-ratios for the significance of this finding are 6.11 and 6.16, respectively at the two significance levels. Thus, we have strong evidence for the statistical significance of conditioning on the state variables when the style benchmarks are employed.[16]

The lagged state variables are used here to model time-variation in the style index betas. The evidence supports our approach of allowing the betas for vary over time, and rejects the restriction that they are always equal to 1.0, as assumed in the traditional returns-based style analysis. This provides evidence of a form of "style drift" at the fund group level. That is, funds tend to vary their sensitivity to the average style exposures, depending on economic conditions. Income funds and market timing funds seem most prone to this behavior.

The average conditional alphas remain centered near zero when measured relative to the style benchmarks. There are twelve positive alphas and 14 negative alphas in Panel B of Table 4A. The only statistically significant conditional alphas are for the timing funds, where the alphas are negative and four of the six t-ratios are below -2.0. Negative alphas for timing funds are to be expected, according to the analysis of Grant (1977), Jagannathan and Korajczyk (1986) and others, as discussed below in the section on market timing.

Panel C of Table 4A summarizes the conditional model regressions when multiple instruments are used, grouped according to the states of the term structure, financial markets or the macroeconomy. Again, we only report the groups where the pvalues are below 10%. The F-test for the exclusion of the instruments produces pvalues this small in 14 of the 24 cases. This implies a multiple-comparisons t-ratio of 7.9, again producing strong evidence that loadings on the style benchmarks vary with the state of the economy. Interestingly, the state variables related to the macroeconomy

[16] These inferences are conditioned on the weights of the style-based indexes, in the sense that the standard errors do not incorporate the estimation errors involved in the construction of the style-based indexes. Accounting for this additional sampling variation is likely to lower the t-ratios.

produce the most frequent examples of changing loadings, whereas it was the term structure state variables when the market index of the CAPM was used. Of the 14 cases where the conditioning variables appear significant, the conditional alphas remain centered near zero, with six of the estimates negative and eight positive. Only two of the t-ratios for the alphas are larger than 2.0, which is about what should be expected when 24 cases are examined and the true alphas are zero.

Performance Conditioned on Discrete States

In the unconditional CAPM we regress the funds' excess returns on the market excess return and the intercept is the Jensen's alpha. The conditional model adds interaction terms to the regression. These terms are motivated, as explained earlier, by models in which a fund manager responds linearly to information. The funds' portfolio betas, in particular, are assumed to vary as a linear function of the instruments. However, the assumption of linear betas is only an approximation of convenience, and funds may respond nonlinearly to information in practice. For example, the use of derivatives is likely to induce a nonlinear relation between a fund and the market. However, there is little direct evidence in the previous literature on how important beta nonlinearity is for mutual funds. If the true relation is far from linear, the interactive regressions are likely to be biased and inefficient. If we can measure conditional performance while avoiding the linear beta assumption, we should obtain in cases where nonlinearity is important, a more reliable picture of the true performance.

The model of Ferson and Schadt (1996) allows only a single conditional alpha, and therefore only captures the overall average conditional performance.[17] This

[17] The average conditional alpha differs from the unconditional alpha to the extent that the conditional beta differs from the unconditional beta and is correlated with the expected market return (see Christopherson, et al., 1998).

may obscure conditional performance that depends on the state. For example, some funds may have positive conditional performance given high values of a state variable and negative performance conditional on low states. The returns in Table 3 suggest just such a possibility. In this case, by averaging the conditional performances together in a fixed measure, as in Ferson and Schadt (1996), we may produce a neutral measure for the average performance. The desire to measure time-varying conditional performance motivated Christopherson, et al. (1998) to generalize the Ferson and Schadt regression (1) to the regression (4), with a time-varying conditional alpha.

This section uses the discrete dummy versions of the lagged state variables to assess performance at the level of the fund groups. We estimate Equation (4), where Z is the vector of dummy variables corresponding to a given state variable. The vector consists of a constant, the dummy variable indicating a high value of the state variable, and the dummy indicating a low value of the state variable. Using the dummy variable instruments in regression (4), we do not assume that betas respond with any particular functional form. The approach is in this sense "nonparametric." We simply measure the average conditional beta and the average conditional alpha, given that the economy is in one of the three states. We allow both the conditional alphas and betas to vary across the states. We do not model how betas or alphas vary over time *within* a state. The potential cost of this dummy variable approach is that it will not capture time-variation in alphas or betas that may occur within a regime. For example, if the economy stays in a low interest rate state for an extended period of time, we capture only the average conditional performance given the low rate state, but not any time-variation in conditional performance during the low interest rate regime.

Table 5 presents the conditional alphas based on the discrete state variables. The figures may be compared with those in Panel B of Table 3, which gives the conditional returns before risk adjustment. The differences between the two tables are dramatic. In Table 3 we found 15 cases where the differences in returns between high and low states produced t-ratios larger than two. After adjustment using the conditional CAPM in Table 5, there are only two such instances. Only eight of the 176 conditional alphas examined have t-ratios larger than 1.6; among those five are positive and three are negative. The conditional alphas are also typically small in economic terms, compared with the return differences before risk adjustment. In Table 3 we found 38 cases where the difference in the conditional mean returns for high and low state variables was larger than one percent per month, and many were much larger. Only five of the 176 conditional alphas examined to construct Table 5 are larger than 1% in absolute magnitude, and the largest conditional alpha is 1.5% per month. The conditional alphas are generally small and their distribution is centered near zero.

The results of Table 5 confirm that the conclusions from the continuous instrument specifications are robust.[18] The strong impression is that the overall conditional performance of the broad fund groups is neutral.

In the Appendix A, Table 5A repeats the analysis of Table 5, replacing the market index with the fund-group specific style benchmarks. Many of the results confirm the findings of Table 5. For example, only nine of the 88 alphas examined in producing the table have absolute t-ratios larger than two, and only three of the conditional alphas are larger than one percent per month. (We only report cases where the absolute t-ratio is larger than 2.0.) The conditional alphas are small and centered

[18] Studies such as Harvey (1989), Ferson and Korajczyk (1995) and Jagannathan and Wang (1996) find that conditional versions of the CAPM explain equity portfolio returns better than the traditional model that ignores conditioning. It remains an interesting topic for future research to explore the performance of conditional CAPMs with nonparametric dummy variables for explaining the cross section of stock returns.

near zero, indicating that the conditional performance is neutral.

An Evaluation of the Time-variation in Risk Exposures

Tables 4 and 4A present evidence of significant time-variation in funds' betas. Betas may vary within an economic regime, and also across economic regimes. We now ask how important is time-variation, across versus within the economic regimes defined by the state variables. Using the discrete dummy versions of the state variables in the regression (4) we estimate the averages of the conditional betas across the months assigned to the high, low or normal states. The differences in these betas show how much of the beta variation occurs across the regimes. If the differences across the regimes are small, we conclude that most of the variation through time that was documented above occurs within the regimes, most likely at higher frequencies than the long swings depicted by the state variable dummies in the figures B1. Such high frequency beta variation may be induced by the relatively high-frequency flow of monies in and out of mutual funds.[19] Beta variation across the states, in contrast, is more likely related to strategic investment choices by the funds.

Conditional betas are shown in Table 6 for the high and low values of the state variables for each fund group, along with a t-ratio for the significance of the difference between the high and low-state conditional betas. Only states that produce an absolute t-ratio larger than 2.0 are shown. The term structure slope variable is where most of the action occurs. This variable is associated with significant shifts in betas for four of the seven fund groups. The betas are higher for the pure equity funds, and lower for the income funds, when the term structure slope is steep than when it is

[19] Spiegel et al. (2003) find that a Kalman filter approach to modelling monthly time-variation in mutual fund betas works well, which is consistent with the importance of relatively high-frequency variation.

shallow. The differences are substantial. For example, the conditional market beta of small company growth funds is 1.66 when the slope of the term structure is steep, only 1.02 when it is shallow. The income funds' betas average 0.19 given a steep term structure, 0.43 when it is flat. This is consistent with the view that equity funds become more aggressive on market exposure when the term structure is steep, perhaps in anticipation of the higher expected market returns illustrated in Table 2 at such times. While these extreme examples are intriguing, overall there is only a little evidence of shifts in the conditional betas at the fund group level in Table 6. About 5% of the t-ratios examined in producing the table are larger than 2.0, just as would be expected if there is actually no variation in beta across the regimes.

In the Appendix A, Table 6A summarizes the results of replicating Table 6, where the style-specific benchmarks replace the market index. The results are largely confirmatory. The timing funds seem to show the most significant tendencies to shift betas across the states, producing t-ratios for the hypothesis of no beta shift that exceed two, in three of the eleven cases. Overall, however, only nine of 88 cases present absolute t-ratios larger than two and there are no clear patterns in the estimates.[20]

In summary, we find that while there is significant time-variation in funds' market and style betas, little of this variation is associated with the discrete shifts in the economic states. It seems likely that much of the time-variation in beta is related to higher-frequency behavior, perhaps associated with redemptions and new money flows. The broad implications for investors and their advisors relate to strategic asset

[20] Of course, we may lose some power to detect beta variation by coarsening the states to three discrete regimes and by concentrating on one state variable at a time, compared to the multivariate analysis in panels C of Tables 4 and 4A. However, the strong results in Tables 2 and 3, which find that expected returns differ across the states, suggest that the loss of power should not be large.

allocation. Some investors may wish to adjust the risk exposures of their portfolios with respect to the states of the economy. For example, an investor who is more risk averse than average about bad economic times may wish to take less risk when the current state has high volatility or when expected economic performance is poor, than at other times during an economic cycle. Our results suggest that such strategies should be implemented by changing the allocation across fund categories. The funds themselves are unlikely to come with such strategic allocations built in, at least at this aggregate level.

6. Individual Fund Performance

While it may not be surprising to find little evidence of significant performance for entire groups of funds with different styles, the groups may mask significant performance at the fund level. Some funds are likely to perform well, and others poorly, even in the same fund group, and the performance of individual funds is of central interest for financial advisors and investors. The next two tables explore the patterns in individual fund performance.

In Table 7 we estimate the performance evaluation regressions for each individual fund with at least 12 months of data available. The instruments are the continuous versions of the lagged variables, grouped as in Panel C of Table 4. We summarize the results by recording the fractions of the individual-fund t-ratios that lie between standard critical values for a normal distribution, which is the asymptotic distribution for the t-ratios. The left-most column of each panel shows the fractions that would be expected under the null hypothesis of no abnormal performance, if the normal distribution provides a good approximation for the t-ratios.

Ferson and Schadt (1996) provided an analysis similar to the column labelled "All" in Panels A and B of Table 7, where all the individual funds are pooled. Their sample was much smaller -- with only 67 funds -- and it used data ending in 1990. They found that the distribution of the unconditional alphas was centered slightly to the left of the distribution under the null hypothesis. We find a similar result in Table 7. The unconditional performance measures suggest a slightly negative performance distribution. Also similar to Ferson and Schadt, the overall distributions of the t-ratios have fatter tails than a normal. There are more extreme negative and more extreme positive alphas for individual funds than would be observed with a normal distribution.[21]

Ferson and Schadt (1996) found that conditional models shift the distribution of individual-fund alphas toward better measured performance. We find no such evidence in Table 7. For example, 9% of the combined sample delivers t-ratios less than -2.36, while only 0.5% is expected if the distribution is normal and centered at zero. Using conditional alphas the fractions are 8-11% depending on the state variable groups, with no clear shifts in the distributions.

Ferson and Schadt (1996) were not able to provide distributions of performance for individual funds *within* their style groups because of their small sample. With the larger sample in this study, we can examine the conditional performance of individual funds relative to other funds with the same style, thus controlling for performance differences associated with style. Table 7 shows that for some fund groups (e.g. Maximum Capital Gains) the conditional alpha distribution looks more favorable than the distribution of unconditional alphas. For other groups (e.g. Growth) the conditional alpha distribution is less favorable, compared with the unconditional alpha distribution. Perhaps most striking is the result for income funds, which seem to produce an out-sized fraction of low alphas under all versions of the model. Thus, the patterns in individual-fund performance are richer than a pooled analysis can reveal.

In the Appendix A, Table 7A repeats the analysis of Table 7, replacing the market index of the CAPM with the style-specific benchmarks. Therefore, the overall

[21] The nonnormality, per se, in the distribution of the t-ratios is difficult to interpret. It could reflect the presence of extreme abnormal performers. Alternatively, nonnormality could reflect a sample size too small for the asymptotic distribution to be accurate. See Kosloski, Timmermann, Wermers and White (2003) for a bootstrap analysis that addresses these issues.

results are similar. The poor conditional performance of the bottom quarter or so of income funds cannot be explained by biases due to the use of the broad market index as the benchmark in the CAPM. In practical terms this analysis suggests that investors and their advisors should be especially careful in their selection of individual income-style funds. Poor risk-adjusted performance is easy to find, and a randomly-chosen fund has about a 25% chance of significant negative performance.

While the results in Table 7 control for the state of the economy through time-varying betas, those models do not allow the actual performance, measured by the alphas, to vary over time with the economic state. Table 5 above looked at models where the alphas are conditioned on the discrete state variable indicators taken one at a time, applied to the equally-weighted portfolios according to fund style groups. This allows the alphas to vary over time across the various states. Now, we look inside the groups at the performance of individual funds, allowing the conditional alphas to shift over time with the states.

Table 8 summarizes an analysis of the conditional performance of the individual funds, using the conditioning dummy variables one at a time. We summarize the results by comparing the individual funds to all other finds in the same style group, again controlling for the performance effects of fund style. There are a large number of cases to summarize, and we simplify the table by reporting only those instances where the distribution of the performance measures' t-ratios depart from the asymptotic distribution under the null hypothesis of no performance. We select those cases using a Chi-square test for the hypothesis that the distributions are normal. Similar to Table 7, the performance measures are divided into 8 bins and the frequency of funds observed in bin *i*, is f_i, i=1,...,8. The theoretical frequency under the null is g_i, i=1,...,8. The statistic $\chi^2 = \Sigma_{i=1,\dots,8} (f_i - g_i)^2/g_i$ is distributed as a Chi-square with seven degrees of freedom if the null hypothesis is correct (see, e.g. Freund (1992), pp. 487-488).

One interesting question that this analysis can address is whether the subset of individual funds with good or bad conditional performance generates that performance mainly in particular economic states. For example, we saw that the bottom 20-25% of income funds in Table 7 turned in highly significant negative alphas. Table 8 shows that their poor performance is not concentrated in particular economic regimes. Consider the states defined by the level of interest rates, for example. About 25% of the income funds have negative alphas with t-ratios larger than 2.36 when interest rates are high, and a similar fraction is found when interest rates are low.

While the poor conditional performance of income funds cannot be attributed to any particular state of the economy, there are interesting cases where Table 8 shows that the extreme performance of individual funds is concentrated in particular economic states. For example, Other Growth style funds have a concentration of poor performers when interest rate volatility is high or stock market volatility is low, while poor performance is relatively rare in this group when interest rate volatility is low. High dividend yield states reveal a large number of individual funds with good performance among the Maximum Capital Gain, Growth-and-Income funds and Sector funds, where none of these appear in low dividend yield states. Growth-and-Income funds produce a large number of positive performers when inflation is high, but not when inflation is low. Many Small Company Growth funds perform poorly when interest rate volatility is high or stock market liquidity is low. These patterns in the conditional performance of individual funds are interesting, both from a style allocation and a fund selection perspective. For style allocation, the results suggest how it is useful to consider the current economic state in setting expectations for individual fund performance, depending on style. For fund selection, the results indicate where poor performance is likely to be harder to avoid, and where extra care in fund selection is relatively likely to pay off.

The analysis of Table 8 suggests that there are several cases where the abnormal measured performance of the extreme-performing individual funds in a style group is concentrated in particular economic states. In the Appendix A, Table 8A replicates the analysis of Table 8, replacing the market index benchmark of the CAPM with the fund style-specific benchmarks. Most of the results emphasized above are robust to this change in the model. These results should be of interest to analysis attempting to pick funds in particular style groups, in search of abnormal risk adjusted returns or in an attempt to avoid poor risk-adjusted performance. The results suggest that certain styles of funds deserve more scrutiny in particular economic states, as the likelihood of finding extreme performers may be higher at some times than at other times.

7. Performance and Individual-Fund Characteristics

In this chapter we expand our fund-level analysis of performance to include the objective, fund-specific characteristics. We conduct this analysis using cross sectional regressions, as illustrated by Equation (6):

$$\alpha_{it} = \alpha_{0t} + \alpha_{1t}'X_{it-1} + \varepsilon_{it}, \quad i=1,\ldots,N_t. \tag{6}$$

At the end of each year we record the vector of fund characteristics denoted by X_{it-1} for fund *i*. We use the following 36 months of data to estimate a measure of performance for each fund, denoted by α_{it}. We estimate the cross-sectional regression each year, attempting to predict fund performance using the lagged fund characteristics.

In each cross sectional year we studentize the fund characteristics, borrowing a technique from quantitative equity models. We subtract the cross sectional mean from each characteristic and divide by the cross-sectional standard deviation. Thus, the coefficients in Equation (6) are interpreted as the percentage increment to alpha associated with a characteristic that is one standard deviation above the mean. For example, using the Growth-style funds the slope coefficient on the characteristic "gains" is about 0.2% per month, with a huge t-ratio, in the regression predicting unconditional alphas. This means that, other things equal, selecting an individual growth fund that earned capital gains in the top third of all growth funds last year (one standard deviation above the mean) is expected to result in 20 basis points per month of extra alpha, over the next three years.

The number of observations in a given year, N_t, is the number of funds for which we have the characteristics data at the end of year t-1 and where we also have at least 24 months of returns data over the next 36 months, to estimate the performance measure.[22] We aggregate the results across years, using the methods of Fama and MacBeth (1973). Fama and MacBeth advocate using the average over time of the cross sectional regression estimates of α_{1t} to conduct inferences about the performance differences associated with the characteristics. The standard error for the average coefficient is computed as the standard error of the mean, using the time-series of the estimated coefficients.[23]

The standard properties of a regression model imply that the analysis using Equation (6) automatically focusses on relative fund performance. This is because a regression slope coefficient is invariant to subtracting the sample mean from the dependent variables. We therefore conduct the cross-sectional analysis within fund-style groups, so the coefficients describe individual fund performance relative to funds with the same style. In our data set only three fund style groups have enough funds to conduct a reasonable cross-sectional analysis, starting with the characteristics in 1972. These are the Growth funds, Income funds and Growth-and-Income funds. We focus on the Growth funds and the Income funds here.

One of the interesting fund characteristics is a fund's turnover. Edelen (1999) argues that it is useful to decompose the cross-section of turnover into two parts. The first component, which we will call "nondiscretionary" turnover, reflects trading in response to flows of new money in or out of the fund. Edelen argues that such nondiscretionary trades may hurt fund performance. The second component is

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[22] This selection criteria may introduce a mild survival selection bias, which seems unavoidable.

[23] Due to the overlapping nature of the data used in constructing the performance estimates, the time series of the regression coefficients inherits a moving average structure of order two, or MA(2). We adjust the standard errors of the coefficients for this effect using Hansen's (1982) consistent covariance matrix estimator.

"discretionary" turnover. This reflects the trading that managers conduct, not because they are forced to, but because they want to. Edelen argues that these are the trades that should enhance performance when managers have skill.

Following Edelen (1999) we use the following cross sectional regression to decompose a fund's reported turnover each year into discretionary and nondiscretionary components:

$$Turn_{it} = d_{0t} + d_{1t}\,Flow_{it} + v_{it},\ \ i=1,\ldots,N_t. \tag{7}$$

The fitted values of the regression for each fund in each year, given by the estimates of $d_{1t}\,Flow_{it}$, measure nondiscretionary turnover. This is the portion of turnover that is explained by the cross-sectional relation between flow and turnover that year. The intercept plus the residuals of the regression, $d_{0t} + v_{it}$, are used as our estimate of discretionary turnover. This is the portion of turnover that is uncorrelated with fund flow in the cross section that year.

Empirical Results

Table 9 summarizes the results of the cross sectional regression analysis of the individual funds. Panel A presents the results when the unconditional CAPM alpha is the measure of performance. Panel B summarizes the regressions for Growth funds using the conditional CAPM alphas as the performance measures, while Panel C summarizes the regressions for the Income funds. Panels D, E and F repeat the analysis, substituting the Sharpe style benchmarks for the broad equity index benchmark. We summarize the conditional model results by focussing on the term structure state variables. The coefficients associated with each characteristic are shown, with the

Fama-MacBeth t-ratios on the second line.

The regressions suggest a number of interesting patterns. In Panels A and D, older growth funds with a longer track record turn in significantly larger unconditional alphas than younger growth funds, although the magnitude of the difference, at less than five basis points, is not large. A fund that is one standard deviation older than the average fund is expected to generate just under five basis points per month of extra alpha over the next three years. The coefficients also suggest that funds with large total net assets have higher alphas than small funds, and that higher load fees are associated with higher unconditional alphas. All of these results are robust to the choice of the benchmark index.

The result on fund loads is consistent with earlier findings from Ippolito (1989), who observed that load funds offer higher average returns than no-load funds. Our regressions show that this extends to conditional measures of performance, at least for Growth funds. However, among Income funds the predictive power of loads for individual fund alpha is diminished. The coefficient is about half the size and the t-ratio is less than two. Of course, some funds may substitute load fees, which are not reflected in the measured returns, against 12b-1 fees, which are taken out of the returns as part of the expense ratio. In practice, it would be important to consider the cost of the load fee, in relation to the investor's horizon, when using these results to guide fund selection decisions.

The strongest results for the unconditional alphas relate to the capital gains and total returns of a fund over the previous year. Both gains and lagret have large positive coefficients (20-50 basis points per month) and t-ratios larger than 9.0 in the Growth fund regressions, but in the Income funds neither effect is significant. This may be interpreted in terms of "momentum" in stock returns and funds. Jegadeesh and

Titman (1993) describe momentum as a cross-sectional pattern in stock returns. Stocks whose relative return over the last year or so was large, tend to have large returns over the next year or so as well, relative to the overall market. Grinblatt, Titman and Wermers (1995) find a similar pattern in equity fund returns. They find that Growth funds in particular, tend to hold momentum stocks. Ferson and Khang (2002), examining the holdings of pension funds, also found that growth-style funds tend to hold momentum stocks, and value-style funds tend to be contrarian, concentrating their holdings in those stocks that have recently performed poorly. The regressions in Table 9 are consistent with these findings. The large positive coefficients on gains and lagret among the growth funds indicate a momentum effect: Growth funds with relatively high returns over the past year tend to have larger unconditional alphas going forward. Income funds, in contrast, display no such momentum. This makes sense as income funds are more likely to hold stocks whose prices are low, relative to dividends and cash flow measures. Such a strategy is unlikely to imply momentum.

We estimate the regressions using conditional performance measures in Panels B, C, E and F. The findings are easy to summarize. Every effect that was significant for the Growth funds using unconditional alphas, is also observed using the conditional alphas. The signs of the coefficients agree in each of these cases. However, the effects are reduced, relative to the unconditional case. The coefficients are uniformly closer to zero and the t-ratios are uniformly smaller. The effects of fund age, load fees and the momentum effects still produce t-ratios larger than two. For the Income funds, the conditional results are also similar to the unconditional results, and the only case where an absolute t-ratio is larger than two is lagret, where the coefficient is negative. The effects of fund flows, discretionary turnover and expense ratios are all insignificant.

8. Market Timing

A classical market-timing model follows from Treynor and Mazuy (1966):

$$r_{pt+1} = a_p + b_p r_{mt+1} + \Lambda_p r_{mt+1}^2 + w_{t+1}. \quad (8)$$

Treynor and Mazuy (1966) argue that $\Lambda p>0$ indicates market-timing ability. The logic is that a market-timing manager will generate a return that bears a convex relation to the market: When the market is up, the fund will be up by a disproportionate amount. When the market is down, the fund will be down by a lesser amount. However, a convex relation may arise for a number of other reasons. One of these is common time-variation in the fund's beta risk and the expected market risk premium, due to public information on the state of the economy. Ferson and Schadt propose a refinement of the Treynor Mazuy model to handle this situation:

$$r_{pt+1} = a_p + b_p r_{mt+1} + C_p'(Z_t r_{m,t+1}) + \Lambda_p r_{mt+1}^2 + w_{t+1}. \quad (9)$$

In Equation (8), the term $Cp'(Z_t r_{m,t+1})$ controls for common time-variation in the market risk premium and the fund's beta, just like it did in the regression (1).[24]

In theoretical market-timing models (see Admati, Ross and Pfleiderer (1986) or Becker et al., 1999) the timing coefficient is shown to depend on both the precision of the manager's market-timing signal and the manager's risk aversion.

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[24] Ferson and Schadt (1996) also derive a conditional version of the market timing model of Merton and Henriksson (1981), which views successful market timing as analogous to producing cheap call options. This model is considerably more complex than the conditional Treynor-Mazuy model, and they found that it produced very similar results. We therefore do not study conditional Merton Henriksson models in this monograph.

Precision probably varies over time, as fund managers are likely to receive information of varying uncertainty about economic conditions at different times. Risk aversion may also vary over time, according to arguments describing mutual fund "tournaments" for new money flows (e.g. Brown, Harlow and Starks, 1996), which may induce managers to take more risks when their performance is lagging and to be more conservative when they want to "lock in" favorable recent performance. Therefore, it seems likely that the timing coefficient which measures the convexity of a fund's conditional relation to the market is likely to vary over time. We allow for such effects by allowing the timing coefficient to vary over time as a function of the state of the economy. We replace the fixed timing coefficient above with $\Lambda p = \Lambda_{0p} + \Lambda_{1p}'Z_t$. Substituting this into Equation (8), we derive a new conditional timing model with time-varying performance:

$$r_{pt+1} = a_p + b_p\, r_{mt+1} + C_p'(Z_t\, r_{m,t+1}) + \Lambda_{0p}\, r_{mt+1}^2 + \Lambda_{1p}'(Z_t\, r_{m,t+1}^2) + w_{t+1}. \quad (10)$$

In this model the new interaction term $(Z_t\, r_{m,t+1}^2)$ captures the variability in the managers timing ability, if any, over the states of the economy. By examining the significance of the coefficients in $\Lambda 1p$, we test the null hypothesis that the timing ability is fixed against the alternative hypothesis that timing ability varies with the economic state.

A special case of the model of Equation (10) occurs when we use the dummy variable versions of the lagged state variables. In this version of the model we estimate the average conditional timing coefficient given high, low and normal values of the state variable. The tradeoffs here are similar to what we face in the estimation of conditional alphas. With the dummy variables we avoid the functional form assumptions, and so the results are robust to mispecification of the functional forms of time varying betas or conditional timing coefficients. However, we only capture variation through time in these aspects of the model that occur across the regimes defined by the state variables.

Empirical Evidence on Timing Ability

Lehmann and Modest (1987), Grinblatt and Titman (1988), Cumby and Glen (1990), Ferson and Schadt (1996) and others estimated Treynor-Mazuy regressions and found a tendency for negative estimates of Λ_p for equity mutual funds in Equation (8). Ferson and Schadt (1996) found that this result is spurious, in that negative Λ_p is also found for a buy-and-hold strategy, while negative Λ_p's are not commonly found in the conditional model of Equation (9). These studies used broad samples of US equity funds that did not focus in on those funds most likely to engage in timing behavior. Becker, et al. (1999), however, found similar results using a different model in a broad sample of funds, and they found less of a tendency for negative timing coefficients in a subsample focussed on market-timing style mutual funds.[25]

Table 10 summarizes the results of estimating the market-timing models (8) and (9) on our sample of market-timing funds for the 1973-2000 period. We concentrate on the estimates of the timing coefficients and on the marginal explanatory power of the lagged state variables in the conditional models. The state variables are measured in their continuous forms and grouped according to the term structure, financial markets and the macro economy. The alphas in these models are difficult to interpret as a measure of abnormal return. This is because the timing term is a squared market return instead of the excess return on an asset. The expected value of the

[25] They used balanced and asset allocator style funds, as we do here, but their data from Morningstar suffered from survivor selection bias.

squared term, multiplied by the timing coefficient, is essentially deducted from the alpha, and this expected value has no clean interpretation as a return premium. While it is possible to modify the timing term in order to interpret the modified alpha as a timing-adjusted excess return (see e.g. Gloston and Jagannathan, 1991), such modifications rely on highly stylized assumptions. The magnitudes of the timing coefficients in Table 10 suggest that such an exercise would offer few new insights, so we avoid the extra complexity here.[26]

The first panel of Table 10 presents the unconditional timing coefficients, γ_u, their t-ratios and the R-squares summarizing the explanatory power of the unconditional timing regression (8). The next three panels present similar information for the conditional models, along with p-values for the F-test of the significance of the lagged state variables. Panel B uses the continuous versions of the state variables related to the term structure, Panel C uses the continuous financial market state variables and Panel D uses the state variables for the macroeconomy. Each row of the table summarizes a particular characteristics-based fund portfolio. To save space, we only show those cases where a t-ratio for a timing coefficient is larger than two or the p-value for the additional conditioning variables is less than 10%.

From the p-values of the F-tests we can draw inferences about the

[26] The largest timing coefficients in Table 10 are about 0.3. Multiplied by the average squared excess return on the market index, the effect of the timing term is no larger than $(.0105-.00606)^2 \times 0.3 = 0.0006\%$. Thus, the intercepts in the timing models are very similar to the alphas in the corresponding models that do not include the squared market term, and these were studied above. In order to adjust the intercepts to compute a timing adjusted alpha, it is necessary to multiply the timing coefficient by the expected excess return on a strategy that buys call options on the market portfolio, with strike prices indexed to the Treasury rate. As call options are much riskier than the market index, the expected risk premiums attached to the options should be much larger than the squared market return, and the timing adjusted alphas could be very different from the intercepts in our regressions.

significance of the lagged state variables in the conditional models. The state variables in these models capture variation over time in the funds' market betas that is correlated with the lagged public information. The number of cases, out of 28 possible, where the right-tail p-values are less than 5% are 3, 16 and 6, respectively in the three panels. Except for Panel B, the small p-values are found more than would be expected under the null hypothesis that the state variables may be excluded from the model. The multiple-comparisons t-ratios for the three panels are 1.39, 12.66 and 3.98, respectively.[27] There is particularly strong evidence of time-varying betas for the market-timing funds in response to the public information represented by the financial market state variables.

Ferson and Schadt (1996) and Becker et al. (1999) found that conditional timing models made funds look better than unconditional models. Table 10 provides mixed evidence on this score. In panel B, conditioning on the term structure state variables, the point estimates of the timing coefficients appear to confirm that result on our sample. Remarkably, in all 28 cases examined the conditional timing coefficient is larger than the unconditional coefficient. However, in panels C and D we do not find the same result, and the differences actually go the other way in all but four or five cases we examine in constructing the table. The most important instruments that were used in the studies of Ferson and Schadt and Becker, et al. are related to interest rates, so this could reconcile our results with those of the earlier studies.

The t-ratios attached to the timing coefficients allow us to address the question of whether the timing funds have significant market timing ability. For the unconditional timing models, four of the 28 fund groupings produce t-ratios larger than

[27] The calculations are as follows. Let x be the number of cases where the p-value is less than 0.05. The multiple-comparisons t-ratio across the 28 cases in each panel is $(x/28 - .05)/(.05^*.95/28)^{1/2}$.

two. On a multiple-comparisons basis, that implies a t-ratio of 2.25, more than would be expected if there is no ability. Only five of the 28 unconditional coefficients are negative. This is consistent with the results of Becker et al. (1999), that negative unconditional timing coefficients are less likely to occur when the sample concentrates on likely market timers. Moving to the conditional timing models, we find 8, 3, and 5 examples in the three panels respectively, where the t-ratios are larger than two in absolute value, and all of these are positive. The multiple-comparisons t-ratios for finding this many large t-ratios out of 28 are 5.72, 1.39 and 3.12, respectively. So there is evidence that some of the market-timing funds may have positive conditional timing ability.

Comparing the timing coefficients across the fund groups with high, medium or low values of the various characteristics provides further insights into which types of timing funds are more likely to be successful. There are several striking results. The strongest results relate to age and fund size as measured by the total net assets (TNA). Older funds tend to be better timers than medium-aged or young funds. Funds with high TNA at the end of the previous year have larger timing coefficients than smaller funds. Funds with the lowest expense ratios have the largest timing coefficients. Medium-expense-ratio funds do not time as well as low-expense funds, and high-expense funds have the smallest timing coefficients. Interestingly, there is some evidence, albeit weaker, that high-load funds may have better market timing ability. This is consistent with the use of load fees as a screening device, to penalize investors who trade frequently, which can make it more difficult for the fund to effectively implement its own active trading strategy. Finally, when the previous year's capital gains distribution is small, it predicts better timing performance over the next year.

We checked these findings by ungrouping the lagged state variables, using them one at a time. We confirmed that the best conditional timers had the longest track records, the largest TNA, the lowest expense ratios, and the smallest capital gains. We also ran the analysis of Table 10, substituting the style-related benchmarks for the market index. In this case we picked a style benchmark at random for each fund-characteristics group. The main findings are also robust to this experiment.

In Table 11 we summarize the results for the market timing model of Equation (10) using the discrete dummy versions of the lagged state variables. In this model we allow timing ability to vary across the states, and as described above, we avoid the assumptions that conditional betas are linear functions or that the timing coefficients have any particular functional form. We estimate the average conditional timing coefficient given high, low and normal values of the state variable; the table summarizes results for the high and low states using the state variables one at a time. We report the timing coefficients in the high and low states, t-ratios for the hypothesis that a coefficient differs from zero, and a t-ratio which examines the hypothesis that the timing coefficients are equal in the high and low states for a given group of funds. Each row of the table summarizes a particular characteristics-based fund portfolio. To conserve space, only cases where an absolute t-ratio is larger than 2.0 are reported.

Much of the evidence of Table 11 remains consistent with neutral conditional timing performance. The fraction of absolute t-ratios larger than two is not significant, given the number of cases examined, when we condition on the level of interest rates, interest rate or stock market volatility, credit spreads or the macro economy state variables. However, in some instances we find significant evidence of conditional timing in certain states.

The most striking example of time-varying timing ability is related to the slope of the term structure. There are 23 cases out of the 56 examined where the absolute t-ratio for the timing coefficient is larger than two. This corresponds to a multiple-comparisons t-ratio of over 40.0. Furthermore, all of the significant cases occur conditional on a high term structure slope, and all of these coefficients are positive. Thus, we have striking evidence that market timing funds can deliver significant conditional timing performance when the term structure slope is steep. In contrast, when the slope is shallow none of the conditional timing coefficients is significant and about 1/4 of the point estimates are negative. The t-ratios testing the hypothesis that the two conditional timing coefficients are equal strongly rejects the hypothesis, with 19 out of 28 t-ratios examined larger than two. The timing funds seem unable to deliver reliable market timing services when the slope of the term structure is flat. The results conditioning on term structure concavity are similar, with significant timing performance when the term structure is highly concave. This probably reflects in large part the high correlation between these two states: When the term structure is steep the yield curve tends to present more concavity.

We find evidence of time-varying conditional timing ability associated with three other state variables relating to the state of the financial markets: dividend yields, short term corporate illiquidity and stock market liquidity. In the case of dividend yields, positive timing ability is found conditional on high yield states. There are ten cases with absolute t-ratios larger than two in these states, which out of the 56 cases examined implies a multiple-comparisons t-ratio of 14.3. For stock market liquidity, there are 12 absolute t-ratios larger than two, which implies a multiple-comparisons t-statistic of 18.3. All of these coefficients are associated with high-liquidity states and all are positive. In low liquidity states there are no t-ratios larger than two on the timing coefficients, and six of the 28 coefficients examined are less than zero. It makes sense that successful market timing should be more likely when the stock market is highly liquid, because market timing trades may be made at lower cost in highly liquid markets. Finally, we find some time-variation in timing ability associated with the states of short term corporate illiquidity. Nine of 56 absolute t-ratios we examine are larger than two (multiple-comparisons t-ratio=12.3.) Among those coefficients with t-statistics larger that two, we find mostly negative coefficients when illiquidity is high, positive coefficients when the markets are more liquid. Thus, the effects of liquidity in the stock and corporate debt markets seem to operate in a similar fashion.

Finally, the results of Table 11 confirm our earlier findings about which types of funds are likely to be the most effective market timers. The model with time-varying timing ability almost always assigns the largest conditional timing coefficients to the funds with the longest track records, the largest TNA, the lowest expense ratios, or the highest load charges.

9. Implications for Practicing Financial Analysts

CPE is potentially important for several areas of investment management, and in academic research. For institutions that hire money managers, such as mutual fund companies, pension plan sponsors, university endowments, foundations and trusts, it is important to know how well a manager has performed. Since CPE uses more information than traditional methods, bringing in additional variables to measure the state of the economy, it has the potential to provide more accurate performance measures. This monograph illustrates versions of conditional performance models that can be easily estimated as multiple regressions. By the choice of the lagged variables in the regressions, it is possible to set the hurdle for superior ability at any desired level of lagged information: Managers have to perform better than a mechanical strategy using the chosen lagged variables in order to record superior performance. Our results provide practical guidance on the regressions to run and the variables to use.

CPE can provide estimates of performance that depends on the economic state, whereas the traditional alpha ignores information about the state of the economy. If managers' performance is variable depending on the economic state, fund sponsors and investors may wish to allocate resources across funds in view of this information. Investors also need to understand how funds implement their investment policies dynamically over time. How, for example, does a fund's equity, bond or style exposure change in a time of high interest rates or market volatility? CPE is designed to provide a rich description of funds' portfolio dynamics in relation to the state of the economy. For pension consultants and the other intermediaries that work with fund managers and their ultimate investors, CPE opens up a wealth of new descriptive and analytical tools. One of the goals of this monograph is to motivate the use of CPE in future financial practice.

The empirical findings in this monograph carry implications for practicing financial analysts relative to three main issues. The first has to do with understanding the expected returns and risks of classes of financial assets and how these vary with the state of the economy over market and economic cycles. An understanding of these broad patterns is an important input for the problem of asset allocation. The second issue has to do with patterns in the expected returns and risks of mutual funds with different investment styles and fund characteristics, and how these behave over market and economic cycles. An understanding of these patterns is important for investors who may choose to implement a portion of their portfolio strategy using mutual funds. The third issue relates to the risk-adjusted, or abnormal performance of mutual funds. The evidence here bears on the desirability of mutual funds relative to other investment vehicles, as well as the characteristics of specific funds to be included in a portfolio.

The Conditional Behavior of Asset Class Returns

Financial analysts need to be aware of time-variation in expected returns and risk for different asset classes such as we document in this study. We group our measures of the state of the economy according to (1) the term structure or government yield curve, (2) the state of general financial markets, and (3) the macroeconomy. We show that states of the term structure are powerful predictors, not just for fixed income but also for equity returns. High levels of short term interest rates predict relatively high and volatile short term bond returns and low stock returns, with a gradual transition as you move from safer and shorter maturity to riskier and longer term asset classes. The level and the slope of the term structure seem to be the most informative predictors of return, with the concavity of the yield curve being less important. High interest rate volatility states are highly correlated with high interest rate levels.

We find that among the variables that measure the state of financial markets, high credit spreads predict high subsequent returns on stocks, and high dividend yields predict high returns on both stocks and bonds. The latter effect has weakened in more recent data, and should probably be viewed with suspicion in the near future. The weakening of the predictive power of dividend yields has been associated with a trend toward lower yields since the early 1990s. Perhaps, as recent tax law changes encourage higher dividend payouts in the future, the predictive ability of aggregate dividend yields could return. The most economically, if not statistically significant predictor among the financial market instruments we study may be the commercial paper - Treasury spread, measuring short term corporate illiquidity. When the spread is high all of the long term bonds and stock indexes earn high returns over the next month. Moreover, these high spread states do not seem to be associated with higher return volatility on these securities.

Among the variables measuring the macro economy, high inflation is bad news for stocks and longer-term bonds. High inflation levels predict low and also relatively volatile returns on long-term bonds and stocks, while short-term cash positions offer relatively high expected returns when inflation is high. When output growth is abnormally low, it predicts high returns, especially for the riskier assets, and the volatility of these investments is also high at such times.

The evidence that the risk and expected returns to different asset classes vary with the states of the economy seems compelling. But how can a financial analyst use this information in practice? Consider an investment advisor for a high-net-worth client. There may be some value added in simply explaining these expected return patterns to the client, relative to the current state of the economy at the time. (We have found a graphical representation of the figures in Table 2 to be especially compelling.)

A client may wish to alter the asset allocation, taking on more exposure to currently high expected return asset classes and less exposure to asset classes whose currently-expected performance is low. This must be considered, of course, in the context of the total portfolio risk and investment objectives, as well as the client's aversion to particular kinds of risks. In general, clients whose aversion to a specific risk is below that of the average investor may be advised to more aggressively tune the asset allocation to take advantage of higher conditional returns associated with state variables representing that risk at certain times. An investor who is more risk averse than average about bad economic times may wish to take less risk when volatility is high or expected economic performance is poor than at other times during an economic cycle.

The Conditional Behavior of Mutual Fund Returns

In addition to the patterns for broad asset classes, this monograph documents predictable patterns in the returns of some mutual fund types. Some of the patterns mirror those found for the passive asset class benchmarks. For example, the term structure state variables seem to be the most powerful predictors of the future fund returns. Low short-term interest rates predict high equity fund returns and high interest rates predict low returns. The differences can be dramatic. The expected returns given low interest rates are more than 2% per month greater than given high interest rates for the Maximum Capital Gains funds and almost that large for the Growth funds. A steep term structure slope also predicts high subsequent returns for most equity fund types. The differences are often economically large, at 3.2% per month for the Maximum Capital Gains funds and just under 2% for the Growth funds. High interest rate volatility is bad news for most fund groups, but the differences here are not significant, except perhaps for timing funds.

We find that there is significant time-variation in funds' market and style betas. However, little of this variation is associated with the discrete dummy variables measuring shifts in the economic states. It seems likely that much of the time-variation in beta is related to higher-frequency investment decisions by funds, perhaps associated with redemptions and new money flows. One of the broad implications for investors and their advisors relates to strategic asset allocation, as discussed above. Our results suggest that such strategies should be implemented by changing the allocation across fund style categories, since funds themselves are unlikely to come with such strategic allocations built in.

Risk-Adjusted Fund Performance

According to the theoretical model of Berk and Green (2004) we should see fund flows in response to informative signals of manager ability, and these flows should occur until expected future performance is neutral in equilibrium after costs. Where the flows in response to performance signals are insufficient to neutralize future performance, we may find predictable abnormal future performance.

Overall, we find that while unconditional measures of fund performance are slightly negative, the theoretically superior conditional measures tend to be centered near zero. This is broadly consistent with equilibrium in the fund management industry, where managers have enough skill to cover their costs and fees on the funds they manage. Investors are left roughly indifferent between a passive position in the asset class and an actively managed fund in the same asset class. Thus, actively managed funds may be viewed as a viable alternative to index funds, ETFs and other passive strategies.

While the overall distribution of conditional performance, based on funds' returns net of trading costs and fees, is centered near zero, the final question is whether funds with particular characteristics may offer higher or lower risk-adjusted returns than a randomly chosen fund. Our analysis of the cross-sectional distribution of fund alphas suggests that this may be the case. We found that the bottom 20-25% of income funds turned in highly significant negative conditional alphas, and this poor performance is not concentrated in particular economic regimes. Unfortunately, our cross sectional analysis of the Income funds turns up no simple relation between performance and the fund characteristics. Thus, we can offer no mechanical rules for avoiding the poorly performing subset of income funds in these market states.

We also find that extremely good and bad conditional performance is concentrated in particular economic states. Concentrations of abnormally high and low conditional alpha t-ratios are associated with dividend yield states for several fund styles. High dividend yield states reveal large fractions of good performers among the Growth, Small Company Growth, Sector and Growth and Income funds, where none of these appear in low dividend yield states. Growth and Income funds are able to generate a large number of positive performers when inflation is high, but not when inflation is low.

Finally, our cross sectional analysis of alphas provides some interesting results on which individual-level fund characteristics are associated with good conditional performance. We find that old growth funds have larger alphas than young funds. Growth funds tend to follow momentum trading strategies and this feeds through to their alphas. Growth funds with relatively high capital gains and total returns over the last year are expected to have higher alphas over the next year. Such a pattern is not to be found, however, among Income funds.

We find that funds with higher load charges are expected to have higher alphas than those with lower load charges. This extends earlier findings of Ippolito (1989) to conditional measures. The coefficients for growth funds are on the order of 20-25 basis points for a one standard deviation increase in load charges. For income funds the effect is smaller (10-13 basis points) and is not statistically significant. These results must be evaluated in relation to the load fees themselves. Unlike the expense ratios and trading costs, our fund return data are not measured net of load charges, which represent a separate expense to the investor. Thus, the investor needs to balance the higher load charge against the expected performance. Clearly, an investor with a short investment horizon would not want to pay the load fee. On the other hand, an investor with a very long horizon may be advised to consider load funds.

Market Timing Ability

A traditional wisdom among many financial analysts is that attempting to time the market is a fool's game. The temptation is great, because if you could correctly call the peaks and troughs and trade accordingly, the returns would be huge. However, the chances of successfully calling market highs and lows are thought to be slim, and in the attempt one is just as likely to buy too high and sell too low, missing out on market returns that a passive investment strategy would capture. In addition, market timing requires costly trades that hurt performance. Much of the "bad press" on the market timing ability of mutual funds, however, is based on unconditional measures of timing ability that are shown to be biased in studies such as Ferson and Schadt (1996) and Becker, et al. (1999). When conditional timing measures are used, the funds that specialize in this activity do not look as bad. We measure timing ability that is neutral to slightly positive. The timing ability comes at a cost in average return. The market-timing funds in our sample earn lower average returns than any other fund groups, excepting the income funds. We do not think the evidence of timing ability is strong enough to justify a ringing endorsement of market timing funds, but neither does our evidence rule out some exposure to this style of fund in a balanced portfolio.

Our analysis of conditional market timing ability provides potentially useful insights into which funds are more likely to be successful timers. We find that the best overall market timers were the largest funds (measured by total net assets), and the funds with the lowest expense ratios. We also find that older funds with a longer track record tend to be better timers. When we allow for time-variation in conditional timing ability, we find some striking evidence that market timing fund are able to time better in some economic states than in others. The best states for successful market timing are when the slope of the term structure is steep, short-term corporate debt markets are relatively liquid or stock markets are relatively liquid. It makes sense that successful market timing should be more likely when the markets are highly liquid, because market timing trades may be made at lower cost in highly liquid markets. On the other hand, market-timing funds seem unable to deliver reliable market timing services when the slope of the term structure is flat or when the markets are in an illiquid state.

10. Summary and Conclusions

As with all studies based on historical data, it is easier to describe past relationships than to infer whether the future will look similar to history. In this study, we expand the data base of mutual funds to include many new funds in recent years. This is both an advantage and a disadvantage. The advantages of a larger sample size are obvious, but new entrants may have different characteristics from more seasoned funds. In this case the underlying relations in the data could shift during the sample. As the figures in Appendix B illustrate, the characteristics of the population of mutual funds has shifted during the period of our analysis. This motivates our use of age as a characteristic in sorting the funds, and we find some differences between the old and young funds in our sample. The unit of analysis in our sample is the fund and not the fund manager, which raises another caveat. The investment style of a fund may change over time with changing managers such that data from a given fund may not represent a consistent style or philosophy across economic and market cycles. This is one motivation for allowing time-varying betas as well as alphas, as we do in this study, that may vary across market and economic cycles. Even so, our analysis presumes enough stationarity in the behavior of funds so that the process generating a fund's return is similar across repeated experiences of, for example, a high or low interest rate or inflationary regime. Thus, it is not obvious that one can safely extrapolate our results into the future.

Subject to these caveats, the results of our study are relevant to fund managers, management companies, financial advisors and their ultimate clients, the individual investors. The results should also be of interest to researchers studying mutual funds and their investment performance. Fund managers are interested in how they stack up relative to their peers, and our analysis of relative performance addresses this issue directly. Management companies, iter alia, care about how different fund styles are expected to perform in different economic states. Our characterization of conditional performance using discrete states should be informative on this issue. Financial advisors who wish to advise clients on asset allocation, fund style and fund selection should find our results directly relevant. Finally, academics should be interested both in the extent to which the "stylized facts" from earlier studies hold up in a broad and updated sample, as well as in the further pursuit of some of the issues raised by the new results of our analysis.

Table 1

Benchmark Returns and Lagged Instruments: Summary Statistics. The sample period for the returns is January, 1973 through December, 2000 (N=336). Returns are monthly rate of return, in percent. The sample period for the lagged instruments is December, 1967-November, 2000. Mean is the sample mean, std is the sample standard deviation and ρ_1 is the first order sample autocorrelation of the series.

series	mean	min	max	std	ρ_1
Panel A: Benchmark Returns					
90-day Bill	0.606	0.19	2.13	0.272	0.7730
One-year Bond	0.661	-1.72	5.61	0.630	0.2748
Government Bond	0.772	-8.40	15.23	3.051	0.1120
BAA Corporate Bond	0.819	-10.29	14.27	2.785	0.1930
Broad Equity Index	1.105	-22.49	16.56	4.618	0.0193
Growth Stocks	1.048	-27.45	17.69	5.834	0.1044
Value Stocks	1.373	-23.33	25.12	4.639	0.1208
Small Capitalization Stocks	1.279	-29.07	26.73	5.701	0.1643
Panel B: Lagged Instruments					
Short-term Interest Rate	6.897	2.785	16.71	2.690	0.9714
Term Stucture Slope	0.9075	-4.259	5.208	1.331	0.8759
Term Structure Convavity	0.09855	-0.6265	0.9035	0.2007	0.7811
Interest Rate Volatility	0.5980	0.000	1.552	0.2449	0.9121
Stock Market Volatility	0.03577	0.0001126	0.2512	0.01841	0.4666
Credit Spread	1.079	0.5500	2.690	0.4395	0.9639
Dividend Yield	3.458	1.450	6.125	1.044	0.9810
Inflation	4.964	-5.412	21.47	3.905	0.5966
Industrial Output Growth	2.884	-50.96	40.14	9.410	0.3804
Short-term Corporate Illiquidity	0.07933	-0.09977	1.149	0.1332	0.7382
Stock Market Liquidity	-0.03129	-0.4689	0.2025	0.05798	0.2100

Notes: The short term interest rate is the bid yield to maturity on a 90-day Treasury bill. Term structure slope is the difference between and five-year and a three-month discount Treasury yield. Term structure concavity is $y_3 - (y_1 + y_5)/2$, where y_j is the j-year fixed maturity yield from the Federal Reserve. Interest rate volatility is the monthly standard deviation of three-month Treasury rates, computed from the days within the month. Stock market volatility is constructed similarly using daily returns for the Standard and Poors 500 index. Dividend yield is the annual dividend yield of the CRSP value-weighted stock index. Inflation is the percentage change in the consumer price index, CPI-U. Industrial production growth is the monthly growth rate of the seasonally-adjusted industrial production index. Short-term Corporate Illiquidity is the percentage spread of three-month high-grade commercial paper rates over three-month Treasury rates. Stock market liquidity is the measure from Lubos and Stambaugh (2003), based on price reversals.

Table 2

Benchmark Return Statistics in Different Economic States. The sample period is January, 1973 through December, 2000 (N=336). Returns are monthly rate of return, in percent. Mean is the expected return, given the indicated state, and sdt is the standard error of the mean.

Asset Return:		90-day Bill		Govt. Bond		BAA Bond		Broad Equity		Growth		Value		Small Cap.	
State	N	mean	std	mean	std	mean	std	mean	std	mean	std	mean	std	mean	std
PANEL A: THE STATE OF THE TERM STRUCTURE															
Short Term Interest Rates:															
high	66.0	0.848	0.0442	0.414	0.442	-0.159	0.470	-0.0647	0.640	-0.213	0.889	0.507	0.662	0.30	0.86
normal	191.	0.585	0.0155	0.831	0.197	1.09	0.187	1.29	0.338	1.22	0.417	1.33	0.340	1.23	0.42
low	79.0	0.453	0.0170	0.927	0.374	0.981	0.223	1.65	0.428	1.69	0.505	2.19	0.409	2.21	0.46
Term Structure Slope:															
high	44.0	0.555	0.0369	1.93	0.393	2.25	0.374	2.04	0.567	2.25	0.780	2.44	0.555	2.66	0.70
normal	200.	0.573	0.0176	0.706	0.216	0.903	0.182	1.18	0.338	1.17	0.418	1.46	0.335	1.41	0.40
low	92.0	0.703	0.0320	0.362	0.326	-0.0466	0.320	0.50	0.477	0.20	0.615	0.68	0.496	0.33	0.63
Term Structure Concavity:															
high	36.0	0.659	0.0687	1.68	0.531	2.10	0.520	1.23	0.698	1.21	0.862	2.14	0.658	2.00	0.83
normal	215.	0.562	0.0151	0.633	0.196	0.827	0.172	1.07	0.306	1.02	0.392	1.26	0.319	1.20	0.38
low	85.0	0.695	0.0315	0.737	0.367	0.260	0.336	1.14	0.560	1.05	0.689	1.33	0.525	1.17	0.68
Interest Rate Volatility:															
high	68.0	0.842	0.0447	0.784	0.467	0.181	0.496	0.457	0.683	0.690	0.660	0.293	0.903	0.488	0.854
normal	193.	0.589	0.0147	0.771	0.195	0.973	0.174	1.19	0.329	1.35	0.337	1.17	0.415	1.30	0.417
low	75.0	0.436	0.0167	0.764	0.360	1.00	0.239	1.46	0.417	2.04	0.414	1.42	0.477	1.95	0.431
PANEL B: THE STATE OF FINANCIAL MARKETS															
Stock Market Volatility:															
high	66.0	0.659	0.0447	1.23	0.428	1.23	0.438	1.45	0.731	1.62	0.968	1.57	0.707	1.81	0.91
normal	238.	0.605	0.0158	0.586	0.189	0.655	0.165	1.04	0.286	0.964	0.352	1.29	0.292	1.13	0.35
low	32.0	0.506	0.0390	1.21	0.549	1.19	0.461	0.870	0.497	0.498	0.610	1.61	0.497	1.29	0.56
Credit Spreads:															
high	64.0	0.754	0.0473	0.646	0.413	1.35	0.455	2.33	0.588	2.81	0.724	2.75	0.686	3.24	0.75
normal	177.	0.597	0.0182	0.609	0.238	0.600	0.202	0.656	0.382	0.374	0.478	0.991	0.367	0.679	0.47
low	95.0	0.523	0.0190	1.16	0.268	0.869	0.229	1.12	0.347	1.12	0.460	1.16	0.328	1.08	0.41
Dividend Yield:															
high	55.0	0.820	0.0502	1.66	0.481	1.47	0.568	1.67	0.752	2.03	0.885	2.23	0.732	2.49	0.86
normal	143.	0.655	0.0208	0.542	0.246	0.712	0.228	1.13	0.376	1.11	0.478	1.38	0.400	1.28	0.48
low	138.	0.470	0.0127	0.655	0.247	0.671	0.171	0.849	0.369	0.590	0.480	1.02	0.350	0.79	0.45

table 2, page 2

Asset Return:		90-day Bill		Govt. Bond		BAA Bond		Broad Equity		Growth		Value		Small Cap.	
State	N	mean	std	mean	std	mean	std	mean	std	mean	std	mean	std	mean	std
Short-term Corporate Illiquidity															
high	36.0	0.576	0.0474	1.13	0.509	1.47	0.536	2.62	0.924	3.17	1.09	2.49	0.707	3.19	0.83
normal	275.	0.614	0.0165	0.759	0.186	0.775	0.167	0.958	0.264	0.829	0.334	1.34	0.281	1.13	0.35
low	25.0	0.566	0.0436	0.403	0.526	0.373	0.441	0.545	1.09	0.407	1.47	0.146	0.969	0.189	1.23
Stock Market Liquidity															
high	46.0	0.569	0.0372	0.766	0.476	0.889	0.396	1.23	0.566	1.37	0.666	1.14	0.473	1.48	0.56
normal	250.	0.605	0.0159	0.788	0.181	0.860	0.169	1.09	0.298	1.00	0.381	1.46	0.305	1.31	0.38
low	40.0	0.653	0.0614	0.682	0.627	0.482	0.563	1.08	0.779	0.967	0.959	1.09	0.775	0.876	0.98
PANEL C: THE STATE OF THE MACROECONOMY															
Inflation:															
high	51.0	0.707	0.0464	0.626	0.546	0.0357	0.560	0.0986	0.880	-0.477	1.11	0.236	0.873	-0.502	1.11
normal	231.	0.583	0.0166	0.655	0.183	0.803	0.161	1.18	0.286	1.20	0.363	1.37	0.290	1.38	0.35
low	54.0	0.609	0.0371	1.41	0.440	1.63	0.348	1.74	0.517	1.82	0.630	2.45	0.480	2.51	0.58
Industrial Output Growth:															
high	40.0	0.560	0.0389	0.433	0.353	0.422	0.326	0.393	0.545	0.185	0.676	1.13	0.492	0.856	0.63
normal	247.	0.595	0.0171	0.738	0.196	0.822	0.176	1.04	0.300	0.889	0.376	1.17	0.298	1.00	0.36
low	49.0	0.701	0.0412	1.22	0.500	1.13	0.481	2.03	0.701	2.55	0.911	2.57	0.763	3.01	0.95

Notes: For each state variable, high (low) values are defined to occur when the difference between the current level of the variable and a lagged, 60-month moving average is more than one 60-month moving standard deviation above (below) zero. Normal is defined as the values that are neither high nor low. The instruments are as follows. The short term interest rate is the bid yield to maturity on a 90-day Treasury bill. Term structure slope is the difference between and five-year and a one-month discount Treasury yield. Term structure concavity is $y_3 - (y_1 + y_5)/2$. Interest rate volatility is the monthly standard deviation of three-month Treasury rates, computed from the days within the month. Stock market volatility is constructed similarly using daily returns for the Standard and Poors 500 index. Dividend yield is the annual dividend yield of the CRSP value-weighted stock index. Inflation is the percentage change in the consumer price index, CPI-U. Industrial production growth is the monthly growth rate of the seasonally-adjusted industrial production index. Short-term Corporate Illiquidity is the percentage spread of three-month high-grade commercial paper rates over three-month Treasury rates. Stock market liquidity is the measure from Lubos and Stambaugh (2003), based on price reversals.

Table 3

Mutual Fund Monthly Returns: Summary Statistics. The sample periods for the returns are indicated under Begin and End. The sample period in Panel B is January of 1973-December of 2000 (336 observations) or the shorter period beginning when the data are available for a given fund group as indicated in Panel A. The returns are percent per month. Mean is the sample mean, std is the sample standard deviation and ρ_1 is the first order sample autocorrelation of the series.

Panel A: Overall Equally-weighted Portfolios

series	Begin	End	mean	min	max	std	ρ_1
Growth Funds	1961	2001	0.9148	-23.41	15.11	4.583	0.1106
Maximum Gain	1968	1992	0.8420	-25.53	15.96	5.925	0.1775
Growth and Income	1961	2001	0.8843	-16.27	23.19	3.757	0.0707
Income Funds	1961	2001	0.6949	-11.78	9.08	2.320	0.0838
Sector Funds	1988	2001	0.9197	-14.71	10.70	3.686	0.0019
Small Co. Growth	1989	2001	1.1740	-19.97	15.35	5.207	0.1020
Other Aggr. Gro.	1989	2001	0.9141	-19.38	15.21	4.604	0.0650
Timing	1962	2000	0.8614	-11.90	9.69	2.843	0.0661

Panel B: Means, Conditioning on States Equally-weighted portfolio of mutual funds, by group:

	nobs	growth	maxcg	other	income	GI	sector	smallcg	timing
STATE OF THE TERM STRUCTURE VARIABLES:									
high Short term rates	66.00	-0.7709	-0.6995	0.0542	-0.5095	-0.6764	0.1334	0.359	-0.525
low	79.00	1.212	1.557	0.8779	0.4729	1.021	0.9296	1.220	0.896
tdiff		**-2.569**	**-2.082**	-0.3242	**-2.803**	**-2.759**	-0.4684	-0.334	**-3.056**
high Term Structure slope	44.00	1.560	1.862	0.4643	0.4494	1.370	0.5186	0.411	0.388
low	92.00	-0.406	-1.388	1.225	-0.0613	-0.2155	0.6936	0.752	-0.264
tdiff		**2.599**	**2.775**	-0.5412	1.622	**2.618**	-0.1890	-0.229	1.161
high Concavity	36.00	0.6472	1.126	-0.7201	0.3473	0.5973	-0.2091	-0.749	-0.230
low	85.00	0.3810	0.3946	0.9286	0.05392	0.3328	0.9348	1.412	-0.070
tdiff		0.3096	0.6082	-1.042	0.7598	0.3742	-1.020	-1.388	-0.290
high Interest Volatility	68.00	-0.9893	-1.115	-0.5759	-0.5926	-0.8631	-0.0101	-0.458	-0.367
low	76.00	1.315	1.480	0.9985	0.6274	1.172	1.130	1.362	0.644
tdiff		**-3.031**	**-2.328**	-0.8939	**-3.474**	**-3.359**	-1.087	-1.148	**-2.164**

table 3, page 2

	nobs	Equally-weighted portfolio of mutual funds, by group: growth	maxcg	other	income	GI	sector	smallcg	timing
STATE OF THE FINANCIAL MARKETS VARIABLES									
high Stock Volatility	66.00	0.4649	0.3877	0.9449	0.2780	0.4144	0.6671	0.899	0.272
low	32.00	0.2364	-0.2894	1.268	0.5007	0.4070	0.923	1.409	0.909
tdiff		0.2580	0.4466	-0.2095	-0.4828	0.0102	-0.2347	-0.319	-1.089
high Credit Spreads	64.00	1.611	1.659	3.740	0.6488	1.297	3.071	4.245	-0.282
low	95.00	0.3523	-0.4880	1.346	0.2194	0.3058	0.9107	1.231	-0.210
tdiff		1.791	**2.039**	1.851	1.254	1.720	**2.595**	**2.360**	-0.136
High Dividend Yield	55.00	0.6094	1.081	0.000	0.1633	0.466	1.764	1.567	-0.565
low	138.0	0.2532	-0.5716	0.000	0.2461	0.303	0.567	0.677	0.790
tdiff		0.4177	1.473	0.000	-0.2350	0.238	0.4907	0.2098	**-3.088**
high Short-term Corp. Illiq.	36.00	2.139	2.125	3.078	0.7176	1.599	2.496	3.311	0.342
low	25.00	0.0627	0.2727	-0.1695	-0.1282	0.0466	0.0029	-0.160	0.587
tdiff		1.561	0.7649	1.577	1.274	1.420	1.804	1.691	-0.351
high Stock Market Liquidity	46.00	0.7608	1.204	0.709	0.112	0.6481	0.617	1.096	0.309
low	40.00	0.0866	-1.447	1.988	0.4062	0.2212	2.111	1.741	0.304
tdiff		0.6987	1.699	-0.8193	-0.6645	0.5334	-1.287	-0.397	0.009
STATE OF THE MACRO ECONOMY VARIABLES:									
high Inflation	51.00	-0.5654	-0.8200	-0.3999	-0.1917	-0.276	-0.1982	-0.477	-0.513
low	54.00	1.041	1.695	0.568	0.3842	0.958	0.6780	0.634	0.766
tdiff		-1.565	-1.741	-0.5588	-1.343	-1.521	-0.8024	-0.653	**-2.278**
high Ind. Output Growth	40.00	-0.1757	-0.5759	0.1082	0.1284	0.0153	0.7709	0.231	0.475
low	49.00	1.296	2.053	0.2571	0.5288	0.9059	1.320	2.576	-0.478
tdiff		-1.591	**-2.274**	-0.0528	-0.7830	-1.184	-0.3601	-1.188	1.522

Table 4

The sample periods for the returns are January, 1973 through December, 2000 (336 observations), or a shorter period as indicated in Table 3. Alphas are the abnormal returns, monthly percent. t(alpha) is a heteroskedasticity-consistent t-ratio. Beta is the CAPM beta and t(beta) is its t-ratio. Rsq is the coefficient of determination of the regression. In panel B, the regression is given by Equation (1) of the text, which is run for one instrument at a time. Results for instruments that produce exclusion F-test pvalues less than 0.10 are shown. Bet0 is the average conditional beta, t(bet0) is its t-ratio, Rsq1 is the regression coefficient of determination and pvalue is the right-tail pvalue of the F-statistic for excluding the lagged instrument multiplied by the excess market return. In panel C the instruments are grouped as follows: Term structure instruments include the interest rate level, slope twist and volatility measure. The Fin. Markets variables include stock market volatility, credit spreads, dividend yield, short term corporate illiquidity and stock market liquidity. The Macro Economy variables are inflation and industrial output growth. Results for groups of instruments that produce exclusion F-test pvalues less than 0.10 are shown.

Panel A: UNCONDITIONAL CAPM REGRESSIONS:

funds	alpha	t(alpha)	beta	t(beta)	Rsq
Growth Funds	-0.0659	-0.8938	0.974	67.88	0.920
Maximum Gain	-0.0004	-0.0028	1.118	40.44	0.856
Other	-0.1007	-0.3956	1.101	17.43	0.7078
Income Funds	-0.0126	-0.1514	0.369	11.32	0.5781
Growth and Income	-0.0003	-0.0052	0.781	62.21	0.9157
Sector	0.0456	0.3853	0.860	28.88	0.8668
Small Co. Growth	-0.0255	-0.1060	1.127	21.16	0.7242

Panel B: CONDITIONAL CAPM REGRESSIONS USING INDIVIDUAL INSTRUMENTS:

funds	instrument	alpha	t(alpha)	bet0	t(bet0)	Rsq1	pvalue
Maximum Gain	Corp. Illiq.	0.00848	0.05956	1.143	43.22	0.8593	0.021
Income Funds	Interest rates	-0.07219	-0.8688	0.3847	11.37	0.6191	0.000
	Term slope	0.01915	0.2161	0.3631	11.25	0.5843	0.090
	Bond volatility	-0.07328	-0.8980	0.3833	11.69	0.6220	0.000
	Credit spreads	0.03231	0.4272	0.3798	12.45	0.6458	0.000
	Dividend Yield	0.00216	0.0282	0.3827	11.00	0.6436	0.000
	Inflation	-0.04619	-0.5450	0.3803	11.22	0.5890	0.014
Sector Funds	Credit spreads	0.04136	0.3481	0.9332	26.77	0.8689	0.066
	Stock Liquid	0.05151	0.4350	0.8541	27.20	0.8689	0.070
Small Co. Growth	Credit spreads	-0.03595	-0.1496	1.304	15.58	0.7305	0.023
	Stock Liquid	-0.01310	-0.05461	1.114	20.57	0.7289	0.060
Other Aggr. Gro.	Stock Liquid	-0.07269	-0.2845	1.101	17.48	0.7136	0.037

Panel C: CONDITIONAL CAPM REGRESSIONS USING GROUPED INSTRUMENTS:

Income	Term Structure	-0.0089	-0.1150	0.8735	10.34	0.6666	0.000
Maximum Gain	Fin. Markets	0.0648	0.4247	1.382	8.511	0.8618	0.0409
Growth and Income	Fin. Markets	-0.0722	-0.2458	0.8128	1.456	0.7183	0.0689
Income	Fin. Markets	0.0102	0.1354	0.8979	10.39	0.6743	0.000
Income	Macro Economy	-0.0482	-0.5622	0.4371	8.584	0.5893	0.0330

Table 5

Alphas Conditioned on Discrete State Variables

Monthly fund group returns in excess of the 90-day Treasury Bill are regressed on a broad equity market excess return and its product with dummy variables for the state of the economy, as in Equation (2) of the text. The dummy variables are the same as in Table 2. Nobs is the number of observations for the growth fund sample period, which is January of 1973 through December of 2000 (336 total observations). Other fund groups may have fewer observations, as indicated in Table 3. Cases with fewer than 12 nonmissing observations are excluded, and shown as 0.000. tdiff is the heteroskedasticity-consistent t-ratio for the difference between the high and low-state conditional alphas. Only states producing an absolute t-ratio larger than 2.0 are shows. The units for alpha are monthly percent.

Equally-weighted portfolio of mutual funds, by group:	nobs	growth	maxcg	other	income	GI	sector	smallcg	timers
high Term Structure slope	44.00	0.1963	0.1434	-0.3582	0.1606	0.3259	-0.0447	-0.4531	0.3851
low	92.00	-0.2053	-0.0653	-0.1201	0.0253	-0.0538	0.0031	-0.1125	-0.2594
tdiff		1.183	0.3352	-0.3176	0.5756	1.202	-0.1489	-0.4181	**3.192**
high Term Structure Concavity	36.00	0.1261	0.2281	-0.6000	0.1766	0.1566	-0.1149	-0.6229	0.2497
low	85.00	-0.0517	0.0683	0.0406	-0.1300	-0.0166	0.0439	0.2778	-0.1936
tdiff		0.7776	0.3356	-0.9690	1.265	1.014	-0.4008	-1.161	**2.657**

Table 6

Betas Conditioned on Discrete State Variables

Monthly fund group returns in excess of the 90-day Treasury Bill are regressed on a broad equity market excess return and the products with dummy variables for the state of the economy. The dummy variables are the same as in Table 2. The growth fund sample period is January of 1973 through December of 2000 (336 total observations). Other fund groups may have fewer observations, as indicated in Table 3. Cases with fewer than 12 nonmissing observations are excluded, and shown as 0.000. tdiff is the heteroskedasticity-consistent t-ratio for the difference between the high and low-state conditional betas. Only states producing an absolute t-ratio greater than 2.0 are shown.

	Equally-weighted portfolio of mutual funds, by group:							
	growth	maxcg	other	income	GI	sector	smallcg	timers
STATE OF THE TERM STRUCTURE VARIABLES:								
high Term Structure slope	0.9165	1.099	1.577	0.1940	0.7018	1.080	1.658	0.5322
low	0.9960	1.236	0.992	0.4286	0.8008	0.8159	1.021	0.5941
tdiff	-1.157	-1.082	**2.230**	**-3.829**	-1.676	**2.449**	**2.219**	-1.293
high Interest Rate Volatility	0.9857	1.176	1.082	0.3675	0.7738	0.8629	1.066	0.5838
low	0.9028	1.015	1.005	0.3567	0.7825	0.8809	1.049	0.5925
tdiff	**2.217**	**2.131**	0.3510	0.1411	-0.2546	-0.1630	0.0958	-0.2569
STATE OF THE FINANCIAL MARKETS VARIABLES								
high Credit Spreads	0.9274	1.040	0.9016	0.3217	0.7498	0.7106	0.882	0.5792
low	0.9776	1.129	1.161	0.4823	0.7939	0.8858	1.143	0.6005
tdiff	-0.8497	-0.9571	-1.018	**-2.414**	-0.9331	-1.585	-0.927	-0.5186
high Short-term Corp. Illiquidity	0.8791	0.958	1.028	0.3068	0.7422	0.7577	1.019	0.5591
low	0.9653	1.154	0.9905	0.3364	0.7591	0.8118	0.946	0.5176
tdiff	**-2.428**	**-2.327**	0.1272	-0.3198	-0.3528	-0.2812	0.228	0.9474

Table 7: The Cross Sectional Distribution of T-ratios for Alpha

The time series regression (1) is estimated for each fund in a style group using the continuous versions of the state variables in the conditional models. Funds with less than 12 observations are excluded. The figures are the fractions of the T-statistics located between standard critical values for a normal distribution. The fraction implied by a normal are listed under the heading "null".

	Null	All	Growth	MCG	Other G	Income	G &I	Sector	SCG
Panel A: Unconditional Alphas									
t>2.36	0.005	0.03	0.02	0.08	0.05	0.02	0.02	0.02	0.05
2.36>t>1.96	0.02	0.02	0.01	0.04	0.02	0.01	0.02	0.02	0.03
1.96>t>1.65	0.025	0.02	0.03	0.05	0.02	0.02	0.02	0.04	0.03
1.65>t>0	0.45	0.38	0.39	0.34	0.39	0.29	0.40	0.54	0.40
0>t>-1.65	0.45	0.40	0.40	0.34	0.41	0.37	0.41	0.32	0.42
-1.65>t>-1.96	0.025	0.03	0.04	0.05	0.03	0.03	0.03	0.01	0.03
-1.96.t>-2.36	0.02	0.03	0.03	0.04	0.02	0.03	0.03	0.01	0.02
t<-2.36	0.005	0.09	0.08	0.05	0.05	0.24	0.07	0.03	0.04
Panel B: Alphas Conditioned on Term Structure									
	Null	All	Growth	MCG	Other G	Income	G &I	Sector	SCG
t>2.36	0.005	0.03	0.03	0.09	0.06	0.02	0.02	0.03	0.06
2.36>t>1.96	0.02	0.02	0.02	0.04	0.02	0.01	0.01	0.03	0.02
1.96>t>1.65	0.025	0.02	0.02	0.05	0.03	0.01	0.01	0.04	0.03
1.65>t>0	0.45	0.38	0.39	0.34	0.48	0.24	0.33	0.55	0.50
0>t>-1.65	0.45	0.40	0.40	0.37	0.35	0.40	0.48	0.29	0.35
-1.65>t>-1.96	0.025	0.03	0.04	0.03	0.02	0.03	0.04	0.01	0.01
-1.96.t>-2.36	0.02	0.03	0.04	0.02	0.01	0.03	0.04	0.02	0.01
t<-2.36	0.005	0.08	0.07	0.05	0.02	0.25	0.06	0.02	0.01
Panel C: Alphas Conditioned on Financial Market									
	Null	All	Growth	MCG	Other G	Income	G &I	Sector	SCG
t>2.36	0.005	0.03	0.04	0.07	0.04	0.02	0.03	0.05	0.02
2.36>t>1.96	0.02	0.01	0.02	0.05	0.01	0.00	0.01	0.01	0.00
1.96>t>1.65	0.025	0.02	0.02	0.05	0.02	0.01	0.01	0.03	0.02
1.65>t>0	0.45	0.25	0.27	0.37	0.29	0.15	0.26	0.35	0.29
0>t>-1.65	0.45	0.45	0.43	0.34	0.48	0.45	0.42	0.43	0.53
-1.65>t>-1.96	0.025	0.06	0.05	0.05	0.07	0.06	0.07	0.06	0.07
-1.96.t>-2.36	0.02	0.05	0.06	0.01	0.04	0.05	0.07	0.03	0.04
t<-2.36	0.005	0.11	0.10	0.05	0.04	0.25	0.14	0.04	0.02
Panel D: Alphas Conditioned on Real Economy									
	Null	All	Growth	MCG	Other G	Income	G &I	Sector	SCG
t>2.36	0.005	0.03	0.02	0.11	0.05	0.02	0.02	0.02	0.05
2.36>t>1.96	0.02	0.02	0.02	0.05	0.03	0.01	0.01	0.01	0.02
1.96>t>1.65	0.025	0.02	0.03	0.03	0.02	0.01	0.02	0.04	0.03
1.65>t>0	0.45	0.38	0.40	0.34	0.40	0.27	0.39	0.54	0.40
0>t>-1.65	0.45	0.41	0.40	0.35	0.42	0.39	0.43	0.33	0.43
-1.65>t>-1.96	0.025	0.03	0.04	0.03	0.02	0.03	0.03	0.02	0.02
-1.96.t>-2.36	0.02	0.03	0.03	0.04	0.02	0.03	0.03	0.01	0.02
t<-2.36	0.005	0.08	0.06	0.05	0.05	0.23	0.06	0.03	0.03

Table 8: The Distribution of T-ratios for alphas in High vs. Low Economic States Using a Broad Market Benchmark

Alphas and their t ratios are based on the regression equation (4), using the conditioning dummy variables one at a time. High (low) means that the value of the state variable is higher (lower) than one standard deviation from its moving average over the past 60 months. The distributions of the t-ratios for alpha are presented in the table, for those cases where a Chi square test for departures from a normal distribution produce right-tail p-values of 10% or less.

Short Term Interest rate High	Short Term Interest rate Low	Term Structure Slope high	Interest rate Volatility high	Interest rate Volatility Low	Stock Market Volatility low	Dividend Yield Low	Dividend Yield High
Income	Income	Income	Income	Income	Income	Income	MCG
0.06	0.05	0.22	0.07	0.08	0.1	0.02	0.26
0.02	0.02	0.05	0.02	0.01	0.02	0.01	0.11
0.03	0.02	0.05	0.01	0.02	0.03	0.02	0.04
0.39	0.32	0.29	0.26	0.25	0.31	0.25	0.37
0.17	0.27	0.21	0.36	0.27	0.23	0.27	0.2
0.03	0.02	0.02	0.02	0.03	0.03	0.00	0.00
0.04	0.03	0.01	0.02	0.04	0.03	0.04	0
0.25	0.26	0.15	0.23	0.31	0.25	0.41	0.01
Interest rate Volatility high	Stock market Liquidity Low	Interest rate Volatility high	Stock market Liquidity Low	Dividend Yield High	Inflation High	Dividend Yield High	Stock market Liquidity Low
SCG	SCG	Other G	Other G	G&I	G&I	Sector	Sector
0.01	0.02	0.01	0.04	0.24	0.22	0.4	0.09
0	0	0	0.01	0.04	0.09	0	0.02
0	0	0.01	0	0.03	0.09	0	0.01
0.1	0.07	0.08	0.12	0.36	0.37	0.3	0.22
0.4	0.29	0.41	0.31	0.29	0.17	0.3	0.36
0.11	0.07	0.10	0.06	0.01	0.01	0.00	0.05
0.13	0.1	0.12	0.08	0.02	0.02	0	0.04
0.25	0.46	0.26	0.37	0.02	0.04	0	0.22

Table 9

Cross-sectional Regressions of abnormal performance measures on lagged fund characteristics. Characteristics are measured each year from 1972-1997, and future returns for the subsequent 36 months are used to estimate the measures of performance. The regressions are aggregated across years using the methods of Fama and MacBeth (1973), adjusting for overlapping data in the standard errors. The units of the average coefficients are percent per month. Fama-MacBeth t-ratios are shown on the second line.

Fund style Group or State Variable	Coefficient and t-ratio for mutual fund characteristic: flow	age	TNA	income	gains	dturn	load	expense	lagret
Panel A: Performance Measured using unconditional CAPM									
Growth	-6.03	0.046	0.473	-0.150	0.213	-0.0329	0.237	0.135	0.506
	-1.02	3.42	1.52	-1.01	9.66	-1.37	4.31	1.76	9.04
Income	0.707	0.177	0.181	0.215	0.059	0.023	0.127	0.033	-0.0724
	1.06	0.551	1.04	1.34	0.753	1.68	1.97	0.582	-1.86
Panel B: Performance Measured using Conditional CAPM, Growth Funds									
Short Rate Level	-8.77	0.032	0.453	-0.141	0.195	-0.029	0.224	0.106	0.502
	-1.02	2.32	1.48	-0.947	8.48	-1.24	4.14	1.76	8.48
Term Slope	-11.4	0.0405	0.437	-0.175	0.205	-0.0333	0.235	0.119	0.504
	-1.03	3.26	1.55	-0.990	9.37	-1.39	4.29	1.84	8.33
Panel C: Performance Measured using Conditional CAPM, Income Funds									
Short Rate Level	0.471	0.177	0.182	0.219	0.0565	0.0197	0.107	0.0364	-0.0679
	1.11	0.557	1.01	1.34	0.732	1.33	1.67	0.620	-1.96
Term Slope	0.480	0.162	0.176	0.200	0.0574	0.0227	0.121	0.0375	-0.0739
	1.08	0.531	1.02	1.32	0.740	1.66	1.95	0.710	-2.06
Panel D: Performance Measured using Unconditional Style Model									
Growth	-3.64	0.049	0.462	-0.152	0.214	-0.034	0.241	0.135	0.511
	-1.01	3.35	1.50	-1.03	9.74	-1.40	4.54	1.75	8.62
Income	0.838	0.166	0.183	0.207	0.062	0.023	0.127	0.031	-0.072
	1.04	0.529	1.04	1.28	0.762	1.71	1.97	0.558	-1.83
Panel E: Performance Measured using Conditional Style Model, Growth Funds									
Short Rate Level	-1.88	0.033	0.461	-0.109	0.196	-0.029	0.228	0.106	0.506
	-0.981	2.31	1.47	-0.966	8.83	-1.14	4.32	1.70	8.20
Term Slope	-10.6	0.044	0.421	-0.181	0.21	-0.034	0.240	0.116	0.510
	-1.03	3.23	1.55	-1.03	9.66	-1.39	4.61	1.77	8.12
Panel F: Performance Measured using Conditional Style model, Income Funds									
Short Rate Level	1.01	0.166	0.183	0.217	0.060	0.020	0.113	0.028	-0.070
	1.05	0.539	1.01	1.25	0.740	1.45	1.67	0.519	-1.98
Term Slope	0.034	0.159	0.181	0.174	0.062	0.022	0.125	0.033	-0.075
	0.793	0.533	1.04	1.26	0.767	1.70	1.97	0.668	-2.04

Table 10

Conditional and Unconditional Market Timing Models

Monthly returns in excess of the 90-day Treasury Bill return for market timing funds grouped by characteristics are regressed on a broad equity market excess return, its square and its products with lagged state variables, with the state variables grouped as in the previous tables. The fund sample period is January of 1973 through December of 2000 (336 total observations). γ_u is the unconditional model timing coefficient and $t(\gamma_u)$ is its heteroskedasticity-consistent t-ratio. Rsq0 is the regression R-squared for the unconditional model. γ_c is the conditional timing coefficient, $t(\gamma_c)$ is its t-ratio and Rsq1 is the conditional model R-squared. Pvalue is the right-tail p-value of the F-test for the null hypothesis that the conditional model's variables may be excluded from the regression. Only cases with absolute t-ratios larger than 2.0 or pvalues less than 10% are shown.

Fund characteristics	γ_u	$t(\gamma_u)$	Rsq0
Panel A: UNCONDITIONAL MODELS			
Hi age	0.2545	**2.744**	0.9054
Hi TNA	0.3383	**3.730**	0.8851
Low gains	0.4658	**2.102**	0.8176
Low expense	0.2299	**2.697**	0.8992

fund characteristics	γ_c	$t(\gamma_c)$	Rsq1	Pvalue
Panel B: CONDITIONING ON TERM STRUCTURE STATE VARIABLES				
Hi flow	0.2407	1.888	0.8525	0.0610
Med flow	0.2007	**2.197**	0.8838	0.2119
Hi age	0.2629	**3.187**	0.9063	0.6882
Hi TNA	0.3541	**3.999**	0.8859	0.8370
Hi income	0.2423	**2.551**	0.8518	0.1833
Med gains	-0.06412	-0.4409	0.8539	0.0528
Low gains	0.5242	**3.261**	0.8241	0.0412
Low turnover	0.3267	**2.053**	0.8748	0.0715
Med load	0.1941	1.763	0.8586	0.0408
Med expense	0.1823	1.702	0.8541	0.0374
Low expense	0.2487	**3.176**	0.9004	0.5601
Med lagret	0.2842	**2.210**	0.8774	0.2155
Panel C: CONDITIONING ON FINANCIAL MARKET STATE VARIABLES				
Hi flow	0.1271	0.8113	0.8540	0.03306
Med flow	0.1198	1.158	0.8881	0.00514
Low flow	-0.05503	-0.3742	0.8972	0.00446

Table 10, page 2

fund characteristics	γ_c	$t(\gamma_c)$	Rsq1	Pvalue
Panel C: CONDITIONING ON FINANCIAL MARKET STATE VARIABLES, cont.				
Hi age	0.1964	**2.126**	0.9090	0.05495
Med age	-0.08550	-0.6139	0.8641	0.01069
Low age	-0.05436	-0.4814	0.8349	0.2120
Hi TNA	0.2158	**2.248**	0.8908	0.01388
Med TNA	-0.01504	-0.1193	0.8582	0.07998
Hi income	0.1341	1.020	0.8564	0.00878
Med income	0.01187	0.1137	0.8871	0.04133
Hi gains	-0.1691	-1.284	0.9085	0.01484
Low gains	0.4060	1.805	0.8291	0.00256
Hi turnover	-0.08277	-0.6799	0.9020	0.02596
Med turnover	0.07848	0.6958	0.8691	0.00374
Low turnover	0.3191	**2.041**	0.8774	0.01098
Med load	0.09496	0.7392	0.8619	0.00462
Low load	-0.09841	-0.9495	0.9096	0.1150
Med expense	0.1130	0.8715	0.8550	0.03227
Low expense	0.1105	1.323	0.9037	0.02641
Med lagret	0.1065	0.9001	0.8819	0.00489
Panel D: CONDITIONING ON MACROECONOMY STATE VARIABLES				
Hi flow	0.1809	1.447	0.8512	0.04788
Low flow	0.05693	0.3770	0.8965	0.00068
Hi age	0.2421	**2.769**	0.9061	0.5051
Med age	0.00622	0.0456	0.8602	0.04548
Hi TNA	0.3353	**3.569**	0.8857	0.6458
Low gains	0.4637	**2.029**	0.8210	0.1043
Hi turnover	0.07905	0.6321	0.9001	0.0342
Low expense	0.2255	**2.688**	0.9003	0.3332
Hi lagret	-0.05452	-0.3298	0.8963	0.0367
Med lagret	0.2342	**2.378**	0.8802	0.0024

Table 11

Conditional Market Timing Models with Time-Varying Ability

Monthly returns for groups of market timing funds in excess of the 90-day Treasury Bill return are regressed on a broad equity market excess return, its square, its products with lagged state variables, and the products of the state variables with the squared excess return. The state variables are the dummy variables for high and low economic states. The fund sample period is January of 1973 through December of 2000 (336 total observations). γ_{hi} is the estimated timing coefficient given a high state and $t(\gamma_{hi})$ is its heteroskedasticity-consistent t-ratio. γ_{lo} is the conditional timing coefficient given a low state and $t(\gamma_{lo})$ is its t-ratio. The right hand column presents t-ratio testing the hypothesis that the timing coefficients are equal in the high and low states. Only cases with absolute t-ratios larger than two are shown.

State	Funds	γ_{hi}	$t(\gamma_{hi})$	γ_{lo}	$t(\gamma_{lo})$	$t(Ho{:}\gamma_{hi}=\gamma_{lo})$
Short term rates	Low flow	-0.1676	-0.4355	0.4686	**2.237**	-1.528
	Hi gains	-0.2143	-0.6171	0.4650	**2.041**	-1.710
Term Structure Slope	All	1.182	**3.832**	0.0329	0.1143	**2.729**
	Hi flow	1.695	**3.233**	0.3195	0.8638	**2.186**
	Med flow	1.582	**4.167**	0.2148	0.7416	**2.854**
	Low flow	0.7967	1.959	-0.3117	-0.8497	**2.056**
	Hi age	1.340	**3.815**	0.3004	1.164	**2.449**
	Med age	1.487	**3.832**	-0.2754	-0.6574	**3.086**
	Hi TNA	1.785	**5.425**	0.3204	1.301	**3.604**
	Med TNA	1.207	**3.116**	-0.0329	-0.093	**2.383**
	Low TNA	0.7717	**3.068**	0.0917	0.242	1.534
	Hi income	1.522	**3.929**	0.1868	0.6728	**2.858**
	Med income	1.201	**3.713**	0.1305	0.4120	**2.413**
	Hi gains	0.9923	**2.062**	0.05035	0.1589	1.640
	Low gains	2.109	**4.062**	0.2036	0.6895	**3.216**
	Hi turnover	1.281	**3.570**	-0.1162	-0.3872	**2.963**
	Med turnover	0.8490	**2.622**	0.3057	0.9710	1.216
	Low turnover	1.861	**4.012**	0.2168	0.6450	**2.910**
	Hi load	1.259	**2.730**	0.3735	1.053	1.532
	Med load	1.467	**3.724**	0.04086	0.1193	**2.765**
	Low load	0.7728	**2.761**	-0.1253	-0.4308	**2.238**
	Hi expense	0.8288	**2.667**	0.2276	0.6061	1.250
	Med expense	1.356	**3.540**	0.01819	0.04606	**2.457**
	Low expense	1.341	**4.125**	0.03097	0.1319	**3.278**
	Med lagret	1.633	**5.009**	0.1360	0.4291	**3.403**
	Low lagret	2.384	**2.894**	0.02229	0.04121	**2.369**
Term Structure Concavity	All	0.6625	1.823	-0.2599	-1.214	**2.230**
	Hi flow	1.038	1.840	-0.3444	-1.221	**2.225**
	Med flow	0.9374	**2.248**	-0.3735	-1.538	**2.766**
	Low flow	0.4214	1.352	-0.3056	-1.175	**1.836**
	Hi age	0.8543	**2.450**	-0.2219	-1.123	**2.733**
	Hi TNA	1.103	**2.590**	-0.1790	-1.030	**2.839**
	Med TNA	0.6338	1.625	-0.4484	**-2.004**	**2.452**
	Low TNA	0.2272	0.608	-0.3343	-1.327	**1.268**

State	Funds	γ_{hi}	$t(\gamma_{hi})$	γ_{lo}	$t(\gamma_{lo})$	$t(Ho{:}\gamma_{hi}=\gamma_{lo})$
Term Structure Concavity	Hi income	0.9737	1.866	-0.3633	-1.641	**2.381**
	Med income	0.6060	1.982	-0.2736	-1.427	**2.505**
	Low gains	1.400	**2.119**	-0.6939	**-2.880**	**3.009**
	Low turnover	1.088	**2.471**	-0.2425	-1.021	**2.684**
	Med load	0.7075	1.212	-0.5114	**-2.195**	1.961
	Low load	0.5145	1.869	-0.3875	-1.664	**2.603**
	Med expense	0.7377	1.739	-0.5246	-1.950	**2.552**
	Low expense	0.7699	**2.076**	-0.106	-0.8321	**2.276**
	Med lagret	1.019	**2.008**	-0.3456	-1.772	**2.536**
	Low lagret	1.553	**4.269**	-0.9025	**-2.383**	**4.948**
Interest Rate Volatility	Low flow	-0.4944	-1.623	0.7279	**2.571**	**-3.062**
	Med age	-0.8208	-1.902	0.3038	0.820	**-2.054**
	Low income	-0.8510	**-2.165**	0.4999	1.147	**-2.397**
	Hi gains	-0.4584	-1.590	0.5799	1.688	**-2.388**
	Hi turnover	-0.4260	-1.478	0.6181	1.735	**-2.350**
	Low load	-0.6713	-2.081	0.4837	1.519	**-2.628**
	Hi expense	-0.6715	-1.358	0.6229	1.562	**-2.102**
	Low lagret	-1.205	-1.713	0.9673	1.711	**-2.498**
Credit Spreads	Low turnover	0.9018	**2.185**	0.8291	1.398	0.1036
Dividend Yields	Hi flow	0.5224	1.105	0.2866	**2.070**	0.4894
	Med flow	0.2591	1.550	0.2807	**2.911**	-0.1176
	Hi age	0.3351	1.490	0.2939	**3.238**	0.1749
	Hi TNA	0.4190	**2.001**	0.3041	**3.002**	0.5038
	Hi income	0.4916	1.885	0.3017	**2.421**	0.6745
	Low gains	0.1839	0.9878	0.6764	**2.967**	-1.732
	Low turnover	0.4682	1.014	0.5137	**3.263**	-0.096
	Med load	0.3231	1.191	0.2308	**2.176**	0.3245
	Low expense	0.3446	1.756	0.1738	**2.138**	0.8171
Short-term Corporate Illiquidity	Hi TNA	0.2845	**2.850**	0.9434	**2.080**	-1.425
	Med income	-0.1544	-1.753	0.8574	**2.116**	**-2.447**
	Hi gains	-0.2442	**-2.333**	0.8889	**2.422**	**-2.996**
	Med gains	-0.4287	**-3.406**	0.2807	0.441	-1.094
	Low gains	0.6123	**3.157**	0.5893	1.233	0.045
	Hi expense	-0.2380	**-2.364**	0.5407	1.603	**-2.225**
	Low lagret	-0.05288	-0.2501	1.242	**2.325**	**-2.241**
Stock Market Liquidity	All	1.791	**2.112**	0.2677	1.176	1.748
	Hi flow	1.992	**3.336**	-0.0043	-0.015	**3.052**
	Hi age	1.198	**2.303**	0.2636	1.101	1.652
	Hi TNA	1.864	**2.317**	0.1351	0.6481	**2.096**
	Med TNA	1.369	**2.047**	0.2105	0.5538	1.554
	Hi income	1.458	**2.297**	0.1586	0.4708	1.851
	Low gains	2.858	**3.558**	0.0456	0.1443	**3.315**
	Med turnover	1.551	**2.133**	0.2228	0.7958	1.733
	Low turnover	1.757	**2.185**	0.1960	0.5698	1.819
	Med load	2.148	**2.640**	0.2211	0.6047	**2.207**

State	Funds	γ_{hi}	$t(\gamma_{hi})$	γ_{lo}	$t(\gamma_{lo})$	$t(Ho{:}\gamma_{hi}=\gamma_{lo})$
Stock Market	Med expense	1.584	**2.355**	0.1868	0.5280	1.886
Liquidity	Med lagret	1.581	**2.436**	0.4784	1.020	1.427
	Low lagret	1.425	1.143	0.0821	0.2556	1.053
Inflation	Hi TNA	0.5861	**2.270**	-0.0052	-0.0111	1.113
Industrial	Low flow	0.5323	1.112	-0.6697	**-2.718**	**2.335**
Output Growth	Hi turnover	0.4275	0.6989	-0.6105	**-2.117**	1.578

Appendix A: Additional Tables

Table 1A reports summary statistics for the dummy variable indicators for the various states and Table 2A reports the correlations of the high and low-state dummy variables. Table 3A presents the style-specific benchmark weights that we apply to the asset class indexes to generate fund style-specific benchmark index returns. Tables 4A - 9A repeat the analyses of tables 4-9, substituting the style-specific benchmark indexes for the broad market index of the CAPM.

Table 1A

Summary Statistics of Discrete Dummy Variable instruments for economic states. The sample period is January, 1973 through December, 2000 (N=336). Mean is the sample mean, std is the sample standard deviation and ρ_1 is the first order sample autocorrelation of the series.

series	mean	min	max	std	ρ_1
Panel A: High State Dummies					
Short-term Interest Rate	0.1964	0.000	1.000	0.3979	0.8333
Term Stucture Slope	0.1310	0.000	1.000	0.3379	0.3981
Term Structure Concavity	0.1071	0.000	1.000	0.3098	0.5641
Interest Rate Volatility	0.2024	0.000	1.000	0.4024	0.6305
Stock Market Volatility	0.1964	0.000	1.000	0.3979	0.5090
Credit Spreads	0.1905	0.000	1.000	0.3933	0.8293
Dividend Yield	0.1637	0.000	1.000	0.3705	0.7385
Short-term Corporate Illiquidity	0.1071	0.000	1.000	0.3098	0.3463
Stock Market Liquidity	0.1369	0.000	1.000	0.3443	0.0928
Inflation	0.1518	0.000	1.000	0.3593	0.3522
Industrial Output Growth	0.1190	0.000	1.000	0.3243	0.0064
Panel B: Low State Dummies					
Short-term Interest Rate	0.2351	0.000	1.000	0.4247	0.8501
Term Structure Slope	0.2738	0.000	1.000	0.4466	0.7186
Term Structure Concavity	0.2530	0.000	1.000	0.4354	0.5778
Interest Rate Volatility	0.2232	0.000	1.000	0.4170	0.6769
Stock Market Volatility	0.0952	0.000	1.000	0.2940	0.2777
Credit Spreads	0.2827	0.000	1.000	0.4510	0.7493
Dividend Yield	0.4107	0.000	1.000	0.4927	0.8185
Short-term Corporate Illiquidity	0.0744	0.000	1.000	0.2628	0.1355
Stock Market Liquidity	0.1190	0.000	1.000	0.3243	0.1482
Inflation	0.1607	0.000	1.000	0.3678	0.3154
Industrial Output Growth	0.1458	0.000	1.000	0.3535	0.3340

Notes: The short term interest rate is the bid yield to maturity on a 90-day Treasury bill. Term structure slope is the difference between and five-year and a one-month discount Treasury yield. Term structure concavity is $y_3 - (y_1 + y_5)/2$, where y_j is the j-year fixed maturity Treasury yield. Interest rate volatility is the monthly standard deviation of three-month Treasury rates, computed from the days within the month. Stock market volatility is constructed similarly using daily returns for the Standard and Poors 500 index. Dividend yield is the annual dividend yield of the CRSP value-weighted stock index. Inflation is the percentage change in the consumer price index, CPI-U. Industrial production growth is the monthly growth rate of the seasonally-adjusted industrial production index. Short-term Corporate Illiquidity is the percentage spread of three-month high-grade commercial paper rates over three-month Treasury rates. Stock market liquidity is the measure from Lubos and Stambaugh (2003), based on price reversals.

Table 2A

Correlations Among the Discrete Dummy Variable instruments for economic states. The sample period is January, 1973 through December, 2000 (N=336).

Panel A: Correlations of High State Dummies

Short-term Interest Rate	1.000	-0.1697	-0.0986	0.7391	0.2081	0.0654	0.2064	0.3754	-0.0892	-0.0017	-0.04436
Term Stucture Slope	-0.1697	1.000	0.5786	-0.1736	0.0079	0.1487	-0.0525	-0.1150	0.1297	0.1222	-0.00061
Term Structure Concavity	-0.098	0.5786	1.000	-0.1266	-0.0259	0.1995	0.0808	-0.1197	0.1401	0.0667	-0.02599
Interest Rate Volatility	0.7951	-0.1955	-0.1266	1.000	0.1984	0.0009	0.1776	0.3237	-0.07080	-0.0547	-0.09287
Stock Market Volatility	0.2081	0.0079	-0.0260	0.1798	1.000	0.1608	0.0647	0.0414	0.00331	0.2647	-0.13150
Credit Spreads	0.0654	0.1487	0.1995	0.0386	0.1608	1.000	0.2156	-0.0573	-0.03789	0.1750	0.04935
Dividend Yield	0.2064	-0.0525	0.0808	0.2376	0.0647	0.2156	1.000	0.1491	-0.06328	0.0548	0.05781
ST Corporate Illiquidity	0.3754	-0.1150	-0.1197	0.2617	0.0414	-0.0573	0.1491	1.000	-0.07867	-0.0661	0.00043
Stock Market Liquidity	-0.0892	0.1297	0.1401	-0.0708	0.0033	-0.0379	-0.0633	-0.0787	1.000	-0.0679	-0.03947
Inflation	-0.0017	0.1222	0.0667	-0.0068	0.2647	0.1750	0.0548	-0.0661	-0.06792	1.000	0.00200
Industrial Output Growth	-0.0444	-0.0006	-0.0259	-0.0929	-0.1315	0.0494	0.0578	0.0004	-0.03947	0.0020	1.000

Panel B: Correlations of Low State Dummies

Short-term Interest Rate	1.000	-0.3247	-0.2096	0.8152	0.1787	0.1194	0.3931	0.0822	-0.1297	-0.1305	-0.05211
Term Stucture Slope	-0.3247	1.000	0.6406	-0.2971	-0.0855	0.1184	-0.0921	-0.1233	0.1056	-0.02150	0.1865
Term Structure Concavity	-0.2096	0.6406	1.000	-0.1804	-0.0722	-0.0005	-0.1101	-0.1242	0.1475	-0.03455	0.1243
Interest Rate Volatility	0.7739	-0.2682	-0.1510	1.000	0.1881	0.1029	0.4307	0.1121	-0.0419	-0.04486	-0.06695
Stock Market Volatility	0.1787	-0.0855	-0.0722	0.2157	1.000	0.0889	0.0795	-0.0592	-0.0766	-0.09199	-0.1193
Credit Spreads	0.1194	0.1184	-0.0005	0.1078	0.0889	1.000	0.0535	-0.0768	-0.1096	-0.02691	0.03450
Dividend Yield	0.3931	-0.0921	-0.1101	0.4387	0.0795	0.0535	1.000	0.1288	-0.1221	0.03993	-0.00800
ST Corporate Illiquidity	0.0822	-0.1233	-0.1242	0.0768	-0.0592	-0.0768	0.1288	1.000	0.0947	-0.03143	-0.03575
Stock Market Liquidity	-0.1297	0.1056	0.1475	-0.1202	-0.0766	-0.1096	-0.1221	0.0947	1.000	-0.02075	0.03038
Inflation	-0.1305	-0.0215	-0.0346	-0.0975	-0.0920	-0.0269	0.0399	-0.0314	-0.0208	1.000	0.1059
Industrial Output Growth	-0.0521	0.1865	0.1243	-0.0867	-0.1193	0.0345	-0.0080	-0.0358	0.0304	0.1059	1.000

Notes: The short term interest rate is the bid yield to maturity on a 90-day Treasury bill. Term structure slope is the difference between and five-year and a one-month discount Treasury yield. Term structure concavity is $y_3 - (y_1 + y_5)/2$, where y_j is the j-year fixed maturity Treasury yield. Interest rate volatility is the monthly standard deviation of three-month Treasury rates, computed from the days within the month. Stock market volatility is constructed similarly using daily returns for the Standard and Poors 500 index. Dividend yield is the annual dividend yield of the CRSP value-weighted stock index. Inflation is the percentage change in the consumer price index, CPI-U. Industrial production growth is the monthly growth rate of the seasonally-adjusted industrial production index. Short-term Corporate Illiquidity is the percentage spread of three-month high-grade commercial paper rates over three-month Treasury rates. Stock market liquidity is the measure from Lubos and Stambaugh (2003), based on price reversals.

Table 3A: Sharpe Style Benchmarks

The sample period is January 1973-December, 2000 (336 observations). The return units are percent per month. Std denotes the sample standard deviation of return and ρ_1 is the sample first order autocorrelation.

Panel A: Weights for each fund group applied to asset class returns:

	growth	MCG	Other G	Income	G&I	Sector	SCG	Timing
TB90	0.250	0.510	0.000	0.000	0.160	0.000	0.000	0.000
GB1	0.000	0.000	0.320	0.240	0.000	0.000	0.210	0.600
GB20	0.002	0.094	0.000	0.018	0.034	0.110	0.068	0.000
BAA	0.008	0.000	0.017	0.110	0.027	0.000	0.000	0.220
Mkt.	0.480	0.040	0.000	0.480	0.670	0.000	0.000	0.037
Value	0.000	0.130	0.000	0.047	0.001	0.110	0.000	0.140
Grow	0.140	0.150	0.420	0.000	0.000	0.780	0.720	0.000
Small	0.120	0.077	0.250	0.100	0.110	0.000	0.000	0.000

Panel B: Summary Statistics for Style Benchmark Returns.

fund group	mean	min	max	std	ρ_1
Growth	0.9900	-17.87	12.76	3.642	0.06856
MCG	0.8599	-9.128	9.129	2.109	0.1098
Other AG	0.9852	-18.24	14.77	3.869	0.1263
Income	0.9855	-13.95	12.12	3.132	0.06749
G & I	1.028	-17.80	12.89	3.728	0.04800
Sector	1.053	-23.13	16.70	5.061	0.1011
SCG	0.9458	-18.91	13.30	4.275	0.09984
Timing	0.8099	-4.444	7.488	1.423	0.1684

Table 4A

Conditional and unconditional alphas relative to Sharpe style benchmarks, based on versions of Equation (1). The sample periods for the returns are January, 1973 through December, 2000 (336 observations), or a shorter period when indicated by fund availability in Table 3. Alphas are the abnormal returns, monthly percent. t(alpha) is a heteroskedasticity-consistent t-ratio. Beta is the CAPM beta and t(beta) is its t-ratio. Rsq is the coefficient of determination of the regression. In panel B, the regression is given by Equation (1) of the text, which is run for one instrument at a time. Results for instruments that produce exclusion F-test pvalues less than 0.10 are shown. Bet0 is the average conditional beta, t(bet0) is its t-ratio, Rsq1 is the regression coefficient of determination and pvalue is the right-tail pvalue of the F-statistic for excluding the lagged instrument multiplied by the style index excess return. In panel C the instruments are grouped as follows: Term structure instruments include the interest rate level, slope, convexity and volatility. The Fin. Markets variables include stock market volatility, credit spreads, dividend yield, short term corporate illiquidity and stock market liquidity. The Macro Economy variables are inflation and industrial output growth. Results for groups of instruments that produce exclusion F-test pvalues less than 0.10 are shown.

Panel A: UNCONDITIONAL CAPM REGRESSIONS:

funds	alpha	t(alpha)	beta	t(beta)	Rsq
Growth Funds	-0.05873	-0.9109	1.247	65.41	0.9394
Maximum Gain	-0.1694	-1.351	2.458	31.56	0.8882
Other	0.07004	0.7882	1.460	61.58	0.9666
Income Funds	-0.04146	-0.5188	0.561	12.51	0.6123
Growth and Income	-0.01874	-0.3080	0.968	60.19	0.9165
Sector	0.1805	1.610	0.761	27.10	0.8892
Small Co. Growth	0.09665	0.7126	1.287	40.80	0.9220
Timers	-0.1201	-1.599	1.841	21.66	0.7900

Panel B: CONDITIONAL CAPM REGRESSIONS USING INDIVIDUAL INSTRUMENTS:

funds	instrument	alpha	t(alpha)	bet0	t(bet0)	Rsq1	pvalue
Growth Funds	Interest rates	-0.0987	-1.235	0.5906	12.30	0.6499	0.000
Maximum Gain	Industrial Ouput	-0.1388	-1.082	2.513	52.24	0.8939	0.000
Income Funds	Interest rates	-0.0722	-0.8688	0.3847	11.37	0.6191	0.000
	Term slope	0.0192	0.2161	0.3631	11.25	0.5843	0.090
	Convexity	-0.0185	-0.2253	0.5524	12.52	0.6186	0.068
	Rate volatility	-0.1062	-1.354	0.5879	12.66	0.6528	0.000
	Credit spreads	0.0098	0.1340	0.5880	13.58	0.6782	0.000
	Dividend Yield	-0.0198	-0.2729	0.5983	11.93	0.6843	0.000
	Inflation	-0.0783	-0.9565	0.5811	12.05	0.6227	0.012
Sector Funds	Convexity	0.1913	1.728	0.7540	29.16	0.8908	0.094
	Stock Liquid	0.0515	0.4350	0.8541	27.20	0.8689	0.070
	Inflation	0.1573	1.406	0.7332	23.11	0.8908	0.085
Small Co. Growth	Stock volatility	0.0891	0.6755	1.322	44.96	0.9247	0.003
	Stock Liquid	-0.0131	-0.05461	1.114	20.57	0.7289	0.060
	Dividend yield	0.0809	0.6117	1.389	41.93	0.9246	0.004
	Indust. Output	0.0868	0.6530	1.287	44.93	0.9243	0.007

funds	instrument	alpha	t(alpha)	bet0	t(bet0)	Rsq1	pvalue
Other Aggr. Gro.	Rate volatility	0.0748	0.8389	1.407	23.19	0.9671	0.087
	Stock volatility	0.0615	0.7118	1.483	61.83	0.9675	0.012
	Inflation	0.0539	0.6375	1.413	26.82	0.9672	0.045
	Indust. Output	0.0796	0.8964	1.468	60.94	0.9681	0.001
Timers	Interest rates	-0.1734	-2.387	1.976	23.74	0.8102	0.000
	Term slope	-0.1690	-2.149	1.891	24.92	0.7962	0.008
	Rate volatility	-0.1894	-2.585	1.964	22.67	0.8089	0.000
	Credit spreads	-0.0979	-1.349	1.931	22.53	0.8013	0.000
	Dividend yield	-0.1141	-1.612	2.008	24.97	0.8098	0.000
	Inflation	-0.1725	-2.242	1.927	25.59	0.7987	0.001

Panel C: CONDITIONAL CAPM REGRESSIONS USING GROUPED INSTRUMENTS:

funds	instruments	alpha	t(alpha)	bet0	t(bet0)	Rsq1	pvalue
Maximum Gain	Term Structure	-0.1707	-1.345	2.375	7.039	0.8930	0.017
Income	Term Structure	-0.0349	-0.4662	1.274	10.20	0.6946	0.000
Small Co. Growth	Term Structure	0.2039	1.748	0.7815	4.669	0.8926	0.075
Timers	Term Structure	-0.1711	-2.314	2.671	10.95	0.8111	0.001
Growth and Income	Fin. Markets	0.1110	1.173	1.887	10.56	0.9688	0.002
Income	Fin. Markets	-0.0111	-0.1544	1.378	10.51	0.7114	0.000
Other Aggr. Gro.	Fin. Markets	0.0965	0.6932	1.320	8.616	0.9260	0.011
Timers	Fin. Markets	-0.1269	-1.803	2.713	8.817	0.8195	0.000
Maximum Gain	Macro Economy	-0.1313	-1.011	2.444	29.45	0.8940	0.001
Growth and Income	Macro Economy	0.0657	0.7664	1.532	33.52	0.9686	0.000
Income	Macro Economy	-0.0783	-0.9428	0.6591	8.840	0.6227	0.031
Small Co. Growth	Macro Economy	0.1524	1.376	0.8149	20.86	0.8919	0.042
Other Aggr. Gro.	Macro Economy	0.0820	0.6274	1.325	22.09	0.9244	0.019
Timers	Macro Economy	-0.1673	-2.148	2.105	17.37	0.7998	0.002

Table 5A

Fund Alphas Relative to Style Indexes, Conditioned on Discrete State Variables

Monthly fund group returns in excess of the 90-day Treasury Bill are regressed on the excess return of a Sharpe style index for the fund group and its product with dummy variables for the state of the economy, as in Equation (2) of the text. The dummy variables are the same as in Table 2. Nobs is the number of observations for the growth fund sample period, which is January of 1973 through December of 2000 (336 total observations). Other fund groups may have fewer observations, as indicated in Table 3. Cases with fewer than 12 nonmissing observations are excluded, and shown as 0.000. tdiff is the heteroskedasticity-consistent t-ratio for the difference between the high and low-state conditional alphas. Only states with an absolute r-ratio greater than 2.0 are shown. The units for alpha are monthly percent.

		Equally-weighted portfolio of mutual funds, by group:							
	nobs	growth	maxcg	other	income	GI	sector	smallcg	timers
STATE OF THE TERM STRUCTURE VARIABLES:									
high Short term rates	66.00	0.0316	0.1265	1.291	-0.1963	-0.019	0.9552	1.629	-0.1693
low	79.00	0.0259	-0.1856	0.079	0.0158	0.0085	0.3407	0.4703	-0.1548
tdiff		0.0255	0.8017	**2.685**	-0.8115	-0.1301	1.014	1.623	-0.0609
high Term Structure Concavity	36.00	0.0266	-0.4712	-0.0783	0.0441	0.0241	0.2887	0.3070	-0.5405
low	85.00	-0.0176	-0.0240	0.4062	-0.1012	-0.0052	0.2256	0.5310	0.0435
tdiff		0.2377	-1.171	-1.856	0.6259	0.1801	0.1607	-0.4806	**-2.300**
STATE OF THE FINANCIAL MARKETS VARIABLES									
high Dividend Yield	55.00	-0.3610	-0.3860	0.000	-0.2303	-0.3021	0.4398	-0.8476	-0.4270
low	138.0	-0.0513	-0.4014	0.000	0.0596	0.0010	0.1437	0.1159	-0.1992
tdiff		-1.005	0.03411	0.000	-1.473	-1.247	**2.252**	**-6.272**	-0.9968
STATE OF THE MACRO ECONOMY VARIABLES:									
high Inflation	51.00	0.2072	0.2298	0.8148	0.0397	0.2652	0.4485	0.7085	-0.0674
low	54.00	-0.1781	-0.6743	-0.2206	-0.1674	-0.0841	0.1860	0.0116	-0.2849
tdiff		**2.889**	**2.875**	**3.651**	0.7203	**2.251**	0.6510	1.304	0.6714

Table 6A

Betas on Style Indexes, Conditioned on Discrete State Variables

Monthly fund group returns in excess of the 90-day Treasury Bill are regressed on a fund group specific style index excess return and the products with dummy variables for the state of the economy. The dummy variables are the same as in Table 2. The growth fund sample period is January of 1973 through December of 2000 (336 total observations). Other fund groups may have fewer observations, as indicated in Table 3. Cases with fewer than 12 nonmissing observations are excluded, and shown as 0.000. tdiff is the heteroskedasticity-consistent t-ratio for the difference between the high and low-state conditional betas. Only states with an absolute tdiff greater than 2.0 are shown.

Equally-weighted portfolio of mutual funds, by group:	growth	maxcg	other	income	GI	sector	smallcg	timers
STATE OF THE TERM STRUCTURE VARIABLES:								
high Short term rates	1.213	2.493	1.474	0.4843	0.9227	0.7012	1.189	1.597
low	1.233	2.488	1.478	0.4971	0.9871	0.7980	1.408	2.043
tdiff	-0.477	0.0428	-0.048	-0.1255	-1.417	-0.8836	**-2.279**	**-2.157**
high Term Structure slope	1.172	2.544	1.466	0.3210	0.8688	0.6343	1.309	1.711
low	1.261	2.511	1.409	0.6396	0.9871	0.7607	1.191	1.732
tdiff	-1.258	0.1691	0.7976	**-3.742**	-1.644	-1.445	1.103	-0.0955
high Term Structure Concavity	1.185	2.460	1.477	0.4373	0.9470	0.7574	1.480	1.760
low	1.254	2.494	1.468	0.6442	0.9859	0.8344	1.267	1.756
tdiff	-1.662	-0.2409	0.1869	**-2.132**	-0.9609	-0.6073	**2.043**	0.0150
high Interest Rate Volatility	1.215	2.541	1.451	0.4985	0.9347	0.6648	1.179	1.615
low	1.275	2.558	1.497	0.5883	1.000	0.8105	1.314	2.172
tdiff	-1.641	-0.1413	-0.5566	-0.8193	-1.449	-1.701	-1.551	**-2.472**
STATE OF THE FINANCIAL MARKETS VARIABLES								
high Credit Spreads	1.188	2.230	1.367	0.4901	0.9285	0.6337	1.115	1.598
low	1.277	2.628	1.532	0.7274	0.9808	0.7480	1.343	1.825
tdiff	-1.033	-1.503	-1.853	**-2.745**	-0.8316	-1.365	-1.342	-1.614
high Dividend Yield	1.234	2.412	0.000	0.4954	0.955	0.7179	1.512	1.680
low	1.276	2.531	0.000	0.6761	1.001	0.7655	1.277	2.221
tdiff	-0.5972	-0.4809	0.000	-1.358	-0.9273	-1.341	**5.345**	**-2.458**

Table 7A: Cross sectional distribution of t-ratios for Alphas using Style benchmarks

This table replicated Table 7, where the Sharpe style benchmarks replace the broad market index.

Panel A: Unconditional Alphas									
	Null	All	Growth	MCG	Other G	Income	G &I	Sector	SCG
t>2.36	0.005	0.12	0.03	0.05	0.15	0.03	0.02	0.06	0.10
2.36>t>1.96	0.02	0.04	0.03	0.03	0.06	0.02	0.02	0.07	0.04
1.96>t>1.65	0.025	0.04	0.03	0.04	0.07	0.03	0.02	0.05	0.05
1.65>t>0	0.45	0.40	0.44	0.25	0.45	0.32	0.43	0.53	0.49
0>t>-1.65	0.45	0.29	0.35	0.41	0.20	0.33	0.42	0.24	0.26
-1.65>t>-1.96	0.025	0.02	0.03	0.05	0.02	0.02	0.02	0.01	0.01
-1.96.t>-2.36	0.02	0.02	0.02	0.07	0.02	0.03	0.03	0.01	0.02
t<-2.36	0.005	0.07	0.06	0.09	0.03	0.22	0.05	0.04	0.03
Panel B: Alphas Conditioned on Term Structure									
	Null	All	Growth	MCG	Other G	Income	G &I	Sector	SCG
t>2.36	0.005	0.13	0.05	0.06	0.14	0.03	0.02	0.09	0.09
2.36>t>1.96	0.02	0.03	0.03	0.03	0.07	0.01	0.01	0.05	0.03
1.96>t>1.65	0.025	0.04	0.03	0.02	0.07	0.02	0.02	0.05	0.04
1.65>t>0	0.45	0.39	0.44	0.25	0.44	0.29	0.38	0.53	0.50
0>t>-1.65	0.45	0.30	0.34	0.42	0.23	0.36	0.45	0.21	0.28
-1.65>t>-1.96	0.025	0.02	0.02	0.05	0.01	0.03	0.04	0.01	0.02
-1.96.t>-2.36	0.02	0.02	0.03	0.03	0.02	0.03	0.03	0.02	0.02
t<-2.36	0.005	0.06	0.06	0.14	0.02	0.24	0.05	0.02	0.01
Panel C: Alphas Conditioned on Financial Market									
	Null	All	Growth	MCG	Other G	Income	G &I	Sector	SCG
t>2.36	0.005	0.12	0.04	0.05	0.08	0.04	0.02	0.06	0.04
2.36>t>1.96	0.02	0.03	0.02	0.03	0.05	0.01	0.02	0.05	0.02
1.96>t>1.65	0.025	0.03	0.03	0.04	0.05	0.01	0.02	0.04	0.05
1.65>t>0	0.45	0.30	0.32	0.29	0.39	0.19	0.31	0.45	0.38
0>t>-1.65	0.45	0.35	0.41	0.41	0.33	0.42	0.41	0.30	0.39
-1.65>t>-1.96	0.025	0.04	0.04	0.05	0.04	0.06	0.05	0.03	0.04
-1.96.t>-2.36	0.02	0.04	0.04	0.05	0.03	0.04	0.06	0.03	0.04
t<-2.36	0.005	0.09	0.09	0.08	0.04	0.23	0.11	0.05	0.04
Panel D: Alphas Conditioned on Real Economy									
	Null	All	Growth	MCG	Other G	Income	G &I	Sector	SCG
t>2.36	0.005	0.12	0.03	0.09	0.14	0.03	0.02	0.07	0.10
2.36>t>1.96	0.02	0.03	0.02	0.03	0.06	0.02	0.01	0.04	0.05
1.96>t>1.65	0.025	0.04	0.03	0.02	0.08	0.03	0.02	0.06	0.05
1.65>t>0	0.45	0.40	0.45	0.30	0.43	0.30	0.44	0.51	0.45
0>t>-1.65	0.45	0.30	0.35	0.40	0.22	0.35	0.41	0.25	0.30
-1.65>t>-1.96	0.025	0.02	0.03	0.06	0.02	0.03	0.03	0.01	0.02
-1.96.t>-2.36	0.02	0.02	0.03	0.03	0.02	0.02	0.03	0.01	0.02
t<-2.36	0.005	0.06	0.05	0.09	0.02	0.22	0.05	0.04	0.02

Table 8A: The Distributions of T-ratios for alphas in High vs. Low Economic States Using Sharpe Style Benchmarks

Alphas and their t ratios are based on the regression equation (4), where the Sharpe Style benchmark replaces the equity market index and the conditioning dummy variables are used one at a time. High (low) means that the value of the state variable is higher (lower) than one standard deviation from its moving average over the past 60 months. The distributions of the t-ratios for alpha are presented, for those cases where a Chi square test for departures from normality produce right-tial p-values of 10% or less.

Short Term Interest Rate High	Short Term Interest Rate Low	Term Structure Slope High	Interest Rate Volatility High	Interest Rate Volatility Low	Stock Market Volatility Low	Dividend Yield Low	Term Structure Slope High	Dividend Yield High
Income	Income	Income	Income	Income	Income	Income	MCG	Growth
0.04	0.05	0.23	0.09	0.07	0.08	0.03	0.02	0.3
0.03	0.03	0.06	0.03	0.02	0.03	0.01	0.03	0.02
0.02	0.03	0.05	0.02	0.02	0.02	0.03	0	0.01
0.41	0.3	0.23	0.26	0.23	0.29	0.28	0.12	0.29
0.18	0.29	0.23	0.32	0.31	0.27	0.22	0.46	0.31
0.04	0.02	0.02	0.03	0.03	0.03	0.01	0.08	0.01
0.03	0.03	0.02	0.01	0.03	0.03	0.01	0.07	0.03
0.24	0.26	0.17	0.23	0.3	0.25	0.41	0.23	0.03

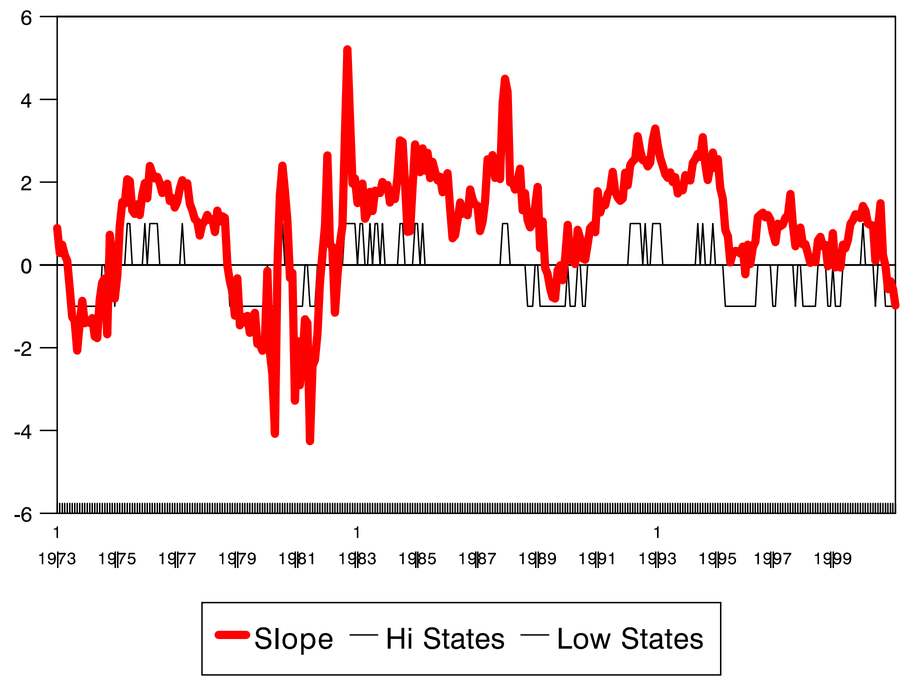
Term Structure Slope High	Interest Rate Volatility Low	Dividend Yield High	Term Structure Slope High	Dividend Yield High	Inflation High	Interest Rate Volatility Low	Dividend Yield High	Stock Market Liquidity Low
SCG	SCG	SCG	Other G	G&I	G&I	Sector	Sector	Sector
0.3	0.26	0.31	0.22	0.27	0.22	0.26	0.46	0.14
0.01	0.03	0	0.01	0.02	0.12	0.04	0	0.05
0.01	0.03	0	0.01	0.02	0.1	0.07	0	0.03
0.3	0.45	0.25	0.38	0.32	0.37	0.4	0.4	0.29
0.32	0.18	0.44	0.34	0.29	0.14	0.2	0.15	0.24
0.01	0.01	0.00	0.01	0.03	0.01	0.00	0.00	0.03
0.01	0	0	0.01	0.02	0.02	0.01	0	0.03
0.05	0.02	0	0.04	0.03	0.02	0.03	0	0.19

Appendix B: Figures

Figure B1 presents plots of the lagged state variables and their associated dummy variables. Figure B2 shows the annual breakpoints for high and low values of the various fund characteristics for the market-timing fund sample.

Figure B1

Term Slope and Associated Hi, Lo Dummies



Short Rate and Associated Hi, Lo Dummies

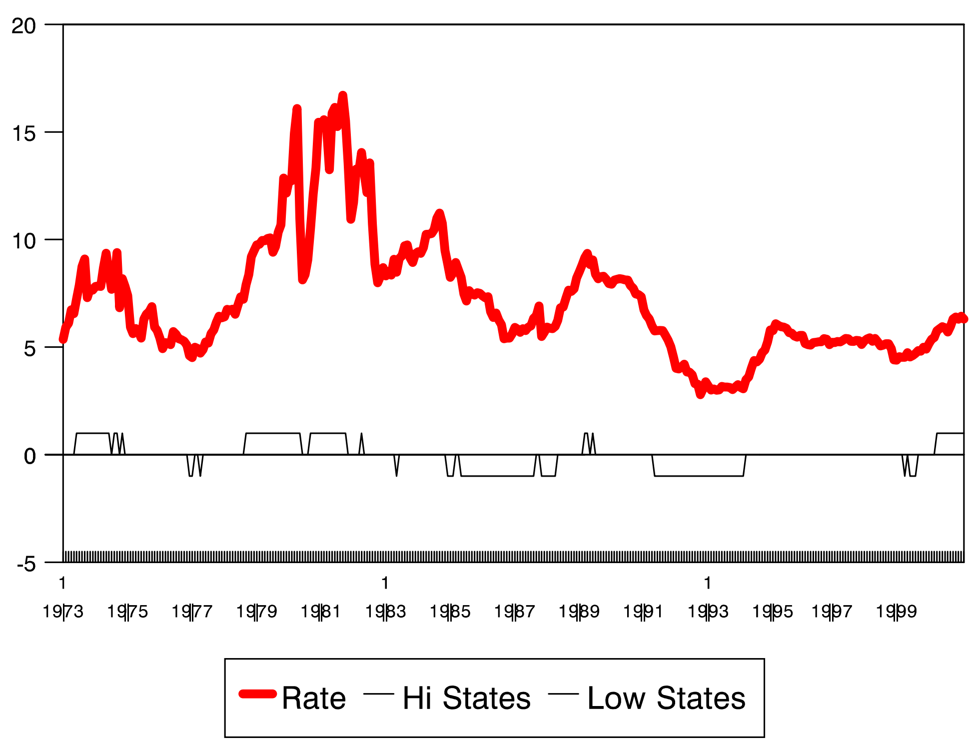
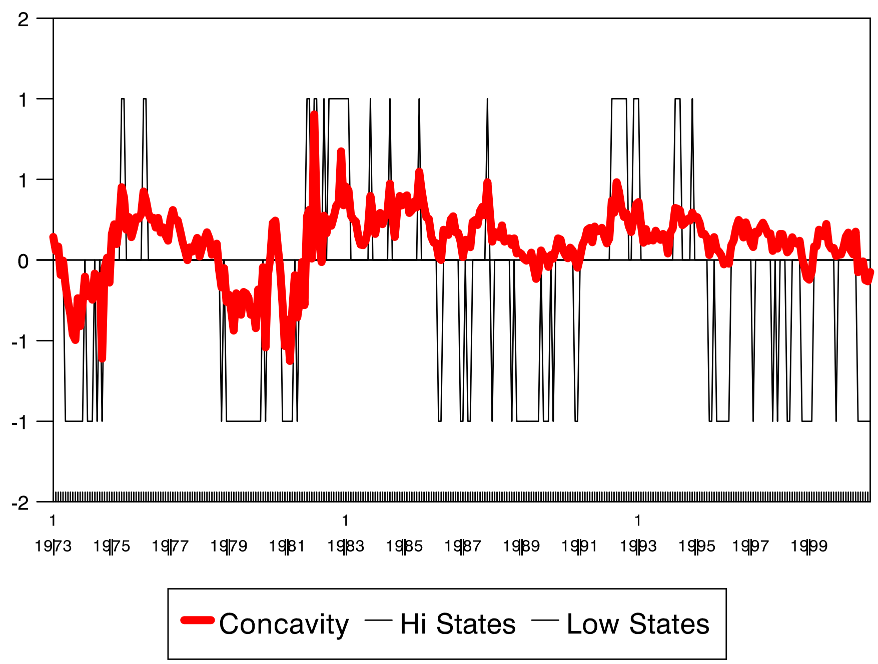


Fig. B1, cont.

Concavity and Associated Hi, Lo Dummies



Interest Rate Volatility and Associated Dummies

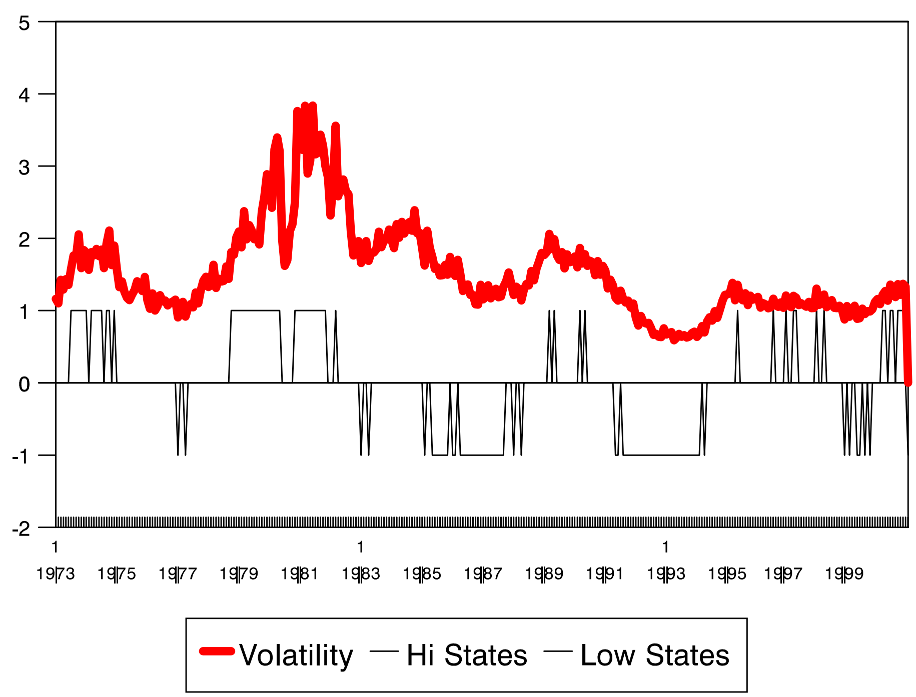
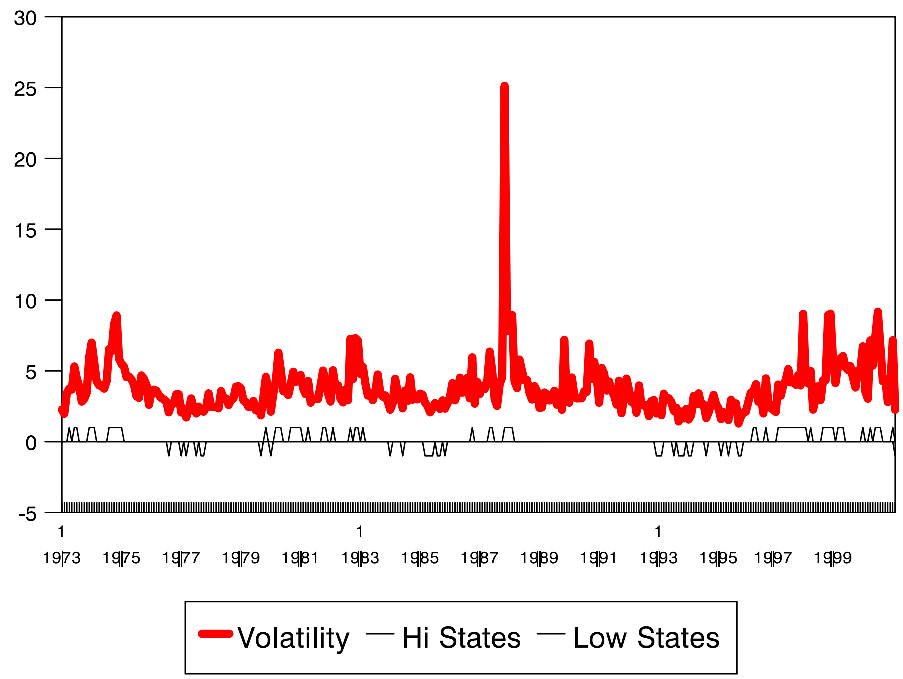


Fig. B1, cont.

Stock Market Volatility and Associated Dummies



Credit Spreads and Associated Dummies

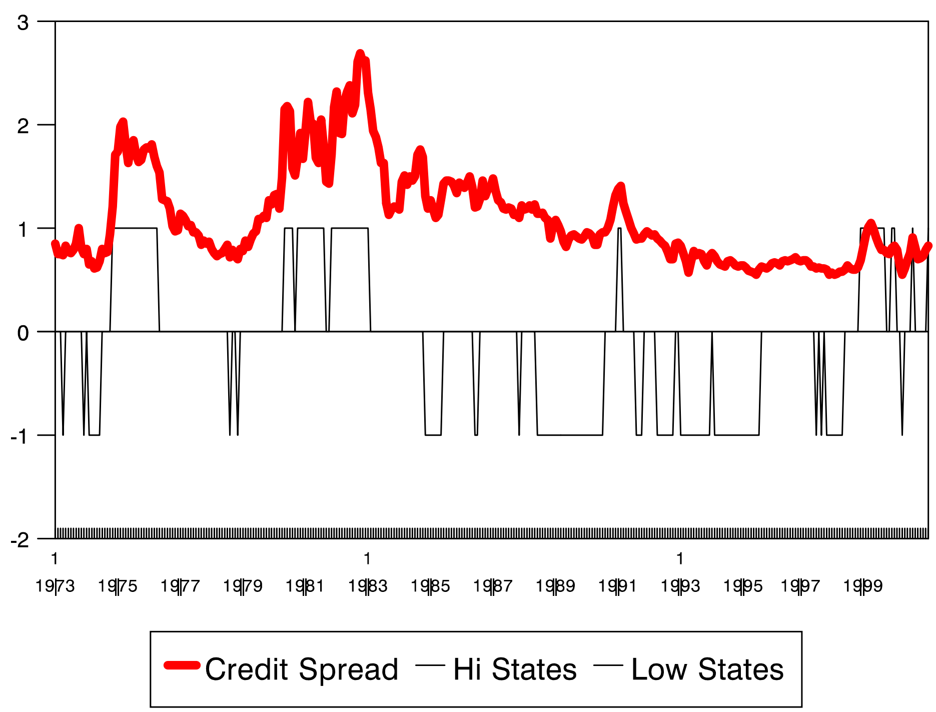
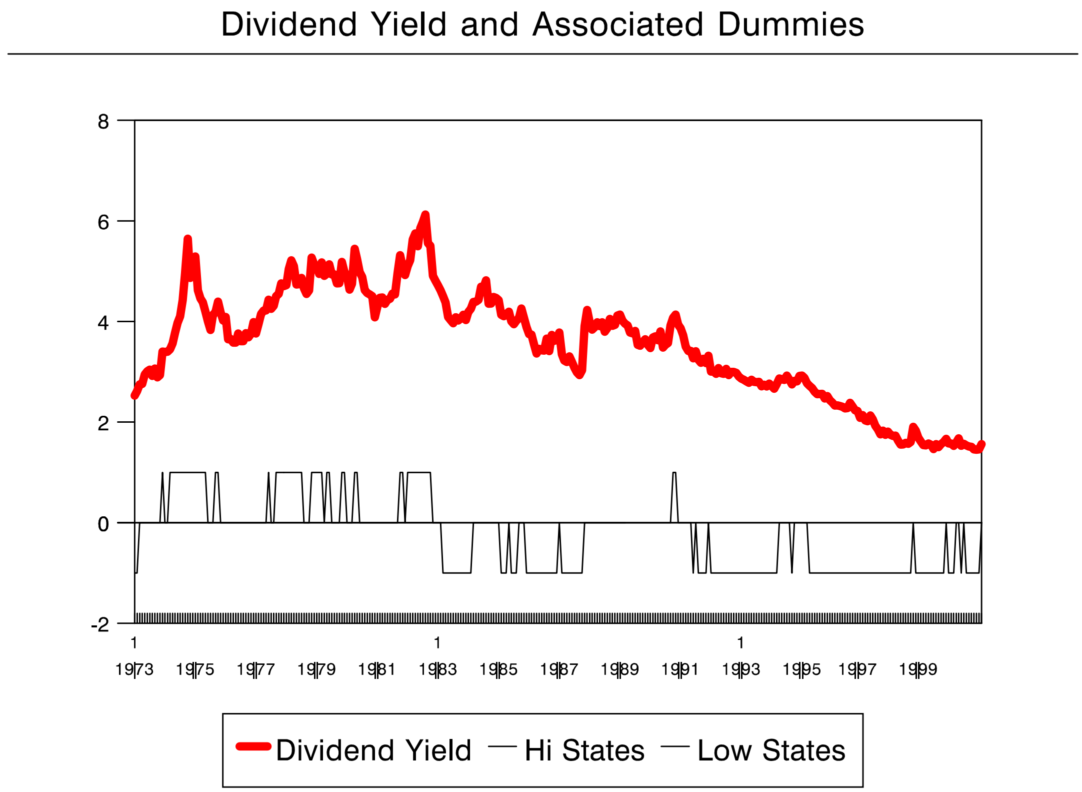
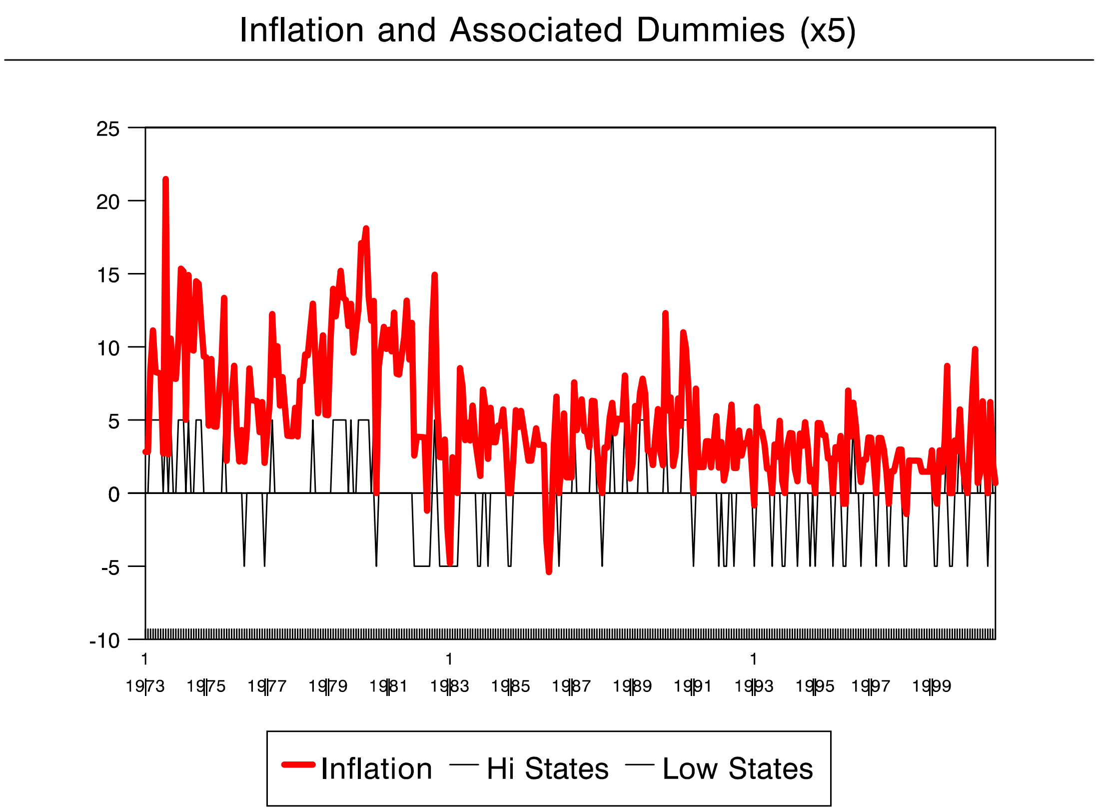


Fig. B1, cont.



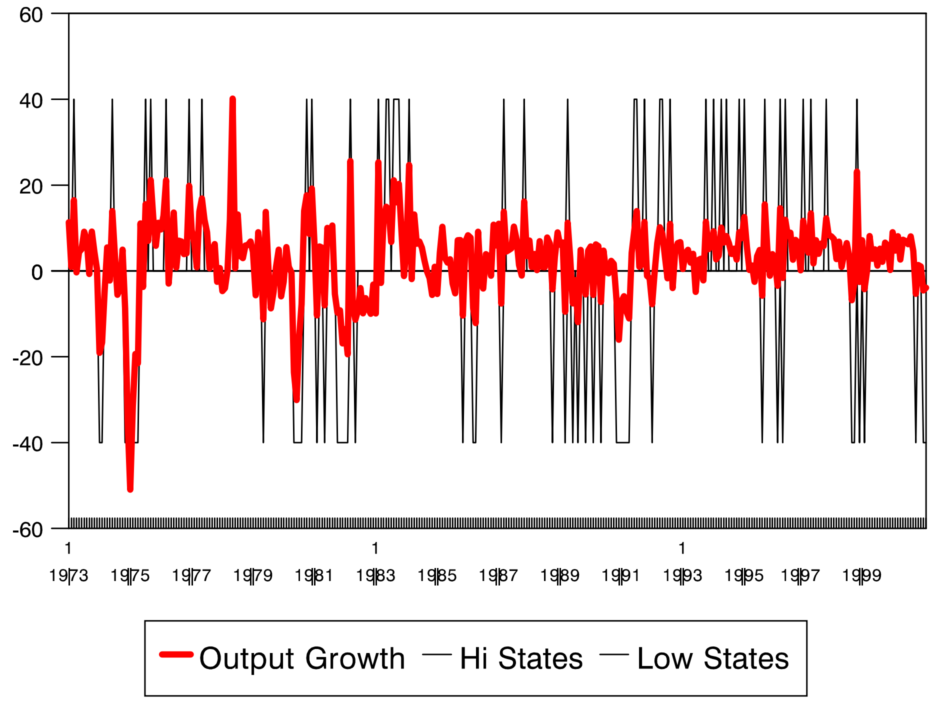
Dividend Yield and Associated Dummies
8
6
4
2
0
-2
1
1
1
1973
1975
1977
1979
1981
1983
1985
1987
1989
1991
1993
1995
1997
1999
Dividend Yield
Hi States
Low States



Inflation and Associated Dummies (x5)
25
20
15
10
5
0
-5
-10
1
1
1
1973
1975
1977
1979
1981
1983
1985
1987
1989
1991
1993
1995
1997
1999
Inflation
Hi States
Low States

Fig. B1, cont.

Industrial Output and Associated Dummies (x40)



ST Corp. Illiquidity and Associated Dummies (x15)

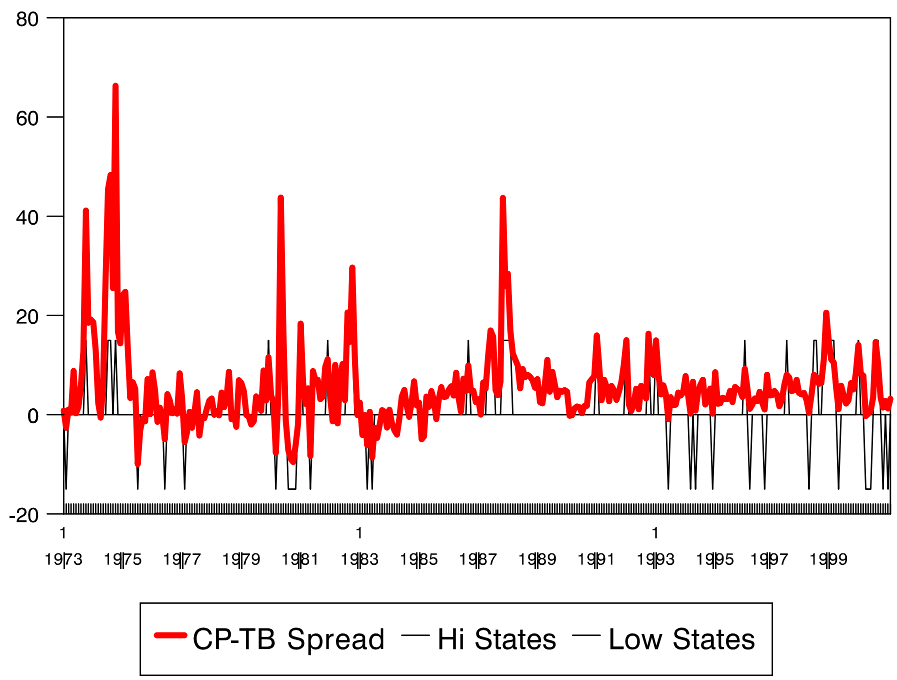


Fig. B1, cont.

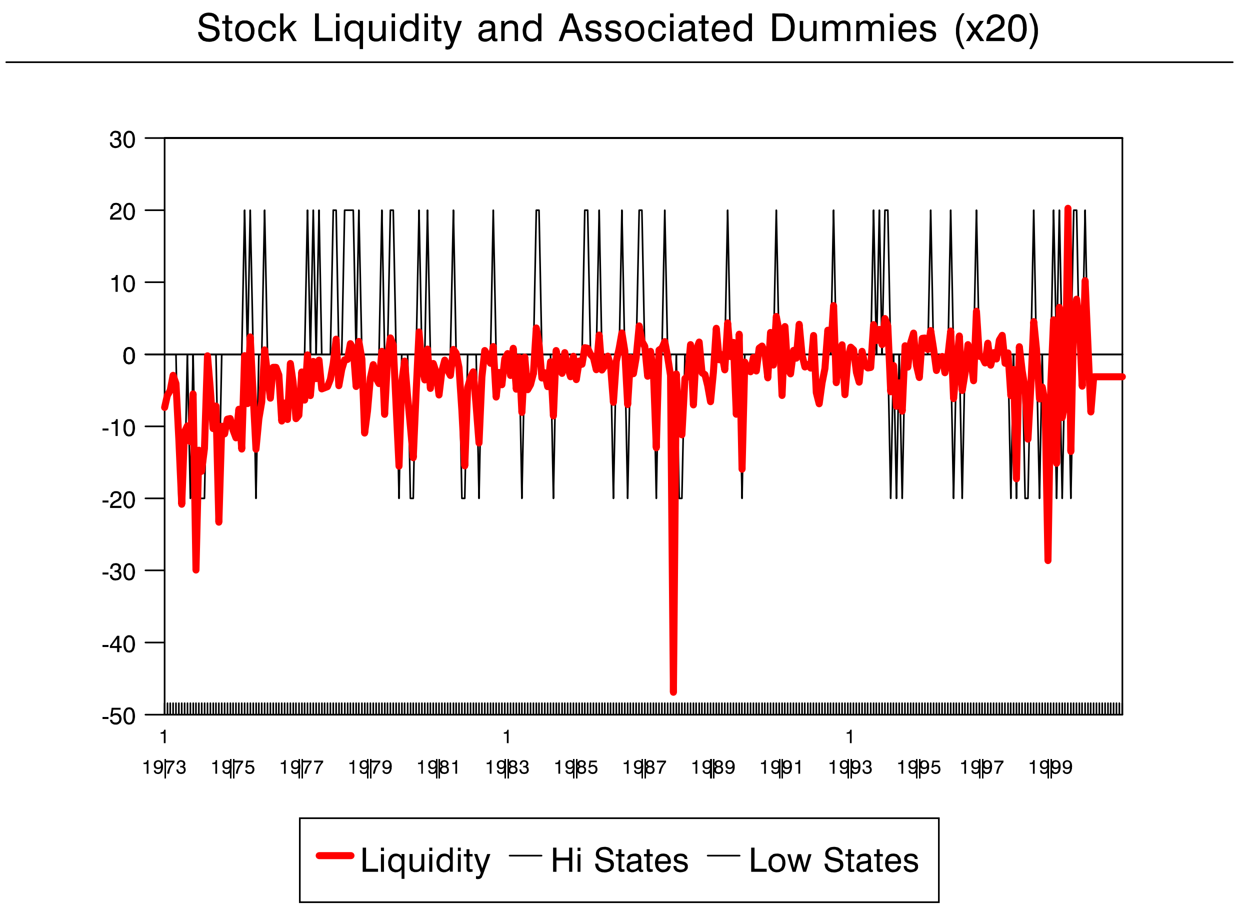
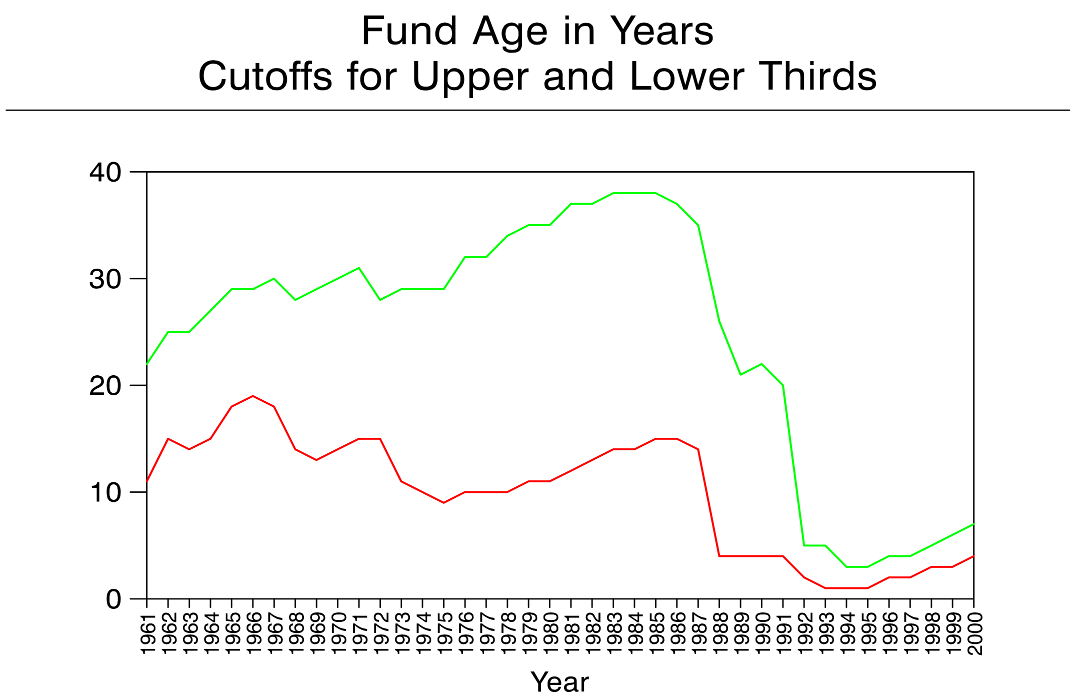

Stock Liquidity and Associated Dummies (x20)
30
20
10
0
-10
-20
-30
-40
-50
1
1
1
1973
1975
1977
1979
1981
1983
1985
1987
1989
1991
1993
1995
1997
1999
Liquidity
Hi States
Low States

Figure B2


Fund Age in Years
Cutoffs for Upper and Lower Thirds
0
10
20
30
40
1961 1962 1963 1964 1965 1966 1967 1968 1969 1970 1971 1972 1973 1974 1975 1976 1977 1978 1979 1980 1981 1982 1983 1984 1985 1986 1987 1988 1989 1990 1991 1992 1993 1994 1995 1996 1997 1998 1999 2000
Year

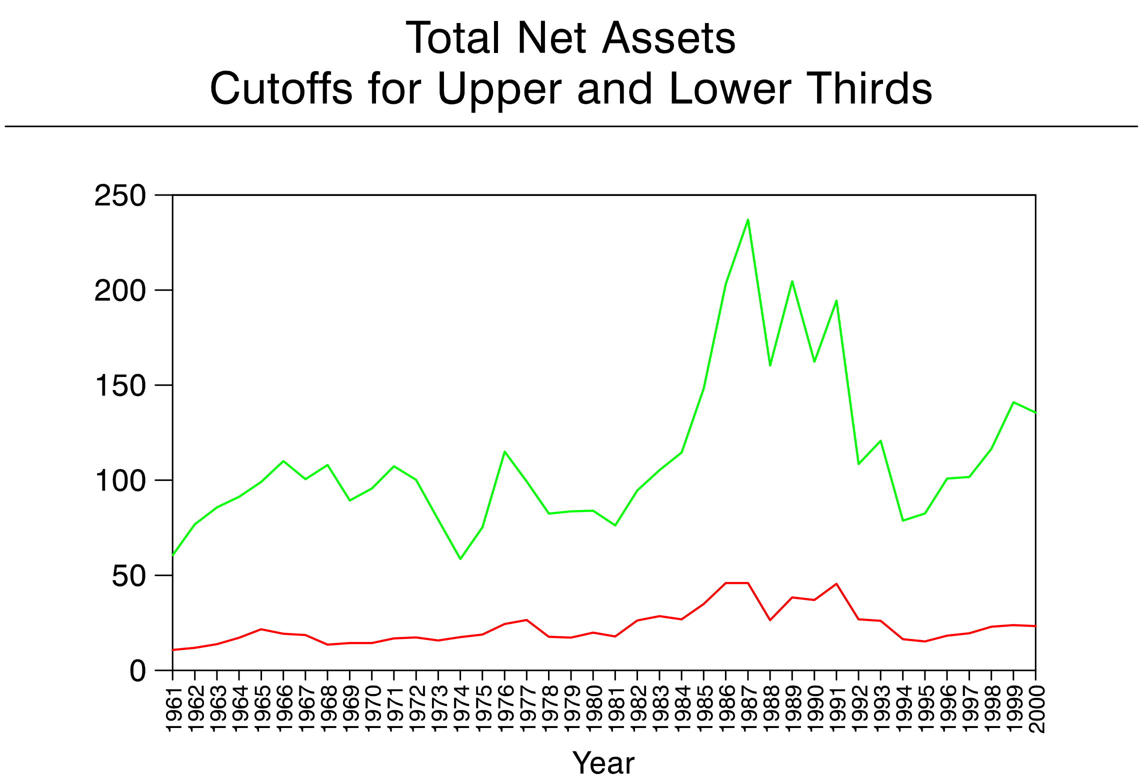
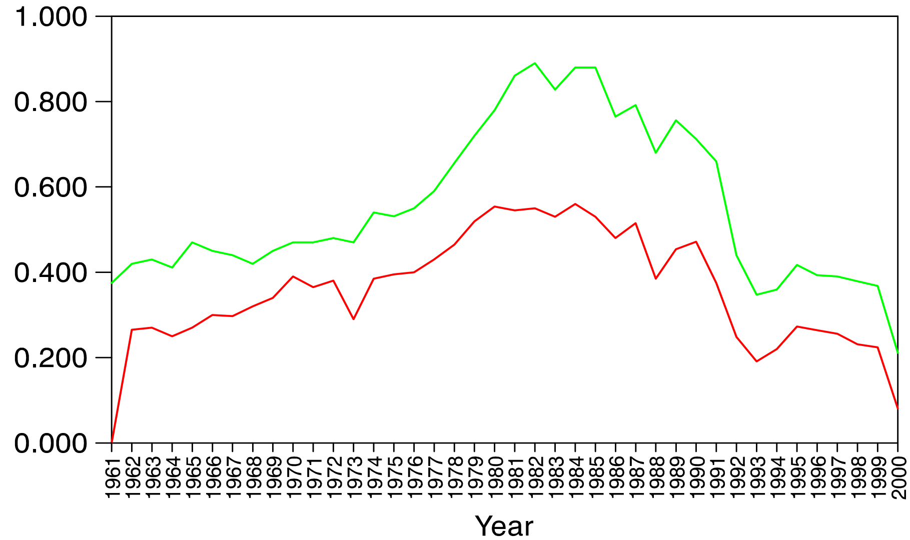

Total Net Assets
Cutoffs for Upper and Lower Thirds
0
50
100
150
200
250
1961 1962 1963 1964 1965 1966 1967 1968 1969 1970 1971 1972 1973 1974 1975 1976 1977 1978 1979 1980 1981 1982 1983 1984 1985 1986 1987 1988 1989 1990 1991 1992 1993 1994 1995 1996 1997 1998 1999 2000
Year

Fig. B2, cont.

Income - Percent Per Month
Cutoffs for Upper and Lower Thirds



Capital Gains - Percent Per Month
Cutoffs for Upper and Lower Thirds

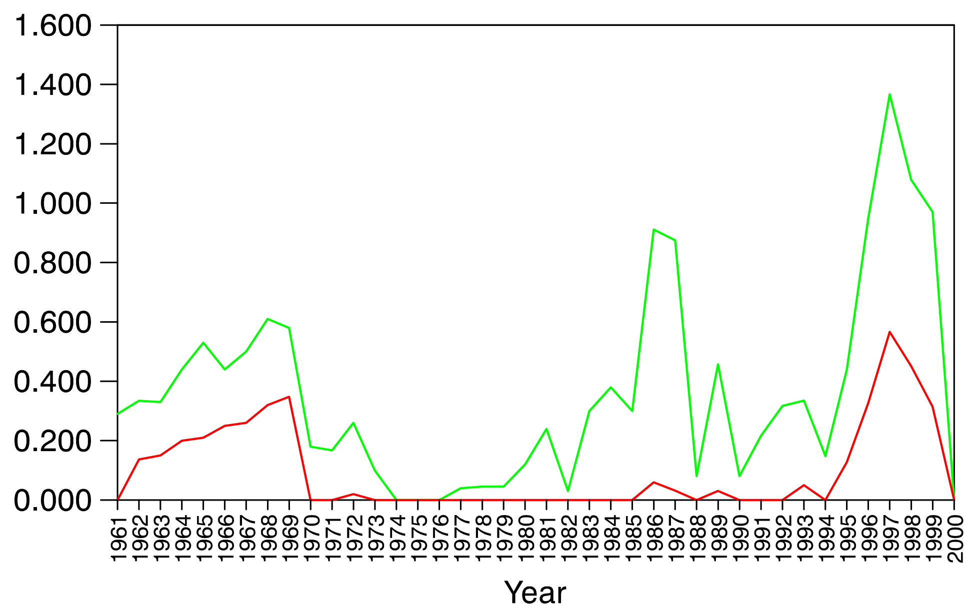
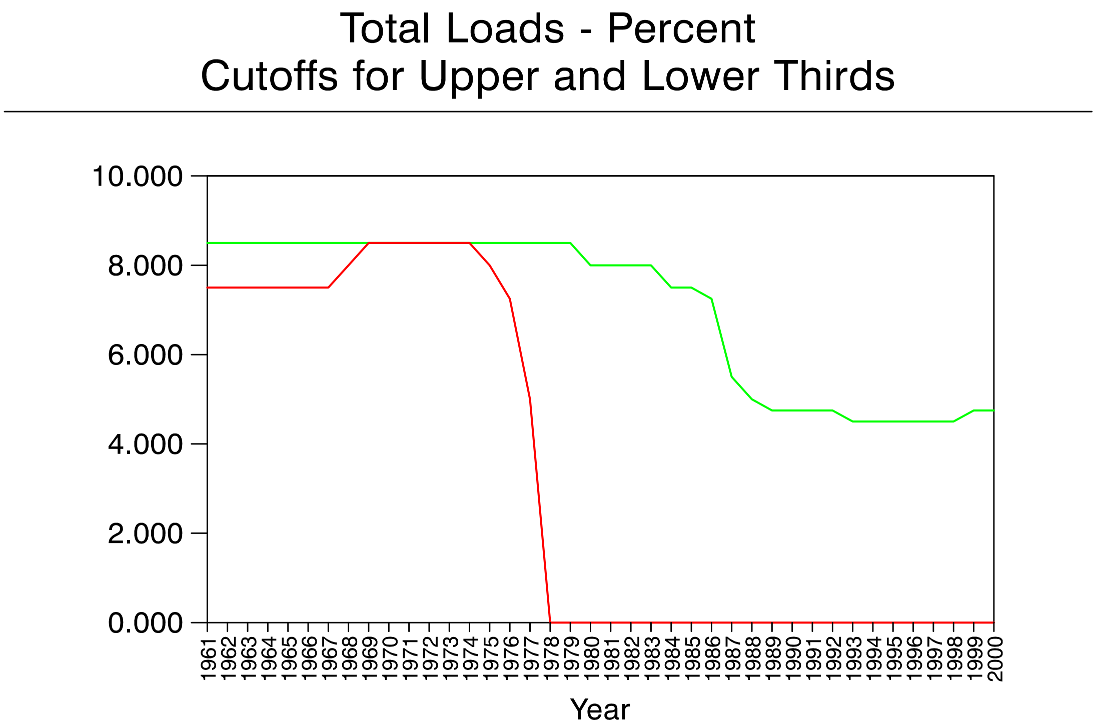


Fig. B2, cont.


Total Loads - Percent
Cutoffs for Upper and Lower Thirds
10.000
8.000
6.000
4.000
2.000
0.000
1961 1962 1963 1964 1965 1966 1967 1968 1969 1970 1971 1972 1973 1974 1975 1976 1977 1978 1979 1980 1981 1982 1983 1984 1985 1986 1987 1988 1989 1990 1991 1992 1993 1994 1995 1996 1997 1998 1999 2000
Year

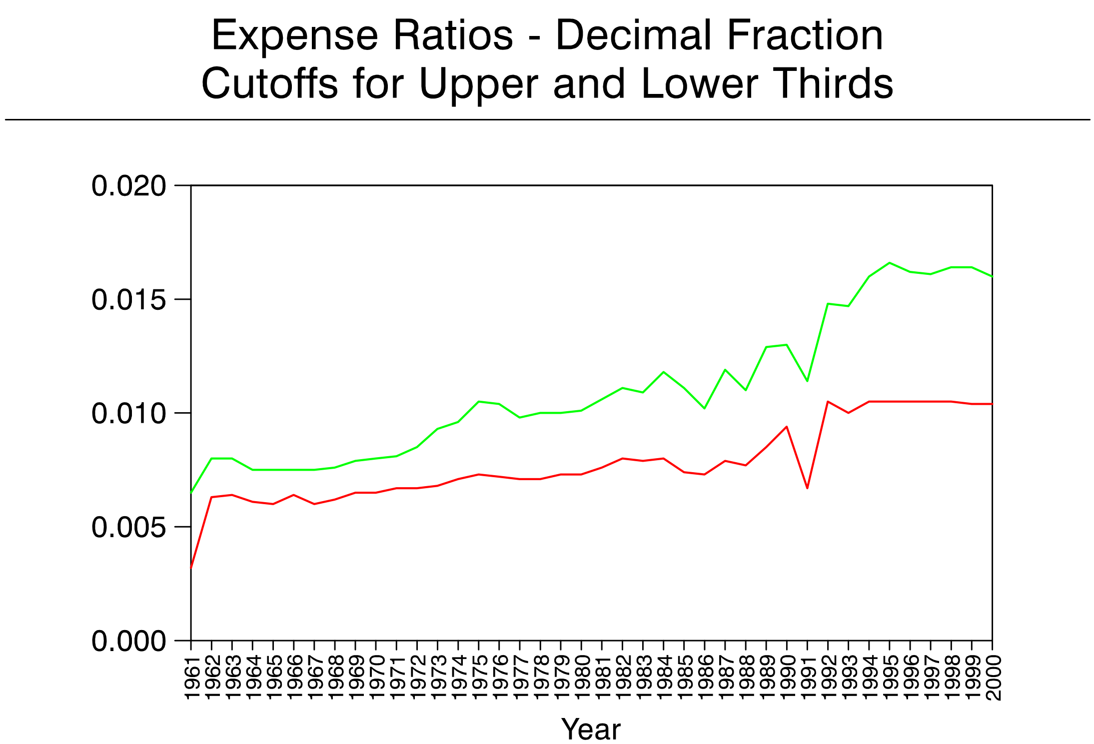
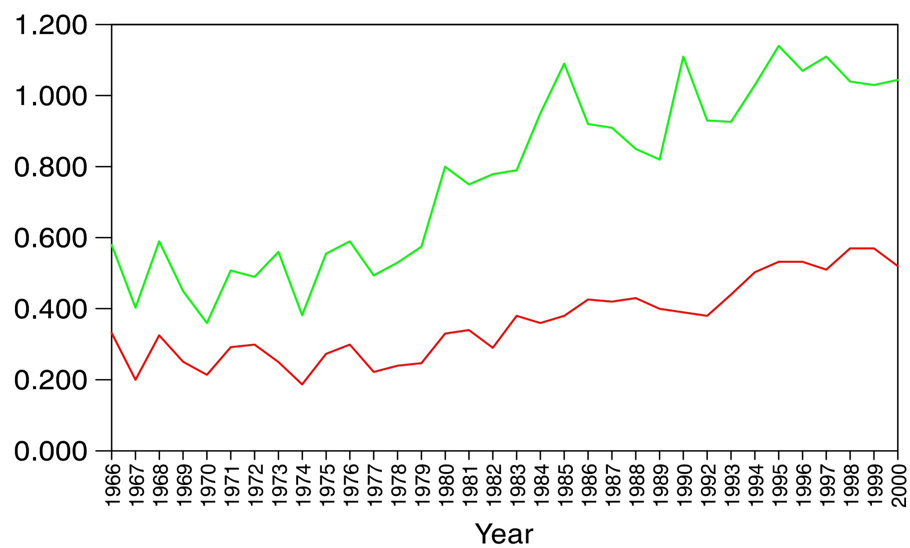

Expense Ratios - Decimal Fraction
Cutoffs for Upper and Lower Thirds
0.020
0.015
0.010
0.005
0.000
1961 1962 1963 1964 1965 1966 1967 1968 1969 1970 1971 1972 1973 1974 1975 1976 1977 1978 1979 1980 1981 1982 1983 1984 1985 1986 1987 1988 1989 1990 1991 1992 1993 1994 1995 1996 1997 1998 1999 2000
Year

Fig. B2, cont.

Turnover - Decimal Fraction
Cutoffs for Upper and Lower Thirds



Previous Year's New Money Flow - Decimal Fraction
Cutoffs for Upper and Lower Thirds

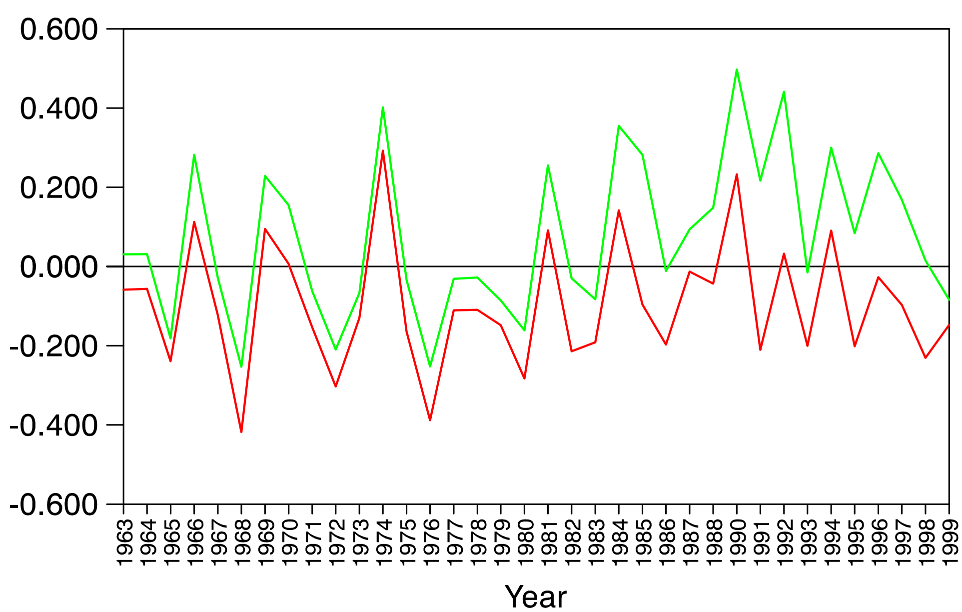
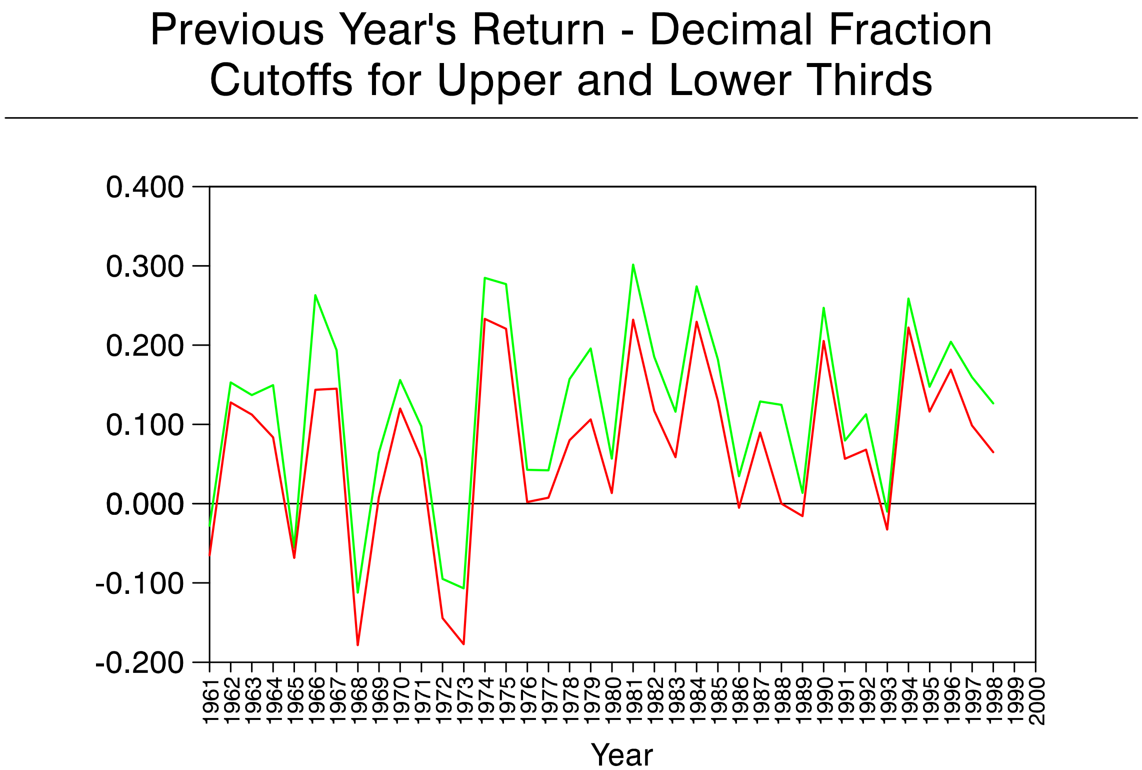


Fig. B2, cont.



Previous Year's Return - Decimal Fraction
Cutoffs for Upper and Lower Thirds
0.400
0.300
0.200
0.100
0.000
-0.100
-0.200
1961 1962 1963 1964 1965 1966 1967 1968 1969 1970 1971 1972 1973 1974 1975 1976 1977 1978 1979 1980 1981 1982 1983 1984 1985 1986 1987 1988 1989 1990 1991 1992 1993 1994 1995 1996 1997 1998 1999 2000
Year

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