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Conditional market timing with benchmark investors[☆]

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Abstract

This paper tests models of mutual fund market timing that allow the manager's payoff function to depend on returns in excess of a benchmark, and distinguish timing based on publicly available information from timing based on finer information. We simultaneously estimate parameters which describe the public information environment, the manager's risk aversion, and the precision of the fund's market-timing signal. Using a sample of more than 400 U.S. mutual funds for 1976–94, our findings suggest that mutual funds behave as highly risk averse, benchmark investors. Conditioning on public information improves the model specification. After controlling for the public

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information, we find no evidence that funds have significant market-timing ability.

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1. Introduction

Recent years have witnessed rapid growth in mutual funds and other professionally-managed investment vehicles, along with research on the performance of managed funds and econometric techniques for measuring performance. In particular, Ferson and Schadt (1996) advocate conditional performance evaluation, building on earlier work of Shanken (1990), Ball et al. (1995), and Chen and Knez (1996). In a market-timing context, the goal is to distinguish timing ability that merely reflects publicly available information, as captured by a set of instrumental variables, from timing based on better information. We call such informed timing ability *conditional market timing*.

Ferson and Schadt (1996) estimate conditional versions of the classic market-timing models of Treynor and Mazuy (1966) and Merton and Henriksson (1981), but they examine a sample of equity funds that are unlikely to aggressively time the market. Harvey and Graham (1996) study conditional market timing information in U.S. investment newsletters, while Kryzanowski et al. (1996) study the timing of macroeconomic variables by Canadian funds. However, the conditional timing ability of market-timing mutual funds remains largely unexplored.

This paper contributes to the literature on performance evaluation by further developing conditional market-timing models. In addition to incorporating public information measures to capture conditional timing ability, our model features explicit performance benchmarks for measuring the relative performance of fund managers. In practice, performance benchmarks represent an important component of managers' incentive system. For example, Schultz (1996) reports that Vanguard includes incentive-based provisions in 24 of 38 compensation contracts with external fund managers. These contracts determine a manager's compensation by comparing fund performance to that of a benchmark portfolio, most typically the Standard and Poors 500 (S&P500). The incentive contracts induce a preference for portfolio return in excess of the benchmark.

Starks (1987) and Admati and Pfleiderer (1997) model incentive-based management contracts, focusing on agency problems between managers and investors. Chiu and Roley (1992) and Brown et al. (1996), among others, examine the behavior of fund managers when relative performance is important. Heinkel and Stoughton (1995) present market-timing models with benchmark investors, but they study unconditional models and do not account for public information. The current paper is the first to incorporate benchmark investors in a conditional market-timing model.

We simultaneously estimate parameters that describe the public information environment, the risk aversion of the fund manager and the precision of the fund's market-timing signal. We are able to estimate the parameters under more general statistical assumptions than have been used in previous market timing studies. Using a sample of more than 400 U.S. mutual funds from 1976 through 1994, we find that both benchmark investing and conditioning information are important in the model. The point estimates suggest that mutual funds behave as highly risk-averse benchmark investors, but the standard errors of the risk-aversion estimates are large. A cross-sectional analysis of mutual fund holdings suggests that the model parameters are informative about managers' portfolio strategies. Once we control for the public information variables, we find little evidence that mutual funds have conditional market-timing ability.

The remainder of the paper is organized as follows. Section 2 presents the model. Section 3 describes our empirical methods. Section 4 describes the data and Section 5 presents our empirical results. Section 6 offers concluding remarks.

2. The model

We present a simple model of market timing in the spirit of Admati et al. (1986). We imagine a manager who maximizes single-period utility given a normally distributed, private signal about the future market return, $r_{m,t+1}$, in excess of a risk-free rate. The signal, S_t is parameterized following the approach of Heinkel and Stoughton (1995), but modified for a conditional model as follows:

$$S_t = K[r_{m,t+1} - E(r_{m,t+1}|Z_t)]/[\sigma_m(1 - R^2)^{1/2}] + \varepsilon_t, \tag{1}$$

where

$Z_t \equiv$ a publicly available vector of information variables,
$E(r_{m,t+1}|Z_t) \equiv$ conditional expected excess return given Z_t,
$R^2 \equiv$ the coefficient of determination from a regression of r_{mt+1} on Z_t,
$\sigma_m \equiv$ the unconditional standard deviation of the market return,
$K \equiv$ a parameter which captures the signal quality, and
$\varepsilon_t \equiv$ a standard normal disturbance term, independent of $r_{m,t+1}$ and Z_t.

Eq. (1) defines the signal as information about the market that is independent of the public information, Z_t. We normalize the signal to have mean zero, conditional on the public information. The parameter K measures the quality of the market timing signal. To interpret K, consider the correlation, ρ, between S_t and the market return, conditional on Z_t:

$$\rho = K/(1+K^2)^{1/2}. \tag{2}$$

When $K=0$ the manager has only public information, and when K becomes large, the manager has nearly perfect information about future market returns.[1] In the empirical analysis, we report an estimate of the squared correlation, ρ^2, to facilitate inferences about the economic significance of timing ability.

2.1. The manager's problem

The portfolio manager is assumed to face a simple market timing problem: the manager must choose between the risky market portfolio, with return R_m, and a risk-free asset with return R_f. The total portfolio return is $R_p = R_f + x r_m$, where x is the portfolio weight of the market portfolio and $r_m = R_m - R_f$. The manager maximizes a utility function that depends on returns in excess of a benchmark:

$$u(x) = \mathrm{E}\{U(R_p - [hR_m + (1-h)R_f])|S, Z\}, \tag{3}$$

where $U(\cdot)$ is a concave utility function and h is an exogenously given *benchmark preference parameter*. For values of h between zero and one, the exogenous benchmark is a combination of R_m and R_f, with a 'policy weight' equal to h on R_m and $(1-h)$ on cash. If $h=1$, the utility is a function $R_p - R_m$, and the manager cares about the portfolio return relative to the 'market' return, R_m. If $h=0$, the utility is a function of $R_p - R_f$, and the manager evaluates the portfolio return relative to the risk-free return on cash. Since the risk-free rate is a constant from the point of view of the manager, we interpret $h=0$ as the case where benchmark investing is irrelevant.

The solution to the manager's portfolio problem depends on the conditional expected value and variance of the market return, given the information (Z_t, S_t):

$$\mathrm{E}(r_{m,t+1}|Z_t, S_t) = \mathrm{E}(r_{m,t+1}|Z_t) + S_t\sigma_m(1-R^2)^{1/2}[K/(1+K^2)], \tag{4}$$

$$\mathrm{Var}(r_{m,t+1}|Z_t, S_t) = \sigma_m^2(1-R^2)/(1+K^2).$$

[1] We model the signal quality with the single parameter, K, which does not allow us to independently control the variance of the signal and its correlation with the market return. We experimented with a more general signal structure, but could not empirically identify more than one parameter for the signal. This may not be surprising, given that we find that the market-timing signals are rarely significant after controlling for public information.

Differentiating (3) with respect to x and setting the result equal to zero yields the optimal weight in the risky asset:

$$x = h + \gamma^{-1}\mathrm{E}(r_{\mathrm{m},t+1}|Z_t, S_t)/\mathrm{Var}(r_{\mathrm{m},t+1}|Z_t, S_t), \tag{5}$$

where γ is the Rubinstein (1973) measure of risk aversion, which we assume to be a fixed parameter. We use Stein's (1973) Lemma in deriving Eq. (5), to express the covariance of the market with the marginal utility in terms of the covariance with the argument of the utility function.

Eq. (5) shows that the manager will hold the benchmark portfolio weight, h, when the information indicates that the expected market return is equal to the risk-free rate. A benchmark investor ($h \neq 0$) treats the benchmark portfolio the way an investor without a benchmark ($h = 0$) treats the risk-free asset, as derived by Malatesta (1992) and Brennan (1993). With a positive expected excess return on the risky asset, the manager puts more weight than h in the risky asset, and the weight depends on the conditional variance and the manager's risk aversion.[2] Malatesta and Brennan explore the equilibrium implications of benchmark investing. In this paper, we do not use a specific equilibrium model for expected returns, but simply assume that the fund manager chooses an optimal portfolio, as expressed by Eq. (5).

Conventional wisdom among practitioners holds that portfolio managers are highly risk averse to deviations from a benchmark return (see, e.g., Grinold and Kahn, 1995). Our model captures this intuition. Using Eq. (5) without conditioning information, and the fact that the portfolio excess return is $r_{\mathrm{p}} = xr_{\mathrm{m}}$, we see that

$$\mathrm{E}(r_{\mathrm{p}})/\sigma^2(r_{\mathrm{p}}) = [h + \gamma^{-1}\mathrm{E}(r_{\mathrm{m}})/\sigma^2(r_{\mathrm{m}})]^{-1}\mathrm{E}(r_{\mathrm{m}})/\sigma^2(r_{\mathrm{m}}). \tag{6}$$

Thus, if $h = 0$ we have the standard result that $\mathrm{E}(r_{\mathrm{p}})/\sigma^2(r_{\mathrm{p}}) = \gamma$. Suppose that $\mathrm{E}(r_{\mathrm{p}})/\sigma^2(r_{\mathrm{p}})$ and $\mathrm{E}(r_{\mathrm{m}})/\sigma^2(r_{\mathrm{m}})$ both have a typical magnitude of approximately equal to two. In this example $h + 2/\gamma \approx 1$, so a benchmark weight of $h = 0.8$ implies $\gamma \approx 10$, and a benchmark weight of $h = 0.9$ implies $\gamma \approx 20$. Thus, benchmark investors are highly risk averse to deviations from the benchmark, and we expect to find estimates of γ for benchmark investors to be large relative to conventional standards of risk aversion.

[2] The model can accommodate an error term in the expression for the weights, assuming that the error is conditionally independent of $r_{\mathrm{m},t+1}$ given Z_t. The error term allows for cross-sectional variation in the portfolio weights of managers who observe a common signal about the market and may be interpreted as capturing the security selection behavior of mutual funds, discussed in Section 5.6 below. Without the error, our finding that the signal quality parameter, K, is not significant implies an extreme form of 'herding' in the model, where all managers respond in the same direction to public information about the future market return. See Grinblatt et al. (1995) for a discussion of herding by mutual fund managers.

2.2. Empirical models

Eq. (5) leads to an empirical model in the spirit of the unconditional models of Treynor and Mazuy (1966) and Admati et al. (1986). The excess portfolio return at time $t+1$ is $r_{p,t+1} = x_t r_{m,t+1}$. Using Eqs. (1), (4) and (5) we obtain

$$r_{p,t+1} = hr_{m,t+1} + Q_1 \mathrm{E}(r_{m,t+1}|Z_t) r_{m,t+1} + Q_2 r^2_{m,t+1} + v_{t+1}, \tag{7}$$

where $Q_1 = 1/[\gamma\sigma^2_m(1-R^2)]$, $Q_2 = K^2/[\gamma\sigma^2_m(1-R^2)]$.

The error term, v_{t+1}, is given by

$$v_{t+1} = Q_3 \varepsilon_{t+1} r_{mt+1},$$

where $Q_3 = K/[\gamma\sigma_m(1-R^2)^{1/2}]$.

Note that, even under the assumption that r_{mt+1}, Z_t, and S_t are normally distributed, the nonlinearity induced by market timing implies that the error term in Eq. (7) is not normally distributed, even conditional on Z_t. Consequently, maximum likelihood methods based on the normal distribution would be inappropriate for estimating the model.

Eq. (7) refines market-timing models studied by Treynor and Mazuy (1966), Admati et al. (1986) and Ferson and Schadt (1996). Admati et al. show how to separately estimate risk aversion and signal quality, but do not account for public information. Ferson and Schadt account for public information, but do not attempt to uncover the deeper structural parameters. Neither study explicitly accounts for benchmark investment behavior.

The model leads to specific hypotheses about the parameters in Eq. (7). The hypothesis that $K=0$ says that the manager uses no market timing information beyond the publicly available instruments, Z_t. Alternatively, $K \neq 0$ implies that the manager has conditional market-timing ability. The hypothesis that $h=0$ says that the manager does not behave as a benchmark investor. If $h \neq 0$, the model suggests that the relevant benchmark has policy weight h in the index R_m and $1-h$ in cash.

2.3. Relation to beta

While the parameter h in Eq. (7) is related to the beta of the fund, it differs from beta because the fund will vary its market exposure in response to both Z_t and S_t. From Eqs. (4) and (5), the conditional beta of the fund, given Z_t, can be derived as:

$$\beta_t = h + \left(\frac{1+K^2}{\gamma}\right)\left(\frac{\mathrm{E}\{r_m|Z_t\}}{\sigma^2_m(1-R^2)}\right) + (K^2/\gamma)\left(\frac{Cov(r_m, r^2_m|Z_t)}{[\sigma^2_m(1-R^2)]^2}\right). \tag{8}$$

The conditional beta depends on the conditional moments of the excess market return and the parameters, h, γ, and K. Beta equals the parameter h only when the final two terms in Eq. (8) are zero, which occurs in the limit as risk aversion becomes infinite. With finite risk aversion, the conditional beta varies over time as a function of the conditional expected premium on the market portfolio and the conditional skewness. If $K = 0$, the portfolio weight changes over time only in response to Z_t. In this case, the conditional beta equals the weight held by the fund in the market index [see Eq. (5)].

3. Econometric methods

To estimate the model, we require the conditional mean of the excess market return, given the instruments Z_t. Normality implies that the conditional mean is a linear regression function:

$$\mathrm{E}(r_{\mathrm{m},t+1}|Z_t) = \delta_0 + Z_t'\delta, \tag{9}$$

where δ is a slope coefficient vector and δ_0 is an intercept. Further, we include a fund-specific 'alpha' coefficient, α_{p}, in the model (see Jensen, 1968). This captures 'selectivity' aspects of performance and other forms of model misspecification (see Section 5.6).

The following system of moment conditions describes the econometric model. Each of the error terms has unconditional mean equal to zero if the model is well specified.

$$\begin{aligned}
u1_{t+1} &= r_{\mathrm{m},t+1} - \mu_{\mathrm{m}},\\
u2_{t+1} &= \sigma_{\mathrm{m}}^2 - (r_{\mathrm{m},t+1} - \mu_{\mathrm{m}})^2,\\
u3_{t+1} &= [r_{\mathrm{m},t+1} - \delta_0 - Z_t'\delta](1, Z_t),\\
u4_{t+1} &= R^2\sigma_{\mathrm{m}}^2 - [\mu_{\mathrm{m}} - \delta_0 - Z_t'\delta]^2,\\
u5_{\mathrm{p},t+1} &= [r_{\mathrm{p},t+1} - \alpha_{\mathrm{p}} - (h + Q_1\delta_0)r_{\mathrm{m},t+1}\\
&\qquad - Q_1(\delta' Z_t r_{\mathrm{m},t+1}) - Q_2 r_{\mathrm{m},t+1}^2](1, Z_t, r_{\mathrm{m},t+1}, r_{\mathrm{m},t+1}^2).
\end{aligned} \tag{10}$$

In the system, the first four equations identify the unconditional mean of the market excess return, μ_{m}, and the other market-wide parameters σ_{m}, δ_0, δ, R^2. The expression for $u5_{\mathrm{p},t+1}$ corresponds to Eq. (7). It identifies the fund-specific parameters of the model, α_{p}, h, K^2 and γ [Q_1 and Q_2, as given by Eq. (7), are functions of these and the other model parameters].

We estimate the system using the Generalized Method of Moments (GMM, Hansen, 1982). If $L + 1$ is the number of instruments in Z_t (including a constant) and N is the number of funds, then the number of moment conditions in the system is $N(L + 3) + L + 4$. The number of parameters equals $4N + L + 4$. Therefore, provided $L > 1$, the model is overidentified and can be tested using Hansen's J-statistic. Since all of the parameters of the system are estimated simultaneously, we obtain consistent and asymptotically efficient GMM estimators, avoiding the two-step methods used in market timing models by Admati et al. (1986), Coggin et al. (1993), and Heinkel and Stoughton (1995).

4. The data

Section 4.1 discusses the mutual fund returns, Section 4.2 describes our style-matched benchmarks, and Section 4.3 presents the market index and lagged instrumental variables.

4.1. The mutual fund returns

We examine open-ended mutual fund returns from the Morningstar, Inc. OnDisc database (quarterly, January 1993 through April 1995 versions). The returns data reflect the reinvestment of dividends and capital gains and are net of expenses, except for front-end load charges and exit fees. We draw two samples of funds from the database. The first is a broad sample of primarily U.S. equity funds. The second is a set of U.S. asset allocation and balanced funds, which we denote as 'asset allocators'. We use this sample to study in more detail funds that are likely to engage in aggressive market timing activities.

For our first sample, we select funds with less than 20% of their holdings in non-U.S. stocks, at least 80% of their holdings in equity, and at least ten years of monthly returns available at the end of 1994. This results in a sample of 303 mutual funds. The time period is January 1976 through December 1994 (228 observations), and the number of funds with return data increases over this period. Morningstar groups these funds according to two alternative criteria, fund objective and investment 'style'. If these groupings are meaningful to investors, then our model implies that the parameters of interest (α, γ, K^2, h) should differ across the groups. Also, working with the grouped funds may produce more precise estimates if the parameters are similar within groups.

Morningstar's first classification scheme uses the traditional self-reported investment objective of the mutual fund (aggressive growth, growth-income, etc.). Our sample includes eleven objectives, reported below in Table 1. We form an equal-weighted portfolio of the funds with each stated objective. The portfolio return for each month is the equal-weighted average for all funds in a given category that did not have a missing return that month.

Morningstar also classifies equity mutual funds according to investment styles. Funds are ranked based on the median value in their holdings, of the sum of the price/earnings ratio (measured relative to the average price/earnings ratio of stocks in the S&P500), plus the market/book ratio (measured relative to the average market/book ratio of stocks in the S&P500). The funds are then split into three groups (value, growth, or a "blend" of value and growth) on the basis

Table 1
Summary statistics for mutual funds, style-matched portfolios, and instrument data sample

Descriptive statistics for the sample mutual funds, the style-matched portfolios, and the instruments data for the period January 1976 through December 1994 (the lagged instruments are known at the end of the previous month). The data are monthly, for a total number of observations of 228, with fewer observations for some fund groups. Returns are decimal fraction per month. Mean is the sample mean, Std is the sample standard deviation, Nobs is the number of observations, and ρ_1 is the first order sample autocorrelation. Fund style is determined by Morningstar on the basis of the price/book and earnings/price ratios of the holdings of the funds. The number of funds is recorded at the beginning and end of the sample period. The data in panel C are from May 1978 through December 1994 (200 observations).

Fund group	Mean	Std	Min	Max	ρ_1	Number of funds	
						Beg.	End.
Panel A: U.S. equity mutual funds grouped by fund objective							
1 Small company	0.01275	0.04579	− 0.2412	0.1326	0.08673	14	37
2 Aggressive growth	0.01266	0.04760	− 0.2329	0.1508	0.04949	14	23
3 Growth	0.01228	0.04454	− 0.2244	0.1319	0.06458	80	136
4 Growth-income	0.01190	0.04297	− 0.2269	0.1257	0.06873	31	73
5 Specialty-utility	0.01198	0.04366	− 0.2379	0.1229	0.05319	6	7
6 Specialty-technology	0.01346	0.04540	− 0.2180	0.1577	0.03195	6	9
7 Specialty-financial	0.01207	0.05155	− 0.2785	0.1510	0.05415	2	3
Spec.-nat. resources	0.01257	0.04916	− 0.2578	0.1405	0.01079	3	4
8 Equity-income	0.01167	0.04530	− 0.2309	0.1286	0.04363	2	7
Specialty-unaligned	− 0.00677	0.04513	− 0.0750	0.0350	− 0.30380	0	3
Specialty-health	0.01315	0.05041	− 0.2147	0.1530	0.04676	2	3
Panel B: U.S. equity mutual funds grouped by style							
1 Large value	0.01120	0.04172	− 0.2251	0.1192	0.05416	12	30
2 Large blend	0.01160	0.04319	− 0.2241	0.1285	0.06277	44	72
3 Large growth	0.01189	0.04346	− 0.2046	0.1269	0.04215	10	22
4 Medium value	0.01305	0.04438	− 0.2342	0.1271	0.07690	16	32
5 Medium blend	0.01285	0.04677	− 0.2343	0.1519	0.06212	15	46
6 Medium growth	0.01270	0.04688	− 0.2360	0.1383	0.05692	37	53
7 Small value	0.01300	0.04205	− 0.2284	0.1146	0.06783	5	22
8 Small blend	0.01232	0.04541	− 0.2192	0.1402	0.07236	12	17
9 Small growth	0.01297	0.04793	− 0.2392	0.1399	0.08072	11	25
Panel C: Style-matched portfolios							
Large value	0.01416	0.04530	− 0.1830	0.1492	0.0193		
Large blend	0.01198	0.04220	− 0.2037	0.1304	− 0.0307		
Large growth	0.01193	0.04772	− 0.2310	0.1418	0.0452		
Medium value	0.01581	0.04881	− 0.2682	0.1256	0.1891		
Medium blend	0.01436	0.04904	− 0.2645	0.1283	0.1430		
Medium growth	0.01271	0.06300	− 0.3114	0.1531	0.1379		

Table 1. Continued.

Fund group	Mean	Std	Min	Max	ρ_1	Number of funds Beg.	Number of funds End.
Small value	0.01431	0.05158	– 0.2793	0.1504	0.2669		
Small blend	0.01394	0.05416	– 0.2921	0.1272	0.2300		
Small growth	0.00887	0.06806	– 0.3203	0.1499	0.2191		
Panel D: The lagged instruments							
Detrended T-bill rate	– 0.00057	0.01494	– 0.05620	0.04896	0.7813		
Dividend yield	0.04025	0.00767	0.02702	0.06128	0.9681		
Term spread	0.00711	0.00866	– 0.02600	0.02231	0.9236		
January dummy	0.08333	0.27700	0.0000	1.00000	– 0.0865		
Panel E: Correlation matrix of the instruments							
Detrended T-bill rate	1.0000	0.1422	– 0.5417	– 0.0580			
Dividend yield		1.0000	– 0.5560	0.0123			
Term spread			1.0000	– 0.0083			
January dummy				1.0000			

Quarter	Nobs	Mean	Std	Min	Max
Panel F: Balanced funds: Percentage cash holdings					
92Q4	43	9.7581	11.0473	– 7.9	58.2
93Q1	43	7.8488	7.7917	– 10.3	27.0
93Q2	44	7.1932	7.1303	– 5.7	25.1
93Q3	47	10.6745	11.6634	– 3.1	55.0
93Q4	49	9.7163	11.0709	– 6.1	58.3
94Q1	52	9.1308	8.7485	– 2.8	47.6
94Q2	56	11.0786	11.6021	– 7.1	61.3
94Q3	56	11.3732	10.9296	– 5.1	62.3
94Q4	62	10.7065	11.6079	– 4.1	62.1
95Q1	62	9.8710	12.2358	– 10.6	61.0
Panel G: Asset allocation funds: Percentage cash holdings					
92Q4	35	13.6086	14.2213	0.0	56.1
93Q1	37	13.3405	12.6512	– 1.0	45.0
93Q2	40	12.6300	10.4907	– 1.0	43.7
93Q3	40	12.7300	13.6372	0.0	59.0
93Q4	41	11.1951	14.6544	0.0	56.0
94Q1	42	13.0048	15.1533	– 1.0	57.0
94Q2	44	18.2341	20.2877	0.0	100.0
94Q3	44	20.8091	24.5259	0.3	100.0
94Q4	48	19.9688	23.4730	0.0	100.0
95Q1	52	17.0404	28.8340	– 31.0	100.0

of these rankings, where the breakpoints are set according to the distribution of the ratios in the stocks of the S&P500 index. A similar ranking is calculated based on the market capitalization of the stocks held by the fund, and the result is a 3×3 classification of the funds according to investment style. Again, we form nine equal-weighted portfolios corresponding to the investment styles. Thus, we have two ways of grouping the same underlying sample of mutual funds.

Our second sample of mutual funds is a set of asset allocation and balanced funds. We select funds with at least five years of monthly returns available at the end of March 1995. This results in a sample of 114 funds, of which 62 are classified as balanced funds and 52 are asset allocation funds.

Our samples of funds suffer from survivorship biases, as they contain only funds that survived until the end of the sample period. It seems likely that survivorship biases would produce a sample that appears better at market timing than an unbiased sample. Thus, evidence of no significant market-timing ability is likely to hold up in a sample without selection biases.

Table 1 presents summary statistics for the equity funds. In panels A and B, we report the number of funds in each portfolio at the beginning and the end of the sample. We omit from further tests the three objective-grouped portfolios which have a limited number of time-series observations. Thus, we analyze eight objective-grouped portfolios and nine style-grouped portfolios. The objective-grouped portfolios that we retain are numbered 1 through 8 in Panel A. Morningstar classifications are available for the ten quarters listed in panels F and G of Table 1. We use the most recently available previous quarter to assign funds to the categories for a given month. In the early part of the sample when the classifications are not available, we use classifications from the fourth quarter of 1992.

The summary statistics in panel B, for the style-grouped equity funds, are of interest because of the controversy over value versus growth strategies. Several studies, including Basu (1977), Fama and French (1992), and Lakonishok et al. (1994) claim that value strategies, which choose stocks with high book/market or earnings/price ratios, outperform growth strategies. However, the realized returns on value versus growth mutual funds are not dramatically different. Indeed, among the large-capitalization equity funds, the growth fund average return for 1976–1994 is 1.19% per month, while the value fund average is 1.12%.

There are two potential differences between the funds summarized in Table 1 and the hypothetical portfolios formed in previous studies: transactions costs and portfolio composition. Thus, one conjecture is that value funds have not delivered higher returns because they have higher expenses than growth funds. We cannot fully address this transactions cost hypothesis without better data on trading costs, but we do have information on expense ratios. Among the large-capitalization funds in our sample, growth funds have the highest average expense ratios – just the opposite of what we would expect under the transactions costs hypothesis. This suggests that the fund portfolios differ in composition from the hypothetical portfolios analyzed in much of the literature on the book-to-market effect.

4.2. Style-matched portfolios

We construct nine portfolios which feature the same style characteristics as the Morningstar equity-style classifications. We use these as alternative style-specific benchmarks to test our models, and to further interpret the summary statistics of the funds. Like the Morningstar classifications, the style-matched portfolios are based on the sum of the price/earnings ratio and market/book ratio (the PEMB index) and on market capitalization.

The portfolios include all firms listed in 1994 on the Center for Research in Security Prices (CRSP) tape and Compustat (including the Research tape). Portfolios are formed at the end of April for each sample year from 1978 to 1994. We rank firms on their PEMB index values and market capitalizations using price and share information at the end of April and book value and earnings information from the previous fiscal year. Firms with negative book values are excluded, and firms must have at least two years of data on Compustat before they are included in the portfolios. This last screen is to minimize the selection bias that occurs when Compustat backfills data, as discussed by Kothari et al. (1995) and Fama and French (1993).

Firms are split annually into three groups on the basis of their PEMB index values, where the breakpoints equal 33.3 and 66.7 percentiles for the NYSE firms in the sample. We use only the NYSE firms to calculate the cut-off points in order to better mirror the Morningstar breakpoints. Similarly, we form three groups based on market capitalization, where the breakpoints equal the 33.3 and 66.7 percentiles of market capitalization for the entire sample of firms. The final result is a 3×3 classification used to allocate the firms into the nine portfolios. We value weight the portfolios monthly.

A firm that delists is excluded from the portfolio in the delisting month and the proceeds are reinvested in the remaining stocks. Shumway (1997) notes that the last return on the CRSP tapes may or may not be the actual delisting return, which imparts a bias in measured returns. The bias could be particularly severe for the small size and value stocks, which are likely to include many troubled firms that are acquired or go bankrupt. Measurement error in the benchmark returns will reduce the efficiency of our estimation and, if the error is correlated with the residual, will result in biased estimators. To test the sensitivity of our results to delisting bias, we perform some of our tests using benchmark returns adjusted for delisting bias, assuming a return of -100% for all performance-related delistings as suggested by Shumway. We find that the results for our models are similar with either return calculation.

Panel C of Table 1 presents summary statistics for the alternative benchmarks (without the delisting adjustment) for May 1978 through December 1994. While the differences in the average returns across the hypothetical style portfolios are not statistically different, they do mirror the patterns found in previous research (e.g., Fama and French, 1992,1993). The value portfolios have higher average returns than the growth portfolios, and the difference is the largest for the small-cap groupings. These results can be compared with the statistics in panel B for the actual mutual funds (although the sample periods are different, the statistics for the funds in Panel B are similar for the shorter subperiod). Even when the hypothetical portfolios use a definition of value investing similar to the funds, they do not reproduce the patterns of the mutual funds. Note, in particular, that the smaller-cap hypothetical portfolios have higher autocorrelations and standard deviations of return than the mutual funds. This suggests that the hypothetical portfolios contain some smaller and/or more thinly traded stocks than the actual funds.

Previous research is consistent with the hypothesis that value-investing mutual funds hold less extreme portfolios than the hypothetical portfolios in some studies. For example, Loughran (1997) finds that the poor performance of hypothetical portfolios of low book-to-market stocks is concentrated in the smaller, newly listed issues. Such stocks may not appear frequently in mutual fund portfolios.

4.3. Market index and information variables

The most well-known benchmark for measuring performance is the S&P500 stock index. The S&P500 return, with dividends, is obtained from the CRSP tapes. We also use a set of market-wide variables to condition the analysis.

The purpose of conditional performance evaluation is to account for any public information that predicts future market returns. Managers who mechanically use only public information to time the market should get no credit for 'superior' ability. By the choice of the instruments Z_t, we define what is considered to be public information, and therefore, the threshold for what is superior ability.

To represent public information in our empirical tests, we use a collection of variables that previous studies find to be useful for predicting security returns over time. The variables are: (1) the lagged level of the one-month Treasury bill yield, less its 12-month lagged moving average (TB), (2) the lagged dividend-to-price ratio for the CRSP value-weighted NYSE and Amex stock index (DP), (3) the lagged slope of the U.S. Treasury yield curve (TERM), measured as the difference between four-year and one-year fixed-maturity bond yields from the CRSP FamaBliss files, and (4) a dummy variable for the month of January (JAN). Pesaran and Timmerman (1995) document the economic and statistical significance of similar variables for the period after 1970. Panel D of Table 1 reports summary statistics for the lagged instruments and Panel E shows their sample correlation matrix.

Although not reported in the tables, we regress over time the equity fund portfolio returns on a constant and the lagged instruments and find that the instruments have significant explanatory power. Four of the 11 coefficients on TB for the objective-grouped funds have t-ratios below -1.65 and eight of the coefficients on DP have t-ratios greater than two. Further, we find significant t-ratios more frequently for the style-grouped portfolios. The regression R^2s for the fund groups are typically somewhat higher than the R^2 for the regression of the S&P500 index return on the same instruments. The regressions suggest that the funds are responding to the information contained in the lagged instruments, which motivates the conditional market timing tests.

5. Empirical results

To set the stage for the conditional tests, we first estimate an unconditional version of the model. When the only instrument in Z_t is the constant, R^2 equals zero and the model reduces to:

$$r_{\mathrm{p},t+1} = a_\mathrm{p} + b_\mathrm{p} r_{\mathrm{m},t+1} + \Lambda_\mathrm{p} r^2_{\mathrm{m},t+1} + w_{t+1}, \tag{11}$$

where

$$b_\mathrm{p} = h + \mu_\mathrm{m}/\{\gamma\sigma^2_\mathrm{m}\},$$

$$\Lambda_\mathrm{p} = K^2/\{\gamma\sigma^2_\mathrm{m}\}.$$

Treynor and Mazuy (1966) first propose the unconditional market-timing regression (11), where b_p and Λ_p are free parameters. They argue that $\Lambda_\mathrm{p} > 0$ indicates market-timing ability. Grinblatt and Titman (1988), Cumby and Glen (1990), and Ferson and Schadt (1996) estimate the regression for mutual funds and find a tendency for negative estimates of Λ_p.

We estimate the unconditional model of Eq. (11) for the grouped equity mutual funds, using GMM and the following system of equations:

$$\begin{aligned}
u1_{t+1} &= r_{\mathrm{m},t+1} - \mu_\mathrm{m},\\
u2_{t+1} &= \sigma^2_\mathrm{m} - (r_{\mathrm{m},t+1} - \mu_\mathrm{m})^2,\\
u3_{t+1} &= [r_{\mathrm{p},t+1} - a_\mathrm{p} - (h + \mu_\mathrm{m}/\gamma\sigma^2_\mathrm{m}) r_{\mathrm{m},t+1}\\
&\qquad - (K^2/\gamma\sigma^2_\mathrm{m}) r^2_{\mathrm{m},t+1}](1, r_{\mathrm{m},t+1}, r^2_{\mathrm{m},t+1}),\\
u4_{t+1} &= u3^2_{t+1} - (\sigma^2_\mathrm{m} + \mu^2_\mathrm{m})(K^2/\gamma^2\sigma^2_\mathrm{m}).
\end{aligned} \tag{12}$$

The model implies $\mathrm{E}\{u1_{t+1}, u2_{t+1}, u3_{t+1}, u4_{t+1}\} = 0$. The fourth moment condition follows from the definition of w_{t+1} in Eq. (11), as a special case of Eq. (7). With a single fund excess return, the model contains six parameters and six moment conditions.

Table 2
Unconditional market timing model

Estimates of Eq. (12) by fund group. The benchmark return is the S&P500 index. The data are monthly from January 1976 through December 1994 (228 months). Fund style is determined by Morningstar on the basis of the price/book and earnings/price ratios of the holdings of the funds and by market capitalization. The symbols are: σ_{m}^2 is the unconditional variance of the S&P500, μ_{m} is the unconditional mean, K measures the quality of the manager's market timing signal, γ is the coefficient of risk aversion, a_{p} is the alpha coefficient for the average abnormal excess return, and h is the benchmark preference parameter. The coefficient estimates are shown on the first line and the standard errors are in parentheses

Fund	σ_{m}^2	μ_{m}	K	γ	a_p	h
Panel A: Equity mutual funds grouped by investment style						
Large value	0.00185[a]	0.00558[b]	0.000669[a]	– 0.000255[a]	0.000849	1.18E + 04[b]
	(0.00028)	(0.00285)	(0.00014)	(0.00006)	(0.00070)	(5.87E + 03)
Large blend	0.00185[a]	0.00558[b]	0.000529[a]	– 0.000155[a]	0.00109	1.94E + 04[b]
	(0.00028)	(0.00285)	(0.00016)	(0.00005)	(0.00089)	(9.80E + 03)
Large growth	0.00185[a]	0.00558[b]	0.000262[c]	– 3.80E-05[c]	0.000734	7.94E + 04[c]
	(0.00028)	(0.00285)	(0.00014)	(0.00002)	(0.00113)	(4.32E + 04)
Medium value	0.00185[a]	0.00558[b]	0.000513[a]	– 0.000144[a]	0.00270[a]	2.09E + 04[c]
	(0.00028)	(0.00285)	(0.00011)	(0.00003)	(0.00096)	(1.08E + 04)
Medium blend	0.00185[a]	0.00558[b]	0.000423[a]	– 9.34E-05[a]	0.00201	3.23E + 04[c]
	(0.00028)	(0.00285)	(0.00015)	(0.00003)	(0.00112)	(1.70E + 04)
Medium growth	0.00185[a]	0.00558[b]	0.000441[a]	– 0.000101[a]	0.00191	2.98E + 04[c]
	(0.00028)	(0.00285)	(0.00015)	(0.00004)	(0.00112)	(1.54E + 04)
Small value	0.00185[a]	0.00558[b]	0.000559[a]	– 0.000184[a]	0.00355[a]	1.64E + 04[c]
	(0.00028)	(0.00285)	(0.00012)	(0.00004)	(0.00097)	(9.48E + 03)
Small blend	0.00185[a]	0.00558[b]	0.000356[b]	– 6.84E-05[b]	0.00148	4.41E + 04[c]
	(0.00028)	(0.00285)	(0.00016)	(0.00003)	(0.00121)	(2.33E + 04)
Small growth	0.00185[a]	0.00558[b]	0.000417[a]	– 8.96E-05[a]	0.00229[c]	3.37E + 04[c]
	(0.00028)	(0.00285)	(0.00145)	(0.00003)	(0.00122)	(1.78E + 04)
Panel B: Mutual funds grouped by fund objective						
Small	0.00185[a]	0.00558[b]	0.000487[a]	– 0.000127[a]	0.00256[b]	2.37E + 04[c]
	(0.00028)	(0.00285)	(0.00012)	(0.00003)	(0.00110)	(1.29E + 04)
Aggressive growth	0.00185[a]	0.00558[b]	0.000378[a]	– 7.36E-05[a]	0.00173	4.10E + 04[c]
	(0.00028)	(0.00285)	(0.00015)	(0.00003)	(0.00124)	(2.17E + 04)
Growth	0.00185[a]	0.00558[b]	0.000477[a]	– 0.000123[a]	0.00160	2.45E + 04[b]
	(0.00028)	(0.00285)	(0.00017)	(0.00004)	(0.00100)	(1.24E + 04)
Growth-income	0.00185[a]	0.00558[b]	0.000540[a]	– 0.000163[a]	0.00149[c]	1.84E + 04[b]
	(0.00028)	(0.00285)	(0.00014)	(0.00004)	(0.00085)	(9.34E + 03)
Spec.-Utility	0.00185[a]	0.00558[b]	0.000548[a]	– 0.000168[a]	0.00188[b]	1.80E + 04[c]
	(0.00028)	(0.00285)	(0.00009)	(0.00003)	(0.00091)	(9.94E + 03)

Table 2. Continued.

Fund	σ^2_{m}	μ_{m}	K	γ	a_p	h
Spec.-Technology	0.00185[a]	0.00558[b]	0.000350[b]	− 6.60E-05[b]	0.00256[b]	4.57E + 04[c]
	(0.00028)	(0.00285)	(0.00016)	(0.00003)	(0.00119)	(2.58E + 04)
Spec.-Financial	0.00185[a]	0.00558[b]	0.000385[a]	− 7.31E-05[a]	0.00156	4.13E + 04[c]
	(0.00028)	(0.00285)	(0.00007)	(0.00001)	(0.00146)	(2.49E + 04)
Equity-income	0.00185[a]	0.00558[b]	0.000238[a]	− 3.13E-05[a]	0.000707	9.65E + 04[b]
	(0.00028)	(0.00285)	(0.00007)	(0.00001)	(0.00121)	(4.78E + 04)

[a]Significance at the 1% level.
[b]Significance at the 5% level.
[c]Significance at the 10% level.

Table 2 reports the results. Each of the 17 point estimates of the risk-aversion parameter, γ, are negative, which seems inconsistent with risk aversion on the part of fund managers. The magnitudes are small, but all except one have absolute t-ratios larger than two. The market-timing parameters, K, are small but indicate significant timing ability for all but one group. Combined with the negative estimates of γ, the estimates of K are consistent with negative values of Λ_{p} in Eq. (11). We also use a simple regression approach to estimate the unconditional model, imposing no restrictions in the first line of Eq. (11). All of the point estimates of Λ_{p} are negative and 13 of the 17 have t-ratios below -2.0.

The evidence is similar to that of previous studies, which find anomalous 'negative' market timing in unconditional models. Obviously, negative timing makes no economic sense. If funds could really time the market but got the direction wrong, astute investors could profit by taking opposite positions. Note that all of the point estimates of a_{p} are positive in Table 2, with five significant at conventional levels, indicating abnormal performance relative to the model. The point estimates of h are huge positive numbers, which again makes little economic sense. As a whole, the results provide convincing evidence that the unconditional model is poorly specified, which further motivates our examination of the conditional market-timing model.

5.1. Results for equity fund groups

Table 3 reports estimates of the conditional market-timing model. We estimate system (10) separately for each of the equal-weighted portfolios of equity

Table 3
A conditional market timing model: Equity funds

Estimates of the system (10) by fund group. The benchmark return is the S&P500 index. The data are monthly from January 1976 through December 1994 (the lagged instruments are known at the end of the previous month), for a total of 228 observations. Fund style is determined by Morningstar on the basis of the price/book and earnings/price ratios of the holdings of the funds and by market capitalization. The symbols are: σ_m^2 is the unconditional variance of the S&P500, R^2 is the coefficient of determination for a regression of the S&P500 excess return on the lagged instruments, γ is the coefficient of risk aversion, α_p is the alpha coefficient for the average abnormal excess return, h is the benchmark preference parameter, ρ^2 is the squared conditional correlation between the manager's market timing signal and the market return, and chisq is the J-test of the model's overidentifying restrictions. The coefficient estimates are shown on the first line and the standard errors are in parentheses (in the case of chisq, the right-tail p-value from the Chi-squared distribution is in parentheses).

Fund group	σ_m^2	R^2	γ	α_p	h	ρ^2	chisq p-value
Panel A: Mutual funds grouped by investment style							
Large value	0.0017[a]	0.047	(87.9	− 0.0001	0.857[a]	0.06E-2	6.580
	(0.0003)	(0.021)	(123.8)	(0.0714)	(0.0708)	(0.0845)	(0.087)
Large blend	0.0017[a]	0.043	57.50	0.0002	0.846[a]	0.49E-7	8.490
	(0.0003)	(0.029)	(82.6)	(0.0010)	(0.0939)	(0.1021)	(0.037)
Large growth	0.0018[a]	0.047[c]	42.50	0.0012	0.846[a]	0.66E-8	16.10
	(0.0003)	(0.021)	(47.2)	(0.0062)	(0.0939)	(0.036)	(0.001)
Medium value	0.0017[a]	0.042	42.62	0.0015	0.815[a]	0.01E-6	6.851
	(0.0003)	(0.030)	(55.7)	(0.0016)	(0.1385)	(0.039)	(0.077)
Medium blend	0.0017[a]	0.041	28.00	0.0002	0.794[a]	0.06E-6	7.740
	(0.0003)	(0.028)	(28.9)	(0.0020)	(0.1607)	(0.0152)	(0.052)
Medium growth	0.0017[a]	0.044	35.87	0.0008	0.849[a]	0.44E-3	8.853
	(0.0003)	(0.029)	(43.6)	(0.0017)	(0.1473)	(0.0678)	(0.031)
Small value	0.0017[a]	0.044	29.2	0.0016	0.683[a]	0.49E-9	7.42
	(0.0003)	(0.029)	(30.5)	(0.0019)	(0.1491)	(0.097)	(0.060)
Small blend	0.0017[a]	0.049[c]	35.0	0.0005	0.814[a]	0.37E-7	11.5
	(0.0003)	(0.030)	(41.9)	(0.0018)	(0.1408)	(0.0761)	(0.010)
Small growth	0.0017[a]	0.045	28.5	0.0009	0.808[a]	0.22E-7	8.860
	(0.0003)	(0.029)	(33.9)	(0.0021)	(0.1749)	(0.0332)	(0.031)
Panel B: Mutual funds grouped by fund objective							
Small company	0.00168[a]	0.039	24.19	0.001	0.711[a]	0.45E-9	6.475
	(0.0003)	(0.028)	(24.6)	(0.0022)	(0.1866)	(0.086)	0.091
Aggressive-	0.0017[a]	0.051	46.88	0.0005	0.891[a]	1.81E-8	10.68
growth	(0.0003)	(0.031)	(68.1)	(0.0014)	(0.1353)	(0.026)	0.014
Growth	0.0017[a]	0.042	39.84	0.0006	0.832[a]	1.37E-8	9.508
	(0.0003)	(0.029)	(46.3)	(0.0013)	(0.1187)	(0.074)	0.023

Table 3. Continued.

Fund group	σ_m^2	R^2	γ	α_p	h	ρ^2	chisq p-value
Growth-income	0.0017[a]	0.037	77.25	− 0.0004	0.831[a]	8.09E-5	6.239
	(0.0003)	(0.028)	(132.4)	(0.0015)	(0.1002)	(0.0487)	0.101
Specialty-utility	0.0017[a]	0.046	41.1	0.0005	0.817[a]	6.81E-9	8.69
	(0.0003)	(0.030)	(54.6)	(0.0016)	(0.1263)	(0.033)	0.034
Specialty-tech	0.0019[a]	0.044	−1.1E +04	0.0027[a]	0.990[a]	1.60E-7	3.05
	(0.0003)	(0.028)	(2.2E +06)	(0.0010)	(0.0812)	(0.144)	0.385
Specialty-fin.	0.0016[a]	0.041	41.9	− 0.0015	0.847[a]	0.0489	5.10
	(0.0002)	(0.030)	(82.97)	(0.0027)	(0.2134)	(0.2296)	0.165
Equity-income	0.0018[a]	0.047	− 6397.0	0.0012	0.997[a]	0.950	5.24
	(0.0003)	(0.031)	(1.08E +06)	(0.0014)	(0.1333)	(11.59)	0.155

[a]Significance at the 1% level.
[b]Significance at the 5% level.
[c]Significance at the 10% level.

funds, and take the benchmark portfolio to be the S&P500. We do not report the estimates of the parameters for the expected market return to save space. These estimates are similar across the equations, even though the estimation allows them to differ without constraint. The coefficients on TB are negative and significant, and the estimates of R^2 range from 3.7% to 5.1%. Thus, the market wide parameter estimates suggest that conditioning on the lagged variables is relevant.

The estimates of the quality of the market-timing signals, given by K or ρ^2, are small and not significantly different from zero in Table 3.[3] Thus, the data present no evidence that these funds have conditional market-timing information. However, the standard errors of ρ^2 are large, so the power of the tests is likely to be low.

The estimates of α_p in Table 3 are small and statistically insignificant (except for the technology funds' t-statistic of 2.64), providing little evidence of 'abnormal' returns relative to the model. This contrasts with the unconditional models of Table 2, where five of the 17 fund groups generate significant positive alphas. Grant (1977), Jagannathan and Korajczyk (1986), and Coggin et al. (1993) interpret significant positive alphas and negative timing coefficients as evidence of model misspecification. Thus, the conditional version of the market timing model appears to be a better specification.

[3] The standard errors of ρ^2 are computed from Eq. (2) using the delta method.

The evidence of insignificant timing ability and small alphas in the conditional market-timing model confirms the conclusions of Ferson and Schadt (1996), who study 68 equity funds from 1968 through 1990. Our refined model produces additional insights. For example, in Table 3, all of the point estimates of the benchmark preference parameter, h, are positive and strongly statistically significant, suggesting the importance of benchmark investing by mutual funds. The estimates are all between 0.68 and 1.00, which imply economically reasonable benchmark policy weights.

The estimates of the risk-aversion parameter, γ, are also interesting. All but two of the objective groups produce positive point estimates in Table 3. While the large standard errors make inferences about the magnitudes imprecise, the values are generally numerically large. The large point estimates support the view that benchmark-investing managers are highly risk averse concerning the 'tracking error' of their portfolios.

We re-estimate the model imposing the restriction that $h = 0$. When $h = 0$ the risk-aversion estimates become much smaller. However, when $h = 0$ the right-tail p-values of the J-tests are also smaller, implying that the estimation procedure 'wants' h to be nonzero.

Despite this encouraging evidence for the conditional market-timing model with benchmark investors, Hansen's J-test provides evidence against the model in Table 3. Eight of the 17 fund groups produce right-tail p-values less than 0.05. The statistical rejections indicate some misspecification of the model when applied at the level of fund groups. As we suggested earlier, our finding that mutual funds have no better than public information at the group level could reflect a lack of power. It is unlikely that a large group of funds can, on average, time the market. Our sample of U.S. equity funds also may not contain many funds that attempt to aggressively time the market. The results for the asset allocator funds should therefore provide additional insights.

5.2. *Results for asset allocator funds*

Tables 4 and 5 report results for the asset allocator funds. Table 4 reports results at the group level, while Table 5 summarizes results for the individual funds. We delete funds with fewer than 60 monthly observations, leaving 106 funds for the analysis. The S&P500 initially serves as the benchmark. We apply Hansen's J-test to the models for the individual funds, and find that we do not reject the model at the 5% level for about 70% of the funds.

In Table 4 the allocator funds are aggregated into two groups: the entire set of 106 funds and funds whose individual test results produced p-values above 0.05 (31 funds). The purpose is to test if the parameter values depend on whether or not the model is rejected by Hansen's J-test. The point estimates of the market wide parameters are similar across the two groups and similar to those for the equity funds. The estimates of the risk-aversion parameter are again large by

Table 4
A conditional market timing model: Asset allocator funds

Estimates of the system (10) for groupings of funds. The benchmark return is the S&P500 index. The data are monthly from January 1976 through December 1994 (the lagged instruments are known at the end of the previous month). Funds are those with Balanced or Asset Allocation objectives as reported by Morningstar. The symbols are: σ_m^2 is the unconditional variance of the S&P500, R^2 is the coefficient of determination for a regression of the S&P500 return on the lagged instruments, γ is the coefficient of risk aversion, α_p is the alpha coefficient for the average abnormal excess return, h is the benchmark preference parameter, ρ^2 is the squared correlation between the manager's market timing signal and the market return, given the lagged instruments, chisq is the J-test of the model's overidentifying restrictions, and p-value is the right-tail area from the chi-squared distribution. The coefficient estimates are shown on the first line and heteroskedasticity-consistent standard errors are in parentheses (in the case of chisq, the right-tail p-value from the Chi-square distribution is in parentheses).

Sample	Number of funds	σ_m^2	R^2	γ	α_p	h	ρ^2	chisq p-value
All funds	106	0.0019[a]	0.053	95.0	0.0003	0.563[a]	1.79E-09	16.50
		(0.0003)	(0.032)	(124.7)	(0.0007)	(0.061)	(0.106)	(0.0009)
Funds with p-value < 0.05	31	0.0019[a]	0.053	96.6	0.0005	0.564[a]	1.67E-11	n.a.
		(0.0003)	(0.031)	(135.5)	(0.0009)	(0.063)	(0.110)	

[a]Significance at the 1% level.

conventional standards and imprecise, but similar for both groups of funds. The estimates of the benchmark preference parameter, h, are 0.563 and 0.564. These values are smaller than the estimates for the equity funds. Smaller values seem sensible, as a market-timing fund is likely to have a smaller policy weight on equity than a straight equity fund. The h parameters are strongly significant, with t-ratios greater than 8.0, confirming the impression that benchmark investing is relevant.

Again, we find no evidence of abnormal performance or timing ability in Table 4. The ρ^2 coefficients, which measure conditional market-timing ability, are not significantly different from zero, and the alphas are small. The overall results are similar for the group of funds for which the J-test rejects the model and for those funds for which the model is not rejected. This increases our confidence about drawing economic conclusions from the model.[4]

[4] We also estimate the model on groups of asset allocator funds, formed according to equity investment style and fixed income style, as reported by Morningstar. The results for these groups are similar.

Table 5
A conditional market timing model: Individual asset allocator funds

System (10) is estimated for each fund with at least 60 observations, and the cross-sectional results for the 106 funds are shown. The benchmark return is the S&P500 index. The data are monthly from January 1976 through December 1994 (the lagged instruments are known at the end of the previous month). The number of observations per fund varies between 60 and 228. Funds are those with Balanced or Asset Allocation objectives as reported by Morningstar. The symbols are: σ_m^2 is the unconditional variance of the S&P500, (δ_C, δ_{TB}, δ_{DP}, δ_{TERM}, δ_{JAN}) are the coefficients in the linear regression model for the market excess return on the lagged instruments, R^2 is the coefficient of determination for this regression, γ is the coefficient of risk aversion, α_p is the alpha coefficient for the average abnormal excess return, h is the benchmark preference parameter, and ρ^2 is the squared conditional correlation between the manager's market timing signal and the market return.

	σ_m^2	δ_C	δ_{TB}	δ_{DP}	δ_{TERM}	δ_{JAN}	R^2	γ	α_p	h	ρ^2
Panel A: Cross-sectional distribution of coefficients											
Mean values	0.0016	– 0.0004	– 0.577	0.192	– 0.431	0.0044	0.042	93.6	0.0003	0.850	0.120
Lower decile values	0.0011	– 0.0031	– 0.873	– 0.000	– 0.883	– 0.0059	0.019	– 111.0	– 0.0027	0.236	0.000
Lower quartile values	0.0012	0.0014	– 0.721	– 0.000	– 0.623	– 0.0002	0.029	– 37.9	– 0.0010	0.518	0.000
Median values	0.0017	0.0048	– 0.629	0.060	– 0.436	0.0038	0.042	– 13.4	0.0001	0.700	0.000
Upper quartile values	0.0019	0.0073	– 0.425	0.098	– 0.294	0.0099	0.048	33.1	0.0013	0.894	0.000
Upper decile values	0.0019	0.0088	– 0.296	0.149	– 0.121	0.0146	0.065	228.0	0.0030	1.090	0.818
Panel B: Cross-sectional correlation of coefficients											
	1.00	– 0.12	– 0.62	0.20	– 0.21	0.46	0.53	– 0.14	– 0.13	– 0.27	0.10
		1.00	– 0.06	– 0.99	– 0.68	0.02	– 0.35	0.14	0.19	0.10	– 0.06
			1.00	0.02	0.61	0.07	– 0.78	0.02	– 0.05	0.20	0.12
				1.00	0.63	0.03	0.37	– 0.15	– 0.21	– 0.11	0.05
					1.00	0.03	– 0.24	– 0.10	– 0.08	0.07	0.11
						1.00	0.04	– 0.05	0.32	0.14	0.15
							1.00	– 0.07	– 0.01	– 0.29	– 0.06
								1.00	– 0.16	– 0.05	0.16
									1.00	0.15	– 0.06
										1.00	– 0.08
											1.00

Table 5 describes the cross-sectional distributions of the parameter estimates for the individual asset allocator funds. Panel A summarizes the point estimates. The market wide parameter estimates complement our previous results. The coefficients are tightly and approximately symmetrically distributed around the values produced by the group averages. The distributions of the fund-specific parameters also generally support the group results. The alpha coefficients are approximately symmetrically distributed around zero, with only a few large values (the maximum alpha is just significant at the 5% level, based on a Bonferroni test). The distribution of the ρ^2 coefficient is tightly concentrated near zero, with a few large values, which is consistent with the group results. The upper quartile of the ρ^2 values is less than 0.0001, but the largest 10% are above 0.80. These few large point estimates of ρ^2 are the only exception to the finding of no abnormal performance or market-timing ability in the conditional model.

The estimates of the benchmark preference parameter, h, have an interquartile range of 0.52 to 0.89. These economically reasonable magnitudes increase our confidence that benchmark investing is relevant for market-timing mutual funds. The estimates of the risk-aversion parameter, γ, have a skewed distribution. The mean, 93.6, is much larger than the median, -13.4. The risk-aversion estimates are very imprecise.

Panel B of Table 5 presents the cross-sectional correlation matrix of the coefficient estimates for the 106 funds. The highest correlations are between the market wide parameters of the model, such as the regression coefficients on the dividend yield and the term spread. Otherwise the cross-sectional correlations are small. However, for a given fund, the estimated correlation between the coefficient estimates for h and γ obtained from the system can be fairly high. We estimate these correlations between 0.76 and 0.96 for the models in Tables 3 and 4.

Previous studies find a strong negative cross-sectional relation between estimates of timing information and alpha in unconditional models, which they interpret as evidence of model misspecification (e.g., Jagannathan and Korajczyk, 1986). In the conditional model, the correlation between ρ^2 and α is only -0.06, the correlation between α_p and γ is -0.16, and the correlation between ρ^2 and γ is 0.16. These results reinforce our impression that the conditional model is better specified.

5.3. Analysis of portfolio holdings

Our model parameters should describe the portfolio weights of mutual funds. The parameters are estimated using only rate of return data, so we can check the validity of the results by examining the actual portfolio weights. We collected end-of-quarter data on the holdings of the asset allocator funds for ten quarters, as shown in panels F and G of Table 1. We use the portfolio weights in U.S.

Table 6
Cross-sectional regressions of conditional market timing model parameters

System (10) is estimated for each asset allocator fund with at least 60 return observations. The benchmark return is the S&P500 index. K measures the quality of the manager's market-timing signal, γ is the coefficient of risk aversion, and h is the benchmark preference parameter. The table shows cross-sectional regressions for (1) the sample average of the portfolio weight in stocks, Mean(x_s), and (2) the sample standard deviation of the weight in stocks, SD(x_s), taken across the quarters available for a given fund. The three parameter estimates are the independent variables in the cross-sectional regressions. Ordinary least squares standard errors are shown in parentheses. The number of cross-sectional observations is 102.

	γ^{-1}	K^2	h
(1) Mean(x_s)	103.7[a]	0.26	19.4[a]
	(31.3)	(0.36)	(5.8)
(2) SD(x_s)	0.32	0.43[a]	−0.50
	(1.52)	(0.18)	(2.9)

[a]Significance at the 1% level.

equities to conduct a number of additional tests, which are summarized in this section.

5.3.1. The cross-section of equity weights

The comparative statics of our model are given by the derivatives of Eq. (5), using Eq. (4) to define the conditional moments. The model implies that the expected value of the portfolio weight in stock should be an increasing function of the parameters h, K^2 and γ^{-1}. The time-series standard deviation of the weight in stock should be increasing in K^2 and γ^{-1} and unrelated to h.

Table 6 reports multiple regressions using the 102 asset allocator funds with at least two quarters of data on their weights. The time-series means of the weights in stock and the standard deviations of the weights are regressed cross-sectionally on the estimates of the parameters h, γ^{-1} and K^2. (Standard errors from the multiple regressions are shown in parentheses.) The first row of the table reports results for the average weights. The coefficients on h, γ^{-1} and K^2 are positive, as predicted by the model, although the coefficient on K^2 is not statistically significant. Thus, funds whose return patterns imply lower risk aversion and higher benchmark policy weights actually hold more equity on average. Market timing does not show up as a significant factor.

The second line of Table 6 reports regressions for the standard deviation of the weights. The coefficients on K^2 and γ^{-1} are positive, as predicted by the model, but the coefficient on γ^{-1} is not statistically significant. Finally, the coefficient on h is insignificant in the regression for the standard deviation, where the model predicts no relation. Overall, the results in Table 6 support the model.

Table 7
Additional tests of market timing ability

Regression results are based on quarterly data from the first quarter of 1992 through the first quarter of 1995. The 93 funds with sufficient data are used in Panel A and 78 funds are used in Panel B. $r_{m,t+1}$ is either the one-month, two-month, or three-month ahead cumulative excess return on the S&P500 index, $\Delta X_{i,t}$ is the change in percentage equity holdings for fund i from quarter $t-1$ to t, and Z_t is the set of instruments for quarter t. Standard errors are shown in parentheses.

Panel A: $r_{m,t+1} = \lambda_{1,i} + \lambda_{2,i}\Delta X_{i,t} + \varepsilon_{i,t+1}$			*Panel B:* $r_{m,t+1} = \lambda_{1,i} + \lambda_{2,i}\Delta X_{i,t} + \lambda_{3,i}Z_t + \varepsilon_{i,t+1}$		
Specification	Pooled regression λ_2	Individual regressions Mean λ_2	Specification	Pooled regression λ_2	Individual regressions Mean λ_2
1-month	− 0.0197	− 0.0506	1-month	− 0.0050	− 0.1769
	(0.0086)	(0.1368)		(0.0039)	(0.5203)
2-month	− 0.0125	− 0.0303	2-month	0.0109	− 0.1323
	(0.0126)	(0.3030)		(0.0078)	(4.410)
3-month	− 0.0333	− 0.0667	3-month	0.0047	− 0.0210
	(0.0115)	(0.1112)		(0.0027)	(0.0344)

5.3.2. Market timing and the portfolio weights

We noted above that the lack of evidence for market timing might reflect low power. One response is to use the portfolio holdings data to take a different tack on the general question: Is there information in the fund portfolio weights about the future market return, and is that information essentially captured by the lagged instruments? To address this question, we employ the portfolio weights in a manner similar to Harvey and Graham (1996), who study the recommended holdings of investment newsletters.

If managers can time the market, we would expect a positive correlation between the change in a fund's stock holdings and the subsequent market return. We run time-series regressions of the future S&P500 excess return on the changes in the equity holdings of the individual funds. We also estimate a pooled, time-series and cross-sectional regression. Panel A of Table 7 provides the results for 1-month, 2-month and 3-month future market returns. The results for the pooled regression show significant negative coefficients on the change in stock holdings, consistent with the previously documented 'negative' market timing results in unconditional models.

We also estimate the regressions including the public information variables as additional regressors, as shown in panel B of Table 7. A positive coefficient on the change in the holdings implies that funds can time market movements conditional on the public information. The pooled regression produces a negative coefficient on the change in the equity holdings for 1-month market returns, and positive coefficients for 2-month and 3-month returns. None are significantly different from zero. These results suggest that fund managers cannot time market movements once we control for the public information variables.

In summary, the results in Table 7 support our findings using returns data. The unconditional analysis appears to detect timing ability, but of the 'wrong' sign. Conditioning on the public information removes the negative market timing and yields no significant evidence of conditional timing.

5.4. Tests using alternative benchmarks

The rejections of the conditional market-timing model could indicate a problem with using the S&P500 as a benchmark, since some funds may use benchmarks that differ importantly from the S&P500. This section describes the results for models using the alternative, style-based benchmarks described in Section 4.2. The sample extends from May 1978 through December 1994, and consists of 28 fewer observations than in the previous analysis. We estimate the models for both the equity and allocator funds grouped by investment style (tables are available by request).

The results generally confirm our previous findings based on the S&P500. The estimates suggest that the funds behave as benchmark investors, as most of the estimates of the h parameter have large t-ratios. The point estimates of h are between 0.46 and 0.68 for the allocator fund groups, with larger values – as high as 1.00 – for the equity funds. We find little evidence that the funds have conditional market-timing ability. The values of ρ^2 are generally small and insignificant. Also, most of the estimates of alpha are numerically small and insignificant. The absolute magnitudes of the estimates of γ are large by conventional standards but imprecise, as we observed before. Finally, Hansen's J-test rejects the model, with five of the 14 cases producing p-values below 0.05. Overall, the tests show that the main results are robust to the use of the alternative benchmarks in place of the S&P500.

5.5. The effects of selectivity

Funds are likely to engage in security selection, so it is important to assess the impact of selectivity on the results of the market-timing model. In the presence of selectivity, we can model the portfolio weight vector held by a fund, w_{p} (where $1 - \Sigma_i w_{i\mathrm{p}}$ represents cash holdings) as the sum of two parts: $w_{\mathrm{p}} = w_{\mathrm{T}} + w_{\mathrm{s}}$. Here w_{s} reflects the fund's selectivity decisions and $w_{\mathrm{T}} = x w_{\mathrm{m}}$ reflects the market timing, where w_{m} is the weight defining the market portfolio and x is the timing decision, given by Eq. (5) of our model. The excess return of the fund is $w_{\mathrm{p}}' r = x r_{\mathrm{m}} + w_{\mathrm{s}}' r$, where r is the vector of the risky assets' excess returns. If this is the 'true' model, it follows by substitution that the error term in Eq. (7) is given by the expression:

$$v_{t+1} = w_s' r_{t+1} + Q_3 r_{m,t+1} \varepsilon_{t+1}. \tag{13}$$

Eq. (13) provides the basis for a specification analysis in the presence of selectivity.

Our tests above are based on the moment conditions from system (10): $\mathrm{E}\{v_{t+1}[1, Z_t, r_{m,t+1}, r_{m,t+1}^2]\} = 0$, where we separate the constant term from the lagged instruments, and the remaining instruments are denoted as Z_t. If there is no selectivity these moment conditions should hold. To consider the effects of selectivity, it is useful to concentrate on the three conditions: (a), $\mathrm{E}(v_{t+1}) = 0$; (b), $\mathrm{E}(v_{t+1} Z_t) = 0$ and (c), $\mathrm{E}\{v_{t+1}[r_{m,t+1}, r_{m,t+1}^2]\} = 0$.

Condition (a) will fail under selectivity, as Eq. (13) implies that $\mathrm{E}(v_{t+1}) = \mathrm{E}(w_s' r_{t+1})$ is the expected selectivity return. The failure of condition (a) is the motivation for including the intercept, α_p, in the empirical model. The intercept guarantees that the error term in the model will average zero. Thus, a failure of condition (a) will not lead to a rejection of the model.

Since the error term v_{t+1} will have mean equal to zero, condition (b) may be interpreted as: $\mathrm{E}(v_{t+1} Z_t) = \mathrm{Cov}(w_s' r_{t+1}, Z_t)$. This term will equal zero only if the return to selectivity is uncorrelated with the lagged instruments. As the selectivity return is likely to be correlated with public information, failure of condition (b) could lead to rejection of the model and biases in the parameter estimates.

To address the sensitivity of the results to the failure of condition (b), we can modify the model to guarantee that the condition will hold. In particular, we replace the constant intercept with a time-varying function of the lagged instruments: $\alpha_0 + \alpha_1' Z_t$. Including this time-varying intercept ensures that the mean of $v_{t+1} Z_t$ is zero in the altered model. Unfortunately, with the new parameters the model is underidentified. However, if we set $K = 0$ – consistent with our empirical findings on the full model – the model is exactly identified and can be estimated (the number of moment conditions equals number of parameters).

We revisit the models of Table 3 using the linear specification for alpha and setting $K = 0$. We find that the market wide parameter values are similar to the original model. We also find that funds act as highly risk averse, benchmark investors. The values of h range from 0.79 to 0.98 and all are highly significant (t-ratios larger than 6.8). The estimates of the risk-aversion parameter, γ, range from 38 to 254, with four t-ratios larger than 2.0 and eight larger than 1.65. Thus, our main results seem robust to correlation between selectivity returns and the lagged instruments.

We now turn to the last condition (c): $\mathrm{E}\{v_{t+1}[r_{m,t+1}, r_{m,t+1}^2]\} = 0$. This condition can fail if the selectivity return is correlated with the market return, r_m, or its square. Timing and selectivity are known to be difficult to separate empirically, so this is a plausible scenario. To investigate the sensitivity of our results, we change the instruments to include only the lagged instruments in the equation for $u5_{p,t+1}$ in the system (10); that is, we drop $r_{m,t+1}$ and $r^2_{m,t+1}$. Estimating this modified model on the grouped equity funds, the estimates of the benchmark preference parameter, h, are generally less precise than before, but the magnitudes are similar. Four of the 17 t-ratios are larger than two and three more are marginally significant at the 10% level. The estimates of the risk-aversion parameter are all positive, and 16 of the 17 are between 7.6 and 54. Thus, the point estimates continue to indicate that mutual funds behave as risk averse, benchmark investors.

The J-test for the overidentifying restrictions no longer rejects the model when condition (c) is not imposed, which could indicate that failure of condition (c) is an important source of the model rejections or it could reflect a test with low power in the modified model. In either case, our main conclusions remain intact. We confirm the significance of benchmark investing and high, but imprecisely-estimated, values of risk aversion for benchmark-investing funds. When we relax the moment conditions that are sensitive to stock picking behavior, we find that our main conclusions still hold.

6. Concluding remarks

This paper studies the market-timing ability of mutual funds using models that (1) allow the utility function to depend on returns in excess of a benchmark, and (2) distinguish timing based on lagged, publicly available information variables from superior information. We simultaneously estimate fund managers' risk aversion for tracking error and the precision of the market-timing signal. We use a sample of more than 400 U.S. mutual funds for 1976–94, including a subsample with explicit asset allocation objectives.

In our conditional market-timing models, the parameter estimates are generally more economically reasonable than in much of the previous literature on market timing. The estimates suggest that U.S equity mutual funds behave as highly risk averse, benchmark investors. After controlling for the public information, we find little evidence that the mutual funds have conditional market-timing ability. However, the risk-aversion estimates are imprecise and the power of the tests for timing ability seem low. To corroborate the validity of these findings, which are based on rate of return data, we perform additional tests using the mutual funds' portfolio holdings. These tests support our conclusions.

We also observe that the value-investing equity mutual funds in our sample do not earn higher average returns than growth-style funds. In contrast, hypothetical value stock portfolios return more than portfolios of growth stocks. A comprehensive empirical analysis of the difference between the mutual funds and the hypothetical portfolios, which are used in much of the research on value and growth effects, is clearly called for.

The results of this paper suggest several avenues for future research. We use a collection of four popular instruments to represent public information and find no evidence of conditional timing ability. The unconditional model finds significant 'timing' coefficients. By varying the instrument set, it should be possible to conduct an attribution analysis of fund performance focusing on the use of information. Conditional estimates of total performance (i.e., timing plus selectivity) could also be developed using contingent claims methods, similar to Connor and Korajczyk (1991) and Glosten and Jagannathan (1994).

Further extensions could improve upon the performance of the models in this paper. One natural extension is a model with multiple asset classes and multiple signals. Another extension could incorporate timing signals that are informative about variance, in view of the results of Breen et al. (1989) and other studies that find the lagged instruments are informative about market volatility. Extending the analysis from the single-period model of this paper to a dynamic intertemporal model should also produce richer predictions about the behavior of fund managers. Also, in addition to trading on market-timing information, funds may trade in response to exogenous liquidity demands (see Edelen, 1996; Ferson and Warther, 1996). These trades might obscure market-timing activity, so a model that incorporates liquidity effects could provide additional insights. Much interesting work remains to be done in the area of conditional performance evaluation.

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