# Volatility Timing in Mutual Funds: Evidence from Daily Returns

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I use daily mutual fund returns to shed new light on the question of whether or not mutual fund managers are successful market timers. Previous studies find that funds are unable to time the market return. I study the funds' ability to time market volatility. I show that volatility timing is an important factor in the returns of mutual funds and has led to higher risk-adjusted returns. The returns of surviving funds are especially sensitive to market volatility; those of nonsurvivors are not.

Over the past 30 years, numerous studies have examined whether or not mutual funds successfully time the market. These studies have focused exclusively on market returns: Do mutual funds capitalize on superior information by increasing market exposure before market upswings or by decreasing market exposure before downturns? [See, e.g., Treynor and Mazuy (1966), Fama (1972), Jensen (1972), Merton (1981), Merton and Henriksson (1981), Chang and Lewellen (1984), Henriksson (1984), Grinblatt and Titman (1989), Ferson and Schadt (1996), and Kryzanowski, Lalancette, and To (1997).] There has been a dearth of analysis on whether or not funds time volatility: Do funds change market exposure when market volatility changes?

This article focuses on volatility for two reasons. First, although market returns are difficult to predict, market volatility is predictable because it persists: high volatility is often followed by high volatility, and low by low [see, e.g., Bollerslev, Chou, and Kroner (1992)]. Second, most measures of performance are risk adjusted. The Sharpe ratio, Jensen's alpha, and more recent conditional metrics evaluate performance by adjusting returns for some measure of risk. Since risk-adjusted performance affects fund cash flows [see Ippolito (1992), Gruber (1996), Sirri and Tufano (1998), and Del Guercio and Tkac (1998)], how funds manage risk has implications for manager compensation.

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It is not a priori clear, however, that a fund manager can increase risk-adjusted performance or investor utility by timing market volatility. On the one hand, empirical studies do not find a reliably positive, simple relation between conditional market returns and conditional market volatility [see, e.g., French, Schwert, and Stambaugh (1987), Campbell (1987), Glosten, Jagannathan, and Runkle (1993), and Whitelaw (1994)]. If market returns and volatility are unrelated, it suggests that fund managers could increase investor utility by decreasing market exposure when conditional volatility increases [also see Breen, Glosten, and Jagannathan (1989)]. On the other hand, Scruggs (1998) finds that reducing stock market exposure when stock volatility is high could be detrimental to the fund investor because it might expose the investor to other risks, such as interest rate risk. I examine whether funds respond to changing market volatility, and how such strategies affect fund performance.

This article is part of the extensive mutual fund timing literature pioneered by Treynor and Mazuy (1966). My focus is similar in some respects to Brown, Harlow, and Starks (1996), Busse (1999), and Koski and Pontiff (1999), who also look at managing fund volatility, though not in relation to market volatility timing. Since I examine managers' response to expected future market conditions, my analysis fits into the conditional mutual fund literature initiated by Chen and Knez (1996) and Ferson and Schadt (1996) and subsequently addressed in Ferson and Warther (1996), Christopherson, Ferson, and Glassman (1998), and Becker et al. (1999). But unlike Ferson and Schadt (1996), who use publicly available economic instruments in the context of conditional market returns, I examine conditional market volatility timing.

My article is the first to use daily data in a mutual fund context. The daily frequency of the data allows for more efficient estimates of time variation in systematic risk than does monthly data. I measure conditional market volatility with an EGARCH specification and find a strong negative relation between fund systematic risk levels and conditional market volatility. When conditional volatility is higher than normal, systematic risk levels are lower. Although it is not clear whether funds predict market volatility better than public information, I document a significant relation between volatility timing and a traditional measure of investment performance. Funds that reduce systematic risk when conditional market volatility is high earn higher risk-adjusted returns.

The article is organized as follows. Section 1 presents a model that shows the relation between fund systematic risk, expected market returns, and volatility. Section 2 describes the sample of mutual funds and two random control samples. Section 3 documents the relation between market returns and volatility for the sample period of this study. Section 4 presents the empirical results and several robustness tests. Section 5 concludes.

# 1. Model

## 1.1 Theoretical analysis

I motivate volatility timing from the fund manager's perspective, assuming that the manager attempts to time market exposure in the fund shareholders' best interests. The results should hold in some form, given incentive contracts that increase in fund return and decrease in fund volatility.

Assuming a $k$-factor return-generating process and factor sensitivity that varies over time, a fund's return at time $t+1$ is given by

$$R_{p,t+1} = \alpha_{pt} + \sum_{j=1}^{k} \beta_{jpt} R_{j,t+1} + \varepsilon_{p,t+1}, \tag{1}$$

where $R_{p,t+1}$ is the excess return of fund $p$ at time $t+1$, $\alpha_{pt}$ is the abnormal return of fund $p$ known at time $t$, $\beta_{jpt}$ is the sensitivity of fund $p$ to factor $j$ chosen by the manager at time $t$, $R_{j,t+1}$ is the excess return of factor $j$ at time $t+1$, and $\varepsilon_{p,t+1}$ is the error term of fund $p$ at time $t+1$. I assume the returns are conditionally normally distributed, $E_t(\varepsilon_{p,t+1}) = 0$, and $E_t(R_{j,t+1}\varepsilon_{p,t+1}) = 0$, where $E_t(\cdot)$ is the expectation conditional on information available at time $t$. The expected return is

$$E_t(R_{p,t+1}) = \alpha_{pt} + \sum_{j=1}^{k} \beta_{jpt} E_t(R_{j,t+1}). \tag{2}$$

Assuming the factors are orthogonal, the conditional variance at time $t$ is given by

$$\sigma_t^2(R_{p,t+1}) = \sum_{j=1}^{k} \beta_{jpt}^2 \sigma_{j,t+1}^2 + \sigma_t^2(\varepsilon_{p,t+1}). \tag{3}$$

From the standpoint of timing, the maximization problem is

$$\max_{\beta_{1pt},\ldots,\beta_{kpt}} E_t[U_{t+1}(R_{p,t+1})]. \tag{4}$$

Differentiating $E_t[U_{t+1}(R_{p,t+1})]$ with respect to $\beta_{jpt}$ for $j = 1$ to $k$ and setting the result equal to zero gives

$$\begin{aligned}
&\frac{\partial}{\partial \beta_{jpt}} E_t[U_{t+1}(R_{p,t+1})] \\
&\quad = E_t[U'_{t+1}(R_{p,t+1})]E_t[R_{j,t+1}] + \mathrm{cov}[U'_{t+1}(R_{p,t+1}), R_{j,t+1}] \\
&\quad = E_t[U'_{t+1}(R_{p,t+1})]E_t[R_{j,t+1}] \\
&\qquad + E_t[U''_{t+1}(R_{p,t+1})]\,\mathrm{cov}(R_{p,t+1}, R_{j,t+1})
\end{aligned}$$

$$= E_t[U'_{t+1}(R_{p,t+1})]E_t[R_{j,t+1}] + \beta_{jpt} E_t[U''_{t+1}(R_{p,t+1})]\,\mathrm{var}(R_{j,t+1})$$
$$= 0 \qquad j = 1, \ldots, k, \tag{5}$$

where the second line in Equation (5) follows from Stein's (1973) lemma. Solving Equation (5) for $\beta_{jpt}$ gives

$$\beta_{jpt} = \frac{1}{a}\frac{E_t(R_{j,t+1})}{\sigma^2_{j,t+1}} \qquad j = 1, \ldots, k, \tag{6}$$

where $a$ is the Rubinstein (1973) measure of risk aversion, $-E_t[U''_{t+1}(R_{p,t+1})]/E_t[U'_{t+1}(R_{p,t+1})]$, assumed to be a fixed parameter.

Taking the partial derivative of the optimal factor beta with respect to factor standard deviation gives

$$\frac{\partial \beta_{jpt}}{\partial \sigma_{j,t+1}} = \frac{1}{a\sigma^2_{j,t+1}}\left[\frac{\partial E_t(R_{j,t+1})}{\partial \sigma_{j,t+1}} - \frac{2E_t(R_{j,t+1})}{\sigma_{j,t+1}}\right] \qquad j = 1, \ldots, k. \tag{7}$$

If

$$\frac{\partial E_t(R_{j,t+1})}{\partial \sigma_{j,t+1}} \leq 0, \tag{8}$$

then the fund's sensitivity to factor $j$ should decrease when the volatility of factor $j$ increases.[1] Given previous empirical evidence, which suggests $\partial E_t(R_{m,t+1})/\partial\sigma_{m,t+1}$ is small or negative, we expect a negative response of $\beta_{mp}$ to $\sigma_m$. Only if $\partial E_t(R_{j,t+1})/\partial\sigma_{j,t+1}$ is positive and larger than $2E_t(R_{j,t+1})/\sigma_{j,t+1}$ should we expect a positive response of $\beta_{jp}$ to $\sigma_j$.

In numerical versions of a dynamic asset pricing theory, Backus and Gregory (1993) show that the relation between the market risk premium and the conditional variance of market return could be decreasing or flat, depending on the preferences of the representative agent and the stochastic structure of the economy. Whitelaw (1997) finds that reasonable parameterizations of a relatively simple equilibrium model are consistent with a negative relation.

Scruggs (1998), however, argues that single-factor models are misspecified. Motivated by Merton's ICAPM, he uses a conditional two-factor model to investigate the intertemporal relation between the market risk premium and the conditional market variance. When he includes government bond returns as the second factor, he finds evidence of a significant positive partial relation between market returns and conditional market volatility. Scruggs' results imply that reducing market exposure when market volatility increases could be detrimental to fund investors if it further exposes them to other unwanted risks, such as interest rate risk.

[1] Of course, not all investors can reduce systematic risk when volatility increases. This analysis can be thought of as a test of whether fund managers are among those investors that reduce systematic risk when volatility increases.

Given the previous empirical findings and theoretical work, it is interesting to see how fund managers react to changes in market volatility. For the factors in the return-generating process that have a large impact on fund volatility, I conduct tests to measure the sign of the relation between factor beta and factor volatility.

There is one possible source of complication. Since a single-index market beta conditional at time $t$ is given by

$$\beta_{mit} = \rho_{mit} \frac{\sigma_{it}}{\sigma_{mt}}, \tag{9}$$

where $\rho_{mit}$ is the correlation between the market and security $i$ at time $t$, $\sigma_{it}$ is the standard deviation of security $i$ at time $t$, and $\sigma_{mt}$ is the standard deviation of the market at time $t$, we might expect market betas of stocks to decrease when market volatility increases. This cannot be the case across all stocks, since market betas must average out to approximately unity at all times regardless of market volatility. However, it can be true for certain sectors of stocks [see Jagannathan and Korajczyk (1986)]. I control for the passive effects of volatility on fund betas by comparing changes in the fund betas to changes in the betas of a randomly formed control sample that holds similar types of stocks as mutual funds.

### 1.2 Empirical analysis

In my empirical analysis, I examine three specifications often used in a monthly context: the single-index model (CAPM); a three-index model that includes size and book-to-market factors; and a four-index model that adds momentum effects. I modify the models for use with daily data and add terms to capture the effects of volatility timing.

The single-factor model is given by

$$R_{pt} = \alpha_p + \beta_{mp} R_{mt} + \varepsilon_{pt}, \tag{10}$$

where $R_{pt}$ is the excess return of fund $p$ on day $t$, $R_{mt}$ is the excess return of the S&P 500 index on day $t$, $\beta_{mp}$ is the coefficient from a regression of $R_{pt}$ on $R_{mt}$, $\alpha_p$ is the abnormal return of fund $p$, and $\varepsilon_{pt}$ is the idiosyncratic return of fund $p$ on day $t$. I derive the daily risk-free rate used to compute excess returns from the daily U.S. 90-day T-bill index on Datastream (code *TBILL90*).[2]

[2] I take the daily risk-free rate for day $t$ to be

$$r_{ft} = \left(\frac{100}{P_t}\right)^{\frac{1}{n_t}} - 1,$$

where $P_t$ is the closing price of the 90-day Treasury bill on day $t$ and there are $n_t$ trading days in the next year (approximately 253, depending on the day).

Daily data present one notable complication relative to monthly data. Scholes and Williams (1977) and Dimson (1979) describe the nonsynchronous trading problem that hampers regression estimates for individual securities. I address this problem by adding a lagged index term to the model:[3]

$$R_{pt} = \alpha_p + \beta_{mp} R_{mt} + \beta_{lmp} R_{m,t-1} + \varepsilon_{pt}. \qquad (11)$$

Finally, to account for volatility timing, I use a simplified Taylor series expansion to express market beta as a linear function of the difference between market volatility and its time-series mean,

$$\beta_{mpt} = \beta_{0mp} + \gamma_{mp}(\sigma_{mt} - \overline{\sigma}_m). \qquad (12)$$

Substituting Equation (12) into Equation (11) gives the daily single-factor volatility timing model:

$$R_{pt} = a_p + \beta_{0mp} R_{mt} + \gamma_{mp}(\sigma_{mt} - \overline{\sigma}_m) R_{mt} + \beta_{lmp} R_{m,t-1} + \varepsilon_{pt}. \qquad (13)$$

Although the volatility term could also interact with the lag index term, such a specification produces results similar to those from the more parsimonious specification in Equation (13).

Elton et al. (1993) present evidence that multifactor models do a better job of capturing the return-generating process of mutual funds. The three-factor model of Fama and French (1993, 1996) includes terms that capture the differential dynamics of small cap stocks relative to large cap stocks (SMB) and high book-to-market stocks relative to low book-to-market stocks (HML) in addition to the market factor. Elton, Gruber, and Blake (1996a, b) use bond returns in their four-index model, but I was unable to find a reliable daily bond index that spanned the sample period. Instead, I add a momentum factor (momentum minus contrarian, MMC) to the three-factor model, as in Carhart (1997). I express the three- and four-index volatility timing models as

$$R_{pt} = \alpha_p + \sum_{j=1}^{k} \left[ \beta_{0jp} R_{jt} + \beta_{ljp} R_{j,t-1} + \gamma_{jp}(\sigma_{jt} - \overline{\sigma}_j) R_{jt} \right] + \varepsilon_{pt}, \qquad (14)$$

with $k = 3$ or $k = 4$. I construct the SMB and HML return series similarly to those in Fama and French (1993), except at a daily frequency. I construct the MMC return series similarly to the momentum index in Carhart (1997), except value weighted and at a daily frequency. I orthogonalize the

[3] Dimson (1979) suggests including as many as three lag and three lead terms. I test several combinations, and only the first lag term is consistently significant. Since they are typically well-diversified portfolios of stocks, mutual funds are not as susceptible to problems associated with nonsynchronous trading as individual securities are. In addition, fund companies are allowed to report estimates of the fund's "fair value" to mitigate potential valuation problems associated with infrequently traded or foreign listed holdings.

SMB, HML, and MMC indices to maintain consistency with the theoretical development in Section 1.1.[4]

## 2. Data

The early mutual fund studies [e.g., Jensen (1968, 1969)] use annual or quarterly return data. Since the mid-1970s, most studies have used monthly data. [The exceptions include Miller and Gressis (1980) and Brauer, Hays, and Upton (1987), who use weekly data.] The frequent use of monthly data could be because it is readily available from several sources. Although it is adequate for many purposes, monthly data cannot fully capture the higher frequency dynamics that characterize the day-to-day activities of actively managed mutual funds. Therefore, I use daily data.

### 2.1 Mutual funds

I use the December 1984 version of Wiesenberger's *Mutual Funds Panorama* for my list of 230 domestic equity funds with a "common stock" investment policy and a "maximum capital gains," "growth," or "growth and income" investment objective and more than $15 million in total net assets. I do not include sector funds (e.g., technology or health care), balanced funds, index funds, or funds that became one of these types in a subsequent year during the sample period. Although balanced funds could actually be more actively engaged in volatility timing than the sample of equity funds examined, I exclude them because there was no reliable daily bond index that covered my sample period. The funds that meet the inclusion criteria are listed in Appendix A, which categorizes the funds by investment objective, as most frequently classified by *Panorama* during the sample period.

I take daily per share net asset values (NAVs) and dividends from January 2, 1985 through December 29, 1995 from Interactive Data Corporation (IDC). The NAV is the price at which open-end funds stand ready to issue new shares or redeem existing shares. Funds compute an NAV each day after the market close in New York and give it to the National Association of Security Dealers for distribution to publications such as the *Wall Street Journal* and data providers such as IDC. The NAVs reflect "fair value pricing," the practice that gives fund companies discretion in reporting their best estimate of fund share value, taking into account the estimated market value of infrequently traded securities or securities listed on foreign exchanges. I

[4] I take the orthogonal SMB factor to be the intercept plus residuals of a regression of the SMB factor on the excess returns of the S&P 500. I take the orthogonal HML factor to be the intercept plus residuals of a regression of the HML factor on the excess returns of the S&P 500 and the orthogonal SMB factor. I take the orthogonal MMC factor to be the intercept plus residuals of a regression of the MMC factor on the excess returns of the S&P 500, the orthogonal SMB factor, and the orthogonal HML factor.

use *Moody's Dividend Record: Annual Cumulative Issue* and *Standard & Poor's Annual Dividend Record* to verify the dividends and to determine split dates. I combine the NAVs and dividends to form a daily return series for each fund:

$$r_{pt} = \frac{NAV_{pt} + D_{pt}}{NAV_{p,t-1}} - 1, \tag{15}$$

where $NAV_{pt}$ is the net asset value of fund $p$ at the end of day $t$ and $D_{pt}$ are the ex-dividend dividends of fund $p$ on day $t$.[5]

To reduce survivorship bias, I include in the sample funds that subsequently merge or liquidate [see Brown and Goetzmann (1995) and Elton, Gruber, and Blake (1996b)]. The sample is biased to some extent, however, because the funds survive as a type (i.e., do not become a sector or balanced fund). I exclude seven funds because they change into an excluded fund type. Table 1 shows summary statistics of the fund sample.

### 2.2 Random portfolios

I use two large samples of random portfolios as control samples. As a group, the random portfolios should exhibit the same time-series characteristics as the mutual fund sample, but without the dynamics specifically attributable to managers. For example, if the betas of the types of securities held by the fund sample increase when volatility increases, the betas of the random portfolios should also increase. I do not consider the funds' coefficients to be significant unless they are significantly different from the coefficients of the matching random portfolios.

My approach in constructing the random control samples is similar in some respects to that of Daniel et al. (1997), who form benchmarks by directly matching size, book-to-market, and momentum characteristics of the actual stocks in the fund portfolios. Since I do not have portfolio holdings, I follow Sharpe's (1992) *style analysis*. For each fund in the sample, I solve a quadratic programming problem to determine the fund's exposures to a number of asset classes. I minimize the variance of the difference between the fund returns and the returns of a mimicking portfolio,

$$\min_{b_{p1}, b_{p2}, \ldots, b_{pk}} \left[ \operatorname{var}\left( r_{pt} - \sum_{i=1}^{k} b_{pi} r_{it} \right) \right], \tag{16}$$

[5] Although the data cannot be verified completely, I run several checks to ensure its quality. One common error involves price adjustments to dividends occurring on the wrong day. Typically the price drops a day before or a day after the recorded ex-dividend date. In these cases I change the ex-dividend date. Other less frequent errors involve incorrectly recorded NAVs. For example, the series drops in half one day and doubles the next.

In total, I adjust approximately 0.5% of the data by changing dividend dates or by changing extreme, obviously erroneous NAV observations. When I compound the daily data to form a monthly series and check this series against the monthly returns of Morningstar and Micropal, I am unable to reconcile a large number of returns for 14 funds (out of 244), and I drop these funds from the sample.

where $r_{pt}$ is the total return of fund $p$ on day $t$, $b_{pi}$ is the nonnegative exposure of fund $p$ to asset class $i$, and $r_{it}$ is the total return of asset class $i$ on day $t$. I use eight asset classes: the six intersections of the equal-weighted size and book-to-market indices [big size and high book-to-market (BH), BM, BL, SH, SM, SL] and the equal-weighted momentum and contrarian indices.

Since mutual funds are usually not fully invested, but typically hold anywhere from 5% to 10% of their total net assets in cashlike securities, I give each random portfolio an allocation of 93% equity and 7% cash. The equity portion consists of 100 securities randomly chosen from the different asset classes in proportions that match the fund exposures to the asset classes as indicated by the solution to the quadratic programming problem.[6] Each security is in the portfolio for an average of 1 year, roughly consistent with the 81% average annual turnover of the mutual fund sample. The security exits on a randomly chosen date and is replaced with a security from the same asset class.

I compute the random portfolio's equity component of returns based on security proportions that are initially equally weighted (each has an initial weight of 1/100). The weights evolve according to a buy-and-hold investment strategy. Since the mimicking portfolios hold individual securities for an average of 1 year before replacement, this random sample mimics a buy-and-hold strategy with annual rebalancing. The resulting random control sample consists of 230 portfolios, one mimicking portfolio for each fund in the mutual fund sample.

The second random control sample is similar to the first, except that it mimics a buy-and-hold strategy without rebalancing. Securities enter the portfolio at the beginning of 1985 and remain there until the end of 1995, unless they cease to exist at an intermediate date, in which case they are not replaced.

Table 1 shows summary statistics of the two random control samples. Compared to the mutual fund sample, the random samples have similar market exposure, SMB exposure, and slightly less growth (low book-to-market) and momentum exposures. To prevent the different exposures to the HML and MMC factors from materially affecting inferences formed in subsequent sections, I also form additional random portfolios that overweight low book-to-market and momentum securities relative to the weights indicated by the quadratic programming procedure. Inferences based relative to these additional random portfolios are identical to those reported (based on the two random control samples).

[6] For example, if the quadratic programming problem gives a coefficient of 0.5 on the BH asset class, 0.3 on SH, and 0.1 on momentum, then I randomly choose $100[0.5/(0.5+0.3+0.1)]$ or 56 of the 100 securities in the mimicking portfolio from among all securities classified as big and high book-to-market. I take 33 from SH and 11 from momentum. I then give the 100 securities an allocation of 0.93 and cash an allocation of 0.07.

**Table 1**
**Summary statistics of mutual fund sample and random control samples**

Panel A: Return statistics

| Fund group | Number of funds | Return | Standard deviation | Skewness | Kurtosis |
|---|---|---|---|---|---|
| All | 230 | 0.0562% | 0.898% | −2.51 | 48.68 |
| Maximum capital gains | 68 | 0.0553 | 0.979 | −2.32 | 42.85 |
| Growth | 107 | 0.0570 | 0.894 | −2.34 | 44.05 |
| Growth and income | 55 | 0.0557 | 0.805 | −3.05 | 64.91 |
| Surviving | 196 | 0.0574 | 0.879 | −2.50 | 49.82 |
| Nonsurviving | 34 | 0.0492 | 1.005 | −2.51 | 42.16 |
| Random samples | | | | | |
| Rebalanced | 230 | 0.0577 | 0.807 | −2.61 | 51.00 |
| Not Rebalanced | 230 | 0.0567 | 0.810 | −2.41 | 47.90 |

Panel B: Model parameters

| | Single-index | | | Three-index | | | | | Four-index | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Fund group | $\alpha$ | $\beta_m$ | $R^2$ | $\alpha$ | $\beta_m$ | $\beta_{SMB}$ | $\beta_{HML}$ | $R^2$ | $\alpha$ | $\beta_m$ | $\beta_{SMB}$ | $\beta_{HML}$ | $\beta_{MMC}$ | $R^2$ |
| All | −0.0064% | 0.921 | 0.770 | −0.0050% | 0.826 | 0.436 | −0.186 | 0.836 | −0.0054% | 0.826 | 0.445 | −0.180 | 0.052 | 0.839 |
| Max capital gains | −0.0088 | 0.981 | 0.694 | −0.0050 | 0.838 | 0.655 | −0.339 | 0.800 | −0.0057 | 0.839 | 0.668 | −0.329 | 0.084 | 0.805 |
| Growth | −0.0066 | 0.921 | 0.781 | −0.0045 | 0.831 | 0.419 | −0.198 | 0.840 | −0.0049 | 0.831 | 0.428 | −0.192 | 0.048 | 0.843 |
| Growth & income | −0.0032 | 0.845 | 0.844 | −0.0060 | 0.800 | 0.197 | 0.028 | 0.871 | −0.0061 | 0.800 | 0.201 | 0.030 | 0.020 | 0.874 |
| Surviving | −0.0035 | 0.917 | 0.777 | −0.0030 | 0.829 | 0.404 | −0.170 | 0.837 | −0.0035 | 0.830 | 0.413 | −0.164 | 0.053 | 0.841 |
| Nonsurviving | −0.0240 | 0.942 | 0.734 | −0.0166 | 0.805 | 0.622 | −0.280 | 0.825 | −0.0167 | 0.805 | 0.630 | −0.274 | 0.043 | 0.829 |
| Random samples | | | | | | | | | | | | | | |
| Rebalanced | −0.0030 | 0.880 | 0.815 | −0.0062 | 0.771 | 0.488 | −0.036 | 0.887 | −0.0063 | 0.771 | 0.489 | −0.035 | 0.007 | 0.888 |
| Not Rebalanced | −0.0044 | 0.886 | 0.844 | −0.0062 | 0.800 | 0.373 | −0.045 | 0.891 | −0.0061 | 0.799 | 0.371 | −0.047 | −0.007 | 0.891 |

The table shows the average daily summary statistics of the mutual fund sample and the two random control samples. The first random control sample mimics an equal-weighted strategy that rebalances annually, and the second random control sample mimics an equal-weighted strategy without rebalancing. The betas are sums of the contemporaneous and lag betas from the single-index model,

$$R_{pt} = \alpha_p + \beta_{mp} R_{mt} + \beta_{lmp} R_{m,t-1} + \varepsilon_{pt}, \quad (11)$$

and three- and four-index specifications. The sample period is from January 2, 1985 to December 29, 1995.

## 3. Factor Returns and Volatility

In this section I estimate each factor's impact on fund volatility. I then estimate the relation between factor returns and factor volatility for those factors that have a large impact on fund volatility.

### 3.1 Factor importance

Over the 1985–1995 sample period, the daily variances of the excess return on the S&P 500, the orthogonal SMB, the orthogonal HML, and the orthogonal MMC indices are 0.0091%, 0.0019%, 0.0008%, and 0.0022%, respectively. Using Equation (3), which decomposes the total variance of the fund return into components associated with each of the four factors, I find that the S&P 500 contributes an average (median) of 90.6% (95.5%) of the variance explained by the four-factor model for the 230 funds in the sample. The S&P 500's contribution is at least 80% for six out of seven funds. Thus the S&P 500 market factor dominates the variance explained by the four-factor returns.[7] The average (median) contributions of the orthogonal SMB, HML, and MMC factors [8.0% (4.1%), 1.0% (0.4%), and 0.3% (0.0%), respectively] are so small that we do not expect managers to strategically alter exposure to these factors as market conditions change. The costs associated with such changes are likely to be greater than the costs of market timing with index futures. Furthermore, there is some controversy about the Fama and French model as an asset pricing model [see Ferson, Sarkissian, and Simin (1999) and Ferson and Harvey (1999)]. I see no clear a priori reason why funds might time the SMB, HML, or MMC volatilities.

### 3.2 Monthly relation

I estimate the monthly standard deviation of excess return on the S&P 500 as

$$\sigma_{mt} = \left[ \sum_{i=1}^{n_t} \left( R_{mti} - \overline{R}_{mt} \right)^2 \right]^{\frac{1}{2}}, \tag{17}$$

where there are $n_t$ daily returns $R_{mti}$ in month $t$. The correlation between this measure of volatility and the monthly return on the S&P 500 from 1985 through 1995 is $-0.47$. Repeating the analysis for the longer 1963–1995 period gives $\rho(R_{S\&P\ 500}, \sigma_{S\&P\ 500}) = -0.25$, that is, no evidence of a positive relation between returns and risk. Correlations for the CRSPVW and CRSPEW indices are more negative.

[7] These contributions depend on the order in which I orthogonalize the factors. For example, if I take the high book-to-market index as the first index instead of the S&P 500, the variance explained by the high book-to-market index dominates that of the other indices.

To examine whether the conditional component of volatility or the volatility shock drives the negative ex post relation, I model monthly volatility with an ARMA(1,1) specification,

$$\sigma_{mt} = \phi\sigma_{m,t-1} + \theta\varepsilon_{m,t-1} + \varepsilon_{mt}. \tag{18}$$

The maximum likelihood estimation of Equation (18) using monthly data from Equation (17) over the 1985–1995 sample period gives an AR coefficient of 0.989 and an MA coefficient of $-0.752$. Taking the fitted part of Equation (18) as the conditional component of volatility and the residual as the volatility shock, the correlations between the monthly S&P 500 return and the conditional and residual components of volatility are 0.00 and $-0.51$, respectively. This indicates that the negative overall relation is entirely driven by the relation between market returns and the volatility shock. These results are similar to the results of French, Schwert, and Stambaugh (1987).

### 3.3 Daily relation

To model the dynamics of daily market volatility, I use the EGARCH model [Nelson (1991)] with one autoregressive term, one moving average term, a leverage term, and a $t$-distributed conditional error term:

$$\begin{aligned} \ln\sigma_{mt}^2 &= a + a_1\frac{|\varepsilon_{m,t-1}| + \gamma_1\varepsilon_{m,t-1}}{\sigma_{m,t-1}} + b_1\ln\sigma_{m,t-1}^2, \\ &\varepsilon_{mt} \mid \varepsilon_{m,t-1}, \varepsilon_{m,t-2}, \ldots \sim t(0, \sigma_{mt}^2). \end{aligned} \tag{19}$$

In Appendix B, I discuss the rationale for choosing this particular specification and show the results of maximum likelihood estimates of the conditional volatility process in Equation (19) for the daily S&P 500 return series over the 1985–1995 sample period. The correlation between daily S&P 500 returns and the conditional volatility series is 0.02. The correlation between the S&P return and $\varepsilon_{mt}^2$ is $-0.40$, again providing no evidence of a positive relation between market returns and market volatility.[8]

[8] I can also model the market return as a function of volatility with an EGARCH-in-mean [Engle, Lilien, and Robins (1987)] specification:

$$r_{mt} - r_{ft} = c_m + \delta_m\sigma_{mt} + \varepsilon_{mt}$$

where $\delta_m$ is the market price of volatility and $\sigma_{mt}$ is the standard deviation of $r_m$ at time $t$. Maximum likelihood estimation of this specification with the volatility specification in Equation (19) for the S&P 500 return series over the 1985–1995 sample period gives a coefficient of 0.184 ($t$-statistic 1.77) on the standard deviation term. Though positive, the coefficient is not significant, and analysis over the longer 1963–1995 time period gives a volatility coefficient of only 0.0210 with a $t$-statistic of 0.523.

### 3.4 Implied volatility

An alternative to the time-series-based EGARCH and ARMA conditional volatility estimates is the implied volatility of an option on a market index. The Chicago Board Options Exchange (CBOE) quotes a daily frequency implied volatility index that begins in 1986. The index is based on the Black–Scholes/Merton implied volatilities of eight near-the-money call and put options on the S&P 100 index. Although the composition of the S&P 100 does not match that of the S&P 500, the correlation between the CBOE S&P 100 implied volatility series and the EGARCH S&P 500 conditional volatility estimates is 0.92. The correlation between the CBOE series at the end of each month and the ARMA S&P 500 conditional volatility estimates is 0.89. The correlations between the S&P 500 return and the CBOE daily and monthly implied volatilities are 0.00 and −0.02, respectively. Thus the time-series-based conditional estimates capture volatility dynamics similar to those in the implied volatility of index options. To prevent my inferences from being sensitive to the particular conditional volatility estimates used, I repeat all of the analysis with the CBOE implied volatility time series, but over a slightly shorter 1986–1995 sample period.

## 4. Empirical Results

### 4.1 Daily

Assuming the market factor dominates explained variance, I express the volatility timing model as

$$R_{pt} = \alpha_p + \sum_{j=1}^{k} \left[\beta_{0jp} R_{jt} + \beta_{ljp} R_{j,t-1}\right] + \gamma_{mp}(\sigma_{mt} - \overline{\sigma}_m) R_{mt} + \varepsilon_{pt}, \quad (20)$$

with $k = 1, 3$, or 4. Since daily fund returns are heteroskedastic, the error terms of Equation (20) are also likely to be heteroskedastic, so OLS coefficient estimates are inefficient but consistent. In addition, the regressions that use a market volatility estimate as a regressor are subject to an errors-in-the-variables problem, which I address below.

Daily OLS regressions of Equation (20) using the EGARCH conditional volatility estimates give the results shown in Table 2. I focus on panel B, which shows the difference between the volatility coefficients of the mutual fund sample and those of the rebalanced random control sample.

For the single-index specification, the volatility coefficients of the mutual funds are significantly less than those of the random control sample. This indicates that, relative to a passive strategy, funds reduce their market exposure during periods of high conditional volatility. The results are particularly strong for growth funds. Although directionally consistent with volatility timing, the results for growth and income funds are not statis-

**Table 2**
**Daily volatility timing results**

| | Single-index | | Three-index | | Four-index | |
|---|---|---|---|---|---|---|
| Fund group | $\gamma_{mp}$ | $t$-statistic | $\gamma_{mp}$ | $t$-statistic | $\gamma_{mp}$ | $t$-statistic |
| Panel A: Sample coefficients | | | | | | |
| All | 0.83 | 1.63 | −3.89 | −7.12** | −5.39 | −9.15** |
| Max capital gains | 1.76 | 1.86 | −5.41 | −5.25** | −7.63 | −6.60** |
| Growth | −0.50 | −0.65 | −4.97 | −6.32** | −6.49 | −7.98** |
| Growth and income | 2.27 | 2.44 | 0.06 | 0.07 | −0.53 | −0.53 |
| Survivors | 0.33 | 0.66 | −3.95 | −7.26** | −5.48 | −9.05** |
| Nonsurvivors | 3.85 | 2.00 | −3.52 | −1.75 | −4.89 | −2.48* |
| Random sample | 4.06 | 24.40 | −0.66 | −3.62** | −0.88 | −4.99** |
| Panel B: Difference between mutual fund and random sample coefficients | | | | | | |
| All | −3.23 | −6.00** | −3.24 | −5.62** | −4.51 | −7.33** |
| Max capital gains | −2.30 | −2.41* | −4.75 | −4.54** | −6.74 | −5.77** |
| Growth | −4.57 | −5.75** | −4.32 | −5.34** | −5.60 | −6.73** |
| Growth and income | −1.80 | −1.91 | 0.72 | 0.74 | 0.35 | 0.35 |
| Survivors | −3.74 | −7.14** | −3.30 | −5.75** | −4.59 | −7.28** |
| Nonsurvivors | −0.22 | −0.11 | −2.86 | −1.42 | −4.01 | −2.02* |

The table shows the average daily volatility coefficients for the single-index volatility timing model,

$$R_{pt} = \alpha_p + \beta_{mp0} R_{mt} + \gamma_{mp}(\sigma_{mt} - \overline{\sigma}_m) R_{mt} + \beta_{lmp} R_{m,t-1} + \varepsilon_{pt}, \quad (13)$$

and three- and four-index volatility timing models,

$$R_{pt} = \alpha_p + \sum_{j=1}^{k} \left[ \beta_{0jp} R_{jt} + \beta_{ljp} R_{j,t-1} \right] + \gamma_{mp}(\sigma_{mt} - \overline{\sigma}_m) R_{mt} + \varepsilon_{pt}. \quad (20)$$

I generate conditional volatility estimates from an EGARCH(1,1) with leverage specification of S&P 500 returns:

$$\varepsilon_{mt} \mid \varepsilon_{m,t-1}, \varepsilon_{m,t-2}, \ldots \sim t(0, \sigma_{mt}^2)$$
$$\ln \sigma_{mt}^2 = a + a_1 \frac{|\varepsilon_{m,t-1}| + \gamma_1 \varepsilon_{m,t-1}}{\sigma_{m,t-1}} + b_1 \ln \sigma_{m,t-1}^2. \quad (19)$$

Panel A shows the sample coefficients, and Panel B shows the difference between the mutual fund coefficients and the coefficients of the random control sample. I base the significance of the sample coefficient $t$-statistics on a two-tailed test. I base the significance of the differences between the mutual fund and random sample coefficients on a difference-in-means test in the hypothesized direction. *, ** Significant at the 5% and 1% level, respectively. The mutual fund sample consists of 230 funds, and the random control sample consists of 230 equal-weighted, annually rebalanced portfolios. The sample period is from January 2, 1985 to December 29, 1995.

tically significant. These results could reflect that growth funds are more aggressive than growth and income funds.

Compared to nonsurviving funds, the volatility coefficients of surviving funds are significantly negative. Given the summary statistics in Table 1, which show that nonsurviving funds underperform survivors, these results suggest the possibility of performance implications for funds that time volatility.

The three- and four-index results also indicate conditional volatility timing. Among the subgroups, maximum capital gains funds join growth and surviving funds as being particularly sensitive to volatility timing. The four-index results are slightly stronger than the three-index results, with coefficients and $t$-statistics that are more negative. More than 70% of the four-index volatility coefficients are negative.

When I use implied volatility in regression Equation (20) and compare the volatility coefficients of the mutual funds to those of the second random control sample, the results are also significant, but slightly weaker. For example, for all funds, the differences between the mutual fund and random sample coefficients are −1.43, −2.05, and −2.84 with $t$-statistics −3.50, −4.30, and −5.77 for the single-, three-, and four-index models, respectively.

Regardless of the specification, comparing the volatility coefficients of the mutual funds to the random control samples leads to the same inference: When conditional volatility is higher than average, the majority of funds reduce their market exposure.

## 4.2 Monthly

**4.2.1 Realized volatility.** I further explore the importance of volatility timing among mutual funds by directly examining monthly changes in systematic risk. For each fund, each month, I estimate single-, three-, and four-index betas, using regression Equation (11) and the three- and four-index models. In each month's regression, I only use the daily returns associated with that month. This gives three monthly time series of S&P 500 betas for each fund. I compute the betas as the sum of the contemporaneous and lag coefficients (i.e., $\beta_{mp\tau} + \beta_{lmp\tau}$). For each of the three specifications, I run regressions

$$\beta_{mpt} = \beta_{0mp} + \gamma_{mp}(\sigma_{mt} - \overline{\sigma}_m) + \varepsilon_{mpt} \tag{21}$$

over the entire sample period, using the time series of S&P 500 betas and the monthly S&P 500 standard deviation estimates.

Table 3 shows the results. Compared to the betas of the rebalanced random control sample, mutual fund betas respond negatively to market volatility for all three specifications, confirming the previous evidence of volatility timing. More than 80% of the four-index volatility coefficients are negative. Of all the fund groups, only the coefficients of growth and income and nonsurviving funds are not statistically significant. Again, the results for survivors and nonsurvivors are very different.

When I compare the volatility coefficients of the mutual funds to those of the second random control sample, the results are even stronger. For example, for all funds, the differences between the mutual fund and random sample coefficients are −5.34, −3.88, and −3.70 with $t$-statistics −11.04, −8.71, and −6.76 for the single-, three-, and four-index models, respectively.

**Table 3**
**Monthly volatility timing results**

| | Single-index | | Three-index | | Four-index | |
|---|---|---|---|---|---|---|
| Fund group | $\gamma_{mp}$ | $t$-statistic | $\gamma_{mp}$ | $t$-statistic | $\gamma_{mp}$ | $t$-statistic |
| Panel A: Sample coefficients | | | | | | |
| All | −3.04 | −6.58** | −4.88 | −11.44** | −5.92 | −11.64** |
| Max capital gains | −4.35 | −4.25** | −6.94 | −7.62** | −7.45 | −6.35** |
| Growth | −3.53 | −5.57** | −5.24 | −8.79** | −6.79 | −10.16** |
| Growth and income | −0.47 | −0.69 | −1.63 | −2.99** | −2.38 | −3.52** |
| Survivors | −3.77 | −8.63** | −4.98 | −11.87** | −5.96 | −11.33** |
| Nonsurvivors | 1.34 | 0.78 | −4.29 | −2.65** | −5.72 | −3.41** |
| Random sample | 0.75 | 4.07 | −2.37 | −20.25** | −3.51 | −18.08** |
| Panel B: Difference between mutual fund and random sample coefficients | | | | | | |
| All | −3.78 | −7.62** | −2.51 | −5.67** | −2.42 | −4.44** |
| Max capital gains | −5.10 | −4.90** | −4.57 | −4.98** | −3.94 | −3.31** |
| Growth | −4.27 | −6.48** | −2.87 | −4.72** | −3.28 | −4.72** |
| Growth and income | −1.21 | −1.72 | 0.74 | 1.34 | 1.13 | 1.61 |
| Survivors | −4.52 | −9.53** | −2.61 | −5.99** | −2.45 | −4.38** |
| Nonsurvivors | 0.59 | 0.34 | −1.92 | −1.18 | −2.21 | −1.31 |

The table shows the average monthly volatility coefficients for the single-, three-, and four-index models:

$$\beta_{mpt} = \beta_{0mp} + \gamma_{mp}(\sigma_{mt} - \overline{\sigma}_m) + \varepsilon_{mpt}. \tag{21}$$

I compute total monthly realized market volatility estimates using

$$\sigma_{mt} = \left[\sum_{i=1}^{n_t}(R_{mti} - \overline{R}_{mt})^2\right]^{\frac{1}{2}}. \tag{17}$$

Panel A shows the sample coefficients and Panel B shows the difference between the mutual fund coefficients and the coefficients of the random control sample. I base the significance of the sample coefficient $t$-statistics on a two-tailed test. I base the significance of the differences between the mutual fund and random sample coefficients on a difference-in-means test in the hypothesized direction. *, ** Significant at the 5% and 1% level, respectively. The mutual fund sample consists of 230 funds, and the random control sample consists of 230 equal-weighted, annually rebalanced portfolios. The sample period is from January 2, 1985 to December 29, 1995.

**4.2.2 Conditional volatility.** To explore whether funds use better than public information to determine when to change their market exposure, I examine the extent to which managers respond to volatility shocks, the components of volatility that are not captured by conditional models. I examine two conditional models, the ARMA(1,1) model and an instrumental variables model. The instrumental variables model is expressed

$$\sigma_{mt} = \sigma_{m0} + \sum_{j=1}^{5}\phi_j z_{j,t-1} + \varepsilon_{mt}, \tag{22}$$

where $\sigma_{mt}$ is the S&P 500 standard deviation estimate for month $t$ [from Equation (17)] and $z_{j,t-1}$ is the realization of instrument $j$ during month $t-1$. I use five instruments: the short-term interest rate, dividend yield, term structure, default spread, and a January dummy variable. The instruments are similar to those used by Ferson and Schadt (1996). I obtain all of the variables from the *Basic Economics* database.[9] The volatility shock is the residual component, $\varepsilon_{mt}$ .

I examine the relation between the volatility shock and lagged betas because I am interested in how funds respond ex ante to volatility. I study the specification

$$\varepsilon^c_{mt} = \sigma_{m0} + \gamma_{mp}\beta_{mp,t-1} + \varepsilon_{mt}, \tag{23}$$

where $\varepsilon^c_{mt}$ is the volatility shock from the ARMA(1,1) or instrumental variables model. If managers can predict volatility and respond to volatility predictions ex ante, then the coefficients of the lagged beta term, $\gamma_{mp}$, for the mutual fund sample should be significantly less than those for the random control sample.

Table 4 shows the results for the mutual fund sample, the rebalanced random control sample, and the difference between the mutual fund and random samples. The results are inconclusive for both conditional models. The $\gamma_{mp}$ coefficients for the mutual funds are significantly less than the random control sample coefficients only in the single-index specification. Although the $\gamma_{mp}$ coefficients for the three- and four-index models indicate a negative response of fund betas to the residual component of volatility, the mutual fund coefficients are not significantly different from the coefficients of the random control sample. If the $\gamma_{mp}$ coefficients of the mutual funds are compared to those of the second random control sample, the results are similarly ambiguous.

The implications of these results are not clear. On the one hand, there is no evidence that funds predict volatility with better than public information. On the other hand, funds might be reacting to volatility at a higher frequency. This analysis measures whether funds modify their market exposure in 1 month in response to volatility predictions for the next month, but funds might modify their market exposure daily based on volatility predictions for the next day. For example, if I run the daily regression,

$$R_{pt} = \alpha_p + \sum_{j=1}^{k}\left[\beta_{0jp}R_{jt} + \beta_{ljp}R_{j,t-1}\right] + \gamma_{mp}(\sigma_{m,t+1} - \sigma_{mt})R_{mt} + \varepsilon_{pt}, \tag{24}$$

where $\sigma_{m,t+1} - \sigma_{mt}$ proxies for the EGARCH volatility shock on day $t+1$, the average $\gamma_{mp}$ coefficient for the fund sample is negative and significantly less than that of the rebalanced random control sample for single-, three-, and four-index specifications.

[9] The *Basic Economics* names for the instruments are as follows: *FYGT1* (1-year T-bill), *FSDXP* (S&P's composite common stock dividend yield), the difference between *FYGT10* (10-year T-bill) and *FYGM3* (3-month T-bill), and the difference between *FYBAAC* (Moody's BAA corporate bond yield) and *FYAAAC* (Moody's AAA corporate bond yield).

**Table 4**
**Conditional monthly volatility timing results**

| ARMA | | | Instruments | | |
|---|---|---|---|---|---|
| Single-index | Three-index | Four-index | Single-index | Three-index | Four-index |
| Mutual fund coefficients | | | | | |
| 0.132 | −0.050 | −0.091 | 0.038 | −0.144 | −0.163 |
| (8.94) | (−4.25)** | (−5.69)** | (2.05) | (−9.77)** | (−9.89)** |
| Random sample coefficients | | | | | |
| 0.333 | −0.057 | −0.137 | 0.234 | −0.139 | −0.190 |
| (22.87) | (−6.40)** | (−11.48)** | (17.99) | (−12.36)** | (−14.81)** |
| Difference between mutual fund and random sample coefficients | | | | | |
| −0.201 | 0.007 | 0.047 | −0.196 | −0.006 | 0.028 |
| (−9.70)** | (0.47) | (2.34) | (−8.68)** | (−0.31) | (1.33) |

The table shows the average $\gamma_{mp}$ coefficients of regressions of the residual component of monthly realized market volatility against the lagged single-, three-, and four-index S&P 500 beta,

$$\varepsilon^c_{mt} = \sigma_{m0} + \gamma_{mp}\beta_{mp,t-1} + \varepsilon_{mt}. \tag{23}$$

I estimate the residual components of volatility from an ARMA(1,1) specification,

$$\sigma_{mt} = \phi\sigma_{m,t-1} + \theta\varepsilon_{m,t-1} + \varepsilon_{mt}, \tag{18}$$

and an instrumental variables specification,

$$\sigma_{mt} = \sigma_{m0} + \sum_{j=1}^{5} \phi_j z_{j,t-1} + \varepsilon_{mt}. \tag{22}$$

I compute the monthly realized market volatility estimates from

$$\sigma_{mt} = \left[\sum_{i=1}^{n_t}\left(R_{mti} - \overline{R}_{mt}\right)^2\right]^{\frac{1}{2}}. \tag{17}$$

The instrumental variables model uses five conditioning variables: T-bill, dividend yield, term structure, default premium, and a January dummy. The table shows the mutual fund coefficients, the random sample coefficients, and the difference between the mutual fund and random sample coefficients. $t$-statistics are in parenthesis. I base the significance of the mutual fund and random sample coefficient $t$-statistics on a two-tailed test. I base the significance of the differences between the mutual fund and random sample coefficients on a difference-in-means test in the hypothesized direction. *, ** Significant at the 5% and 1% level, respectively. The mutual fund sample consists of 230 funds, and the random control sample consists of 230 equal-weighted, annually rebalanced portfolios. The sample period is from January 2, 1985 to December 29, 1995.

## 4.3 Performance

**4.3.1 Performance versus volatility timing.** If funds time volatility, then to what extent does this behavior result in superior returns? To answer this question, I examine two different measures of risk-adjusted performance: the Sharpe ratio and the conditional four-index alpha. I examine the contemporaneous relation between volatility timing and performance and also whether volatility timing predicts the performance of the next period.

I analyze the contemporaneous relation between volatility timing and the Sharpe ratio. Each year, I assign funds to cells in two-by-two contingency tables based on their four-index volatility coefficient $\gamma_{mp}$ [from Equation (20)] and Sharpe ratio,

$$S_{pt} = \frac{r_{pt} - r_{ft}}{\sigma_{pt}}, \tag{25}$$

relative to the median fund volatility coefficient and Sharpe ratio. After aggregating the annual cell allotments, I empirically estimate a $p$-value to determine whether a significant relation exists between volatility timing and the Sharpe ratio.[10] Panel A of Table 5 shows the results for all funds. The results indicate that higher Sharpe ratios are associated with funds that time conditional market volatility to the greatest extent.

I next examine whether a fund's volatility timing during the previous period predicts its performance during the next period. I estimate performance with the conditional four-index alpha. For each fund, for each nonoverlapping 6-month period, I run the four-index volatility timing regression [Equation (20)]. Based on the volatility coefficient from the previous 6-month period and the conditional four-index alpha from the next 6-month period, I assign funds to cells in two-by-two contingency tables. After aggregating the cell allotments, I empirically estimate a $p$-value to determine whether a significant relation exists between volatility timing in the previous period and the conditional four-index alpha in the next. I also repeat the analysis using the Sharpe ratio instead of the conditional four-index alpha.

Panel B of Table 5 shows the results. The results indicate no relation between volatility timing in the previous 6-month period and performance in the next. This suggests investors cannot use volatility timing estimates to choose funds that will subsequently earn higher risk-adjusted returns. The failure of volatility timing to predict performance might be due to the dynamic relation between market returns and volatility [see Whitelaw (1994)], which could translate into volatility timing payoffs that vary over time, or because $\gamma_{mp}$, estimated using only 6 months of data, is very noisy. In addition, funds that time volatility during one period of time might not time volatility during the next.

**4.3.2 Conditional alphas.** Christopherson, Ferson, and Glassman (1998) point out that when managers adjust portfolio weights in response to information that is not reflected in conditional models, the portfolio weights are conditionally correlated with future returns, given the public information. In such cases, the alpha is a time-varying function of the conditional covariance between the manager's weights and the future returns, given the public information.

[10] I determine the empirical $p$-values by comparing the actual aggregations to a bootstrapped distribution of aggregations constructed under the null hypothesis that there is no relation between volatility timing and risk-adjusted performance. I simulate the null by running the analysis with a randomly ordered volatility time series. This procedure maintains the cross-correlation of fund returns while removing any potential relation between timing and performance. The bootstrap distribution consists of 10,000 replications.

**Table 5**
**Relation between volatility timing and performance**

Panel A: Contemporaneous performance

| | High Sharpe ratio | Low Sharpe ratio | |
|---|---|---|---|
| Volatility timer | 620 | 552 | 1172 |
| Not volatility timer | 551 | 621 | 1172 |
| | 1171 | 1173 | 2344 |
| Chi-square | | | 7.89 ($p = .0587$) |

Panel B: Predicted performance

B1: Sharpe ratio

| | High Sharpe ratio | Low Sharpe ratio | |
|---|---|---|---|
| Volatility timer | 1092 | 1155 | 2247 |
| Not volatility timer | 1153 | 1093 | 2246 |
| | 2245 | 2248 | 4493 |
| Chi-square | | | 3.26 ($p = .2471$) |

B2: Conditional alpha

| | High conditional alpha | Low conditional alpha | |
|---|---|---|---|
| Volatility timer | 1113 | 1133 | 2246 |
| Not volatility timer | 1132 | 1115 | 2247 |
| | 2245 | 2248 | 4493 |
| Chi-square | | | 0.27 ($p = .5320$) |

The table shows the number of funds allotted to each of four cells in two-by-two contingency tables based on the volatility coefficient, $\gamma_{mp}$, in the four-index version of

$$R_{pt} = \alpha_p + \sum_{j=1}^{k} \left[\beta_{0jp} R_{jt} + \beta_{ljp} R_{j,t-1}\right] + \gamma_{mp} \left(\sigma_{mt} - \overline{\sigma}_m\right) R_{mt} + \varepsilon_{pt} \tag{20}$$

and the Sharpe ratio (panel A and panel B1),

$$S_{pt} = \frac{r_{pt} - r_{ft}}{\sigma_{pt}}, \tag{25}$$

or the conditional alpha $\alpha_p$ (panel B2) in Equation (20). In Panel A, the volatility coefficients and Sharpe ratios are annual and contemporaneous. In Panel B, I compute the volatility coefficients over one six-month time period and the Sharpe ratios or conditional alphas over the next six-month time period. I generate the conditional volatility estimates from an EGARCH(1,1) with leverage specification of S&P 500 returns. I determine the p-values empirically by comparing the actual cell allotments to the distribution of 10,000 bootstrapped allotments constructed under the null hypothesis that no relation exists between volatility timing and performance. The sample consists of 230 mutual funds. The sample period is from January 1, 1985 to December 29, 1995.

To examine the conditional nature of fund alphas, I express alpha as a function of conditional volatility. Substituting the time-varying alpha into the volatility timing specification in Equation (20) gives

$$\begin{aligned} R_{pt} \;=\; & \alpha_{0p} + \phi_{mp}(\sigma_{mt} - \overline{\sigma}_m) + \sum_{j=1}^{k}(\beta_{0jp} R_{jt} + \beta_{ljp} R_{j,t-1}) \\ & + \gamma_{mp}(\sigma_{mt} - \overline{\sigma}_m) R_{mt} + \varepsilon_{pt}. \end{aligned} \tag{26}$$

The sign and significance of the $\phi_{mp}$ coefficient indicates whether performance is enhanced during periods of high or low conditional volatility. This regression uses all the data, not just 6 months, to estimate the relation.

Table 6 shows the results from running regression Equation (26) for single-, three-, and four-index specifications using the EGARCH conditional volatility estimates. For all specifications, the conditional component of the alpha for the mutual fund sample is positive and significantly greater than that of the random control sample. This indicates that fund performance is higher during periods of higher than normal conditional volatility, periods of time when volatility timing reduces systematic risk. The inferences are identical when I use implied volatility in regression Equation (26) and compare the $\phi_{mp}$ coefficients of the mutual funds to those of the second random control sample.

This result could suggest one reason for why investors are willing to invest in actively managed mutual funds, despite evidence that they underperform passive benchmarks. By responding to volatility information, funds could provide those investors who do not closely monitor market volatility with a valuable volatility hedge. Alternatively, this result might indicate some more general ability, the dynamics of which could be an interesting subject of future research.

**4.3.3 Interest rate risk.** As mentioned earlier, Scruggs' (1998) two-factor model implies that if a fund lowers its stock market exposure when market volatility is high, it could increase its exposure to other risks, such as interest rate risk. I examine whether funds that time volatility have higher interest rate risk as follows. For each fund, I run the four-index volatility timing regression [Equation (20)] once over the 11-year sample period. I take each fund's interest rate exposure to be the correlation between its monthly returns and the CRSP *USTRET* monthly T-bill returns. For most of the funds in the sample (180 out of 230), this measure of interest rate exposure is negative.

Of the 115 funds with the most negative volatility coefficients, only 51 (44.3%) have more interest rate exposure (a more negative correlation between fund returns and T-bill returns) than the median fund interest rate exposure. Furthermore, the cross-sectional correlation between the volatility coefficients and interest rate exposure is less than $-0.025$. If a downside to volatility timing exists, this evidence suggests it is not related to interest rate risk.

### 4.4 Robustness tests

**4.4.1 Errors-in-the-variables.** As noted earlier, the regressions that use a market volatility estimate as a regressor are subject to an errors-in-the-variables problem. I use the instrumental variables method to examine the robustness of the monthly results to the errors in the variables. As in Fleming (1998), I use Parkinson's (1980) extreme-value estimator of historical

**Table 6**
**Conditional alphas**

| Single-index | Three-index | Four-index |
|---|---|---|
| Mutual fund coefficients | | |
| 0.315 | 0.187 | 0.289 |
| (5.11)** | (3.18)** | (4.80)** |
| Random sample coefficients | | |
| 0.067 | 0.027 | 0.041 |
| (3.17)** | (1.84) | (2.95)** |
| Difference between mutual fund and random coefficients | | |
| 0.249 | 0.160 | 0.248 |
| (3.81)** | (2.65)** | (4.01)** |

The table shows the average daily conditional alpha coefficients, $\phi_{mp}$, for the four-index conditional alpha model,

$$\begin{aligned} R_{pt} &= \alpha_{0p} + \phi_{mp}\left(\sigma_{mt} - \overline{\sigma}_m\right) \\ &\quad + \sum_{j=1}^{k}\left(\beta_{0jp}R_{jt} + \beta_{ljp}R_{j,t-1}\right) \\ &\quad + \gamma_{mp}\left(\sigma_{mt} - \overline{\sigma}_m\right)R_{mt} + \varepsilon_{pt}. \end{aligned} \tag{26}$$

I generate the conditional volatility estimates from an EGARCH(1,1) with leverage specification of S&P 500 returns:

$$\begin{aligned} &\varepsilon_{mt}|\varepsilon_{m,t-1}, \varepsilon_{m,t-2}, \ldots \sim t(0, \sigma_{mt}^2) \\ &\ln\sigma_{mt}^2 - a + a_1\frac{|\varepsilon_{m,t-1}| + \gamma_1\varepsilon_{m,t-1}}{\sigma_{m,t-1}} + b_1\ln\sigma_{m,t-1}^2 \end{aligned} \tag{19}$$

The table shows the mutual fund coefficients, the random sample coefficients, and the difference between the mutual fund and random sample coefficients. $t$-statistics are in parenthesis. I base the significance of the mutual fund and random sample coefficient $t$-statistics on a two-tailed test. I base the significance of the differences between the mutual fund and random sample coefficients on a difference-in-means test. *, ** Significant at the 5% and 1% level, respectively. The mutual fund sample consists of 230 funds, and the random control sample consists of 230 equal-weighted, annually rebalanced portfolios. The sample period is from January 2, 1985 to December 29, 1995.

volatility as an instrument for the monthly market volatility in regression Equation (21). The Parkinson estimator is given by

$$\sigma_{mt} = \sqrt{\frac{0.361}{n_t}\sum_{i=1}^{n_t}\ln(H_i/L_i)^2}, \tag{27}$$

where $H_i$ and $L_i$ are the high and low S&P 500 index levels, respectively, during day $i$, and there are $n_t$ trading days in month $t$. The 0.361 constant arises when the probability distribution of the extreme value is used to compute the expected value of the square of the extreme value.

The instrumental variables results are very similar to the OLS results. For example, with instrumental variables, the differences between the monthly volatility coefficients of the mutual funds and those of the rebalanced random control sample are −3.95, −2.46, and −2.60 with $t$-statistics −7.78, −5.54, and −4.69 for the single-, three-, and four-index models, respectively. (These compare with differences of −3.78, −2.51, and −2.42 with $t$-statistics −7.62, −5.67, and −4.44, respectively, when estimated with OLS.) The results indicate that the inferences are not affected by the errors in the variables.

**4.4.2 Returns timing. Realized market returns.** Given the modest negative correlation between the S&P 500's monthly returns and standard deviation of returns, it could be that funds are successfully timing market returns, and that the timing manifests itself in the volatility coefficients. This would not explain the daily results, however, since the correlation between the S&P 500's daily returns and conditional volatility is so small. Nonetheless, I examine the robustness of the results to returns timing by expressing fund beta as a function of both market volatility and excess market return. The monthly specification is

$$\beta_{mpt} = \beta_{mp0} + \gamma_{mp}(\sigma_{mt} - \overline{\sigma}_m) + \phi_p R_{mt} + \varepsilon_{mpt}, \tag{28}$$

and the daily specification is

$$\begin{aligned} R_{pt} \ &= \ \alpha_p + \beta_{mp0} R_{mt} + \gamma_{mp}(\sigma_{mt} - \overline{\sigma}_m) R_{mt} \\ &\quad + \phi_p R_{mt}^2 + \beta_{lmp} R_{m,t-1} + \varepsilon_{pt}. \end{aligned} \tag{29}$$

Table 7 shows the results from running regression Equations (28) and (29). The daily regressions use the EGARCH conditional volatility estimates, and the monthly regressions use realized standard deviation estimates. The results shown are for all funds and are the differences between the volatility coefficients of the mutual fund sample and the rebalanced random control sample.

The results indicate that adding the market return term to the fund return specification does not materially affect the volatility coefficient. This indicates that the volatility coefficients do not appear because of the nonzero correlation between the monthly S&P 500 returns and volatility.

**Conditional market returns.** The specification in Equation (28) controls for market return timing, but does so without specifically controlling for the strategy used to predict the market. Fund managers who attempt to time the market might use publicly available information [see Ferson and Schadt (1996)]. If the conditional excess return on the market as a function of

**Table 7**
**Volatility and market timing results**

| Daily | | Monthly | | |
|---|---|---|---|---|
| | | | Treynor-Mazuy $\phi_p$ | |
| Volatility $\gamma_{mp}$ | Treynor-Mazuy $\phi_p$ | Volatility $\gamma_{mp}$ | Realized market | Conditional market |
| −3.23 | | −3.78 | | |
| (−6.00)** | | (−7.62)** | | |
| −2.91 | 0.20 | −4.25 | −0.12 | |
| (−5.80)** | (3.30)** | (−6.12)** | (−1.41) | |
| | | −4.49 | | −1.34 |
| | | (−7.84)** | | (−6.16) |

The table shows the daily and monthly volatility coefficients for a single-index specification without a market return term:

Daily
$$R_{pt} = \alpha_p + \beta_{mp0} R_{mt} + \gamma_{mp} \left(\sigma_{mt} - \overline{\sigma}_m\right) R_{mt} + \beta_{lmp} R_{m,t-1} + \varepsilon_{pt} \tag{13}$$

Monthly
$$\beta_{mpt} = \beta_{mp0} + \gamma_{mp} \left(\sigma_{mt} - \overline{\sigma}_m\right) + \varepsilon_{mpt},$$

and with a Treynor–Mazuy (TM) market return term using the actual market returns:

Daily
$$\begin{aligned} R_{pt} &= \alpha_p + \beta_{mp0} R_{mt} + \gamma_{mp} \left(\sigma_{mt} - \overline{\sigma}_m\right) R_{mt} \\ &\quad + \phi_p R_{mt}^2 + \beta_{lmp} R_{m,t-1} + \varepsilon_{pt} \end{aligned} \tag{29}$$

Monthly
$$\beta_{mpt} = \beta_{mp0} + \gamma_{mp} \left(\sigma_{mt} - \overline{\sigma}_m\right) + \phi_p R_{mt} + \varepsilon_{mpt}, \tag{28}$$

and using the conditional market returns

Monthly
$$\beta_{mpt} = \beta_{mp0} + \gamma_{mp} \left(\sigma_{mt} - \overline{\sigma}_m\right) + \phi_p R_{mt}^c + \varepsilon_{mpt}. \tag{31}$$

I compute the conditional market return as a function of five known instruments,

$$R_{mt}^c = R_{m0}^c + \sum_{i=1}^{k} \phi_i z_{i,t-1}. \tag{30}$$

The data represent the difference between the average of all mutual funds and a random control sample. I generate the daily conditional volatility estimates from an EGARCH(1,1) with leverage specification of S&P 500 returns. I take the monthly volatility estimate for month $t$ as the standard deviation of the daily returns that fall within month $t$. $t$-statistics are in parenthesis. I base the significance of the $t$-statistics on a two-tailed difference-in-means test in a direction consistent with skillful timing. *, ** Significant at the 5% and 1% level, respectively. The mutual fund sample consists of 230 funds, and the random control sample consists of 230 equal-weighted, annually rebalanced portfolios. The sample period is from January 2, 1985 to December 29, 1995.

economic instruments is given by

$$R_{mt}^c = R_{m0}^c + \sum_{i=1}^{k} \phi_i z_{i,t-1}, \tag{29}$$

where $z_{i,t-1}$ is the realization of instrument $i$ during month $t-1$, fund systematic risk can then be expressed

$$\beta_{mpt} = \beta_{mp0} + \gamma_{mp}(\sigma_{mt} - \overline{\sigma}_m) + \phi_p R^c_{mt} + \varepsilon_{mpt}. \tag{30}$$

This specification measures volatility timing after specifically controlling for market return timing associated with publicly available instruments. The five instruments analyzed in Section 4.2.2 are used in Equation (30).

Table 7 shows the results from running regression Equation (31) for all funds using realized standard deviation estimates. The table shows the differences between the volatility coefficients of the mutual funds and the rebalanced random control sample. Even after taking into account the time variation in systematic risk that is associated with conditional market return timing, the volatility coefficients remain significant. I conclude that the appearance of volatility timing is not a spurious consequence of market return timing.

**4.4.3 Cash flows.** Ferson and Warther (1996) point out that when a fund receives a large inflow of cash, it might not immediately invest the cash in the stock market. In such instances, as the new cash earns a return that is not highly correlated with the stock market, the systematic risk of the fund could decline. If cash flows are positively correlated with volatility, then even when fund managers are not actively timing volatility, the reductions in systematic risk during periods of high volatility could give the appearance of volatility timing.

To examine whether the observed volatility timing pattern is due to cash flows, I estimate the four-index volatility timing regression for each fund each quarter from 1985 to 1994, the time period over which the cash flow data was available. Then, each quarter, I assign funds to cells in two-by-two contingency tables, based on their volatility coefficient and normalized cash flow, relative to the median fund volatility coefficient and normalized cash flow. For the period from $t$ to $t + 1$, normalized cash flow is defined

$$NCF_{t,t+1} = \frac{TNA_{t+1} - TNA_t(1 + r_{t,t+1})}{TNA_t}, \tag{31}$$

where $TNA_t$ are the fund's total net assets at time $t$ and $r_{t,t+1}$ is the fund's return from time $t$ to $t + 1$. After aggregating the annual cell allotments, I empirically estimate a $p$-value to determine whether a significant relation exists between volatility timing and normalized cash flow. The results, not shown, indicate no relation between volatility coefficients and normalized cash flows ($p$-value $= 0.47$).

**4.4.4 Market crash of 1987.** Around the time of the 1987 market crash, market volatility was inordinately high. The results previously reported in this article would lose much of their appeal if the outliers associated with this unusually volatile, but short, period of time drive their significance.

To examine the impact of the market crash on the results, I repeat the analysis, excluding the 6 months from September 1987 through February 1988. When I exclude these data, the results are stronger. For example, for all funds, the difference between the average daily four-index volatility coefficient of the mutual funds and the rebalanced random control sample drops from $-4.51$ (including the crash) to $-5.49$ (excluding the crash). The difference between the average monthly four-index volatility coefficient of the mutual funds and the rebalanced random control sample drops from $-2.42$ to $-7.40$. Noncrash coefficients for the single- and three-index specifications show similar improvements. I conclude that volatility outliers surrounding the 1987 market crash do not drive the results.

## 5. Conclusions

In this article, I use daily returns for the first time in a mutual fund context to study how managers react to changes in market volatility. Because I examine how managers respond to publicly available information, my study adds to the conditional mutual fund literature that has been gaining increasing importance in recent years. Focusing on volatility timing rather than returns timing, I examine the timing problem from a new perspective.

I show that funds decrease market exposure when market volatility is high. The systematic risk of surviving funds is especially sensitive to market volatility, whereas that of nonsurvivors is not significantly different from randomly formed portfolios of stocks.

Volatility timing has paid off in the form of higher Sharpe ratios without exposing fund investors to additional interest rate risk. Conditional alphas indicate that fund performance is especially enhanced during periods of high conditional volatility, suggesting that actively managed funds can potentially provide investors with a valuable volatility hedge.

My approach in this study illustrates the advantages of analyzing mutual funds in a conditional framework. Conditional analysis allows for richer explanations of the dynamics of mutual fund risk not only by indicating how risk changes, but also by suggesting why it changes. By differentiating between passive effects, effects produced by using public information, and effects from using better than public information, a conditional approach can more clearly differentiate among active managers of varying ability. Ultimately, this could lead to better asset allocation decisions and more equitable compensation schemes.

## Appendix A

**Mutual Fund Sample**

| Maximum capital gains funds | |
|---|---|
| 44 Wall Street Fund* | New Beginning Growth Fd |
| Acorn Fund | New York Venture Fund A |
| Afuture Fund | Omega Fund |
| Am. Capital Comstock A | Oppenheimer Fund A |
| Am. Capital Enterprise A | Oppenheimer Special Fund |
| Am. Capital OTC Sec. | Oppenheimer Time Fund |
| Am. Capital Pace Fund A | Over-the-Counter Securities* |
| Am. Capital Venture Fd | Partners Fund |
| Am. Investors Fund | Pennsylvania Mutual Fund |
| Am. National Growth Fd | Pilot Fund* |
| Columbia Growth Fund | Putnam Vista Fund A |
| Constellation Growth Fund | Putnam Voyager Fund A |
| Cumberland Growth Fund | Quasar Associates |
| Dean Witter Develop. Growth | Quest for Value Fund A |
| Dreyfus Leverage Fund | Scudder Capital Growth Fd |
| Evergreen Fund Y | Scudder Development Fund |
| Explorer Fund | Security Ultra Fund A |
| Fidelity Contrafund | Selected Special Shares |
| Fidelity Magellan Fund | Seligman Capital Fund, Inc. A |
| Financial Dynamics Fund | Sequoia Fund |
| First Investors Discovery Fd | Shearson Aggress. Growth Fd |
| First Investors Fd for Growth | Sigma Capital Shares |
| Founders Growth Fund | SteinRoe Special Fund |
| Founders Special Fund | SteinRoe Universe Fund |
| Franklin Equity Fund | SteinRoe & Farn. Cap. Opp. |
| Fund of America | Strong Total Return Fund |
| Hartwell Leverage Fund | T. Rowe Price New Hor. Fd |
| IDS Discovery Fund | Tudor Fund |
| IDS Progressive Fund | Twentieth Cent. Grwth. Invest. |
| Investment Portfolios-Equity* | Twentieth Cent. Ultra Invest. |
| Kemper Summit Fund | Twentieth Century Vista |
| Keystone S-4 (Aggress. Grwth.) | USAA Mutual Sunbelt Era |
| Lord Abbett Develop. Grwth. Fd | Value Line Leveraged Grwth. |
| Mass. Fin. Emerg. Growth Tr. | Value Line Special Situations |
| Mathers Fund | Vance Sanders Special Fund |
| Neuwirth Fund | Weingarten Equity Fund |
| **Growth funds** | |
| Alpha Fund | Manhattan Fund |
| AMCAP Fund | Mass. Capital Develop. Fd |
| American Growth Fund | Mass. Financial Special Fd |
| American Leaders Fund A | Mass. Invest. Growth Stk. A |
| Axe-Houghton Stock Fund | Meeschaert Cap. Accum. Fd* |
| Babson (D.L) Growth Fund | Merrill Lynch Fd for Tomorr. |
| BLC Growth Fund | Merrill Lynch Phoenix Fund |
| Boston Co. Capital Apprec. | Merrill Lynch Spec. Value Fd |

Growth funds (continued)

| | |
|---|---|
| Boston Co. Special Growth | MidAmerica Mutual Fund |
| Bull & Bear Capital Growth | Midwest .- Bart. Bas. Val. |
| Cardinal Fund | Morgan (W.L.) Growth Fund |
| Carnegie-Cappiello Growth Tr. | Mutual of Omaha Growth* |
| Charter Fund | National Growth Fund |
| Chemical Fund | Nationwide Growth Fund |
| CIGNA Growth Fund | NEL Growth Fund |
| Colonial Growth Shares Inc. A | NEL Retirement Equity Fd |
| Country Capital Growth | New Economy Fund |
| Dean Witter Indust. Val. Sec. | Newton Growth Fund |
| DeVegh Mutual Fund | Nicholas Fund |
| Drexel Burnham Fund | North Star Apollo Fund |
| Dreyfus Fund | North Star Regional Fund |
| Dreyfus Growth Oppor. Fd | Nova Fund |
| Dreyfus Third Century Fund | Oppenheimer Regency Fund |
| Eaton Vance Growth Fund | Oppenheimer Target Fund |
| Eaton Vance Spec. Equities Fd | Phoenix Growth Fd Series A |
| Fidelity Destiny Fund | Phoenix Stock Fund |
| Fidelity Discoverer Fund | Pilgrim Fund |
| Fidelity Mercury Fund | Plitrend Fund |
| Fidelity Trend Fund | Pro Fund |
| FPA Capital Fund, Inc. | Prudential Bache Equity Fd |
| Franklin Growth Series | Prud. Bache Nw. Dec. Grw. Fd |
| Gintel Fund* | Putnam Investors Fund A |
| Good & Bad Times Fund | Royce Value Fund |
| Growth Fund of America | SAFECO Growth Fund |
| Growth Industry Shares | Security Action Fund |
| Guardian Park Avenue Fund | Security Equity Fund A |
| Hancock (John) Growth Fund | Seligman Growth Fund A |
| Hutton Invest. - Emerg. Grwth.* | Sentinel Growth Fund |
| Hutton Invest. – Growth | Sentry Fund |
| IDS Growth Fund | Shearson Appreciation Fund |
| IDS New Dimensions Fund | Sigma Special Fund |
| IDS Variable Payment | Sigma Venture Shares* |
| Investors Research Fund | Smith Barney Equity Fund |
| Ivy Growth Fund A | St. Paul Growth Fund |
| Janus Fund | St. Paul Special Fund |
| JP Growth Fund | State Bond Common Stock Fd |
| Kemper Growth Fund A | State Farm Growth Fund |
| Keystone K-2 (Growth Fd) | SteinRoe Discovery Fund |
| Keystone S-3 (Growth) | SteinRoe & Farn. Stock Fd |
| Legg Mason Value Trust | Sunbelt Growth Fund |
| Lehman Capital Fund | T. Rowe Price Growth Stk. Fd |
| Lehman Opportunity Fund | Twentieth Cent. Select Invest. |
| Leverage Fund of Boston | United Accumulative Fund* |
| Lindner Fund | United New Concepts |
| Loomis-Sayles Cap. Devel. Fd | USAA Mutual Growth Fund |
| Lord Abbett Value Apprec. | Value Line Fund |
| Lowry Market Timing Fund* | Westergard Fund |
| Mairs & Power Growth Fund* | |

| Growth & income funds | |
|---|---|
| ABT Growth and Income Tr. | Mass. Investors Trust A |
| Affiliated Fund | Merrill Lynch Basic Val. Fd |
| Bullock Dividend Shares | National Industries Fund |
| Bullock Fund | National Stock Fund |
| Colonial Fund* | Nicholas II |
| Commerce Income Shares | North Star Stock Fund |
| Corporate Leaders Trust B* | Penn Square Mutual Fund |
| Dean Witter Div. Growth Sec. | Philadelphia Fund |
| Dodge & Cox Stock Fund | Pine Street Fund |
| Eaton & Howard Stock Fund | Pioneer Fund |
| Endowments Inc. | Pioneer II Fund |
| Farm Bureau Growth Fund | Pioneer III Fund |
| Fidelity Fund | Prudential Bache Research Fd |
| Fiduciary Capital Growth Fd | Putnam Fd for Grwth. & Inc. A |
| Financial Industrial Fund | SAFECO Equity Fund |
| Founders Mutual Fund | Scudder Growth & Inc. Fd |
| FPA Paramount Fund, Inc. | Selected American Shares |
| Fundamental Investors Fund | Seligman Comm. Stock Fd A |
| Gintel ERISA Fund | Sentinel Common Stock Fd |
| Guardian Mutual Fund | Shearson Fundamental Value |
| Hamilton Funds, Inc. | Sigma Investment Shares |
| IDS Stock Fund | Sovereign Investors |
| Investment Co. of America | St. Paul Capital Fund |
| Investment Trust of Boston | State Street Investment C |
| Istel Fund | T. Rowe Price Growth & Inc |
| Ivy Institutional Investors | Trustees Comm.-U.S. Eq. Port. |
| Keystone S-1 (High Grade) | Washington Mutual Investors |
| Lehman Investors Fund | Windsor Fund |
| Mass. Financial Develop. Fd | |

* Indicates the daily data could not be reconciled with the monthly Morningstar or Micropal samples, and the fund was dropped from the sample.

## Appendix B

### GARCH Specification

In addition to a regular GARCH specification, I consider several other GARCH models, including exponential GARCH (EGARCH), power GARCH (PGARCH), and threshold GARCH (TGARCH). Besides using specifications with one autoregressive and one moving average term [e.g., GARCH(1,1)], I also consider (1,2), (2,1), and (2,2) specifications. I model each specification with and without leverage terms and using Gaussian distributions for the error terms as well as generalized Gaussian distributions, $t$-distributions, and double exponential distributions.

Since there is no theoretical rationale for choosing one specification over another, I choose the model that best fits the data: the EGARCH(1,1) specification with a leverage term and $t$-distributed errors. This specification is among those with the largest AIC, BIC, and likelihood test statistics, and of those with higher AIC, BIC, or likelihood statistics, the EGARCH specification is the only one that completely eliminates (at standard statistical levels) correlation in the 1-day lag in squared residuals for the specification in

**Table B.1**
**Summary of EGARCH(1,1) model of daily S&P 500 returns**

Panel A: Estimated coefficients

| Parameter | Value | $t$-statistic |
|---|---|---|
| $c$ | 0.00048 | 3.79 |
| $a$ | −0.436 | −5.23 |
| $a_1$ | 0.093 | 5.76 |
| $b_1$ | 0.966 | 133 |
| $\gamma_1$ | −0.538 | −3.73 |

Panel B: Test statistics

| | Jarque-Bera normality test for S&P 500 returns | Ljung-Box test for standardized residuals | Ljung-Box test for squared standardized residuals |
|---|---|---|---|
| Statistic | 6692 | 17.08 | 8.16 |
| $p$-value | 0.00 | 0.15 | 0.77 |

Panel A shows the estimated coefficients and test statistics for an EGARCH(1,1) with leverage term specification of daily S&P 500 returns:

$$
\begin{aligned}
&r_{mt} - r_{ft} = c_m + \varepsilon_{mt} \\
&\varepsilon_{mt}|\varepsilon_{m,t-1}, \varepsilon_{m,t-2}, \ldots \sim t(0, \sigma_{mt}^2) \\
&\ln \sigma_{mt}^2 = a + a_1 \frac{|\varepsilon_{m,t-1}| + \gamma_1 \varepsilon_{m,t-1}}{\sigma_{m,t-1}} + b_1 \ln \sigma_{m,t-1}^2
\end{aligned} \tag{19}
$$

Panel B shows the test statistics associated with the EGARCH estimation. I assume error terms are $t$-distributed. The sample period is from January 2, 1985 through December 29, 1995.

Equation (19). Table B.1 summarizes the coefficient estimates and test statistics of the chosen specification.

**References**

Backus, D. K., and A. W. Gregory, 1993, "Theoretical Relations Between Risk Premiums and Conditional Variances," *Journal of Business & Economic Statistics*, 11, 177–185.

Becker, C., W. E. Ferson, D. Myers, and M. Schill, 1999, "Conditional Market Timing with Benchmark Investors," *Journal of Financial Economics*, 52, 119–148.

Bollerslev, T., R. Y. Chou, and K. F. Kroner, 1992, "ARCH Modeling in Finance," *Journal of Econometrics*, 52, 5–59.

Brauer, R. J., P. A. Hays, and D. E. Upton, 1987, "Parameter Instability in Mutual Fund Portfolios: A Shifting Regimes Test," *Quarterly Journal of Business and Economics*, 26, 50–62.

Breen, W., L. R. Glosten, and R. Jagannathan, 1989, "Economic Significance of Predictable Variations in Stock Index Returns," *Journal of Finance*, 44, 1177–1189.

Brown, K. C., W. V. Harlow, and L. Starks, 1996, "Of Tournaments and Temptations: An Analysis of Managerial Incentives in the Mutual Fund Industry," *Journal of Finance*, 51, 85–110.

Brown, S. J., and W. Goetzmann, 1995, "Performance Persistence," *Journal of Finance*, 50, 679–698.

Busse, J. A., 1999, "Another Look at Mutual Fund Tournaments," working paper, Emory University.

Campbell, J. Y., 1987, "Stock Returns and the Term Structure," *Journal of Financial Economics*, 18, 373–399.

Carhart, M. M., 1997, "On Persistence in Mutual Fund Performance," *Journal of Finance*, 52, 57–82.

Chang, E. C., and W. G. Lewellen, 1984, "Market Timing and Mutual Fund Performance," *Journal of Business*, 57, 57–72.

Chen, Z., and P. J. Knez, 1996, "Portfolio Performance Measurement: Theory and Applications," *Review of Financial Studies*, 9, 511–555.

Christopherson, J. A., W. E. Ferson, and D. A. Glassman, 1998, "Conditioning Manager Alphas on Economic Information: Another Look at the Persistence of Performance," *Review of Financial Studies*, 11, 111–142.

Daniel, K., M. Grinblatt, S. Titman, and R. Wermers, 1997, "Measuring Mutual Fund Performance with Characteristic-Based Benchmarks," *Journal of Finance*, 52, 1035–1058.

Del Guercio, D., and P. A. Tkac, 1998, "The Determinants of the Flow of Funds of Managed Portfolios: Mutual Funds versus Pension Funds," working paper, University of Oregon.

Dimson, E., 1979, "Risk Measurement when Shares are Subject to Infrequent Trading," *Journal of Financial Economics*, 7, 197–226.

Elton, E. J., M. J. Gruber, and C. R. Blake, 1996a, "The Persistence of Risk-Adjusted Mutual Fund Performance," *Journal of Business*, 69, 133–158.

Elton, E. J., M. J. Gruber, and C. R. Blake, 1996b, "Survivorship Bias and Mutual Fund Performance," *Review of Financial Studies*, 9, 1097–1120.

Elton, E. J., M. J. Gruber, S. Das, and M. Hlavka, 1993, "Efficiency with Costly Information: A Reinterpretation of Evidence from Managed Portfolios," *Review of Financial Studies*, 6, 1–22.

Engle, R. F., D. Lilien, and R. Robins, 1987, "Estimating Time Varying Risk Premia in the Term Structure: The ARCH-M Model," *Econometrica*, 55, 391–407.

Fama, E. F., 1972, "Components of Investment Performance," *Journal of Finance*, 27, 551–567.

Fama, E. F., and K. R. French, 1993, "Common Risk Factors in the Returns on Bonds and Stocks," *Journal of Financial Economics*, 33, 3–56.

Fama, E. F., and K. R. French, 1996, "Multifactor Explanations of Asset Pricing Anomalies," *Journal of Finance*, 51, 55–84.

Ferson, W. E., and R. W. Schadt, 1996, "Measuring Fund Strategy and Performance in Changing Economic Conditions," *Journal of Finance*, 51, 425–461.

Ferson, W. E., and V. A. Warther, 1996, "Evaluating Fund Performance in a Dynamic Market," *Financial Analysts Journal*, 52, 20–28.

Ferson, W. E., and C. R. Harvey, 1999, "Conditioning Variables and the Cross Section of Stock Returns," *Journal of Finance*, 54, 1325–1360.

Ferson, W. E., S. Sarkissian, and T. Simin, 1999, "The Alpha Factor Asset Pricing Model: A Parable," *Journal of Financial Markets*, 2, 49–68.

Fleming, J., 1998, "The Quality of Market Volatility Forecasts Implied by S&P 100 Index Option Prices," *Journal of Empirical Finance*, 5, 317–345.

French, K. R., G. W. Schwert, and R. F. Stambaugh, 1987, "Expected Stock Returns and Volatility," *Journal of Financial Economics*, 19, 3–30.

Glosten, L. R., R. Jagannathan, and D. E. Runkle, 1993, "On the Relation between the Expected Value and the Volatility of the Nominal Excess Return on Stocks," *Journal of Finance*, 48, 1779–1801.

Grinblatt, M., and S. Titman, 1989, “Portfolio Performance Evaluation: Old Issues and New Insights,” *Review of Financial Studies*, 2, 393–421.

Gruber, M. J., 1996, “Another Puzzle: The Growth in Actively Managed Mutual Funds,” *Journal of Finance*, 51, 783-810.

Henriksson, R. D., 1984, “Market Timing and Mutual Fund Performance: An Empirical Investigation,” *Journal of Business*, 57, 73–96.

Ippolito, R., 1992, “Consumer Reaction to Measures of Poor Quality: Evidence from the Mutual Fund Industry,” *Journal of Law and Economics*, 35, 45–70.

Jagannathan, R., and R. A. Korajczyk, 1986, “Assessing the Market Timing Performance of Managed Portfolios,” *Journal of Business*, 59, 217–235.

Jensen, M. C., 1968, “The Performance of Mutual Funds in the Period 1945–1964,” *Journal of Finance*, 23, 389–416.

Jensen, M. C., 1969, “Risk, the Pricing of Capital Assets, and the Evaluation of Investment Portfolios,” *Journal of Business*, 42, 167–247.

Jensen, M. C., 1972, “Optimal Utilization of Market Forecasts and the Evaluation of Investment Performance,” in G. P. Szego and K. Shell (eds.), Mathematical Methods in Investment and Finance. Amsterdam: North Holland.

Koski, J., and J. Pontiff, 1999, “The Use of Derivatives by Mutual Funds,” *Journal of Finance*, 54, 791–816.

Kryzanowski, L., S. Lalancette, and M. C. To, 1997, “Performance Attribution using an APT with Prespecified Macrofactors and Time–Varying Risk Premia and Betas,”*Journal of Financial and Quantitative Analysis*, 32, 205–224.

Merton, R. C., 1981, “On Market Timing and Investment Performance. I. An Equilibrium Theory of Value for Market Forecasts,” *Journal of Business*, 54, 363–406.

Merton, R. C., and R. D. Henriksson, 1981, “On Market Timing and Investment Performance II: Statistical Procedures for Evaluating Forecasting Skills,” *Journal of Business*, 54, 513–534.

Miller, T. W., and N. Gressis, 1980, “Nonstationarity and Evaluation of Mutual Fund Performance,” *Journal of Financial and Quantitative Analysis*, 15, 639–654.

Nelson, D. B., 1991, “Conditional Heteroskedasticity in Asset Returns: A New Approach,” *Econometrica*, 59, 347–370.

Parkinson, M., 1980, “The Extreme Value Method for Estimating the Variance of the Rate of Return,” *Journal of Business*, 53, 61–66.

Rubinstein, M., 1973, “A Comparative Statics Analysis of Risk Premiums,” *Journal of Business*, 46, 605–615.

Scholes, M., and J. Williams, 1977, “Estimating Betas from Nonsynchronous Data,” *Journal of Financial Economics*, 5, 309–328.

Scruggs, J. T., 1998, “Resolving the Puzzling Intertemporal Relation between the Market Risk Premium and Conditional Market Variance: A Two-Factor Approach,” *Journal of Finance*, 53, 575–603.

Sharpe, W. F., 1992, “Asset Allocation: Management Style and Performance Measurement,” *Journal of Portfolio Management*, 18, 7–19.

Sirri, E. R., and P. Tufano, 1998, “Costly Search and Mutual Fund Flows,” *Journal of Finance*, 53, 1589–1622.

Stein, C., 1973, "Estimating the Mean of a Multivariate Normal Distribution," Proceedings of the Prague Symposium on Asymptotic Statistics, Prague.

Treynor, J. L., and K. Mazuy, 1966, "Can Mutual Funds Outguess the Market?" *Harvard Business Review*, 44, 131–136.

Wiesenberger Inc., *Mutual Funds Panorama*, 1985–1994, Wiesenberger Investment Companies, New York.

Whitelaw, R. F., 1994, "Time Variations and Covariations in the Expectation and Volatility of Stock Market Returns," *Journal of Finance*, 49, 515–541.

Whitelaw, R. F., 1997, "Stock Market Risk and Return: An Equilibrium Approach," working paper, New York University.