# Behavior and Performance of Investment Newsletter Analysts*


Alok Kumar
*Cornell University*
*Department of Economics*
ak272@cornell.edu

Vicente Pons
*Yale University*
*School of Management*
vicente.pons@yale.edu


November 2002
(First version: June 2001)


**Address for Correspondence:* Alok Kumar, Department of Economics, Uris Hall, Cornell University, Ithaca, NY 14853. *email:* ak272@cornell.edu.


We would like to thank Mark Hulbert of *Hulbert Financial Digest* (http://www.hulbertdigest.com) for providing the data on investment newsletter recommendations. We also thank Bruno Biais, Arturo Bris, William Goetzmann, Raghavendra Rau, Martin Weber, Joseph Zechner and seminar participants at the Behavioral Finance conferences at the University of Mannheim and the Scottish Institute for Research in Finance, the European Finance Association meeting in Berlin, and the European Economics Association meeting in Venice. Pons is grateful to Fundación Ramón Areces for financial support. We are responsible for all remaining errors and omissions.

# Behavior and Performance of Investment Newsletter Analysts

## Abstract

This study analyzes the behavior and performance of 353 investment newsletters that make asset allocation recommendations during a period covering more than 21 years (June 1980 – November 2001). Newsletters change their asset mix between equity and cash using relatively simple rules that are strongly influenced by past market returns while macro-economic variables have only a very weak influence on their asset allocation decisions. On aggregate, newsletters do not outperform a passive investment strategy but there exist well-defined newsletter sub-groups (active newsletters, contrarian newsletters) that exhibit market-timing ability. Furthermore, when we examine the recommendations of individual newsletters at a higher frequency (daily as opposed to monthly), we find considerable evidence of timing-ability. There is also evidence of persistence in newsletters' performance and a trading strategy that follows the average recommendations of newsletters that have performed well in the past 10 months is capable of outperforming the market on a risk-adjusted basis (the annual over-performance is 2.56%).

**Keywords:** Market-timing, Performance persistence, Active investing, Investment newsletters, Positive-feedback trading.

**JEL Classification:** G11, G14.

Market timing involves predicting correctly the movements of the market. A successful timer recommends an increase (decrease) in the equity component of his investment portfolio before the market rises (falls). What market and macro-economic conditions prompt market-timers to change the asset mix between equity and cash? Can these market-timers outperform a passive investment strategy and more importantly, is there any evidence of persistence in their performance (i.e., do "winners" repeat)? Can one devise a profitable trading strategy to exploit persistence in performance?

In this paper, we analyze the behavior and performance of 353 investment newsletter analysts[1] (market-timers) that make asset allocation recommendations during a period covering more than 21 years (June 1980 – November 2001). First, we examine the asset allocation decisions of these newsletters and investigate if there is any evidence of similarity in their asset allocation strategies. Our results suggest that newsletter analysts change their asset mix between equity and cash using relatively simple rules. Most newsletters are of the positive-feedback type (DeLong, Shleifer, Summers, and Waldmann 1990) – they increase (decrease) the equity allocation following a rise (fall) in the market. However, there is also a small group of newsletters that act on the basis of contrarian beliefs. Furthermore, macro-economic variables have a only very weak influence on their asset allocation decisions. This finding is quite surprising since several studies[2] suggest that macro-economic variables may have the power to predict future equity and bond returns as well as their volatility.

Next, we examine the performance and market-timing ability of newsletters at three different levels: (i) individual newsletter level, (ii) sub-group level, and (iii) aggregate level covering the entire set of newsletters. We use seven different (but related) performance and market-timing measures and consistent with previous newsletter studies (Graham and Harvey 1996, Jaffe and Mahoney 1999, Metrick 1999), we find that, at an aggregate level, newsletters neither exhibit superior performance nor an ability to successfully time the market. However, certain well-defined sub-groups of newsletters do have market-timing ability. We find evidence of market-timing ability among newsletters that follow a very short-term (weekly) contrarian strategy and also among newsletters that provide equity allocation rec-

[1]Since several newsletters have more than one explicitly stated investment strategy, the unit of analysis in this paper is a "newsletter strategy". Throughout the paper we use the terms "newsletter", "newsletter strategy", and "newsletter analyst" synonymously to refer to a specific newsletter strategy.

[2]See Chen, Roll, and Ross (1986), Campbell (1987), Fama and French (1988), Breen, Glosten, and Jagannathan (1989), Schwert (1990), Ferson and Harvey (1993), Glosten, Jagannathan, and Runkle (1993), and Pesaran and Timmermann (1995), among others.

ommendations on a more frequent (2-20 days) basis.

When we examine the equity recommendations of *individual* newsletters at a higher frequency (daily as opposed to monthly), we find considerable evidence of market-timing ability. Out of 329 newsletters for which we have at least one year of recommendations available, 128 (39%) outperform the market on a risk-adjusted basis (i.e., they have a Sharpe ratio greater than the market). The Jensen's alpha is also positive for 212 (64%) newsletters but most of these estimates (both positive and negative estimates) are statistically insignificant. Measuring newsletter performance using the two Graham-Harvey measures (Graham and Harvey 1997), we find that 83 (25%) newsletters exhibit evidence of superior ability under the first measure while 75 (23%) newsletters exhibit evidence of superior ability under the second measure.

Examining the market-timing abilities of newsletters, we find that 81 (24%) newsletters have a positive and significant (at 0.05 level) Treynor-Mazuy measure (Treynor and Mazuy 1966), 65 (20%) have a positive and significant (at 0.05 level) parametric Henriksson-Merton measure of market timing, and 150 (46%) have a non-parametric Henriksson-Merton measure (Henriksson and Merton 1981) greater than 0.50. Using Monte Carlo simulations we find that the number of "star newsletters" (i.e., individual newsletters that are successful in timing the market) is greater than the number one expects to find by chance. These results are consistent with studies (Kon 1983, Lee and Rahman 1990, Bollen and Busse 2001) which show that although mutual funds as a group are unable to outperform the market on a risk-adjusted basis, "star" individual fund managers do exist.

Finally, we examine persistence ("hot hands") in newsletter performance. We find that newsletters with superior performance during the past 9 months (i.e., "winners") outperform newsletters that perform poorly during the past 9 months (i.e., "losers") by 3.5% in the 10 months following the portfolio formation period. Beyond 10 months, the performance differential between winners and losers disappears.

To exploit persistence in newsletters' performance, we construct a trading strategy where we follow the equity recommendations of newsletters that have performed well in the recent past. We find that our persistence-based trading strategy is able to outperform the market on a risk adjusted basis. According to the Jensen's alpha measure, our trading strategy outperforms the market by 2.56% on an annual basis. The Sharpe ratio of the strategy is 30% higher than the market and it also has positive and significant Graham-Harvey measures (GH1 = 0.15 and GH2 = 0.19). Furthermore, the market-timing measures (Henriksson-Merton and Treynor-Mazuy) are positive and significant (at 0.05 level) for our trading strategy (HM = 0.87 and TM = 0.22).

The rest of the paper is organized as follows: in the next section we position our paper in the appropriate research context. In Section II, we briefly describe the newsletters database. A characterization of the behavior of newsletter analysts follows in Section III. In this section, we also examine some potential determinants of newsletters' equity allocation decisions. Newsletters' performance is investigated in Section IV. In Section V, we examine persistence in newsletter performance and devise a trading strategy that benefits from such persistence. We conclude in Section VI with a summary of our main results.

## I Related Research

Due to limited data availability, investment newsletters have not received as much attention by the academic community as other groups of market-timers. However, there are certain notable exceptions. Graham and Harvey (1996, 1997) analyze the asset allocation recommendations of newsletters and find no evidence of timing ability at an aggregate level. Jaffe and Mahoney (1999) and Metrick (1999) evaluate the stock picking abilities of newsletters using a different version of the newsletters database where in addition to recommending a specific equity allocation, newsletters either explicitly recommend a stock portfolio or they provide a ranked list of desirable stocks that can be used to construct a stock portfolio. Both these studies find that, at an aggregate level, newsletters exhibit very weak stock-picking and market-timing abilities. These studies also document some evidence of performance persistence among newsletters. In a related study, Graham (1999) uses the newsletters database to empirically test a model of herding and finds that a high reputation, low ability newsletter is more likely to herd on the "Value Line" investment newsletter which is explicitly chosen as the market leader.

Our paper differs from previous studies on investment newsletters and active investing in several significant ways. First, previous newsletter studies have primarily focused on the timing-ability of newsletters and they do not examine the determinants of their asset allocation decisions. Without any knowledge about the information sets used by the newsletters, their asset allocation strategies cannot be identified accurately. Nonetheless, using a set of variables that are likely to influence newsletters' asset allocation decisions, we are able to characterize their behavior in a parsimonious manner.

Second, most previous studies have used monthly data to measure performance even when recommendations are often made at a lower frequency. A growing number of studies (Goetzmann, Ingersoll, and Ivković 2000, Barber, Lehavy, McNichols, and Trueman 2001, Bollen and Busse 2001, Busse 2001, Chance and Hemler 2001) recommend the use of high-frequency daily data rather than weekly or monthly data to measure performance and market-timing ability. These studies show that the frequency with which recommendations are observed can affect conclusions about market-timing ability in a significant manner. For instance, using daily data, Chance and Hemler (2001) find significant unconditional and conditional market-timing ability. However, when recommendations are observed at a monthly frequency, superior timing-ability weakens considerably.

We find that market returns a few days immediately preceding the recommendation date has a strong influence on the asset allocation decisions of newsletters. This finding suggests that ignoring intra-month recommendations is likely to provide an imprecise measure of their market-timing abilities. Thus, we examine the performance and market-timing ability of newsletters at a daily frequency. Our results support and provide an explanation for the argument in favor of using high frequency data when measuring the performance of active investors.

Third, we focus on heterogeneity in newsletters' performance and market-timing ability. Even in the absence of superior performance and market-timing ability at an aggregate level, individual outperformers ("star newsletters") may exist (Kon 1983, Lee and Rahman 1990, Bollen and Busse 2001). We measure the performance and timing-ability of each individual newsletter to determine if there exists a significant number of individual newsletters (more than one expects to find by chance) that exhibit superior performance and market-timing ability.

Fourth, our dataset covers a longer period of time (over 20 years) and provides an explicit account of the decisions of a large number (more than 350) of "experts". This extensive dataset allows us to provide a more robust measure of newsletters' behavior and their ability to successfully time the market.

Finally, the unbiased nature of our newsletters dataset allows us to identify genuine investment ability in a way that is usually not possible with other datasets that are generated under restrictive conditions. Most studies that examine the performance of active investors focus exclusively on *realized* returns. A natural question that arises then is: are we measuring true, unconstrained performance? Investment newsletters are arguably free from the conflicts of interest that affect the recommendations of stock analysts (Rajan and Servaes 1997, Michaely and Womack 1999, Krigman, Shaw, and Womack 2001, Bradley, Jordan, and Ritter 2002) and also from the impact of uninformed, liquidity-motivated trading (Edelen 1999) that may negatively bias the performance of mutual funds[3] and pension funds.

## II Data and Sample Selection

The main ingredient to this study is an investment newsletters database which consists of asset allocation recommendations made by a large number of investment newsletters. The database consists of a total of 45,673 recommendations provided by 525 different newsletter strategies during a 21-year period (June 1980 - November 2001). The newsletters database is compiled by Mark Hulbert of *Hulbert Financial Digest* and it contains recommendations from newsletters such as the Value Line Investment Survey, Dow Theory Letters, Granville Market Letter, Elliott Wave Theorist, etc.

The newsletters discuss the prevailing economic conditions and provide market-timing advice to their subscribers. A newsletter recommendation is an explicit statement about the fraction of the investment portfolio that should be allocated to the risky (the equity component) and the riskless (the cash component) asset classes. A valid recommendation has Long Equity + Short Equity +TBills − Margin = 100. Due to the presence of margin accounts, the recommended allocation in the risky asset class can be more than 100%. In this case, the allocation to cash is obviously negative.

Newsletters are published at different frequencies. Some newsletters also offer recommendation updates via a telephone "hotline". A new recommendation is entered in the database

[3] In mutual fund studies, fund flows correlated with subsequent fund returns can have a dilution impact on the performance of open-end funds (Greene and Hodges 2002). Beyond this dilution impact, fund flows affect other mutual fund direct and indirect costs, such as processing fees, increased cash holdings, and transaction costs (Wermers 2000).

on the day a newsletter is received in the mail and in addition, all newsletter telephone hotlines are checked frequently to obtain updated recommendations. A newsletter is not removed from the database after it ceases to exist, so this database is free of any survivorship bias.

Simple filtering rules are applied to "clean" the data. We exclude newsletters that have less than 10 recommendations (172 newsletters, 627 recommendations) or keep the recommended equity allocation fixed. We also identify and remove "allocation duplicates", i.e., successive recommendations by a specific newsletter which simply reiterates the previous equity allocation. These duplicates arise because Mark Hulbert sometimes adds a recommendation on the first and/or the last day of a year. Allocation duplicates also arise when a newsletter recommends a different set of stocks but keeps the overall allocation to equity unchanged. Since our objective is to analyze newsletters' recommended allocations between equity and the riskless asset (i.e., their market-timing skill), such equity allocation reiterations are not informative. We remove 14,433 duplicate recommendations from our sample. A clean database consisting of 30,626 recommendations covering 353 newsletters is used in this study.

Newsletters make on average 87 (median is 42) recommendations during their life-time and stay active for an average of 7 (median is 6) years. On average, newsletters provide a recommendation approximately once per month. In Table I, we present the summary statistics of the newsletters database and in Figure 1 we plot the time-series of newsletters' average recommended allocation in equity during the June 1980 - November 2001 sample period. For comparison, we also show the monthly market return time-series and its volatility. During our sample period, the average monthly equity allocation is approximately 70% with a standard deviation of 9%.

## III Behavior of Investment Newsletter Analysts

### *III.A Unconditional Newsletter Behavior*

The asset allocation task faced by newsletters involves two key decision variables: (i) change in the recommended equity allocation ($\Delta E = E(t_2) - E(t_1)$) and (ii) time between two recommendations ($\Delta t = t_2 - t_1$). Together with the recommended allocation in equity ($E$) at time $t$, $(E, \Delta E, \Delta t)$ constitute an *allocation strategy* which defines a 3-dimensional "strategy space" in which the dynamics (behavior) of each newsletter evolves. A sequence of allocation strategies (i.e., a trajectory in the strategy space) characterizes the unconditional behavior of a newsletter.

Using a clustering algorithm (Hartigan 1975), a parsimonious representation of the unconditional newsletter behavior is obtained. We find that newsletters in our sample use only a handful of distinct allocation strategies. Table II describes the 10 main allocation strategies employed by the newsletters. They reflect the "intrinsic" styles of newsletters, independent of the existing market conditions.

Most newsletters recommend a certain level of allocation in equity ($E_i$) and change the allocations around this fixed value. This equity weight forms a "natural attractor" for the newsletter and there are additional "attractors" at $0, -100$, and $+100$. The allocation in equity recommended by a typical newsletter bounces among the four attractors, three generic and one newsletter specific. Transitions from $0 \rightarrow 100$, $100 \rightarrow 0$, $-100 \rightarrow 100$ and $100 \rightarrow -100$ are common but surprisingly very few newsletters recommend a 100% short position in equity when they are holding a 100% position in cash and vice versa, i.e., transitions from $0 \rightarrow -100$ and $-100 \rightarrow 0$ are rare. In addition, there is a significant degree of similarity in the manner in which a newsletter moves from one attractor to another. "Jumps" (strategies 1,2,3,4 and 7) and very small changes (strategies 8,9 and 10) are common while a moderate change (strategies 5 and 6) is recommended less frequently.

Using the 10 allocation strategies, six broad newsletter styles are identified (see Figure 2). These six styles represent three distinct behavioral patterns. Newsletters belonging to type I use a mix of strategies and represent "uniform behavior". The majority of newsletters (75 of them) are of type I. Types II and III represent "extreme behaviors". Newsletters under this category recommend "jumps" in equity weights and switch equity allocations among $0, +100, +200, -100, -200$. 34 newsletters belong to type II and 48 belong to type III. Newsletter types IV, V and VI represent "conservative" behavior where the newsletters usually recommend "small changes" in equity weights. The number of newsletters belonging to groups IV, V and VI are 71, 65 and 60 respectively. In Figure 2, the number in parenthesis for each newsletter type is its entropy[4] which measures the degree of predictability in a newsletter's behavior. The higher the entropy of a newsletter, the lower is its predictability, and hence, the higher is the "behavioral complexity". With 10 allocation strategies, the entropy for the newsletter type with the largest possible degree of uncertainty is 3.32 ($-10 \times \frac{1}{10} \times \log_2 \frac{1}{10}$) which corresponds to a uniform distribution.

### *III.B Conditional Newsletter Behavior*

Without any explicit knowledge about the information sets used by the newsletters, their asset allocation strategies cannot be identified accurately. However, given the strong degree of similarity in newsletters' behavior, it is likely that they respond to common economy-wide signals. We consider two sets of potential determinants of newsletters' equity allocation changes: (i) past market returns, and (ii) innovations in macro-economic variables. Newsletters may follow returns-based trading rules or they may use the information contained in macroeconomic indicators that are known to predict future equity and bond returns and volatility.[5]

Following Pesaran and Timmermann (1995) and Ferson and Schadt (1996), we consider innovations in the following four macro-economic variables as potential determinants of newsletters' equity allocation changes: (i) **STIR**: the level of short-term interest rate (annualized 30-day Treasury bill yield), (ii) **TS**: the term-spread which provides a measure of the term structure; it is the difference between the yield of a constant-maturity 10-year Treasury bond and the yield of a 3-month Treasury bill, (iii) **VS**: the value-spread which represents the difference between the yields of Moody's BAA-rated corporate bond and AAA-rated corporate bond, and (iv) **DY**: the dividend yield of the S&P 500 index.

First, to gain insight into the conditional behavior of newsletters, we examine the market

[4] If $X$ is a random variable which takes on a finite set of values ($X_i, i = 1, 2, \ldots, N$) according to a probability distribution $p(X)$, then the entropy (H) of this probability distribution is given by $H(X) = -\sum_{i=1}^{N} p(X_i) \log_2(p(X_i))$. The entropy is undefined if any of the probabilities is zero.

[5] Chen, Roll, and Ross (1986) find that innovations in the spread between long and short interest rates, expected and unexpected inflation, industrial production, and the spread between high- and low-grade bonds, are risks that are rewarded in the stock market. Other studies (Campbell 1987, Breen, Glosten, and Jagannathan 1989, Ferson 1989, Glosten, Jagannathan, and Runkle 1993) document that interest rates are useful in forecasting the sign as well as the variance of the excess return on stocks. Ferson and Harvey (1993) show that most of the predictability in equity market returns is due to time variation in the global economic risk premia. Fama and French (1988) argue that the power of dividend yields to forecast stock returns increases with the return horizon.

conditions prior to changes in newsletter recommended equity allocation. The entire set of equity allocation changes in our sample is first divided into two groups: (i) positive equity allocation changes, and (ii) negative equity allocation changes. Each of these groups are further divided into quartiles and a mean cumulative raw return path is obtained for each of these 8 groups (see Figure 3). We find that an increase in equity allocation is preceded by a sequence of positive market returns while a decrease in equity allocation is preceded by a sequence of negative market returns. Furthermore, the sharper the rise (fall) in the market, the larger is the increase (decrease) in the recommended equity allocations.

To examine the relation between past market returns and equity allocation changes more formally, we obtain the distributions of the mean $k$-day market return immediately preceding increases and decreases in newsletter recommended equity allocation. The mean 10-day market return prior to an increase in the equity allocation is 0.88% while the mean 10-day market return prior to a recommended equity decrease is -0.59%. Using the Kolmogorov-Smirnov test[6] we find that the two mean return distributions are significantly different from each other ($p$-val $< 0.001$). These results suggest that, at an aggregate level, newsletters exhibit positive-feedback behavior (DeLong, Shleifer, Summers, and Waldmann 1990).

A similar analysis is carried out using macro-economic variables. Figure 5 shows the distributions of the quarterly change in the quality spread preceding increases and decreases in newsletter recommended equity allocation. In this case, the Kolmogorov-Smirnov test reveals that there is no difference between the two quarterly change distributions.[7] This

[6]The Kolmogorov-Smirnov (KS) test (Press, Teukolsky, Vetterling, and Flannery 1992) is a non-parametric procedure that makes no assumptions about the underlying population distributions and compares the entire distribution instead of a distribution parameter. To compare two distributions (say $S_{N_1}(x)$ and $S_{N_2}(x)$), the KS-test uses the maximum value of the absolute difference between the two cumulative distributions as a test statistic:

$$D_{\text{observed}} = \max_{-\infty < x < \infty} \parallel S_{N_1}(x) - S_{N_2}(x) \parallel$$

A large value of $D_{\text{observed}}$ provides a strong evidence against the null hypothesis of no difference between the two cumulative distributions. The significance level (p-value) of $D_{\text{observed}}$ is approximately given by:

$$\text{Prob}\{D_{\text{actual}} > D_{\text{observed}}\} = Q_{\text{KS}}(D_{\text{observed}}(\sqrt{N}_e + 0.12 + \frac{0.11}{\sqrt{N}_e}))$$

where

$$N_e = \frac{N_1 N_2}{N_1 + N_2} \qquad Q_{\text{KS}}(x) = 2\sum_{n=1}^{\infty}(-1)^{(n-1)}e^{-2n^2x^2} \qquad Q_{\text{KS}}(0) = 1, Q_{\text{KS}}(\infty) = 0$$

$N_e$ is the effective number of data points and $Q_{\text{KS}}(x)$ is a monotonically decreasing function.

[7]Due to space constraints, we do not report the distributions for the other three macro-economic variables

suggests that newsletters are less responsive to innovations in macro-economic variables.

To examine the relative roles of market returns and macro-economic variables in newsletters' asset allocation decisions, we estimate a pooled regression specification using newsletter- and year-fixed effects (Greene 1997, pp. 615-623). We posit the following regression specification:

$$\begin{aligned}
\Delta\text{Equity}_{it} &= b_1\text{S\&P500}_t + b_2\text{S\&P500}_{t-1} + b_2\text{S\&P500}_{t-2} + b_3\text{S\&P500}_{t-3} \\
&+ b_4\text{S\&P500}_{t-4} + b_5\text{S\&P500}_{t-5} \\
&+ b_6\text{S\&P500}_{t-20:t-1} + b_7\text{S\&P500}_{t-60:t-1} \\
&+ b_8\Delta\text{STIR}_{t-5:t-1} + b_9\Delta\text{STIR}_{t-20:t-1} + b_{10}\Delta\text{STIR}_{t-60:t-1} \\
&+ b_{11}\Delta\text{TS}_{t-5:t-1} + b_{12}\Delta\text{TS}_{t-20:t-1} + b_{13}\Delta\text{TS}_{t-60:t-1} \\
&+ b_{14}\Delta\text{QS}_{t-5:t-1} + b_{15}\Delta\text{QS}_{t-20:t-1} + b_{16}\Delta\text{QS}_{t-60:t-1} \\
&+ b_{17}\Delta\text{DY}_{t-5:t-1} + b_{18}\Delta\text{DY}_{t-20:t-1} + b_{19}\Delta\text{DY}_{t-60:t-1} + \varepsilon_{it} \qquad (1)
\end{aligned}$$

Here, $\Delta\text{Equity}_{it}$ is the change in the recommended equity allocation by newsletter $i$. $\text{S\&P500}_t$ is the market return on day $t$, $\text{S\&P500}_{t-j:t-k}$ is the cumulative market return from day $t-j$ to day $t-k$ where $j > k$, $\Delta\text{STIR}_{t-j:t-k}$ is the change in the short-term interest rate (annualized 30-day Treasury bill yield) during the period spanning day $t-j$ to day $t-k$, $\Delta\text{TS}_{t-j:t-k}$ is the change in the term spread (difference between the yield of a constant-maturity 10-year Treasury bond and the yield of a 3-month Treasury bill) during the period spanning day $t-j$ to day $t-k$, $\Delta\text{QS}_{t-j:t-k}$ is the change in the quality spread (the difference between the yields of Moody's BAA-rated corporate bond and AAA-rated corporate bond) during the period spanning day $t-j$ to day $t-k$, $\Delta\text{DY}_{t-j:t-k}$ is the change in the dividend yield of the S&P 500 index during the period spanning day $t-j$ to day $t-k$, and $\varepsilon_{it}$ is the error term.

Table III presents the regression estimates. Several features of the results are noteworthy. First, the coefficient estimates on the contemporaneous and four lagged market return variables are positive and significant. In contrast, the coefficient estimates for longer term (1-month and 3-months) lagged returns are negative though only the estimate for the lagged 1-month return is significant (at 0.05 level). Furthermore, the coefficient estimates for 1-day and 2-days lagged market return variables are considerably larger and have significantly

considered in our study. The results for these macro-economic variables are very similar to the reported results for the quality spread. They are available from the authors upon request.

larger $t$-values. On any given day, a one standard deviation shift in the market return leads to a 12% change in the average newsletter recommended equity allocation on the following day. Overall, the market return coefficient estimates suggest that recent market returns have a strong influence on the equity allocation decisions of newsletters.

Unlike the strong influence of market returns, innovations in macro-economic variables have, at the very best, a weak influence on the equity allocation decisions of newsletters. The coefficient estimates for most macro-economic variables are statistically insignificant. The two exceptions are the estimates for the quarterly (60-days) innovation in short-term interest rate and weekly (5-days) innovation in dividend yield variables. Both these estimates are negative and significant. However, there does not appear to be any systematic pattern in newsletters' response to innovations in macro-economic variables. The fact that newsletters are only weakly influenced by macroeconomic factors when making their portfolio recommendations is quite surprising since several studies (Chen, Roll, and Ross 1986, Campbell 1987, Fama and French 1988, Breen, Glosten, and Jagannathan 1989, Schwert 1990, Ferson and Harvey 1993, Glosten, Jagannathan, and Runkle 1993, Pesaran and Timmermann 1995) suggest that macro-economic variables may have the power to predict future equity and bond returns as well as their volatility.

### *III.C Momentum and Contrarian Newsletters*

At an aggregate level, newsletters appear to respond strongly to lagged market returns but is there any evidence of heterogeneity in their behavior? Motivated by the investor classification algorithms in Goetzmann and Massa (2000) and Dhar and Kumar (2001), we use a randomization algorithm to classify newsletters into momentum or contrarian (or unclassified) groups using their equity allocation recommendations. A momentum (or positive-feedback) newsletter is more likely to increase (decrease) the recommended equity allocation following positive (negative) market returns. In contrast, a contrarian (or negative-feedback) newsletter is more likely to exhibit an opposite behavior pattern.

For each newsletter $i$, we first compute the 5-day mean cumulative excess (relative to the riskfree rate) market return prior to upward ($\mathrm{MMR}_i^+$) and downward ($\mathrm{MMR}_i^-$) revisions in the recommended equity allocation. Next, we randomly draw recommended equity allocations from the set of observed equity allocation recommendations for newsletter $i$. We compute $\text{MMR}_i^+$ and $\text{MMR}_i^-$ for this set of randomized equity allocation recommendations and repeat the process 500 times. Empirical distributions of $\text{MMR}_i^+$ and $\text{MMR}_i^-$ are obtained which are used to examine if the observed values of $\text{MMR}_i^+$ and $\text{MMR}_i^-$ lie in the tails of the two empirical distributions respectively. A newsletter is classified as momentum if the observed $\text{MMR}_i^+$ ($\text{MMR}_i^-$) lies in the right (left) tail of its empirical distribution. Similarly, a newsletter is classified as contrarian if the observed $\text{MMR}_i^+$ ($\text{MMR}_i^-$) lies in the left (right) tail of its empirical distribution.

Using this classification algorithm, we find that out of 329 newsletters with at least one year of equity allocation recommendations, 179 (54.41%) are of the momentum type, 58 (17.63%) are of the contrarian type, and 92 (27.96%) are unclassified at 0.10 significance level. These results suggest that even though a majority of newsletters in our sample are of the momentum or positive-feedback type, a considerable number of them act on the basis of contrarian beliefs. To examine if there are significant differences in the market-timing abilities of these newsletter sub-groups that hold diagonally opposite beliefs, in the following section, we analyze their performance (along with the performance of individual newsletters) in considerable detail.

## IV Performance and Market-Timing Ability of Investment Newsletters

To examine the performance and market-timing ability of newsletters, we use four performance measures: Jensen's alpha (Jensen 1967), relative Sharpe ratio (Sharpe 1966), and two performance measures proposed in Graham and Harvey (1997). In addition, we use three measures of market-timing ability: the Treynor-Mazuy measure (Treynor and Mazuy 1966), and Henriksson-Merton parametric and non-parametric measures of market-timing (Henriksson and Merton 1981). Clearly, these market-timing measures and performance measures are not mutually exclusive but they do measure different aspects of market-timing skill.

### *IV.A Performance and Market-Timing Measures: An Overview*

We use two different methods for computing the risk-adjusted performance of newsletters. First, we employ a model of expected returns to measure newsletter performance. Our model of expected returns is the traditional CAPM where we estimate:

$$R_{i,t} = \alpha_i + \beta_i \text{RMRF}_t + \varepsilon_{it} \quad t = 1, 2, \ldots, T \tag{2}$$

Here, $R_{i,t}$ is the excess (over the riskfree rate) return of newsletter $i$ at time $t$ and $\text{RMRF}_t$ is the market return in excess of the riskfree rate. In this model, $\beta_i$ is the market beta, and $\alpha_i$ is the Jensen's alpha which is the main performance measure. It represents the extra return earned by a portfolio over that predicted by CAPM.

Second, using the portfolio standard deviation as a measure of portfolio risk, we obtain another measure of risk-adjusted portfolio performance, namely, the Sharpe ratio. It is defined as the risk-adjusted excess (relative to the riskfree rate) return of a portfolio and is computed as:

$$\text{SR}_i^k = \frac{\bar{R}_i^k - \bar{R}_f^k}{\sigma_i^k} \tag{3}$$

$\bar{R}_i^k$ is the average return on the portfolio during a $k$-day (or $k$-month) period, $\bar{R}_f^k$ is the average riskfree rate during the same time-period, and $\sigma_i^k$ is the standard deviation of the portfolio returns during the chosen time-period. We compute the Sharpe ratio for each newsletter portfolio ($\text{SR}_i$) as well as the market portfolio (S&P 500 index) during the period newsletter $i$ is active ($\text{SR}_{im}$). Using these two measures, we compute the relative Sharpe ratio (RSR) and excess Sharpe ratio (ESR) for each newsletter:

$$\text{RSR}_i = \frac{\text{SR}_i}{\text{SR}_{im}} \qquad \text{ESR}_i = \frac{\text{SR}_i - \text{SR}_{im}}{\text{SR}_{im}} \times 100 \tag{4}$$

In addition to the two traditional performance measures, we compute the Graham and Harvey (1997) performance measures for each newsletter. Under the Graham-Harvey measures, the performance of a market-timer is compared with a benchmark efficient-frontier portfolio. In the first measure (GH1), the S&P 500 futures index is levered up or down to match the volatility of the newsletter portfolio. GH1 is the difference between the mean return on the newsletter portfolio and the mean return on the volatility-matched portfolio. This measure rewards newsletters that correctly anticipate market returns and penalizes changes in the recommended equity portfolio that are unrelated to market movements.

The second performance measure (GH2) is computed by levering up or down each newsletter's recommended portfolio to match the volatility of the S&P500 futures index. GH2 is the difference between the mean return on the volatility-matched portfolio and the return on the S&P500 futures index. In both cases, the volatilities are computed for the time-period in which a newsletter is active and the appropriate portfolio is levered up or down by combining it with T-bills. A newsletter exhibits superior performance if GH1 and GH2 measures are significantly positive.

Given that the newsletters in our sample are restricted to a choice between equity and cash, any evidence of superior ability is more likely to come from their ability to time the market. We use three different measures of market-timing. Our first measure of market-timing is the Treynor-Mazuy (TM) measure (Treynor and Mazuy 1966). It is the coefficient estimate $\gamma_i^{tm}$ in the following quadratic regression specification:

$$R_{i,t} = \alpha_i + \beta_i \mathrm{RMRF}_t + \gamma_i^{tm} \left[\mathrm{RMRF}_t\right]^2 + \varepsilon_{i,t} \tag{5}$$

Second, we measure newsletters' market-timing ability in the Henriksson-Merton (HM) framework (Henriksson and Merton 1981) where we estimate the following regression:

$$R_{i,t} = \alpha_i + \beta_i \mathrm{RMRF}_t + \gamma_i^{hm} \left[\mathrm{RMRF}_t\right]^+ + \varepsilon_{i,t} \tag{6}$$

In these two regression specifications, $R_{i,t}$ is the excess (over the riskfree rate) return of newsletter strategy $i$ at time $t$, $\mathrm{RMRF}_t$ is the market return in excess of the riskfree rate, and $[\mathrm{RMRF}_t]^+$ is defined as $\mathrm{Max}\,[0, \mathrm{RMRF}_t]$. The coefficient estimate $\gamma_i^{hm}$ measures market-timing ability. For a successful market timer, the coefficients $\gamma_i^{tm}$ and $\gamma_i^{hm}$ must be positive.

Finally, we utilize a non-parametric measure of market-timing (HM2) proposed in Henriksson and Merton (1981). To compute HM2, we define $\Delta E_{i,t-2:t-1} = E_{i,t-2} - E_{i,t-1}$ as the change in the equity recommendation by newsletter $i$ from period $t-2$ to period $t-1$. In addition, we define $p_i^+(t)$ as the probability that newsletter $i$ correctly predicts the direction of the market movement in period $t$ and increases the equity allocation:

$$p_i^+(t) = \mathrm{Prob}[\Delta E_{i,t-2:t-1} > 0\,|\mathrm{RMRF}_t > 0]\,. \tag{7}$$

and $p_i^-(t)$ as the probability that newsletter $i$ appropriately decreases the equity allocation prior to a market decline:

$$p_i^-(t) = \mathrm{Prob}[\Delta E_{i,t-1:t-2} < 0\,|\mathrm{RMRF}_t < 0]\,. \tag{8}$$

The Henriksson and Merton (1981) non-parametric measure of market timing (HM2) is given by $p_i^+(t) + p_i^-(t)$. The HM2 measure must be greater than 0.50 for a successful market-timer.

To summarize, we use four performance measures and three market-timing measures to evaluate the ability of each newsletter. Our performance measures are: (i) Jensen's alpha, (ii) relative Sharpe ratio (RSR), (iii) Graham–Harvey Measure 1 (GH1), and (iv) Graham–Harvey Measure 2 (GH2). Our market-timing measures are: (i) Henriksson-Merton parametric measure (HM), (ii) Henriksson-Merton non-parametric measure (HM2), and (iii) Treynor-Mazuy measure (TM). The set $\{\alpha$, RSR, GH1, GH2, HM, HM2, TM$\}$ characterizes the performance and timing-ability of a newsletter.

### *IV.B Aggregate Level Performance*

To examine the timing-ability of newsletters at an aggregate level, we compute the seven performance and market-timing measures for "representative" newsletters that are defined in several ways. First, we define a mean (median) newsletter by obtaining, on each day, the mean (median) of the most recent recommended equity allocations of all newsletters in our sample. We obtain a daily returns time-series for representative newsletters where we assume that the fraction of the portfolio allocated to equity is invested in S&P500 index futures while the cash allocation is invested in 30-day Treasury bills.

Table IV (Panel A) reports the performance and market-timing measures for mean and median "representative" newsletters. For the mean newsletter, the RSR is 0.98 which suggests that on a risk-adjusted basis, newsletters as a group do not outperform the market. The Jensen's $\alpha$ measure of the representative newsletter is positive but insignificant (0.019 with a $t$-value of 1.08). The GH measures are also positive (0.14 and 0.21 respectively) but they are statistically insignificant. The market-timing measures, HM and TM, are both negative ($-0.16$ and $-0.74$ respectively) which provides evidence of lack of timing-ability at an aggregate level. Furthermore, the HM2 measure is 0.49 which also suggests absence of timing-ability. The performance and market-timing measures for the median representative newsletter is quite similar to the mean representative newsletter. Overall, these performance measures do not provide any evidence of timing-ability at an aggregate level.

For robustness, we use an alternative method for measuring the aggregate level performance of newsletters. In this approach, we exclude "stale" recommendations and consider only "new" newsletter recommendations. In each time-period (say, monthly), we consider only new newsletter recommendations to obtain a mean newsletter recommended equity allocation. This mean equity allocation is used to construct an equity-cash portfolio which is implemented in the next time-period.

In Table IV (Panel B), we report the performance and market timing measures for this representative newsletter for five different aggregation time-periods: daily, weekly, semi-monthly, monthly, and quarterly. We find that under the RSR measure, the representative newsletter performs worse than the market in all five cases. However, RSR is largest (= 0.96) for the monthly aggregation. Furthermore, both the Jensen's $\alpha$ and the GH measures are negative in all five cases but insignificantly so. The HM and TM measures portray a slightly positive picture – TM is significantly positive for daily, weekly, and semi-monthly aggregation periods (0.74, 0.17, and 0.38 respectively) while HM is positive for daily and semi-monthly aggregation periods but significantly negative for the other three aggregation periods. HM2 measure does not have any discriminative power. In sum, the evidence from our alternative procedure for measuring aggregate level performance does not provide conclusive evidence about the timing-ability of newsletters either.

### *IV.C Performance of Newsletter Sub-Groups*

Even though we do not find evidence of timing-ability among newsletters at an aggregate level, are there certain well-defined sub-groups of newsletters that possess considerable market-timing ability? To examine the possibility of superior-performance among newsletter sub-groups, we measure the performance and market-timing abilities of two well-defined sub-groups of newsletters that can be identified on the basis of their past equity allocation recommendations: (i) momentum and contrarian newsletters, (ii) newsletter groups defined on the basis of their recommendation frequency.

#### *IV.C.1 Performance of Momentum and Contrarian Newsletters*

The performance and market-timing statistics for the momentum and the contrarian sub-groups are reported in Table V. For comparison, we also report the performance and market-timing statistics for the unclassified newsletters. It appears that regardless of the measure used, the contrarian newsletters exhibit superior ability relative to both momentum and unclassified groups of newsletters. On average, all three sub-groups under-perform the market (the mean RSR is less than 1) but the contrarian newsletters have the highest mean RSR (= 0.96). In addition, the contrarian newsletters have the largest mean TM measure. The mean TM measure for the momentum, contrarian, and unclassified newsletter sub-groups is 0.09, 0.60, and 0.31 respectively. Using the Kolmogorov-Smirnov (KS) test (see Panel D) we find that the TM distribution of the contrarian sub-group is significantly different from the corresponding TM distribution of the momentum ($p$-value = 0.12) and the unclassified ($p$-value = 0.13) newsletter sub-groups.

The contrarian newsletters also exhibit superior ability according to the HM measure and significantly so – the $p$-values from the KS tests which compare the HM distributions of momentum-contrarian and unclassified-contrarian sub-groups are 0.03 and 0.13 respectively. Furthermore, we find that a greater proportion of contrarian newsletters have positive Jensen's alpha and positive GH measures. Overall, our evidence suggests that the contrarian newsletters have considerable market-timing ability.

*IV.C.2 Performance of Active Newsletters*

Active newsletters that process the market-wide information with a greater frequency may exhibit better market-timing skills. To examine the relation between frequency of recommendation and market-timing ability, we define newsletter sub-groups (quintiles) on the basis of their average recommendation frequency. Quintile 1 consists of the most active newsletters while quintile 5 consists of those newsletters that alter their equity allocation recommendations least frequently. The range of average number of days between two recommendations for the five quintiles are 2-20, 20-31, 31-47, 27-75, and 75-374 respectively.

In Table VI, we present the performance measures for newsletter sub-groups defined on the basis of their recommendation frequency. We find that active newsletters exhibit superior performance on several measures. They have positive mean Jensen's alpha, GH1, GH2, HM, and TM measures. The mean RSR is 0.95 suggesting a slight under-performance relative to the market but the median RSR is 1.00 and 25% of active newsletters have RSR > 1.28. We also find that the GH measures are quite high for a significant number of active newsletters – the 75$^{\text{th}}$ percentile value for GH1 and GH2 measures are 0.51 and 0.78 respectively. It is also noteworthy that for active newsletters, the performance measures have very large standard deviations which suggests that more extreme performers are present in this sub-group.

In Panel F of Table VI we report the $p$-values from the KS tests where the performance distributions of two sub-groups are compared. The Jensen's alpha, GH1, GH2, HM, and TM distributions of active newsletter sub-group (Q1) are different from the corresponding distributions of the other four sub-groups. The RSR and the HM2 distributions of Q1 sub-group, however, are not significantly different (at 0.10 level) from the corresponding distributions of the other sub-groups.

Overall, our results suggest that newsletters that provide more frequent recommendations, on average, have better timing-ability than newsletters that update their equity allocation recommendations on an infrequent basis. Furthermore, we find a greater number of extreme performers in this sub-group.

### *IV.D Performance of Individual Newsletters*

The evidence of superior performance among newsletter sub-groups is encouraging because it suggests that "star" newsletters (i.e., individual newsletters that are successful in timing the market) are likely to exist in our sample. To examine market-timing ability at the individual newsletter level, we measure the performance and market-timing ability of each newsletter.

The results are presented in Table VII. We find that out of 329 newsletters for which we have at least one year of recommendations available, 128 (39%) outperform the market on a risk-adjusted basis (i.e., they have a Sharpe ratio greater than the market). The Jensen's alpha is also positive for 212 (64%) newsletters but most of these estimates (both positive and negative estimates) are statistically insignificant. Measuring newsletter performance using the two Graham-Harvey measures, we find that 83 (25%) newsletters exhibit evidence of superior ability under the GH1 measure while 75 (23%) newsletters exhibit evidence of superior ability under the GH2 measure. Examining the market-timing abilities of individual newsletters, we find that 81 (24%) newsletters have a positive and significant (at 0.05 level) Treynor-Mazuy (TM) measure, 65 (20%) have a positive and significant (at 0.05 level) parametric Henriksson-Merton measure (HM) of market timing, and 150 (46%) have a non-parametric Henriksson-Merton measure (HM2) greater than 0.50.

The descriptive statistics for the performance measures are reported in Panel B of Table

VII and in Figure 6 we show the distributions of four of the seven performance measures.[8] A rich cross-sectional variation in performance and market-timing ability is evident from these performance distributions. Furthermore, more than 25% of the newsletters have superior ability (though some of these are likely to be statistically insignificant) under each of the seven performance and market-timing measures.

These results suggest that there is a considerable evidence of timing-ability at the individual newsletter level. However, even if the newsletters in our sample had no ability to time the market, due to pure chance, one expects some newsletters to perform well. To examine if the observed number of superior performing newsletters could have occured purely by chance, we carry out Monte Carlo (MC) simulations.

#### *IV.D.1 Monte-Carlo Simulations*

Our null hypothesis is that newsletters in our sample do not have any timing-ability and pure chance can lead to the observed number of superior performing newsletters. The alternative hypothesis is that a considerable number of newsletters in our sample have market-timing ability.

To test the null hypothesis, the Monte-Carlo simulation is carried out separately for each newsletter. For each newsletter $i$, we keep the date of its recommendations fixed but on each recommendation date we assign the newsletter a randomly chosen equity allocation. This equity allocation is chosen either from (i) the entire set of equity allocations (all newsletters, full time-period) or (ii) the set of equity allocations recommended by newsletter $i$. Using the "simulated" equity allocations, the seven performance and market-timing measures are computed for each newsletter. Then, for each set of simulations, the number of over-performing newsletters is computed according to each of the seven performance measures and this entire process is repeated 500 times.

Let $N_j^{\text{MonteCarlo}}$ be the number of over-performing newsletters according to performance measure $j$ in the Monte Carlo simulation and let $N_j^{\text{Actual}}$ be the actual number of newsletters that exhibit superior performance according to the performance measure $j$ in the observed sample. Then, significance level ($p$-value) with which the null hypothesis can be rejected is

[8]Due to space constraints we do not report the distributions of all seven performance and market-timing measures. They are available from the authors upon request.

defined as:

$$p = \frac{1 + \text{NF}}{1 + \text{NREP}} \tag{9}$$

where NF is the number times $N_j^{\text{MonteCarlo}} \geq N_j^{\text{Actual}}$ and NREP is the number of times the MC simulations are repeated. Clearly, if p is small, we can reject the null hypothesis that the number of superior performers could have occured by chance.

Using our MC results we can reject the null hypothesis with a $p$-value $< 0.10$ for all seven performance measures. The $p$-values for the seven measures, namely, RSR, Jensen's $\alpha$, GH1, GH2, HM, HM2, and TM, are $0.024, 0.004, 0.06, 0.06, 0.016, 0.032,$ and $0.012$ respectively. The results are quite similar when the random equity allocations are chosen only from the set of observed equity allocations for each newsletter. Overall, the results from our MC-tests suggest that the observed number of superior performing newsletters could not have occured purely by chance. A considerable number of newsletters in our sample do have market-timing ability.

In sum, our results reinforce the importance of measuring performance at an individual level. Although there is no evidence of superior performance and market-timing ability of newsletters as a group, individual out-performers ("star newsletters") do exist. We also find some evidence of timing-ability among well-defined sub-groups of newsletters. These results are consistent with studies (Kon 1983, Lee and Rahman 1990, Bollen and Busse 2001) which show that although mutual funds as a group are unable to outperform the market on a risk-adjusted basis, "star" individual fund managers do exist.

## V Persistence in Newsletter Performance

### *V.A Do Past Winners Repeat?*

Prior evidence on performance persistence has been mixed. Mutual fund studies have documented some evidence (Elton, Gruber, Das, and Hlavka 1992, Grinblatt and Titman 1992, Hendricks, Patel, and Zeckhauser 1993, Goetzmann and Ibbotson 1994, Brown and Goetzmann 1995) of performance persistence for periods up to five years[9] and there is also

[9] Grinblatt, Titman, and Wermers (1995) and Carhart (1997), however, contend that the superior performance of funds is due to the Jegadeesh and Titman (1993) momentum effect.

evidence (Agarwal and Naik 2000, Bollen and Busse 2002) of short-term persistence that lasts a quarter, even after controlling for momentum.

There is also some prior evidence of performance persistence among newsletters. Jaffe and Mahoney (1999) and Metrick (1999) find little evidence of short-run performance persistence among investment newsletters while Graham and Harvey (1996, 1997) show that newsletters that appropriately altered their previous three equity allocations appear to possess "hot hands".

Motivated by the findings of Graham and Harvey (1996, 1997), we also examine persistence in newsletter performance but follow a different methodology. At the end of each month, we sort newsletters based on their past $J$-month performance (raw returns). We build a "winner" (top quintile) and a "loser" (bottom quintile) portfolio and track the performance differential of these two portfolios during the next $K$-months.

Figure 7 shows the cumulative return differential between the winner and the loser portfolio. We find that there is persistence in performance that lasts for approximately 10 months, irrespective of the choice of $J$. After 10 months, the performance differential disappears. The difference in performance is greatest when we rank newsletters based on past 9-month performance. In this case, past winners outperform past losers by 3.20% in the 10 months following the portfolio construction date. Overall, these results suggest that newsletters that have performed well in the past continue to do so in the future. A trading strategy that follows the recommendations of past winners may be able to outperform a passive investment strategy.

### *V.B Trading Strategy to Exploit Performance Persistence*

To examine if it is possible to profit from the observed persistence in newsletter performance, we devise a trading strategy that tracks the recommendations of past winners. We create a portfolio whose equity allocation is determined as follows: at the end of each month, using the past $J$-month raw return, we select the top $P^{\text{th}}$ percentile newsletters (i.e., the "winners"). The equity allocation of the portfolio is set equal to the average equity allocation of the past "winners" and the composition of the portfolio is held fixed for one month. The pair $(J, P)$ defines a persistence-based trading strategy.

Table VIII reports the performance measures for persistence-based trading strategies defined using $J = 2, 4, \ldots, 16$ and $P = 5, 10, 20, 25$. In Panel A we report the excess Sharpe ratio (ESR) and Jensen's alpha measures. The Jensen's alpha is positive for several $(J, P)$ strategies but it attains a maximum value for the (10,5) strategy. The monthly Jensen's alpha is 0.213% and 0.193% for the (10,5) and the (10,10) strategies respectively. In both cases, there is evidence of economically significant over-performance. For instance, a monthly Jensen's alpha of 0.213% corresponds to an annual over-performance of 2.56%. The excess Sharpe ratio (ESR) is positive for several $(J, P)$ strategies but it also attains a maximum for $J = 10$. The ESR measure is 30.90% and 29.53% for the (10,5) and the (10,10) strategies respectively. These two performance measures suggest that a persistence-based trading strategy is capable of out-performing the market by a considerable margin.

For robustness, we also compute the two Graham-Harvey performance measures (GH1 and GH2) for the persistence-based trading strategies. The results are reported in Panel B of Table VIII. Again, we find that the GH measures increase with $J$ and attain a maxima for $J = 10$. The GH1 measure is 0.15 and 0.14 for the (10,5) and the (10,10) strategies respectively. Similarly, the GH2 measure is positive (0.19 and 0.18) and significant for the (10,5) and the (10,10) strategies.

Finally, we examine the market-timing ability of our persistence-based trading strategies. We compute the Treynor-Mazuy (TM) and Henriksson-Merton parametric (HM) market-timing measures for the set of persistence-based strategies examined above. The results are reported in Panel C of Table VIII. Quite surprisingly, we find yet again that both the TM and the HM measures attain a maxima for $J = 10$. The TM measure is 0.22 for both the (10,5) and the (10,10) strategies while the HM measure is 0.87 and 0.83 for the (10,5) and the (10,10) strategies respectively. We find strong evidence of superior market-timing under both the measures.

Overall, we find that the (10,5) and the (10,10) persistence-based strategies exhibit remarkably strong performance under all six performance and market-timing measures. However, the superior performance is not restricted to strategies defined using past 10-month performance (i.e., $J = 10$). Other strategies, such as (8,5) and (8,10) also exhibit superior performance under some of our measures but the strength of over-performance is much weaker.

#### *V.B.1 A Note on Transaction Costs*

There are both fixed and variable costs in following a persistence-based trading strategy. It is necessary to subscribe to all active newsletters. Table I shows that there are approximately 160 active newsletter strategies at any given time. Given that the average annual subscription rate is about $200 (Hulbert 1993), subscription costs render the strategy infeasible for an average individual investor. However, given that newsletter subscription costs are independent of the size of an investor's portfolio, following a persistence-based trading strategy is likely to be feasible and profitable for institutional investors who hold relatively larger portfolios.

Our rebalancing strategy involves transaction costs but we feel that these costs do not weaken our results because trading in the S&P 500 index futures carries very low transaction costs and furthermore, our strategy requires portfolio rebalancing only once per month. In most cases the recommended change in the equity allocation is only moderate. For instance, with the (10,10) strategy, the mean absolute change in equity allocation is 19.56% (median is 13.12%).

When analyzing the net performance of our trading strategy, it is also important to correctly account for the transaction costs of the benchmark used for comparison. To invest "in the market" is not costless. Passive mutual funds that track the S&P 500 index have management fees and a portfolio fully invested in index derivatives has to be rolled-over when the derivative products expire. These costs are likely to be significantly higher than the cost of trading in S&P 500 index futures.

## VI Summary and Conclusions

This study analyzes the behavior and performance of 353 investment newsletters that make asset allocation recommendations during a period covering more than 21 years (June 1980 – November 2001). We find that newsletters change their asset mix between equity and cash using simple rules. Most newsletters are of the positive-feedback type (DeLong, Shleifer, Summers, and Waldmann 1990) – they increase (decrease) the equity allocation following a rise (fall) in the market. However, there is also a small group of newsletters that act on the basis of contrarian beliefs. Using a classification algorithm, we find that out of 329 newsletters, 179 (54.41%) are of the momentum type, 58 (17.63%) are of the contrarian type, and 92 (27.96%) are unclassified at 0.10 significance level.

We also observe that the recent (past 1-2 days) market returns have a considerably stronger influence on newsletters' equity allocation decisions. For instance, on any given day, a one standard deviation shift in the market return leads to a 12% change in the average newsletter recommended equity allocation on the following day. In contrast, we find that innovations in macro-economic variables have, at the very best, only a weak influence on their asset allocation decisions. This finding is quite surprising since several studies suggest that macro-economic variables may have the power to predict future equity and bond returns as well as their volatility.

On aggregate, newsletters do not outperform a passive investment strategy but there are certain well-defined newsletter sub-groups that exhibit timing-ability. We find evidence of market-timing ability among newsletters that follow a very short-term (weekly) contrarian strategy and also among newsletters that provide recommendations on a more frequent (2-20 days) basis. Furthermore, when we examine the recommendations of individual newsletters at a higher frequency (daily as opposed to monthly), we find considerable evidence of market-timing ability. The number of "star newsletters" (i.e., individual newsletters that are successful in timing the market) is greater than the number one expects to find by pure chance.

We find evidence of persistence in newsletters' performance and a trading strategy that follows the average recommendations of newsletters that have performed well in the past 10 months is capable of outperforming the market on a risk-adjusted basis (the annual over-performance is 2.56%). The fact that a portfolio which tracks the recommendations of past best performing newsletters is able to outperform the market is clearly inconsistent with the semi-strong form of market efficiency.

# References


Agarwal, Vikas, and Narayan Y. Naik, 2000, Multi-period performance persistence analysis of hedge funds, *Journal of Financial and Quantitative Analysis* 35, 327–342.

Barber, Brad, Reuven Lehavy, Maureen McNichols, and Brett Trueman, 2001, Can investors profit from the prophets? Security analyst recommendations and stock returns, *Journal of Finance* 56, 531–564.

Bollen, Nicolas P.B., and Jeffrey A. Busse, 2001, On the timing ability of mutual fund managers, *Journal of Finance* 56, 1075–1094.

——— , 2002, Short-term persistence in mutual fund performance, Working Paper, Emory University.

Bradley, Dan, Brad Jordan, and Jay Ritter, 2002, The quiet period goes out with a bang, *Journal of Finance* Forthcoming.

Breen, William, Lawrence R. Glosten, and Ravi Jagannathan, 1989, Significance of predictable variations in stock index returns, *Journal of Finance* 44, 1177–1189.

Brown, Stephen J., and William N. Goetzmann, 1995, Performance persistence, *Journal of Finance* 50, 679–698.

Busse, Jeffrey A., 2001, Another look at mutual fund tournaments, *Journal of Financial and Quantitative Analysis* 36, 53–73.

Campbell, John Y., 1987, Stock returns and the term structure, *Journal of Financial Economics* 18, 373–399.

Carhart, Mark, 1997, On persistence in mutual fund performance, *Journal of Finance* 52, 57–82.

Chance, Don M., and Michael L. Hemler, 2001, The performance of professional market timers: Daily evidence from executed strategies, *Journal of Financial Economics* 62, 377–411.

Chen, Nai-Fu, Richard Roll, and Stephen A. Ross, 1986, Economic forces and the stock market, *Journal of Business* 59, 383–403.

Cover, Thomas A., and Joy A. Thomas, 1991, *Elements of Information Theory* (John Wiley and Sons, Inc., New York, NY).

DeLong, J. Bradford, Andrei Shleifer, Lawrence H. Summers, and Robert J. Waldmann, 1990, Positive feedback investment strategies and destabilization rational speculation, *Journal of Finance* 45, 379–395.

Dhar, Ravi, and Alok Kumar, 2001, A non-random walk down the main street: Impact of price trends on trading decisions of individual investors, Working Paper, Department of Economics, Cornell University, December 2001.

Edelen, Roger M., 1999, Investor flows and the assessed performance of open end mutual funds, *Journal of Financial Economics* 53, 439–66.

Elton, Edwin J., Martin J. Gruber, Sanjiv Das, and Matt Hlavka, 1992, Efficiency with costly information: A reinterpretation of the evidence for managed portfolios, *Review of Financial Studies* 6, 1–22.

Fama, Eugene F., and Kenneth R. French, 1988, Dividend yields and expected stock returns, *Journal of Financial Economics* 22, 3–25.

Ferson, Wayne E., 1989, Changes in expected security returns, risk, and the level of interest rates, *Journal of Finance* 44, 1191–1217.

——— , and Campbell Harvey, 1993, The risk and predictability of international equity returns, *Review of Financial Studies* 6, 527–566.

Ferson, Wayne E., and Rudi W. Schadt, 1996, Measuring fund strategy and performance in changing economic conditions, *Journal of Finance* 51, 425–461.

Glosten, Lawrence R., Ravi Jagannathan, and David 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.

Goetzmann, William N., and Roger G. Ibbotson, 1994, Do winners repeat?, *Journal of Portfolio Management* 20, 9–18.

Goetzmann, William N., Jonathan Ingersoll, and Zoran Ivković, 2000, Monthly measurement of daily timers, *Journal of Financial and Quantitative Analysis* 35, 257–290.

Goetzmann, William N., and Massimo Massa, 2000, Daily momentum and contrarian behavior of index fund investors, *Journal of Financial and Quantitative Analysis* Forthcoming.

Graham, John R., 1999, Herding among investment newsletters: Theory and evidence, *Journal of Finance* 54, 237–268.

———, and Campbell R. Harvey, 1996, Market timing ability and volatility implied in investment newsletters' asset allocation recommendations, *Journal of Financial Economics* 42, 397–421.

———, 1997, Grading the performance of market-timing newsletters, *Financial Analysts Journal* 53, 54–66.

Greene, Jason T., and Charles W. Hodges, 2002, The dilution impact of daily fund flows on open-end mutual funds, *Journal of Financial Economics* Forthcoming.

Greene, William H., 1997, *Econometric Analysis* (Prentice-Hall, Inc., Upper Saddle River, NJ).

Grinblatt, Mark, and Sheridan Titman, 1992, The persistence of mutual fund performance, *Journal of Finance* 47, 1977–1984.

———, and Russ Wermers, 1995, Momentum investment strategies, portfolio performance, and herding: A study of mutual fund behavior, *American Economic Review* 85, 1088–1105.

Hartigan, John A., 1975, *Clustering Algorithms* (John Wiley and Sons, Inc., New York, NY).

Hendricks, Darryll, Jayendu Patel, and Richard Zeckhauser, 1993, Hot hands in mutual funds: Short-run persistence of performance, *Journal of Finance* pp. 93–130.

Henriksson, Roy D., and Robert C. Merton, 1981, On market timing and investment performance. II. Statistical procedures for evaluating forecasting skills, *Journal of Business* 54, 513–533.

Hulbert, Mark, 1993, *The Hulbert Guide to Financial Newsletters* (Dearborn Financial Publishing, Inc., Chicago, IL).

Jaffe, Jeffrey F., and James M. Mahoney, 1999, The performance of investment newsletters, *Journal of Financial Economics* 53, 289–307.

Jegadeesh, Narasimhan, and Sheridan Titman, 1993, Returns to buying winners and selling losers: Implications for market efficiency, *Journal of Finance* 48, 65–91.

Jensen, Michael C., 1967, The performance of mutual funds in the period 1945-1964, *Journal of Finance* 23, 389–416.

Kon, Stanley J., 1983, The market-timing performance of mutual fund managers, *Journal of Business* 56, 323–47.

Krigman, Laurie, Wayne H. Shaw, and Kent L. Womack, 2001, Why do firms switch underwriters?, *Journal of Financial Economics* 60, 245–284.

Lee, Chang Few, and Shafiqur Rahman, 1990, Market timing, selectivity, and mutual fund performance: An empirical investigation, *Journal of Business* 62, 261–78.

Metrick, Andrew, 1999, Performance evaluation with transactions data: The stock selection of investment newsletters, *Journal of Finance* 54, 1743–1775.

Michaely, Roni, and Kent L. Womack, 1999, Conflict of interest and the credibility of underwriter analyst recommendations, *Review of Financial Studies* 12, 653–686.

Pesaran, Hashem M., and Allan Timmermann, 1995, Predictability of stock returns: Robustness and economic significance, *Journal of Finance* 50, 1201–1228.

Press, William H., Saul A. Teukolsky, William T. Vetterling, and Brian P. Flannery, 1992, *Numerical Recipes in C: The Art of Scientific Computing, Second Edition* (Cambridge University Press, Cambridge, UK.).

Rajan, Raghuram, and Henri Servaes, 1997, Analyst following of Initial Public Offerings, *Journal of Finance* 52, 507–529.

Schwert, William G., 1990, Stock returns and real activity: A century of evidence, *Journal of Finance* 45, 1237–1257.

Sharpe, William F., 1966, Mutual fund performance, *Journal of Business* 39, 119–138.

Treynor, Jack, and F. Mazuy, 1966, Can mutual funds outguess the market?, *Harvard Business Review* 44, 131–136.

Wermers, Russ, 2000, Mutual fund performance: An empirical decomposition into stock picking talent, style, transactions costs, and expenses, *Journal of Finance* 55, 1655–1695.

**Table I**
## Summary Statistics: Newsletters Database

This table reports four annual statistics for the investment newsletters database and two annual measures of the market returns (for comparison). The sample period is June 1980 – November 2001. The four annual newsletter statistics reported are: (i) the number of active newsletters, (ii) the number of equity recommendations, (iii) the average number of recommendations per active newsletter, and (iv) the average equity allocation. The two market measures are: (i) annual market return (in percent), and (ii) monthly market volatility (in percent). The last three columns of the table complement the information provided in Figure 1 where the three time-series are plotted at a monthly frequency. We collect data on newsletter recommendations from *Hulbert Financial Digest* and market returns data is obtained from Datastream.

| Year | Number of Newsletters | Number of Reco | Reco per Newsletter | Equity Allocation (%) | Annual Market Return (%) | Monthly Market Volatility (%) |
|---|---|---|---|---|---|---|
| 1980 | 21 | 53 | 2.52 | 62.86 | 18.84 | 5.22 |
| 1981 | 18 | 128 | 7.11 | 50.71 | -9.73 | 3.68 |
| 1982 | 22 | 218 | 9.91 | 42.63 | 14.76 | 5.51 |
| 1983 | 28 | 275 | 9.82 | 64.52 | 17.27 | 2.89 |
| 1984 | 54 | 510 | 9.44 | 55.84 | 1.40 | 4.04 |
| 1985 | 61 | 767 | 12.57 | 68.40 | 26.33 | 3.46 |
| 1986 | 76 | 969 | 12.75 | 57.31 | 14.62 | 5.13 |
| 1987 | 100 | 1298 | 12.98 | 64.39 | 2.03 | 8.82 |
| 1988 | 120 | 1356 | 11.30 | 61.49 | 12.40 | 2.95 |
| 1989 | 141 | 1312 | 9.30 | 66.33 | 27.25 | 3.61 |
| 1990 | 161 | 1899 | 11.80 | 54.38 | -6.56 | 5.24 |
| 1991 | 162 | 1911 | 11.80 | 59.67 | 26.31 | 4.55 |
| 1992 | 176 | 1842 | 10.47 | 60.05 | 4.46 | 2.15 |
| 1993 | 149 | 1788 | 12.00 | 65.29 | 7.06 | 1.72 |
| 1994 | 165 | 2012 | 12.19 | 57.56 | -1.54 | 3.06 |
| 1995 | 158 | 1965 | 12.44 | 68.13 | 34.11 | 1.47 |
| 1996 | 164 | 1981 | 12.08 | 70.06 | 20.26 | 3.13 |
| 1997 | 153 | 2055 | 13.43 | 69.90 | 31.01 | 4.60 |
| 1998 | 153 | 2041 | 13.34 | 64.38 | 26.67 | 6.20 |
| 1999 | 159 | 2245 | 14.12 | 61.95 | 19.53 | 3.79 |
| 2000 | 168 | 2290 | 13.63 | 70.07 | -10.14 | 4.94 |
| 2001 | 150 | 1711 | 11.41 | 68.76 | -13.04 | 5.73 |

**Table II**

## Newsletter Allocation Strategies: Unconditional Behavior of Newsletters

This table lists the 10 equity allocation strategies identified using a clustering algorithm. An allocation strategy is defined by 3 attributes: original allocation in equity, time between allocations, and change in equity allocation. The recommendations made by the entire population of newsletters are clustered to identify distinct types of allocation strategies. A 24-cluster solution is obtained, where the number of clusters is determined by visual inspection of the solutions in a reduced 2-D space. The 24 clusters are further merged into 10 meaningful clusters, each one corresponding to a distinct type of allocation strategy. We collect data on newsletter recommendations from *Hulbert Financial Digest*.

| Strategy # | Allocation Strategy | Percent of Total | Description |
|---|---|---|---|
| 1 | $100 \overset{d}{\to} 0$<br>$d \in (2\text{wk}, 1.5\text{mo}, 3\text{mo}, 6\text{mo})$ | 6.51% | Switch from 100% in equity to 100% in cash (0% in equity). |
| 2 | $0 \overset{d}{\to} 100$<br>$d \in (2\text{wk}, 2\text{mo})$ | 6.12% | Switch from 100% in cash (0% in equity) to 100% in equity. |
| 3 | $-100 \overset{d}{\to} 100$<br>$d \in (1\text{mo}, 6\text{mo})$ | 2.45% | Switch from a 100% short position to a 100% long position in equity. |
| 4 | $100 \overset{d}{\to} -100$<br>$d \in (2\text{wk}, 2.5\text{mo})$ | 2.31% | Switch from a 100% long to a 100% short position in equity. |
| 5 | $x \overset{d}{\to} x + \delta; 15 < \delta \leq 75$<br>$d \in (2\text{wk}, 3\text{mo}, 6\text{mo}, 1\text{yr})$ | 2.41% | *Moderate to large positive* change in equity holding. |
| 6 | $x \overset{d}{\to} x - \delta; 15 < \delta \leq 75$<br>$d \in (2\text{wk}, 2\text{mo}, 4\text{mo}, 1\text{yr})$ | 1.36% | *Moderate to large negative* change in equity holding. |
| 7 | $200(\text{approx}) \overset{d}{\to} 0$<br>$d \in (2\text{wk}, 2\text{mo}, 6\text{mo})$ | 0.09% | Switch from 200% in equity (using a margin account) to 100% in cash. |
| 8 | $x \overset{d}{\to} x - \delta; 2 < \delta \leq 15$<br>$d \in (2\text{mo}, 6\text{mo})$ | 36.31% | *Small negative* change in equity holding. |
| 9 | $x \overset{d}{\to} x + \delta; 2 < \delta \leq 15$<br>$d \in (1\text{mo})$ | 8.07% | *Small positive* change in equity holding. |
| 10 | $x \overset{d}{\to} x \pm \delta; \delta \leq 2$<br>$d \in (1\text{wk}, 1\text{mo}, 2\text{mo}, 3\text{mo})$ | 34.37% | A very small positive or negative change (Change < 2%). |

**Table III**

## Determinants of Changes in Recommended Equity Allocation

This table reports the estimation results for the following pooled time-series regression:

$$\begin{aligned}\Delta\text{Equity}_{it} &= b_1\text{S\&P500}_t + b_2\text{S\&P500}_{t-1} + b_2\text{S\&P500}_{t-2} + b_3\text{S\&P500}_{t-3} \\ &+ b_4\text{S\&P500}_{t-4} + b_5\text{S\&P500}_{t-5} \\ &+ b_6\text{S\&P500}_{t-20:t-1} + b_7\text{S\&P500}_{t-60:t-1} \\ &+ b_8\Delta\text{STIR}_{t-5:t-1} + b_9\Delta\text{STIR}_{t-20:t-1} + b_{10}\Delta\text{STIR}_{t-60:t-1} \\ &+ b_{11}\Delta\text{TS}_{t-5:t-1} + b_{12}\Delta\text{TS}_{t-20:t-1} + b_{13}\Delta\text{TS}_{t-60:t-1} \\ &+ b_{14}\Delta\text{QS}_{t-5:t-1} + b_{15}\Delta\text{QS}_{t-20:t-1} + b_{16}\Delta\text{QS}_{t-60:t-1} \\ &+ b_{17}\Delta\text{DY}_{t-5:t-1} + b_{18}\Delta\text{DY}_{t-20:t-1} + b_{19}\Delta\text{DY}_{t-60:t-1} + \varepsilon_{it}\end{aligned}$$

Here, $\Delta\text{Equity}_{it}$ is the change in the recommended equity allocation by newsletter $i$. S&P500$_t$ is the market return on day $t$, S&P500$_{t-j:t-k}$ is the cumulative market return from day $t-j$ to day $t-k$ where $j > k$, $\Delta\text{STIR}_{t-j:t-k}$ is the change in the short-term interest rate (annualized 30-day Treasury bill yield) during the period spanning day $t-j$ to day $t-k$, $\Delta\text{STIR}_{t-j:t-k}$ is the change in the term spread (difference between the yield of a constant-maturity 10-year Treasury bond and the yield of a 3-month Treasury bill) during the period spanning day $t-j$ to day $t-k$, $\Delta\text{VS}_{t-j:t-k}$ is the change in the value spread (the difference between the yields of Moody's BAA-rated corporate bond and AAA-rated corporate bond) during the period spanning day $t-j$ to day $t-k$, $\Delta\text{DY}_{t-j:t-k}$ is the change in the dividend yield of the S&P 500 index during the period spanning day $t-j$ to day $t-k$, and $\varepsilon_t$ is the error term. The estimation period is July 1980 - November 2001. We use newsletter- and year-fixed effects in the estimation. The Newey-West adjusted $t$-values of the coefficient estimates are reported in the parentheses.

| Variable Type | Variable | Coeff. | t-value | Coeff. | t-value | Coeff. | t-value |
|---|---|---|---|---|---|---|---|
| | S&P500$_t$ | 2.70 | 8.83 | | | 2.72 | 8.89 |
| | S&P500$_{t-1}$ | 11.47 | 38.24 | | | 11.63 | 33.84 |
| | S&P500$_{t-2}$ | 5.38 | 16.21 | | | 5.39 | 14.85 |
| Market | S&P500$_{t-3}$ | 2.60 | 7.65 | | | 2.34 | 6.37 |
| Returns | S&P500$_{t-4}$ | 1.02 | 3.09 | | | 0.57 | 1.61 |
| | S&P500$_{t-5}$ | 1.03 | 3.08 | | | 0.34 | 0.90 |
| | S&P500$_{t-20:t-1}$ | -0.17 | -1.68 | | | -0.49 | -2.59 |
| | S&P500$_{t-60:t-1}$ | -0.20 | -3.52 | | | -0.19 | -1.26 |
| | $\Delta\text{STIR}_{t-5:t-1}$ | | | 0.07 | 1.08 | 0.03 | 0.56 |
| | $\Delta\text{STIR}_{t-20:t-1}$ | | | -0.21 | -3.47 | -0.06 | -1.03 |
| | $\Delta\text{STIR}_{t-60:t-1}$ | | | -0.07 | -1.56 | -0.09 | -2.06 |
| Innovations in | $\Delta\text{TS}_{t-5:t-1}$ | | | -0.05 | -3.43 | -0.00 | -0.21 |
| Macro-Economic | $\Delta\text{TS}_{t-20:t-1}$ | | | 0.01 | 0.09 | 0.01 | 0.74 |
| Variables | $\Delta\text{TS}_{t-60:t-1}$ | | | 0.00 | 0.99 | -0.00 | -0.17 |
| | $\Delta\text{QS}_{t-5:t-1}$ | | | -0.07 | -0.90 | -0.09 | -1.14 |
| | $\Delta\text{QS}_{t-20:t-1}$ | | | -0.01 | -0.25 | 0.05 | 0.94 |
| | $\Delta\text{QS}_{t-60:t-1}$ | | | 0.08 | 2.76 | 0.02 | 0.91 |
| | $\Delta\text{DY}_{t-5:t-1}$ | | | -1.67 | -10.19 | -0.79 | -4.11 |
| | $\Delta\text{DY}_{t-20:t-1}$ | | | 0.21 | 1.95 | -0.20 | -1.13 |
| | $\Delta\text{DY}_{t-60:t-1}$ | | | 0.33 | 5.36 | 0.02 | 0.16 |
| | Adj. $R^2$ | | 0.06 | | 0.01 | | 0.08 |

**Table IV**

## Aggregate Level Performance and Timing Ability of Investment Newsletters

This table reports the performance and market-timing measures for "representative" newsletters that are defined in several ways. In Panel A, a representative newsletter is defined by taking the mean (median) of the most recent recommended equity allocations of all newsletters in our sample. In Panel B, we define a representative newsletter where we exclude "stale" recommendations and consider only "new" newsletter recommendations during a certain fixed time-period. In each time-period, we use all new newsletter recommendations to compute a mean newsletter recommended equity allocation. This mean equity allocation is implemented in the following time-period. We report the performance and market timing measures for this representative newsletter for five different aggregation time-periods: daily, weekly, semi-monthly, monthly, and quarterly. The following seven measures are reported: Jensen's alpha (Jensen 1967), excess Sharpe ratio (Sharpe 1966), Graham-Harvey Measures 1 and 2 (Graham and Harvey 1997), Treynor-Mazuy measure (Treynor and Mazuy 1966), and Henriksson-Merton parametric and non-parametric measures (Henriksson and Merton 1981). In obtaining the newsletter performance series, we assume that the fraction of the portfolio allocated to equity is invested in S&P500 index futures while the cash allocation is invested in 30-day Treasury bills. The Newey-West adjusted $t$-values of the coefficient estimates are reported in the parentheses. For the Graham-Harvey measures, the $t$-values are for the null hypothesis that the GH measure is equal to zero. *bp:* basis point.

*Panel A: Performance of representative newsletters: all recommendations*

| Newsletter Type | RSR | Jensen's $\alpha$ (bp) | GH1 (bp) | GH2 (bp) | HM | HM2 | TM |
|---|---|---|---|---|---|---|---|
| *Mean* | 0.98 | 1.87 | 0.14 | 0.21 | -0.16 | 0.49 | -0.74 |
| | | (1.08) | (1.12) | (1.01) | (-6.46) | | (-5.04) |
| *Median* | 0.95 | 2.32 | 0.31 | 0.42 | -0.18 | 0.49 | -0.84 |
| | | (1.21) | (1.22) | (1.48) | (-6.48) | | (-4.89) |

*Panel B: Performance of representative newsletters: new recommendations only*

| Newsletter Type | RSR | Jensen's $\alpha$ (bp) | GH1 (bp) | GH2 (bp) | HM | HM2 | TM |
|---|---|---|---|---|---|---|---|
| *Daily* | 0.66 | -0.19 | -0.28 | -0.45 | 0.03 | 0.52 | 0.74 |
| | | (-0.71) | (-1.00) | (-1.02) | (3.32) | | (14.10) |
| *Weekly* | 0.78 | -0.14 | -0.18 | -0.29 | -0.01 | 0.51 | 0.17 |
| | | (-0.75) | (-0.96) | (-0.95) | (-1.86) | | (4.86) |
| *Semi-monthly* | 0.89 | -0.06 | -0.09 | -0.15 | 0.01 | 0.51 | 0.38 |
| | | (-0.38) | (-0.56) | (-0.66) | (1.27) | | (12.79) |
| *Monthly* | 0.96 | -0.02 | -0.03 | -0.05 | -0.02 | 0.52 | -0.21 |
| | | (-0.13) | (-0.27) | (-0.25) | (-5.74) | | (-9.28) |
| *Quarterly* | 0.79 | -0.16 | -0.17 | -0.27 | -0.04 | 0.54 | -0.52 |
| | | (-1.58) | (-1.69) | (-1.97) | (-15.28) | | (-7.26) |

**Table V**

## Performance of Momentum and Contrarian Newsletters

This table reports the descriptive statistics for performance and market-timing measures for momentum (positive-feedback type) and contrarian (negative-feedback type) newsletters (see Section III.C). For comparison, we also report the performance and market-timing measures for unclassified newsletters. The following seven measures are reported: Jensen's alpha (Jensen 1967), excess Sharpe ratio (Sharpe 1966), Graham-Harvey Measures 1 and 2 (Graham and Harvey 1997), Treynor-Mazuy measure (Treynor and Mazuy 1966), and Henriksson-Merton parametric and non-parametric measure (Henriksson and Merton 1981). In Panel D, we report the $p$-values obtained from Kolmogorov-Smirnov tests where we compare the performance distributions of each of the three group-pairs (momentum-contrarian, momentum-unclassified, and contrarian-unclassified). We collect data on newsletter recommendations from *Hulbert Financial Digest*. *bp:* basis point.

*Panel A: Momentum newsletters ($N = 179$)*

| Statistic | RSR | Jensen's $\alpha$ (bp) | GH1 (bp) | GH2 (bp) | HM | HM2 | TM |
|---|---|---|---|---|---|---|---|
| Mean | 0.75 | -0.39 | -0.74 | -1.33 | 0.03 | 0.46 | 0.09 |
| Median | 0.89 | 0.44 | -0.45 | -0.57 | -0.07 | 0.48 | 0.33 |
| Std. Deviation | 2.67 | 4.89 | **5.39** | 2.68 | 0.15 | 0.11 | 2.12 |
| $25^{\text{th}}$ Percentile | 0.65 | -0.73 | -1.39 | -2.17 | -0.02 | 0.42 | -0.54 |
| $75^{\text{th}}$ Percentile | 1.12 | 1.38 | 0.02 | 0.03 | 0.09 | 0.53 | 1.05 |

*Panel B: Contrarian newsletters ($N = 58$)*

| Statistic | RSR | Jensen's $\alpha$ (bp) | GH1 (bp) | GH2 (bp) | HM | HM2 | TM |
|---|---|---|---|---|---|---|---|
| Mean | **0.96** | **0.17** | -0.31 | -0.32 | **0.06** | 0.51 | **0.60** |
| Median | 0.93 | 1.00 | -0.40 | -0.50 | 0.05 | 0.50 | **0.77** |
| Std. Deviation | **1.29** | 3.85 | 1.43 | 2.44 | 0.13 | 0.10 | 1.70 |
| $25^{\text{th}}$ Percentile | 0.69 | -0.32 | -0.88 | -1.21 | 0.00 | 0.46 | -0.23 |
| $75^{\text{th}}$ Percentile | 1.14 | 2.02 | **0.33** | **0.42** | 0.11 | 0.56 | 1.34 |

*Panel C: Unclassified newsletters ($N = 92$)*

| Statistic | RSR | Jensen's $\alpha$ (bp) | GH1 (bp) | GH2 (bp) | HM | HM2 | TM |
|---|---|---|---|---|---|---|---|
| Mean | 0.70 | -0.28 | -0.66 | -0.55 | 0.02 | 0.50 | 0.31 |
| Median | 0.95 | 0.33 | -0.23 | -0.31 | 0.02 | 0.52 | 0.23 |
| Std. Deviation | 1.82 | 3.19 | 2.05 | 1.33 | 0.09 | 0.11 | 2.29 |
| $25^{\text{th}}$ Percentile | 0.77 | -0.28 | -0.73 | -0.90 | -0.02 | 0.45 | -0.70 |
| $75^{\text{th}}$ Percentile | 1.05 | 1.23 | 0.07 | 0.09 | 0.06 | 0.57 | 1.01 |

*Panel D: Kolmogorov-Smirnov Test Results (p-values)*

| Groups Compared | RSR | Jensen's $\alpha$ | GH1 | GH2 | HM | HM2 | TM |
|---|---|---|---|---|---|---|---|
| Momentum-Contrarian | 0.79 | 0.03 | 0.22 | 0.18 | 0.13 | 0.87 | 0.12 |
| Momentum-Unclassified | 0.20 | 0.56 | 0.01 | 0.00 | 0.32 | 0.00 | 0.97 |
| Contrarian-Unclassified | 0.17 | 0.01 | 0.26 | 0.39 | 0.03 | 0.01 | 0.13 |

**Table VI**

## Performance of Newsletter Groups defined using Recommendation Frequency

This table reports the descriptive statistics for performance and market-timing measures for newsletter groups (quintiles) defined on the basis of their average recommendation frequency. Quintile 1 consists of most active newsletters while quintile 5 consists of the least active newsletters. The range of average number of days between two recommendations for the five quintiles are: 2-20, 20-31, 31-47, 27-75, and 75-374. The following seven measures are reported: Jensen's alpha (Jensen 1967), excess Sharpe ratio (Sharpe 1966), Graham-Harvey Measures 1 and 2 (Graham and Harvey 1997), Treynor-Mazuy measure (Treynor and Mazuy 1966), and Henriksson-Merton parametric and non-parametric measure (Henriksson and Merton 1981). In Panel D, we report the $p$-values obtained from Kolmogorov-Smirnov tests where we compare the performance distributions of each of the ten group-pairs that can be defined using the five recommendation-frequency based newsletter groups. We collect data on newsletter recommendations from *Hulbert Financial Digest. bp:* basis point.

*Panel A: Most active (Quintile 1) newsletters ($N = 70$)*

| Statistic | RSR | Jensen's $\alpha$ (bp) | GH1 (bp) | GH2 (bp) | HM | HM2 | TM |
|---|---|---|---|---|---|---|---|
| Mean | 0.95 | 0.13 | **0.11** | **0.17** | **0.06** | 0.50 | **0.67** |
| Median | 1.00 | 0.44 | 0.19 | 0.28 | 0.04 | 0.51 | 0.69 |
| Std. Deviation | 2.79 | **7.54** | **9.49** | **8.01** | **0.25** | 0.07 | **2.93** |
| 25$^{\text{th}}$ Percentile | 0.66 | -0.16 | -2.06 | -2.18 | -0.01 | 0.47 | -0.24 |
| 75$^{\text{th}}$ Percentile | **1.28** | 1.49 | **0.51** | **0.78** | 0.12 | 0.54 | 1.64 |

*Panel B: Moderately active (Quintile 2) newsletters ($N = 70$)*

| Statistic | RSR | Jensen's $\alpha$ (bp) | GH1 (bp) | GH2 (bp) | HM | HM2 | TM |
|---|---|---|---|---|---|---|---|
| Mean | 0.56 | -0.12 | -0.44 | -0.52 | 0.03 | 0.50 | 0.30 |
| Median | 0.95 | 0.29 | -0.43 | -0.49 | 0.02 | 0.50 | 0.33 |
| Std. Deviation | 3.92 | 2.53 | 1.30 | 2.27 | 0.09 | 0.07 | 2.26 |
| 25$^{\text{th}}$ Percentile | 0.73 | -0.76 | -1.08 | -1.36 | -0.02 | 0.47 | -0.50 |
| 75$^{\text{th}}$ Percentile | 1.16 | 1.59 | 0.16 | 0.22 | 0.07 | 0.54 | 0.92 |

*Panel C: Moderately active (Quintile 3) newsletters ($N = 70$)*

| Statistic | RSR | Jensen's $\alpha$ (bp) | GH1 (bp) | GH2 (bp) | HM | HM2 | TM |
|---|---|---|---|---|---|---|---|
| Mean | 0.74 | -0.23 | -0.73 | -0.85 | 0.03 | 0.51 | 0.11 |
| Median | 0.91 | 0.42 | -0.45 | -0.52 | 0.04 | 0.52 | 0.37 |
| Std. Deviation | 1.39 | 3.36 | 1.54 | 1.61 | 0.10 | 0.10 | 2.06 |
| 25$^{\text{th}}$ Percentile | 0.67 | -0.81 | -1.02 | -1.40 | -0.00 | 0.46 | -0.21 |
| 75$^{\text{th}}$ Percentile | 1.08 | 1.63 | 0.10 | 0.16 | 0.08 | 0.56 | 1.05 |

*Panel D: Moderately active (Quintile 4) newsletters ($N = 70$)*

| Statistic | RSR | Jensen's $\alpha$ (bp) | GH1 (bp) | GH2 (bp) | HM | HM2 | TM |
|---|---|---|---|---|---|---|---|
| Mean | 0.98 | -1.28 | -1.24 | -1.59 | 0.04 | 0.45 | 0.34 |
| Median | 0.91 | 0.51 | -0.63 | -0.83 | 0.03 | 0.48 | 0.02 |
| Std. Deviation | 1.18 | 4.46 | 2.17 | 2.85 | 0.09 | 0.14 | 1.59 |
| 25$^{\text{th}}$ Percentile | 0.76 | -0.87 | -1.19 | -1.91 | -0.02 | 0.40 | -0.46 |
| 75$^{\text{th}}$ Percentile | 1.12 | 1.36 | -0.19 | -0.22 | 0.10 | 0.52 | 1.08 |

*Panel E: Least active (Quintile 5) newsletters ($N = 73$)*

| Statistic | RSR | Jensen's $\alpha$ (bp) | GH1 (bp) | GH2 (bp) | HM | HM2 | TM |
|---|---|---|---|---|---|---|---|
| Mean | 0.92 | 0.26 | -0.72 | -1.01 | -0.01 | 0.47 | -0.10 |
| Median | 0.88 | 0.56 | -0.39 | -0.48 | 0.02 | 0.47 | 0.31 |
| Std. Deviation | 0.79 | 2.19 | 1.49 | 1.86 | 0.09 | 0.12 | 1.64 |
| 25$^{\text{th}}$ Percentile | 0.68 | -0.05 | -0.99 | -1.36 | -0.04 | 0.41 | -0.87 |
| 75$^{\text{th}}$ Percentile | 1.02 | 1.21 | 0.01 | 0.01 | 0.06 | 0.56 | 1.01 |

**Table VI**
**Performance of Newsletter Groups defined using Recommendation Frequency (Continued)**

*Panel F: Kolmogorov-Smirnov Test Results (p-values)*

| Groups Compared | RSR | Jensen's $\alpha$ | GH1 | GH2 | HM | HM2 | TM |
|---|---|---|---|---|---|---|---|
| Q1-Q2 | 0.15 | 0.19 | 0.10 | 0.09 | 0.14 | 0.86 | 0.05 |
| Q1-Q3 | 0.17 | 0.10 | 0.06 | 0.06 | 0.09 | 0.38 | 0.12 |
| Q1-Q4 | 0.23 | 0.07 | 0.01 | 0.01 | 0.06 | 0.84 | 0.07 |
| Q1-Q5 | 0.11 | 0.07 | 0.02 | 0.03 | 0.04 | 0.03 | 0.04 |
| Q2-Q3 | 0.29 | 0.80 | 0.96 | 0.88 | 0.19 | 0.35 | 0.56 |
| Q2-Q4 | 0.52 | 0.41 | 0.12 | 0.09 | 0.72 | 0.61 | 0.78 |
| Q2-Q5 | 0.05 | 0.09 | 0.15 | 0.27 | 0.63 | 0.04 | 0.66 |
| Q3-Q4 | 0.18 | 0.47 | 0.26 | 0.10 | 0.64 | 0.55 | 0.14 |
| Q3-Q5 | 0.35 | 0.07 | 0.60 | 0.59 | 0.18 | 0.02 | 0.32 |
| Q4-Q5 | 0.06 | 0.13 | 0.29 | 0.13 | 0.27 | 0.01 | 0.32 |

**Table VII**

## Performance of Individual Newsletters

This table reports the descriptive statistics for performance and market-timing measures for individual newsletters. In Panel A, for each measure, we report the number of newsletters that exhibit positive (superior) and negative (inferior) ability. We also report the number of newsletters with significantly positive (negative) measures at 0.05 and 0.10 significance levels. Panel B provides descriptive statistics for the following seven measures: Jensen's alpha (Jensen 1967), excess Sharpe ratio (Sharpe 1966), Graham-Harvey Measures 1 and 2 (Graham and Harvey 1997), Treynor-Mazuy measure (Treynor and Mazuy 1966), and Henriksson-Merton parametric and non-parametric measure (Henriksson and Merton 1981). We collect data on newsletter recommendations from *Hulbert Financial Digest*. *bp:* basis point.

*Panel A: Frequency of Superior Performing Newsletters*

| | RSR | Jensen's $\alpha$ | GH1 | GH2 | HM | HM2 | TM |
|---|---|---|---|---|---|---|---|
| Superior (All) | **128** | **212** | 97 | 97 | 218 | **150** | 196 |
| Significantly Superior ($p = 0.10$) | | 22 | 84 | 80 | 71 | | 85 |
| Significantly Superior ($p = 0.05$) | | 11 | **83** | **75** | **65** | | **81** |
| | | | | | | | |
| Inferior (All) | 201 | 117 | 232 | 231 | 111 | 179 | 133 |
| Significantly Inferior ($p = 0.10$) | | 26 | 120 | 124 | 54 | | 76 |
| Significantly Inferior ($p = 0.05$) | | 17 | 114 | 115 | 51 | | 74 |

*Panel B: Descriptive Statistics*

| Statistic | RSR | Jensen's $\alpha$ (bp) | GH1 (bp) | GH2 (bp) | HM | HM2 | TM |
|---|---|---|---|---|---|---|---|
| Mean | 0.77 | -0.26 | -0.64 | -0.93 | 0.03 | 0.48 | 0.24 |
| Median | 0.92 | 0.44 | -0.44 | -0.54 | 0.03 | 0.49 | 0.34 |
| Std. Deviation | 2.26 | 4.29 | 4.16 | 2.37 | 0.13 | 0.11 | 2.11 |
| $25^{\text{th}}$ Percentile | 0.69 | -0.60 | -1.11 | -1.55 | -0.02 | 0.43 | -0.48 |
| $75^{\text{th}}$ Percentile | **1.10** | **1.40** | **0.09** | **0.10** | **0.08** | **0.54** | **1.07** |

**Table VIII**
## Performance of Persistence-Based Trading Strategies

This table reports the performance and timing measures for a set of trading strategies that tries to exploit the persistence in newsletter performance. The strategies track the recommendations of past winners. A portfolio is created whose equity allocation is determined as follows: each month, using the past $J$-month raw return, we select the top $P^{\text{th}}$ percentile newsletters. The equity allocation of the portfolio is set equal to the average allocation of the past winners. The performance measures are computed for strategies defined using $J = 2, 4, \ldots, 16$ and $P = 5, 10, 20, 25$. The following six performance measures are reported: Jensen's alpha (Jensen 1967), excess Sharpe ratio (Sharpe 1966), Graham–Harvey Measures 1 and 2 (Graham and Harvey 1997), Treynor-Mazuy measure (Treynor and Mazuy 1966), and Henriksson-Merton parametric measure (Henriksson and Merton 1981). In Panels A and C, the Newey-West adjusted $t$-values of the coefficient estimates are reported in the parentheses. In Panel B, the $t$-values are for the null hypothesis that the GH measure is equal to zero.

*Panel A: Excess Sharpe Ratio (ESR) and Jensen's Alpha*

| | *Excess Sharpe Ratio (%)* | | | | *Monthly Jensen's Alpha (%)* | | | |
|---|---|---|---|---|---|---|---|---|
| J | Top $5^{\text{th}}$ Pctl | Top $10^{\text{th}}$ Pctl | Top $20^{\text{th}}$ Pctl | Top $25^{\text{th}}$ Pctl | Top $5^{\text{th}}$ Pctl | Top $10^{\text{th}}$ Pctl | Top $20^{\text{th}}$ Pctl | Top $25^{\text{th}}$ Pctl |
| 2 | -47.230 | -60.275 | -61.968 | -58.598 | -0.116 | -0.177 | -0.186 | -0.176 |
| | | | | | (-0.685) | (-1.103) | (-1.325) | (-1.327) |
| 4 | -29.774 | -40.668 | -40.301 | -39.987 | -0.044 | -0.092 | -0.098 | -0.099 |
| | | | | | (-0.300) | (-0.649) | (-0.821) | (-0.860) |
| 6 | 14.244 | 8.134 | -4.236 | -5.961 | 0.137 | 0.101 | 0.039 | 0.028 |
| | | | | | (1.062) | (0.817) | (0.359) | (0.262) |
| 8 | 11.298 | 16.499 | 1.911 | -1.574 | 0.124 | 0.139 | 0.065 | 0.044 |
| | | | | | (1.940) | (2.112) | (1.596) | (1.419) |
| 10 | **30.899** | **29.529** | 14.193 | 10.933 | **0.213** | **0.193** | 0.112 | 0.096 |
| | | | | | **(2.668)** | **(2.620)** | (1.951) | (1.983) |
| 12 | 6.608 | 5.476 | 4.504 | 3.464 | 0.090 | 0.085 | 0.073 | 0.065 |
| | | | | | (0.795) | (0.763) | (0.720) | (0.668) |
| 14 | -4.269 | -8.916 | -12.307 | -10.887 | 0.038 | 0.016 | -0.011 | -0.011 |
| | | | | | (0.344) | (0.137) | (-0.110) | (-0.116) |
| 16 | -25.474 | -20.604 | -14.537 | -13.544 | -0.090 | -0.051 | -0.028 | -0.027 |
| | | | | | (-0.794) | (-0.446) | (-0.264) | (-0.267) |

**Table VIII(Continued)**

## Performance of Persistence-Based Trading Strategies

*Panel B: Graham-Harvey Measures*

| | *Graham-Harvey Measure 1* | | | | *Graham-Harvey Measure 2* | | | |
|---|---|---|---|---|---|---|---|---|
| | Top $5^{th}$ | Top $10^{th}$ | Top $20^{th}$ | Top $25^{th}$ | Top $5^{th}$ | Top $10^{th}$ | Top $20^{th}$ | Top $25^{th}$ |
| J | Pctl | Pctl | Pctl | Pctl | Pctl | Pctl | Pctl | Pctl |
| 2 | -0.233 | -0.284 | -0.273 | -0.254 | -0.283 | -0.361 | -0.371 | -0.351 |
| | (-1.438) | (-1.880) | (-2.075) | (-2.050) | (-1.548) | (-1.821) | (-2.576) | (-2.251) |
| 4 | -0.133 | -0.172 | -0.162 | -0.159 | -0.167 | -0.229 | -0.227 | -0.225 |
| | (-0.930) | (-1.301) | (-1.409) | (-1.435) | (-1.033) | (-1.503) | (-1.312) | (-1.637) |
| 6 | 0.065 | 0.037 | -0.019 | -0.026 | 0.086 | 0.049 | -0.026 | -0.036 |
| | (0.545) | (0.323) | (-0.177) | (-0.257) | (0.646) | (0.520) | (-0.478) | (-0.296) |
| 8 | 0.051 | 0.073 | 0.008 | -0.007 | 0.067 | 0.097 | 0.011 | -0.010 |
| | (1.409) | (1.628) | (1.073) | (-0.071) | (1.511) | (1.346) | (1.274) | (-0.170) |
| 10 | **0.148** | **0.135** | 0.062 | 0.047 | **0.187** | **0.179** | 0.086 | 0.066 |
| | **(2.561)** | **(2.236)** | (1.620) | (1.478) | **(2.587)** | **(2.357)** | (1.921) | (1.679) |
| 12 | 0.032 | 0.026 | 0.020 | 0.015 | 0.041 | 0.034 | 0.028 | 0.021 |
| | (1.289) | (1.235) | (1.200) | (1.156) | (1.348) | (1.324) | (1.121) | (1.346) |
| 14 | -0.023 | -0.047 | -0.064 | -0.056 | -0.030 | -0.062 | -0.086 | -0.076 |
| | (-0.213) | (-0.434) | (-0.646) | (-0.615) | (-0.315) | (-0.336) | (-0.449) | (-0.518) |
| 16 | -0.139 | -0.106 | -0.072 | -0.067 | -0.169 | -0.137 | -0.097 | -0.090 |
| | (-1.359) | (-1.015) | (-0.780) | (-0.766) | (-0.990) | (-0.960) | (-0.481) | (-0.567) |

*Panel C: Treynor-Mazuy (TM) and Henriksson-Merton Parametric (HM) Measures*

| | *Treynor-Mazuy Measure* | | | | *Henriksson-Merton Parametric Measure* | | | |
|---|---|---|---|---|---|---|---|---|
| | Top $5^{th}$ | Top $10^{th}$ | Top $20^{th}$ | Top $25^{th}$ | Top $5^{th}$ | Top $10^{th}$ | Top $20^{th}$ | Top $25^{th}$ |
| J | Pctl | Pctl | Pctl | Pctl | Pctl | Pctl | Pctl | Pctl |
| 2 | -0.044 | -0.083 | -0.060 | -0.050 | -0.156 | -0.352 | -0.226 | -0.162 |
| | (-0.319) | (-0.592) | (-0.463) | (-0.398) | (-0.323) | (-0.713) | (-0.481) | (-0.358) |
| 4 | 0.033 | 0.038 | 0.076 | 0.067 | 0.356 | 0.381 | 0.499 | 0.463 |
| | (0.217) | (0.255) | (0.565) | (0.500) | (0.713) | (0.775) | (1.137) | (1.023) |
| 6 | 0.128 | 0.155 | 0.099 | 0.095 | 0.595 | 0.648 | 0.489 | 0.499 |
| | (0.969) | (1.258) | (0.790) | (0.775) | (1.375) | (1.678) | (1.170) | (1.232) |
| 8 | 0.102 | 0.144 | 0.098 | 0.104 | 0.479 | 0.582 | 0.458 | 0.505 |
| | (0.717) | (1.083) | (0.776) | (0.850) | (0.968) | (1.346) | (1.043) | (1.209) |
| 10 | **0.216** | **0.215** | 0.171 | 0.152 | **0.867** | **0.825** | 0.692 | 0.622 |
| | **(1.896)** | **(1.852)** | (1.505) | (1.270) | **(2.557)** | **(2.382)** | (1.867) | (1.533) |
| 12 | 0.119 | 0.113 | 0.154 | 0.148 | 0.573 | 0.542 | 0.669 | 0.651 |
| | (0.919) | (0.855) | (1.223) | (1.184) | (1.264) | (1.152) | (1.566) | (1.524) |
| 14 | 0.048 | 0.029 | 0.037 | 0.061 | 0.411 | 0.322 | 0.322 | 0.413 |
| | (0.350) | (0.202) | (0.267) | (0.467) | (0.824) | (0.603) | (0.616) | (0.866) |
| 16 | -0.044 | -0.032 | 0.016 | 0.037 | 0.124 | 0.138 | 0.260 | 0.352 |
| | (-0.303) | (-0.216) | (0.112) | (0.261) | (0.218) | (0.234) | (0.466) | (0.673) |

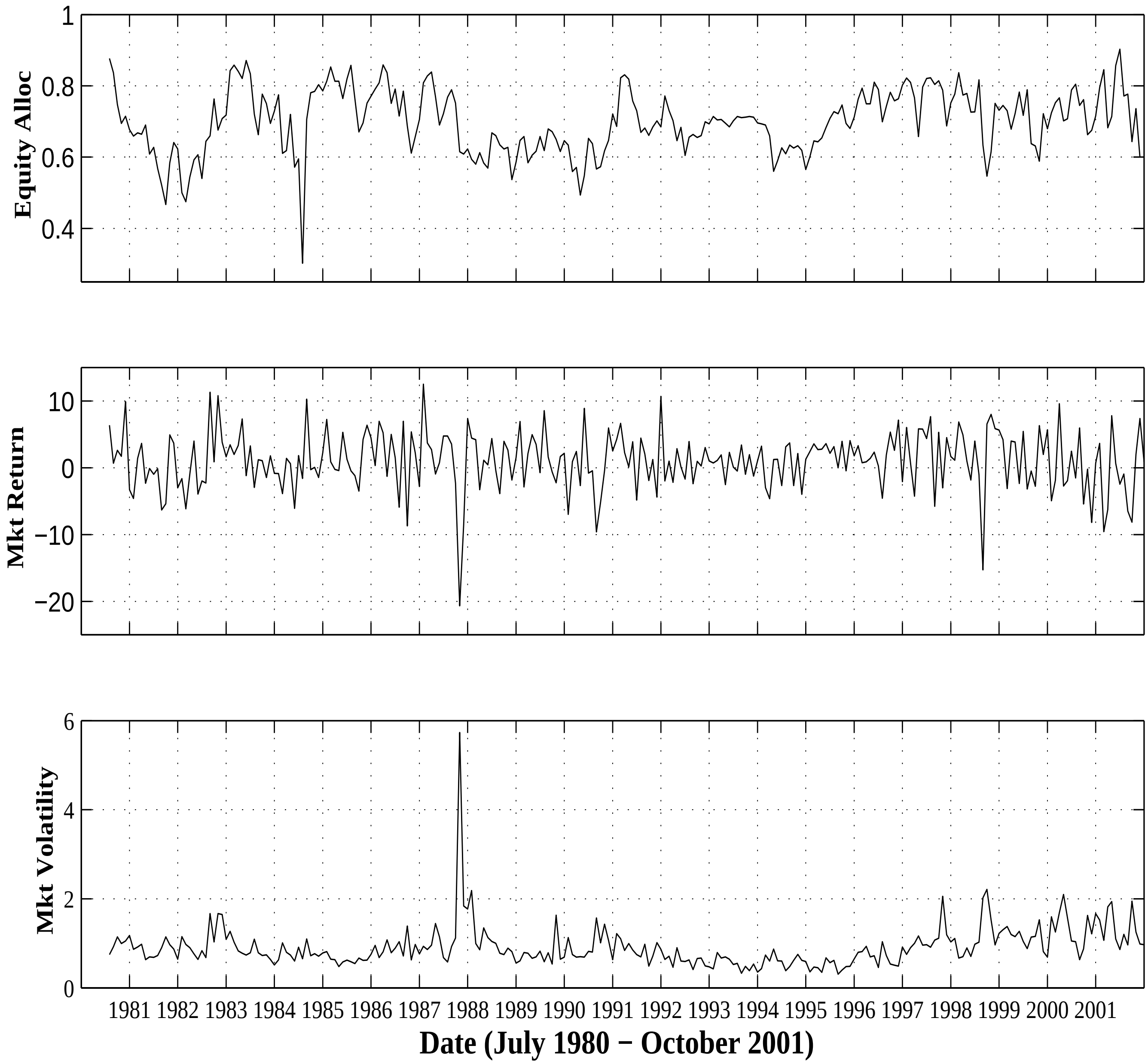


**Figure 1. Monthly equity recommendations, market returns, and market volatility time-series.** This figure shows the average monthly equity allocation recommended by 353 newsletter strategies during the June 1980 - November 2001 sample period (top panel). The middle and the bottom panels show the monthly market return and volatility respectively for the same time period. We use the S&P 500 index as a proxy for the market. We collect the data on newsletter recommendations from *Hulbert Financial Digest* and market returns data is obtained from Datastream.

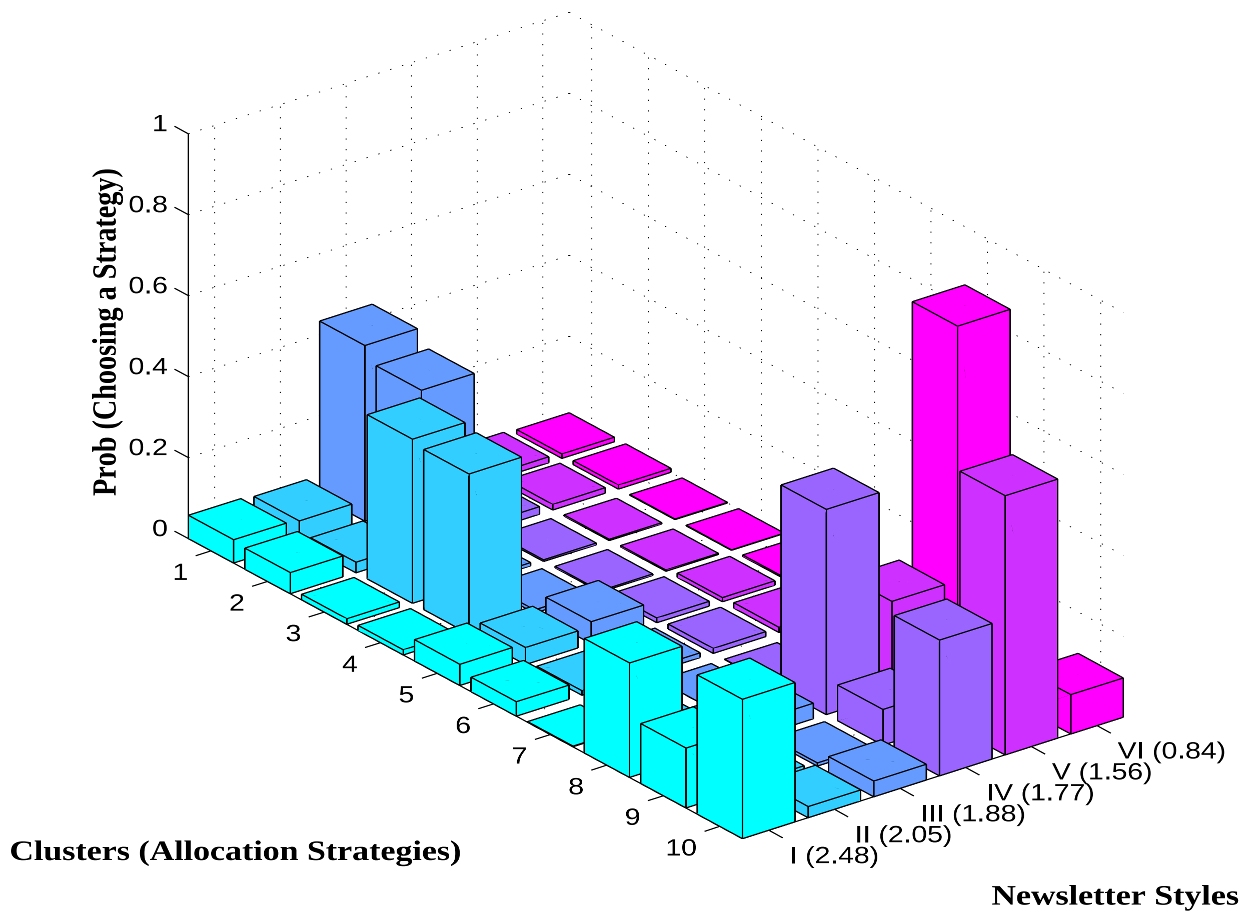


**Figure 2. Newsletters' styles representing six broad behavioral patterns.** Simple unconditional behavior patterns are observed among our sample of newsletters. Newsletter style 1 is of *moderate* nature and it uses all 10 strategies *uniformly* (except strategy 7 which occurs very rarely). Newsletter styles 2 and 3 are *true timers.* They use only two dominant strategies, both of which recommend *large* allocation changes ($0 \leftrightarrow 100, -100 \leftrightarrow 100$). Newsletter styles 4, 5, and 6 are *conservative* and they primarily use strategies that recommend *small* allocation changes. The number in parenthesis for each newsletter type is its entropy which is indicative of the predictability of newsletter behavior. The higher the entropy, the lower is the predictability, and hence, the higher is the "behavioral complexity". The entropy for the case with highest degree of uncertainty is 3.32 (corresponds to a uniform distribution). We collect the data on newsletter recommendations from *Hulbert Financial Digest.*

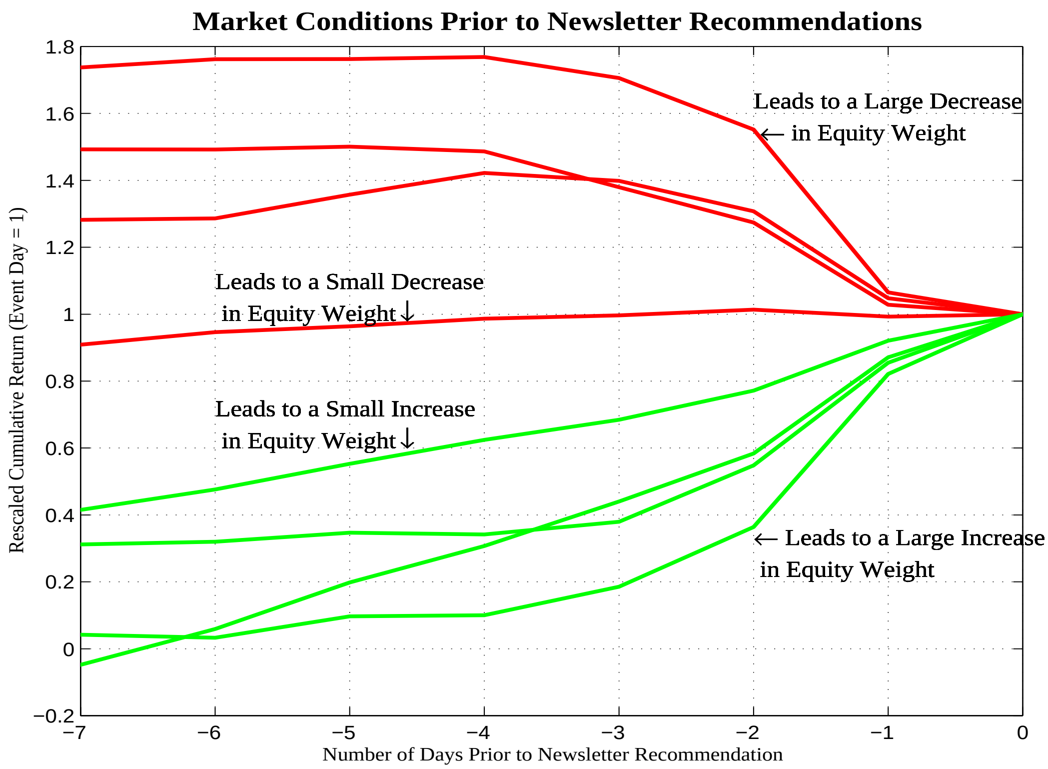


**Figure 3. Market conditions prior to newsletter recommendations.** This figure shows the mean cumulative raw market (S&P 500 index) return paths prior to changes in newsletter recommended equity allocation. The entire set of equity allocation changes in our sample is first divided into two groups: (i) positive equity allocation changes, and (ii) negative equity allocation changes. Each of these groups are further divided into quartiles and a mean cumulative raw return path is obtained for each of these 8 groups. All 30,626 recommendation changes covering the entire sample period (June 1980 – November 2001) are used to generate the return paths. We collect the data on newsletter recommendations from *Hulbert Financial Digest* and the market returns data is obtained from Datastream.

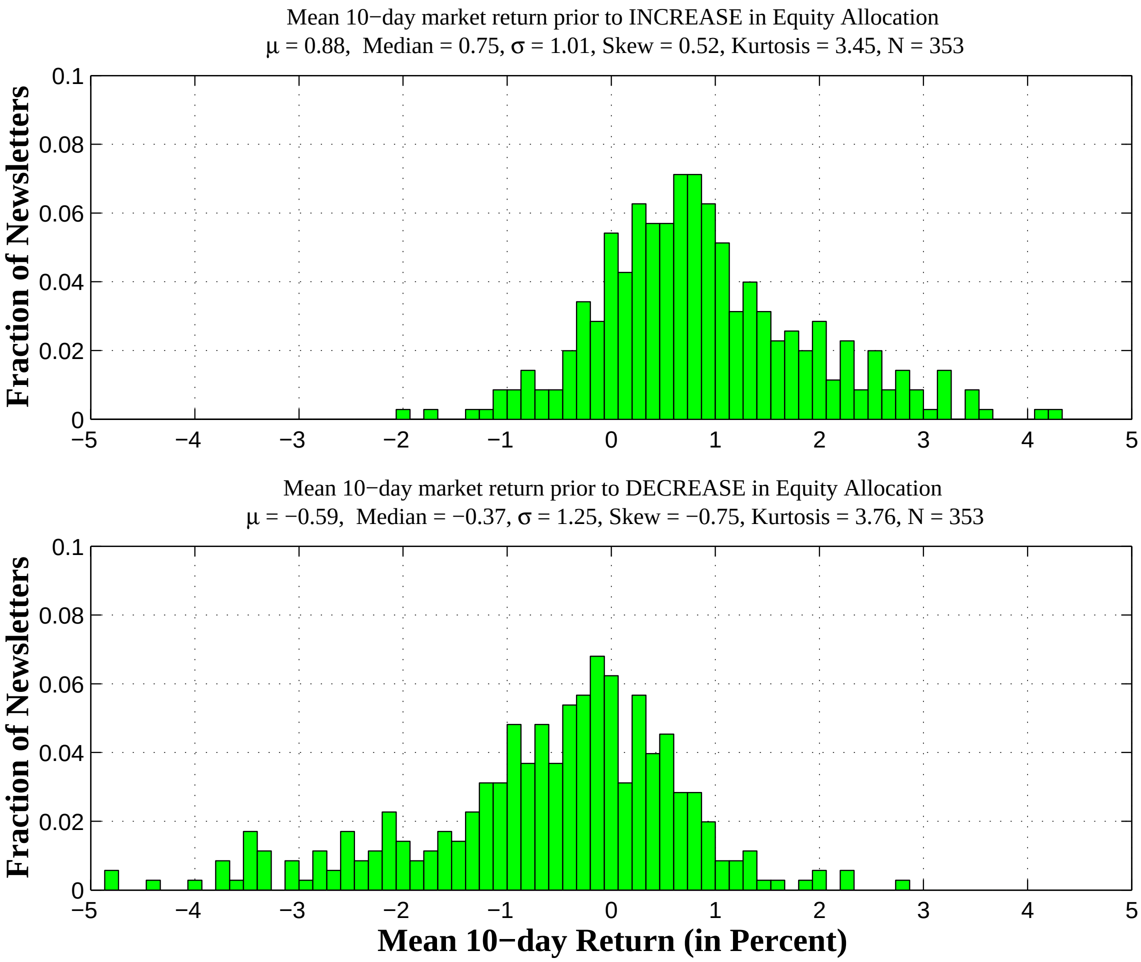


**Figure 4. Short-term market (S&P 500 index) behavior and equity allocation changes.** This figure shows the mean 10-day market return prior to changes in newsletter recommended equity allocation. The top (bottom) panel shows the mean market return distribution prior to an increase (decrease) in the equity portion of the newsletter recommended portfolio. All 30,626 recommendation changes covering the entire sample period (June 1980 – November 2001) are used to generate the two mean return distributions. The Kolmogorov-Smirnov test shows that the two distributions are significantly different from each other ($p$-value $< 0.001$). We collect the data on newsletter recommendations from *Hulbert Financial Digest* and the market returns data is obtained from Datastream.

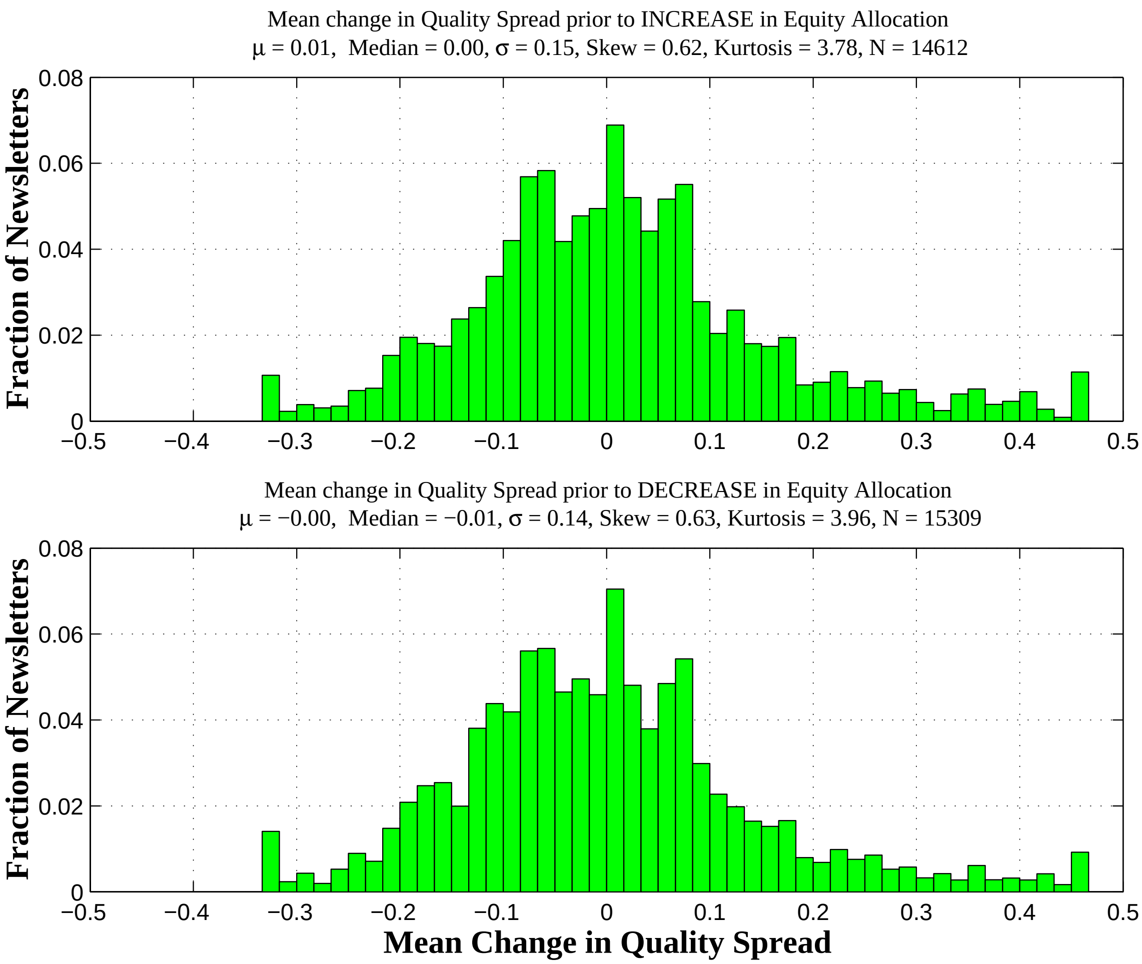


**Figure 5. Innovations in quality spread and equity allocation changes.** This figure shows the distributions of quarterly changes in the quality spread (the difference between the yields of Moody's BAA-rated corporate bond and AAA-rated corporate bond) prior to changes in newsletter recommended equity allocation. The top (bottom) panel shows the quality spread change distribution prior to an increase (decrease) in the equity portion of the newsletter recommended portfolio. All $30,626$ recommendation changes covering the entire sample period (June 1980 – November 2001) are used to generate the two mean return distributions. We collect the data on newsletter recommendations from *Hulbert Financial Digest* and the quality spread data is obtained from Datastream.

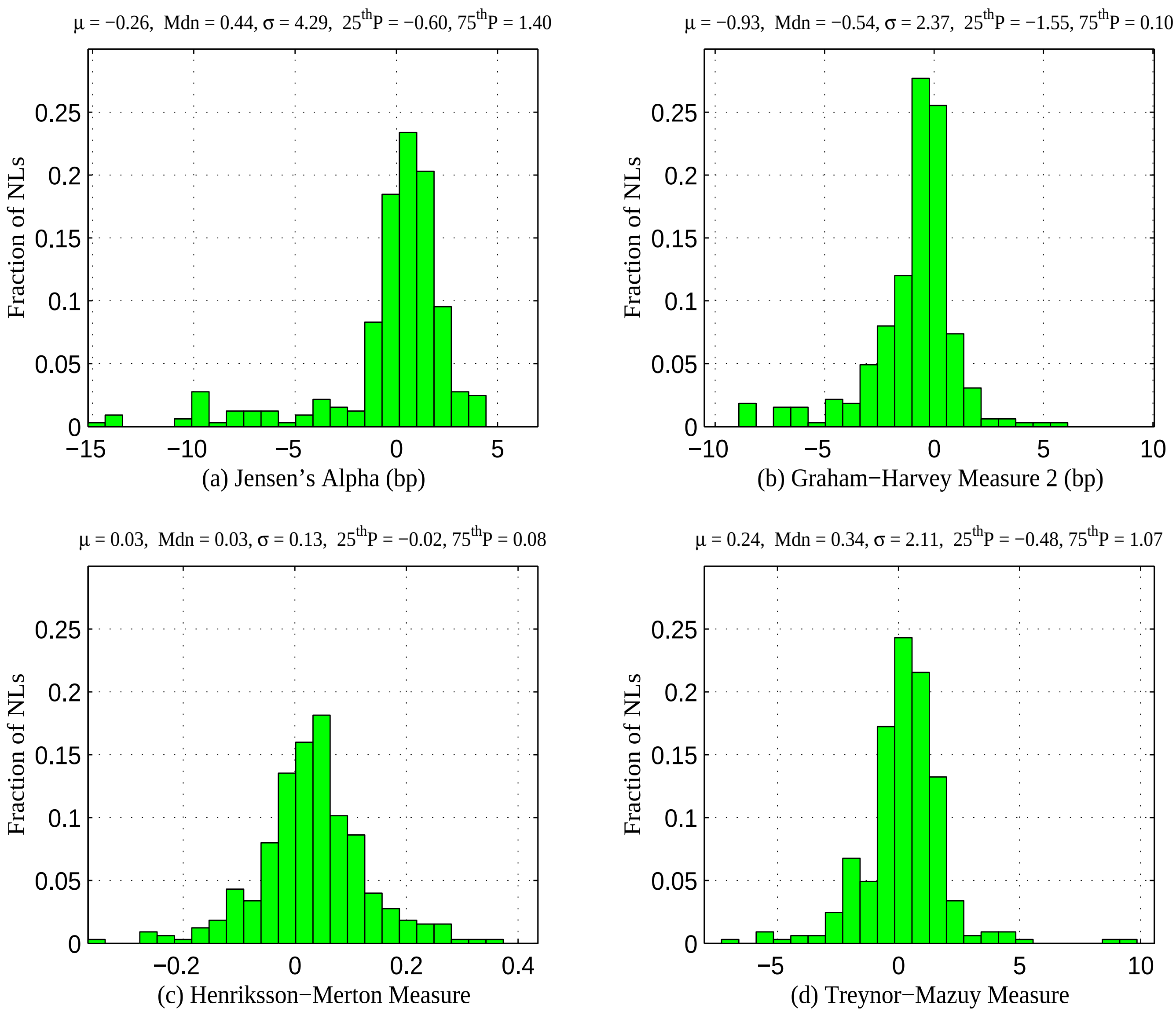


**Figure 6. Individual newsletter performance distributions.** This figure shows the distributions of the following four performance and market-timing measures: (i)Jensen's alpha (Jensen 1967), (ii) Graham–Harvey Measure 2 (Graham and Harvey 1997), (iii) Henriksson-Merton parametric measure (Henriksson and Merton 1981), and (iv) Treynor-Mazuy measure (Treynor and Mazuy 1966). These measures are computed for each of the 353 newsletters in our sample where the performance of each newsletter is measured for its entire "life-time". We collect the data on newsletter recommendations from *Hulbert Financial Digest*. *bp:* basis point.

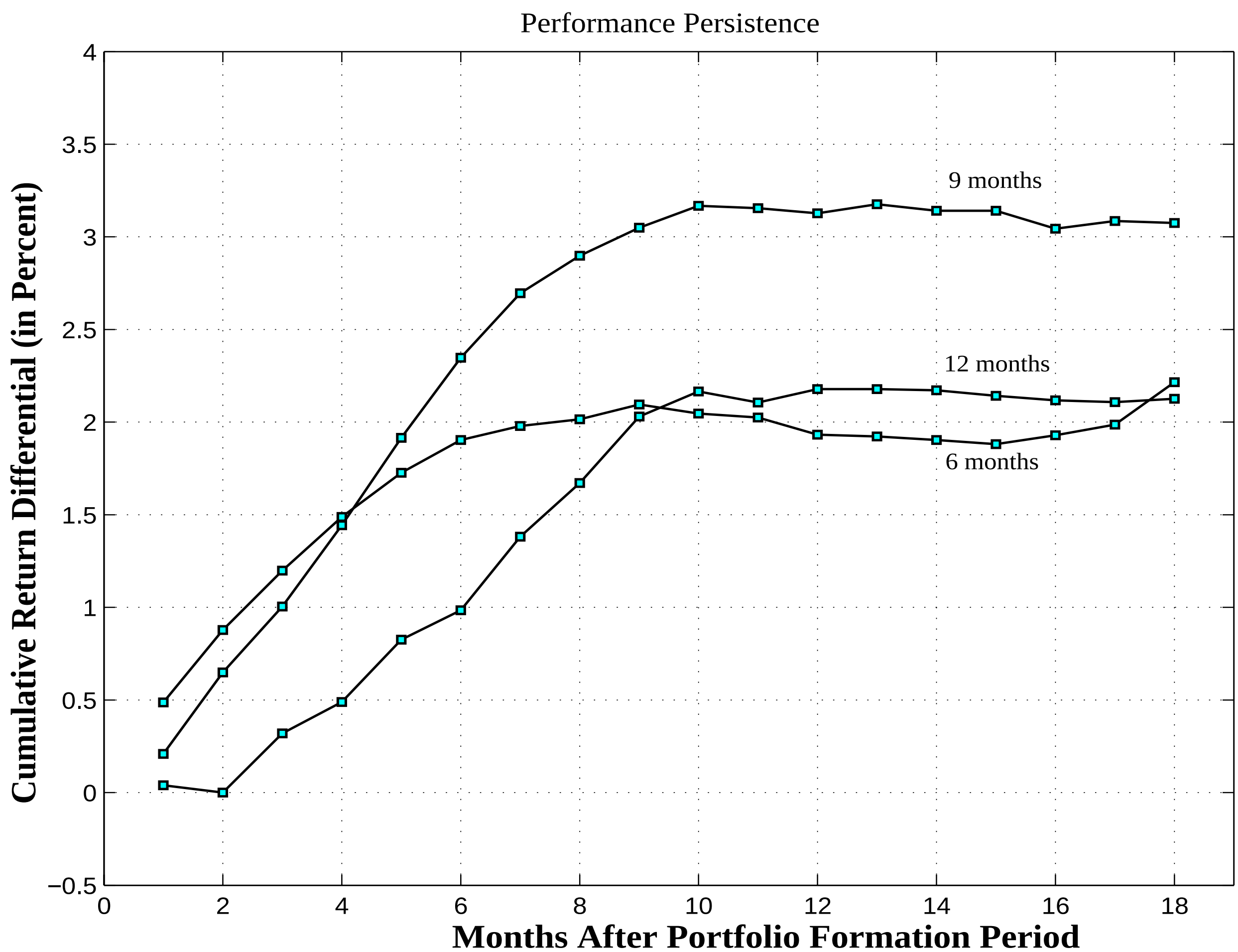


**Figure 7. Persistence in newsletter performance.** This figure shows the cumulative performance differential between a "winner" and a "loser" portfolio. At the end of each month, we sort newsletters based on their past $J$-month performance. We build a "winner" (top quintile) and a "loser" (bottom quintile) portfolio and track the difference in performance of these two portfolios during the next $K$-months. The cumulative performance differential plots are shown for $J = 6, 9, 12$. We collect the data on newsletter recommendations from *Hulbert Financial Digest*.