

# Behavior and Performance of Investment Newsletters Analysts<sup>⌘</sup>

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## Abstract

We analyze the behavior of a group of investment newsletters that provide explicit recommendations about the fraction of the investment portfolio that should be allocated to the market and to the riskless asset. Newsletters recommendations are mainly influenced by very short term market dynamics, while macroeconomic factors do not seem to play a big role. The group of newsletters exhibit few types of simple behaviors and a most of them can be classified as either momentum followers or contrarians. Our analysis shows that, although it is not clear that investment newsletters as a group are able to outperform the market, the portfolios recommended by both momentum following and contrarian individual newsletters are capable of outperforming a fully invested benchmark portfolio. We find persistence in newsletters performance and market timing ability. Overall, these results indicate that by using simple trading strategies and proper timing, some newsletters are able to exhibit superior performance. The results also provide empirical support for models that posit feedback based investor behavior and provide a useful parametrization for researcher modelling investor behavior.

# 1 Introduction

Market timing involves predicting correctly the movements of the market. A successful timer would recommend an increase (decrease) in the equity component of the investment portfolio before the market rises (falls). Several studies have evaluated the performance of market timers<sup>1</sup>, but very few of them have analyzed their decision-making processes. What market and macro-economic conditions prompt the timers to rebalance their portfolios? What trading strategies (if any) do they use? Are they momentum followers or contrarians? Do the interactions among the newsletters influence their decision-making process? Do they behave differently following large movements in the market? How do they react after large gains and large losses? If implemented, can a newsletter's investment strategy be profitable? Market and macro-economic factors are assumed to influence the decisions of market timers but the exact nature of this relationship is not well understood. In this paper, we investigate how market timers perceive and process information that is available to them and how performance feedback influences their behavior patterns. In particular, we focus on four aspects of the trading behavior of a particular group of market timers: investment newsletters. (i) First, we try to find out whether the newsletters in our sample have a similar behavior. (ii) We then analyze the reasons for this similarity. Since we do not observe the information set of the newsletters, we hypothesize that their trading strategy is influenced by three factors that the literature has shown that affect the behavior of active investors: market dynamics, macro-economic indicators, and own past performance. (iii) We then turn to the specific strategies that newsletters use to time the market. We classify newsletters into momentum followers and contrarians, depending on how they react to short term market movements. (iv) Once characterized the behavior of the newsletters and their trading strategies, the last part of this paper measures the ability of the newsletters, both as a group and individually, to time the market. We also analyze the related question of whether there is persistence in performance or "hot hands" in our sample.

The main source of data for this study is an investment newsletters database which consists of asset allocation recommendations made by a

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<sup>1</sup>There are so many papers that deal with this topic that any literature review would be necessarily incomplete and beyond the scope of this paper. Some of the most recent articles on this issue are Ackermann et. al (1999); Becker et. al (1999); Blake et. al (2000); Bollen and Busse (2001); Brown and Goetzmann (1997); Chance (2001); Edelen (1999); Graham and Harvey (1996); Kosowski et. al (2001); Metrick (1999); Wermers (2000); Jaffe and Mahoney (1999); Womack (1996); Zheng (1999).

group of investment newsletters for a period from June 1980 to November 2001. A recommendation explicitly states the fractions of the investment holding that must be allocated to risky and riskless asset classes. Few previous studies have analyzed the behavior and performance of investment newsletters using this same database. In a series of papers, Graham and Harvey (1996, 1997) analyze the asset allocation recommendations made by the newsletters and find no evidence of timing ability. More recently, Graham (1999) has used the newsletters database to empirically test a model of herding. He finds that a high reputation, low ability newsletter is more likely to herd on the "Value Line" investment newsletter, which is explicitly chosen as a market leader. Jeffrey and Mahoney (1999) and Metrick (1999) evaluate the stock picking ability of the newsletters using a different version of the database where, in addition to recommending a specific equity allocation, the newsletters either explicitly recommend a portfolio of equities or they provide a ranked list of desirable stocks that can be used to construct an equal-weighted portfolio of equities. Both these studies find that the newsletters, both at an aggregate level and individually, show very weak stock picking ability.

The market timing ability of professional timers has been investigated in a variety of other contexts with mixed results. Chang and Lewellen (1984) find that few fund managers have market-timing skills, and that they are unable collectively to outperform a passive investment strategy. Henriksson (1984) and Becker et al. (1999) find no evidence of signi-

cant market-timing ability for a sample of U.S. mutual funds. Coggin et al. (1993) find that U.S. equity pension fund managers display positive stock selection and negative market timing abilities. However, they argue that this negative correlation is largely an artifact of negatively correlated sampling errors for the two estimates. Cheng and Rahman (1990) indicate that at the individual fund level there is some evidence of superior micro- and macroforecasting ability on the part of the fund manager. Womack (1996) argues that stock analysts appear to have market timing and stock picking abilities. Graham and Harvey (1996) find no evidence that letters increase equity weights before market rises or decrease weights before market declines. Bollen and Busse (2001) find that mutual funds exhibit significant timing ability more often in daily tests than in monthly tests.

This paper differs from the previous studies in several significant ways. First of all, unlike previous papers which have primarily analyzed the timing skills among professional market timers, we also focus on the decision-making behavior of individual newsletters. The goal

is to understand how market and macro-economic factors influence the trading strategies of newsletters<sup>2</sup>. Without any knowledge of the information set of the newsletters, the exact form of trading strategies cannot be identified and so the goal of this paper is to identify the fundamental nature of trading strategies used by the newsletters. We find that newsletters are insensitive to changes in the macro-economic variables, but very short-term market dynamics (S&P500 returns) seem to have a big impact on newsletter behavior. The majority of them are momentum followers but a small group of them also act on the basis of contrarian beliefs. The fact that newsletters do not take macroeconomic factors into account when making their portfolio recommendation is surprising since Breen et al. (1989), Campbell (1987), Chen et al. (1986), Fama and French (1988), Ferson and Harvey (1993), Glosten et al. (1993), Pesaran and Timmermann (1995), Schwert (1990) and others have shown that the information contained in different macroeconomic indicators helps to predict future equity and bond returns and volatilities.

Secondly, most previous studies have used monthly data to measure performance even when recommendations are made at a much lower frequency. Chance and Hemler (2001) argue that the frequency with which recommendations are observed can change inferences regarding ability. They examine the performance of 30 professional market timers during 1986–1994. Using daily data, they find significant unconditional and conditional ability. However, when recommendations of successful timers are observed monthly instead of daily, significant ability generally disappears. If, as we show, market dynamics a few days immediately before the recommendation date is the most important factor driving the behavior of newsletters, and if short-term trends are an important characteristics of the market; ignoring intra-month observations can lead to inaccurate inferences. Our results support, and provide an explanation for, the argument in Bollen and Busse (2001), Busse (2001), Chance and Hemler (2001) and Goetzmann et al. (2000) that stresses the advantages of using daily rather than monthly data.

Thirdly, our analysis of superior performance and market timing ability not only looks at the newsletter industry as a whole, but also addresses the question of whether there are more individual newsletters that beat the market that can be expected by pure chance or sample variability. We find that although it is not clear that newsletters as a group exhibit superior performance, there is a subset of newsletters that

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<sup>2</sup>In a separate study, the impact of news events on the trading behavior of newsletters and individual investors will be reported.

do have market timing ability. Out of 329 newsletter strategies, 131 (39.82%) beat the market on a risk-adjusted basis (i.e. have a Sharpe ratio greater than the market); 172 (52.28%) have a positive Jensen's alpha, significantly different from zero at the 5 percent level. Regarding market timing ability, 101 (30.7%) newsletter strategies have a positive (significant at the 5% level) Treynor and Mazuy (1966) measure; 81 (24.62%) have a significantly positive at the 5% level Henriksson-Merton (1981) measure of market timing. We find evidence that superior performers exist in both the momentum follower and contrarian categories. We use Monte Carlo simulations to confirm that the number of superior performers is larger than what can be expected by sample variability or "luck". Bollen and Busse (2001), Kon (1983), Lee and Rahman (1990) provide evidence that although mutual funds as a group are unable to outperform the market on a risk-adjusted basis, "star" individual fund managers do exist. Our result confirms that active investment can be profitable and that a thorough analysis must be performed to pick newsletters.

In the last part of the paper we show that there is persistence in performance among newsletters. At any given month, we sort newsletters based on past 3, 6 and 12 performance. We build a "winners" (top quintile) and "losers" (bottom quintile) portfolio based on past performance, and calculate the difference in performance for these two portfolios in the next 18 months. Past 6-month winners outperform past 6-month losers by 3.5% in the 10 months that follow the portfolio construction; after 10 months, the difference in performance disappears.

The rest of the paper is organized as follows: in the next section the newsletters database is described. A discussion of the unconditional behavior of newsletters follows. The second part of Section III identifies the distinct behavior patterns observed among the group of newsletters and parametrizes those behavior patterns. The performance of newsletters is discussed in Section IV and the relationships between newsletter types, behavior patterns and performance are analyzed. The paper concludes in Section V with a summary of key results.

## 2 Investment Newsletters Database

We gather information from Hulbert Financial Digest, the investment newsletters database compiled by Mark Hulbert. The database consists of over 21 years of data (June 30, 1980-November 30, 2001) a total of

45,673 observations, covering 525 different newsletter strategies<sup>3</sup>, and 7,823 days (including weekend days). The newsletters discuss the prevailing economic conditions and based upon these provide market timing advice to the investors<sup>4</sup>. A recommendation is an explicit statement about the fraction of the investment portfolio that should be allocated to the risky (the equity component) and riskless (the cash component) asset classes. A valid recommendation has Long Equity + Short Equity + TBills; Margin = 100. Due to the presence of a margin account, the recommended allocation in the risky asset class can be more than 100%. The newsletters are published at different frequencies and in addition, they offer recommendation updates via a telephone "hotline". A new recommendation is entered in the database on the day a newsletter is received in mail (and not on the day a newsletter is published); however, all telephone hotlines are checked on a daily basis to obtain updated recommendations. A newsletter is not removed from the database after it ceases to exist, so the data is free of any survivorship bias.

Simple filtering rules are applied to "clean" the data. We remove newsletters that have less than 10 recommendations (172 newsletters, 627 recommendations) and those that do not show significant allocation dynamics (equity allocation is fixed). A few observations recommend an equal mix in long and short equities and these are replaced with an allocation consisting of 100% investment in the riskless asset class (13 such cases). We identify and remove "allocation duplicates", that is, successive recommendations for the same newsletter that repeat the equity allocation. These duplicates can arise because of two different reasons. Hulbert sometimes adds an additional observation on the first and/or the last day of the year for each of the active newsletters. An "allocation duplicate" may also arise when a newsletter recommends different stocks but maintains constant the proportion allocated to equity. Since our objective is to analyze the allocation between equity and the riskless asset, such recommendations are redundant. We remove 14,420 duplicates. A clean database, consisting of 30,626 observations and covering 353 newsletters, is used in this paper.

[Insert Figure I]

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<sup>3</sup>Several newsletters have more than one explicitly stated investment strategies and so the unit of analysis is actually a "newsletter strategy".

<sup>4</sup>See Hulbert (1993) for a brief description and long-term performance of the newsletters that were published before 1993.

Figure I shows the monthly market return and volatility, and the newsletters' allocation in equity from October, 1980 to December, 1981. The market return for our purposes is the return for the S&P500 index. The average monthly equity allocation and market return are 62.01% and 0.98%, respectively. Monthly market volatility, as measured by the standard deviation of the S&P500 returns, remain at 2-5% until June, 1996. From there, it raises significantly. The median monthly volatility is 2.91%. Interestingly, at the aggregate level, equity allocation is unrelated to current market returns and volatility. A simple regression of equity allocation on these two variables yields coefficients indistinguishable from zero at the 10% level. Equity allocation is negatively related though to future market volatility. A regression of current equity allocation on next month market volatility yields a coefficient of -0.425 and a p-value of 0.024.

[Insert Table I]

Newsletters make on average 87 recommendations in their "life" and stay active for an average of 7 years. There is a newsletter that makes 2,472 recommendations. More representatively, the median number of recommendations is 42; the median "life" of the newsletters is 6 years. Only 6 newsletters that were active by the end of 1980 remained active by the end of 2000. In Table I, we observe that the number of active newsletters per year increases steadily from 1980 to 1990 (21 to 161), and shows no clear trend afterwards. From 1985 onwards, the average number of recommendations per newsletter per year is between 12 and 13. This implies that, on average, newsletters rebalance their portfolio every month, approximately. It is possible to argue both ways regarding the relationship between the number of newsletters and past market returns. If investors' interest in the stock market rises following an upward trend in the market, as it happened in the recent internet bubble, we should observe a positive relationship between the number of active newsletters and past market returns. If, on the other hand, investors reassess their investment ability by the raw returns of their investments and switch to professional advice after realizing negative returns, following a market downward trend we should see increase demand for the newsletters' advice and a negative relationship between the number of active newsletters and past market returns. The data does not support any of this hypothesis. When we regress the number of active newsletters on last year's market return, we obtain a coefficient insignificantly different from zero at the 10% level. Perhaps more interestingly, when we regress



the number of active newsletters on last year's market volatility, we obtain a positive coefficient (0.4162), significant at the 5% level (p-value equals 0.02136). Apparently, after a period of market uncertainty, there is increased demand for the advice offered by the newsletters.

### 3 Newsletters Decision Process

#### 3.1 Unconditional Newsletter Behavior

We turn now to the first objective of the paper: to determine whether investment newsletters show a similar behavior. The portfolio allocation task faced by the newsletters involves two key decision variables: (i) change in 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  $T_1$ ,  $(E; \Delta E, \Delta T)$ , they constitute an allocation strategy<sup>5</sup> and they define a 3-dimensional "strategy space" in which the dynamics (behavior) of each newsletters lies. A sequence of allocation strategies (i.e., a trajectory in the strategy space) characterize the behavior (allocation dynamics) of a newsletter.

[Insert Figure II]

Figure II shows the three attributes that uniquely define an allocation strategy: the original allocation in equity, change in the equity recommendation, and time between recommendations. The mean equity recommendation is 62.39%; the median is 68%. The two most common recommendations are to allocate the entire portfolio to cash (i.e. equity equals 0%; 3,641 cases), or to the market (i.e. equity equals 100%; 4,295 cases). A small number of "extreme" allocations is observed. In 62 cases there is a recommendation to hold more than 200% in equity; in 102 cases the short position in equity is greater than 100% (i.e. equity is smaller than -100%). In 17 cases the recommendation is to short the

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<sup>5</sup>In this paper, the terms allocation, allocation recommendation and recommended allocation have the same meaning. They all refer to the fraction of the investment portfolio that must be allocated to risky and riskless asset classes. An allocation strategy, on the other hand, is defined by three elements: the recommended allocation in equity, the change between the current and the previous allocation in equity, and the time elapsed between the current and the last recommended allocation.

market (i.e. equity equals -100%). The mean and median time between recommendations are 30 and 10 days, respectively. In 13,330 cases the time between recommendations is one week or less.

Most newsletters recommend a certain level of allocation in equity (say,  $E_i$ ) and then they change the allocations around this fixed value. This equity weight forms a “natural attractor” for the newsletter. We have already seen that there are two additional “generic attractors” at 0; and +100. The allocation in equity recommended by a typical newsletter bounces between these three attractors. Transitions from 0 ! 100 (2,606 cases), 100 ! 0 (2,630 cases), are common; similarly, 12,888 recommendations involve an equity change smaller than 10%.

The group of newsletters use only a handful of allocation strategies. Using a series of clustering<sup>6</sup>, a parsimonious representation of the newsletter behavior is obtained. The algorithm used for identifying newsletter types is provided in the Appendix. Table II describes the 7 main allocation strategies identified through a variation<sup>7</sup> of the K-means clustering procedure. These unconditional behavior types reflect the “intrinsic” trading styles of newsletters, irrespective of the market conditions.

### [Insert Table II]

Depending on the use the newsletters make of the seven allocation strategies, eight main types of newsletters are identified. The eight newsletter types represent four broad behavioral patterns. Newsletter types 1, 2 and 7 are true timers. Type 1 newsletters shift mainly allocations in only cash (equity is 0%) and portfolios wholly invested in the market (equity equal to 100%). Type 2 (12 cases) newsletters make mostly large changes in equity recommendations, both positive and negative. Newsletter Type 7 (43) uses the four extreme trading strategies. Type 3 (10) newsletters make moderate rebalancing recommendations; whereas Type 4 (14) newsletters tend to stick to the same equity allocation (i.e. they make small recommendation changes). Newsletter Types 5 (51) and 6 (91) exhibit a mixed behavior; the former recommends large and moderate equity changes, the latter moderate and small. Newsletter Type 8 (43 cases) uses the seven allocation strategies uniformly.

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<sup>6</sup>See Hartigan (1975) and Bezdek (1981).

<sup>7</sup>The search method is “perturbed” in the beginning to avoid local minima and the perturbation is slowly reduced as the search progresses. “Simulated annealing” based search procedures use a similar heuristic for avoiding local minima.

[Insert Figure III]

To measure the complexity of the allocation strategy used by the different newsletters we use the concept of entropy. The entropy of newsletter  $i$  is calculated as

$$\text{ent}_i = - \sum_j p_{ij} \log_2(p_{ij}) \quad (1)$$

where  $p_{ij}$  is the probability that newsletter  $i$  uses strategy type  $j$ . The higher the entropy for a newsletter, the less predictive its behavior is. A newsletter that uses uniformly the seven strategy types will have an entropy equal to 2.81. A newsletter that always followed the same strategy would have an entropy of 0; the entropy of a newsletter that followed only two strategies with equal probability would be 1. From Figure 3, we observe that newsletters follow on average a simple strategy. Type IV has an entropy smaller than 1; ...ve types have an entropy smaller than 2. Only Type VIII exhibits a complex behavioral pattern.

### 3.2 Characteristics of Newsletter Strategies

In the previous section we have seen that newsletters exhibit very simple, similar trading strategies. We now try to determine the reason for this similarity. Since we do not have any explicit knowledge of the information set of the newsletters, the exact form of their trading strategies cannot be identified. The newsletters probably make recommendations using a complex trading strategy but these strategies can be classified as momentum or contrarian based on their inherent characteristics. At the same time, we hypothesize that newsletters' behavior is driven by two distinct feedback signals: (i) influence of market dynamics and (ii) portfolio performance feedback. The combination of these two effects, and the information contained in macroeconomic indicators, determines the direction of change, i.e., whether the equity weight will be increased or decreased and the timing of recommendations.

Momentum strategies are based on the belief that the market underreacts to information and hence prices evolve slowly over time leading to a trend in the market (Jegadeesh and Titman, 1993). As a result, trend chasing or momentum following strategies would increase (decrease) the exposure to equity when there is an upward (downward) trend in the price movements. The trading decision is based on the assumption that the trend that has started will continue in the future. In contrast, contrarian strategies develop from the market overreaction hypothesis in

DeBondt and Thaler (1985), and are based on the expectation of short-term price reversals. Contrarian trading strategies would decrease (increase) the exposure to equity when there is an upward (downward) trend in the price movements. The trading decisions are in “contrary” with the direction of the prices, hence the name contrarians. Jegadeesh

and Titman (1993) show that strategies that buy stocks that have performed well in the past and sell stocks that have performed poorly in the past generate significant positive returns over 3- to 12-month holding periods. The authors argue that the profitability of these strategies are not due to their systematic risk or to delayed stock price reactions to common factors. Rouwenhorst (1998) shows that the momentum effect also holds internationally. Between 1980 and 1995 an internationally diversified portfolio of past medium-term winners outperforms a portfolio of medium-term losers by more than 1 percent per month, after correcting for risk. On the other hand, DeBondt and Thaler (1985) show that portfolios of losers abnormal positive January returns as late as three years after portfolio formation. Balvers et al. (2000) gather national stock index data of 18 countries during the period 1969 to 1996, and find strong evidence of mean reversion in relative stock index prices over a period of three to three and one-half years.

Several authors have tried to explain the success of following a momentum or contrarian strategy; that is why short term market underreaction and long term overreaction occurs. Hong and Stein (1999) con-

struct a model of two groups of boundedly rational agents: ‘newswatchers’ and ‘momentum traders.’ Newswatcher observe some private information, but fail cannot extract other newswatchers’ information from prices. When information diffuses gradually across the population of agents, prices underreact in the short run, so momentum traders can profit by trend-chasing. However, if momentum traders can only implement simple strategies, their attempts at arbitrage lead to overreaction at long horizons. Daniel et al. (1998) build a theory of securities market under- and overreactions based on two psychological biases: investor overconfidence about the precision of private information; and biased self-attribution, which causes asymmetric shifts in investors’ confidence as a function of their investment outcomes. Overconfidence implies negative long-lag autocorrelations, excess volatility, and, when managerial actions are correlated with stock mispricing, public-event-based return predictability. Biased self-attribution adds positive short-lag autocorrelations (‘momentum’), short-run earnings ‘drift,’ but negative correlation between future returns and long-term past stock market and account-

ing performance. Chan et al. (1996) argue that the market responds only gradually to new information. Hong et al. (2000) find that firm-specific information, especially negative information, diffuses only gradually across the investing public.

Regardless of the underlying reason, market dynamics affect the trading behavior of market investors. Grinblatt et al. (1995) find that 77 percent of the mutual funds in their sample were "momentum investors," buying stocks that were past winners; however, most did not systematically sell past losers. Chan et al. (1996) finds that security analysts' earnings forecasts respond sluggishly to past news, especially for the stocks with the worst past performance. Dhar and Kumar (2001) analyze the impact of price trends on trading decisions of more than 40,000 individual investors. The authors find that buying and selling decisions of investors in their sample are influenced by short-term (less than 3 months) price trends.

#### [Insert Figure IV]

Figure 4 shows the market conditions prior to equity weight changes. In particular, the mean 10-day market return prior to a recommended equity increase is 0.88%; on the contrary, the mean 10-day market return prior to a recommended equity decrease is -0.59%. In essence, the majority of the newsletters base their strategies on the feedback in the form of short-term market returns<sup>8</sup>.

Chen et al. (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. Ferson and Harvey (1993) find that most of the predictability in national equity market returns is due to time variation in the global economic risk premia. Campbell (1987), Breen et al. (1989), Ferson (1989) and Glosten et al. (1993) find that interest rates are useful in forecasting the sign as well as the variance of the excess return on stocks. Fama and French (1988) argue that the power of

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<sup>8</sup>The terms trend chasers, momentum followers and positive feedback traders (DeLong et al., 1990) are used synonymously to indicate trading strategies which are based on the anticipation that the market trend (upward or downward) will continue in the short run.

dividend yields to forecast stock returns increases with the return horizon. Balvers et al. (1990), Fama (1990) and Schwert (1990) show that future production growth rates explain a large fraction of the variation in stock returns. Elton et al. (1995) ...nd that economic variables help explaining the cross-section of expected bond returns. We thus assume that macroeconomic factors belong to the information set of variables used by investment newsletters to devise their trading strategies.

Past performance does affect future trading behavior. Gervais and Odean (2001) develop a multi-period market model in which a trader does not know initially his own ability but infers it from his successes and failures. In assessing his ability the trader takes too much credit for his successes, and becomes overcon...dent. Brown et al. (2001), Busse (2001) and Koski and Pontia (1998) show that mutual funds actively alter the risk of their portfolios in response to past performance. Brown et al. (2001) analyze the performance of 334 growth-oriented mutual funds during 1976 to 1991 and show that mid-year losers tend to increase fund volatility in the latter part of an annual assessment period to a greater extent than mid-year winners. Koski and Pontia (1998) show that beginning of the year changes in risk and positively correlated with end of prior year performance.

We perform a set of event studies to gain insights into the behavior patterns of newsletters. We examine the impact of three information variables on the behavior of newsletters as a whole and also individually: short term market dynamics; macroeconomic factors; and each newsletter past performance. In general, the equity allocation rule of a given newsletter  $i$  can be represented as:

$$\Phi \text{Equity}^i(t) = f[\Phi \text{Market}(t_j - k); \Phi \text{Macro}(t_j - k); \text{Perf}^i(t_j - k)]$$

where  $k$  is the number of lags considered.  $i = 1; :: :: N$ . The following linear regression model specifies the relationship between changes in the newsletter recommendations (equity weights) and the set of driving factors:

$$\begin{aligned} (\Phi \text{Equity})_t &= b_0 + \sum_{i=1}^k b_i (\text{S\&P500 Return})_{t_i - i} \\ &+ b_{k+1} (\text{Short Term Perf})_{t_i - 1} + b_{k+2} (\text{Long Term Perf})_{t_i - 1} \\ &+ b_{k+3} (\Phi \text{Term Spread})_{t_i - 1}^{\text{wk}} + b_{k+4} (\Phi \text{Term Spread})_{t_i - 1}^{\text{mo}} \\ &+ b_{k+5} (\Phi \text{Quality Spread})_{t_i - 1}^{\text{wk}} + b_{k+6} (\Phi \text{Quality Spread})_{t_i - 1}^{\text{mo}} \\ &+ b_{k+7} (\Phi \text{Short Term Int Rate})_{t_i - 1}^{\text{wk}} \\ &+ b_{k+8} (\Phi \text{Short Term Int Rate})_{t_i - 1}^{\text{mo}} + \epsilon_t \end{aligned} \tag{1}$$

We use the S&P 500 return as a measure of market dynamics.  $S\&P500\ Ret_{t-k}$  is the return in the S&P500 futures from the last  $k$  days prior to the change in the equity recommendation. Following Pesaran and Timmerman (1995) and Ferson and Schadt (1996), we use the following macroeconomic indicators: the 30-day annualized Treasury bill yield (Short Term Int Rate); the difference between a constant-maturity 10-year Treasury bond yield less the 3-month Treasury bill yield (Term Spread), as a measure of the term structure of interest rates; the difference between the Moody's BAA-rated corporate bond yield less the AAA-rated corporate bond yield (Quality Spread); the dividend yield in the CRSP value-weighted market index. Weekly ( $^{wk}$ ) and monthly ( $^{mo}$ ) changes in macro-economic variables are considered since daily changes in the variables are not significant. Short term performance (Short Term Perf) is the cumulative return of the newsletter recommended portfolio for 5 days before the recommended change; long term performance (Long Term Perf) is the cumulative return of the newsletter recommended portfolio since the last recommendation.

[Insert TABLE III]

In Table II we see that the coefficient for the market dynamics variables for the first 5 days are all positive and significantly different from zero at the 5 percent level. Furthermore, the coefficients for the first three days are larger indicating that the market returns in the recent past have a higher impact on the decision-making process of the newsletters. The recent market returns and past performance are the key factors influencing the behavior of newsletters at an aggregate level. Changes in macro-economic variables do not impact the behavior of newsletters. Very slow variation in the macro-economic variables might be one of the reasons for this relatively surprising result. Note that if market dynamics a few days immediately before the recommendation date is the most important factor driving the behavior of newsletters and if short-term trends are an important characteristics of the market, ignoring intra-month observations<sup>a</sup> can lead to inaccurate inferences. The fact that newsletters do not take macroeconomic factors into account when making their portfolio recommendations is puzzling since, among others, Breen et al. (1989), Campbell (1987), Chen et al. (1986), Fama and French (1988), Ferson and Harvey (1993), Glosten et al. (1993), Pesaran and Timmermann (1995), Schwert (1990) have shown that the information contained in different macroeconomic indicators helps to predict future equity and bond returns and volatilities.

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<sup>a</sup>An equally-spaced monthly recommendation series is used in [?, ?, ?].

In order to identify the individual newsletter strategies, a bootstrap with 1000 iterations is used with only 5-day lagged S&P500 returns. We use the SOM<sup>y</sup> clustering procedure to identify sub-groups of newsletters that have similar market timing strategies<sup>z</sup>. The results are reported in Table IV. We observe that the majority of the newsletters are momentum followers but a small group of them also act on the basis of contrarian beliefs.

[Insert TABLE IV]

## I Performance measurement.

In the previous sections, we have seen that newsletters exhibit a similar behavior; they try to time the market using very simple trading strategies. Newsletters change their equity recommendation based on very short term market dynamics, without paying much attention to the information contained by macroeconomic variables. In this part of the paper, we analyze whether newsletters are successful in their attempt to time the market, both as an aggregate and individually. That is, even if newsletters as a group do not have market timing ability, it is still interesting to find out whether there are "star newsletters" (i.e. individual newsletters that are successful in timing the market). Using a bootstrap analysis, we show that the existence of individual outperformers cannot be explained by sample variability or "luck". We deal with the existence of persistence in market timing ability at the end of the section, and try to devise a trading strategy that benefits ex ante from such persistence.

From the analysis of newsletter behavior it is clear that they are primarily trying to exploit the known characteristics of the market (momentum and price reversals) using simple technical trading rules. Recent studies show that these technical trading rules can be profitable. In an extensive study, Conrad and Kaul (1998) provide evidence that both momentum and contrarian investment strategies can be profitable, though under different market conditions. Brock et al. (1992) investigate the profitability of two popular technical trading rules, moving average (MA) and trading range breaks (TRB), and show that both rules have predictive power. Sullivan et al. (1999) find that technical trading rules tested in Brock et al.

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<sup>y</sup>SOM or self-organizing map is a neural network based clustering procedure that essentially maps data points in a higher dimensional space into a 2-dimensional space using a nonlinear mapping function. See [?] for details.

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<sup>z</sup>Only the regressions that have statistically significant parameters are included in cluster analysis.

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(1992) (and several other rules) are robust to data snooping biases and are indeed capable of generating superior returns. Brown et al. (1998) show that the trading strategies that constitute the Dow Theory (as interpreted by Hamilton, the editor of Wall Street Journal from 1902-29) are able to beat a buy and hold strategy<sup>x</sup>. So it appears that simple technical trading rules have the potential to be profitable, if properly timed. There are also characteristics of the market index in the short run that may be responsible for profitability of simple trading strategies. Bremer (1991) show that a large drop in prices is followed by a larger than expected positive returns over the next several days. For example, they found that a 10% negative return on a given day is followed by a 1.77% above average return on the next day and 2.22% cumulative return on the second day. Under these circumstances, a contrarian strategy can be profitable in a very short time horizon (less than 5 days).

We now analyze in more depth the performance of investment newsletters as a group; and provide more robust evidence that some individual newsletters are able to beat the market (i.e. that there are more newsletters that beat the market that can be explained simply by "luck" or sample variability). Since we consider only the allocation between cash and equity, not the individual stocks recommended by newsletters, any evidence of superior performance must come from market timing ability. For those newsletters that do recommend individual stocks rather than exposure to the market as a whole, the results in the coming section reflect the gains (loses) that would obtain an investor who discarded the individual stock recommendations of the newsletter and invested in S&P 500 futures the fraction of the recommended portfolio allocated to individual stocks.

The value of active investment management has been seriously questioned. Daniel et al. (1997) analyze the portfolio holdings of over 2500 equity funds from 1975 to 1994. Their results show that mutual funds, particularly aggressive-growth funds, exhibit some selectivity ability, but funds exhibit no timing ability. Ackermann et al (1999), using a large sample of hedge fund data from 1988 to 1995, found that hedge funds consistently outperform mutual funds, but not standard market indices. Hedge funds, however, are more volatile than both mutual funds and market indices. Metrick (1999) analyzes the equity-portfolio recommendations made by investment newsletters, and finds no significant evidence of superior stock-picking ability. Wermers (2000) finds that mutual funds hold stocks that outperform the market by 1.3

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<sup>x</sup>Transaction costs and other market frictions are not considered in any of these analyses. In fact [?] shows that the technical trading rules identified in [?] and [?] have performed poorly on more recent data (1989 onwards) and those trading rules do not beat a buy and hold strategy due to the presence of price slippage and significant transaction costs.

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percent per year, but their net returns underperform by one percent. Of the 2.3 percent difference between these results, 0.7 percent is due to the underperformance of nonstock holdings, whereas 1.6 percent is due to expenses and transactions costs. Chen et al. (2000) found that stocks widely held by funds do not outperform other stocks; but stocks purchased by funds have significantly higher returns than stocks they sell.

Since in this study we are interested in analysing the market timing ability of newsletters, we limit our analysis of overall performance measures to Jensen's alphas and Sharpe ratios. These are probably the most widely used measures of performance by both academics and practitioners. Moreover, since we restrict our analysis to the choice between equity and cash, any evidence of abnormal performance must come from market timing ability. To obtain Jensen's (1966) alpha, we fit the following model by least squares

$$r_{i;t} = \alpha_i + \beta_i r_{m;t} + \epsilon_{i;t} \quad (2)$$

where  $r_{i;t}$  is the return of newsletter  $i$  in period  $t$ , and  $r_{m;t}$  is the return on the market portfolio in period  $t$ . Abnormal performance for newsletter  $i$  requires  $\alpha_i > 0$ . On the other hand, the Sharpe Ratio indicates the historic average differential return per unit of historic variability of the differential return. Let  $D_t = r_{i;t} - r_{f;t}$  be the differential return between newsletter  $i$  and the riskless asset in period  $t$ ;  $\bar{D}_t = \frac{1}{T} \sum_{t=1}^T D_t$

the average value of  $D_t$  over the historic period from  $t = 1$  through  $T$ ; and  $\sigma_D = \frac{1}{\sqrt{T-1}} \sqrt{\sum_{t=1}^T (D_t - \bar{D}_t)^2}$  the standard deviation of  $D_t$  over the period  $t = 1$  to  $T$ . The Sharpe ratio is then defined as  $SR = \frac{\bar{D}_t}{\sigma_D}$ . We report the ratio between the Sharpe ratio for newsletter  $i$  and the market Sharpe ratio for the market for the whole period in which newsletter  $i$  is active. We also show the results for a variant of the Sharpe ratio, normally used in the investment community. This new measure,  $SR'$ , is defined as  $SR' = \frac{\frac{1}{T} \sum_{t=1}^T r_{i;t}}{\frac{1}{\sqrt{T-1}} \sqrt{\sum_{t=1}^T (r_{i;t} - \bar{r}_{i;t})^2}}$ : That

is, the difference between  $SR'$  and the traditional Sharpe ratio is that under  $SR'$  raw returns are used to calculate the mean return and the standard deviation of returns. Under  $SR$ , excess returns (above the risk free rate) are used. As for the Sharpe ratio, we report the ratio between the modified Sharpe ratio for newsletter  $i$  and the modified Sharpe ratio for the market for the whole period in which newsletter  $i$  is

active. Under both variants of the Sharpe ratio, a newsletter is said to exhibit superior performance if it has a higher Sharpe ratio than the market during the period in which the newsletter is active, that is, if  $\frac{SR_i}{SR_m} > 1$ .

We also report four different measures of market timing. The Treynor-Mazuy (1966) measure of market timing is described by the following stochastic relationship:

$$r_{i;t} = \alpha_i + \beta_i r_{m;t} + \gamma_{tmu} [r_{m;t}]^2 + \epsilon_{i;t} \quad (3)$$

Likewise, to measure market timing ability in the Henriksson-Merton (1981) framework, we must estimate the following regression:

$$r_{i;t} = \alpha_i + \beta_i r_{m;t} + \gamma_u [r_{m;t}]^+ + \epsilon_{i;t} \quad (4)$$

where  $r_{i;t}$  is the excess return of newsletter strategy  $i$  at time  $t$ ,  $r_{m;t}$  is the excess return on the market and  $\gamma_{tmu}$  and  $\gamma_u$  measure market timing ability;  $\gamma_u [r_{m;t}]^+$  is defined as  $\text{Max}[0; r_{m;t}]$ ; and the previous equations are estimated using OLS. For a successful market timer  $\gamma_{tmu}$  and  $\gamma_u$  must be larger than zero.

Henriksson-Merton (1981) also present a non-parametric measure of market timing. Define  $\Phi E_{i;T_{i-1};T_{i-2}} = E_i(T_2)_i - E_i(T_1)$  as the change in the equity recommendation by newsletter  $i$  from period  $t_{i-2}$  to period  $t_{i-1}$ : That is,  $\Phi E_{i;T_{i-1};T_{i-2}} > 0$  represents an increase in the equity recommendation of newsletter  $i$  from  $t_{i-2}$  to  $t_{i-1}$ . Define  $p_i^+(t)$  as the probability that newsletter  $i$  correctly predicts whether the market in period  $t$  is going to achieve a higher rate of return than the risk free asset, that is whether  $r_{m;t} > r_{f;t} > 0$ : That is,

$$p_i^+(t) = \text{Prob}[\Phi E_{i;T_{i-1};T_{i-2}} > 0 | r_{m;t} > r_{f;t} > 0] \quad (5)$$

Similarly, define  $p_i^-(t)$  as the probability that newsletter  $i$  correctly predicts whether the market in period  $t$  is going to achieve a lower rate of return than the risk free asset. Then,

$$p_i^-(t) = \text{Prob}[\Phi E_{i;T_{i-1};T_{i-2}} < 0 | r_{m;t} < r_{f;t} < 0] \quad (6)$$

Henriksson-Merton (1981) non-parametric measure of market timing is then given by  $p_i^+(t) + p_i^-(t)$ : We present a variant of this measure. Assume that newsletters only try to time the market, regardless of the

return of the risk free rate. Then, this type of timer will increase their equity allocation if he forecasts than the return of the market during next period will be positive. Under this new measure, market timing ability is given by  $p_i^+(t)^0 + p_i^-(t)^0$ ; where

$$p_i^+(t)^0 = \text{Prob}[\Phi E_{i;T_i 1;T_i 2} > 0 | r_{m;t} > 0] \quad (7)$$

$$p_i^-(t)^0 = \text{Prob}[\Phi E_{i;T_i 1;T_i 2} < 0 | r_{m;t} < 0] \quad (8)$$

To measure the performance of newsletters as a group, we need to define "an aggregate" newsletter. We use a rebalancing strategy, that for any given frequency uses the average equity recommendation by all newsletters. As an example, our monthly newsletter computes the average recommendation made by all newsletters in a given month and carries it forward to the following month. In Table V we display performance and market timing measures for the "aggregate newsletter" at different rebalancing frequencies. At the aggregate level, we cannot clearly establish whether newsletters exhibit superior market performance or market timing ability. The two versions of the Sharpe Ratio provide contradicting results. When excess returns are used to calculate Sharpe Ratios, newsletters exhibit inferior performance for all rebalancing frequencies. The exact opposite result holds when we use raw returns. The measure of performance by Jensen's alpha gives a clearer and more positive answer. All aggregate newsletters exhibit a positive alpha, significantly different from zero at the 1 percent level. The excess annual return measured by Jensen's alpha varies from 2.07% to 2.82%. The parametric HM and TM measures of market timing do not provide conclusive results. The TM measure is positive for shorter frequencies, but negative when rebalancing is done monthly or quarterly. The HM non-parametric measure is only below 0.5 for the daily rebalancing newsletter. However, only for monthly rebalancing the results seem strong enough to claim market timing ability.

[Insert TABLE V]

Although it is not clear that newsletters as a group exhibit superior performance, there is a subset of newsletters that do have market timing ability. Out of 329 newsletter strategies, 131 (39.82%) beat the market on a risk-adjusted basis (i.e. have a Sharpe ratio greater than the market); 172 (52.28%) have a positive Jensen's alpha, significantly different from zero at the 5 percent level. Regarding market timing ability, 101 (30.7%) newsletter strategies have a positive (significant at the 5% level) Treynor and Mazuy (1966) measure; 81 (24.62%) have a significantly positive at the 5% level Henriksson-Merton (1981) measure of market timing. We find evidence that superior performers exist in both the momentum follower and contrarian categories. We use Monte Carlo simulations to confirm that the number of superior performers is larger than what can be expected by sample variability or "luck". Bollen and Busse (2001), Kon (1983), Lee and Rahman (1990) provide evidence that although mutual funds as a group are unable to outperform the market on a risk-adjusted basis, "star" individual fund managers do exist. Our result confirms that active investment can be profitable and that a thorough analysis must be performed to pick newsletters.

## A Persistence in Performance

Elton et al. (1996); Hendricks et al. (1997) and Carpenter and Lynch (1999) examine predictability for stock mutual funds using risk-adjusted returns. They find that past performance is predictive of future risk-adjusted performance. Brown and Goetzmann (1995) also find that relative risk-adjusted performance of mutual funds persists; however, the authors argue that persistence is mostly due to funds that lag the S&P 500. Carhart (1997) demonstrates that common factors in stock returns and investment expenses almost completely explain persistence in equity mutual funds' mean and risk-adjusted returns. The author finds that the only significant persistence not explained is concentrated in strong underperformance by the worst-return mutual funds. Agarwal and Narayan (2000) find that persistence among hedge fund managers is short term in nature.

To find out whether there is performance persistence or "hot hands" in our sample of newsletters, at any given month, we sort newsletters based on past 3, 6 and 12 performance. We build a "winners" (top quintile) and "losers" (bottom quintile) portfolio based on past performance, and calculate the difference in performance for these two portfolios in the next 18 months. In Figure VI, we see that past 6-month winners outperform past 6-month losers by 3.5% in the 10 months that follow the portfolio construction; after 10 months, the difference in performance disappears.

[Insert Figure VI]

## II Conclusion

Several theoretical models have been proposed to explain investor behavior but direct empirical evidences have been scarce. Our analysis of a group of professional market timers provide direct evidence of feedback based trading strategies and provide some useful insight into investor behavior. Our main results suggest that at an aggregate level, the group of newsletters are quite similar in their behavior. This is not surprising since they all are strongly driven by the dynamics of the market. In fact, the trend feedback is strong for a majority of newsletters. Surprisingly, the macro-economic factors do not appear to have any impact on newsletters' behavior. The decision rules used by the newsletters are simple but effective technical trading rules. Approximately one-third of the newsletters perform better than a "buy and hold" strategy. These

newsletters are able to reduce the volatility of the recommended portfolios and hence provide higher Sharpe ratios and positive Jensen's alphas. Unfortunately, about an equal number of newsletters continue to hold a losing portfolio (primarily a short position in equity) inspite of a series of strong negative performance feedback. Extreme care must be exercised in picking possible "newsletter" stars.

| Year | Active Newsletters | Recommendations | Rec. per Newsletter | Equity Allocation | S&P500 Return | S&P500 Volatility |
|------|--------------------|-----------------|---------------------|-------------------|---------------|-------------------|
| 1980 | 21                 | 53              | 2.52                | 62.86%            | 18.84%        | 6.23              |
| 1981 | 18                 | 128             | 7.11                | 50.71%            | -9.73%        | 5.65              |
| 1982 | 22                 | 218             | 9.91                | 42.63%            | 14.76%        | 11.00             |
| 1983 | 28                 | 275             | 9.82                | 64.52%            | 17.27%        | 8.18              |
| 1984 | 54                 | 510             | 9.44                | 55.84%            | 1.40%         | 5.73              |
| 1985 | 61                 | 767             | 12.57               | 68.40%            | 26.33%        | 9.46              |
| 1986 | 76                 | 969             | 12.75               | 57.31%            | 14.62%        | 12.30             |
| 1987 | 100                | 1,298           | 12.98               | 64.39%            | 2.03%         | 28.64             |
| 1988 | 120                | 1,356           | 11.30               | 61.49%            | 12.40%        | 8.84              |
| 1989 | 141                | 1,312           | 9.30                | 66.33%            | 27.25%        | 23.83             |
| 1990 | 161                | 1,899           | 11.80               | 54.38%            | -6.56%        | 17.60             |
| 1991 | 162                | 1,911           | 11.80               | 59.67%            | 26.31%        | 18.26             |
| 1992 | 176                | 1,842           | 10.47               | 60.05%            | 4.46%         | 8.61              |
| 1993 | 149                | 1,788           | 12.00               | 65.29%            | 7.06%         | 10.10             |
| 1994 | 165                | 2,012           | 12.19               | 57.56%            | -1.54%        | 9.38              |
| 1995 | 158                | 1,965           | 12.44               | 68.13%            | 34.11%        | 45.93             |
| 1996 | 164                | 1,981           | 12.08               | 70.06%            | 20.26%        | 38.24             |
| 1997 | 153                | 2,055           | 13.43               | 69.90%            | 31.01%        | 75.61             |
| 1998 | 153                | 2,041           | 13.34               | 64.38%            | 26.67%        | 68.24             |
| 1999 | 159                | 2,245           | 14.12               | 61.95%            | 19.53%        | 58.35             |
| 2000 | 168                | 2,290           | 13.63               | 70.07%            | -10.14%       | 57.28             |
| 2001 | 150                | 1,711           | 11.41               | 68.76%            | -13.04%       | 86.75             |

**Table I: Market Conditions and Active Newsletters.**

This table reports, on a yearly basis, the number of active newsletters and the number of equity recommendations. The coefficient of this two variables gives the average number of recommendations per active newsletter for each year. The last three columns complement the information provided by Figure I, since they report the equity allocation and market return and volatility on an annual basis. Note that for 1980, data is only available starting June, 30. For November 2001, the latest recommendation recorded is for November 2001.



| AST #                   | ALLOCATION STRATEGY                                | PERCENT OF TOTAL | DESCRIPTION  |
|-------------------------|--|------------------|--|
| 1                       | $0 \xrightarrow{d} 100$                            | 8.61%            | Switch from cash (0% equity) to 100% equity                    |
| 2                       | $x \xrightarrow{d} x + \delta; \delta > 20$        | 10.29%           | Large increase in the equity allocation, other than Strategy 1 |
| 3                       | $100 \xrightarrow{d} 0$                            | 8.69%            |  |
| 4                       | $x \xrightarrow{d} x - \delta; \delta > 20$        | 11.34%           | Large decrease in the equity allocation, other than Strategy 2 |
| Large Equity Changes    |  | 38.93%           |  |
| 5                       | $x \xrightarrow{d} x + \delta; 5 \geq \delta > 20$ | 15.44%           | Moderate increase in the equity allocation                     |
| 6                       | $x \xrightarrow{d} x - \delta; 5 \geq \delta > 20$ | 18.83%           | Moderate decrease in the equity allocation                     |
| Moderate Equity Changes |  | 34.27%           |  |
| 7                       | $x \xrightarrow{d} x \pm \delta; \delta < 5$       | 26.80%           | Small variations in the equity allocation                      |
| Small Equity Changes    |  | 26.80%           |  |

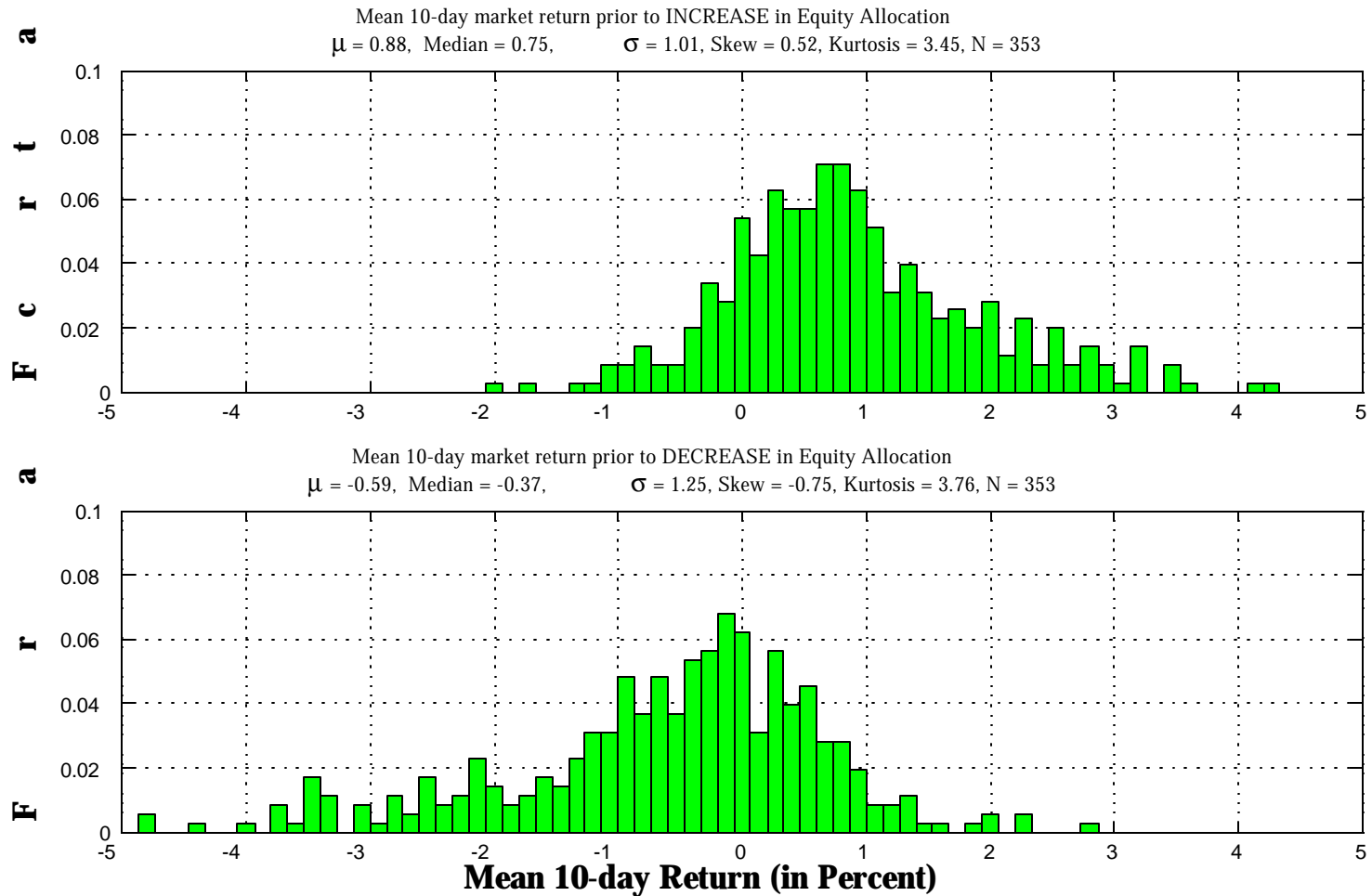
**Table II: Types of Allocation Strategies.**

An allocation strategy is defined by 3 attributes: original allocation in equity, time between allocations, and change in equity allocation. The recommendations (N=30,626) 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 7 meaningful clusters, each one corresponding to a distinct type of allocation strategy.

| INDEP<br>VARIABLE                        | VALUE | t-STAT | INDEP<br>VARIABLE   | VALUE | t-STAT |
|--|-------|--------|---|-------|--------|
| Intercept                                | -3.32 | -2.75  |   |       |        |
| (S&P500 Ret) <sub>t<sub>i</sub>-1</sub>  | 16.05 | 33.62  | (Short Term Perf) <sub>t<sub>i</sub>-1</sub>                | 5.56  | 20.05  |
| (S&P500 Ret) <sub>t<sub>i</sub>-2</sub>  | 8.52  | 15.62  | (Long Term Perf) <sub>t<sub>i</sub>-1</sub>                 | 0.06  | 3.17   |
| (S&P500 Ret) <sub>t<sub>i</sub>-3</sub>  | 3.53  | 6.06   | (☉ Term Spread) <sub>t<sub>i</sub>-1</sub> <sup>wk</sup>    | -3.28 | -1.03  |
| (S&P500 Ret) <sub>t<sub>i</sub>-4</sub>  | 1.33  | 2.44   | (☉ Term Spread) <sub>t<sub>i</sub>-1</sub> <sup>mo</sup>    | 3.73  | 1.78   |
| (S&P500 Ret) <sub>t<sub>i</sub>-5</sub>  | 1.41  | 2.55   | (☉ Quality Spread) <sub>t<sub>i</sub>-1</sub> <sup>wk</sup> | 10.63 | 1.16   |
| (S&P500 Ret) <sub>t<sub>i</sub>-6</sub>  | -0.21 | -3.42  | (☉ Quality Spread) <sub>t<sub>i</sub>-1</sub> <sup>mo</sup> | 19.43 | 2.88   |
| (S&P500 Ret) <sub>t<sub>i</sub>-7</sub>  | -0.98 | -1.61  | (☉ STerm Int Rate) <sub>t<sub>i</sub>-1</sub> <sup>wk</sup> | 75.32 | 1.87   |
| (S&P500 Ret) <sub>t<sub>i</sub>-8</sub>  | -1.23 | -2.19  | (☉ STerm Int Rate) <sub>t<sub>i</sub>-1</sub> <sup>mo</sup> | -6.69 | -0.29  |
| (S&P500 Ret) <sub>t<sub>i</sub>-9</sub>  | -0.02 | -1.72  |   |       |        |
| (S&P500 Ret) <sub>t<sub>i</sub>-10</sub> | -1.90 | -4.18  |   |       |        |

Table III: Newsletter Recommendation Changes and Information Variables.

This Tables shows the relationship between short term market dynamics, macroeconomic factors and past performance with changes in the recommendation make by investment newsletters. Market returns and macro data are from Datastream.



**Figure IV: Short Term Market Dynamics and Equity Recommendations.**

This figure shows the mean 10-day market return prior to a recommended equity change. The top panel shows that the market rises on average 0.88% in the ten days that precede a recommendation to increase the equity portion of the investment portfolio. Prior to a recommendation to increase the cash part of the portfolio, the market declines 0.59% on average during the previous ten days.

| AST #                   | DESCRIPTION  | LAST 5 DAYS | LAST 10 DAYS | LAST 20 DAYS |
|-------------------------|--|-------------|--------------|--------------|
| 1                       | Momentum on Increase, Momentum on Decrease         | 192         | 170          | 150          |
| 2                       | Momentum on Increase, Undetermined on Decrease     | 8           | 9            | 2            |
| 3                       | Undetermined on Increase, Momentum on Decrease     | 5           | 10           | 1            |
| Momentum Strategies     |  | 205         | 189          | 153          |
| 4                       | Contrarian on Increase, Contrarian on Decrease     | 24          | 27           | 19           |
| 5                       | Contrarian on Increase, Undetermined on Decrease   | 11          | 9            | 27           |
| 6                       | Undetermined on Increase, Contrarian on Decrease   | 12          | 17           | 24           |
| Contrarian Strategies   |  | 47          | 53           | 70           |
| 7                       | Undetermined on Increase, Undetermined on Decrease | 100         | 100          | 126          |
| Unclassified Strategies |  | 100         | 100          | 126          |

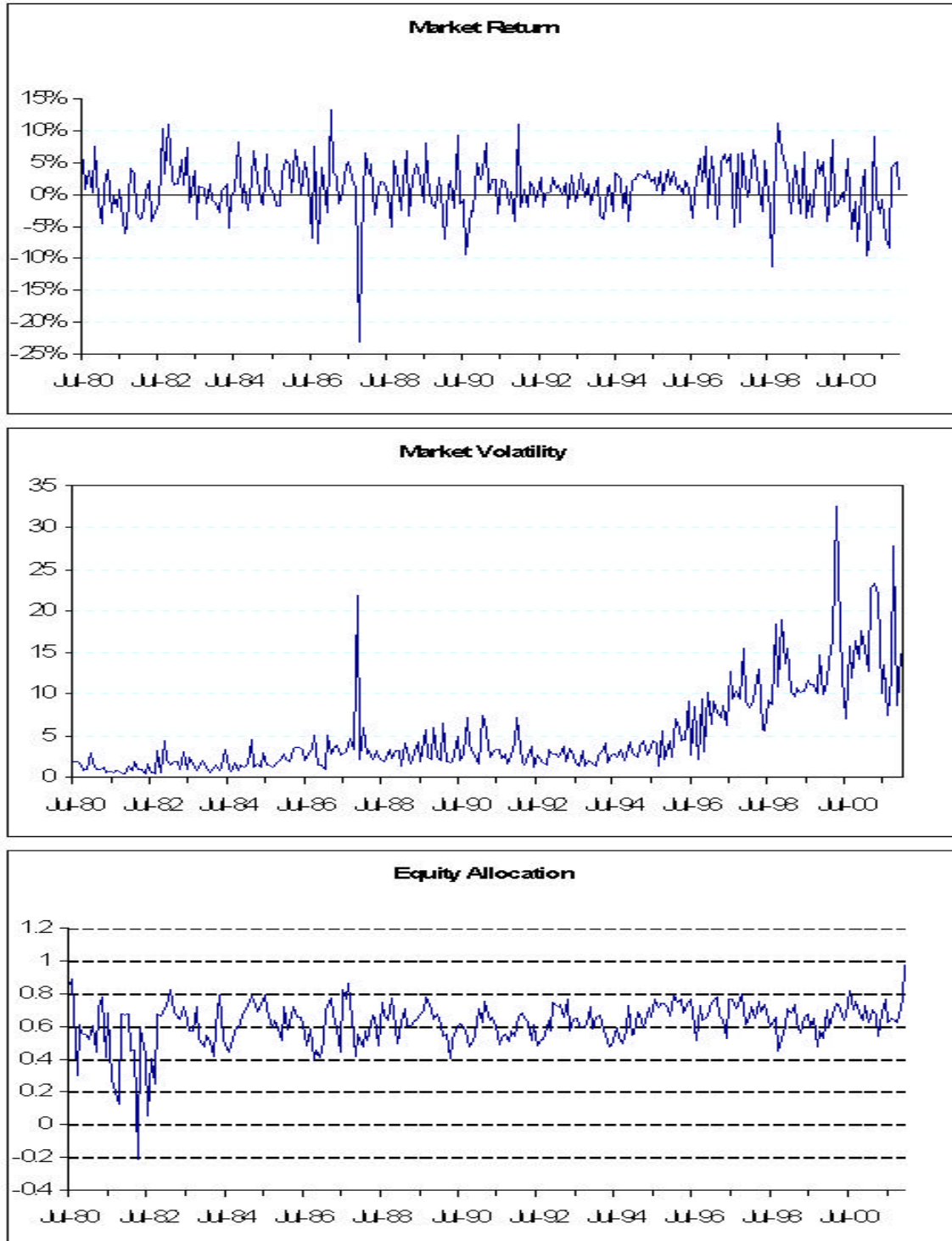
**Table IV: Momentum and Contrarian Allocation Strategies.**

We use a bootstrap with 1000 iterations to classify newsletters based on their behavior in relation to 5-, 10- and 20-day lagged S\&P500 returns. We use the SOM clustering procedure to identify sub-groups of newsletters that have similar market timing strategies. Seven types are identified, depending on whether they act as momentum followers, contrarians or in unidentifiable way following market increases and decreases. The numbers in the table refer to the number of newsletters for each category for the corresponding length of past-days market returns. 352 newsletters are classified using this procedure.

|              | Sharpe Ratio - 1 | Sharpe Ratio - 2 | Jensen Alpha | Parametric HM | Non-Parametric HM | Treynor - Mazuy |
|--------------|------------------|------------------|--------------|---------------|-------------------|-----------------|
| Daily        | 0.66             | 1.22             | 0.000068     | 0.03          | 0.41              | 0.74            |
| Weekly       | 0.78             | 1.29             | 0.000068     | -0.01         | 0.50              | 0.17            |
| Semi-Monthly | 0.89             | 1.35             | 0.000078     | 0.01          | 0.51              | 0.38            |
| Monthly      | 0.96             | 1.35             | 0.000076     | -0.02         | 0.54              | -0.21           |
| Quarterly    | 0.79             | 1.27             | 0.000058     | -0.04         | 0.52              | -0.52           |
| % Individual | 39.82%           |                  | 52.28%       | 24.62%        |                   | 30.70%          |

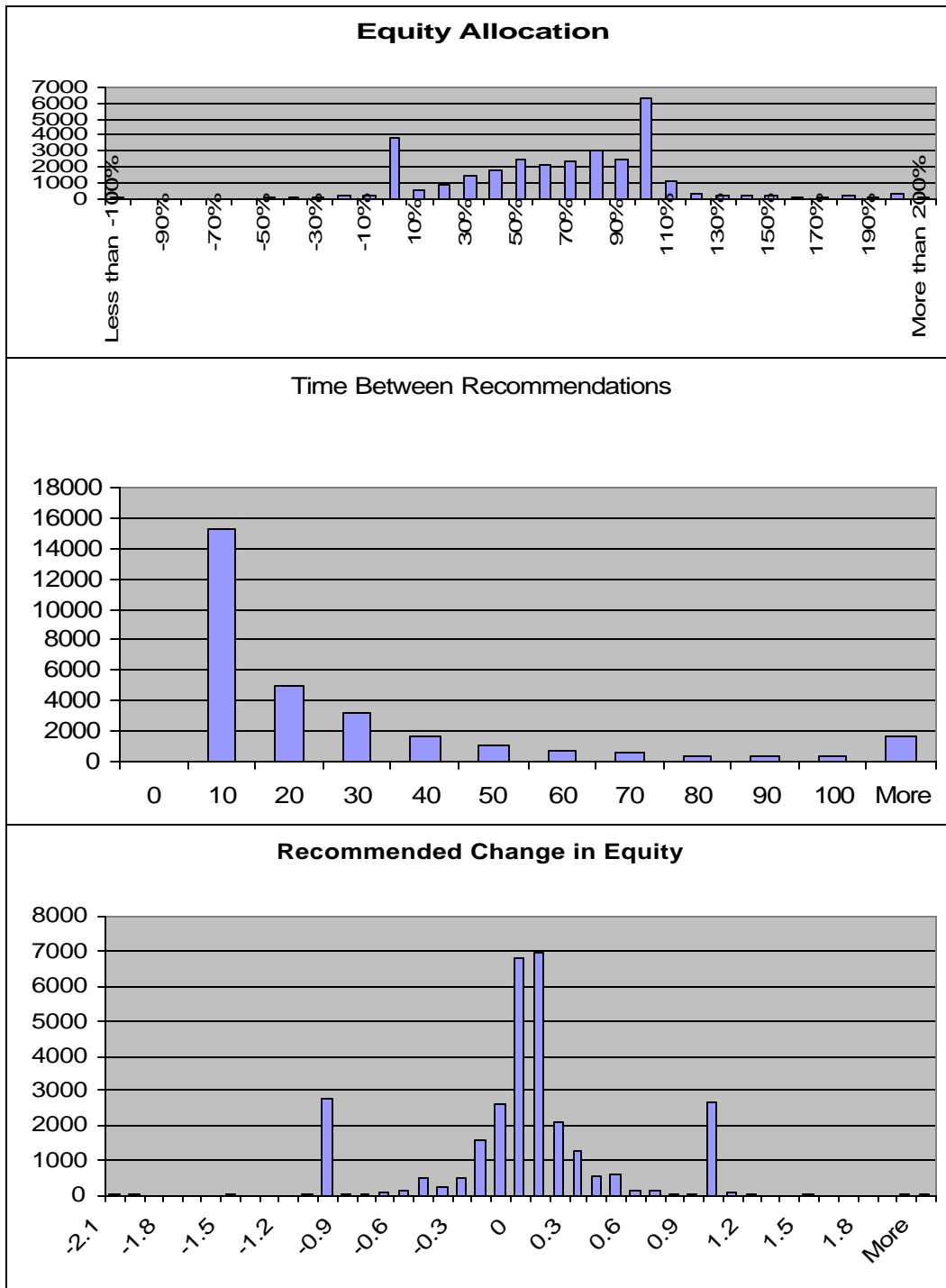
**Table V: Performance Measurement at the Aggregate and Individual Levels.**

This Tables report the Sharpe Ratio (using raw and excess returns), Jensen's alpha, parametric Henriksson and Merton and Treynor and Mazuy and non-parametric Henriksson and Merton measures of market timing and performance. At the aggregate level, results are reported for newsletters formed rebalancing daily, weekly, every two weeks, monthly and quarterly, the recommendations made by the newsletters. The last row shows the percentage of newsletters with superior performance and market timing ability.



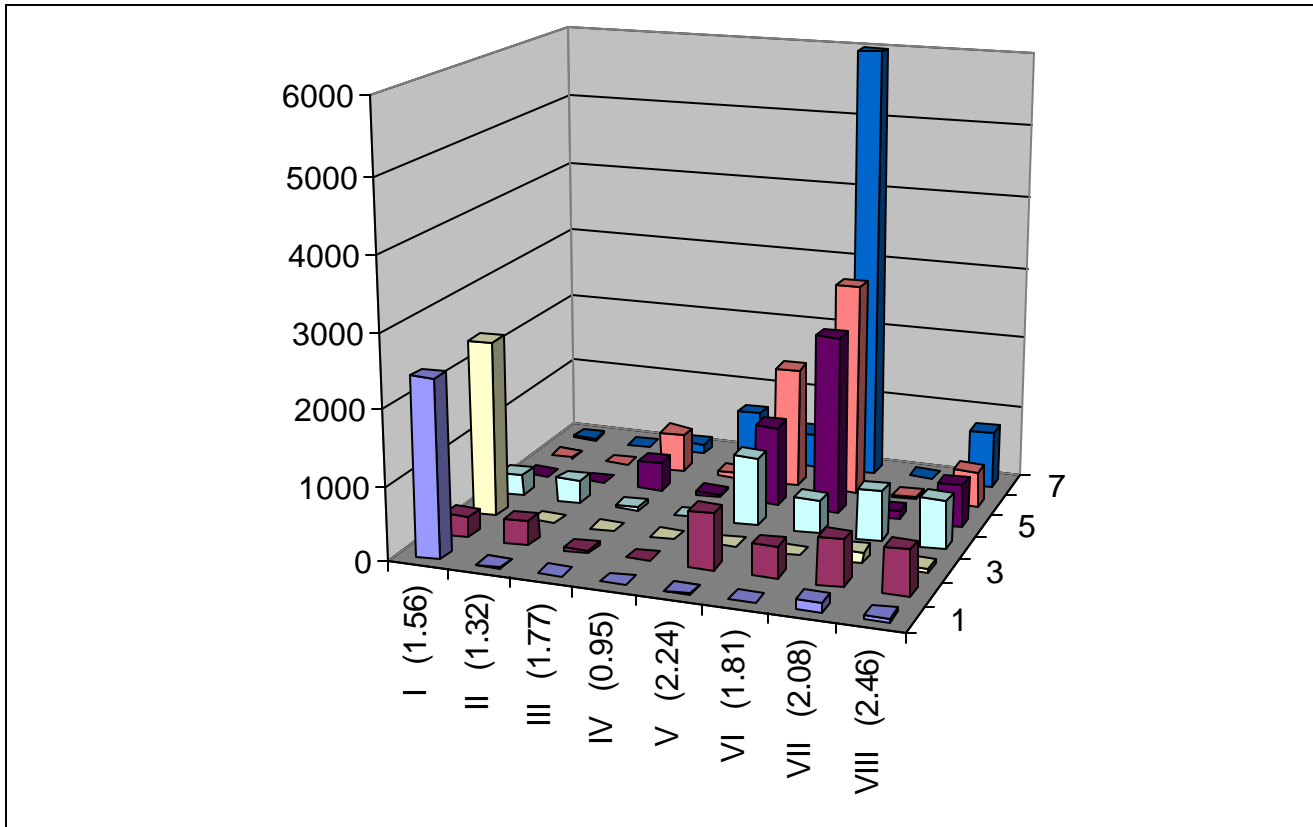
**Figure I: Market Returns, Market Volatility and Newsletters' Equity Allocation.**

This figure shows, at the monthly level, the market return (top panel) and volatility (middle panel) for the period June, 1980 to December, 2001. The S&P 500 is used as a proxy for the market. The bottom panel shows the average monthly equity allocation for our sample of investment newsletters. We gather information from Hulbert Financial Digest. A clean data set consisting of 30,626 equity recommendations from 353 newsletter strategies is used in this project. S&P 500 returns are obtained from Datastream.



**Figure II: Allocation Strategies Attributes.**

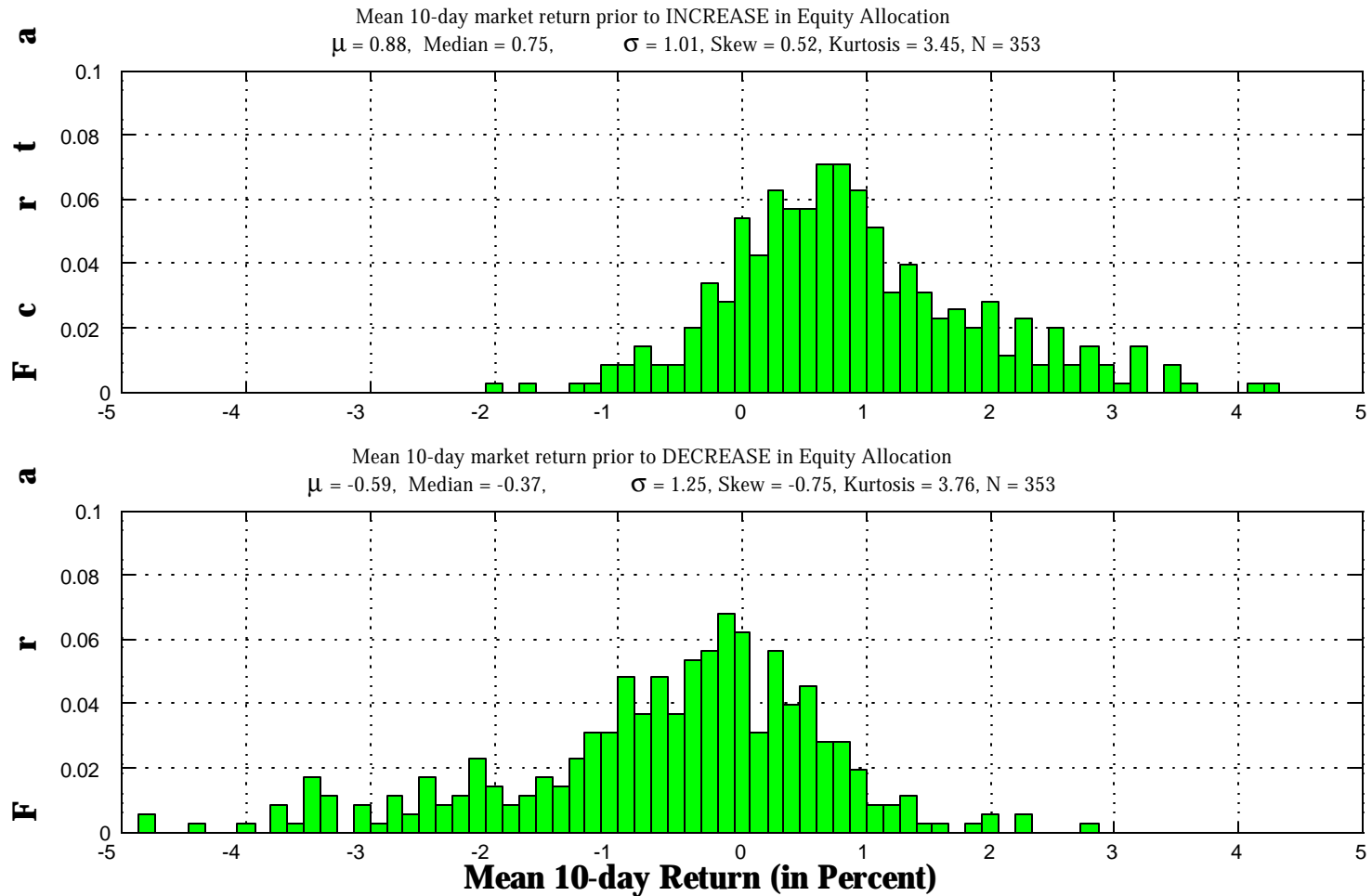
This figure illustrates the three attributes that define an allocation strategy: equity recommendation, change in the equity recommendation, and time between recommendations. The top panel shows a histogram of the percentage allocated to equity in the newsletters recommendations. Clearly, the two most common recommendations are full allocations in the riskless asset and in the market. The middle panel shows a histogram for the time between recommendation changes. The average time between recommendations is 30 days, the median is only 10 days. The bottom panel shows a histogram for the recommended change in the equity allocation. 12,888 recommendations involve a change in equity smaller than 10%.



**Figure III: Newsletter Types Representing Four Broad Behavioral Patterns.**

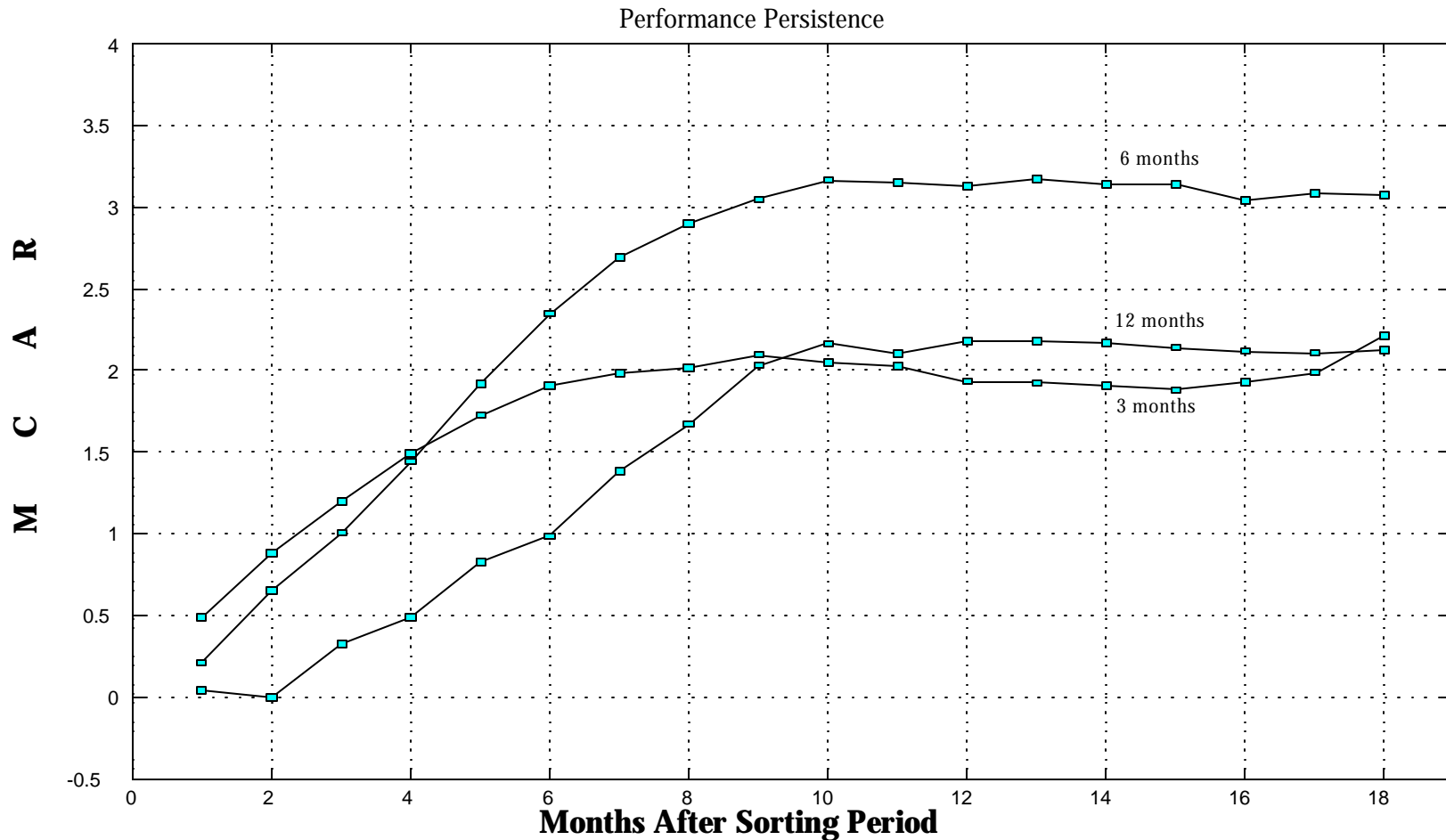
This Figure shows eight newsletter types represent four broad behavioral patterns. Newsletter types 1, 2 and 7 are true timers. Type I newsletters shift mainly allocations in only cash (equity is 0 %) and portfolios wholly invested in the market (equity equal to 100%). Type 2 (12 cases) newsletters make mostly large changes in equity recommendations, both positive and negative. Newsletter Type 7 (43) uses the four extreme trading strategies. Type 3 (10) newsletters make moderate rebalancing recommendations; whereas Type 4 (14) newsletters tend to stick to the same equity allocation (i.e. they make small recommendation changes). Newsletter Types 5 (51) and 6 (91) exhibit a mixed behavior; the former recommends large and moderate equity changes, the latter moderate and small. Newsletter Type 8 (43 cases) uses the seven allocation strategies uniformly. To measure the complexity of the allocation strategy used by the different newsletters we use the concept of entropy. Entropy numbers are reported in brackets.





**Figure IV: Short Term Market Dynamics and Equity Recommendations.**

This figure shows the mean 10-day market return prior to a recommended equity change. The top panel shows that the market rises on average 0.88% in the ten days that precede a recommendation to increase the equity portion of the investment portfolio. Prior to a recommendation to increase the cash part of the portfolio, the market declines 0.59% on average during the previous ten days.



**Figure V: Persistence in Performance.**

This Figure shows that there is persistence in performance among newsletters. At any given month, we sort newsletters based on past 3, 6 and 12 performance. We build a "winners" (top quintile) and "losers" (bottom quintile) portfolio based on past performance, and calculate the difference in performance for these two portfolios in the next 18 months. Past 6-month winners outperform past 6-month losers by 3.5% in the 10 months that follow the portfolio construction; after 10 months, the difference in performance disappears.

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## Appendix: Algorithm for Identifying Newsletter Types

The main steps in identifying newsletter types using allocation strategies are:

1. *Define allocation strategies:* An allocation strategy consisting of 3 attributes is formed for each of the newsletter recommendations and a matrix of allocations,  $X$  ( $N \times 3$ ,  $N=30478$ ), is obtained.
2. *Partition the allocation strategy space:* Using a variation of the K-Means clustering procedure, the set of allocation strategies ( $S$ ) are divided into  $K$  groups.
3. *Compute probabilities:* For each newsletter, using the frequencies of occurrences in the  $K$  clusters, the probabilities that it belongs to each of the identified clusters (i.e., the probability that the newsletter  $i$  chooses allocation strategy  $S_j, j = 1, \dots, K$ ) are computed.

$$\mathbf{P}(X_i = S_j) = \frac{N_{ij}}{\sum_{j=1}^K N_{ij}}$$

4. *Identify newsletter types:* Using the probability mass functions identified in the previous step, clustering is used one more time to obtain newsletter “types” that have *similar probability mass functions*. The symmetric Kullback-Leibler (KL) divergence which measures the distance between two probability mass functions  $p(x)$  and  $p(y)$  is used as a distance metric in the clustering procedure. KL divergence is defined [Cover and Thomas, 1991] as:

$$D2(p \parallel q) = D(p \parallel q) + D(q \parallel p)$$

where

$$D(p \parallel q) = \sum_x p(x) \log_2 \frac{p(x)}{p(y)} = \mathbf{E}_p \log \frac{p(x)}{p(y)}$$

The *asymmetric* KL divergence,  $D(p \parallel q)$ , is not a distance function since it is not symmetric (i.e.,  $D(p \parallel q) \neq D(q \parallel p)$ ) and hence I use the *symmetric* KL divergence as a distance metric in the clustering procedure<sup>19</sup>.

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<sup>19</sup>For more details on information-theoretic measures, refer to an excellent book by [Cover and Thomas, 1991]. The notation and definitions of information-theoretic measures in this

Note that the distance matrix used in the clustering procedure can be interpreted as a correlation matrix after two simple transformations (rescale the distances so that they lie between 0 and 1, and then replace each element  $x$  of the matrix by  $1 - x$ ).

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paper are derived from the discussion in the book.