The "CAPS" Prediction System and Stock Market Returns

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Abstract: We study the predictive power of approximately 5.0 million stock picks submitted by individual users to the "CAPS" website run by the Motley Fool company (www.caps.fool.com). These picks prove to be surprisingly informative about future stock prices. Indeed, a strategy of shorting stocks with a disproportionate number of negative picks on the site and buying stocks with a disproportionate number of positive picks produces a return of over twelve percent per annum over the sample period. These results are mostly driven by the fact that negative picks on the site strongly predict future stock price declines; positive picks on the site produce returns that are statistically indistinguishable from the market. A Fama French decomposition suggests that these results are largely due to stock-picking rather than style factors or market timing.

1 Introduction

"Crowdsourcing" websites attempt to forecast stock price performance by aggregating predictions from individual website participants. We analyze the informational content of these predictions for the future price movements of individual stocks. Our data consists of more than 5 million stock picks provided by more than 60,000 individuals from November 1, 2006 to December 31, 2011, a period with significant swings in stock market performance. These individuals made predictions through the CAPS open access website created and operated by the Motley Fool company (www.caps.fool.com). The Motley Fool prediction system is motivated by a hypothesis, contrary to the efficient markets hypothesis, that posits that many individuals—each with limited information—can provide accurate assessments of future movements in individual stock prices, if their information is elicited and appropriately aggregated.

While collaborative filtering has been demonstrated to be useful in a wide variety of contexts (such as the Ebay user rating system or the Amazon recommender system), its value has not been demonstrated in the challenging context of predicting stock price movements. It is natural to ask how aggregation of information elicited by a website could possibly produce information that is not already incorporated into stock prices: why would participants not trade on information rather than volunteer it without prospect of financial gain to a public website?

One plausible rationale for collaborative filtering of stock opinions is the possibility that individuals have high trading costs and imprecise information. Individuals whose trading costs exceed the expected value of their imprecise information will rationally choose not to trade to the point where this information is fully reflected in prices. Furthermore, fully exploiting the individual's information would sacrifice diversification. Thus, the idea behind collaborative filtering is that the underutilized information of such individuals is valuable if elicited and appropriately aggregated.[1].

We analyze the informational content of stock market picks submitted to CAPS by tracking the performance of portfolios formed on the basis of those picks. We intentionally use simple algorithms to create portfolios based on positive and negative picks (predictions of increases and decreases in the prices of individual stocks, respectively). We show that buying positive picks and shorting negative picks produces annual returns of over twelve percent over our sample period after adjusting for style and risk factors.

This paper contributes to a burgeoning literature on the role of the Internet in creating and disseminating information that is potentially relevant to security prices. One theme of prior research is that the Internet may exacerbate behavioral biases that lead to suboptimal investments (Barber and Odean, 2001b), and possibly even create new methods for stock manipulation (Frieder and Zittrain, 2007). However, a number of authors have utilized textual analysis techniques to examine the relationship between the sentiment or valence of messages posted online and stock movements to

[1] Why individuals bother to post their information is another interesting question. As discussed below, Motley Fool labels and promotes top performers in the CAPS system. This may be a source of utility in it of itself

determine whether useful information is disseminated.

A series of recent papers assesses the informational content of postings on message boards such as Yahoo! and Raging Bull as well as the effect of these messages on stock trading and prices. The literature identifies a connection between the volume of messages about a stock and future trading of that stock—a high volume of messages tends to predict higher future trading volumes and pricing volatility (Antweiler and Frank, 2004). In terms of information, message board postings overlap in content with forthcoming news stories (Antweiler and Frank, 2004), and earnings announcements (Bagnoli, Daniel and Watts, 1999), but message boards promulgate them before traditional media sources.

Several papers demonstrate that message board postings have a limited ability to predict future price movements for individual stocks. Even though message board postings may predict future news articles, the news articles themselves have limited and short-lived predictive power on future stock prices (Tetlock, 2007). Similarly, the assessed correlation between message board content and stock price movements is generally small and short-lived (Das and Chen, 2007, Tumarkin and Whitelaw, 2001, Antweiler and Frank, 2004), though very unusual volumes of message board activity correlate with substantial next-day price movements for thinly traded microcap stocks (Sabherwal, Sarkar, and Zhang, 2008) and with negative future returns for a broader set of stocks (Antweiler and Frank, 2006).

Similarly, Sprenger et. al. (2013) examine stock microblogs, tweets on the Twitter service that refer to specific stocks. They find that tweeting activity and sentiment is related to contemporaneous returns, but does not predict future returns. Tweeting activity does predict future volume. Individuals who have provided above-average investment advice are more likely to be retweeted (have their tweets forwarded to other users), but individual tweets that are more correlated with future market movements are not more likely to be retweeted.

The work on message boards and Twitter described above focuses on venues in which messages are open, unstructured, and very short. In contrast, Chen, De, Hu, and Hwang (2014) examine the informativeness of posts on Seeking Alpha. Posts on Seeking Alpha are long-form articles similar in format to the reports written by sell-side analysts. This site uses an editorial board and submissions from "credible authors" are reviewed for clarity, consistency, and impact. The site publishes only fundamental analysis; it does not generally post pure technical analysis. Published articles must conform to Seeking Alpha's standards of "rigor and clarity". Chen et. al. (2014) demonstrate that stocks discussed more favorably on Seeking Alpha outperform those discussed more negatively. As in the literature on message boards, the authors use textual analysis to evaluate the posts. Specifically, the authors count the fraction of negative words used in the article.

This paper departs substantially from the previous literature on the informative of Internet stock fora because of the nature of the data compiled by the Motley Fool CAPS website. CAPS differs from stock message boards in two important ways that facilitate our research. First, CAPS users make specific predictions about the future price of a particular stock. In contrast, analysis of message board postings requires a systematic language-extraction algorithm to classify each message imperfectly as (say) "Buy/Sell/Hold".

Second, CAPS is designed to promote the reputations of its participants. Each player is rated based on the performance of previous picks, and each player's past history of picks and performance can be viewed by others.

Another set of related papers concerns online prediction markets such as Intrade. These websites host competitive prediction markets for the trade of shares that will pay off if a particular event occurs (e.g. Rick Santorum receives the Republican presidential nomination). Recent works, such as Wolfers and Zitzewitz (2004) and Wolfers (2004), examine the functioning of markets. In many ways, CAPS can be thought of as a hybrid of a message board and a prediction market. First, like a prediction market, but unlike a message board, CAPS users make very specific predictions. Second, CAPS synthesizes the history of past picks to produce a rating for each stock (from the worst rating of "One Star" to the best rating of "Five Stars". Prediction markets aggregate predictions by displaying a market price that clears the market. Message boards do not generally attempt to aggregate predictions. Third, message boards do not typically attempt to provide incentives for participants to produce high quality predictions. An exception is Seeking Alpha which pays writers for the articles published on the site. In contrast, participants in prediction markets make (lose) money if their predictions are right (wrong). In contrast, incentives in Motley Fool exist, but they involve reputations rather than money. Participants have no direct financial incentives to participate. Instead, participants receive reputation scores and the players with the best reputation scores are highlighted on the site.

Finally, our research relates to the literature examining the extent to which retail investors appear to make informed or uninformed trades. For example, Kelley and Tetlock (2013) examine retail trades and demonstrate that aggressive (market) orders predict firm news such as earnings surprises while passive (limit) orders do not. They find that the predictability of returns from market orders vary substantially at different brokers. Thus, they find that segments of retail investors are "wise" in that they predict the cross-section of stock returns.

The paper proceeds as follows. Section 2 describes the data. Section 3 provides descriptive statistics based only on absolute returns. Section 4 analyzes portfolio returns using a Four-Factor decomposition. Section 5 concludes.

2 Data and Details of the CAPS Ranking System

The data for this study was provided by the Motley Fool company under a license agreement with Harvard University. The data contain all stock market picks from the CAPS website from November 1, 2006 through December 31, 2011.

The CAPS system allows participants to predict future movements of individual stocks relative to their current prices. Each participant creates an account with a username and may submit stock picks attached to that username. Each pick consists of a company name (or more precisely a stock ticker symbol), a prediction of "Outperform" or "Underperform" and a time frame for that pick. Possible time frames are listed in a menu and range from a few weeks to 5+ years. For the majority of the sample period, CAPS only allowed picks for stocks that had a price of at least $1.50 per share and a market cap of at least $100 Million at any given time.[2]

Each player's picks, and the actual stock returns associated with those individual picks, are posted on a publicly observable webpage associated with the player's username. CAPS assigns a rating to each participant as a function of the objective performance of the stocks that she/he picked and posts that player's current percentile ranking (from 0 to 100) on that player's page.[3] Participants with ratings of 80 or above, representing those in the top fifth of player ratings, are labelled as "CAPS All Stars". Their picks are highlighted throughout the website. In addition, each player's picks are cross-listed by stock, making it simple to track the overall CAPS record of anyone who has made a pick for a particular stock of interest. Regardless of the player's initial choice of time frame for a particular pick, each pick continues to count towards a players CAPS rating until that player formally ends (or closes) that pick. CAPS also uses a proprietary algorithm to rank stocks on a 1-star (worst) to 5-star (best) basis. The CAPS website states that this algorithm aggregates individual player positive and negative picks (see http://caps.fool.com/help.aspx for additional details). We do not use CAPS's aggregation scheme in this research; rather, we construct our own aggregation methodology.

Many websites, including CAPS, Amazon.com, and eBay use some kind of reputation system to measure past performance of website participants. Similar to Amazon.com's "top reviewers" program (but in contrast to eBay),

[2]As of May 2014, CAPS allows picks for stocks that "have an average three-month volume in excess of $50,000, a previous days volume above $50,000 and a current share price greater than 50 cents." (caps.fool.com/help.aspx)

[3]Participants with fewer than seven CAPS picks are not given player ratings.

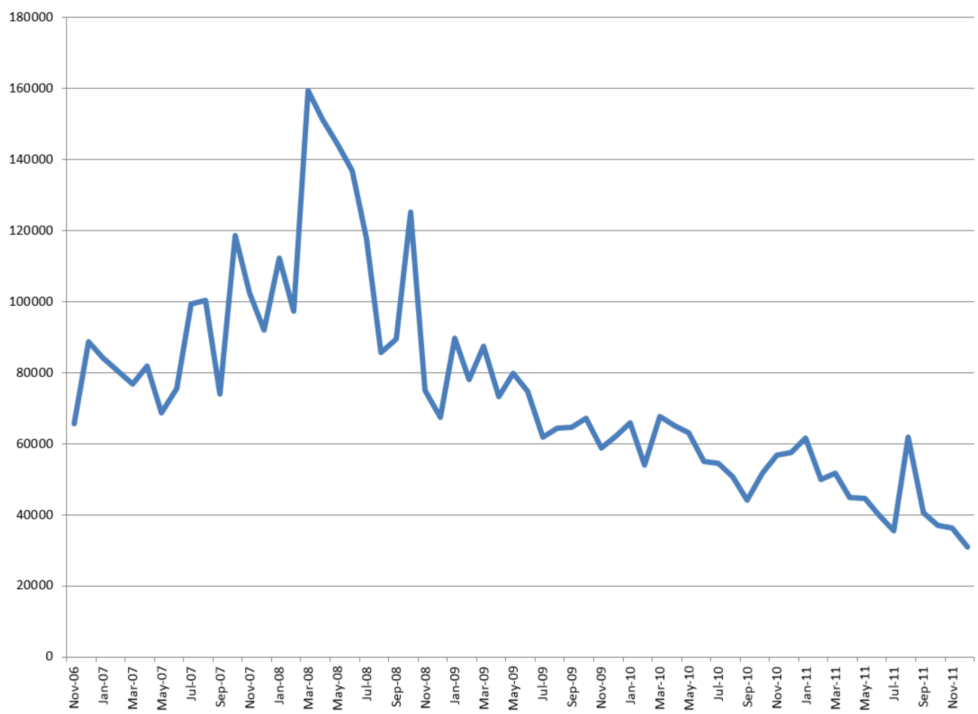

Figure 1: Total CAPS Picks by Month

it is not clear what material benefit a participant gains from garnering a positive reputation on CAPS, though CAPS includes a number of features that promote interest in participant reputation, such as the "CAPS All Stars" designation.

The data provided by Motley Fool for the study consists of 5,152,746 distinct picks encompassing 10,243 different stocks. Figure 1 graphs the number of picks submitted to the CAPS website by calendar month from the launch of CAPS in November 2006 to the end of the sample period in December 2011. As shown in Figure 1, activity on the CAPS website peaked in early 2008 and fell off for the remainder of our sample period. Even so, the website still received at least 40,000 picks per month in every month prior to December 2011.

Table I presents summary statistics for the number of picks submitted to the CAPS website. On average, CAPS participants, like most stock market analysts, were relatively bullish, producing about five positive picks per negative pick. Further, this ratio remained fairly constant over time. Since the instruction given to CAPS participants is to identify stocks that will either “outperform” or “underperform” the market, there may be no reason to expect that the inclination to identify one group or another would vary over time or over the market cycle. CAPS participants were significantly more likely to submit negative picks for Small Cap stocks than for Medium or Large Cap stocks.

We compiled stock price data from the Center for Research and Security Prices (CRSP) for November 1, 2006 (the official launch date for CAPS) to June 30, 2012 (six months after the end of our sample of CAPS stock picks). Since CRSP and CAPS use different identification numbers for stocks, we matched stocks across the two databases by ticker symbol and by name. We were able to match 7,892 stocks and 4,978,455 of the picks (96.6%) in the CAPS database. The remaining unmatched picks are primarily for small and often de-listed stocks. We used standard methods to adjust the CRSP prices for dividends and splits, essentially assuming that dividend distributions are reinvested in the given stock.

We will present results for stocks in different size classes. We classify companies with market caps of more than $5 Billion as “Large Caps”, companies with market caps between $1 and $5 Billion as “Medium Caps” and

Table I: Positive and Negative Picks Submitted to the CAPS Website

	Number of Picks	Percent of all Picks	Share Positive
ALL	4,654,757	100%	82.3%
Nov 2006 - Dec 2006	154,371	3.4%	85.3%
Jan 2007 - Dec 2007	1,054,883	22.7%	81.8%
Jan 2008 - Dec 2008	1,361,486	29.3%	81.2%
Jan 2009 - Dec 2009	862,392	18.5%	81.6%
Jan 2010 - Dec 2010	686,778	14.8%	84.9%
Jan 2011 - Dec 2011	534,847	11.5%	82.8%
Small Cap	1,746,139	37.5%	78.2%
Medium Cap	1,205,887	25.9%	82.6%
Large Cap	1,702,731	36.6%	86.3%

Notes: Summary of total picks submitted to the CAPS website by time period. Companies with market caps of more than $5 billion are categorized as large caps; companies with market caps between $1 and $5 billion are categorized as medium caps and companies with market caps less than $1 billion but more than $100 million are categorized as small caps.

companies with market capitalizations less than \$1 Billion as "Small Caps". Given the requirements for entering a pick in the CAPS system, these small cap stocks will still have market capitalizations that exceed \$100 Million.

3 Returns by CAPS Pick

Table II lists the average one-month, three-month, and six-month market returns for Positive and Negative picks for one-, three-, and six-month holding periods.[4] To avoid possible complications related to the time of day that each pick was submitted, we employ a one-day lag in the computations of these market returns. Thus, for a pick that was submitted at any time on Wednesday, we use the closing price at the end of the day on Thursday as the base price and compute the one-, three-, and six-month returns for that pick based on the closing prices 21, 42, and 63 trading days from Thursday. Note that, for the year groupings below, the year denotes the year in which the pick was made on the CAPS system. Thus, for example, a pick made in late December 2007 is included in the 2007 row of the table, but the returns are calculated for holding periods stretching into 2008.

Comparing the raw average market returns on Positive and Negative Picks, the results in Table II are variable but indicate that Positive Picks typically outperform Negative Picks, whether we group picks by year or by Market Cap. Taking simple differences across all picks, there is a difference of 0.4% in one-month returns, 2.0% in three-month returns, and 2.4% in six-month returns between Positive and Negative picks, corresponding to

[4] We assume 21 trading days per month for these computations.

Table II: Average Holding Period Returns Per Pick by Year and Market Cap

	Pos Pick	Neg Pick	Pos Pick	Neg Pick	Pos Pick	Neg Pick
ALL	-0.04%	-0.43%	-0.11%	-2.09%	-0.80%	-3.19%
2007	-0.33%	-1.89%	-0.91%	-5.95%	-2.62%	-10.98%
2008	-3.33%	-2.43%	-11.41%	-13.13%	-23.18%	-22.09%
2009	+4.18%	+3.71%	+15.93%	+15.94%	+27.86%	+29.72%
2010	+1.52%	+1.26%	+4.77%	+4.04%	+9.28%	+7.28%
2011	-0.50%	-0.43%	-1.35%	-1.25%	-3.81%	-6.99%
Small Cap	+0.05%	-0.19%	+0.27%	-2.13%	-0.91%	-3.52%
Medium Cap	-0.10%	-0.27%	+0.47%	-0.94%	+0.02%	-1.10%
Large Cap	-0.10%	-0.95%	-0.29%	-3.03%	-1.26%	-4.53%
Holding Period	1 month		3 months		6 months	

Notes: Summary of raw returns for picks submitted to the CAPS website by time period. Each pick is assumed to be purchased the day after it was entered into the CAPS system and held for the holding period listed in the table. The date groupings refer to the date that the pick was made; the holding period used in calculating the return can extend into the next year.

annualized differences of roughly 3.5 to 7 percentage points in returns.

There are several ways to compare the pick returns to measures of market returns. This analysis is complicated by the fact that the participants submit picks whenever they wish; some days have many picks some days have relatively few. In Table III, we compare three-month positive and negative picks from Table II to four measures of market returns. First, we construct a capitalization-matched universe with positive pick timing. This mimics a scenario in which, every time a positive pick is initiated, one unit of the universe of securities eligible for Motley Fool selection is purchased, for the capitalization category matching the pick (Small, Medium, or Large). Each of these units is held for three months. The averages by time period are reported as in Table II. Thus, days on which many Motley Fool picks are entered are weighted more than days in which fewer picks are entered. Next, we similarly construct the capitalization-matched universe with negative pick timing. Every time a negative pick is initiated, one unit of the universe of securities eligible for Motley Fool selection is purchased, for the capitalization category matching the pick. Third, we construct a capitalization-matched universe with overall pick timing. This mimics a scenario in which, every time a negative or positive pick is initiated, one unit of the universe of securities eligible for Motley Fool selection is purchased, for the capitalization category matching the pick. This third categorization is our preferred comparator. Recall that Motley Fool participants are asked to rate stocks based on whether they will outperform or underperform the market. The system does not ask them to (or evaluate them regarding) market timing. Thus, this third measure evaluates Motley Fool picks against a three-month market return initiated at the same time as the picks.

Finally, for comparison, we also construct a market universe where picks are assumed to occur evenly each trading day. The market capitalization ratios are equivalent to the market capitalization ratios in the picks for the time period. For individual years, none of these measures differs substantially from one to another. For the overall measure, the evenly-weighted daily measure is much more positive than any of the pick-weighted measures because the pick-weighted measures weight the negative-performing years much more heavily. This occurs because Motley Fool participation grew steadily for the period leading up to the market crash.

When comparing the returns earned by Motley Fool picks to the measures of market returns, the most striking feature is the poor performance of the stocks that participants have identified as Negative Picks. While Positive Picks have performed roughly equal to our preferred measure of market performance, the stocks that participants have identified as Negative Picks have greatly underperformed the stock universe over equivalent three-month horizons. Using a six-month horizon, actual positive picks had a return of -0.8% and actual negative picks had a return of -3.19%, as shown in Table II. The cap-matched universe with all-pick timing had a return of -0.65%. As in the three-month horizon, the return is similar to the positive pick return but notably different from the negative pick return.

4 Nominal Returns by Stock Rating

The computations underlying the results in Table II did not attempt to aggregate picks and compare stocks that many participants recommended to stocks that few participants recommended. In this section, we create rank orderings of stocks on each trading day to measure the extent to which individual stocks are favored by Motley Fool participants.

We construct a “Pick Percentage Rating” for each stock. To do this, as each pick is entered by a Motley Fool participant, it is considered to be active for a three-month window. For each date, we count how many positive and negative picks are active for the stock. For any trading date, we exclude all stocks with fewer than ten active picks. Then, for each stock-trading day, we calculate the percentage of active picks that are positive for each stock. We then construct quintile portfolios of stocks based on the Pick Percentage Rating. Thus, Quintile 1 consists of stocks with relatively few active positive

Table III: Three-Month Pick Returns Compared to Cap-Matched Motley Fool Stock Universe

	(1) Actual Positive Picks	(2) Actual Negative Picks	(3) Cap matched Universe with Pos Pick Timing	(4) Cap matched Universe with Neg Pick Timing	(5) Cap matched Universe with All Pick Timing	(6) Cap matched Universe with Even Daily Timing
ALL	-0.11%	-2.09%	0.24%	-0.21%	0.16%	1.38%
2007	-0.91%	-5.95%	-1.87%	-2.48%	-1.98%	-1.65%
2008	-11.41%	-13.13%	-9.55%	-9.94%	-9.63%	-11.1%
2009	15.93%	15.94%	13.71%	13.97%	13.76%	13.21%
2010	4.77%	4.04%	5.43%	5.56%	5.45%	5.97%
2011	-1.35%	-1.25%	0.55%	0.708%	0.58%	0.46%

Notes: Summary of three-month raw returns for picks submitted to the CAPS website by time period. Each pick is assumed to be purchased the day after it was entered into the CAPS system and held for three months. The comparable market return is calculated assuming that a unit of the stock universe with the same capitalization category as the actual pick is made instead of the actual pick and held for three months. Column three calculates the returns of the cap-matched universe purchased on the day after each positive pick; Column four calculates the returns of the cap-matched universe purchased on the day after each negative pick; Column five calculates the returns of the cap-matched universe purchased on the day after each pick (positive or negative); Column six calculates the returns of the cap-matched universe assuming that an equal number of units of the cap-matched universe is purchased each day. The date groupings refer to the date that the pick was made; the holding period used in calculating the return can extend into the next year.

picks relative to overall picks in the CAPS system on any given trading day. Each trading day receives equal weight in our analysis. Table IV reports the raw returns by calendar year for stocks in each quintile according to Pick Percentage Rating. In each of the five years, the bottom (1st) quintile portfolio has lower absolute returns than the top (5th) quintile. Cumulating over the full sample period of five years, the top quintile of stocks gained more than 40 percentage points in value whereas the bottom quintile of stocks lost nearly 30 percentage points in value. [5]

Tables V through VII summarize the nominal returns by year for each quintile in Pick Percentage for Large, Medium, and Small Cap stocks respectively. The cumulative performance difference between the top and bottom quintile is clearly greatest for small cap stocks. However, in every case, Top Quintile stocks increased in value by more than 20 percentage points while Bottom Quintile stocks declined in value by more than 20 percentage points during the sample period.

[5] As mentioned above, Motley Fool also ranks stocks in 5 tiers according to a proprietary algorithm that uses picks as an input. Thus, this algorithm is an alternative to our pick percentage rankings. In a prior working paper, we use data for a shorter time horizon and examine the performance of the propietary prediction system. There we find, for the first two and half years of our current sample, that the difference in returns between their highest and lowest quintile stocks averaged 18 percentage points per year. This is roughly similar to the differences reported for the earlier part of our sample in Table IV.

Table IV: Aggregated Returns by Pick Percentage Rating

	Quintile:	1^{st}	2^{nd}	3^{rd}	4^{th}	5^{th}
Year	Cumulative	-29.8%	+3.0%	+17.0%	+23.4%	+41.0%
	2007	-19.2%	-3.4%	+6.9%	+14.2%	+13.9%
	2008	-39.2%	-36.4%	-38.3%	-37.0%	-37.0%
	2009	+39.6%	+55.2%	+48.5%	+54.8%	+58.5%
	2010	+26.6%	+26.4%	+27.4%	+21.4%	+28.1%
	2011	-19.2%	-14.6%	-6.3%	-8.7%	-3.2%

Notes: Summary of cumulative and annual returns for quintile portfolios of stocks. Stocks are allocated into quintiles based on the percentage of picks on the CAPS system that are positive. Thus, for Quintile 1 stocks a relatively high share of the picks are negative and for Quintile 5 a relatively high share are positive. The portfolio is rebalanced daily. All days are equally weighted.

Table V: Large Cap Aggregated Returns by Pick Percentage Rating

	Quintile:	1^{st}	2^{nd}	3^{rd}	4^{th}	5^{th}
Year	Cumulative	-23.3%	+10.8%	+5.4%	+27.9%	+23.0%
	2007	-12.9%	+7.0%	+9.7%	+24.2%	+20.9%
	2008	-43.4%	-40.5%	-34.9%	-37.4%	-38.6%
	2009	+33.1%	+43.6%	+25.9%	+41.8%	+35.2%
	2010	+24.4%	+20.0%	+19.7%	+18.9%	+16.5%
	2011	-6.1%	+1.0%	-2.1%	-2.6%	+5.2%

Notes: Summary of cumulative and annual returns for quintile portfolios of stocks including only stocks with market capitalization of greater than $5 billion. Stocks are allocated into quintiles based on the percentage of picks on the CAPS system that are positive. Thus, for Quintile 1 stocks a relatively high share of the picks are negative and for Quintile 5 a relatively high share are positive. The portfolio is rebalanced daily. All days are equally weighted.

Table VI: Medium Cap Aggregated Returns by Pick Percentage Star Rating

	Quintile:	1st	2nd	3rd	4th	5th
Year	Cumulative	-18.1%	+8.3%	+25.9%	+30.7%	+31.9%
	2007	-14.9%	+0.6%	+9.5%	+17.2%	+13.9%
	2008	-34.2%	-33.7%	-36.2%	-37.4%	-36.3%
	2009	+30.8%	+45.9%	+45.6%	+55.2%	+45.7%
	2010	+28.8%	+22.8%	+28.1%	+25.1%	+23.5%
	2011	-13.2%	-9.4%	-3.4%	-8.2%	+0.9%

Notes: Summary of cumulative and annual returns for quintile portfolios of stocks including only stocks with market capitalization of less than $5 billion and greater than $1 billion. Stocks are allocated into quintiles based on the percentage of picks on the CAPS system that are positive. Thus, for Quintile 1 stocks a relatively high share of the picks are negative and for Quintile 5 a relatively high share are positive. The portfolio is rebalanced daily. All days are equally weighted.

Table VII: Small Cap Aggregated Returns by Pick Percentage Star Rating

	Quintile:	1st	2nd	3rd	4th	5th
Year	Cumulative	-38.1%	-13.4%	+7.0%	+19.9%	+45.2%
	2007	-21.5%	-12.3%	+3.0%	+8.7%	+10.7%
	2008	-38.7%	-38.0%	-41.9%	-38.0%	-35.5%
	2009	+41.7%	+60.7%	+59.3%	+70.4%	+68.1%
	2010	+24.3%	+34.2%	+30.8%	+23.2%	+33.9%
	2011	-27.1%	-26.2%	-14.2%	-15.2%	-9.7%

Notes: Summary of cumulative and annual returns for quintile portfolios of stocks including only stocks with market capitalization of less than $1 billion and greater than $100 million. Stocks are allocated into quintiles based on the percentage of picks on the CAPS system that are positive. Thus, for Quintile 1 stocks a relatively high share of the picks are negative and for Quintile 5 a relatively high share are positive. The portfolio is rebalanced daily. All days are equally weighted.

5 Performance Decomposition

We have demonstrated that the stocks ranked highly by Motley Fool participants earn higher subsequent raw returns than the stocks ranked poorly by Motley Fool participants during our sample period and relative to measures of market performance. Of course, the portfolios of stocks favored by Motley Fool participants may have different returns from the portfolios of stocks disfavored by Motley Fool participants because they have different risk or style factors on average. Thus, we decompose the differences in returns between stocks favored and disfavored by Motley Fool participants into those that can and cannot be attributed to market or style factors. In doing so, we note that Motley Fool is asking participants to identify stocks that will outperform the market, not stocks that will generate excess returns relative to other style and risk factors. In theory, participants could rate well in Motley Fool by loading up on known style and risk factors.

We use the classic style/risk factors identified by Fama and French (1993) and Carhart (1997) to decompose performance. Fama and French (1993) identified three measures that have been demonstrated to predict future stock returns, **RMRF**, **HML**, and **SMB**. We use the three factors identified by Fama and French in our analysis along with a fourth factor, Momentum, **Mom**, identified by Carhart (1997). Thus, we estimate standard equations of the following form:

$$r_{it} - rf_t = \alpha_i + \text{RMRF}_t\beta_1 + \text{SMB}_t\beta_2 + \text{HML}_t\beta_3 + \text{Mom}_t\beta_4 + e_{it} \quad (1)$$

That is, we regress the returns of portfolio i at time t (minus the risk-free rate) on the factor portfolio returns. We observe Motley Fool participants in the aggregate over 5 years. We undertake daily regression specifications for the 1260 trading days under study because our aggregation methodology generates an updated portfolio each day. We examine the quintile portfolios for the percentage pick ranking and also examine the investment strategy of buying the 5th quintile portfolio (top, or 5 star) and shorting the 1st quintile portfolio (bottom, or 1 star).

Table VIII presents the estimated alpha values and factor loadings for stocks in each quintile according to the Percentage Pick Ratings. Several properties of the regression coefficients stand out. First, there appear to be distinct differences in the underlying nature of stocks by quintile ranking: higher-ranked stocks exhibit higher corrrelation with market returns, lower values of the SMB and HML factors and higher values of the momentum index. Second, consistent the the nominal return findings, portfolios of higher-ranked stocks have higher estimated alphas after Fama-French filtering. Top quintile stocks are estimated to outperform the market by 28 basis points per trading day, whereas bottom quintile stocks are estimated to underperform the market by 23 basis points per trading day. This difference in returns of 51 basis points per day corresponds to a 12.8% difference in

Table VIII: Fama French Filtering of Portfolios by Percentage Positive Pick Rating

Quintile	1st	2nd	3rd	4th	5th	5 - 1
Mktrf	0.997***	1.097***	1.120***	1.154***	1.086***	.088***
	(0.008)	(0.006)	(0.007)	(0.009)	(0.009)	(0.013)
Smb	0.815***	0.571***	0.418***	0.328***	0.381***	-0.434***
	(0.018)	(0.013)	(0.015)	(0.020)	(0.018)	(0.028)
Hml	0.384***	0.070***	-.040***	-0.110***	-0.063***	-.446***
	(0.021)	(0.015)	(0.018)	(0.024)	(0.021)	(0.033)
Mom	-0.281***	-0.110***	-.055***	-0.019	0.014	0.295***
	(0.012)	(0.008)	(0.010)	(0.013)	(0.012)	(0.018)
Constant	-0.021*	0.005	0.015	0.019	0.029**	.050***
(Alpha)	(0.012)	(0.010)	(0.010)	(0.013)	(0.012)	(0.018)
Obs	1,260	1,260	1,260	1,260	1,260	1,260
R^2	0.965	0.979	0.967	0.945	0.948	0.494

Notes: Summary of Fama French regressions of returns portfolios formed from the universe of Motley Fool stocks and sorting into quintiles on the basis of the fraction of picks in the CAPS system that are positive. Thus, for Quintile 1 stocks a relatively high share of the picks are negative and for Quintile 5 a relatively high share are positive. The 5-1 portfolio is a zero investment portfolio in which Quintile 5 is bought and Quintile 1 is shorted. Standard errors are in parentheses. * indicates significance at the 10 percent confidence level, ** indicates significance at the 5 percent confidence level and *** indicates significance at the 1 percent confidence level. The portfolio is rebalanced daily.

returns on an annualized basis (or 13.7% with compounded interest). [6]

Tables IX and Table X present alternative measurement strategies for

[6] In unreported results, we incorporated the Pastor and Stambaugh (2003) monthly liquidity factor measure and our results are substantially the same as reported here.

Table IX: Fama French Filtering of Portfolios by Absolute Positive Pick Rating

Quintile	1st	2nd	3rd	4th	5th	5 - 1
Mktrf	1.019***	1.039***	1.066***	1.118***	1.213***	.194***
	(0.006)	(0.004)	(0.006)	(0.009)	(0.012)	(0.014)
Smb	0.759***	0.609***	0.540***	0.419***	0.186***	-0.573***
	(0.013)	(0.009)	(0.013)	(0.018)	(0.025)	(0.030)
Hml	0.184***	0.068***	0.042***	0.054	-0.103***	-0.287***
	(0.015)	(0.011)	(0.015)	(0.021)	(0.029)	(0.036)
Mom	-0.158***	-0.106***	-0.084***	-0.077***	-0.026	0.132***
	(0.008)	(0.006)	(0.008)	(0.012)	(0.016)	(0.020)
Constant	-0.004	0.018***	0.015*	0.011	0.006	0.009
(Alpha)	(0.008)	(0.006)	(0.009)	(0.012)	(0.016)	(0.018)
Obs	1,260	1,260	1,260	1,260	1,260	1,260
R^2	0.982	0.985	0.976	0.957	0.923	0.346

Notes: Summary of Fama French regressions of returns portfolios formed from the universe of Motley Fool stocks and sorting into quintiles on the basis of the number of positive picks in the CAPS system. Portfolios are constrained to have the same fraction of stocks in each of the three market capitalization categories as the Positive Percentage Pick Portfolio. Standard error are in parentheses. * indicates significance at the 10 percent confidence level, ** indicates significance at the 5 percent confidence level and *** indicates significance at the 1 percent confidence level. The portfolio is rebalanced daily.

creating quintile portfolios. In Table IX, we construct quintile portfolios as before, but use only the information in the positive picks. For each of the three market capitalization categories, all stocks with more than 10 active

Table X: Fama French Filtering of Portfolios by Absolute Negative Pick Rating

Quintile	1st	2nd	3rd	4th	5th	5 - 1
Mktrf	1.082***	1.154***	1.120***	1.074***	1.023***	-0.059***
	(0.009)	(0.007)	(0.006)	(0.006)	(0.006)	(0.010)
Smb	0.527***	0.516***	0.464***	0.492***	0.519***	-0.008***
	(0.019)	(0.015)	(0.015)	(0.013)	(0.013)	(0.022)
Hml	0.259***	0.027	-0.019	-0.015	-0.005	-0.264***
	(0.022)	(0.018)	(0.018)	(0.016)	(0.015)	(0.026)
Mom	-0.219***	-0.114***	-0.072***	-0.031***	-0.018**	0.201***
	(0.012)	(0.010)	(0.010)	(0.009)	(0.008)	(0.014)
Constant	-0.021*	0.005	0.011	0.018**	.032***	0.052***
(Alpha)	(0.012)	(0.010)	(0.010)	(0.009)	(0.008)	(0.014)
Obs	1,260	1,260	1,260	1,260	1,260	1,260
R^2	0.959	0.971	0.968	0.971	0.972	0.470

Notes: Summary of Fama French regressions of returns portfolios formed from the universe of Motley Fool stocks and sorting into quintiles on the basis of the number of negative picks in the CAPS system. Portfolios are constrained to hold the same fraction of stocks in each of the three market capitalization categories as the Positive Percentage Pick Portfolio. Standard error are in parentheses. * indicates significance at the 10 percent confidence level, ** indicates significance at the 5 percent confidence level and *** indicates significance at the 1 percent confidence level. The portfolio is rebalanced daily.

picks are sorted based on raw counts of their positive picks only. We construct the positive pick quintile portfolios by using the market capitalization composition of each of the Percentage Positive Pick Portfolios, but assigning stocks to quintiles based on their raw counts of positive picks only. Thus, for example, if the first Percentage Positive Pick quintile portfolio held one-third each of large, medium, and small-cap stocks, the Absolute Positive Pick Rating portfolio would also consist of one-third each of large, medium, and small-cap stocks, but it would contain the stocks within those capitalization categories with the lowest number of positive picks. Similarly, Table X uses the Absolute Negative Pick Rating Portfolio which is constructed similarly to the Absolute Positive Pick Rating quintile portfolio, but uses only the information contained in the raw counts of negative picks.

Tables IX and Table X present Fama-French regressions based on these alternative measurement strategies for creating quintile portfolios. The results in these two tables suggest that the significant differences in returns for the top and bottom quintile portfolios in Table VIII derive almost entirely from information derived from the negative picks rather than the positive picks. The estimated alpha values for the top and bottom quintile portfolios are significantly different from zero at the 5% level for Negative Pick portfolios and if anything these estimated alpha values are even larger in magnitude than those reported in Table VIII. By contrast, the estimated alpha values for the top and bottom quintile portfolios drawn from Positive Picks are almost identical and both are very close to 0.

Note that while our results stem largely from the informativeness of the negative picks, this does not imply that a short position is required to exploit the information. The results in Table X suggest that buying stocks that very few Motley Fool participants identified as negative picks would be a profitable strategy in our analysis.

6 Robustness

6.1 Capitalization

An immediate concern with our analysis is that the exceptional performance of the top and bottom quintile portfolios may derive from thinly traded Small Cap stocks. To address this concern, first recall that, at the time of our study, CAPS only allowed picks for stocks that have a price of at least $1.50 per share and a market cap of at least $100 Million at any given time. To further examine the small cap explanation, we repeat the analyses above by separately examining the performance of the Percentage Positive Pick Portfolio ratings within market capitalization grouping. Table XI reports the alpha coefficients only for the specification in Equation (1) where the portfolios are separated by capitalization grouping. Each row and column entry in Table XI represents the alpha coefficient and standard error from a different regression specification.

While the strongest performance results are for the difference between the bottom (Quintile 1) and top (Quintile 5) portfolio stocks in the Small Capitalization grouping, the signs of the coefficients are consistent across capitalization groups and the positive performance results for Quintile 4 and Quintile 5 Medium Capitalization stocks are statistically different from zero at the ten percent confidence level.

6.2 Buy and Hold

The results above all are based on portfolios that change composition on a daily basis in response to an inflow of new picks. However, tracking these

Table XI: Fama French Filtering of Percentage Positive Pick portfolios by Capitalization Size

	Cap Size All	Cap Size Large	Cap Size Med	Cap Size Small
Quintile 1	-0.0210*	-0.0090	-0.0064	-0.0320**
	(0.0120)	(0.0120)	(0.0150)	(0.0140)
Quintile 2	0.0051	0.0120	0.0089	-0.0088
	(0.0083)	(0.0080)	(0.0099)	(0.0116)
Quintile 3	0.0147	0.0069	0.0202*	0.0085
	(0.0101)	(0.0086)	(0.0110)	(0.0136)
Quintile 4	0.0194	0.0225**	0.0240*	0.0179
	(0.0132)	(0.0111)	(0.0146)	(0.0161)
Quintile 5	0.0287**	0.0197	0.0231*	0.0309**
	(0.0121)	(0.0125)	(0.0122)	(0.0141)

Notes: Summary of alpha value estimates from Fama French regressions of returns portfolios formed from the universe of Motley Fool stocks and sorting into quintiles on the basis of the fraction of picks that are positive in the CAPS system. Each Row and Column entry represents the alpha coefficient estimate from a different specification. Standard error are in parentheses. * indicates significance at the 10 percent confidence level, ** indicates significance at the 5 percent confidence level and *** indicates significance at the 1 percent confidence level. Companies with market caps of more than $5 billion are categorized as large caps; companies with market caps between $1 and $5 billion are categorized as medium caps and companies with market caps less than $1 billion but more than $100 million are categorized as small caps. The portfolio is rebalanced daily.

daily changes in a real money portfolio would incur considerable transaction costs. To examine a strategy with lower transactions costs, we repeat our earlier analysis for portfolios that remain fixed for periods of 1, 3, or 6 months. In each case, we use a starting date of January 1, 2007 to identify the initial five quintile portfolios. We then rebalance those portfolios at regular intervals after that. To ensure that each pick influences portfolio composition, we match the holding period with the window used to identify active picks. Thus, for example, with a three-month holding period, we use a previous period of three months of active picks to rank the stocks for the next change in portfolios. Therefore, even for the one-month holding window, all of the picks used are slightly "stale". Each entry in Table XII is the estimated alpha coefficient from a separate regression. Despite the staleness of the picks, the estimated values shown in Table XII remain surprisingly close to those in Table VIII, especially for the one- and three-month holding periods. This result suggests that it is not essential to change portfolios every day in order to achieve profitable results – consistent once again with the view that CAPS players are not particularly trying (or at least are not succeeding if they are trying) to time the market.

Conclusion

This investigation of the Motley Fool CAPS system shows that CAPS predictions are informative about future stock prices. In particular, while positive stock picks have little predictive content, negative picks predict future stock price declines. Our Fama-French decomposition suggests that these

Table XII: Alphas from Buy and Hold Strategies for Percentage Positive Portfolios

	One-Month Rebalancing	Three-Month Rebalancing	Six-Month Rebalancing
Quintile 1	-0.022*	-0.021*	-13.000
	(0.012)	(0.012)	(0.012)
Quintile 2	0.004	0.011	0.004
	(0.008)	(0.008)	(0.008)
Quintile 3	0.009	0.014	0.016*
	(0.010)	(0.010)	(0.009)
Quintile 4	0.024*	0.019	0.017
	(0.013)	(0.013)	(0.012)
Quintile 5	0.025**	0.020*	0.015
	(0.012)	(0.012)	(0.013)

Notes: Summary of alpha value estimates from Fama French regressions of returns portfolios formed from the universe of Motley Fool stocks and sorting into quintiles on the basis of the fraction of picks that are positive in the CAPS system. Portfolios are rebalanced only every one, three, or six months in each of the columns. Each Row and Column entry represents the alpha coefficient estimate from a different specification. Standard error are in parentheses. * indicates significance at the 10 percent confidence level, ** indicates significance at the 5 percent confidence level and *** indicates significance at the 1 percent confidence level.

are results are due to stock picking and not due to style factors or market timing.

It may not be surprising that the collaborative filtering technology is more successful at obtaining predictive negative picks rather than predictive positive picks. The literature surrounding short sales (for example, Jones and Lamont, 2002 and Boehme, Danielsen, and Sorescu, 2006), suggests that acting on negative information about the prospects for a stock can be more costly and difficult than acting on positive information about the prospects for a stock. Purchasing stocks for which a fairly small fraction of Motley Fool participants have expressed negative information is a profitable strategy.

The literature has produced limited evidence that the short communications in tweets and stock message boards are informative. Our results complement those of Chen et. al. (2014) who demonstrate the informativeness of articles on Seeking Alpha. These two papers, taken together, suggest that peer-generated advice can contain information that has not been fully captured in securities prices and that therefore predict future returns. Our results demonstrate that excess returns using a simple aggregation of information in the Motley Foot CAPs system are about twelve percent per year over our sample period.

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