

The Value of Amateur Analysts' Recommendations Extracted from Online Investment Communities

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Abstract

Understanding the value of information content of online investment communities is a fundamental issue for investors to leverage the content to make financial decisions. This study tries to investigate the relationship between economic variables and the content of amateur analysts' opinions on online investment communities. We consider two specific research questions: (1) Do recommendations posted by amateur analysts on online investment communities help investors predict stock returns? (2) Is disagreement among the recommendations positively associated with trading volume? Our sample includes 95,784 pieces of financial analysis submitted by amateur analysts to Seeking Alpha which is an open online investment community for investment research. The results show that bearish recommendations from amateur analysts on Seeking Alpha predict stock returns, and the disagreement among the recommendations is positively related to trading volume. Overall, our findings suggest that amateur analysts' recommendations are a valuable source of information in stock markets.

Keywords: Online investment communities, amateur financial analysis, stock recommendations, disagreement, stock returns, trading volume

Introduction

Online investment communities have offered venues for individuals to contribute and consume investment analysis on financial securities (Bartov et al., 2017). Thanks to the low cost of online publishing and the popularity of online investment communities, new forms of financial analysis have emerged and the era of DIY financial analysis is dawning (Chen et al., 2014). Recently, large amounts of amateur financial analysis are shared by amateur analysts who have unique insights into a certain industry or launch an in-depth investigation of a certain company via online investment communities, thereby changing the way in which market participants acquire information. Instead of following sell-

side analysts, investors increasingly turn to rely on advice from amateur analysts and use the collective intelligence to make financial decisions.

Like professional analysts, amateurs' investment analysis usually includes three parts: earnings forecasts, recommendation ratings and textual analysis. When examining outputs from amateur analysts, researchers focus on earnings forecasts and textual analysis. Prior studies have shown that textual analysis and earnings forecasts shared by amateurs can predict future stock performance (Chen et al., 2014; Drake et al., 2017; Jame et al., 2016). In addition to earnings forecasts and textual analysis, financial analysis also provides a rating recommending an investment action, e.g. to buy, sell, or hold a security. As the recommendation is a summary measure of stock performance and a quantitative element of financial analysis, investors usually pay more attention to it. Although there are several studies which examine the value of recommendations shared via nontraditional channels, such as newspapers (Barber and Loeffler, 1993), internet stock message boards (Antweiler and Frank, 2004), television (Engelberg et al., 2012), spam email messages (Nelson et al., 2013), and online communities for buy-side analysts (Crawford et al., 2017), whether recommendations from amateur analysts on online investment communities can predict stock performance is unclear. Therefore, this study tries to address this gap, and consider two specific research questions: Can recommendations posted by amateur analysts on online investment communities predict returns? Is disagreement among the recommendations related to trading volume?

The rest of the paper is organized as follows. We first put forward our research hypotheses in Section 2. Section 3 describes our data and research methodology. We present the empirical results and discuss our findings in Section 4. In the final section, we conclude this paper by discussing the results, contributions, limitations, and future directions.

Theoretical Background and Hypotheses Development

Amateur Financial Analysis

Investors always rely on financial analysts to acquire value-relevant information on financial securities (Bartov et al., 2017). Previous research on financial analysis focuses mostly on analysts' research outputs, including stock recommendations, earnings forecasts, target prices, and textual analysis. Overall, the findings of these studies suggest that analyst outputs are informative (Asquith et al., 2005; Barber et al., 2001; Brav and Lehavy, 2003; Francis and Soffer, 1997; Hsieh et al., 2016; Huang et al., 2017; Huang et al., 2014; Loh and Stulz, 2010; Womack, 1996). With the increasing popularity of social media, peer opinions have begun to play a great role in financial markets (Chen et al., 2014). Social media has a stronger relationship with firm stock performance than conventional media (Yu et al., 2013). Drake et al. (2017) find that the impact of different types of social media varies significantly, and demonstrate that semi-professional intermediaries (e.g. newspaper websites, business news websites, and online investment communities) are associated with positive capital market effects. Amateur financial analysis refers to investment research contributed by amateur analysts via online investment communities (e.g. Seeking Alpha, Estimize, and The Motley Fool). The amateur financial analysis is similar in format to the reports written by sell-side analysts, which usually consist of earnings forecasts, recommendation ratings and textual analysis. Recent research shows earnings forecasts and textual analysis posted by amateur analysts on online investment communities can help forecast earnings and stock returns (Chen et al., 2014; Jame et al., 2016). Since recommendations are also measures of future stock performance, it is also important to understand the value of amateur analysts' recommendations, in addition to earnings forecasts and textual analysis.

Hypotheses Development

Online investment communities provide nature settings for amateur analysts to commit and share information about securities. Several studies suggest that individuals contribute knowledge to social network when they perceive that it establishes or enhances their professional reputations (Chang and Chuang, 2011; Chiu et al., 2006; Hu et al., 2012; Wasko and Faraj, 2005). Besides, social interaction plays an important role in the decision to share information on social media (Chiu et al., 2006; Hsu et

al., 2007). Especially, reputation and social interaction have positive effects on the quality, but not the quantity, of shared knowledge (Chang and Chuang, 2011). Thus, amateur analysts may use online investment communities as new channels to signal their expertise and to build their reputation. In particular, amateur analysts who want to be opinion leaders will issue high-quality investment analysis (e.g. stock recommendations, earnings forecasts, target prices, and textual analysis).

Chen et al. (2014) investigate the informativeness of textual analysis posted by amateur analysts on Seeking Alpha which is a popular online investment community for investment research. Textual analysis on Seeking Alpha is long-form articles similar in format to the reports written by sell-side analysts (Avery et al., 2015). They find that investment research expressed on the site is significantly associated with future returns and earnings surprises. Jame et al. (2016) use crowdsourced earnings forecasts from Estimize and show that earnings forecasts posted by amateur analysts are incrementally useful in forecasting earnings and measuring the market's expectations. Drake et al. (2017) indicate that social investment platforms as semi-professional intermediaries are associated with capital market effects. Overall, existing research provides robust evidence that amateur financial analysis has investment value, and that online investment communities are new sources of information.

Prior studies comparing the stock recommendations of analysts from affiliated and unaffiliated firms (e.g., Lin and McNichols (1998), Michaely and Womack (1999)) show that existing and potential investment banking relationships can affect analyst judgment, and recommendations from underwriter analysts show significant evidence of optimistic bias. In particular, bearish recommendations and the change of bearish recommendations have more information about future returns (Womack, 1996). The lower precision of bullish recommendations relative to bearish recommendations derives from the observed distribution of stock recommendations, which is skewed toward bullish recommendations (Beneish, 1991). As bearish recommendations and the change of bearish recommendations are accompanied by negative returns, we propose that:

H1: Bearish recommendations from amateur analysts on online investment communities predicts negative stock returns.

H2: Increased bearish recommendations from amateur analysts on online investment communities predicts negative stock returns.

Trading volume provides another measure of market behavior. Financial theory indicates that disagreement induces trading. Disagreement has long been considered as a possible motivation for trading (Antweiler and Frank, 2004). Prior studies (e.g. Hirshleifer (1977), Diamond and Verrecchia (1981), Karpoff (1986), Harris and Raviv (1993)) have carried out related theoretical analysis. Disagreement causes trading volume to rise because trading occurs when two market participants assign different values to an asset. Social media is a natural place to investigate this theory since disagreement is rather observable (Antweiler and Frank, 2004). Research on social media finds disagreement among retail investors is related to increased trading volume (Antweiler and Frank, 2004; Das and Chen, 2007; Kim and Kim, 2014; Leung and Ton, 2015; Sabherwal et al., 2011). Both theory and empirical evidence support the notion that disagreement would lead to increases in volume. Ajinkya et al. (1991) indicate a significant positive relation between the disagreement in analysts' financial analysis and the trading volume. In the context of online investment communities, disagreement among amateur financial analysis (e.g. recommendations) may induces trading. This leads to the following empirical prediction.

H3: Disagreement among amateur analysts' recommendations is positively related with trading volume.

Research Methodology

Data

Seeking Alpha (SA) was launched in early 2004 for investment research. It aims to mine the wisdom of the crowds for insights into every topic of interest to investors. SA has become a popular source for current news and information, stock analysis, and investment recommendations. Its users generate 42

million visits monthly and spend 18 minutes per visit on average. SimilarWeb ranks SA first for time spent by users per visit in its January-March 2018 report, ahead of Yahoo! Finance, Google Finance and Wall Street Journal Online.

Stock analysis on SA is a long-form article similar in format to the report written by sell-side analysts. There are over 0.9 million articles in total in the “Analysis” section which are posted by 16 thousand contributors who are traders, economists, academics, financial advisors and industry experts. Before published, articles are reviewed by SA editors for clarity, consistency and impact. Editorial feedback never interferes with the substance of the author's argument or viewpoints. In addition, SA editors tag each article with “About ticker” to indicate the focus of the article and analysis. If an article analyzes more than one stock, “About ticker” will contain multiple tickers. In order to extract the author's opinion accurately, we only focus on the single-ticker articles which account for one-third of all articles. When authors compose articles, they may choose a theme tag. “Long ideas” means that the author recommends buying a stock, industry, or sector, and “Short ideas” means that the author recommends shorting it. So all stock analysis has been coded as recommendation ratings: bullish, bearish, or neither.

In this research, we develop a crawler to collect all the single-ticker stock analysis on SA about S&P 500 component stocks between January 1, 2005 and April 30, 2018. For each stock analysis, we collect time stamp, “About ticker” and analysis content (text and recommendation tags). We totally collect 95,784 pieces of single-ticker financial analysis about S&P 500 component stocks between January 1, 2005 and April 30, 2018 from SA. There are 28,781 pieces of single-ticker financial analysis tagged with “Long ideas”, while there are 3,485 pieces of single-ticker financial analysis tagged with “Short ideas”. In this study, we move the day on which financial analysis is published via SA to ensuing trading date if the financial analysis appears on a non-trading day. Our sample contains 65,893 firm-days. In addition, our study uses financial market data from the Center for Research in Security Prices (CRSP), financial analyst data from the Institutional Brokers' Estimate System (IBES), and financial statement data from Compustat.

Main Variables

Dependent Variables

According to the hypotheses, there are two dependent variables, abnormal return and trading volume.

Following literature, we use the characteristic-based benchmarks of Daniel et al. (1997) to compute abnormal returns. To compute the four-day cumulative buy-and-hold abnormal return (CAR) from trading day t to $t+3$ for stock i , we define

$$CAR_{i,[t,t+3]} = \prod_{j=0}^3 (1 + Ret_{i,t+j}) - \prod_{j=0}^3 Ret_{i,t+j}^{DGTW} \quad (1)$$

$Ret_{i,t}$ is the raw return of the stock i on day t , and $Ret_{i,t}^{DGTW}$ is the return on a value-weighted portfolio with similar size, book-to-market ratio, and momentum characteristics.

Turnover is a measure of trading volume, which is defined as the ratio of trading volume for the period to the number of shares outstanding. Following Garfinkel and Sokobin (2006), we calculate the change in turnover ($\Delta TO_{i,t}$) using a two-step process. Since some stock/days may exhibit more trading because some macro condition creates significant trading in the whole market, we compute market-adjusted turnover for stock i on day t ($MATO_{i,t}$) as the difference between stock's daily turnover and market-wide turnover calculated across all NYSE/AMEX stocks. Then we subtract a rolling average of the past 20 trading days of market-adjusted turnover from the above measure of market-adjusted turnover to obtain the change in turnover $\Delta TO_{i,t}$.

$$\Delta TO_{i,t} = MATO_{i,t} - \sum_{j=1}^{20} MATO_{t-j} \quad (2)$$

Independent Variables

According to the hypotheses, we consider bearish recommendations, the change in bearish recommendations and disagreement index as independent variables.

When a user composes stock analysis, s/he may choose a theme tag: “Long ideas”, “Short ideas”, or neither. “Long ideas” means that the author recommends buying a stock, industry, or sector, and “Short ideas” means that the author recommends shorting it. Therefore, we use the percent of “Short ideas” in all stock analysis for stock i on day t ($Short_pct_{i,t}$) to capture the degree of bearish recommendations contained in stock analysis. To examine whether increased bearish recommendations contains any informativeness in predicting stock returns, we also consider the change in the percent of “Short ideas” ($\Delta Short_pct_{i,t}$).

To capture whether the stock analysis has the same view, or whether there is dispersion of stock analysis, we calculate disagreement index ($Disag_{i,t}$) among the recommendations following Das and Chen (2007).

$$Disag_{i,t} = \left| 1 - \left| \frac{L - S}{L + S} \right| \right| \quad (3)$$

L is the number of Long ideas and S is the number of Short ideas for stock i on day t . If all the stock analysis is on the buy or sell side of the market, this index is zero; if the number of long ideas and the number of short ideas are exactly balanced, the index is 1.

Control Variables

To robustly test the hypotheses, we include a set of sell-side analyst earnings forecasts and recommendations as control variables. We use the IBES detail recommendation file to calculate the number of recommendation upgrades and downgrades for stock i on day t ($Upgrade_{i,t}$, $Downgrade_{i,t}$). We use IBES unadjusted detail history file and summary history file to compute earnings surprise, the difference between the reported earnings-per-share (EPS) and the median of financial analysts' current quarterly EPS forecasts issued and updated within 30 days prior to the earnings announcement. We also include two binary variables in the regression indicating the sign of earnings surprise. $PosES_{i,t}$ is one when earnings surprise is positive and zero otherwise, and $NegES_{i,t}$ is one when earnings surprise is negative and zero otherwise

Other control variables include: $Volatility_{i,t}$, measured by the sum of squared daily returns within 20 trading days prior to day t ; $ARet_{i,t-1}$, $ARet_{i,t-2}$, measured by abnormal return on day $t-1$, $t-2$; and $CAR_{i,[t-60,t-3]}$, measured by cumulative abnormal returns over 58 trading days before day $t-2$.

Empirical Model

In order to test H1 and H2, we regress short-window abnormal returns on amateur recommendations, similar to Chen et al. (2014), using the following models:

$$CAR_{i,[t,t+3]} = \alpha_0 + \beta_1 Short_pct_{i,t} + \gamma_1 Volatility_{i,t} + \gamma_2 Upgrade_{i,t} + \gamma_3 Downgrade_{i,t} + \gamma_4 PosES_{i,t} + \gamma_5 NegES_{i,t} + \gamma_6 ARet_{i,t-1} + \gamma_7 ARet_{i,t-2} + \gamma_8 CAR_{i,[t-60,t-3]} + \varepsilon_{i,t} \quad (4)$$

$$CAR_{i,[t,t+3]} = \alpha_0 + \beta_1 \Delta Short_pct_{i,t} + \gamma_1 Volatility_{i,t} + \gamma_2 Upgrade_{i,t} + \gamma_3 Downgrade_{i,t} + \gamma_4 PosES_{i,t} + \gamma_5 NegES_{i,t} + \gamma_6 ARet_{i,t-1} + \gamma_7 ARet_{i,t-2} + \gamma_8 CAR_{i,[t-60,t-3]} + \varepsilon_{i,t} \quad (5)$$

Another interesting issue is the turnover predictability of amateur recommendations. To test this issue, we estimate the following regression model:

$$\Delta TO_{i,t} = \alpha_0 + \beta_1 Disag_{i,t} + \gamma_1 Upgrade_{i,t} + \gamma_2 Downgrade_{i,t} + \gamma_3 PosES_{i,t} + \gamma_4 NegES_{i,t} + \varepsilon_{i,t} \quad (6)$$

Since disagreement is a motivation for trading, we expect a positive relation between disagreement and turnover.

We include year-month fixed effect in all above models. To correct for serial-correlation, cross-correlation, and heteroscedasticity in error terms, we use T-statistics clustered by firm and year-month.

Results

Descriptive Analysis

Table 1 reports the description statistics of key variables in our study. Statistics for $Short_pct_{i,t}$ suggest that approximately 3.66 percent of articles are tagged with “Short ideas” by amateurs. Table 2 provides the correlation matrix and Variance Inflation Factor (i.e., VIF) values of main variables in our study. Consistent with H1, we observe a significantly negative correlation of -0.01 between $Short_pct_{i,t}$ and $CAR_{i,[t,t+3]}$. We also observe a significantly negative correlation of -0.01 between $\Delta Short_pct_{i,t}$ and $CAR_{i,[t,t+3]}$. Consistent with H3, we observe a significantly positive correlation of 0.05 between $Disag_{i,t}$ and $\Delta TO_{i,t}$. To formally test multicollinearity, we calculated the VIF values for all independent variables. It shows the maximum VIF value is 2.71, indicating that multicollinearity is not a threat to our study.

Table 1. Descriptive Statistics of Key Variables

Variable	Observation #	Mean	S.D.	Min	Median	Max
$CAR_{i,[t,t+3]}$	65870	0.0001	0.0481	-0.9140	-0.0003	1.7280
$\Delta TO_{i,t}$	65830	0.0029	0.0234	-0.4160	0.0001	1.4530
$Short_pct_{i,t}$	65890	0.0366	0.1790	0.0000	0.0000	1.0000
$\Delta Short_pct_{i,t}$	65240	-0.0001	0.2400	-1.0000	0.0000	1.0000
$Disag_{i,t}$	25410	0.0167	0.1230	0.0000	0.0000	1.0000
$PosES_{i,t}$	65890	0.0417	0.2000	0.0000	0.0000	1.0000
$NegES_{i,t}$	65890	0.0139	0.1170	0.0000	0.0000	1.0000
$Upgrade_{i,t}$	65890	0.0388	0.2380	0.0000	0.0000	9.0000
$Downgrade_{i,t}$	65890	0.0334	0.2030	0.0000	0.0000	7.0000
$ARet_{i,t-1}$	65880	-0.0002	0.0277	-0.8200	-0.0001	0.8650
$ARet_{i,t-2}$	65880	0.0000	0.0242	-0.8200	-0.0001	0.7220
$CAR_{i,[t-60,t-3]}$	65720	-0.0050	0.1420	-1.3950	-0.0064	2.7940
$Volatility_{i,t}$	65830	0.0147	0.0556	0.0000	0.0050	2.0340

Table 2. Correlation Matrix and VIFs of Main Variables

Variable	1	2	3	4	5	6	7	8	9	10	11	12	13
1	1.00												
2	-0.07	1.00											
3	-0.01	0.01	1.00										
4	-0.01	0.00	0.67	1.00									
5	0.00	0.05	0.15	0.10	1.00								
6	0.04	0.09	-0.03	-0.01	0.01	1.00							
7	-0.08	0.09	-0.01	0.00	0.01	-0.02	1.00						

8	-0.12	0.21	0.01	0.01	0.03	0.01	0.05	1.00					
9	0.08	0.12	-0.00	-0.00	0.01	0.02	0.01	0.06	1.00				
10	-0.03	-0.06	-0.00	0.01	-0.01	0.01	-0.00	-0.04	0.02	1.00			
11	-0.04	-0.06	-0.01	-0.01	-0.01	0.00	0.00	-0.01	0.00	0.01	1.00		
12	0.00	-0.05	0.01	0.00	0.01	0.01	-0.01	-0.02	0.00	0.01	0.02	1.00	
13	0.06	0.15	0.02	-0.00	0.02	-0.01	0.01	0.05	0.03	0.04	-0.02	-0.17	1.00
VIF			2.71	2.64	1.03	1.02	1.01	1.02	1.02	1.02	1.02	1.03	1.19

Notes: 1: $CAR_{i,[t,t+3]}$; 2: $\Delta TO_{i,t}$; 3: $Short_pct_{i,t}$; 4: $\Delta Short_pct_{i,t}$; 5: $Disag_{i,t}$; 6: $PosES_{i,t}$; 7: $NegES_{i,t}$; 8: $Upgrade_{i,t}$; 9: $Downgrade_{i,t}$; 10: $ARet_{i,t-1}$; 11: $ARet_{i,t-2}$; 12: $CAR_{i,[t-60,t-3]}$; 13: $Volatility_{i,t}$.

Main Analysis

H1 predicts that as bearish recommendations increases, the four-day cumulative buy-and-hold abnormal return tends to decrease. We report results for this prediction in column 1 of table 3 using equation (4). As presented, we find strong support for H1 as the coefficient on $Short_pct_{i,t}$ is significantly negative. The results show that the bearish recommendations are generally confirmed by subsequent stock performance. We also use changes in bearish recommendations instead of the bearish recommendation. The results in column 2 are qualitatively similar. Overall, bearish recommendations from amateur analysts on the online investment communities convey information about stock performance.

Column 3 of table 3 provides support for the Harris and Raviv (1993) hypothesis that disagreement is related with trading. We find that there is a positive coefficient on the disagreement index, supporting H3.

Table 3. Results of Main Analysis

	DV = $CAR_{i,[t,t+3]}$		DV = $\Delta TO_{i,t}$
	Column 1	Column 2	Column 3
$Short_pct_{i,t}$	-0.004***(-3.33)		
$\Delta Short_pct_{i,t}$		-0.002**(-2.39)	
$Disag_{i,t}$			0.007***(4.19)
$PosES_{i,t}$	0.010***(8.39)	0.010***(8.46)	0.012***(12.10)
$NegES_{i,t}$	-0.034***(-12.67)	-0.034***(-12.65)	0.019***(6.58)
$Upgrade_{i,t}$	-0.026***(-15.51)	-0.026***(-15.37)	0.019***(7.90)
$Downgrade_{i,t}$	0.020***(11.85)	0.020***(11.71)	0.012***(8.39)
$ARet_{i,t-1}$	-0.067**(-2.30)	-0.068**(-2.30)	
$ARet_{i,t-2}$	-0.079***(-2.71)	-0.079***(-2.68)	
$CAR_{i,[t-60,t-3]}$	0.003(0.87)	0.003(0.87)	
$Volatility_{i,t}$	0.061** (2.45)	0.061** (2.40)	
Observation #	65702	65104	25385
R^2	0.042	0.042	0.098

Notes: T statistics in parentheses. *: $p < 0.1$, **: $p < 0.05$, ***: $p < 0.01$.

Robustness Check

We also examined the robustness of our results by considering simultaneously bullish and bearish recommendations shared by amateur analysts. In particular, we calculate the percent of “Long ideas” in all financial analysis for stock i on day t ($Long_pct_{i,t}$). To examine whether increased long ideas contains any informativeness in predicting stock returns, we also consider the change in the percent of “Long ideas” ($\Delta Long_pct_{i,t}$). The results show that the bullish recommendations are generally also confirmed by subsequent stock performance, but the change in bullish recommendations provides limited predictability.

To confirm the robustness of the relationship between $\Delta TO_{i,t}$ and $Disag_{i,t}$, we test the sensitivity of the results by using different measures of disagreement. We replicate the results using alternative measures of disagreement ($Disag_{i,t}$) based on Antweiler and Frank (2004).

$$Disag_{i,t} = -1 + \sqrt{1 - \left(\frac{L - S}{L + S}\right)^2} \quad (7)$$

We find the similar results.

Table 4. Results of Robustness Check

	DV = $CAR_{i,[t,t+3]}$		DV = $\Delta TO_{i,t}$
	Column 1	Column 2	Column 3
$Long_pct_{i,t}$	0.001***(2.79)		
$Short_pct_{i,t}$	-0.003***(-2.97)		
$\Delta Long_pct_{i,t}$		0.000(1.29)	
$\Delta Short_pct_{i,t}$		-0.002**(-2.21)	
$Disag_{i,t}$			0.007***(4.18)
$PosES_{i,t}$	0.010***(8.52)	0.010***(8.47)	0.012***(12.11)
$NegES_{i,t}$	-0.034***(-12.61)	-0.034***(-12.64)	0.019***(6.58)
$Upgrade_{i,t}$	-0.026***(-15.50)	-0.026***(-15.37)	0.019***(7.89)
$Downgrade_{i,t}$	0.020***(11.87)	0.020***(11.71)	0.012***(8.39)
$ARet_{i,t-1}$	-0.067**(-2.31)	-0.068**(-2.30)	
$ARet_{i,t-2}$	-0.079***(-2.71)	-0.079***(-2.68)	
$CAR_{i,[t-60,t-3]}$	0.003(0.86)	0.003(0.87)	
$Volatility_{i,t}$	0.062**(2.45)	0.061**(2.40)	
Observation #	65702	65104	25385
R^2	0.042	0.042	0.098

Notes: T statistics in parentheses. *: $p < 0.1$, **: $p < 0.05$, ***: $p < 0.01$.

Conclusion

With the development of online investment communities, amateur financial analysis is taking root in the investment research industry. This paper aims to investigate the value of amateur financial analysis, especially bearish recommendations extracted from Seeking Alpha. We find that the degree of bearish recommendations contained in amateur financial analysis can predict future stock returns,

and the predictability holds even after controlling for traditional opinions from sell-side analysts. In addition, our analysis shows that the disagreement among the bearish recommendations is positive related to trading volume. Overall, we conclude that amateurs' recommendations are incrementally useful in predicting market activity such as stock return and trading volume. This suggests that amateur analysts share valuable private information on online investment communities.

Our first contribution is to introduce a new phenomenon, amateur analysts' recommendations, and assess its value. The results complement literature which investigates the informativeness of earnings forecasts and textual analysis contained in amateur financial analysis. Our study also contributes to the literature that explores various approaches to predicting stock performance. Specially, recommendations from amateur analysts are available for more small-cap stocks and at much shorter time horizons than buy-side and sell-side analysis. With the popularity of social media, amateurs' recommendations are increasingly accessible to market participants. Therefore, it is critical to assess the role of amateurs' recommendations in predicting stock performance.

However, this study inevitably has some limitations. In this study, our sample only covers S&P 500 component stocks. Future research should increase the sample size to improve generalizability. Further, we will empirically test whether market value has a moderating effect on the relationship between amateur analysts' recommendations and market activity.

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