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Will the reddit rebellion take you to the moon? Evidence from WallStreetBets

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Abstract

In early 2021, several stocks receiving attention from retail traders known as "meme stocks" soared in value. A primary source of information regarding these stocks is from the social media platform Reddit, specifically from a subreddit known as WallStreetBets (WSB).This paper investigates whether a simple and easily implementable trading strategy following the WallStreetBets (WSB) subreddit can produce alpha. We document no evidence this is the case. Though we do observe a positive relation between WSB submissions and abnormal trading volume, we find that a portfolio that goes long buy recommendations and short sell recommendations each day is not profitable on a risk-adjusted basis. Holding periods from one day to one year fail to produce alpha. These findings are robust to a variety of different portfolio formation strategies. Our results provide an early look at the data following the explosion of interest in social media inspired retail investing.

Keywords Reddit · Retail investors · Wallstreetbets · Trading

JEL Classification G1 · G4 · G5

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1 Introduction

Individual investors have greater access to financial markets than ever before. Historically, retail investors with four or five digit investment accounts would need to aggregate their capital into a professionally managed fund in order to impact equity markets. In recent times, retail investors have begun banding together through the use of online social platforms and executing strategies like short squeezes and gamma squeezes. It is undeniable that these groups, perhaps the most famous of which is the subreddit thread "WallStreetBets" (WSB), have had a material impact on certain stocks and commodities such as GameStop, AMC Theaters, and Silver. It is less obvious, however, whether these groups can consistently produce a profitable trading strategy for their followers. In this paper, we aim to address this very question.

A unique sequence of events has led to significantly increased interest in stock and option trading by retail investors. First, Robinhood, a retail broker whose mission is to "democratize finance for all" introduced zero-commission stock trading and easy to access options trading.[1] This ultimately led to a "race to zero" from other major brokers. Second, the COVID-19 pandemic caused non-essential workers to largely remain at home for most of 2020, leading to lower consumer spending and greater time to pursue alternative ventures. Finally, the largest monetary and fiscal stimulus packages to ever occur led to a significant increase in the amount of cash in retail investors' hands. According to Barron's analysis of data from the Bureau of Economic Analysis (BEA), Americans have saved about \$1.8 trillion more than they otherwise would have since the pandemic begun (Klein 2021). This unique combination of lower trading frictions, more time, and greater capital has led to a boom in retail accounts.[2]

In this paper, we investigate whether a trading strategy that follows the WSB subreddit can consistently produce alpha. The literature to date has been mixed regarding whether individual opinions posted to social media are informative for stock prices. Two examples include Philipp and von Nitzsch (2013) who find no evidence of information content in aggregated recommendations and Chen et al. (2014) who find online opinions can predict stock returns.

Our approach is unique because rather than examining how opinions on a given forum can predict individual stock prices, we focus on whether a simple and easily implementable trading strategy following WSB can produce alpha. Our perspective is that of a typical retail trader that uses the WSB thread to make stock picks. As evidenced by the creation of the VanEck Vectors Social Sentiment ETF (ticker BUZZ) which tracks the 75 large U.S. stocks with the most bullish perception from social media and other alternative datasets, there appears to be interest in such a trading strategy.

We scrape buy and sell submissions from the WSB subreddit from its inception in 2012 through the first quarter of 2021 when the GameStop short squeeze occurred. We then form a daily rebalancing long-short portfolio that goes long "buy" suggestions and short "sell" suggestions, where the suggested stocks can be held for one day, one

[1] https://robinhood.com/us/en/support/articles/our-mission/.

[2] Other factors likely contributing to retail interest in trading are larger than typical stock returns following March 2020 and the significant growth of cryptocurrencies. However, the direction of causality is not obvious and likely dynamic.

week, one month, or one year. We find no evidence of a profitable trading strategy. We examine various alternative portfolio formation strategies, and the result is robust.

A large literature documents the effect of investor sentiment on asset prices (Baker and Wurgler, 2007; Stambaugh et al., 2012, among many others). Kumar and Lee (2006) document evidence that retail traders are specifically impacted by investor sentiment. Given the nature of the WSB thread and its rise to fame following widespread bullish sentiment on meme stocks like GME and AMC, we consider whether returns to portfolios following the thread are impacted by market sentiment. A popular and simple method for estimating investor sentiment is the put–call ratio (Bandopadhyaya and Jones 2006 and 2008). It is plausible that WSB investors are profitable on days with strong investor sentiment because meme stock trades may outperform on those days. We test whether there is any difference in performance on bullish or bearish days, and however, in all days, alpha continues to be nonexistent.

We next examine whether there exists a relation between trading activity and WSB submissions. Loh and Stulz (2011) and Chacon et al. (2021), among others, use abnormal turnover as a measure of whether analyst recommendations induce trading. We apply a similar framework to WSB submissions and find there is significant abnormal turnover surrounding the typical WSB submission. This finding suggests, consistent with anecdotal evidence, that investors do indeed track and trade on WSB submission information.

Finally, although our goal is to evaluate a simple trading strategy, we recognize there is likely heterogeneity of skill across posters. To this end, we identify the top 40 posters by submission volume and examine their individual performance. For this set of tests, we examine the two-day trading window following the buy or sell submission. We find a wide range of performance across the top 40 posters, ranging from an average of 14.86% long-short cumulative abnormal returns (CAR) to a −14.73% long-short CAR. CARs are measured as benchmark adjusted returns where the benchmark model is the Fama French 5 factor model plus momentum (Fama and French 2015). Interestingly, the average long-short CAR for the top 40 posters is 0.25%, and the median is −0.38%, both very close to 0.

It is important to note that our results do not indicate that one cannot profit from advice on WSB or that no WSB posters are informed. Certainly, there were great successes by the early investors in GameStop, and there are examples of detailed and quality stock analysis. Rather, the objective of our paper is to take an early look at a simple and easily implementable trading strategy that follows trading advice from WSB subreddit and evaluate the strategy's performance over time.

Our paper contributes to the growing literature on retail trading and specifically the impact of social media on retail trading activities. The early literature has generally found individual investors to be uninformed traders. Perhaps the most notable example is Barber and Odean (2000) who find trading is hazardous to retail traders' wealth. More recent research has been more positive on retail trading skill. One of several examples includes Boehmer et al. (2021) who find stocks with strong buying from retail outperform stocks with strong selling.

New research on the topic is critical because the landscape for retail investment is shifting. With the cost of information decreasing exponentially and the cost of active trading approaching zero, significant frictions are dissipating in the current environment. Another notable difference is the generation of traders using WSB is generally thought to be new to the market. How this generation of traders performs relative to past generations is interesting. Whether the new generation of retail traders can succeed in the more favorable environment is an important research question we aim to address. One avenue by which the costs of information have decreased is the rise of social media platforms to exchange ideas. The literature to date has been mixed whether opinions on these social media platforms can predict stock returns. Our study contributes to this literature by focusing on a trading strategy that can be easily implementable by a retail investor and observing how that investor would perform.

The remainder of the paper is organized as follows: Sect. 2 reviews the relevant literature, Sect. 3 describes the data and empirical methods utilized in the study, Sect. 4 presents the results, Sect. 5 presents robustness tests, and Sect. 6 concludes.

2 Literature review

Two strands of relevant literature focus on retail trading performance and the impact of social media on financial markets. The retail trading performance literature is broad and mixed, with early findings generally documenting a lack of skill of retail investors (see Barber and Odean 2013 for an excellent review). Barber and Odean (2000) document utilize retail trading account data and find that households tend to underperform the market, and those who trade actively are the greatest underperformers. The authors have a stream of future papers that document further retail underperformance across time and geography. One example is Barber et al. (2009) who analyze the trading records of Taiwanese investors and document underperformance.

However, the aforementioned studies mostly focus on long-term performance. In our setting, traders tend to have shorter horizons. Studies focused on shorter horizons tend to document more evidence of success for the retail investor. For example, Kaniel et al. (2008) show the retail investor trading positively predicts short-term returns. Kaniel et al. (2012) find similar results of informed trading around earnings announcements. Similarly, Barber et al. (2009) document that stocks heavily bought in retail books positively predict performance. Boehmer et al. (2021) document retail skill over a week-long horizon. Other papers focus on subsets of retail investors. For example, Fong et al. (2014) find that trades of full service brokers outperform those of discount brokers.

Another strand of the literature focuses specifically on social media-based investment advice for retail investors. Papers have focused on different social media outlets including Motley Fool (Hirschey et al. 2000), Raging Bull (Tumarkin and Whitelaw, 2001; Antweiler and Frank 2004), Yahoo! Finance (Das and Chen 2007), Twitter (Giannini et al. 2018; Garcia, 2021; Bartov et al. 2018), Seeking Alpha (Chen et. al 2014), SumZero (Crawford et al. 2018), and Estimize (Jame et al. 2016; Da and Huang, 2020), Spekunauten (Philipp and von Nitzsch 2013), and Forcerank (Da et al. 2021).[3] Findings have been mixed regarding the information content of the various groups.

[3] Additionally, Bradley et al. (2021) have a contemporaneous working paper that also examines WSB posts and find positive returns following certain types of posts. However, they focus only on "Due Diligence" posts from 2018–2020.

The lack of consensus findings is unsurprising given the various different types of media outlets being used, varying timeframes, and different types of users on the site. For example, Crawford et al. (2018) use SumZero, a private social networking for buy side analysts. In contrast, Giannini et al. (2018) use Twitter which is open to all types of investors.

Our work differs from the existing literature in that rather than estimating the information content of a given submission by examining the stock price reaction to the submission, we focus on the retail trader's perspective. Specifically, we form portfolios following a trading strategy that most retail traders on Reddit would be able to implement and evaluate its profitability. This perspective is in the same spirit as Foltice and Langer (2015) and Siganos (2010) who test whether the momentum effect can actually be exploited my individual investors.

3 Data and empirical methods

Our data span from the inception of the WSB subreddit in 2012 through the first quarter of 2021. Using textual analysis from WSB submissions, we identify the ticker and whether the submission indicates a recommendation to buy or sell. We proceed with a restrictive set of screens as there is considerable noise in these submissions which are not intended to be analyst recommendations. To identify buy and sell submissions, we use key word searches that include common vernacular for these threads to identify bullish or bearish recommendations. Specifically, for buy recommendations, we flag submissions with the following words: buy, bought, moon, hold, call, bull, like, moon, and yolo. For sell recommendations, we flag submissions with the following words: sell, bear, liquidate, sold, put. In order to ensure data integrity, we do not include an analysis of comments or "upvotes" as these occur over time and we drop submissions with conflicting buy and sell signals. This procedure began with a pull of 1,963,471 submissions that contain either a ticker or a buy or sell keyword. Of those submissions, 474,787 contained a buy signal and no sell signal (i.e., no conflict) and 73,776 contained a sell signal with no buy signal. Many of these submissions include false ticker identifiers, for example, "YES" or "BTD" may be identified as tickers. We then merge this dataset with CRSP to weed out false tickers and merge in stock price data. After this procedure, we are left with 221,255 recommendations, 192,550 of which are buy recommendations and 28,708 of which are sell recommendations.

In the appendix, we provide examples of the content of the submissions. The sample submissions show various ways of identifying buy and sell signals. As noted in the table, some are simple submissions with nothing more than a ticker and a direction. Others include technical reasoning such as MACD crossovers or low trading volumes allowing for more price impact. We then merge these data with CRSP and Compustat for stock information and accounting variables, respectively. Table 1 describes the results from this WSB data scrape, and Table 2 presents the accounting variable descriptive statistics.

Panel A of Table 1 presents the number of submissions with buy or sell signals by year. We also include the number of unique posters by year. Unsurprisingly, the number of submissions increases dramatically over time. The number of unique posters

Table 1 Summary statistics

Year	# Submissions	# Posters	# Buy	# Sell
Panel A: Number of posts				
2012	145	32	110	35
2013	184	64	148	36
2014	532	184	465	67
2015	2102	859	1842	260
2016	5161	2079	4359	802
2017	6187	2617	5432	755
2018	11,542	4837	9184	2358
2019	8817	4357	6979	1838
2020	44,136	21,006	34,869	9267
Q12021	142,449	77,885	129,162	13,287
Full sample	221,255	107,821	192,550	28,705

Full Sample		Pre-2021		Post-2021	
Company	# Submissions	Company	# Submissions	Company	# Submissions
Panel B: Most mentioned tickers					
Gamestop Corp	56,223	Spdr S & P 500 ETF Trust	5338	Gamestop Corp New	55,012
AMC Entertainment Inc	25,325	Tesla Inc	4528	AMC Entertainment Inc	25,129
Blackberry Ltd	8444	Advanced Micro Devices Inc	2843	Blackberry Ltd	8323
Nokia Corp	7222	Palantir Technologies Inc	2359	Nokia Corp	7100
Spdr S & P 500 ETF Trust	5538	Direxion Shares ETF Trust	1893	Direxion Shares ETF Trust	2843
Tesla Inc	5315	Apple Inc	1654	Canaan Inc	1874
Direxion Shares ETF Trust	4736	Micron Technology Inc	1602	Sundial Growers Inc	1844
Palantir Technologies Inc	3683	Microsoft Corp	1442	Naked Brand Group Ltd	1394

Table 1 (continued)

Full Sample		Pre-2021		Post-2021	
Company	# Submissions	Company	# Submissions	Company	# Submissions
Advanced Micro Devices Inc	3126	Gamestop Corp New	1211	Palantir Technologies Inc	1324
Canaan Inc	1967	NIO Inc	1097	Atlantic Power Corp	1258

Panel A reports the number of posts per year, number or buy recommendations per year, and number of sell recommendations per year. *Panel B* details the most mentioned tickers

Table 2 Target firm characteristics

Long		Short	
Year	# firms	Year	# firms
Panel A: Number of unique firms			
2012	69	2012	24
2013	106	2013	29
2014	214	2014	50
2015	603	2015	162
2016	1050	2016	306
2017	998	2017	258
2018	1069	2018	465
2019	1292	2019	454
2020	2283	2020	1007
2021	2319	2021	527

	Long	Short	S&P500
Panel B: Firm characteristics (means)			
Total assets (in $ million)	44,231	71,823	147,765
Market value of equity $_{t-1}$	21,203	34,586	81,815
Market to Book $_{t-1}$	24.14	2.71	3.88
Last month return	0.02	0.01	0.01
Short interest (% of float)	0.09	0.10	0.03

Panel A reports the number of unique firms per year in the sample. Panel B depicts firm characteristics broken down across long and short positions increased from 32 in 2012 to 77,885 in 2021. The GameStop short squeeze began in late 2020 and as news outlets continued to publicize WSB, the subreddit following and posting grew exponentially. The first quarter of 2021 has almost four times as many submissions as all of 2020 and about sixteen times more submissions than all of 2019. Because of this rapid increase, we break out our key analyses by full sample, pre-2021, and post-2021. Panel B presents the most frequent tickers suggested for the full sample and split out by pre-2021 and post-2021. GameStop represents 25.41% of all submissions with 56,233 mentions, most of which occur in 2021. Although GameStop submissions make up a quarter of the total number of submissions, our empirical strategy ensures our sample is not heavily influenced by any one security. Prior to 2021, the most popular tickers include an S&P500 ETF, Tesla, and Advanced Micro Devices (ADM). Tesla and ADM are unsurprising as they had been popular companies prior to the meme stock explosion. Tesla and ADM both notably had significant exposure to Bitcoin on their balance sheets, making them attractive stocks for retail investors seeking volatility and high potential expected returns.

To form portfolios, we separate stocks by day into long and short. If a stock has been suggested as a buy and a sell in the same day, we take the net effect. For example, if GameStop is suggested 1000 times to be bought and 100 times to be sold in a given day, we put one equal-weighted share of GameStop in the long portfolio on that day.[4] This method ensures that the portfolio is not overweight in any one stock. If the stock suggestion is made in day t before trading close of 4 pm eastern, we assume the security is bought on day t. If the security is suggestion is made after 4 pm eastern, we assume the security is bought the following day. This is to ensure there is no look-ahead bias in the data.

We then hold (short) the stock for either one day, one week, one month, or one year before selling (covering). The portfolio is rebalanced daily as new submissions come in daily. For example, for the one-day horizon, every day whatever stocks suggested are bought and they are sold the next day. For the monthly horizon, the investor would buy following a recommendation on day t and hold that security until day $t + 30$. On day $t + 1$, they would buy whatever stocks were suggested on that day and sell them on day $t + 31$, and so on.

To evaluate performance, we use the Fama and French five factor model (Fama and French 1993, 2015) that contains excess market return MKT (R_m–R_f) which is the market return in excess of one-month T-bill rate; SMB which is the average return of the nine small stock portfolios minus that of the nine big stock portfolios; HML that longs the two value portfolios and shorts the two growth portfolios; CMA that is the average return on the two conservative investment portfolios minus those on the two aggressive investment portfolios and RMW that buys the two robust operating profitability portfolios and sells the two weak operating profitability portfolios. We also include a momentum factor, denoted MOM. The factor is calculated using six value-weighted portfolios formed on size and prior ($t-12$, $t-12$) monthly returns. The factor captures the average return on the two high prior return portfolios minus that of the two low prior return portfolios. We connect the daily excess portfolio returns to

[4] Later we use method that gives more weight to heavily suggested stocks and results are similar.

these factors[5] and run the time-series regression of each portfolio return on the returns of five factors in this specification:

$$R^e_{w,t} = \alpha_i + \beta_w R_{\mathrm{MKT},t} + \beta_w R_{\mathrm{SMB},t} + \beta_w R_{\mathrm{HML},t} + \beta_w R_{\mathrm{CMA},t} + \beta_w R_{\mathrm{RMW},t} + \beta_w R_{\mathrm{MOM},t} + \varepsilon_{i,t} \tag{1}$$

where β_w measures the factor loadings of our portfolios constructed based on WSB recommendations on the five factors, or w portfolios. We focus on α_i that measures the abnormal daily returns the WSB portfolios earn after being explained by common risk factors in the return space. Importantly, our findings are robust to the use of simple excess returns. Because we are focused on the profitability of a trader's performance, we adjust returns for the bid-ask spread by taking the bid-ask spread, dividing by two, and subtracting from the daily return.[6] Returns are total returns and include dividends. Standard errors in parentheses are heteroskedasticity and autocovariance consistent (HAC).

Table 2 displays how many unique firms are in the long and short portfolios each year. Although some firms like GameStop and others are Reddit favorites, there exists a wide breadth of firms that are suggested on the thread. In the first quarter of 2021 alone, there are 2319 unique firms in the long portfolio and 527 in the short portfolio.

Panel B presents the characteristics of the typical stock suggested by the subreddit and compares it to the S&P500. The typical firm suggested as a buy in WSB is more than three times smaller than the typical firm in the S&P500. This finding speaks to the risk profile of the investment strategy. Generally, Redditors are seeking high risk, high reward opportunities. Additionally, the average market to book ratio is 24.14 for buy recommendations, 2.71 for sell recommendations, and 3.88 for the S&P500. Redditors generally appear to prefer growth firms such as Tesla over value firms. Lastly, consistent with the group seeking out short-squeeze opportunities, the typical short interest as a percent of float for buy recommendations is 9% compared to just 3% for the S&P500. For their short recommendations, the typical firm is larger than the long recommendations but still about half the size as the average S&P500 firm. Interestingly, short suggestions tend to be value firms with market to book ratios below that of the S&P500. Short interest is 10% for these firms, suggesting they are popular shorts. Taken together, the WSB community focuses on small growth firms with high short interest for buys and somewhat larger value firms with high short interest for sells.

We are also interested in how these portfolios perform bifurcated by market sentiment. To proxy for market sentiment, we use the put–call ratio. This ratio is obtained from the Chicago Mercantile Exchange and is the daily number of traded put options relative to the number of traded call options. When the ratio is above 1, it suggests bearish sentiments as options traders are favoring puts over calls. We rerun the portfolio regressions to test whether alpha is different from 0 when sentiment is bullish or bearish.

[5] We download factor data from the French Data Library.

[6] Results are not sensitive to the choice to include or exclude the bid-ask spread adjustment. We implicitly assume trading commissions are $0, consistent with the current environment.

Furthermore, we examine the abnormal trading volumes surrounding the posting date. We use abnormal stock turnover similar to Llorente et al. (2002) to standardize the abnormal trading volumes. Specifically, turnover is log-transformed daily trading volume scaled by total shares outstanding. To calculate abnormal turnover, we calculate average of daily log turnover over the past year. Then, we subtract the average turnover from the days turnover to obtain the abnormal turnover. The following equation displays the calculation:

$$\text{Abnormal Turnover}_t = \text{Log}\left(\frac{\text{Volume}}{\text{Shares Outstanding}}\right)_t - \text{Average Log}\left(\frac{\text{Volume}}{\text{Shares Outstanding}}\right)_{t-6,t-252} \quad (2)$$

We calculate abnormal turnover for each day within 6 days before and after the submission. Any abnormal volume greater than 0 suggests higher than typical trading volumes for the day relative to the previous year. The average abnormal turnover by day is calculated and plotted based on buy and sell groups in Fig. 1. We include 95% confidence interval bands to show whether these abnormal turnover values are statistically different from zero.

Finally, we are interested in differential ability to predict stock performance by various WSB users. We employ an event study strategy to investigate the cumulative abnormal returns (CAR) for the top 40 WSB users ranked by the total number of daily submissions.[7] We calculate the CAR in the window of $[t+1, t+2]$ following the submission. We use the Fama French 5 factors plus a momentum factor in running the Event Study, which first obtains abnormal returns in this specification:

$$\text{AR}_{W,t} = R_{W,t} - \left(\alpha_i + \beta_w R_{\text{MKT},t} + \beta_w R_{\text{SMB},t} + \beta_w R_{\text{HML},t} + \beta_w R_{\text{CMA},t} + \beta_w R_{\text{RMW},t} + \beta_w R_{\text{MOM},t}\right) \quad (3)$$

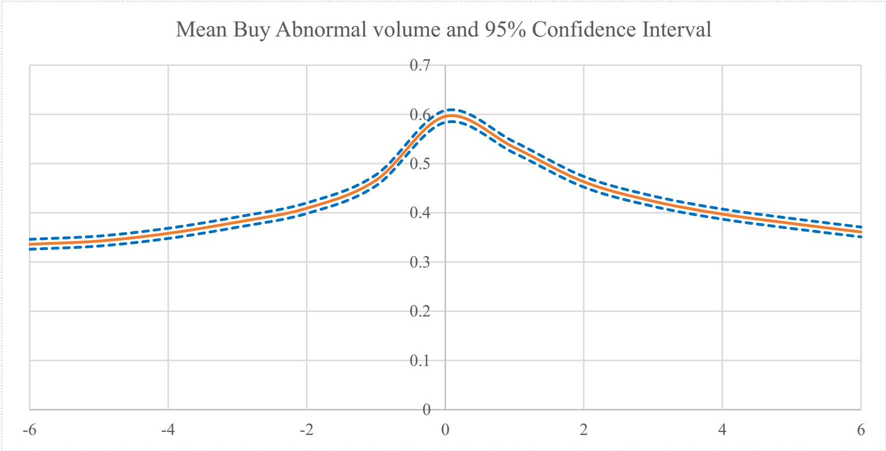
next, it calculates CAR as follows:

$$\text{CAR}_{W,t} = \sum_{t=1}^{2} \text{AR}_{W,t} \quad (4)$$

4 Results

We begin by examining the abnormal turnover around WSB stock recommendations. Abnormal turnover measures trading volume relative to the stocks previous year's moving average volume. Figure 1 displays the results. A similar pattern emerges whether the stock is suggested as a buy or sell. In each case, abnormal turnover peaks on the day of the stock recommendation. However, there also appears to be a run up in the days leading to the announcement, suggesting stocks that are recommended are "hot" leading up the WSB crowd's involvement. Abnormal turnover around buy signals is slightly greater than sell signals. That is, investors following WSB are more likely to trade following a buy recommendation than a sell. This is perhaps explainable by the ease of which one can enter a long position compared to a short one.

[7] Results are similar using the top 50 posters.



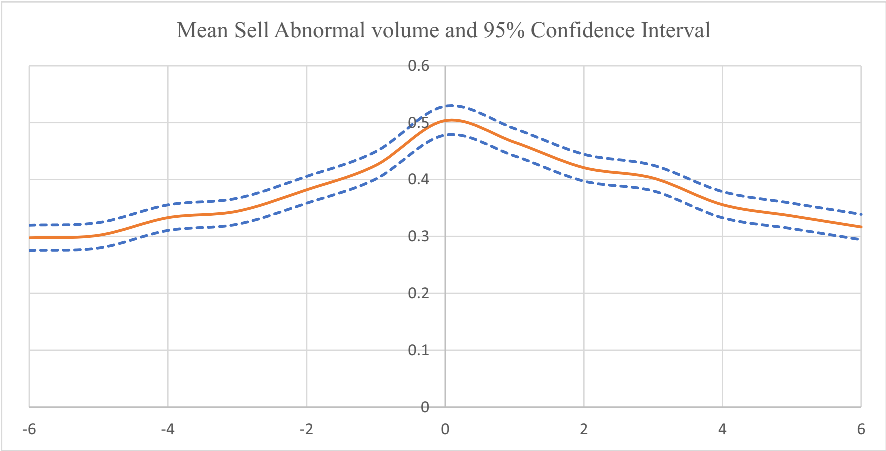


Fig. 1 Abnormal volume, displays the mean abnormal trade volume for a window of [− 6; 6] days around Reddit posts. The abnormal trading volumes is defined as log-transformed daily stock turnover minis the average of daily trading turnover in the past three month

Confidence interval bands at the 95% level are included to visualize the statistical significance of these values. For all days in the [− 6, + 6] trading day window, abnormal turnover is positive and statistically significant well beyond the 5% level. Although day $t + 1$ has lower positive turnover than day t, on both days, there is significant trading activity around these stocks. Overall, this evidence suggests WSB community submissions may incite trading activity on the equities.[8] The more critical question, however, is whether these suggestions lead simply to trading activity

[8] In untabulated results we split this analysis out by pre-2021 and post-2021. Both subsamples provide similar results with the weakest result being around sell recommendations in the post-2021 subsample.

or persistent profitability. We next examine returns to portfolios formed using these recommendations.

Table 3 presents the results of the portfolio analysis for the full sample of data. Each panel displays daily alphas for the long portfolio, the short portfolio, and the long minus short portfolio. Columns 1 to 3 are based on each stock being held (short) for one trading day and then sold (covered). Columns 4 to 6 are based on holding each stock for one week, columns 7 to 9 are based on holding the stock for one month, and columns 10–12 are based on holding each stock for one year.

The primary coefficient of interest is alpha. Across all holding periods, the long minus short portfolio fails to produce alpha that is indistinguishable from zero. For holding periods of one day to one week, the alpha coefficient is positive but insignificant. At longer horizons, it is negative and insignificant. The only statistically significant alpha is the short leg of the one-week portfolio which is significant at the 10% level. In untabulated analysis, we find similar results for if the stock is held for two days or three days. Interestingly, the long portfolio across every holding period is negative, directionally inconsistent with achieving good performance.

The factor loadings provide useful information regarding the types of stocks in the long and short portfolios. Across each time horizon, the market factor loads greater than one and significantly on both the long and the short portfolios. This suggests that Redditors target high market beta stocks both to buy and to sell. These cancel out on the long short and lead to a statistically insignificant factor loading. Additionally, HML always loads negatively and significantly in the long portfolio and the short portfolio. This is consistent with Redditors targeting growth stocks over value stocks for buy and sell recommendations. CMA loads negatively across most portfolios as well, suggesting Redditors target firms that invest heavily more so than those that invest conservatively. MOM tends to be positive and significant in the long portfolios as well. This suggests Redditors are more likely to target past winners. For the longer horizons, there are some positive loadings on RMW and negative loadings on SMB. These findings are somewhat surprising because they suggest the portfolio contains more profitable and larger stocks.

We recognize there is a significant uptick in WSB activity in 2021. There are counteracting forces regarding whether WSB submissions would be more or useful in a trading strategy post-2021. On the positive side, there is more investor attention focused on this thread, so submissions may be visible by more parties willing to push prices in the direction of the submission. On the negative side, many new users join the thread and perhaps new users are not as informed as the original users that made WSB famous in the first place.

Table 4 presents portfolio results split out by pre-2021 and post-2021. Panel A presents the pre-2021 results, and Panel B presents results for only the first quarter of 2021 when the platform increased most significantly in popularity. The pre-2021 results are very similar to the full sample results regarding alphas and many of the factor loadings. This alleviates the concern that the results are driven only by the recent GameStop and other meme stock trading activities. Interestingly, in the post-2021 sample, none of the alphas are statistically different from zero. Though the one-day-long minus short portfolio is positive, the one-week holding period and one

Table 3 Reddit strategy performance

	One day			One week			One month			One year		
	Long	Short	L–S	Long	Short	L–S	Long	Short	L–S	Long	Short	L–S
R_m—R_f	1.035***	1.187***	0.036	1.057***	1.070***	0.051	1.049***	1.073***	0.005	1.059***	1.062***	− 0.002
	(0.049)	(0.073)	(0.078)	(0.030)	(0.035)	(0.042)	(0.020)	(0.022)	(0.027)	(0.015)	(0.013)	(0.011)
SMB	− 0.109	0.069	− 0.126	− 0.080	0.051	− 0.103	− 0.037	− 0.022	− 0.008	− 0.105***	− 0.109***	0.005
	(0.087)	(0.165)	(0.154)	(0.055)	(0.066)	(0.079)	(0.037)	(0.039)	(0.047)	(0.028)	(0.023)	(0.022)
HML	− 0.283***	− 0.320**	− 0.047	− 0.171***	− 0.170**	0.003	− 0.225***	− 0.135***	− 0.083*	− 0.214***	− 0.169***	− 0.045*
	(0.073)	(0.162)	(0.161)	(0.053)	(0.075)	(0.088)	(0.035)	(0.044)	(0.050)	(0.031)	(0.025)	(0.026)
MOM	0.026	− 0.176	0.184	0.103**	0.057	0.057	0.071***	0.004	0.077**	0.037*	− 0.004	0.040**
	(0.063)	(0.128)	(0.121)	(0.041)	(0.060)	(0.070)	(0.024)	(0.032)	(0.037)	(0.019)	(0.018)	(0.017)
RMW	0.102	− 0.404	0.346	0.111	0.028	0.039	0.205***	− 0.012	0.217**	0.302***	0.120**	0.182***
	(0.114)	(0.286)	(0.253)	(0.079)	(0.130)	(0.139)	(0.058)	(0.080)	(0.088)	(0.051)	(0.057)	(0.057)
CMA	− 0.360**	− 0.231	− 0.169	− 0.449***	− 0.142	− 0.327**	− 0.573***	− 0.326***	− 0.247**	− 0.685***	− 0.412***	− 0.273***
	(0.147)	(0.391)	(0.360)	(0.097)	(0.142)	(0.160)	(0.083)	(0.094)	(0.098)	(0.077)	(0.068)	(0.068)
Daily alphas (%)	− 0.022	− 0.135	0.067	− 0.035	− 0.104*	0.065	− 0.015	− 0.008	− 0.009	− 0.009	− 0.007	− 0.006
	(0.055)	(0.106)	(0.094)	(0.035)	(0.053)	(0.057)	(0.019)	(0.031)	(0.032)	(0.015)	(0.015)	(0.016)
N	1443	1051	1443	2146	1858	2146	2250	2102	2250	2253	2249	2253
R^2	0.242	0.153	0.006	0.359	0.226	0.004	0.629	0.431	0.013	0.747	0.741	0.031

Reports the performance of the *Reddit strategy* for the full sample. Alphas are in percent and standard errors are reported in parentheses. R_m–R_f is the value-weighted return on the market portfolio of all sample stocks minus the one-month Treasury bill rate. SMB is the average return on the nine small stock portfolios minus the that on the nine big stock portfolios; HML is the return on a factor that longs the two value portfolios and shorts the two growth portfolios; CMA is the average return on the two conservative investment portfolios minus those on the two aggressive investment portfolios; RMW is the return from buying two robust operating profitability portfolios and selling two weak operating profitability portfolios. MOM is the average return on the two high prior returns portfolios minus the average return from two low prior return portfolios, in which both high and low prior returns were determined using prior 2–12 months returns. ***, **, and * denote significance of coefficients at the 1%, 5%, and 10% levels, respectively

Table 4 Reddit strategy performance—Pre & Post 2021

Portfolio	One day			One week			One month			One year		
	Long	Short	L–S	Long	Short	L–S	Long	Short	L–S	Long	Short	L–S
Panel A: Pre 2021												
R_m–R_f	1.04***	1.03***	0.17	1.04***	1.12***	− 0.01	1.05***	1.09***	− 0.00	1.05***	1.06***	− 0.01
	(0.06)	(0.11)	(0.11)	(0.04)	(0.06)	(0.06)	(0.02)	(0.03)	(0.03)	(0.02)	(0.02)	(0.02)
SMB	− 0.11	0.07	− 0.11	− 0.11	0.03	− 0.10	− 0.09**	− 0.04	− 0.04	− 0.16***	− 0.14***	− 0.01
	(0.12)	(0.22)	(0.20)	(0.07)	(0.11)	(0.12)	(0.04)	(0.06)	(0.07)	(0.03)	(0.03)	(0.03)
HML	− 0.24*	− 0.16	− 0.13	− 0.13	− 0.19	0.06	− 0.19***	− 0.10	− 0.08	− 0.19***	− 0.17***	− 0.02
	(0.14)	(0.24)	(0.23)	(0.08)	(0.12)	(0.13)	(0.04)	(0.07)	(0.08)	(0.03)	(0.03)	(0.04)
MOM	− 0.00	− 0.09	0.09	0.08	0.09	0.02	0.06**	0.04	0.03	0.01	− 0.01	0.02
	(0.09)	(0.16)	(0.15)	(0.05)	(0.08)	(0.09)	(0.03)	(0.05)	(0.05)	(0.02)	(0.02)	(0.02)
RMW	0.02	− 0.69**	0.48	0.08	0.02	0.00	0.18***	0.02	0.16	0.30***	0.11**	0.20***
	(0.19)	(0.33)	(0.32)	(0.11)	(0.17)	(0.18)	(0.06)	(0.10)	(0.10)	(0.05)	(0.04)	(0.05)
CMA	− 0.63***	− 0.61	− 0.15	− 0.69***	0.01	− 0.71***	− 0.69***	− 0.34***	− 0.36***	− 0.84***	− 0.47***	− 0.37***
	(0.24)	(0.41)	(0.39)	(0.14)	(0.21)	(0.23)	(0.07)	(0.12)	(0.13)	(0.06)	(0.06)	(0.06)
Daily alphas (%)	− 0.03	− 0.35***	0.23**	− 0.03	− 0.10*	0.07	0.01	0.01	− 0.01	0.00	0.01	− 0.01
	(0.07)	(0.12)	(0.11)	(0.04)	(0.06)	(0.06)	(0.02)	(0.03)	(0.04)	(0.02)	(0.02)	(0.02)
Panel B: Post 2021												
R_m–R_f	1.09***	1.39***	− 0.30	1.11***	1.19***	− 0.08	1.07***	1.09***	− 0.02			

Table 4 (continued)

Portfolio	One day			One week			One month			One year		
	Long	Short	L–S	Long	Short	L–S	Long	Short	L–S	Long	Short	L–S
	(0.12)	(0.21)	(0.22)	(0.10)	(0.16)	(0.19)	(0.09)	(0.12)	(0.13)			
SMB	− 0.16	− 0.77**	0.63*	− 0.24*	− 0.02	− 0.22	− 0.17	− 0.11	− 0.06			
	(0.18)	(0.31)	(0.31)	(0.12)	(0.20)	(0.25)	(0.12)	(0.17)	(0.17)			
HML	− 0.14	0.46	− 0.59*	− 0.25*	− 0.04	− 0.21	− 0.33***	− 0.13	− 0.20			
	(0.17)	(0.30)	(0.31)	(0.12)	(0.20)	(0.25)	(0.11)	(0.17)	(0.17)			
MOM	0.38***	0.17	0.20	0.29***	0.10	0.19	0.19**	0.21	− 0.01			
	(0.13)	(0.22)	(0.23)	(0.10)	(0.17)	(0.20)	(0.09)	(0.13)	(0.14)			
RMW	− 0.04	− 1.11***	1.07***	− 0.12	0.12	− 0.24	− 0.07	0.24	− 0.31			
	(0.22)	(0.38)	(0.39)	(0.17)	(0.27)	(0.33)	(0.15)	(0.22)	(0.23)			
CMA	0.59**	0.65	− 0.07	0.65***	0.08	0.57*	0.62***	0.32	0.29			
	(0.22)	(0.39)	(0.40)	(0.16)	(0.26)	(0.32)	(0.15)	(0.22)	(0.22)			
Daily alphas (%)	0.11	− 0.07	0.18	0.05	0.12	− 0.07	0.03	0.07	− 0.03			
	(0.10)	(0.16)	(0.17)	(0.08)	(0.12)	(0.15)	(0.07)	(0.10)	(0.10)			

Reports the performance of the *Reddit strategy* by breaking down the sample into the pre 2021 period (*Panel A*) and the Post 2021 period (*Panel B*). Alphas are in percent and standard errors are reported in parentheses. R_m–R_f is the value-weighted return on the market portfolio of all sample stocks minus the one-month Treasury bill rate. SMB is the average return on the nine small stock portfolios minus the that on the nine big stock portfolios; HML is the return on a factor that longs the two value portfolios and shorts the two growth portfolios; CMA is the average return on the two conservative investment portfolios minus those on the two aggressive investment portfolios; RMW is the return from buying two robust operating profitability portfolios and selling two weak operating profitability portfolios. MOM is the average return on the two high prior returns portfolios minus the average return from two low prior return portfolios, in which both high and low prior returns were determined using prior 2–12 months returns. ***, **, and * denote significance of coefficients at the 1%, 5%, and 10% levels, respectively month holding period long minus short alphas are negative, driven by positive average alpha around sell recommendations.

Given we are constrained to one quarter of data in the post-2021 era, we are careful to draw conclusions from a small sample. However, differences in factor loadings can be instructive as the post-2021 era includes a different set of WSB users. The most notable difference between the post-2021 factor loadings and the pre-2021 factor loadings is the coefficient on the momentum and investment factors. For both the full sample and the pre-2021 samples, the loading on momentum is zero on the one-day portfolio and positive and marginally statistically significant on the long portfolios in the one-week and one-month holding periods. However, in the post-2021 sample, the MOM factor in the long portfolio loads positive and significant in every time horizon. The magnitude of the coefficients is significantly larger as well. This result is consistent with intuition that much of the meme stock trading is driven by momentum. However, the MOM factor does not load in the long short portfolio except for the one-month holding period because Redditors also tend to recommend selling positive momentum stocks. The difference in the investment factor loading is less obvious economically. While in the pre-2021 period, the loading suggests the firms in the portfolio are firms that invest aggressively, the post-2021 loading suggests the firms invest more conservatively.

Overall, we interpret these findings as evidence that a trading strategy following WSB recommendations does not produce alpha. In no cases were the buy recommendations as a group fruitful and in very few cases were the sell recommendations useful. As the viewership and contribution to this public thread have grown, alpha is equally elusive.

We next examine whether the returns to a portfolio following the WSB thread differ by market sentiment. We calculate the daily put–call ratio and group days where sentiment is bearish (put–call > 1) and bullish (put–call < 1). We focus on the daily holding period horizon as sentiment shifts day to day and many Reddit traders are short-term oriented. The results are presented in Table 5.

In both subgroups, alpha is insignificant. Although the long short alpha continues to be indistinguishable from zero, there are a few notable differences between the two subsets of results. First, alpha is directionally positive on bullish days and negative on bearish days. Interestingly, on the bullish days, alpha on the short leg of the portfolio is marginally significant at the 10% level. Although the results are weak, this would imply Reddit posters are able to identify opportunistic times to sell when the market is bullish. Overall, these results mirror the primary finding of this study that the strategy following the WSB strategy fails to produce alpha.

The focus of our paper is to address whether a simple trading strategy following WSB submissions is a profitable endeavor. However, undoubtedly, there are an infinite number of ways to disaggregate the data in search of other strategies. One such strategy may be to take recommendations only from well-known or frequent posters. To this end, we identify the top 40 most frequent posters and examine the average long minus short one-day CAR following their submission. If new and infrequent posters are producing uninformed stock opinions, perhaps the top 40 posters would eliminate some noise. The results of this exercise are presented in Table 6.

There exists considerable heterogeneity across top posters, and the symmetry around 0 is striking. The top 40 posters make up 1.6% of total submissions, a niche

Table 5 Market sentiment

Portfolio	*Optimistic market sentiment* (Put–Call ratio < 1)			*Pessimistic market sentiment* (Put–Call ratio > 1)		
	Long	Short	L-S	Long	Short	L-S
R_m–R_f	1.059***	1.300***	− 0.004	0.987***	1.120***	0.012
	(0.102)	(0.153)	(0.151)	(0.051)	(0.069)	(0.084)
SMB	− 0.041	0.107	− 0.057	− 0.267*	− 0.067	− 0.271
	(0.114)	(0.261)	(0.226)	(0.154)	(0.147)	(0.198)
HML	− 0.310***	− 0.441**	0.076	− 0.220	− 0.017	− 0.329
	(0.090)	(0.217)	(0.212)	(0.152)	(0.218)	(0.229)
MOM	0.057	− 0.261	0.311*	− 0.051	− 0.135	0.063
	(0.082)	(0.194)	(0.176)	(0.104)	(0.131)	(0.142)
RMW	0.077	− 0.394	0.372	0.264	− 0.429	0.411
	(0.138)	(0.393)	(0.336)	(0.194)	(0.315)	(0.337)
CMA	− 0.163	− 0.238	0.035	− 0.922***	− 0.585*	− 0.466
	(0.176)	(0.590)	(0.533)	(0.270)	(0.308)	(0.373)
Daily alphas (%)	− 0.011	− 0.284*	0.212	− 0.054	0.028	− 0.155
	(0.081)	(0.154)	(0.138)	(0.084)	(0.138)	(0.131)
N	979	720	979	422	307	422
R^2	0.155	0.103	0.006	0.443	0.399	0.027

Reports the performance of the *Reddit strategy* for the full sample, accounting for market sentiment. To account for market sentiment, we run our test looking at periods where market sentiment is optimistic (Put–Call ratio < 1) and compare it to periods where market sentiment is pessimistic (Put–Call ratio > 1). Alphas are in percent and standard errors are reported in parentheses. R_m–R_f is the value-weighted return on the market portfolio of all sample stocks minus the one-month Treasury bill rate. SMB is the average return on the nine small stock portfolios minus the that on the nine big stock portfolios; HML is the return on a factor that longs the two value portfolios and shorts the two growth portfolios; CMA is the average return on the two conservative investment portfolios minus those on the two aggressive investment portfolios; RMW is the return from buying two robust operating profitability portfolios and selling two weak operating profitability portfolios. MOM is the average return on the two high prior returns portfolios minus the average return from two low prior return portfolios, in which both high and low prior returns were determined using prior 2–12 months returns. ***, **, and * denote significance of coefficients at the 1%, 5%, and 10% levels, respectively

subsample. Although the average long minus short CAR is 25 basis points, 21 of the posters have negative average CARs and 19 have positive average CARs. This evidence is generally consistent with our baseline portfolio results that alpha is elusive in following WSB submissions. A strategy following only frequent posters does not improve the ability to predict stock prices in the short term. However, it is notable that some posters individually were quite successful in their stock picking.

While the mean value of the long minus short CAR is 25 basis points, additional statistics regarding the distribution of performance is useful. The median is -38 basis points, reflecting that more top posters have negative CARs than positive ones. The 95 confidence interval around the mean of 25 basis points is -1.61% and 2.11%,

Table 6 Top posters return

Rank	Poster	# Posts	Long CAR	Short CAR	L-S CARs
1	Andynyc	46	3.96%	– 10.90%	14.86%
2	Camcamwabam	42	14.30%	2.14%	12.16%
3	c0mputar	65	13.60%	2.93%	10.67%
4	Robinhood***	45	– 0.42%	– 8.78%	8.36%
5	SIThereAndThere	73	– 1.44%	– 9.08%	7.64%
6	Experiencedbroke	50	5.93%	– 0.92%	6.85%
7	Screw7788	42	– 1.16%	– 7.12%	5.96%
8	Badtradesguy	41	0.59%	– 3.04%	3.63%
9	jjd1226	41	– 1.45%	– 4.56%	3.11%
10	Simon_Inaki	82	9.39%	6.39%	3.00%
11	Patrickbateman02	56	2.75%	0.68%	2.07%
12	SoRefreshing	87	0.62%	– 1.11%	1.73%
13	Vegaseller	71	0.55%	– 0.75%	1.30%
14	Swaggymedia	117	– 3.79%	– 4.86%	1.07%
15	1poundbookingfee	76	– 0.25%	– 1.19%	0.94%
16	Fallouthong	45	0.33%	– 0.50%	0.83%
17	Thewhiterider256	53	0.70%	– 0.01%	0.70%
18	Ganjaguy27	59	– 0.33%	– 1.01%	0.68%
19	Water_boat	42	0.29%	– 0.26%	0.54%
20	QuantalyticsRese	148	– 0.84%	– 0.48%	– 0.36%
21	TripleBrain	43	– 7.54%	– 7.15%	– 0.39%
22	TodayInTheMahket	45	– 0.31%	0.24%	– 0.55%
23	Londonistani	72	2.55%	3.13%	– 0.58%
24	Bigbear0083	207	– 1.00%	– 0.35%	– 0.65%
25	Particular-Weddi	63	– 1.13%	– 0.47%	– 0.66%
26	Sultanmirza007	46	– 1.08%	– 0.34%	– 0.74%
27	TheFadedBull	92	– 0.10%	0.66%	– 0.76%
28	Teenoh	598	0.58%	1.59%	– 1.02%
29	WSBConsensus	277	0.46%	1.86%	– 1.40%
30	0toHeroInvesting	58	– 1.71%	– 0.05%	– 1.66%
31	MaxAds1	53	– 0.19%	2.05%	– 2.24%
32	Pitole1	45	– 1.50%	1.03%	– 2.53%
33	Nicocappa	55	0.32%	3.27%	– 2.95%
34	StockPollsEnterp	49	– 0.73%	2.59%	– 3.32%
35	Texas_Rangers	54	– 2.61%	1.28%	– 3.89%
36	Expander2	79	– 1.07%	3.66%	– 4.73%
37	GrapeJelly33	55	– 10.10%	– 1.04%	– 9.06%

Table 6 (continued)

Rank	Poster	# Posts	Long CAR	Short CAR	L-S CARs
38	Dhsmatt2	52	– 2.40%	8.57%	– 10.97%
39	Bobbythebich	49	– 2.91%	10.20%	– 13.11%
40	Noentic	184	– 3.53%	11.20%	– 14.73%
Average		86.43	0.23%	– 0.01%	0.25%

Ranks the top 40 Reddit posters by mean CARs per post. We breaks down average CARs per long and short positions as well as well as both long and short combined in the *Combined CARs* column

indicating the mean of 25 basis points is statistically indistinguishable from zero. Overall, these results suggest that the most frequent posters are no more likely to generate alpha on average.

5 Robustness

We next conduct several robustness tests to ensure that our primary results are not driven by certain design choices. Specifically, we address three concerns. First, in our baseline design, we do not overweight stocks that are recommended more times in given day. For example, if GameStop was recommended 100 times on day t and Apple was recommended only 5 times, they are equally weighted in the portfolio on that day. This choice reflects the simple choice of a trader following the thread to buy each stock she sees. However, arguably a trader could overweight stocks that are recommended more frequently.

To address this comment, we rerun our daily horizon portfolio tests but weight holdings by the number of submissions. In the previous example, GameStop would receive 20 times greater weight than Apple on the trading day. Results of these regressions are presented in Table 7 in the first three columns. Alpha continues to be insignificantly different from zero. Other patterns are also similar to the baseline tests in that alpha for the long portfolio is negative and alpha for the short portfolio is negative as well, although the short portfolio alpha is significant.

Next, in our baseline portfolio formation, we do not distinguish between submissions based on any proxy for submission quality. A submission that simply says “Buy Apple” would receive the same weight as one that contains a long report on fundamental or technical reasons to buy Apple. Bradley et al. (2021) focus on a subsample of the highest quality WSB submissions and find that these recommendations do have predictive power. To alleviate the concern that a trader following the WSB thread would focus on submissions of higher quality, we weight submissions by word count, where we add the title and body of the submission together. Word count is an imperfect proxy for how much information a poster provides when recommending a stock. In this weighting scheme, a recommendation with more words recommending Apple would receive a higher weight in a portfolio than one with less words recommending AMC Theaters. Results from these tests are in columns 4 to 6 of Table 7. Consistent

Table 7 Number of post weighted portfolio & word count weighted portfolio

Portfolio	Number of Post weighted portfolio			Word count weighted portfolio		
	Long	Short	L–S	Long	Short	L–S
R_m–R_f	0.872***	1.103***	− 0.056	0.914***	1.039***	0.042
	(0.105)	(0.084)	(0.128)	(0.065)	(0.092)	(0.103)
SMB	1.129***	0.574***	0.695*	0.314**	0.660***	− 0.187
	(0.351)	(0.186)	(0.372)	(0.124)	(0.199)	(0.201)
HML	− 0.770***	− 0.375**	− 0.521*	− 0.190	− 0.339*	0.026
	(0.287)	(0.190)	(0.312)	(0.122)	(0.200)	(0.207)
MOM	0.007	− 0.298**	0.267	− 0.255**	− 0.235	− 0.046
	(0.161)	(0.142)	(0.186)	(0.101)	(0.146)	(0.153)
RMW	− 0.106	− 0.535*	0.237	− 0.597***	− 0.451	− 0.316
	(0.434)	(0.317)	(0.479)	(0.180)	(0.311)	(0.302)
CMA	2.593**	0.312	2.337*	0.149	0.224	− 0.032
	(1.319)	(0.380)	(1.347)	(0.211)	(0.387)	(0.389)
Daily alphas (%)	− 0.188	− 0.315***	0.028	− 0.200***	− 0.301***	0.006
	(0.117)	(0.116)	(0.142)	(0.072)	(0.115)	(0.109)
N	1443	1051	1443	1442	1051	1442
R^2	0.086	0.129	0.024	0.146	0.122	0.001

Reports the performance of the *Reddit strategy* for the full sample. To account for post quality, we run our tests using a portfolio weighted by number of posts, and portfolio weighted by word count. Alphas are in percent and standard errors are reported in parentheses. R_m–R_f is the value-weighted return on the market portfolio of all sample stocks minus the one-month Treasury bill rate. SMB is the average return on the nine small stock portfolios minus the that on the nine big stock portfolios; HML is the return on a factor that longs the two value portfolios and shorts the two growth portfolios; CMA is the average return on the two conservative investment portfolios minus those on the two aggressive investment portfolios; RMW is the return from buying two robust operating profitability portfolios and selling two weak operating profitability portfolios. MOM is the average return on the two high prior returns portfolios minus the average return from two low prior return portfolios, in which both high and low prior returns were determined using prior 2–12 months returns. ***, **, and * denote significance of coefficients at the 1%, 5%, and 10% levels, respectively

with our primary results, alpha on the long short portfolio is indistinguishable from zero. Alpha on the long portfolio is negative and statistically significant, indicating underperformance of this portfolio.

Finally, the number of WSB submissions increased significantly over the sample period. A potential concern is that early in the sample the portfolios have much fewer stocks than those in the later periods. For days that are in the sample, the buy and sell portfolios have an average of 1.65 and 1.38 stocks in long and short portfolios per day, respectively, for the daily horizon portfolio in 2012.[9] Portfolio size rises significantly over time to include 194.12 stocks (long) and 14.57 stocks (short) per day in 2021. The number of stocks in the portfolio is larger for longer holding periods. The underlying

[9] There are several days, especially in early years, where there are no recommendations made. Those days are not included in the sample.

assumption of our baseline tests is that a trader following Reddit would have the same amount of capital in 2012 as they would in 2021 and they would allocate the capital among the stocks evenly depending on how many recommendations exist at a given time. To alleviate the concern that the thinnest years of the sample are driving the result, we rerun the baseline tests dropping the first two years of observations (2012 and 2013). Results are presented in Table 7, columns 6 to 9. Again, results are very similar to the baseline regressions. Across all robustness specifications, consistent with our main findings, alpha continues to be indistinguishable from zero.[10]

6 Conclusion

We investigate whether a simple and intuitive trading strategy following WSB submissions can produce alpha. Rather than develop a more sophisticated method for following WSB, our goal is to mimic the trading strategy a typical retail investor may follow to see how they would perform. Overall, we document that while WSB do induce increased trading activity, there is no evidence of outperformance on a risk-adjusted basis.

Our findings contribute to a timely discussion on retail investors in financial markets that are more available than ever. Additionally, the results serve as useful information to the droves of retail investors searching the internet for trading advice. Productive future work will disaggregate the WSB subreddit data and identify pockets of successes and failures as we learn more about fruitful sources of information.

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Code availability Custom code was used for this project.

Declarations

Conflict of interest The authors declare they have no conflict of interest.

Ethical approval N/A.

Consent to participate N/A.

Consent for publications All authors consent for publication.

[10] In untabulated analysis, we also run portfolio regressions in the post-2021 period with GameStop removed. Results are similar.

Appendix 1: Example of WSB Posts

Date	User	Title	Content	Ticker	Signal
03/05/2012	entsportsjunkie	FSLR	I have puts	FSLR	SELL
09/09/2016	bicape	Rob Riggle is KFC's new colonel. YUM to the moon	N/A	YUM	BUY
05/10/2017	timmyt03	Here comes MACD cross into bull run on $AAPL daily chart	https://stockcharts.com/h-sc/ui?s=AAPL	AAPL	BUY
26/06/2018	Bchenks	$WWE Muun Thread	7/20 $60 calls! Thanks FOX and USA Networks!	WWE	BUY
13/01/2020	grantanade	TSLA going to the Moon	N/A	TSLA	BUY
27/01/2021	NeighborlyGoat	WWR TO THE MOON	Nuclear stonk that is powered by moon technology for us r******. low volume, we can rocket this thing to mid double digits no problem!	WWR	BUY
27/01/2021	ohDeevo	AMC TO THE MOON	N/A	AMC	BUY
22/06/2018	cloudninexo	Sell Sell Sell $IQ	N/A	IQ	SELL
14/02/2021	BIGJAYsmalljay	Puts on Chinese EVs $NIO, $XPEV, Wish Me Luckin	N/A	NIO, XPEV	SELL

Appendix 2: Variable definitions

Variable	Definition
CMA	The average return from two conservative investment portfolios minus two aggressive investment portfolios. Source: French Data Library
Daily alphas	Daily alphas are the intercepts of the regression models of WSB mentioned stocks' excess returns on six factor models, including market excess return, SMB, HML, CMA, RMW and MOM factors
HML	The average return on a factor that longs the two value portfolios and shorts the two growth portfolios. Source: French Data Library
Last month return	The previous month returns of each stock mentioned in WSB. Source: CRSP
Market to Book	Market value of equity divided by book value of equity. Source: CRSP and COMPUSTAT
Market value of equity	Market value of equity. Source: CRSP
MOM	Average return on the two high prior returns portfolios minus the average return from two low prior return portfolios, in which both high and low prior returns were determined using prior 2–12 months returns. Source: French Data Library
R_m—R_f	Value-weighted return on the market portfolio minus the one-month Treasury bill rate. Source: French Data Library
RMW	The average return from buying two robust operating profitability portfolios and selling two weak operating profitability portfolios. Source: French Data Library
Short interest	Total adjusted short interest scaled by shares outstanding. Source: COMPUSTAT
SMB	The average return on the nine small stock portfolios minus the that on the nine big stock portfolios. Source: French Data Library
Total assets	Total value of assets. Source: COMPUSTAT

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