WallStreetBets: Assessing the Collective Intelligence of Reddit for Investment Advice

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The WallStreetBets (WSB) community on Reddit gained prominence for its role in the GameStop saga and the resulting *meme stock* phenomenon. Concurrently, this has boosted the popularity of finance-related communities on Reddit, with the top five totaling more than 25 million subscribers at the time of writing. However, little is known about the reliability of the advice disseminated in these communities, which is a relevant research question within the field of social computing. In this study, we examine the collective intelligence of WSB, the largest and most active subreddit focused on the stock market, and assess its potential as a democratizing force in enabling access to financial knowledge. First, we establish that WSB meets several criteria to be considered a collectively intelligent crowd. Then, we test our hypothesis quantitatively by analyzing Reddit posts and financial data from a 28-month period to evaluate how successful an investor relying on WSB recommendations could have been. We define a portfolio of WSB's most discussed stocks which shows significant growth, outperforming the S&P 500 index over the reviewed time frame. We further find that following buy signals at the time they are posted on WSB leads to positive outcomes over the long run, and that the GameStop hype merely amplified previously existing characteristics. The WSB portfolio underperforms the broader market during downturns, but recovers more quickly and achieves higher profits afterwards. The results of our work can be generalized to comparable finance-related communities, indicating that their original purpose of leisurely entertainment has already been extended towards tangible real-world value.

CCS Concepts: • **Information systems → World Wide Web**; **Web mining**; **Social networks**; • **Human-centered computing → Collaborative and social computing theory, concepts and paradigms**; **Social media;**

Additional Key Words and Phrases: Open finance, social computing, collaborative investing, web mining

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1 Introduction

Membersof Reddit's r/WallStreetBets (WSB) community often make a point to emphasize that their posts should not be deemed as constituting financial advice. Yet, the forum appears to

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have profoundly affected a number of specific stock prices, most prominently in the January 2021 GameStop short squeeze. Some of these have since been known as *meme stocks*, reflecting the social contagion arising from trending posts in the forum. The community's size and reach likely contributed to its important role during the GameStop hype: r/WallStreetBets has since been the largest trading-focused online community and has drawn substantial attention to social communities on the platform of Reddit. Unlike traditional online services, the WSB community's language is notably profane and users are often ridiculed when posting their losses and analyses, yet they appear united by a common goal of yielding high profits on the stock market. In contrast to financial news outlets and online publishers (e.g., The Motley Fool) as well as reports published by investment banks or prominent individuals on TV or social media, a topic-focused community such as WSB offers a more democratic environment for obtaining investment signals: WSB's posts are freely accessible, contributed by a large number of users, and filtered for quality to a certain degree using WSB's guidelines and Reddit's voting mechanism. While WSB is widely known for its highly speculative and unorthodox forms of sharing and debating investment strategies, little is known about the reliability of the disseminated recommendations. WSB users are well aware of and often mention the constant risk of "pump and dump" schemes, of simply being too late on a trend, or of manipulation through malicious third parties, which can lead to financial losses and "bag holding".

Does this community fulfill the criteria to be a "wise crowd", i.e., collectively intelligent? Can the social dynamics in a community of anonymous traders generate investment advice that outperforms the broader market? With the aim to answer these questions, we perform an analysis based on WSB posts spanning a time period that includes the two years prior to the GameStop hype of 2021 as well as the year following the COVID-19-related stock market crash in spring 2020. In the first step, we investigate whether WSB fulfills the requirements to be considered collectively intelligent, which shapes our hypothesis for this work. Then, we present new insights from a data-driven perspective on the WSB community's proficiency in order to evaluate how well investors following the submissions and buy recommendations in the forum would have performed financially in this period. Furthermore, we specifically analyze the WSB portfolio's performance during the market downturns of March 2020 and the year 2022. As the stock market is a complex system influenced by a multitude of factors, we do not aim to answer how and to what extent WSB might have the power to move financial markets, as may have occurred temporarily with some of the *meme stocks*. Instead, we investigate to what extent specific patterns in the posts on r/WallStreetBets may have anticipated corresponding stock price movements that occurred later, by acquiring a large WSB dataset and enriching it with financial data. We establish techniques to identify the most popular stocks within thousands of text snippets, identify the portfolio of most discussed stocks, and assess how reliable the community's buy and sell signals would have been if taken as investment advice. Our analysis shows that WSB indeed satisfies requirements of a collectively intelligent group and, while not every single investment decision shared on WallStreetBets leads to financial success, the signals achieve average investment returns that can significantly outperform the S&P 500 index, which we here consider as a proxy for the broader market. We further develop means to distinguish different sorts of posts and identify proactive buy signals with promising prospects. Additionally, we compare analysis results based on data from the *pre-hype* and *post-hype* time frames, as the rapid rise to prominence of the WSB community in January 2021 also entailed an explosive growth in user numbers and generated content.

Ourwork contributes to understanding the changing role of WSB and similar online communities in our society with direct implications for this field of research, as these communities originally designed as a medium for leisurely entertainment and informal exchanges demonstrate tangible real-world value. We show that WSB and comparable communities can have an impact

on the personal and professional lives of their large user bases by offering a valuable source of information and democratic access to investment advice that otherwise requires trusting single sources of truth, and, in many cases, paying large amounts of money for access.

2 Background

2.1 Reddit, WSB, and the Short Squeeze

Reddit was established in 2005 and is a popular social media platform that provides a place for communities (known as *subreddits*) on specific topics, such as humorous memes, politics, or computer games. The platform has since grown to host over 100,000 subreddits with more than 70 million daily active participants, accumulating more than 50 billion monthly views (according to redditinc.com). Members can post submissions, comment on them, and use up-/down-vote buttons to rate submissions and comments. According to web analytic estimates, approximately 70% of Reddit's users originate from English-speaking countries (47.8% U.S., 7.2% United Kingdom, 7.1% Canada, 4.0% Australia) and Germany (3.2%), 72.7% of users are male, and 61% between 18 and 34 years old (source: similarweb.com/website/reddit.com/).

WallStreetBets (WSB) is a subreddit created on January 31, 2012 and accessible via www.reddit.com/r/wallstreetbets. WSB's number of subscribers increased rapidly from 1.7 million to approximately 8.5 million within January 2021 (according to our dataset), due to the media attention received in the context of the GameStop hype. At the time of writing, WSB has approximately 15 million subscribers. In early 2023, the website subredditstats.com ranked WSB 49th of all subreddits in terms of subscriber count, 11th with respect to the number of comments per day (in March/April 2021 even second rank), and 32nd regarding the number of posts per day—this suggests a highly active community. WSB is the largest of all finance-related Reddit communities regarding subscriber count (with the exception of r/personalfinance, which is a broader community that includes topics such as budgeting, saving, and retirement planning). It describes itself as *a community for making money and being amused while doing it. Or, realistically, a place to come and upvote memes when your portfolio is down.* WSB is notorious for its unique slang and the pervasive use of offensive terms, e.g., WSB subscribers are officially referred to as "degenerates" and often call each other "apes" or "retards". Notable differences have been found between WSB and other finance-related communities on Reddit [1]. While WSB is characteristic and unique, we argue that it provides particularly rich data for assessing the finance skills of Reddit users. The community allows the users to interact with the least amount of moderation, which enables the dissemination of a more diverse set of investment signals, while avoiding hate speech and inappropriate content—a property that we consider to be relevant for exhibiting collective intelligence.

WSB saw an unprecedented rise in popularity and news coverage when the community started debating a particular set of stocks, including GameStop, that were in part deemed undervalued while simultaneously exhibiting a high short interest, i.e., the ratio of shares being sold short (or *shorted*) by financial institutions. Short-selling a stock refers to the practice of borrowing shares of a stock in order to sell them immediately with the goal of buying them back later at a lower price. This practice is a speculative move often employed by professional investors on stocks that are considered overvalued and expected to lose value in the near future. However, if the stock price instead increases, a short position can lead to considerable losses.

Discussingpotentially undervalued investment opportunities is common in investment-focused communities, but GameStop's high short interest led to WSB's situation being portrayed as an ideological David-and-Goliath battle of small retail investors rallying against hedge funds: by buying and holding the stock, its price could be driven up, thus forcing the financial institutions to close their short positions at a significant loss, which in turn drove the stock price up even further – a phenomenon known as a *short squeeze*. This made WallStreetBets a place where the

broader community of Reddit users could come together to unite in a movement, driven by the prospect of large financial gains through risky investments, with the added appeal of supposedly advancing the greater cause of punishing the financial institutions, particularly hedge funds. The latter are accused by the WSB community of having ruined many people's lives during the financial mortgage crisis of 2008, among other events.

2.2 Related Research

Social media can be a valuable source of data for assessing the public sentiment on specific topics, or analyzing how individuals, groups or institutions communicate and interact on these platforms, and is studied in various scientific disciplines. Several studies reviewed the effects of social media on different target groups and how they access and utilize its information during their daily lives [17, 23]. Another line of work focuses on the forms of interaction in modern online platforms. For instance, emotionally charged messages in social media have been shown to spread more quickly [38]. Similarly, one can assess the spread of false information [9] and quantify controversy in discussions [15]. In the field of social computing, social media has been found to yield valuable insights, including on the development of social movements [28, 31], social media's influence on politics on an international scale [16, 19], identification of users' political stance [29], and the analysis of user requests [14]. While there is significantly less research on Reddit than on Twitter (renamed to "X" in 2023),[1] the academic community has been gaining interest in extracting information and patterns from Reddit due to its rich variety of interesting communities [35]. Some studies have considered particular Reddit communities, e.g., analyzing the r/StopSmoking Reddit community to understand their social support mechanisms [12], assessing social roles within the r/userexperience community [24], or the analysis of interactions, language, and anonymity in parenting-related subreddits [2, 37]. Our work complements this field of research.

From the perspective of economics and finance, research suggests that there are important ties between social media sentiment and macroeconomic factors such as consumer confidence [11] and that the general sentiment may help understanding a firm's stock performance [47]. Extensive research has attempted to show how particular cues from social media can enable predicting stock price changes [13, 32, 39]. Some research adopts the term *social sensing* [41] for approaches similar to those of the papers mentioned above—typically focusing on applying sentiment analysis to data from Twitter/X to derive predictions from it. While there are numerous studies following a comparable approach, there does not appear to be prior work in this area that (1) investigates the reason for the success of the techniques in terms of an underlying collective intelligence of the social media users, (2) uses metrics other than sentiment, e.g., lexical features relating to buying or selling, or (3) derives predictions from social media platforms other than Twitter/X, specifically Reddit, with its unique traits. The theory of collective intelligence supports the ability of online communities to achieve common goals through participation and collaboration [25, 34, 40]. This work continues to be considered foundational in more recent research [8, 33, 46], as it remains applicable to new kinds of channels, communities, and forms of interaction that the internet has enabled. However, there is only limited prior work studying in detail how the theory applies to more recent forms of groups such as Reddit communities [6, 45]. In this work, we review the WSB community from the perspective of collective intelligence theory to understand whether the necessary criteria are met, then conduct our quantitative analysis to validate this hypothesis.

Fuelled by the 2021 GameStop hype on WallStreetBets, recent research has provided a number of insights on the dynamics and background of the matter. This includes studies on the social

[1]Google Scholar yields 2.5 million results for "Reddit" vs. 8 million about "Twitter"; when adding "finance", 300,000 vs. 3.5 million, respectively.

dynamics within the WSB community that led to the hype [26, 36] and on the idea of retail investors fighting against Wall Street [10, 22]. Other studies considered the financial mechanisms driving the sudden price spike [3, 43] and the effect of retail traders on prices and volatility, along with their participation in transactions [18]. Further research assessed the implications of the events for market regulators and brokerages [21, 42]. One study conducted an analysis of selected posts from an anthropological perspective [30]. Some studies investigate the social interactions on WSB and explain the community's particular style of conversations and language [1, 5]. Most of the existing research focuses on socio-economic and general market effects and implications.

Little is known about the financial skills of the community of retail traders organized in WSB and the merits of their investment advice [7]. Recent work [44] investigates the performance of retail traders from the brokerage Robinhood from a finance perspective and finds predictive value (alpha) in their actions, but it does not consider ties to WallStreetBets or to collective intelligence theory. There is also a lack of research from an information science perspective studying data that span a longer time frame, a large number of different postings, and assessing longer-term effects and trends. We contribute to the field of social computing by extending the existing literature with a data-driven, larger-scale analysis of the information that can be acquired from WallStreetBets, one of Reddit's most unique communities, and its evaluation from an interdisciplinary perspective of collective intelligence, data mining, and finance.

3 Collective Intelligence

We have identified two relevant frameworks for investigating a group's collective intelligence: the criteria described by Surowiecki in *Wisdom of Crowds* [40] and by Malone et al. in their *Collective Intelligence Genome* framework [27].

3.1 Wisdom of Crowds

The framework by Surowiecki defines four requirements that a "wise crowd" ought to fulfill: *diversity*, *independence*, *decentralization*, and *aggregation*.

Diversity does not necessarily refer specifically to demographic diversity, but rather to cognitive diversity, i.e., different levels of skill, knowledge, and intelligence, as well as varying educational and cultural backgrounds among the group of participants. In the specific finance context of WallStreetBets, this criterion also includes a diverse set of risk attitudes, time horizons, investing styles, and amounts of information and research about specific securities. The group does not have to be an exclusive coalition of trained domain experts—on the contrary, the "Wisdom of Crowds" framework values group members with less experience, as long as they possess a minimal set of skills relevant for solving the task, i.e., having a basic understanding of the stock market and the discussed securities in the case of WSB. In the WSB community, the large number of participants from across the glove inevitably entails a certain amount of demographic diversity within the group, even if there is an imbalance towards young males from western cultures. Cognitive diversity is evinced by the variety of investment ideas spanning across a broad range of sectors (as can be seen below in Table 3), as well as in the fact that WSB members do not hesitate to criticize and disagree with each other in a submission's comments, particularly if they consider an analysis flawed or lazily written. The comments for submissions of the categories "Due Diligence" and "Discussion" (see Section 4.1 for more details on submission categories) show that community members that disagree are similarly free to express their opinion as those that agree.

Independence postulates that members of the group be able to make decisions on their own with some degree of freedom from other group members, even if not completely isolated. For this purpose, they have to be able to rely on private information that is not shared within the whole group – this can be their own interpretation of analyses, doing their own analysis, reading

about the discussed securities in other sources, or even using their own intuition. *Independence* in decision-making avoids the correlation of errors that influential group members make and therefore reduces a potential systemic bias. When members start following shared investment advice blindly and exhibit herding behavior, this tends to lead to the loss of the wisdom of the crowd effect. Surowiecki argues that an important factor for group members' independence is the incentive they receive for performing well: A crowd can only act wisely when good, independent decisions are rewarded, e.g., good investment decisions lead to a group member's personal financial gain. In contrast, if there is a strong incentive to imitate other group members' actions, e.g., by investing a large sum into a *meme stock* with the aim to post it and receive a high amount of upvotes, without care for whether they will lose money with the investment, this will most likely be an unwise action. The WSB community is no stranger to imitative acts, as notably evinced by the *meme stock* hype phenomena (e.g., with GameStop). However, we have observed during our analysis that this phenomenon is limited to two types of posts: highly popular *meme stocks*, and high-quality investment analyses (due diligences). While *meme stock* hypes are usually highly risky and a bad decision for many investors (except for those that are sufficiently early), due diligence analyses shared within the community are assessed and vetted by the community and only receive praise when the arguments and conclusions are convincing. A good due diligence is likely to receive a high upvote score and more agreement in the comments, while poorly conducted analyses are tend to be "downvoted" and criticized. Therefore, it may seem that the comments on a highly rated due diligence lack independence due to statements such as "to the moon!" and "Didn't read any of this but it looks good"—however, these comments rarely appear below a low-quality, criticized analysis.[2] Additionally, there are community guidelines in place that prevent "pump and dump schemes" and dubious investment advice, which are enforced by the community's moderators. Importantly, group members are frequently reminded to do their own analysis before investing, and at the very least have to make their own decisions about setting up a brokerage account, allocating a part of their financial funds for specific investments and executing these investments independently.

Decentralization requires that the group does not follow a top-down hierarchical structure for decision making, but should instead be organized as flat as possible and source its information and ideas from the group's members, which all provide information from their local or personal perspective. This enables the group to access a wider range of information and to benefit from local or domain expertise of group members. In the case of WSB, decentralization is inevitable, as the number of participants is too large and too loosely organized to be managed in a centralized, hierarchical structure. The members of WSB are encouraged to share their opinions and expertise in detailed analysis posts, which are by definition created in a non-central manner and are more valuable when users tap into their "local" expertise. A minor degree of centralization is manifested by the community's moderation—while interventions by moderators reduce the total number of posts and comments, they contribute to the group's quality by removing non-informative, hateful, and dubious content.

Aggregation is necessary in order to bring many different opinions together to form a collective decision. Reddit offers a suitable method for this due to its voting mechanism, which is an effective way for the community to distinguish between good and bad content. Every user account has only one vote per piece of content (submission or comment) and can express further thoughts in a submission's comment section. As explained above, a post's comments usually provide insights into why a post has received a certain score. While the score does reflect the community's short-term assessment on how diligent and well a post has been written, it cannot indicate whether the

[2]Well-received due diligence example: reddit.com/12bsszu; criticized due diligence example: reddit.com/129js4w

Table 1. Our Summary of the Collective Intelligence Genes as Defined by Malone et al. [27]

Questions	Gene	Variation/Detail
What is being accomplished and how is it being done?	Create	Collection (can be a contest)
		Collaboration
	Decide	Individual decision (Markets, Social Networks)
		Group decision (Voting, Consensus, Averaging, etc.)
Who is performing the task?	Hierarchy	Central decision-making unit
	Crowd	Can be dependent or independent
Why are they doing it?	Money	Direct payment or future profit
	Love	Enjoyment, socializing, or contributing to a cause
	Glory	Recognition, score or rank

advice shared in the post would actually lead to a profitable investment, as this usually happens after a longer time frame. For this purpose, we conduct our quantitative analysis further below, which involves extracting stock discussions and detecting the most frequently discussed securities (see Section 5), and calculating a consensus of votes per stock ticker per day to evaluate the success of the community's investment signals over different time windows (see Section 6).

Furthermore, Surowiecki defines three types of problems that a wise crowd can tackle: *cognition* problems, *coordination* problems, and *cooperation* problems [40]. The task of predicting how stock prices will perform in the future can be considered a *cognition* problem and represents the main goal of the analyses shared within the community. Additionally, one may argue that a *meme stock* rally is a *coordination* or *cooperation* problem, as the process requires coordinated investment activity with the right timing and suitable cooperation between participants to trust each other to continue investing, although selling their shares and taking the profits are individual incentives that encourage selfish behaviour. However, the phenomenon of *meme stock* rallies appears to have been limited to the year 2021, as after a few unsuccessful rally attempts and the downturn of markets in 2022, most group members refocused on serious analyses.

3.2 The Collective Intelligence Genome

Malone et al. definea comprehensible framework for understanding and designing groups that exhibit collective intelligence, which investigates the following questions: What is being accomplished? How is it being done? Who is performing the task? Why are they doing it? [27]. Table 1 provides our summary of the genes and additional details associated with each of the questions. The genes defined in this framework can be applied to any group to understand the different dimensions of their activities. Mapping these dimensions to the community of WSB creates its specific collective intelligence genome, which is provided in Table 2. We have defined a new gene for the act of moderating content, *Moderation*, as we see this as a necessary addition to the framework to represent this essential activity within the WSB community, i.e., *Moderation* as an (arguably independent) decision enforced by the hierarchy. It should be noted that moderation within the WSB is different than on other subreddits—as the community allows explicit language and (critical) opinions to be voiced more freely, but restricts discussion topics that may be considered "unsafe" (e.g., so-called penny stocks, due to the high risk for investors). It is important to note that principal motivators for the WSB community are *Love* and *Glory*, as there are no immediate monetary incentives neither for the crowd nor for the moderators. The group's participants interact in order to socialize and gain recognition (via their upvote score and awards), and therefore have to produce and share content that the community accepts and deems valuable. In conclusion, we can see that the main

Table 2. Mapping the Collective Intelligence Genome for WallStreetBets

What		Who	Why	How
Create	Share stock analysis	Crowd	Love, Glory	Collection
Create	Share other content	Crowd	Love, Glory	Collection
Create	Write comment for post	Crowd	Love, Glory	Collection
Decide	Vote on post	Crowd	Love, Glory	Voting
Decide	Moderate posts	Hierarchy	Love, Glory	Moderation

activities of WSB can be mapped to a *Collective Intelligence Genome*, which shows that this community successfully employs multiple mechanisms to leverage the power of collective intelligence.

Summary: Collective intelligence frameworks offer a valuable foundation to understand the facets of collective intelligence in the context of modern online communities. The qualitative analysis of criteria provided above enables us to develop the hypothesis that the WSB community may exhibit collectively intelligent behavior in its interactions. In the next step, we aim at validating this hypothesis and the question of whether the advice shared on WSB can indeed lead to profitable investments. We have developed a quantitative approach to investigate this, which is explained in the following sections.

4 Dataset Compilation

4.1 Data Acquisition

The data considered in our study was collected programmatically by accessing the Pushshift Reddit archiving service [4]. The latter allows requesting data exports in JSON format based on submissions or comments. In order to compile a representative dataset, submissions from January 1, 2019 to April 4, 2021 were retrieved in a first step. This covers a time span to analyze the activity on WSB starting two years before the January 2021 GameStop incident until a year after the COVID-19 pandemic affected stock markets in March/April 2020. We employ an upvote score threshold to reduce noise, as posts with an upvote-to-downvote ratio below 50% do not offer valuable content—these submissions were often deleted by the author or a moderator, do not meet quality or community standards, are duplicate posts created by bots, or are unfit in some other way. This ensures that the dataset is representative of what community members normally see, as the above kinds of posts do not appear in a WSB visitor's standard view.

The data provided by the Pushshift API include additional metadata, e.g., the time of posting, the author identifier, a potential category tag ("flair"), and so on. While the service also offers the option of collecting comments provided in response to submissions, in this analysis, we focus on submissions only, because they represent the main topics that a user encounters when visiting and browsing WallStreetBets. Comments are typically short replies to the topic presented in the submission, but are not as prominently displayed and very heterogeneous in terms of their information value. It should be noted that the Reddit data provided by the Pushshift service may deviate from the original data in minor ways. For some posts, the upvote scores provided by the API are lower than the true value. Additionally, in the beginning of February 2021, the service was offline for multiple days. We acknowledge the risk that due to similar outages in the past, Pushshift may not have been able to scrape Reddit consistently. However, other relevant metadata, e.g., creation date and number of comments, were always correct in our sample comparison. Thus, we conclude that apart from the score value, the data is sufficiently reliable to conduct the analysis.

4.2 Dataset Statistics

The overall dataset consists of 778,288 submissions, of which 238,001 include a body text (while those lacking a body text may have included an image or video instead). A significant portion of these submissions was posted in 2021 (494,885 in total, 124,704 with body text), due to the aforementioned dramatic expansion of the community's subscriber count and amount of posted content. This shows how much traction the subreddit gained in 2021, in large part due to the GameStop hype, and is in line with the growth of subscribers from 1.7M to 8.5M within January 2021. In general, the vocabulary sizes are fairly large, which in part stems from the fact that the corpus consists of user-generated text from social media and hence harbors substantial numbers of typos, emojis, symbols, and similar phenomena that can increase the vocabulary size. On WSB, a system of tags, known as link *flairs* (Explained in the guidelines accessible via https://www.reddit.com/r/wallstreetbets/wiki/linkflair), serve as labels to categorize posts as *Discussion*, *DD* (due diligence), *News* (concerning specific stocks or markets), *Gain* and *Loss* (recounting gains or losses that need to surpass a certain monetary value threshold in order to be approved), or *YOLO* (high-risk high-value investments), among others. In our dataset, 718,517 submissions are labeled with such a tag either by their author or by the moderators. A review of this feature shows the following distribution: 23.5% *Discussion*, 22.1% *Meme*, 12.6% *YOLO*, 8.6% *News*, 7.7% *Gain*, 7.6% *Shitpost*, 4.9% *Loss*, 4.5% *DD*, and 8% others. This suggests that WSB serves two functions: for discussing investment ideas and news on one hand, and entertainment on the other.

5 The WallStreetBets Portfolio

5.1 Methodology: Detecting Stock Tickers

Each stock can be identified by its ticker, which is usually an abbreviation related to the company, conventionally written in capital letters, and sometimes adorned with a prefixed "$" (e.g., $AAPL for Apple Inc.) in order to identify them as stock tickers—this is particularly helpful when it could otherwise be mistaken for a regular word or abbreviation (e.g., $COST for Costco Wholesale Corp.). Unfortunately, WSB users frequently omit the prefixed dollar sign, sometimes use lowercase letters for the tickers, or write sentences or their entire posts in uppercase letters to convey urgency. Additionally, many common abbreviations of business- or sector-related terms can be mistaken for stock tickers, e.g., GM for General Motors Co. or General Manager. Sometimes, posts about a particular stock may include mentions of additional companies, e.g., if the bank JPMorgan Chase & Co. (JPM) has commented on buying or selling a specific stock. This makes it challenging to detect stock tickers correctly without false positives or false negatives. We adopt the following methodology as described in Algorithm 1: After tokenizing and removing punctuation of each submission text, we filter for tokens (w) with a length of 2–5 alphabetic characters or tokens starting with "$" followed by 1–5 alphabetic characters. Single-character stock tickers are considered only with a prefixed "$" to avoid false positives, e.g., "$F" is the stock ticker for Ford Motor Co., while "F" usually refers to a popular swear word. We define a list of relevant tickers L, which includes 7,100 stock tickers from the NASDAQ Stock Screener extended with a list of ETF tickers (extracted manually from the WSB community's discussions about ETFs). Tokens without a prefixed dollar sign are counted if they are included in L, while not part of a list of potential false positives F (a list of short tokens that are often used as words or abbreviations and could be mistaken as stock symbols). This decision is based on our observation that the WSB community usually prefixes a "$" to specify stock tickers that could be taken as normal words or are single letters. While a high-precision method to detect stock tickers could be to focus on tickers mentioned with a preceding dollar sign only, this would have very low recall—e.g., only 13.4% of all $GME (GameStop) and

ALGORITHM 1: Our Stock Ticker Detection Algorithm for WallStreetBets

Input: Text corpus as list of tokens $w_1 \dots w_N$, Relevant Tickers L, Potential False Positives F
Output: result ← Dictionary of detected tickers with occurrence count

```
function Extract_Tickers(T, L, F)
    result ← 0
    for k ← 1 to N do
        if 2 ≤ length(w_k) ≤ 5 & w_k is alphabetic then
            if w_k ∈ L & w_k ∉ F then
                result[w_k] ++
            end if
        else if w_k[0] = $ & length(w_k) ≤ 6 & w_k[1 :] is alphabetic then
            if w_k ∈ L then
                result[w_k] ++
            end if
        end if
    end for
    return result
end function
```

11.6% of all $MSFT (Microsoft) mentions had a preceding "$". The strategy proposed above instead constitutes a method of detecting the vast majority of stock tickers, while minimizing the amount of false positives and false negatives. To validate the accuracy, we tested the algorithm on 100 randomly selected posts and found that it was only wrong in three cases where the company name was misspelled (by accident or on purpose) and the ticker was not mentioned or a false-positive candidate without a preceding "$". In summary, our approach can be deemed as accurate as the authors' (educated) perception and therefore sufficient to detect relevant tickers within the dataset.

5.2 Analysis

Invoking the technique described above, we identify the 100 most frequently mentioned stock and ETF tickers for different time windows: the dataset's full range, as well as each year separately (2019, 2020, 2021). Grouping the tickers contained in these lists by sector shows that the WSB community focuses primarily on stocks from the sectors *Consumer Cyclical* (non-essential consumer goods), *Technology* (manufacturers of tech hardware and software), *Healthcare* (including pharmaceuticals, cannabis companies), and *Communication Services* (including interactive media, entertainment, telecommunications), as reported in Table 3. The distribution of the sectors' market capitalization shows that WSB appears to focus on sectors that are close to consumers.

Particular attention is given to stocks of younger companies, which are often considered growth stocks. These tend to be riskier, but exhibit a higher growth potential (in contrast to low-volatility value stocks such as The Coca-Cola Company): The three sectors that performed better than the S&P 500 index regarding their 3-year growth (*Technology*, *Consumer Cyclical*, and *Communication Services*) are all ranked within the community's top four sectors. Regarding the 1-year growth, WSB's focus on the same three sectors and *Industrials* and *Financial services* outperformed the S&P 500 as well, although the community seems to have missed out on the strong growth in *Basic Materials* and *Energy*. We have selected the S&P 500 index as a benchmark, because it is considered a good reference for the broader (U.S.) market. While this comparison may not be perfect, it covers

Table 3. Distribution of Top 100 WSB-Mentioned Tickers per Sector per Year with Market Capitalization, 1-year, and 3-year Change (as of March 2021)

	Count per year			Financial data		
Sector	'21	'20	'19	Cap.	1Y-Chg.	3Y-Chg.
Consumer Cyclical	22	24	20	$8.9T	87.8%	58.5%
Technology	17	22	24	$13.3T	75.7%	86.6%
Health	14	11	13	$7.4T	37.4%	35.1%
Communication Services	9	10	16	$6.2T	68.7%	54.4%
Industrials	11	11	6	$5.5T	79.7%	26.3%
Financial Services	10	5	6	$8.1T	79.3%	18.0%
Consumer Defensive	1	5	6	$4.3T	19.0%	23.4%
Materials	5	2	0	$2.6T	89.5%	31.7%
Energy	1	2	2	$2.6T	105.7%	−25.7%
Utilities	0	2	2	$1.5T	13.3%	23.0%
Real Estate	4	0	0	$1.5T	33.1%	23.9%
S&P 500					54.0%	51.2%
Russell 3000					61.0%	53.6%

more of the WSB portfolio (11 out of 19, specifically all companies except for meme stocks and the two Asian companies Alibaba and NIO) than other indices such as the NASDAQ100. We further consider the Russell 3000 index, which contains the 3,000 largest stock-listed U.S. companies and provides a slightly broader coverage (13 out of 19, specifically GameStop and AMC in addition to those covered in the S&P 500). However, it is less known and contains a much higher number of stocks in total. Its performance is relatively similar to the S&P 500 index for the reviewed time windows shown in Table 3.

We can conclude that WSB's focus on stocks from consumer- and technology-related sectors correspond to those that have generally seen beneficial outcomes in terms of the longer-term sector growth compared with the broader market performance. This conclusion is supported when taking a closer look at the most popular stocks and their products. We define the "WSB portfolio" based on the following rule: We identify the intersection of the 100 most frequently discussed stocks and ETFs on WSB across each of the years 2019, 2020, and 2021. This yields a list of 21 tickers that have consistently been among WSB's most discussed stocks. While the list contains GameStop ($GME) and AMC Entertainment Holdings Inc. ($AMC), which have been referred to as "meme stocks" after peaking in early 2021, the fact that they have been discussed so consistently over the years justifies their place within the WSB portfolio.

The list is given in Table 4. We can group these stocks based on the respective industry: Entertainment & Internet (AMC, FB), Auto Manufacturers & Retail (GM, NIO, TSLA, AMZN, BABA, GME), Consumer Technology & Semiconductors (AAPL, AMD, INTC, NVDA), Technology & Software Infrastructure (BB, NOK, MSFT), Cannabis Companies (ACB, TLRY), and Industrials (GE, BA), ETFs (SPY, QQQ).

The detailed results in Table 4 reveal that 10 out of 18 tickers (NIO and TLRY went public at a later time) performed better than the S&P 500 ETF ($SPY) with respect to the 3-year change, and 14 out of 20 outperformed the S&P 500 ETF with respect to the 1-year change – both as of March 20, 2021. 11 of the 18 stocks (excluding the ETFs) are part of the S&P 500 index. While $SPY achieved 51.93% growth over three years and 72.96% over the final year, a hypothetical, equally-weighted portfolio of these most frequently and consistently discussed stocks from WSB grew by 198.60% (mean)/72.53% (median) over the final three years and by 483.20% (mean)/103.74% (me-

Table 4. Consistently and Frequently Discussed Stock Tickers with 1-year and 3-year Price Development (as of March 20, 2021)

Ticker	Company name	1Y-Chg. (%)	3Y-Chg. (%)
AAPL	Apple	110.99	183.88
ACB	Aurora Cannabis	15.75	−89.29
AMC	AMC Entertainment	336.68	20.10
AMD	AMD	99.60	611.61
AMZN	Amazon.com	66.57	93.82
BA	Boeing Co.	169.26	−20.88
BABA	Alibaba Group	32.26	20.53
BB	BlackBerry	223.96	−16.28
FB (META)	Facebook (now Meta)	93.76	72.53
GE	General Electric Co.	103.74	3.82
GM	General Motors Co.	229.77	76.24
GME	GameStop Corp.	5226.33	1446.41
INTC	Intel Corp.	42.74	33.10
MSFT	Microsoft Corp.	69.41	157.43
NIO	NIO	1706.25	N/A
NOK	Nokia Corp	51.13	−25.67
NVDA	NVIDIA Corp	150.00	107.47
QQQ	Invesco QQQ Trust [ETF]	84.49	90.68
SPY	SPDR S&P 500 [ETF]	72.96	51.93
TLRY	Tilray, Inc.	594.52	N/A
TSLA	Tesla, Inc.	665.88	954.37
Mean		483.20	198.60
Median		103.74	72.53

dian) over the final year. Even if GameStop is excluded, the portfolio has grown by 129.2% (mean) / 62.2% (median) over the final three years and 246.0% (mean) / 101.7% (median) over the final year, outperforming the market benchmark. The performance without $GME as well as the WSB portfolio's median values show that the portfolio outperformed the broader market in the reviewed time frame even without the extraordinary effects of the 2021 meme stock rally. Thus, the WSB portfolio grew faster than the broader market on average – particularly following the market crash caused by the COVID-19 pandemic. In conclusion, this means that during the longer term of two to three years as well as throughout the final year, investing in the most popular stocks on WSB most likely would have been a good investment decision (compared to overall market growth).[3]

6 Investment Advice Reliability

Having assessed the overall portfolio, we now consider the reliability of particular investment advice at a more fine-granular level, investigating whether specific types or intensity levels of WSB activity *at particular points in time* indicate a good timing for an investment decision. To this end, we evaluate how the value of the investment developed over specific short-term time frames, after a hypothetical investor decides to follow a WSB buy signal for a specific stock on a specific

[3]The investment's timing is critical: the 1-year change coincides with the low-point of stock prices right after the COVID-19-related market crash in March 2020, which is why many 1-year performances beat the 3-year values.

day. We assess price developments at specific points in time relative to the date in question, e.g., after one day, after three days, after a week, and so on.

6.1 Methodology

Our methodology aggregates the investment signals shared in the posts of each day. This represents the real-life situation of a Reddit user visiting the community frequently or at least once per day, and looking at the recent posts in their feed. The standard setting for the Reddit feed (called "hot") presents the most recent (from the last 1–2 days) and popular posts (regarding their upvote score) to the visitor, while hiding posts that are downvoted by the community or deleted by moderators or the author.

In order to measure stock-related activity on WallStreetBets, multiple features are derived from the underlying data. As a baseline signal, we count mentions of a stock ticker or company name. For a more targeted assessment we count transaction-related words that are mentioned in the same submission as the respective ticker mentions, specifically "buy", "hold", "sell", "call", and "put" (and their variations), while excluding their negated forms, e.g., "not buy" and "don't buy". The collected word and ticker counts of each WSB post are aggregated per day in order to create a daily consensus for each stock ticker. This is then enriched with financial data taken from Yahoo! Finance with each stock's daily closing price, high and low, and trading volume. We calculate a relative volatility as the difference between a day's high and low values with regard to the closing price. As the stock markets are closed on weekends and public holidays, the volume and volatility on those days are set to zero and values for closing price and daily high and low are taken from the previous day. This helps in assessing time windows that fall on closed-market days—e.g., if someone bought a specific stock on a Friday at a price of $30 and 30 days later on Sunday the closing price was at $40, this is considered a positive price development. This results in a dataset consisting of WSB signals as well as financial data at a daily granularity level for each selected stock.

For a more detailed analysis, we compute a number of indicators. For each day, buy and sell mentions are compared—whichever count is higher defines whether the day is regarded as a *buy signal* or *sell signal*, which is treated as a piece of investment advice in this context. Additionally, for every day, we compute relative changes of the closing price per respective date compared with 1 day, 3 days, and 1 week before, as well as 1 day, 3 days, 1 week, 1 month, and 3 months later (time window x). Based on these price differences, we add various Boolean features to identify specific cases, e.g., price increased or decreased since/after x, Buy and Sell accuracy (a buy signal is considered accurate if the price increased after x). With these features, we assess the success rate of WSB's signals for each time window x: For an evaluation of signal accuracy, all signals per selected stock ticker are tracked with the respective price changes before and after in order to determine whether an investment made on a specific day would have gained or lost in value. A buy signal is considered successful within a specific time window if and only if the closing stock price increased within the same window—if it decreases or stays equal, the buy signal is considered a failure. For sell signals, the converse applies. We create such daily data summaries with WSB signals and financial data for each of the WSB portfolio stocks as well as for the overall S&P 500 index.

Note that we do not assume that all stock price movements are reflected in the WallStreetBets community's discussions, let alone caused by the community—the stock market is a complex system affected by countless factors, of which one might be the WSB community. One may consider WSB activity that *precedes* significant changes in the stock market as indicative of WSB being a good source of information, even if the primary cause lies somewhere else and WSB only picked up on the development. However, the success of some pieces of information could also be due to external effects in the market rather than the community's proficiency. We consider the commu-

Table 5. Averages of Relative Price Change (per Time Window), Mentions, Daily Volatility, and Daily Volume – for S&P 500 and WSB Portfolio (Jan 2019–Apr 2021)

		S&P	WSB Portfolio when bought on:			
	after	500	All	Mention	Buy Signal	Sell Signal
Price chg. (%)	1d	0.07	0.17	0.29	0.29	0.65
	1w	0.44	1.24	2.07	2.19	3.77
	1m	1.79	5.14	7.77	9.88	8.12
	3m	4.89	16.65	27.32	32.03	28.53
Avg. ment.		–	28.28	51.69	89.50	15.53
Avg. volat.		0.8%	2.9%	3.7%	4.2%	3.7%
Avg. vol.		3.0B	25.6M	32.1M	38.0M	32.6M

nity's investment signals to be valuable if they prove their predictive power consistently over the large time frame that we analyze.

6.2 Short-Term Performance

On average, the WSB portfolio stocks have grown 3–6 times more than the S&P 500 – if an investor bought shares of the WSB portfolio on every day between January 2019 and December 2020, their investments would have grown by more than 16% on average after 3 months, while the S&P 500 would have grown slightly less than 5% (see Table 5). Indeed, the table shows that if an investor had chosen to buy on days of WSB activity regarding the respective portfolio tickers, the average 3-month growth would have reached 27.32% (buying if the ticker was mentioned), 32.03% (if additionally a buy signal was detected), or 28.53% (when buying despite a sell signal). Similar patterns can be observed for the shorter time frames of a day, a week, and a month. Overall, this reveals that on average the WSB portfolio outperformed the S&P 500 in short-term investment windows since 2019, if the timing of the investments followed WSB's activity or signals. It should be noted that sell signals have been quite unsuccessful within the reviewed time windows—interpreting sell signals as buy signals would have generated a similarly beneficial outcome as relying on actual buy signals, with even higher average price increases for short term windows of one day and one week. This can be due to two reasons: The market has been in a general upward trend invalidating many sell signals at some point, and selling stocks at the right time is more difficult than buying them, as prices tend to go down much more quickly and abruptly than they go up.

The average volatility of the S&P 500 is low, as the index value is an average of 500 stocks. The WSB portfolio stock's average daily volatility increases when there is activity on WSB, especially when there are buy signals. In total, the WSB portfolio's 21 stocks unsurprisingly generate a much lower trading volume on average than the S&P 500. Still, an average stock listed in the S&P 500 corresponds to a daily trading volume of c. 5.98 million USD (1/500 of the S&P 500 volume), i.e., the average WSB portfolio stock is traded with a five times higher volume than the average S&P 500 stock. The average daily trading volume is significantly higher on days with WSB activity, especially if a buy signal is detected (c. 49% higher than on average). This implies that WSB activity increases when markets are volatile and volume is high or possibly that increased WSB activity may lead to higher volatility and volume in financial markets.

6.3 Reliability of Buy and Sell Signals

The average performance of the portfolio has proven beneficial, but which percentage of signals from WallStreetBets was actually successful? For each of the WSB portfolio's tickers, we evaluate

the accuracy of the community's buy and sell signals by determining the respective price developments over specific time windows – if the price increased after a buy signal, it is considered successful (conversely for sell signals). This assessment can reveal whether the buy and sell signals would have led to better investment decisions than investing continuously or randomly in the same stocks over the same time frame, with a focus on short-term windows. We compare the success rate of all buy signals for a given stock to three baselines of when a stock is bought or sold on: *equally distributed* days, *randomly distributed* days (average over 5 independent trials for a more robust estimate), *every day*. For the former two, we use a sample size identical to the number of buy signals. These baselines simulate three alternative types of hypothetical investors: one investing every $\lfloor \frac{D}{n} \rfloor$ days, one choosing n random days to invest, and one investing every day (with n being equal to the number of buy or sell signals that the baseline is compared to and D being the total number of days in the data). More formally, let $X_i \in \mathcal{X}$ denote the i^{th} data point from the reviewed dataset $\mathcal{X}$ for $i \in \{1, \ldots, D\}$, where D is the total number of days in the dataset. Each such X_i provides the pertinent data for a stock at day i, including the stock value and its relative price changes. Further, let n denote the total number of a signal type (buy or sell) within the corresponding time period. The three different baselines are then defined as follows:

(a) Equally distributed sample of investment days using the same sample size as the actual amount of buy signals detected per ticker: We consider all samples $X_i \in \mathcal{X}$ such that
- $i = \lfloor \frac{D}{n} \rfloor k + \delta$ for $k \in \{1, \ldots, n\}$ and $\lfloor \frac{D}{n} \rfloor k + \delta \leq D$,
- where δ is an optional offset to avoid all X_i falling on the weekend. It is 0 in the vast majority of cases, but instead set to $\lfloor \frac{1}{2} \frac{D}{n} \rfloor$ in the special circumstance of $\lfloor \frac{D}{n} \rfloor = 7$ and simultaneously all X_i for $i = \lfloor \frac{D}{n} \rfloor k$ falling on the weekend.

(b) Randomly distributed values: We select n samples of X_i such that
- $i \in I$ where I is a set of n random numbers from $\{1, \ldots, D\}$ sampled without replacement,
- and, in order to increase robustness, the procedure is repeated across 5 trials and the average is computed.

(c) Every day: We consider
- all X_i within the date range, i.e., for all $i \in \{1, \ldots, D\}$.

Our analysis reports the average price change after predefined time windows depending on when an investment was made. The difference between three different baseline distributions are not particularly strong. Buy signals on WSB portfolio stocks were accurate (positive price development): after one day in 51.75% of the cases, after three days in 52.88%, after one week in 55.02%, after one month in 61.28%, and after three months in 69.94% of cases. In comparison, the baselines achieved accuracies of 51.08–52.80%, 52.70–53.19%, 54.40–54.93%, 58.12–59.19%, and 60.52–61.60% respectively. Within the shorter time frames of one day to one week, following the buy signals is approximately equally often successful as the baselines. However, WSB's buy signals seem to be more successful across longer time frames, as the buy signals' success rate is up to 5.4% higher (after one month) and up to 15.6% higher (after three months) than the baselines' success rates. This means that an investment decision following a WSB buy signal increased in price after three months in almost 70% of the cases.

In the next step, we review the average price changes to produce more detailed insights than comparing general upward or downward movement of prices. Table 6 compares the average price development for different investment patterns: the equally and randomly distributed baselines introduced above, and WSB activity signals. The results suggest that investment decisions based on WSB activity entailed significantly larger subsequent price increases. Again, it should be noted that the detected sell signals have been highly unsuccessful, as the prices increased even more after those days than when selling on days without community activity. For a more fine-granular anal-

Table 6. WSB Portfolio's Price Development for Different Investment Patterns (Jan 2019–Apr 2021)

	Avg. price change (%) after			
Investment Pattern	1 day	1 week	1 month	3 months
Average	0.17	1.24	5.14	16.65
Mention	0.29	2.07	7.77	27.32
Buy Signal	0.29	2.19	9.88	32.03
Sell Signal	0.65	3.77	8.12	28.53
Equal Dist.	0.19	1.21	5.10	14.64
Random Dist.	0.13	1.44	5.36	15.86

ysis, the comparison of the price development of buy signals versus the average may be reviewed on a per-stock basis. Table 7 provides notable examples of the price development for specific WSB portfolio stocks for investments following a buy signal as well as the average price development. Such a fine-grained analysis shows that following buy signals only led to a consistently better outcome for a few selected stocks: $GME, $AMC, $BB, $AMZN, $TLRY, $TSLA—the first three ($GME, $AMC, $BB) belong to the four *meme stocks* that were at the center of attention at the end of January 2021, $TLRY is a cannabis stock that achieved *meme stock* status in February due to its sudden increase in popularity, and $TSLA has been a highly popular stock throughout the last years. However, WSB did not produce reliable buy signals for the other prominent *meme stocks* $NOK and $ACB.

When focusing on price developments after three months, a few tickers can be added to the list above: $AAPL, $AMZN, $BA, $FB, $GE, $NIO, $QQQ—following buy signals with these stocks resulted in higher growth than the average price development. This means that despite volatility in the short term, following buy signals would have turned profitable after three months for 14 of the 20 stocks. When excluding the stocks that incurred losses on average ($NOK, $ACB, $BA), following buy signals achieved a 56% (mean) or 17% (median) higher price growth than the average price increase. In conclusion, we distinguish two cases: In the short term (1 day, 1 week), an investment strategy following buy signals actually was not more successful than the average price increase with respect to short-term windows since January 2019—instead the success of buy signals was mostly driven by *meme stocks*, which biased the average results (especially GameStop). In the longer term (3 months), however, the buy signals turned out to provide better growth than the average price development on average. This confirms the findings of the previous analysis: trusting buy signals on the very short term seems to be successful as often as it fails, but for more patient investors, the portfolio of WSB's preferred stocks performed well and the buy signals turned out to be valuable indicators.

6.4 Proactive vs. Reactive Signals

While WSB has shown a tendency to bet on stocks that were likely to perform better than the broader market, an investment strategy following WSB buy signals would not necessarily be successful. With the goal of separating valuable signals from those that are unsuccessful, we investigate whether signals can be classified as proactive or reactive. Reactive signals (e.g., a buy signal just after the stock price rose significantly) are usually not helpful (at least in the short term)—they can lead to financial losses if the timing is poor. However, they occur very frequently due to users sharing their gains or losses from recent investments or posting news articles on specific stocks that recently made headlines due to notable price changes. The most valuable form of (short-term) investment advice is one received before a change in stock price occurs, thus constituting a proactive signal. In order to validate this assumption, we have labelled the data for each case (with x

Table 7. Average Price Change vs. Average Price Change after Buy Signal (Selected WSB Portfolio Stocks; January 2019–April 2021)

		Avg. price change (%) after			
Ticker	Pattern	1 day	1 week	1 month	3 months
GME	Average	0.76	7.00	29.95	109.16
	Buy Signal	2.86	22.35	100.66	355.36
AMC	Average	0.40	2.30	8.70	8.80
	Buy Signal	0.92	11.50	33.75	28.11
BB	Average	0.10	0.73	3.68	10.43
	Buy Signal	0.10	1.12	4.54	14.38
NOK	Average	0.00	−0.06	−0.52	−2.29
	Buy Signal	−0.28	−0.64	−3.00	−0.69
ACB	Average	−0.04	−0.24	−2.73	−10.25
	Buy Signal	0.29	−1.39	−4.45	−9.38
AMD	Average	0.22	1.48	6.19	19.61
	Buy Signal	0.09	1.35	5.34	17.10
AMZN	Average	0.10	0.68	2.74	9.12
	Buy Signal	−0.01	0.77	3.19	11.80
BA	Average	0.03	0.34	0.80	−1.56
	Buy Signal	0.08	0.03	−0.58	0.46
NIO	Average	0.36	2.76	13.60	62.35
	Buy Signal	0.02	0.36	12.30	69.92
TLRY	Average	0.08	0.80	2.02	7.54
	Buy Signal	0.46	0.45	14.12	35.62
TSLA	Average	0.35	2.54	11.95	45.19
	Buy Signal	0.55	3.49	13.31	47.18

referring to 1 day, 3 days, or 1 week).
Reactive: the price increase in the preceding x is *higher* than the price change in the following x.
Proactive: the price change in the preceding x is *lower* than the price increase in the following x.

Following this classification, only 46.5% of all buy signals were proactive on average. Our analysis reveals clearly different patterns for reactive and proactive signals—investments following reactive signals performed significantly worse in comparison. This suggests that a distinction between both types may be useful to identify the most valuable pieces of investment advice. Nonetheless, even the average of reactive signals achieved higher growth than the average price increase. Investments made after reactive buy signals follow after a period of above-average price increase and show above-average volatility and trading volume on days of the signal (conversely for proactive buy signals). These effects are amplified when the time x for detecting a reactive or proactive signal is longer, but apply to all evaluated time windows. Drawing on this distinction, an investor following only proactive buy signals would have been able to achieve 700% higher growth after a single day and 50% higher growth after three months on average. This conclusion also applies when excluding the *meme stocks* of January 2021 from the calculation—in this case, 2,400% higher growth after a single day and 75% higher growth after three months could be achieved on average. This suggests that distinguishing reactive and proactive buy signals is highly relevant for WSB-guided investors to be successful in the short term.

Obviously, a stock's future price development is uncertain, making it much easier to decide retrospectively whether a signal was proactive or reactive. Hence, we also evaluated a simple heuristic

for making this distinction using historic price information only: We only select buy signals on days that show a closing price below its moving average over 30 days. While this does not detect all proactive signals, it provides a reasonable workaround. In future work, more sophisticated analysis approaches could be investigated.

6.5 Before and After the Hype

It is important to note that the rapid increase in community members and generated content in and after January 2021 entails a strong shift in the dataset towards the newest posts and discussions, which were also coupled with high-volatility price movement in the financial markets. In order to assess whether the observations from the analysis above also hold for the time before the January hype phase, we applied the same analysis to the subset of data from the time frame spanning January 1, 2019 through December 31, 2020. The results indicate that for the time frame before 2021, buy signals were much less effective over the short term than in 2021, but still showed better performance over longer time periods than the average price development. The overall impact of buy signals is weaker in contrast to the post-hype values – nonetheless, similar tendencies can be detected. We obtain the same effect for the comparison of reactive and proactive signals.

6.6 Bull and Bear Market

The broader context of historic stock market data shows that the main considered time window has primarily been a *bull market*, i.e., a phase during which the stock market exhibited a clear upward trend, despite the stock market crash in spring 2020 due to the coronavirus outbreak. This was fuelled by low interest rates and a common belief in the future of growth stocks of companies that could borrow large amounts of money at low interest rates to fuel their growth. However, with the year 2022 came record-high inflation, causing central banks to increase interest rates, accompanied by rising energy prices and a disruption due to the war in Ukraine – multiple factors that have significantly affected the markets. While experts disagree whether or not there is a recession, the S&P 500 index has shown a significant decline from previous highs, with its price falling from above 4,700 points in January 2022 to below 3,700 points in June 2022, a decline of more than 20%—a common indication for a bear market. To review the performance of the WSB portfolio after the time windows shown in the previous tables, we have evaluated its performance on more recent data, as shown in Table 8. During the second half of 2021, the WSB portfolio was almost able to match the performance of the S&P 500 ETF, despite the poor performance of some positions, especially the cannabis *meme stocks* and Alibaba. However, the performance is subpar in 2022: while the S&P 500 ETF declines by 20%, the WSB portfolio declines by an average of 47%, significantly under-performing the broader market. This is mainly due to the fact that a significant part of the portfolio are technology and growth companies, which have suffered most from the market-affecting events explained above. Nonetheless, the portfolio's performance in the first three months of 2023 shows that when the market is recovering, it recovers faster than the broader market (with the exception of the cannabis stocks, which seem to have lost their appeal after a short hype back in 2021. It should be noted that, for simplicity and comparability, this approach assumes that the WSB portfolio has remained consistent over this relatively long time frame—however, a more realistic approach could alter the portfolio based on changes in WSB discussions, as the sentiment towards multiple of the listed companies has turned since 2021 due to their poor performance or developments in their management.

Table 9 shows an alternative WSB portfolio created by using all submissions posted during only February 2020 (i.e., directly before the COVID-19-related stock market crash), providing further insights into the community's performance during a market downturn and right afterward. These stocks are all most frequently mentioned tickers that have a median of daily mentions larger than

Table 8. The WSB Portfolio's Performance in the Bear Market of 2022, with SPY Simultaneously as a Market Benchmark (Stock Prices at the Beginning and End of the Year, and Relative Change)

		Stock Price Change (%)		
Ticker	Company name	Apr 21 – Jan 22	Jan 22 – Dec 22	Jan 23 – Mar 23
AAPL	Apple	43.81	−27.79	26.50
ACB	Aurora Cannabis	−42.00	−83.85	−23.60
AMC	AMC Entertainment	168.04	−85.27	21.53
AMD	AMD	81.06	−56.06	51.07
AMZN	Amazon.com	7.47	−50.39	22.91
BA	Boeing Co.	−20.52	−8.09	12.93
BABA	Alibaba Group	−48.25	−26.75	17.62
BB	BlackBerry	8.50	−65.45	18.63
FB	Facebook (renamed to Meta)	13.37	−65.07	75.39
GE	General Electric Co.	−10.03	−12.93	46.06
GM	General Motors Co.	3.37	−44.33	8.82
GME	GameStop Corp.	−22.82	−51.89	24.51
INTC	Intel Corp.	−20.19	−49.85	22.78
MSFT	Microsoft Corp.	40.63	−28.97	19.11
NIO	NIO	−19.35	−70.67	4.88
NOK	Nokia Corp	58.00	−26.74	4.97
NVDA	NVIDIA Corp	119.68	−51.92	89.34
QQQ	Invesco QQQ Trust	23.52	−33.94	19.84
SPY	**SPDR S&P 500 ETF**	**19.55**	**−20.08**	**6.31**
TLRY	Tilray, Inc.	−69.30	−63.42	−3.04
TSLA	Tesla, Inc.	66.73	−68.65	64.68
Mean		19.11	−47.24	25.30
Median		8.50	−50.39	19.84

zero (i.e., mentioned at least on half of all days of the month). While the portfolio is more strongly negatively impacted during the market downturn, it recovers much faster from it (being profitable after three months while the broader market is still at a loss) and yields significantly higher profits than the broader market after six months and one year. We have added the average sentiment of each stock's submissions as an additional indicator, and our analysis shows that following the discussions with positive sentiment only would exclude the two worst performers of this portfolio ($ACB and $CCL) and further improve median performance, while reducing mean performance (due to the exclusion of $NIO, which was highly successful after one year). In general, the WSB portfolios exhibit stronger movements than the market in both directions. Therefore, it could be seen as a limitation that in the long run, it depends on how much the markets are bullish versus bearish to see whether the WSB strategy will outperform the market or not. Historically, however, stock markets have recovered from bear markets and recessions, exhibiting an overall pattern of growth. Therefore, a strategy like this may outperform the broader market in the long run, as long as its positions are able to recover from downturns.

7 Conclusion

WallStreetBets has emerged as a community for unconventional discussions about high-risk investment ideas. In this article, we investigate whether a finance-related Reddit community like WSB can be considered a collectively intelligent group, and assess the quality of investment sig-

Table 9. Alternative WSB Portfolio Created Only from Submissions Posted in February 2020 with Price Change after March 1st, 2020, Average Sentiment, and Mean and Median Portfolio Performance (Sentiment Calculated using VADER [20], the highlighted S&P 500 ETF Simultaneously Acting as the Market Benchmark)

		Price change after (%)					
Ticker	Company name	1w	1m	3m	6m	1y	sentiment
AAPL	Apple Inc.	−10.92	−19.38	7.99	80.42	72.39	+
ACB	Aurora Cannabis Inc.	−30.21	−40.50	−13.60	−43.01	−32.35	−
AMD	Advanced Micro Devices	−8.83	−8.01	13.00	94.23	82.03	+
BABA	Alibaba Group Holding Limited	−6.31	−11.10	−2.09	41.25	14.56	+
AMZN	Amazon	−7.85	−2.36	26.46	79.08	61.01	+
BYND	Beyond Meat, Inc.	−8.47	−33.22	44.32	40.73	53.08	+
CCL	Carnival Corporation	−34.24	−73.38	−49.18	−50.06	−20.42	−
DIS	The Walt Disney Company	−13.03	−20.89	−1.01	11.31	62.51	+
FB	Facebook (now Meta)	−13.71	−18.75	18.06	50.40	34.86	+
GE	General Electric Company	−26.69	−37.13	−39.64	−44.64	17.55	+
GILD	Gilead Sciences, Inc.	−2.49	−2.94	0.60	−11.10	−13.80	+
MSFT	Microsoft Corporation	−12.83	−11.97	6.11	32.22	38.52	+
NIO	NIO Inc.	−19.95	−35.52	3.65	389.54	1110.71	−
NOK	Nokia Corporation	−15.73	−24.27	6.93	20.53	2.93	+
NVDA	Nvidia	−11.22	−12.08	27.42	100.13	100.49	+
PTON	Peloton	−16.87	0.14	64.22	199.68	343.45	+
QQQ	Invesco QQQ Trust [ETF]	−10.56	−15.58	8.38	39.12	50.37	+
ROKU	Roku, Inc.	−16.05	−28.12	−1.50	56.34	266.54	+
SHOP	Shopify Inc.	−14.35	−21.23	55.20	132.25	168.20	+
SPCE	Virgin Galactic Holdings, Inc.	−25.17	−48.81	−32.56	−32.99	46.81	+
SPY	**SPDR S&P 500 [ETF]**	**−11.28**	**−20.36**	**−1.15**	**14.08**	**26.04**	+
TQQQ	ProShares UltraPro QQQ [ETF]	−30.04	−52.29	−4.27	93.97	121.70	+
TSLA	Tesla, Inc.	−18.24	−35.24	20.78	219.45	383.11	+
UBER	Uber Technologies, Inc.	−14.25	−22.62	9.04	4.41	65.60	+
Mean		−15.80	−24.82	6.97	63.22	127.33	
Median		−13.98	−21.06	6.52	40.99	57.05	

nals shared by its authors. While there are some cases in which the community does not act like a "wise crowd", WSB's general setup, interactions, and enforced guidelines enable it to satisfy a sufficient amount of the criteria required to demonstrate *Wisdom of Crowds* and collective intelligence. We believe that our findings in this regard can be applied and generalized to similar finance-related communities that fulfill the same criteria as presented in Section 3.

We complement this qualitative evaluation with an extensive quantitative analysis to test the hypothesis of collective intelligence. Our results indicate that past signals on WSB could have lead to profitable investments on multiple levels, confirming the assumption of collective intelligence:

(1) WSB's discussions have focused mostly on sectors that performed better over the reviewed time frames than the S&P 500 index. Investing in these sectors, e.g., via an **exchange-traded fund** (**ETF**), and holding for a longer period similar to the time frame that we have analyzed would have yielded better results than the average market growth.
(2) A hypothetical portfolio created by mining the most frequently and consistently discussed stocks over multiple years has outperformed the most relevant market benchmark, the S&P 500 index, on average over the reviewed time windows. This indicates that the aggregated discussions within the community can act as a valuable source for picking stocks.

(3) An investment strategy following buy signals would have achieved higher average growth on the longer term than distributing investments equally or randomly over the same time window—while in the short term these strategies performed similarly. This suggests that the timing of the discussions and buy signals is relevant and valuable, as they have exhibited predictive power by leading to increased profits in comparison to time-independent investing in the same stocks.
(4) Distinguishing signals as proactive or reactive helps in achieving even more successful outcomes on average as well as in the short term. Moving averages constitute a simple heuristic for this distinction. This is a matter that we will investigate further in future work, as we expect a significant performance uplift when being able to successfully select proactive posts that inherently possess larger predictive power.
(5) The observed tendencies were amplified by WSB's strong growth and the success of *meme stocks* in 2021, but they can still be found in a weaker form when only considering earlier data, corroborating the above results. Even when the significant profits of GameStop are excluded, the WSB portfolio outperforms the market benchmark on the reviewed time frame. This indicates that the success of WSB's signals is not merely caused by the success of a few single *meme stocks*, but the results of a systematically substantiated financial capability.

Overall, these results suggest that an investment-focused social community such as WallStreetBets can indeed serve as a source of valuable investment advice. Although care needs to be taken to identify promising signals among the posts, e.g., by aggregating signals and filtering for posts with a proactive nature, WSB and similar communities constitute a freely accessible alternative to other sources such as financial news outlets or individual experts on Twitter. While retail traders can leverage WSB as a source of financial knowledge and entertainment, professional investors may benefit from regular visits by learning about trending topics and stocks as well.

The comprehensive approach that we demonstrate can be generalized to evaluate the value of similar finance-related online communities. When applying our methodology to other communities, we recommend a two-step approach to firstly investigate whether the criteria for collective intelligence are fulfilled and secondly adopt our approach of extracting and evaluating investment signals. In this process, it is important to avoid evaluating single posts and instead create a (daily) consensus of signals by aggregating all posts within the time frame—this reduces the noise of outliers while also agreeing with collective intelligence theory, which advocates the analysis of a group's consensus or average opinion. Furthermore, it is important to understand the nature of the community that is investigated: for example, only a part of their posts may be relevant for extracting investment signals, they may utilize specific "insider" terms and phrases to express certain things, and some may have strict guidelines that prevent or discourage interactions and discussions to such an extent that the community is not able to exhibit collective intelligence. The example of WallStreetBets has shown that, while the nature of their interactions may often be vulgar and eccentric, the relatively low amount of moderation allows the users to voice their opinions and criticize other users' opinions freely, resulting in a better selection of high-quality investment signals. With these results, we contribute a new perspective on how to acquire information from social media for generating valuable insights and aim at motivating further research on the diverse and interesting communities of the Reddit platform. In future work, the specific way WSB is moderated and its impact on the community's ability to exhibit collective intelligence could be investigated further through a detailed comparison to other finance-related subreddits.

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