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Herding in Financial Markets:

Evaluating Leadership Signal Mechanisms Behind Meme Stock Phenomena on Social Media

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An abstract of
a thesis submitted to the Faculty of Emory College of Arts and Sciences
of Emory University in partial fulfillment
of the requirements of the degree of
Bachelor of Science with Honors

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Abstract

Evaluating Leadership Signal Mechanisms Behind Meme Stock Phenomena on Social Media
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This study investigates leadership signals based on r/WallStreetBets data from August 2020 to September 2021, and then supplements it with a between-group experimental design to draw causal inference between one leadership signal (leader popularity) and audience tendency in conducting herding behaviors. The observational study reveals statistically significant outperformance (benchmark Russell 1000 and Fama French model) of portfolios derived from two leadership signal mechanisms that indicate the appearance of herding behaviors based on leadership signals among r/WallStreetBets retail investors during that time period. However, in spite of the initial hypothesis of drawing causal inference between leadership popularity and people's herding tendency in the experimental setting, we fail to find statistically significant results and surprisingly find opposite correlations compared to our initial hypothesis. This may be the result of several contributing factors, including, but not limited to, the timing of the data, attention-driven stock picking tendencies, and source credibility evaluations, that are different between r/WallStreetBets retail investors and our experiment participants.

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Introduction

Over the past 50 years, retail investor trading has changed significantly. Most recently, the commission-free mobile app Robinhood, along with other fintech brokerage platforms, has dramatically increased the number of retail investors participating in the financial market. Historically, due to the limitation of resources and also the scattered purchasing patterns by individuals, retail investors have had little power in driving dramatic changes in stock prices. However, this situation ended when an unprecedented short-squeeze of the stock GameStop happened. Retail investors started to discuss stocks (later called 'meme stocks') on the Reddit forum r/WallStreetBets. They gathered together to act against hedge funds and other financial institutions with their huge accumulated buying power. This led to tremendous losses among many hedge funds that were holding short positions on those meme stocks. Thus, r/WallStreetBets acts as an information platform for retail investors to get together and share their investment information quickly and effectively. In this way, r/WallStreetBets can be a great data source to observe and analyze the herding behaviors of retail investors.

When an individual tries to make decisions in the financial market (e.g. stock purchases), there is often an incorrect assumption that they will stick to their own information and act accordingly. However, in reality, people, at many times (if not most of the time), choose to act according to others' actions instead of their own information. This phenomenon is known as 'herding effect'. As defined by Bikhchandani, Hirshleifer, and Welch (1992), the herding effect refers to the idea that, when people have both public information and private information for their decision making, they may choose to ignore their private information and act according to public information, even when the public information contradicts their private preferences. For financial markets, herding by investors in the equity market is found to be one of the most frequent behavioral biases (Kumar and Goyal, 2015), and is found in both developed (Christie and Huang, 1995; Hwang and Salmon, 2004) and emerging markets (Kim and Wei, 2002; Chang et al., 2000).

Even though the herding effect is a well-discussed topic in behavioral economics, previous studies usually quantify people's decision-making processes with the Bayes Nash Equilibrium (Banerjee, 1992) and assume people are all rational thinkers. However, this fails to incorporate the complex cognitive evaluating process people have – and how, in most cases, people are not rational. People can think heuristically when the problem becomes uncertain (Avery and Zemsky, 1998) and ambiguous (Ford et al., 2005), e.g. in many of the typical situations found in the equity market.

This study utilized a data-driven approach on r/WallStreetBets to detect whether herding effects happened based on leadership signals (leader sentiment, leader perceived popularity, and leader efforts) and the intensity of those signals, and then supplemented the observational study with a between-groups experimental economics design, with the primary objective of establishing leadership signals' causal influence on retail investors' herding behaviors. To detect herding behaviors, the observational study benchmarked the leadership-signal-based WallStreetBets portfolios with general market index Russell 1000 and the updated 5-factor asset pricing model Fama French (Fama and French, 2015). After finding significant outperformance of two leadership signal metrics, we proceeded with a stock simulation game via survey format to see if, in an experimental setting, we could draw causal inference between leadership signals and investors' decisions. The treatments were the number of followers of the account (@RoaringBunny) that discusses a hypothetical stock Moonlight Pizza, and the dependent variable was the amount of money the participants are willing to invest in the stock after seeing the Twitter Post from @RoaringBunny.

Our results show that, between August 2020 and September 2021, r/WallStreetBets retail investors had a strong tendency to conduct herding behaviors upon the leadership signals (from WSB influencers' messages). The herding behaviors happened in the majority through r/WallStreetBets investors' timing selections of the purchased meme stocks. Moreover, two out of the seven leadership signals have more influence on the herding behaviors of r/WallStreetBets investors compared to the other signals. Last but not least, it is very likely that r/WallStreetBets retail investors have different investment evaluation processes about leadership signals compared to general retail investors based on our experimental study.

The study makes several contributions to the literature. First, previous research found evidence of good performances of WSB portfolios (Buz and Melo, 2021) but, to my knowledge, has not yet investigated the mechanisms behind the strong performance. Also, our experimental design of the stock simulation game mimics real-life situations with social media investment messages and investment motivation, which adds to previous understanding of retail investors as well as of the influence of leadership signals on top of the classic herding effect experiments. From a practical perspective, the results of this study will contribute to a better understanding of features (leadership-signal related) of meme stocks and decrease unnecessary loss due to herding bias in the future.

In the following sections, we first give a quick background of meme stocks and r/WallStreetBets for readers not familiar with the issue. Then, we review previous literature on related works in Section 2. Section 3 introduces the data and our methods for both observational and experimental studies. Section 4 presents the empirical results and Section 5 discusses our results and several interesting and surprising findings outside of our initial hypothesis. Section 6 reflects on our consideration of the designs and also points out potential future research directions. Section 7 presents our conclusion.

Background about r/WallStreetBets and Meme Stocks

Reddit is a social media website that has communities (known as subreddits) dedicated to a variety of themes, including humorous memes, politics, relationship advice, individual sports teams, and video games, among many others. The subreddit r/WallStreetBets was founded at http://www.reddit.com/r/wallstreetbets on January 31, 2012. On January 1, 2019, there were roughly 450,000 subscribers; at the time of writing, there were approximately 12,700,000.

After the community focused discussions on a series of stocks that were in part deemed undervalued while simultaneously exhibiting a high short interest ratio (the ratio of shares being shorted by financial institutions), WSB saw an unprecedented rise in popularity and news coverage in January 2021. Short-selling a stock stands for borrowing shares of a stock in order to sell them right away with the intention of repurchasing them at a cheaper price later, which is frequently used on companies that are overpriced and projected to fall in value in the near future. The trend was formed even earlier in August 2020, when Ryan Cohen, Chewy’s founder, bought 9% of GME stock, which sparked discussions in WSB and gave the community confidence in purchasing their previously discussed stocks. In January 2021, Ryan Cohen joined GME’s board – having outlined at the end of a 2020 letter that GME had a great customer base but lacked an online platform, i.e. one in which his expertise would be able to bring change. This set a milestone on the WSB community, with the community reacting by saying “everything is ready”, and “it’s time.”

While discussions of potentially undervalued investment opportunities with growth potential are common in investment-focused online communities, the fact that institutional investors were shorting the GameStop stock led to the situation being portrayed as an ideological battle between retail investors and institutions like hedge funds: by buying and holding the stock, its price could be driven up, forcing financial institutions to buy and hold the stock.

This made r/WallStreetBets a place where the larger Reddit community could come together to form a movement, driven by the prospect of large financial gains through risky investments, with the added appeal of allegedly furthering the greater cause of punishing financial institutions, particularly hedge funds. In the following sections, we define popular stocks discussed on the r/WallStreetBets forum as ‘meme stocks’, to be in line with how generally people think of “meme stocks.”

Literature Review

2.1 Financial Herding Behavior (Informational Cascade) as a Phenomena

Evidence of the failure of rational expectations and market efficiency assumptions has called into question traditional herding effect theories. An informational cascade arises at time when informed people act independently based on their own signals (i.e., private information). In other words, herding behaviors happen when a person chooses to follow public information even when it contradicts their private information. Bikhchandani, Hirshleifer and Welch (1992) and Banerjee (1992), who coined the term 'informational casacade', observed that it can be perfectly rational from an individual point of view to ignore one's private information. BHW's and Banerjee's information cascade pioneer the explanation of the herding behavior mechanisms. These two theoretical literature stems from an mathematically elegant, yet cognitively challenging implementation of Bayes' rule. Given the Bayes' rule, $P(A|B) = \frac{P(B|A)\,P(A)}{P(B)}$, the participants' rational decision under the experimental setting should be herding with other people, and thus explains the existence of herding behaviors in their experiments. Anderson and Holt (1997) discovered evidence of informational cascades in the laboratory setting and interpret their findings as indicating that individuals made rational decisions. Research has also shown that informational cascades are fragile and can be upset easily by the arrival of new public information (Bikhchandani et al. 1992).

Not all research on informational cascades arrives at the same conclusion. Huck and Oechssler (2000), for example, reported on an experiment designed to find out whether observed informational cascades are indeed due to rational Bayesian updating suggested by previous studies and found little support to it. They confronted their subjects with related single-person decision tasks and found that the simple heuristic 'follow your own signal' did much better in explaining their data than Bayesian rationality, which brings other factors into consideration of the herding theory. Noth and Weber (1999) designed an experiment that has almost the same setup as the one by Anderson and Holt except that there were two different signal qualities. They also found that, when decisions are difficult, subjects primarily follow their own signals rather than making decisions according to Bayes' rule, which also contrasts with previous studies.

Zooming in on an informational cascade specifically in the financial market, Christie and Huang (1995) showed that herding is not an important factor in determining equity returns during periods of market stress. Hwang and Salmon (2004) later challenged Christie and Huang's study. They believed that Christie and Huang failed to find herding during market crises given that herding has often turned down before a crisis comes about and represents a flight to fundamentals. In other words, macro factors do not explain herd behaviors.

The previous debate about herding effects spurred numerous new discussions as well as the developments of a new quantitative model trying to more accurately portray the herding effects in the financial market. Previously, BHW's informational cascade model limited its explanatory power by assuming the asset prices to be exogenous. Avery and Zemsky (1998) proposed an endogenous price model to solve this problem and prove that herd behavior may distort the stock price if there is not only value uncertainty but multi-dimensional uncertainty. If there is value uncertainty, event uncertainty, and composition uncertainty, a short-term price bubble may come into existence. Decamps and Lovo (2003) studied the impact of risk aversion on herd behavior and found that herd behavior may occur when market makers and traders have varying degrees of risk aversion. Ford et al. (2005) apply CEU (Choquet-Expected Utility) to deal with ambiguity and identified the relationship between ambiguity aversion and herding behavior. They found that price deviation from the fundamental value will not typically persist for long, even though there can be short-term bubbles. Dong et al. (2010) pointed out that most of the existing models on herd behaviors had overlooked the impact of ambiguity on investors' decisions. Their numerical simulation found that herd buying behavior mostly occurs at the peak of stock prices.

2.2 Identifying Potential Roots

In identifying the roots of this phenomena, several mechanisms have been investigated by researchers. Individuals' investment decisions are inevitably influenced by others. Convergent behaviors like herding can be caused by agents' observations of predecessors' actions (Cipriani and Guarino, 2008) or the observation of the aggregate consequences of actions such as the market price (Avery and Zemsky, 1998; Cipriani and Guarino, 2008).

Herding behavior can be built up through direct communication in a social network (Ellison and Fudenberg, 1995). In financial market settings, the market can be more efficient or more volatile, often determined by the quality of the informed agents' signals, whether these are authentic or useless (Bommel, 2003).

Another factor researchers have considered to explain herding behavior is ambiguity. Herding can also be driven by irrational motives. People have difficulty making decisions when the quality of the information signal is unknown (Epstein and Schneider, 2008). Social psychology research has shown that people are more likely to follow others to feel more confidence into their decision making process when facing ambiguous information (Vaughan & Hogg, 2005). These studies combined might explain why investors have a higher tendency to mimic actions of their peers. The effect is especially strong for retail investors when their private signals are usually of unknown quality and they have ambiguous judgement about the quantity and quality of their signals compared to other more experienced market participants.

There have been several other mechanisms that have been studied already by the researchers, such as how herding effects increase with fear (Economous et al. 2018) as well as the influence of group identities on the herding effect in a laboratory setting – people are more likely to follow an ingroup rather than an outgroup member's choice (Berger et al., 2018).

2.3 Past Studies, Factors & Solutions

1. Retail investors' behavioral finance vs. professionals'

The lack of commission fees as well as the simplicity involved reduce the costs and barriers to investing in the stock market nowadays, and that brings in more retail investors to the money game. Studies focused on retail investors' behaviors touch on how inexperienced stock investors are more heavily influenced by attention (Seasholes and Wu, 2007) and by biases that lead to return chasing (Greenwood and Nagel, 2009). Also, according to research, Robinhood investors engage in more attention-induced trading, and intense buying by Robinhood users forecasts negative returns (Barber et al. 2021).

WallStreetBets-focused studies include research on the social dynamics within the WSB community that contributed to the meme stock hype (Lyócsa et al., 2021; Semenova and Winkler, 2021), as well as research on the concept of retail investors battling Wall Street (Lyócsa et al., 2021). Other research looked at the financial processes behind the price increase (Aharon et al., 2021), the impact of retail investors on prices and volatility, and their involvement in transactions (Aharon et al., 2021).

For finance professionals, Lin (2018) paid special attention to herding in financial analysts and found that professional managers like stock analysts are not immune to the effects of herding instincts (Clerment & Tse, 2005). There are several rational reasons why analysts herd besides information cascades, including reputation-based (Graham, 1999) and compensation-based herding (Chakrabarti & Roll, 1999; Scharfstein & Stein, 1990).

2. Natural Language Processing and Financial Predictions

Natural language processing is a subfield of using quantitative methods (e.g. artificial intelligence) to program computers to process and analyze large amounts of natural language data. It has been a heated topics in recent year, and there has already been a lot of developments in both the natural language processing model and case studies in analyzing financial market data with the help of textual analysis. In this study, specifically the observational study section, we used the natural language processing tool to process textual information in Reddit.

1) Text classification (RoBERTa model)

Text classification is a fundamental topic in natural language processing, and several machine learning algorithms have been investigated throughout history. In shallow learning models, there have been text representation approaches such as Bag-of-Words (BOW) (Wallach, 2006), term frequency-inverse document frequency (TF-IDF) (Zhang et al., 2005), or word2vec (Bhatta et al., 2020). These models process the raw input text into a simpler representation that is easier to classify. Beyond these models, there are deep learning models like neural networks that automatically learn high-level features from data, and these models yield better results than shallow learning models. Basic deep learning architectures for text classification are Feed-Forward neural networks, Convolutional Neural Networks (CNN), Recurrent Neural Networks (RNN), and attention mechanisms. Most of the research consists of improving or merging these basic architectures to improve text classification algorithms' performances on benchmark datasets.

The development of BERT architecture (Bidirectional Encoder Representations from Transformers) (Devlin et al., 2018) was a milestone in the NLP field. It makes use of Transformer, an attention model (Bahdanau, Cho, & Bengio, 2014) that uses contextual relations between words to learn robust representations that can be re-used for downstream tasks. On top of BERT, there are new models trained on different sets of labelled training data to obtain good performing sentiment classification models for different needs. For example, there is FinBERT (Araci, 2019), which is trained on financial data like annual and quarterly reports released by public companies, and RoBERTa (Liu et al., 2021), which is specifically trained on social media data, including considerations of trending internet slang as well as emojis, since part of their underlying training corpora contains Reddit data (38GB) – specifically the web content extracted from URLs shared on Reddit with at least three upvotes. Specifically, we used RoBERTa which is found to be most suitable due to the nature of its training data.

2) Financial predictions using sentiment analysis

Studies on sentiment-analysis-based financial predictions have majorly divided into three different focuses: market, scope, and documents. For different markets, a couple of studies investigate on companies included in the S&P 500 Index (Lee et al., 2014; Ding, Zhang, Liu, & Duan, 2015; Rekabsaz et al., 2017) or pay attention to different stock exchanges, like the NASDAQ (Grant & Conlon, 2006). Meanwhile, other scholars committed their research to companies within specific sectors. For example, Kloptchenko et al. (2002) focused specifically on telecommunication sectors. Some of the studies may concentrate on specific companies such as Apple Inc. (Joshi, H. N, & Rao, 2016). For different scope, the covered time period largely varies in existing studies. For example, some of them focus on a longer time period (more than 5 years) (Rokabsaz et al. 2017), while others focus on shorter-term (Kloptchenko et al., 2002; Grant & Conlon, 2006).

For documents, two major categories of research focus are on news articles from different sources like Bloomberg and Reuters (Ding et al. 2015), and company-generated sources that contain textual information like annual and quarterly reports. Several research studies have focused on 10-K (and 10-Q) reports that are mandatorily published by publicly-listed U.S. companies (Kloptechenko et al., 2002; Grant & Conlon, 2006).

Though not a major trend, due to the spike of meme stocks in 2021, there have been new studies focusing on social media's impact on stock performances. Buz and Melo (2021) developed a portfolio consisting of all posts from January 1, 2019, to April 4, 2021, on WallStreetBets and found that the activities on r/WallStreetBets could have served as profitable investment advice on multiple levels. The difference of this study compared to previous ones is that the study is not based on sentiment but rather based on counting transaction-related words that occur in the context of the ticker mentions, specifically 'buy', 'hold', 'sell', 'call', 'put' and similar words. Another line of work focuses on the ties between social media sentiment and financial predictions. According to research, significant links are found between social media sentiment and macroeconomic indicators like consumer confidence (Daas and Puts 2014). Also, research has found that general social media mood may influence a company's stock performance (Yu et al. 2013). Extensive research has been conducted to demonstrate how specific social media cues may be used to forecast stock price fluctuations (Duz Tan and Tas 2021; Nguyen et al. 2015; Sul et al. 2017). Another area of research focuses on the many types of interactions that may be found on current internet platforms. Specifically for social media, emotional statements have been found to transmit information swiftly (Stieglitz and DangXuan 2013).

2.4 Looking forward: the Study at Hand

Building off the previous studies regarding herding effect in the financial market, it is shown that simple mathematical updating of Bayes' rule finds it hard to catch people's investment behaviors, as people are not rational at all times. Thus, it is important to incorporate the psychological aspect to better portray what influences people's herding decisions.

Based on previous studies on herding effect mechanism, our study evaluates how leadership signals play a role in influencing the audience's decisions in herding phenomena. Specifically, we narrow our lenses to the Reddit forum r/WallStreetBets and limit the investment horizon from August 2020 to September 2021, which is the year that the idea of meme stocks was introduced to the public and when the spike of prices happened in meme stocks. The most closely-related work is of Buz and Melo (2021); it does not include sentiment analysis as well as the other metrics we include in our following analysis, but uses transaction words to build WallStreetBets portfolios. The motivation of us choosing to focus on leadership signal is to evaluate the process of how people form herding behaviors. The potential motivation behind people's herding behaviors is that they believe in the intelligence of the group/authority, and believe they are less likely to be wrong to follow trustworthy others' signals compared to acting as an individual, which makes leadership signal mechanism an interesting angle to look at the issue.

Regarding our contribution to the herding mechanism studies, our experimental study mimics real life situations in the financial market as much as possible, including financial incentives for participants to make their best investment decisions, compared to previous experimental designs that have focused on more general herding mechanisms (Banerjee, 1992), but are likely not fully transferable to the financial market setting. In addition, in our study, we will focus on leadership signals' (e.g. influencer popularity) influence on the herding effects, which have not been explored by any of the previous studies. For studies focused on leadership signals, the closest one by Wang and Wang (2018) investigated information manipulation by gurus (i.e. leaders) that cannot be directly observed by followers. In our study, since we are analyzing social media leaders' influences, the announcements by the gurus in both observational and experimental studies are transparent and permit direct communication to their followers, which is another layer of difference compared to historical studies. Generally speaking, our study will improve understandings of the herding effects, adding additional layers of people's cognitive evaluation of information and heuristic thinking process, rather than assuming everyone is rational (Banerjee, 1992). Also, our result can show the possibilities of multiple factors that will influence the leadership signal mechanism. Practically speaking, our findings may help detecting certain features of the newly appeared "meme stocks" based on herding effect theories, and decrease potential loss due to herding bias.

Research Questions:

1. *Is the WallStreetBets portfolio outperforming?*

   (Is there performance value in a strategy that trades on herding?)

   As investors' investing decisions are not transparent and there is no direct data reflecting people's decisions, we observe the price of the stocks in the portfolio and calculate return, since we believe the aggregate price of the market reflects general market decisions in investing in certain stocks.

2. *Is the return explained by the market? Do we have significant alpha based on our portfolio signals?*

   (What is the herding mechanism behind the promising returns of WallStreetBets portfolios? What herding mechanism creates the best signal?)

   Based on the result from question 1, we cannot isolate the signals and the influence we get from the general market movements, thus, through answering question 2, we will be able to catch the investment alpha of the signals that cannot be explained by the market fundamentals.

3. *Is high social media popularity causing people to herd?*

   Based on the result from question 2, we cannot draw a causal inference out of the observational data from the WallStreetBets forum. Thus, we conduct an experimental study with a survey of 300 participants in an effort to derive causal inference out of the result and prove the causal relationship between leader popularity and herding behavior.

Methodology

3.1 Observational Study

3.1.1 Data Acquisition

The dataset was collected with a script accessing the official Reddit API: PRAW (Boe, 2014). The script allows requesting data from subreddit exports into JSON format. The dataset spans from August 01, 2020 to September 30, 2021 (in total, 425-day duration), which is the time we concluded the data collection process for the observational study. We define this time period as “meme stock era”, representing the hype of meme stocks that was a well-known phenomenon on the market. It is worth discussing whether the phenomenon is still taking place, especially after the correction of pandemic stocks such as e-commerce stocks in January and February. We will leave this discussion to a later section of this research.

We believe this dataset covers a sufficiently long time span to analyze the activity on WSB during the meme stock hype. Due to PRAW API’s limitation, we are only allowed to scrape down top/hot/recent posts categorized by Reddit. We choose to scrape down maximum numbers of top posts possible in the history, in this case, 975 entries, from r/WallStreetBets. The top posts are selected by the Reddit system based on the score (i.e., net upvotes), which we believe may serve to reduce noise, and will not lose the significant value of earlier time (like posts in 2020) compared to using the hot or recent post feature. Additionally, we use other service code of PRAW so that all redditors from each post, the posts’ first comment as well as all of its replies (on average 10 per post, thus we have roughly 10*975 datapoints) are extracted by additional codes respectively. We acknowledge the risk of using the top posts rather than a full representative set of posts. However, the Pushshift service, which is another API service we considered using, usually deviates in the upvote scores and thus makes the score substantially lower than the true value. Since we will be using upvotes as one of the testing signals, we need more accurate data on upvotes. In that way, we chose to stick to the official PRAW API. Despite the limitation of our access to the full dataset, the PRAW service provides us a valuable source for historical posts and other post features that may otherwise be non-trivial to collect.

3.1.2 Data Analysis Plan

1. Extracting Leadership Signals

We used a mix of R and python codes in the data analysis in our observational study. Based on our research questions, in order to detect signals out of the original JSON file, we took several further steps illustrated below to process data. In the end, we got 7 signals to run the 7 oscillators, which output 7 different monthly updated portfolios based on those oscillators. For a better understanding of what each signal stands for, we will first describe how we derive the data for 7 signals. The chart in Appendix 5 illustrates the information we could get out of one post.

1) *Sentiment signal*
   For all of the textual information in the reddit forum, we used natural language processing analysis, specifically the RoBERTa dictionary to derive sentiment scores for each entry of the textual data. The output were to be inclusive {positive, neutral, negative} of sentiment scores, all scaled between 0 and 1. We used the difference between positive and negative scores to calculate the sentiment, quantified as posdiff = positive - negative, which we believed capture both the positive and negative linguistic elements in the text and should be the most representative way to show the overall sentiment of the text. We use the sentiment signal to see if people are more

likely to herd when the author of the post is more emotional in the content he/she writes, as well as if that evokes more emotional reaction from the audience (the comment sentiment).

a. Title sentiment:
   We directly used the title data scrapes from PRAW.
b. Comment sentiment:
   For each post, we scraped down its comments with additional PRAW codes. Due to the limitation of our device's computational power, we were able to scrape down only the top 1 comment under each post along with all of its replies (on average, 10). We then wrote and applied a flattening algorithm to flatten the comment and its replies into a single vector and added them back to the original dataset. The flattened vector included tickers mentioned in the comment as well as the sentiment for each discussed ticker (derived by running RoBERTa on the sentence that the ticker has been mentioned).
c. Post sentiment:
   I. Self-text:
      The original text in the post, we directly used the self_text data scraped from PRAW.
   ii. Picture:
      Memes are PNG or JPEG files usually included in the post content. To get a sense of what is discussed in the meme, we extracted all of the JPEG and PNG format files through PRAW from r/WallStreetBets original posts, and then used the text detection feature of *Amazon Rekognition* to get the textual data out of the pictures and cleaned the data to be useful for our study. *Amazon Rekognition* is based on proven, highly scalable, deep learning technology developed by Amazon's computer vision scientists to analyze billions of images and videos daily.

2) *Upvote signal*
   We used the score, which stands for the net upvotes (upvotes - downvotes), scraped from the PRAW API. There were two different upvote signals, the first one was the upvote for tickers in the post, which we recognized the tickers in a post and then associated the post's upvotes with it; the other signal was the upvote for tickers in the comments, for which we recognized the tickers in the comments and, in the same way, we associated the post's upvotes with it. We used the upvote signal to see if people are more likely to herd when the author has more people agree with him/her on that specific post.

3) *Karma signal*
   We ran additional codes on PRAW API to derive redditors' data for each post. We combined link karma and comment karma to get combined karma which we will use in our study. Reddit's link karma was calculated as: users gain one point of link karma when another user votes up their submission and lose a point when a user votes down their submission. Similar concepts apply for comment karma, which is the karma point cumulatively calculated based on the votes the user received on their historical comments. Even though karma feature is unique on Reddit, we believe it is similar to the "follower" feature on other social media platform like Twitter or Instagram, reflecting popularity of the account user. We used the karma signal to see if people are more likely to herd when the author is historically more popular.

4) *Post length signal*
   We wrote word_count code on self_text to obtain the post length signal. Some of the posts were purely a meme without any text in it, while some of them were very long and, most of the time, analytical. We used the post length signal to gauge if people are more likely to herd on posts that

are lengthier (which may also stand for more efforts of the author compared to the more meme-ish ones).

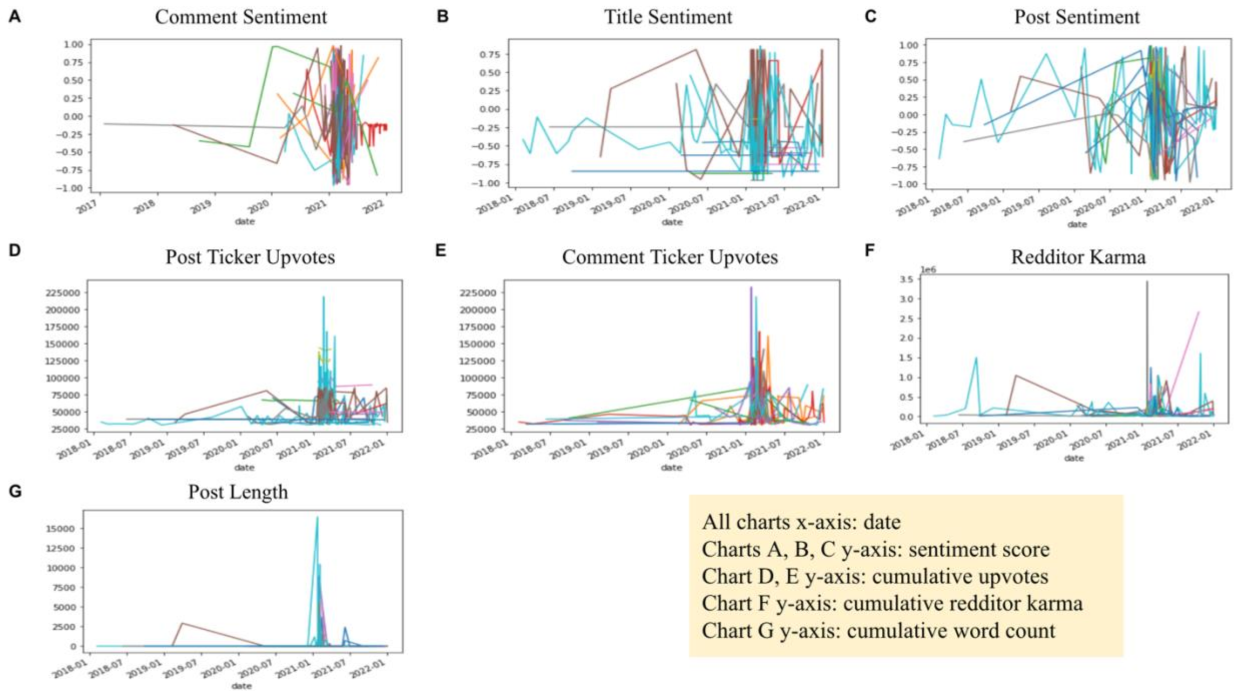

Fig. 1. The variation check of 7 leadership signals in r/WallStreetBets

Notes: 1) Graph A-G, each picture shows variations for one leadership signal: comment sentiment, title sentiment, post sentiment, post upvote, comment upvote, redditor karma, post length, respectively;
2) Each color line indicate one ticker in the WSB ticker universe

As the graph above has shown, all of the signals have good variations, so that we were able to proceed to our next step with all 7 signals, to develop portfolios as well as run regression on the returns of all strategies.

2. Detecting Tickers

Each stock can be identified by its ticker, which is usually an abbreviation related to the company's name or main product (e.g. GME for Gamestop). These tickers are conventionally written in capital letters and sometimes preceded by dollar sign '$'. We used both of these criteria to gather Reddit WSB tickers and to build an universe dictionary, and then manually went through the dictionary to remove misidentified tickers or meme words in order to have more accurate ticker universe which we adopted in our study.

3. Developing WallStreetBets Signal Portfolios

PERMCO

DATE	COMNAM	TICKER	PERMCO
2012-05-07	PHILIP MORRIS INTERNATIONAL INC	PM	52978
2017-02-02	TESLA INC	TSLA	53453
2015-01-02	ADVANCED MICRO DEVICES INC	AMD	211
2004-06-10	MICROSOFT CORP	MSFT	8048
2020-02-24	VIRGIN GALACTIC HOLDINGS INC	SPCE	56082
2017-01-03	R H	RH	54265
2019-11-08	N I O INC	NIO	56508
2012-02-21	MICROVISION INC WA	MVIS	14931
2020-03-26	DUPONT DE NEMOURS INC	DD	56027
2017-10-16	BLACKBERRY LTD	BB	16396
2020-09-30	PALANTIR TECHNOLOGIES INC	PLTR	57309
2020-03-27	GAMESTOP CORP NEW	GME	42775
2020-03-19	AMAZON COM INC	AMZN	15473
2017-03-22	ALIBABA GROUP HOLDING LTD	BABA	55003
2013-12-18	A M C ENTERTAINMENT HOLDINGS INC	AMC	54665
2004-06-10	CENTER BANCORP INC	CNBC	14751
2014-01-22	INTERNATIONAL BUSINESS MACHS COR	IBM	20990
2017-03-24	NOKIA CORP	NOK	30453
2014-01-08	GENERAL ELECTRIC CO	GE	20792
2017-12-28	APPLE INC	AAPL	7
2017-01-26	CATERPILLAR INC	CAT	20408
2010-01-11	KOSS CORP	KOSS	2573
2004-06-10	NEW YORK TIMES CO	NYT	21280
2020-11-11	SUNDIAL GROWERS INC	SNDL	56866
2020-05-01	TORONTO DOMINION BANK ONT	TD	29152
2004-06-10	BED BATH & BEYOND INC	BBBY	11558
2019-08-22	CREDIT SUISSE GROUP	CS	42125
2017-02-02	TESLA INC	TSLA	53453
2020-09-23	CORSAIR GAMING INC	CRSR	57341
2020-05-28	JPMORGAN CHASE & CO	JPM	20436
2020-02-26	PUBLIC STORAGE	PSA	4289
2020-06-08	APHRIA INC	APHA	56575
2020-11-18	M P MATERIALS CORP	MP	57062
2020-04-01	TILRAY INC	TLRY	56465

Fig. 2. The r/WallStreetBets ticker universe and corresponding CRSP PERMCO codes

We detected tickers through capital letters, and then manually walked through all of the sequential capital letters to eventually derive the WallStreetBets ticker universe shown above. Here are all of the tickers discussed in all top posts in r/WallStreetBets from August 10, 2020 to January 01, 2022, with their PERMCO code from the Center for Research in Security Prices (CRSP) US Stock Databases. We filter out CRSP data for this universe which we care about, and through coding to get returns by time-slice (daily).

oscillator_karma

date	GME	DD	PM	TSLA	IBKR	RH	UWMC	AMC	MP	MMC	ENPH	GE	PLTR	BB	EL	TD	CNBC	CS	NOK	PRPL	BMW
2020-08-01	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA
2020-09-01	LONG	LONG	LONG	LONG	LONG	LONG	LONG	LONG	LONG	NONE	NONE	NONE	NONE	NONE	NONE	NONE	NONE	NONE	NONE	NONE	NONE
2020-10-01	LONG	LONG	LONG	LONG	LONG	LONG	LONG	LONG	LONG	NONE	NONE	NONE	NONE	NONE	NONE	NONE	NONE	NONE	NONE	NONE	NONE
2020-11-01	LONG	LONG	LONG	LONG	LONG	LONG	LONG	LONG	LONG	NONE	NONE	NONE	NONE	NONE	NONE	NONE	NONE	NONE	NONE	NONE	NONE
2020-12-01	LONG	LONG	LONG	LONG	LONG	LONG	LONG	LONG	LONG	NONE	NONE	NONE	NONE	NONE	NONE	NONE	NONE	NONE	NONE	NONE	NONE
2021-01-01	LONG	LONG	LONG	LONG	LONG	LONG	LONG	LONG	LONG	NONE	NONE	NONE	NONE	NONE	NONE	NONE	NONE	NONE	NONE	NONE	NONE
2021-02-01	LONG	SHORT	LONG	SHORT	LONG	LONG	SHORT	LONG	SHORT	LONG	LONG	LONG	LONG	LONG	SHORT	SHORT	SHORT	SHORT	SHORT	NONE	NONE
2021-03-01	LONG	SHORT	SHORT	SHORT	SHORT	LONG	SHORT	LONG	LONG	LONG	LONG	SHORT	SHORT	SHORT	LONG	SHORT	LONG	SHORT	SHORT	LONG	LONG
2021-04-01	LONG	SHORT	LONG	LONG	SHORT	LONG	LONG	SHORT	LONG	LONG	SHORT	SHORT	SHORT	SHORT	LONG	LONG	LONG	SHORT	SHORT	NONE	SHORT
2021-05-01	LONG	SHORT	LONG	LONG	LONG	SHORT	LONG	SHORT	LONG	LONG	SHORT	SHORT	SHORT	LONG	SHORT	LONG	LONG	SHORT	SHORT	NONE	SHORT
2021-06-01	LONG	SHORT	LONG	SHORT	LONG	SHORT	LONG	SHORT	SHORT	LONG	SHORT	SHORT	LONG	LONG	SHORT	LONG	LONG	SHORT	LONG	NONE	SHORT
2021-07-01	LONG	SHORT	SHORT	SHORT	SHORT	SHORT	SHORT	LONG	SHORT	LONG	LONG	SHORT	LONG	LONG	LONG	LONG	LONG	SHORT	SHORT	NONE	LONG
2021-08-01	LONG	LONG	SHORT	SHORT	SHORT	SHORT	LONG	LONG	SHORT	LONG	SHORT	SHORT	LONG	LONG	SHORT	LONG	LONG	SHORT	SHORT	NONE	LONG
2021-09-01	SHORT	LONG	SHORT	SHORT	SHORT	SHORT	LONG	LONG	SHORT	LONG	LONG	SHORT	LONG	LONG	SHORT	LONG	LONG	SHORT	SHORT	NONE	LONG
2021-10-01	SHORT	LONG	SHORT	SHORT	SHORT	SHORT	NONE	LONG	SHORT	LONG	LONG	SHORT	LONG	LONG	LONG	LONG	LONG	SHORT	SHORT	NONE	LONG
2021-11-01	LONG	LONG	SHORT	SHORT	SHORT	SHORT	NONE	LONG	SHORT	LONG	SHORT	SHORT	LONG	LONG	LONG	LONG	LONG	SHORT	SHORT	NONE	LONG
2021-12-01	LONG	SHORT	SHORT	SHORT	SHORT	LONG	NONE	LONG	SHORT	LONG	LONG	SHORT	SHORT	LONG	LONG	LONG	LONG	SHORT	SHORT	NONE	LONG
2022-01-01	SHORT	SHORT	LONG	SHORT	SHORT	SHORT	SHORT	LONG	SHORT	LONG	SHORT	SHORT	SHORT	LONG	LONG	LONG	LONG	SHORT	LONG	LONG	LONG

Fig. 3. The oscillator of the redditor karma signal (leadership popularity signal)

The graph above is an example of an oscillator for karma signal. Each day, we (to be more accurate, our code) observe every ticker in the universe, over the set period of time (one month). A value that is the weighted average of sentiment, or the upvotes, or the karma of the redditor who post content, or the length of the post associated with that ticker. Then, we code for an oscillator rule. Every month, we look at our portfolio and then rank the stocks in terms of their respective signals. The oscillator then outputs "buy" and "short" signals based on the ranking. In the next month, we make trades (to mimic the predictive process of buying a stock). Based on our different trials of possible combinations of buying and selling strategies, we recognize that take actions only on the long/buying signals create the best performances. Our finding of trading WallStreetBets signals with only 'long' actions leads to the best performance is consistent with the result of Buz and Melo (2021) based on their transaction-words-based WallStreetBets portfolio strategy.

Our final step is to test the performance of our portolios based on different leadership signals, as well as running regression to see if we have significant alpha out of the 7 strategies. We run the portfolios performance that benchmark with both the general market index Russell 1000 and Five-Factor Fama French models. More details will be discussed in the 'Results' section.

3.2 Experimental Study: A Survey Design

An online survey experiment was developed to focus on manipulating leadership popularity signal – in this case, followers – to see its effect on herding behaviors. We tested it with a 3-group (with low, mid, high followers) between-subjects design. Participants (N=249) were randomly assigned to one of the three possible conditions, in which the Twitter account that publishes a post has a different number of followers. After viewing the Twitter feed, participants were asked about their investment decisions: how much they were willing to invest and what were their predictions of the MLP stock price after 2 weeks. (*Survey example attached to Appendix 1*)

3.2.1 Participants

Two hundred and forty-nine participants from the United States were recruited to participate in the study using the crowdsourcing website, *Amazon Mechanical Turk* (Buhrmester et al. 2011). Each participant was paid 1 dollar for his or her participation in the study. The study was approved by the Institutional Review Board at Emory University. All participants provided informed consent on an online questionnaire before participation. Participants were 55% male with ages spanning from 24 to 78. MTurk samples, like the one used in this study, generally do not reflect the composition of the US population but do demonstrate greater variability in terms of respondent age and race than traditional college-student samples (e.g. Paolacci et al. 2014).

3.2.2 Procedure

1. Stock Simulation task

a. Stimuli

Participants were exposed to a series of stimuli intended to simulate what retail investors usually encounter on Yahoo finance and on a social media feed. Participants were shown a price chart (of a hypothetical stock Moonlight Pizza) and then asked to browse a Twitter feed that said the MLP stock should be at $100 based on his valuation. We chose to use Twitter instead of Reddit as stimuli for two reasons. First, during our pilot study, the pilot study participants reflected their concerns about how some of them were not familiar with the karma feature on the Reddit forum. As Mechanical Turk participants do not represent the specific population familiar with Reddit, we decided to use more straightforward information like the followers feature on Twitter to represent leadership signals. Second, Twitter has a more researched distribution of account followers based on previous studies (Bakshy et al., 2011) and online data simulations, which we will discuss more in the treatment conditions.

b. Treatment condition

The treatment condition was developed based on the distribution of followers of different accounts on Twitter. Twitter has never released account follower distribution in company's public documents, but many studies have tried to investigate the numbers in previous years. Academic research by Bakshy et al. (2013) investigates the distribution of Twitter account followers in 2009, while in the same year Jon Bruner (2013) published his study that random sampling of about 400,000 Twitter accounts in 2013, which we believe is the most recent reference about Twitter account distribution we can get access to. In our study, we used the median, 99 percentile, and 99.9 percentile of active Twitter accounts, which indicated having 61 followers, 2991 followers and 24964 followers respectively. The participants were randomly assigned one of the three treatments with equal chance (33.33…%). As shown in the picture below (figure 4), everything, except for the follower of the @RoaringBunny (indicated by the point the yellow arrow points at), looks the same.

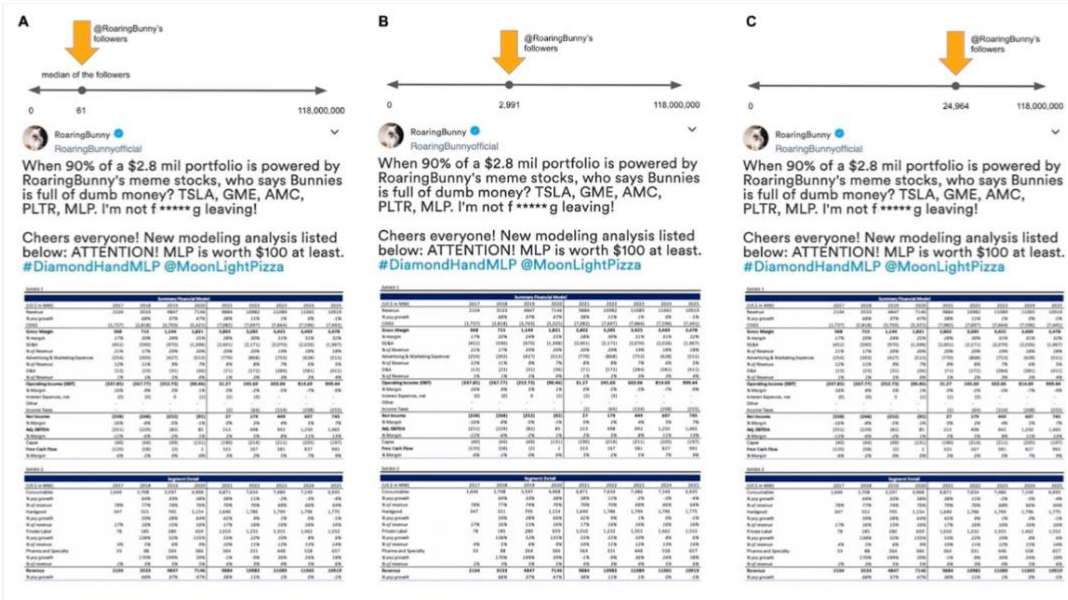

Fig. 4. Three different level of leadership popularity signal treatments (61 vs. 2991 vs. 24964 followers)

Before the post, we also showed the participants general statistics about the overall follower distribution (max, min and median) so that the participants had a general idea about how the distribution of Twitter followers of all accounts looked like, and where @RoaringBunny's follower was. For more details, please refer to appendix 1. After seeing the price chart and @RoaringBunny's post, participants were asked about how much money out of $10,000 they were willing to invest $MLP, and we used it as the dependent variable in the regression analysis. We believe amount invested more accurately reflect retail investors' investment decisions than other variables because, in general, retail investors are less familiar with technical terms like price target (appendix 2). Also, the stock prices are eventually determined by the quantity of buying and selling actions on the market, so the amount invested variable depicts investors' investment decisions more directly.

2. Demographics and post-decision questionnaire

To avoid skewing participants' decisions in the stock simulation game investment decisions, we left all other questions about their demographic background as well as their previous exposure to the issue to the end of the survey.

a. Demographic measurements

After the stock simulation game, participants were asked to report their age, gender, income, job relevance to finance, as well as two classic risk tolerance questions (Charness et al., 2013) that measured their risk tolerance level.

b. Other covariate measurements – exposure to the issue

Participants were asked to report their time exposure to Reddit and social media in the previous week. We chose a week as the measurement unit since it was easier for participants to remember, but, at the same time, capturing the variations of participants' different daily activities among different days in the week (e.g. weekdays vs. weekend). Also, participants were asked whether they had heard about meme stocks before or not.

c. Other reactions to the stimuli

Besides amounts of money (the dependent variable in our study) they were willing to invest in $MLP, participants were also asked about their feelings about the post: how credible they found the post content to be; how likely they would be to hit ‘like’ under the post. We added these two questions in the survey to give us more insight about participants’ feelings towards different leadership signals, and hoped to see if that can give us any insight on why they make certain investment decisions in the analysis process.

3.2.3 Data Analysis

Data analyses were conducted on RStudio Version and Python, using an alpha level of $p<0.05$ (we also show other significance level: $p<0.1$, $p<0.01$ in all of the regression analysis tables). Descriptive statistics were first calculated for all relevant variables, followed by an analysis of variance (ANOVA) test to assess if investment amount varied across the three treatment groups. Since the ANOVA result was out of our expectations, we wanted to be more confirmed and accurate about our results. Thus, on top of the ANOVA test, we conducted a regression analysis between each of the treatment groups and the control group: we compared between two groups, and checked for any statistical difference between x with respect to the location of the mean.

Notes: For Quick References of all experimental survey collected variables, please see Appendix 6.

Results

4.1 Observational Study

4.1.1 Preliminary Analysis: WallStreetBets Signals Returns vs. Russell 1000

Prior to formal hypothesis testing, it is important to establish the returns of the eight signals and to gauge how “successful” each portfolio performs based on different signals. For most of the signals (Figure 5. A-F), the returns reflect significant successful returns compared to market benchmark Russell 1000. We chose Russell 1000 as a benchmark index because the meme stock companies not only have mega-size companies but also include numerous small-to-mid-cap companies, which makes Russell 1000 an ideal benchmark.

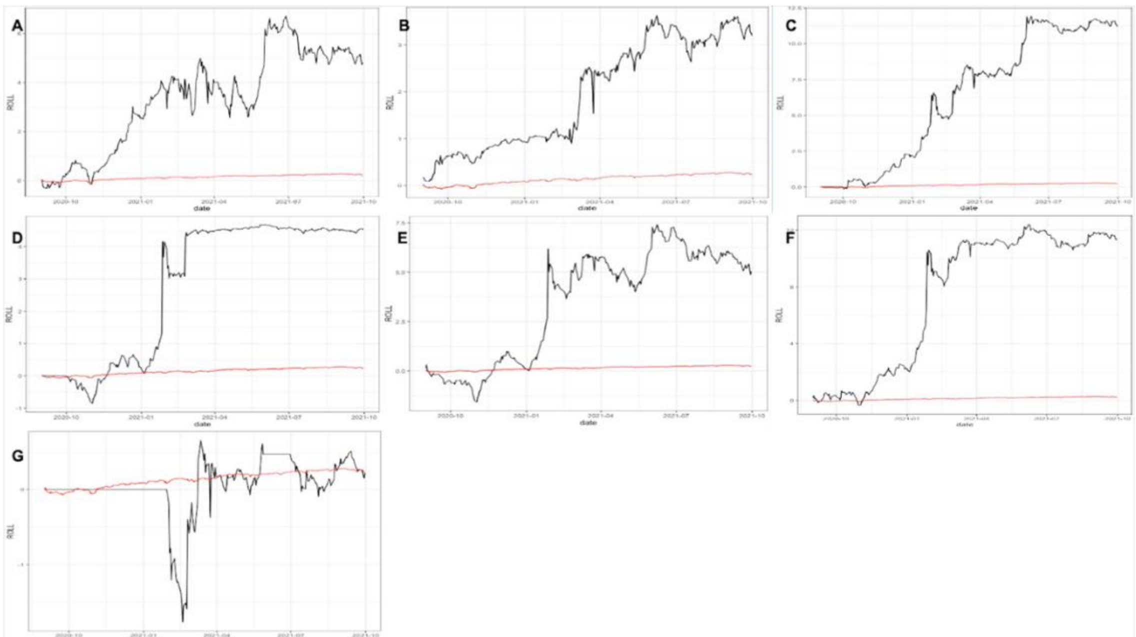

Fig. 5. Portfolio returns of 7 portfolios developed on 7 leadership signals in r/WallStreetBets

4.1.2 Primary Analysis: Looking for WallStreetBets Strategies’ Alpha

1. WallStreetBets Strategies Returns vs. Russell 1000

Table 1: Sentiment Strategies Regression Results

	Dependent variable:		
	STRATRET		
	comment sentiment	title sentiment	post sentiment
	(1)	(2)	(3)
BENCHRET	9.909*** (7.377, 12.440)	5.137*** (3.974, 6.299)	3.531** (0.905, 6.156)
Constant	0.009 (−0.015, 0.033)	0.007 (−0.004, 0.018)	0.038** (0.013, 0.063)
Observations	273	273	273
Note:			*p<0.1; **p<0.05; ***p<0.01

Table 2: Upvote Strategies Regression Results

	Dependent variable:	
	STRATRET	
	upvote (post ticker)	upvote (comment ticker)
	(1)	(2)
BENCHRET	−1.293 (−3.313, 0.726)	3.154 (−0.147, 6.456)
Constant	0.018 (−0.002, 0.037)	0.016 (−0.016, 0.047)
Observations	273	273
Note:		*p<0.1; **p<0.05; ***p<0.01

Table 3: Other Signal Strategies Regression Results

	Dependent variable:	
	STRATRET	
	karma	post length
	(1)	(2)
BENCHRET	1.167 (−2.529, 4.862)	1.600** (0.529, 2.672)
Constant	0.041* (0.006, 0.076)	−0.003 (−0.013, 0.007)
Observations	273	273
Note:		*p<0.1; **p<0.05; ***p<0.01

To quantify previous return graphs with statistical results, a simple regression test was run to compare the return of the WallStreetBets signal portfolios and the return of investing in the Russell 1000 index over a one-year investment horizon. Refer to tables above, the result shows post sentiment signal and redditor karma signal are statistically significant [with C.I (0.013, 0.063), (0.006, 0.076) respectively], indicating that the return of these two portfolios cannot be purely explained by the market movements.

2. WallStreetBets Strategies Returns vs. Fama French Factors

Table 4: Sentiment Strategies Regression Results

	Dependent variable:		
		STRATRET	
	comment sentiment	title sentiment	post sentiment
	(1)	(2)	(3)
MktRFA	0.076*** (0.054, 0.097)	0.044*** (0.033, 0.055)	0.019 (−0.004, 0.042)
SMB	0.081*** (0.047, 0.114)	0.041*** (0.024, 0.058)	0.079*** (0.043, 0.115)
HML	−0.050*** (−0.077, −0.024)	−0.004 (−0.017, 0.010)	−0.061*** (−0.089, −0.033)
RMW	−0.114*** (−0.158, −0.071)	−0.019 (−0.041, 0.003)	−0.054* (−0.101, −0.008)
CMA	0.165*** (0.111, 0.218)	0.030* (0.004, 0.057)	0.256*** (0.199, 0.313)
Constant	0.007 (−0.013, 0.027)	0.005 (−0.005, 0.014)	0.034*** (0.013, 0.055)
Observations	273	273	273
Note:			*p<0.1; **p<0.05; ***p<0.01

Table 5: Upvote Strategies Regression Results

	Dependent variable:	
	STRATRET	
	upvote (post ticker)	upvote (comment ticker)
	(1)	(2)
MktRFA	−0.016 (−0.035, 0.004)	0.013 (−0.016, 0.041)
SMB	0.023 (−0.007, 0.053)	0.088*** (0.044, 0.133)
HML	−0.028* (−0.052, −0.005)	−0.072*** (−0.106, −0.037)
RMW	−0.019 (−0.058, 0.020)	−0.092*** (−0.150, −0.035)
CMA	0.174*** (0.126, 0.222)	0.343*** (0.273, 0.414)
Constant	0.016 (−0.002, 0.033)	0.011 (−0.015, 0.037)
Observations	273	273
Note:		*p<0.1; **p<0.05; ***p<0.01

Table 6: Other Signal Strategies Regression Results

	Dependent variable:	
	STRATRET	
	karma	post length
	(1)	(2)
MktRFA	−0.010 (−0.041, 0.022)	0.007 (−0.003, 0.018)
SMB	0.099*** (0.050, 0.148)	0.033*** (0.017, 0.049)
HML	−0.103*** (−0.141, −0.064)	−0.021*** (−0.034, −0.009)
RMW	−0.061 (−0.124, 0.002)	−0.023* (−0.043, −0.002)
CMA	0.432*** (0.354, 0.510)	0.052*** (0.027, 0.078)
Constant	0.037** (0.008, 0.065)	−0.004 (−0.013, 0.006)
Observations	273	273
Note:		*p<0.1; **p<0.05; ***p<0.01

MktRFA The return spread between the capitalization weighted stock market and cash.
SMB The return spread of small minus large stocks (i.e., the size effect).
HML The return spread of cheap minus expensive stocks (i.e. the value effect).
RMW The return spread of the most profitable firms minus the least profitable.
CMA The return spread of firms that invest conservatively minus aggressively.

The previous regression results serve more like a teaser for a more comprehensive regression model which regresses on Fama French factors here. The same results are supported by the Fama French 5-factor regression. The Fama French 5-factor model is an asset pricing model that expands on the capital asset pricing model by adding size risk, value risk, profitability risk and investment risk to the market risk factors. The most recent 5-factor model was developed by Nobel laureates Eugene Fama and his colleague Keneth French (Fama & French, 2015). The model is essentially the result of an econometric regression of historical stock prices, and this is the reason why we believe it may be a good regressor to check if our WallStreetBets Strategies have alpha outside of market beta. As the result has indicated, it is consistent with the results benchmark with Russell 1000 index: post sentiment and redditor karma are statistically significant [with C.I (0.013, 0.055), (0.008, 0.065) respectively] in its regression to Fama French factors, indicating we have found market alpha with the two strategies based on these two signals.

4.1.3 Secondary Analysis: Correlations Between Post Sentiment/Redditor Karma Factor with 5 Fama French Factors

Table 7: Post Sentiment: Fama French Factors Regression Results

	Dependent variable:					
	MktRFA	STRATRET	SMB	HML	RMW	CMA
	(1)	(2)	(3)	(4)	(5)	(6)
STRATRET	0.351 (−0.083, 0.785)		0.589*** (0.320, 0.858)	−0.752*** (−1.096, −0.407)	−0.253* (−0.468, −0.037)	0.666*** (0.518, 0.814)
MktRFA		0.019 (−0.004, 0.042)	0.200*** (0.140, 0.260)	−0.220*** (−0.299, −0.142)	0.079*** (0.030, 0.129)	−0.022 (−0.059, 0.016)
SMB	0.500*** (0.349, 0.651)	0.079*** (0.043, 0.115)		0.756*** (0.652, 0.860)	−0.483*** (−0.546, −0.421)	0.098*** (0.040, 0.157)
HML	−0.335*** (−0.455, −0.216)	−0.061*** (−0.089, −0.033)	0.460*** (0.397, 0.524)		0.292*** (0.238, 0.347)	0.164*** (0.121, 0.208)
RMW	0.319*** (0.120, 0.518)	−0.054* (−0.101, −0.008)	−0.779*** (−0.880, −0.678)	0.773*** (0.629, 0.917)		0.267*** (0.196, 0.337)
CMA	−0.158 (−0.427, 0.112)	0.256*** (0.199, 0.313)	0.283*** (0.115, 0.452)	0.777*** (0.572, 0.981)	0.477*** (0.351, 0.602)	
Constant	0.064 (−0.027, 0.156)	0.034*** (0.013, 0.055)	0.001 (−0.058, 0.059)	0.050 (−0.024, 0.125)	0.019 (−0.027, 0.065)	−0.032 (−0.066, 0.002)
Observations	273	273	273	273	273	273
Note:						*p<0.1; **p<0.05; ***p<0.01

Table 8: Redditor Karma: Fama French Factors Regression Results

	Dependent variable:					
	MktRFA	STRATRET	SMB	HML	RMW	CMA
	(1)	(2)	(3)	(4)	(5)	(6)
STRATRET	−0.097 (−0.416, 0.222)		0.398*** (0.200, 0.596)	−0.659*** (−0.905, −0.413)	−0.152 (−0.310, 0.006)	0.551*** (0.452, 0.650)
MktRFA		−0.010 (−0.041, 0.022)	0.216*** (0.157, 0.276)	−0.235*** (−0.312, −0.158)	0.073** (0.024, 0.123)	−0.003 (−0.039, 0.032)
SMB	0.540*** (0.391, 0.690)	0.099*** (0.050, 0.148)		0.746*** (0.643, 0.848)	−0.490*** (−0.552, −0.429)	0.084** (0.028, 0.140)
HML	−0.369*** (−0.489, −0.248)	−0.103*** (−0.141, −0.064)	0.468*** (0.404, 0.533)		0.293*** (0.238, 0.349)	0.170*** (0.129, 0.212)
RMW	0.296** (0.096, 0.496)	−0.061 (−0.124, 0.002)	−0.792*** (−0.892, −0.692)	0.755*** (0.612, 0.897)		0.245*** (0.178, 0.313)
CMA	−0.027 (−0.309, 0.256)	0.432*** (0.354, 0.510)	0.265** (0.088, 0.442)	0.856*** (0.647, 1.065)	0.480*** (0.347, 0.612)	
Constant	0.080 (−0.011, 0.172)	0.037** (0.008, 0.065)	0.007 (−0.052, 0.065)	0.048 (−0.025, 0.121)	0.016 (−0.030, 0.062)	−0.028 (−0.061, 0.004)
Observations	273	273	273	273	273	273
Note:						*p<0.1; **p<0.05; ***p<0.01

Inspired by perspectives shared by co-founder of AQR Cliff Asness (2014), we regressed the monthly returns on each of the factors in the Fama French model, also added our newly-found statistically significant signals: post sentiment and redditor karma signals.

Focusing on the first row on each table, for post sentiment, it is positively correlated with size factor, and investment factor, while negatively correlated with value and profitability factors; for redditor karma factor, it is positively correlated with size factor and investment factor, while negatively correlated with value and profitability factor (we only focus on significant results here).

4.2 Experimental Study

In the survey experiments, we were able to collect 249 responses through the Amazon Mechanical Turk system. We incorporated sample mean value for all of the NA values so that we did not drop any of values in our experimental analysis. The majority of the NAs happened in demographic questions, and for dependent variables in our study, there were, on average, single digit NAs. We list more details of NAs in Appendix 4. We chose this approach rather than deleting all responses with any NA, because, for many of the responses, the participants missed one or two demographic questions since we considered research ethics and did not force participants to answer any question. Getting rid of all responses with any NA will shrink our responses significantly. In addition, we chose to use mean value over median to represent the overall distribution of the non-NA values after we carefully examined the distributions of the non-NA values of each variable: they were generally symmetrical, and with no clear outliers. Based on the distributions, we believed mean value is more representative, thus better to use in this case. At the end of the survey, we used one validation check question (“what is the company the post discussed?”) to check the percentage of participants who had paid attention to the study, and found the correct response rate be 92.7% (231/249).

4.2.1 Preliminary Analysis: Demographic info of participants

Participants were 55% male, 79% of them were with annual income below $75,000. Their ages spanned from 24 to 78, but majority of their age range was between 30 and 46 (63%). 46% of them said their work is not related to finance at all, with most of the participants ranking their work as having low relevance to finance (scale 1-3). Also, one survey question was designed to understand subjects' previous exposure to meme stock, and we were surprised to find that near half (48%) of the participants had never heard about meme stocks before. For more details about the demographic information of participants, please refer to Appendix 4.

4.2.2 Primary Analysis: Investment Decisions - Amount as Dependent Variable

We initially planned to use participants' predicted price as dependent variable, but later changed it to the amount of money participants were willing to invest as the dependent variable to quantify their investment decision. One main concern we had of using price as dependent variable was that the significant outliers we found based on the responses we collected on the price question reflected the potential that retail investors might not think of investment decisions in terms of price target. It is very likely that they did not understand the question, and we did not want misunderstanding of the question to bias our findings. For more details about why we thought amount would be a better dependent variable for our study, please refer to Appendix 2. For all of the dependent variable in the primary analysis below, we are discussing the amount invested as dependent variable. We also applied top coding, which changes all the investment amount responses above $10,000 to $10,000. Our question asked if they have $10,000, how much they would be willing to invest, so that it sets an upper limit as $10,000. Top coding is a common and allowed practice in statistics (2005).

1. One way ANOVA

We defined control groups, mid-follower treatment group, and significant-follower treatment group as the groups exposed to @RoaringBunny's account with 61, 2991, and 24964 followers respectively. For control group (M = 3359.15, SD = 357.15), mid-follower treatment group (M = 2856.45, SD = 326.05), and significant-follower treatment group (M = 2384.70, SD = 245.71), we first ran a one-way ANOVA test on amount dependent variable to see if there is any significant difference among the three groups in their investment decisions. The F-statistics is 2.307 with degree of freedom of 2, showing a probability above F (Pr > F) being 0.102 which failed to reject the null hypothesis. Thus, we found no evidence that any of the groups is significantly different from each other's investment amount dependent variable, and in turn, how leadership signal will influence retail investors' investment decisions.

2. Regression

Since the result was non-significant and we could not draw causal inference for all three groups, we wanted to run regression analysis with the two treatments to see the relationship between leadership signals and retail investors' investment decisions for control group vs. treatment1 and control group vs. treatment2. Thus, we ran a simple regression first with the two treatment as dummy variables (mid-follower group $Z_1 = 1$ and significant-follower group $Z_2 = 1$). We acknowledge the most accurate regression model currently available for analysis may be Augmented Inverse Propensity Weighted (AIPW) regression (Glynn and Quinn, 2010), but there is no need for this study to run AIPW regression, since we randomly assigned the participants in each of the groups. As shown in the table below, only the Z_2 treatment group has significant regression results: the investment amount significantly decreases as the @RoaringBunny's account has much more followers.

Table 9: Survey Experiment Investment Amount (not controlled) Regression Results

	Dependent variable:
	unlist(invest_amount)
Z_1	−502.703 (−1,237.132, 231.726)
Z_2	−974.449** (−1,723.691, −225.207)
Constant	3,359.155*** (2,806.099, 3,912.211)
Observations	249
Note:	*p<0.1; **p<0.05; ***p<0.01

3. Regression (controlled for covariates)

Table 10: Survey Experiment Investment Amount Regression Results

	Dependent variable:
	unlist(invest_amount)
Z_1	−366.297 (−1,116.979, 384.386)
Z_2	−830.628* (−1,608.899, −52.356)
age	−5.943 (−37.176, 25.289)
finance_rel	257.717** (73.723, 441.710)
rain	−199.956 (−487.188, 87.276)
days_reddit	−20.886** (−37.508, −4.264)
hours_media	36.938* (4.882, 68.994)
memeYN	−604.033 (−1,243.319, 35.252)
gender_Woman	12.569 (−627.040, 652.177)
income_0	3,069.147 (−2,395.742, 8,534.035)
income_between0and14999	−673.389 (−3,476.771, 2,129.993)
income_between100000and150000	751.448 (−2,167.158, 3,670.055)
income_between15000and29999	−711.875 (−3,508.031, 2,084.282)
income_between30000and49999	−37.540 (−2,859.130, 2,784.051)
income_between50000and74999	−335.897 (−3,164.492, 2,492.699)
income_between75000and99999	−4.423 (−2,916.246, 2,907.400)
income_over150000	−761.861 (−3,987.227, 2,463.505)
Constant	3,874.217* (596.965, 7,151.468)
Observations	249
Note:	*p<0.1; **p<0.05; ***p<0.01

We found heterogeneous treatment effects from the previous regression, showing that for mid-follower treatment, it has no effect, while for significant-follower treatment, it has negative effect on participants' investment decisions. We ran another regression then, including control for all other independent variables (e.g. demographic, previous exposure to Reddit and meme stocks). We no longer found Z_2 treatment to be statistically significant at $p<0.05$. Thus, we cannot draw causal inference about leadership signals' effect on retail investors' investment decisions based on our experiment.

We were surprised at the result, since a lot of the times, when the researchers controlled for other variables, the previously significant result should be even more significant. We thus hypothesized that the investment decision differences between groups were to be explained by other metrics, and we wanted to draw attention to the correlations between other independent variables with participants' invested amount in MLP stock.

We acknowledge that, for sections below, we cannot draw causal inference from this study without randomnized assignments on these variables, but we just want to show results about correlations and provide some insights for future researchers. We found finance relevance significantly and positively correlated to the investment amount while days spent on Reddit in the previous week have significantly negative correlation with the amount invested. Also, we found age, risk tolerance level (the lower the number in the survey, the more conservative is the participant) and previous exposure to meme stock to be negatively correlated with the investment amount, while hours spent on media in the previous week and self-identified as woman to have positive correlation with investment amount willing to put in MLP. For more implications of these demographic correlations, please refer to our discussion section.

4.2.3 Secondary Analysis: Explore other reactions as DV besides investment amount

Inspired by Jin et al. (2021) who wrote about different variables' effect on social media perceived credibility, we wanted to give more insights about leadership signals' impact on participants' psychological reactions towards the post. We used two other dependent variables, credibility and hit_like, to learn more about how participants feel about the content posted by @RoaringBunny at different account-follower levels. The credibility variable includes participants' responses towards how much they found @RoaringBunny's post content credible, and hit_like variable is how likely they will hit the 'like' button under the post. The hit_like variable also serves as mediator variable, as more people are willing to hit the "like" button will lead to the post having more likes, and potentially the likes under post has effects on audience investment decision. The distributions of the two variables are shown below in figure 6, and they show heterogenous correlations. Thus, to quantify the correlation, we ran a regression analysis.

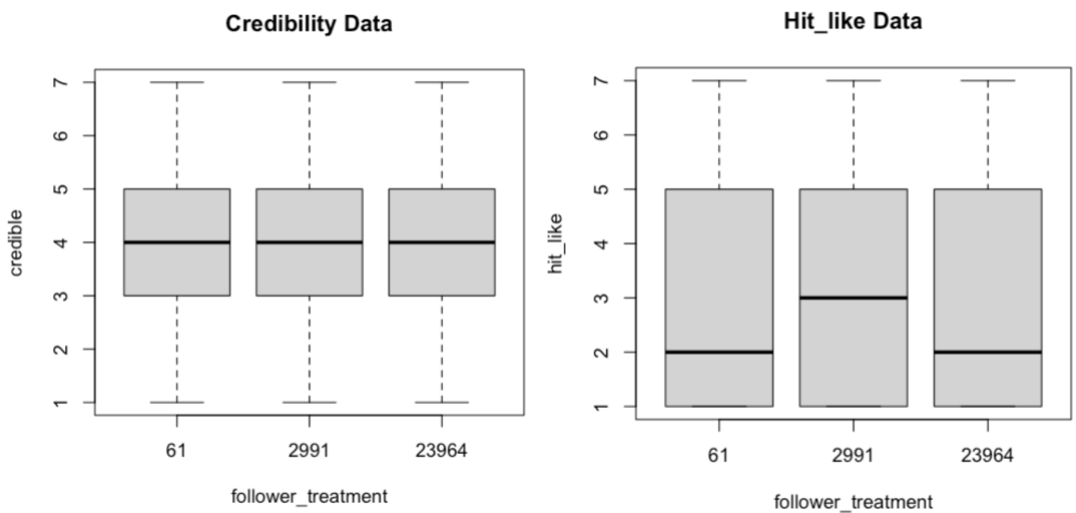

Fig. 6. The box plots of credibility and hit_like variables in the leadership popularity mechanism experiment

Based on the regression analysis, we found no significant relationship between the different follower treatments with either credibility or hit_like dependent variable. However, although not statistically significant, we did find negative correlation of leadership follower treatment with all three dependent variables we use in this study – investment amount, credibility, and hit_like. This gives us more insights about how participants generally have more negative reactions towards content released by @RoaringBunny (investment decisions and feelings) when @RoaringBunny has more account followers.

Table 11: Survey Experiment Regression Results

	Dependent variable:		
	unlist(invest_amount) $invest_{a}mount$	unlist(credibility) credibility	unlist(hit_like) $hit_{l}ike$
	(1)	(2)	(3)
Z_1	−366.297 (−1,116.979, 384.386)	−0.018 (−0.423, 0.387)	−0.020 (−0.526, 0.486)
Z_2	−830.628* (−1,608.899, −52.356)	−0.035 (−0.455, 0.385)	−0.092 (−0.617, 0.432)
age	−5.943 (−37.176, 25.289)	−0.002 (−0.019, 0.015)	−0.025** (−0.046, −0.004)
finance_rel	257.717** (73.723, 441.710)	0.300*** (0.201, 0.399)	0.425*** (0.301, 0.549)
rain	−199.956 (−487.188, 87.276)	0.035 (−0.120, 0.190)	0.053 (−0.141, 0.246)
days_reddit	−20.886** (−37.508, −4.264)	−0.007 (−0.016, 0.002)	−0.006 (−0.017, 0.005)
hours_media	36.938* (4.882, 68.994)	0.014 (−0.004, 0.031)	0.013 (−0.008, 0.035)
memeYN	−604.033 (−1,243.319, 35.252)	−0.594*** (−0.939, −0.249)	−0.357 (−0.788, 0.074)
gender_Woman	12.569 (−627.040, 652.177)	0.217 (−0.128, 0.562)	0.343 (−0.088, 0.774)
income_0	3,069.147 (−2,395.742, 8,534.035)	−2.506 (−5.454, 0.441)	−3.432 (−7.114, 0.249)
income_between0and14999	−673.389 (−3,476.771, 2,129.993)	−1.258 (−2.770, 0.254)	−1.698 (−3.587, 0.191)
income_between100000and150000	751.448 (−2,167.158, 3,670.055)	−1.344 (−2.918, 0.230)	−2.181* (−4.148, −0.215)
income_between15000and29999	−711.875 (−3,508.031, 2,084.282)	−0.957 (−2.465, 0.551)	−1.504 (−3.388, 0.380)
income_between30000and49999	−37.540 (−2,859.130, 2,784.051)	−1.323 (−2.845, 0.199)	−2.140* (−4.041, −0.239)
income_between50000and74999	−335.897 (−3,164.492, 2,492.699)	−0.844 (−2.370, 0.682)	−2.043* (−3.949, −0.138)
income_between75000and99999	−4.423 (−2,916.246, 2,907.400)	−1.281 (−2.852, 0.289)	−2.088* (−4.050, −0.126)
income_over150000	−761.861 (−3,987.227, 2,463.505)	−1.879* (−3.619, −0.139)	−2.452* (−4.625, −0.279)
Constant	3,874.217* (596.965, 7,151.468)	4.462*** (2.694, 6.230)	4.824*** (2.617, 7.032)
Observations	249	249	249
Note:			*p<0.1; **p<0.05; ***p<0.01

Discussion

There are several points in the observational study we want to highlight and discuss, which are included in *Discussion about the Observational Study*. After this section, we zoom into the experimental study, and want to find patterns and see what is the story and implications behind the seemingly contradicting results from the observational and experimental studies. We will call the section *Discussion about the Leadership Signals in the r/WallStreetBets*.

5.1 Discussion about the Observational Study

The first question we wanted to answer was whether people have herded or not on WallStreetBets. Research has found similar patterns between herding behaviors' deviated biases, and how institutional investors profit off of that (Viktoria, 2016). Meme stocks usually are selected from stocks that institutions want to short. In the observational study, as shown in the results section, we found all 7 leadership signal metrics to have largely outperformed portfolios. Thus, we believe that herding behaviors take place and lead to the meme stocks' price deviating from their fundamentals.

The next question we tried to answer through the observational study was – what are the trading signals that have the best performances? We first benchmarked them with the market index *Russell 1000*, and by eliminating the market beta, we wanted to see if there is significant alpha in the strategies. Then, we further confirmed our findings by regressing the portfolio strategies with the classic asset pricing model Fama French model (Fama & French, 2015). Specifically, the same 2 metrics, post sentiment and Redditor karma, have shown significant alphas which means part of these two portfolio strategies cannot be explained by the Fama-French model factors.

First, for sentiment metrics – title, post, and comments sentiments – some possible reasons can explain why the post metric has a significant alpha but not the other two sentiment metrics: comments are typically short replies to the topic presented in the submission, but are not as prominently displayed and not as carefully curated as submissions. They are very heterogeneous in terms of their information value. Also, if a comment provides substantial criticism or corrections, the authors of the original post may incorporate such information into the post through subsequent edits. On the other hand, titles are just too short to create significant impacts on the audience. Second, for two upvotes metrics, we find upvotes are more like mediators: when people herd, it then leads to they hit 'like' under the posts, and compromises the significance of statistical correlation. For the post length metric, the performance is not as good as other signals, and one of the main reasons is probably that on an online community known for being more on the "savage" side, the lengthy posts with detailed explanations are probably not welcomed.

In the secondary analysis, we evaluated the correlation between 2 significant leadership signal metrics with the 5 factors in the Fama French model. We found both the post sentiment strategy and the Redditor karma strategy to be negatively correlated with HML (value effect) and RMW (profitability effect), while positively correlated with SMB (size effect) and CMA (investment effect). To be more specific, these two metrics are positively correlated to small stocks and more conservatively invested stocks, while negatively correlated to more valuable and more profitable stocks: which fits into the general image of a meme stock.

Interestingly, as shown in the primary analysis, even for the statistically significant leadership signals, we found WSB portfolio returns can be largely explained by classic Fama French data, which means eventually these meme stock hype can be explained by the market. However, this could not explain why the WSB portfolios we developed based on leadership signal metrics had very impressive returns. For this phenomenon, we found one possible explanation, which is that people herd based on timing – the timing for a significant amount of Reddit retail investors to pick stock is what leads to the outperforming stock picking based on the WSB community information. The r/WallStreetBets forum acts as a medium/information platform for retail investors in the community to share their signals in a timely manner, and allow the information to spread very fast, even might be much faster than the general market. In this way, the portfolio returns are largely benefited through the spike in purchasing behaviors at a time earlier than the signal being realized by the general public.

Another possible explanation is how the leadership signals help the audience in the r/WallStreetbets community to narrow the stock universe. Research has shown that retail investors prefer attention-driven investment, have more reactions to sentiment, and thus are more likely to conduct repeat purchases (Barber et. al, 2020). Following this logic, the high return based on our signal metrics can be explained by a snowball effect, with an increasing number of audience influenced by increasing sentiment, repeatedly. This can also lead to significant outperformance of our leadership signal portfolios.

5.2 Discussion after looking at the Experimental Study

From the ultimate result of our experimental study, we failed to draw a causal inference, since the results for both treatments were not statistically significant. However, a surprising finding we got is that the leadership signal, in this case, the follower treatment, yields a negative correlation with the groups' investment decisions. People are less likely to invest in the stock $MLP if @RoaringBunny has more followers: this contradicts our initial hypothesis and contradicts with our findings from the observational study (the portfolios derived from leadership signals are significantly outperforming).

Combining the findings from both observational and experimental studies, we want to discuss several implications of the study. We found largely outperforming leadership signal metrics in the observational data, but failed to draw causal inference between follower-treatment leadership signal and investment decisions. The combined narrative is interesting and worth discussing.

Theoretically, during an informational cascade/herding effect, an informed trader makes the same trading decisions whatever signal he/she may receive: the probability of action is independent of the private signal (Cipriani and Guariano, 2008). The previous studies have also shown that a lack of confidence in the private signal will lead people to herd (Vaughan & Hogg, 2005). Based on these studies, our original hypothesis for the experimental study is that people will be more likely to herd when the post account has more followers (leadership popularity). In this study, we quantified herding behavior as investing more money in MLP. Especially since $MLP is a hypothetical stock, there are only two signals that exist in the world, and they do not have any other private information to make any further judgment. As a result, participants should make their decisions based on the two public signals available. We used the amount of money participants willing to invest as the dependent variable to measure their' investment decisions and then to give us insights into how retail investors are influenced by leadership signals to conduct herding behaviors.

The results of the study, however, paint a different story: first, when we control for all of the covariates, the result is no longer significant; second, when the followers of @RoaringBunny is substantially more than the control group, we find it has a negative correlation with the amount of money that the participants are willing to invest. In other words, when the account has more followers, people are less willing to invest in the $MLP stock. Below are some possible factors we think might contribute to the heterogeneous results from the observational (outperformance portfolios) and the experimental (negative correlation) studies. For experimental design reflections, please refer to our next section, *Design Considerations & Future Directions*. One thing we want to highlight here is that one of the covariate variable we included in the experimental study regression was people's previous exposure to Reddit. We used this question initially to factor out the influence of participants' previous exposure to r/WallStreetBets and meme stocks. However, since we used Twitter as the environment to mimic the leadership signal, this question may better be phrased as participants' previous exposure to Twitter, and this regressor could potentially distort our results for the experimental study. More details about future possible improvements on the designs are included in the *Design Considerations & Future Directions* section. For possible theoretical explanations, we discuss several points we consider to be most important below:

Attention-Grabbing Stocks The lack of observable true values of stocks leads people rarely talk about a stock's true value, and finance industry experts can easily justify the stock price by slightly changing in assumptions about future values. Viktoria (2016) found that investors' choices are based on beliefs and perceptions and can be influenced by "price-sensitive" information. According to Barber and Odean (2008), individual investors are net buyers of attention-grabbing stocks. This set the difference between the retail investors and institutional investors: even as both view the same price-sensitive information, institutional investors do pay full attention to it and are less influenced by attention-grabbing stocks compared to retail investors. For the stocks in our observational study, the r/WallStreetBets ticker universe is comprised of attention-grabbing stocks that become famous through the meme stock discussion (like GameStop). The attention-induced investment strategies of retail investors can explain our findings from the observational study and why the portfolios based on leadership signals significantly outperform. In our experimental study, however, 49% of the participants have never heard of meme stocks before and thus are less likely to be familiar with those stocks or pay attention to those stocks. In the r/WallStreetbets community, it will be a different story. People are familiar with those tickers as there were heated discussions in the forum, and their attention is more likely to be grabbed by those tickers. This may leads to the deviation in results for our observational and experimental studies.

Momentum Momentum is also a possible factor to explain the phenomenon. Value investing looks into long term performance while momentum is market reaction in a short period of time. Financial institutions always look at catalysts when it comes to investing, since the market gives valuable information about the optimal buying and holding time. r/WallStreetBets meme stocks, based on our observational study, had shown significant outperformance during the meme stock era with its leadership signals, and the dramatic increase in their stock values indicated strong buying momentum in the market. However, momentum is not a long term thing, and portfolios based on momentum usually do not generate persistent high performance. This is one of the reasons why, for several times, we reinforce the limitation of the time horizon for our observational study. The most recent 5 Factor Fama French model (Fama and French, 2015) gives us two leadership signals that could not be explained by the classic asset pricing model, so we believe the post sentiment and leadership popularity to be significant to the herding behaviors on meme-stock investing. However, momentum is not counted in that Fama French model. Cliff Asness (2014), for the first time, included momentum as one of the factors in his model, and has shown significant result. However, that article is not peer reviewed and does not reveal its Fama French factors data. If we have the chance to access Asness's Fama French data with the momentum factor and rerun the regression, it is possible that the two leadership mechanisms we found are no longer significant.

On the other hand, the characteristic of momentum being short term can explain why observational study yielded significant outperformance, while we failed to find positive causal relationship between leadership signals and investment decisions in the experimental setting. The time for the meme stock momentum is likely to already pass, and people are no longer interested in investing in them. Da et al. (2012) zoomed in momentum factor in financial market, and explained how continuously change in small amount in information induces strong persistent return continuation that does not reverse in the long run while discrete information yields opposite outcome. We hypothesize that r/WallStreetBets gave out discrete yet very intense signals during the meme stock era, which led to the significant outperformance during that time period (our observational study time horizon), yet reversed its effect post the meme stock era (our experimental study time horizon). Our hypothesis is also supported by the risky investing behaviors that r/WallStreetBets retail investors often conduct, as they are known for investing with leverage portfolios (e.g. options) which can also intensify the momentum's influence.

Timing differences, and the "meme stock era" Another possible explanation is the timing for our observational and experimental data are not the same. The timing is critical to the herding behaviors in the r/WallStreetbets and thus creates differences in the observational and experimental results. Viktoria (2016), in her perception alignment hypothesis, discussed how price-sensitive information media outlets must have the ability to reach a large number of investors in a short timeframe. In other words, relevance, credibility, and publicity need to be in place simultaneously. The r/WallStreetBets forum has all of the features above during the time between August 2020 and September 2021, which is the time span our observational study data comes from. We define this time period as the "meme stock era." However, the popularity of the forum decrease dramatically after the meme stock era, with its followers' monthly growth decreasing from 262% in February 2021 to 1.8% in February 2022 (calculated based on subredditstats.com). During the "meme stock era," some finance professionals even participated in the process even when they believed it makes no sense to them and they were just conducting gambling-like behaviors. This can reflect how popular the r/WallStreetBets was during that "era," and why the observational study portfolios have very impressive returns. Since we do not conduct a time series analysis, we cannot draw a conclusion for any time after September 2021.

In January 2021, due to the market self-correction and the change of interest rate, many pandemic stocks that were overly priced during the previous year have crushed, along with many meme stocks. This may hurt people's perceived credibility of r/WallStreetBets even more during the post-meme stock era. Bikhchandani et al. (1992) discovered that the informational cascades are fragile and can be upset easily by the arrival of new public information. The crush of the meme stocks in January 2022 during the market correction could be perceived as the negative signal that significantly hurt or even put an end to the herding behaviors in regards of meme stocks. Also, Berger et al. (2018) have shown that people are more likely to follow an ingroup rather than an outgroup member's choice. The drop in meme stock values in early 2022 may also crush the previous in-group identity of the meme stock investors in r/WallStreetBets, and further forbid us from extending the outperformance in the observational study to time span outside of the one-year meme stock era. This leads to our next bullet point, which discusses the dramatic drop in source credibility of the Reddit forum.

Source Credibility The observational study reflects the positive influences of r/WallStreetBets leadership signals. In the experimental study, the result tells a different story. We tried to mimic the real-life scenarios in social media, and limited the signals in the stock game to two public information, the price chart as well as the @RoaringBunny's post, to avoid noises; however, there might be implied private signals that already exist in participants' minds that lead to the contradicting results in the experimental study.

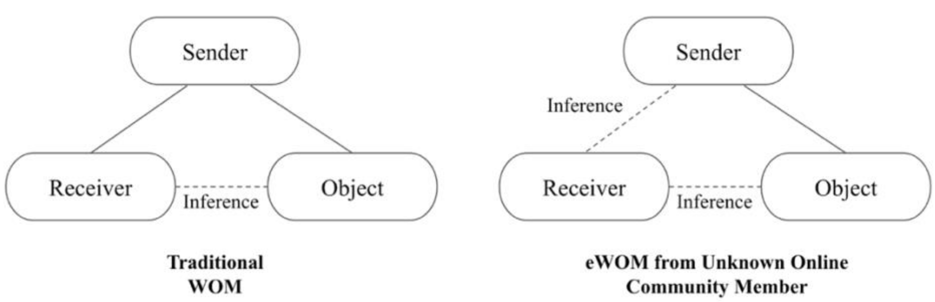

Fig. 7. Differences between traditional word-of-mouth (WOM) and eWOM from online community

Word-of-Mouth (WOM) referred to messages sent and received between people (Westbrook, 1987). Current day, with advanced technology, people shift from traditional WOM to electronic WOM (eWOM), which are communicated via the Internet, such as the r/WallStreetBets example in our study. As shown in the graph above, the big difference between WOM and eWOM is that in eWOM, receivers lack interpersonal knowledge about the sender. It requires the receiver to have an additional layer of inference about the credibility of the source to alter his/her attitude towards the object (Lim, 2014). The source may be perceived as credible because of his/her competence (ability) and trustworthiness. It has been found to play an important role in recipients' judgments of cognitive authority (Rieh & Belkin, 1998) and content usefulness (Sussman & Siegal, 2003). Relating back to our findings, how people perceive the r/WallStreetBets community matters. After the numerous news reports about the crush of meme stocks in January 2022, it is possible that our participants in the survey experiment develop their own private signal: their perception about the r/WallStreetBets forum. Based on our result, it looks like the perception is negative, which makes sense after the meme stock crush. Thus, the drop in credibility in the forum might lead to our experimental participants showing a negative correlation between the followers they saw of the @RoaringBunny account and the amount of money they are willing to invest in $MLP.

This leads to us thinking about we might need to distinguish WSB retail investors from general retail investors. As most of our participants report their jobs not relevant to finance at all and had no previous exposure to meme stocks, we suspect our sample in the experiment is not representative of the r/WallStreetBets community retail investors. Chiou et al. (2013) found that brand attachment can reduce the effects of negative online information on perceived negative change in the brand evaluation and perceived brand risk significantly. Extending to more general herding behaviors, Berger et al. (2018) designed a laboratory experiment and find that laboratory subjects are significantly more likely to follow an ingroup rather than an outgroup member's choice. Following the same logic, people who are in the community of r/WallStreetBets are more likely to decrease the perceived risks about the meme stock investments, and thus willing to conduct the "diamond-hands" behaviors suggested by the WSB influencers even when the risks about the investments are extremely high. This is probably a major difference between the r/WallStreetBets community and the experimental design participants in our study. The observational study's data is based on the WSB community, so it leads to significant outperformance. While the experiment participants are not in the WallStreetBets community, thus are unwilling to bear this significant risk. According to research, websites may be considered to be analogous to individuals as information sources whose characteristics engender greater or lesser credibility – and in general, the news resources like Wall Street Journal as perceived as more credible than special interest sites like Reddit (Flanagin et al., 2007). In addition, Cotte et al. (2005) conducted a cognitive evaluation of advertisements and suggested people can be reviewed as active and skeptical readers of the persuasion attempt in the textual content. So the general public outside of WSB may very likely not find any signal by @RoaringBunny to be credible at all. It is confirmed also by our experimental results, as most of the responses towards the credibility question clustered around score 1-3 (out of 7). Especially after the crush of meme stocks in early 2022, which is right before we released our experimental survey, the participants might even perceive more-follower @RoaringBunny's opinion more likely lead to the next bubble, and thus less willing to invest in the MoonLight Pizza Stock.

Design Considerations & Future Directions

6.1 Strength and Limitations

Strength First, the study adds novelty and relevance to the existing studies. We zoom in on herding behaviors that happen in the r/WallStreetBets community and find that WSB leadership signals do generate above-average returns between August 2020 and September 2021, which reflects the existence of herding behaviors on meme stocks. The portfolios based on leadership signals have not been studied before, and the specific WSB community is not well-explored by previous research yet. Second, we include advanced textual linguistic analysis models like RoBERTa to quantify the real life leadership signals in the r/WallStreetBets forum, which is also new to the field. In addition, the experimental design is polished. Our sampling method leads to a sample from diverse backgrounds and elicited a sample of 249 individuals. The design set-up, like the social media post simulation and how we related the participants' decisions outcome with their compensations, also is different from previous classic experiment on herding behaviors. We add on to the previous herding effect behavioral economic games by mimicing real life situations to specifically focus on decisions related to stock investment. We also include both quantitative (price and investment amount) and qualitative (credibility and willingness to hit like) measures. We use quantitative data as our primary dependent variable but the qualitative ones later help us explain the surprising results we derived from our research.

For the future use of this study, we extend academic understandings of mechanisms behind herding effects from a psychological perspective (rather than classic economic theories assuming people are rational and using Bayes' theorem in decision making) to account for the irrational heuristic decisions people make, and we specifically focus on the leadership signal mechanisms. For more practical application, this study can help extend understanding about the leadership-signal-related features of meme stocks and potentially help people avoid unnecessary loss due to the herding behavior bias.

Limitations Despite its originality and relevance, this study had a few shortcomings that may be addressed and improved in future versions. First, the data we can access for the observational study is limited due to the limitation threshold of the official Reddit API, PRAW. Also, the time horizon of our observational data is from August 2020 to September 2021, so the study is not a time series analysis and does not have predictive power towards meme stocks outside of this one-year time horizon. Better access to more comprehensive Reddit data as well as the better computational power of devices may improve the study. For the sampling method of the experimental design, since we find possible differentiations between r/WallStreetBets retail investors and the experimental participants, a more community-focused and larger-size sample would improve the robustness of the experimental study. Also, the experimental study exclusively relies on self-reported data, provided directly from participants themselves. There may be some different interpretations that may skew the results in ways that bias study findings. Future improvement in assurance of participants' understanding of the questions would benefit the study. Last but not least, the experimental study focuses on using Twitter environment to mimic leadership signals, which may not be the most accurate depiction of how r/WallStreetBets community consider leadership popularity.

6.2 Future Directions

Based on the strengths and limitations of the study, future studies and extensions are highly encouraged to further explore the role of leadership signals in retail investors' herding behaviors on their investment decisions.

As stated prior, this study is limited by the data access to Reddit scripts as well as the computational power of my laptop (scrapped down all comments related variables took my laptop 4 days to run day-and-night). Future studies may improve upon the current observational study through acquiring more representative and comprehensive r/WallStreetBets data. Similarly, our data in the observational study is restricted to a time between August 2020 and September 2021. With more comprehensive data, future studies can also analyze the pre-meme stock era and post meme stock era leadership signals, and extend the analysis time coverage.

Through the finding of the experimental studies, we find differences between r/WallStreetBets retail investors and general retail investors, so the survey experiment may be more accurate using in-group samples and focus on the r/WallStreetBets population. Similarly, our experimental design uses Twitter to mimic social media leadership signals. It would also be interesting to use Reddit to mimic the social media environments when future researchers specifically sample within the r/WallStreetbets population.

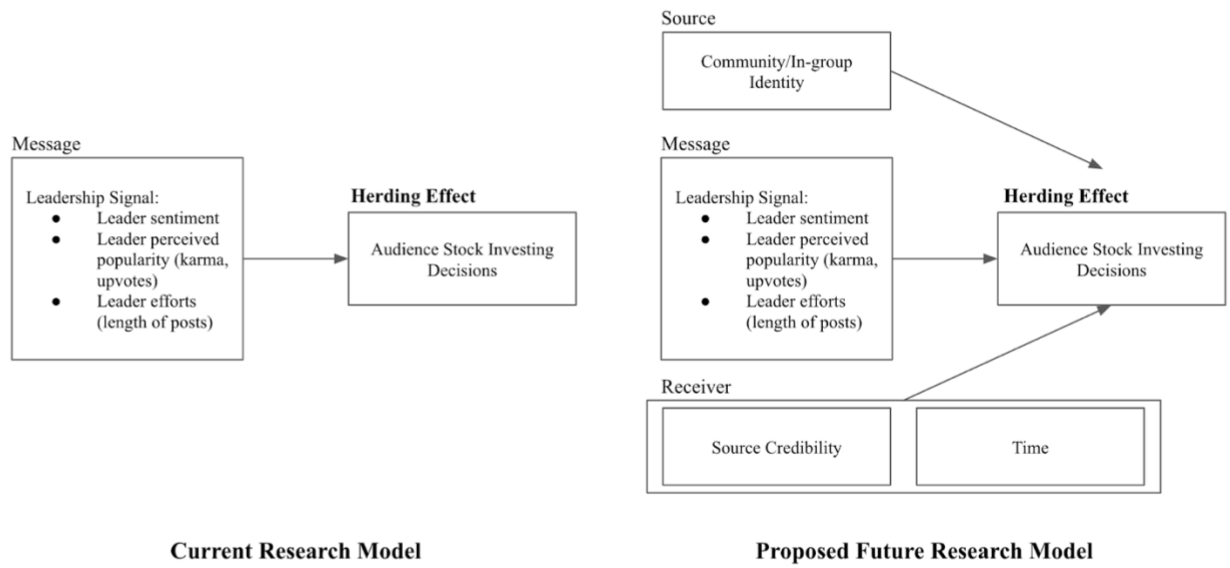

Fig. 8. Current research model and hypotheses for future research

Future variations may also choose to investigate the theories proposed in the discussion section, factoring how the source and receiver's differences may vary the leadership signal mechanisms on herding effect. A proposed research structure is shown above: the model on the left is what we investigated in our study, and the model on the right is based on possible mechanisms we derive from our studies' results. By incorporating more factors in the retail investors' cognitive evaluation process of leadership signals, we can obtain a better picture of leadership signal mechanisms behind the herding behaviors on r/WallStreetBets.

Conclusions

Herding behavior bias is an important behavioral economics phenomenon that explains the volatility and mispricing in the financial markets. Also, during the Covid-19 pandemic, the growing population of the r/WallStreetBets community gave researchers sufficient and transparent data, for the first time, to analyze retail investors' behaviors.

This study set out with the intent to better understand r/WallStreetBets retail investors and their decision-making processes. The motivation came from how past studies elegantly defined the herding behaviors with Bayes' theorem but did not sufficiently incorporate people's complex cognitive evaluation processes (Lim, 2014) and heuristic thinking tendencies (Huck and Oechssler, 2000) in the light of herding behaviors. Thus, this study first evaluated the herding behaviors in r/WallStreetBets under the scope of leadership signals and herding mechanisms, and then evaluated the causal relationship between leadership signals and investors' decisions in an experimental setting.

Our primary observational study conducted a data-driven approach to analyze real r/WallStreetBets data and found outperformance of leadership-signal-derived portfolios, which confirmed the appearance of herding behaviors between August 2020 and September 2021. In addition, we performed further data analysis and specifically found two herding mechanisms out of the total seven leadership signals that were statistically significant to r/WallStreetBets retail investors' decision making process.

In spite of the motivating hypothesis for the experimental study to draw the causal inference after the positive correlation between leadership signals and herding behaviors we found in the observational study, the experimental study surprisingly found that participants are less likely to invest in the MLP stock under the increasing intensity of the follower treatments. Although surprising, several explanations exist as to explain why these results were found. Whereas further studies are required to pinpoint the exact leadership signal evaluating processes of r/WallStreetBets investors that may have caused the herding behaviors on meme stocks during the meme stock era.

Overall, when studying herding effects, it is important to acknowledge the complex cognitive perspectives of how people evaluate different information, and not to assume everyone is rational. By understanding different market participants better and not assuming any group is better than one another in terms of decision-making, we can better navigate the heterogeneous investment decisions people make in the equity market. Also, when evaluating broad and complex market behaviors, like the herding effect, it is valuable to incorporate a cross-subject approach (e.g. combining economics and social psychology) to gain a better academic understanding of the theory.

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Appendix

Appendix 1. Experimental Survey Questions:

Moonlight Pizza Corp. is a company similar to franchised pizza shops you are familiar with. Below is a description of the company from a professional finance platform:

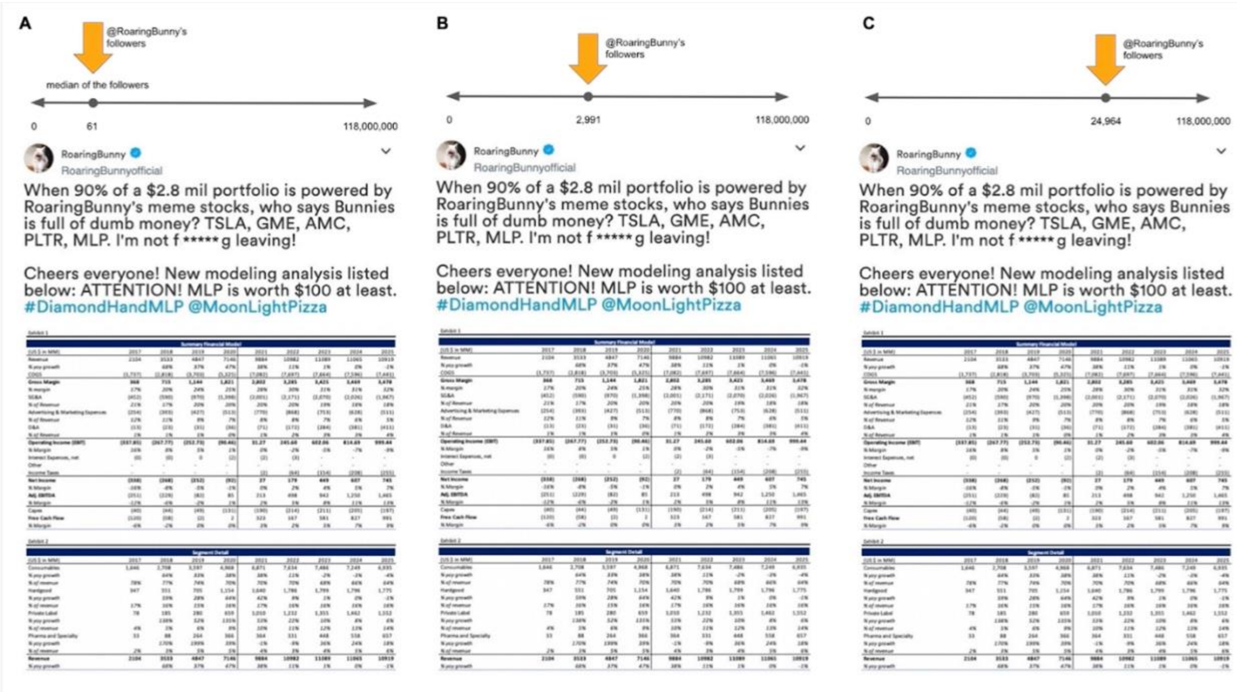
Moonlight Pizza Corp. (NYSE: MLP) is a United States-based pizza delivery company. The Company holds the franchise rights to own, operate and franchise Moonlight's stores in the United States and Mexico. Its pizzas are made with sourced ingredients, such as cream mozzarella, vine-ripened tomato sauce, and its signature dough.

Currently, Moonlight Pizza is trading at $50 per share, with its historical trading value shown below (Reference A). Moonlight Pizza just released this quarter’s earnings report, and the news media commented that it was strong.

Your task is to determine how much you would be willing to invest in the stock, and what price you expect to sell it after exactly 2 weeks. We will select the participant who predicts the most accurate stock price and the highest dollar-based return, and grant him/her a $100 reward through the MTurk bonus system. Good luck!

Reference A

Reference B



(Note: randomization, equally 33% chance to see either A, B or C)

1. If you were currently to have $10,000 in cash available for investing, would you choose to use any of this money to invest in the stock MLP? <u>(Yes/No)</u>
2. If yes, how much of the $10,000 will you be willing to put in the MLP stock? If no, just enter 0. Please enter below: (enter only numerical value, DO NOT include unit/symbol like $) (______)
3. You expect to sell the MLP stock at $ per share after 2 weeks: (enter only numerical value, DO NOT include unit/symbol like $) (______)
4. On a scale of 1-7, how much do you find the post content by @RoaringBunny credible? (1 being not credible at all and 7 being find it extremely credible) <u>(1/2/3/4/5/6/7)</u>
5. On a scale of 1-7, how likely are you going to hit "like" under @RoaringBunny's post? (1 being not likely at all and 7 being extremely likely) <u>(1/2/3/4/5/6/7)</u>
6. What is your gender <u>(Woman/Man/Other[please specify])</u>
7. What is your age (______)
8. What is your annual income level? <u>($0/Between $0 and $14,999/Between $15,000 and $29,999/Between $30,000 and $49,999/Between $50,000 and $74,999/Between $75,000 and $99,999/Between $100,000 and $150,000/Over $150,000)</u>
9. On a scale of 1-7, how relevant is your current job to finance? (1 being least relevant, 7 being extremely relevant) <u>(1/2/3/4/5/6/7)</u>
10. What chance of rain will prompt you to take an umbrella when you go out? <u>(20%/40%/60%/80%/100%)</u>
11. Suppose there was a lottery worth $1,000 USD with a 1% chance of winning. What is the most that you would pay for the lottery ticket? [...] USD <u>($1/$5/$10/$15/$20)</u>
12. From which of the following resources have you heard anything about financial markets in the past week? <u>(Television/Newspaper(either physical or digital)/Podcasts/Internet sites, chat rooms, blogs/Online forums/Have not heard anything about financial markets from any of these resources)</u>
13. How many days in the past week did you use the website Reddit? (No units needed, just enter the numerical value) (______)

14. How many hours did you spend on social media in the past week? (No units needed, just enter the numerical value) (______)
15. Have you heard about meme stocks before? Yes/No
16. What is the name of the company in the previous case study? Blaze Pizza/Domino's Pizza/Moondust Pizza/Moonlight Pizza

Appendix 2. Experimental: Price as DV discussion – the pitfall of audience understanding

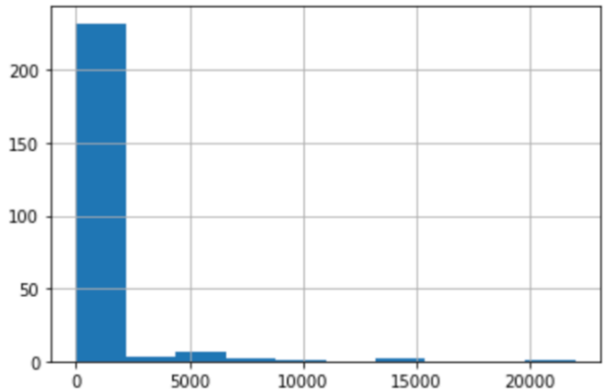


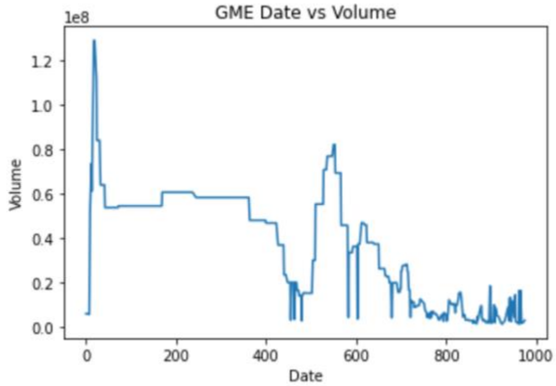
Fig. 9. Distribution of price target responses as dependent variable

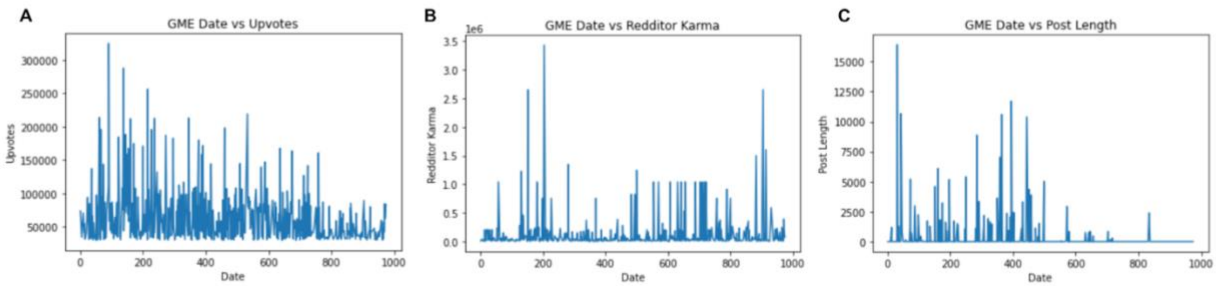
Initially, we are planning to use price as the dependent variable (DV): the objective price reflected from the market being $50 (shown in the price chart in the survey) so that the participants' predicted amount above $50 should be the amount influenced by the leadership signals. However, with the maximum of price prediction responses we collected being $22,000/per share, so that we highly suspect whether all of our participants understand our questions correctly or not. Thus, we draw a distribution of the price dependent variable and find that many of the responses are distributed to values above 5000 which do not make sense if they really understand the most bullish signal they have received is $100/per share. As a result, we highly suspect some participants misunderstand the question as to what do they expect their investment to be at after 2 weeks. An interpretation of this phenomenon is that when Reddit retail investors think about investing, they might not usually think of it professionally in terms of forecasting price per share like equity analysts. Instead, they might think more heuristically as to whether they believe the investment will increase their return in general in the future and predict their portfolio performance as a whole. This is just one of the hypotheses that we find might be interesting to the readers. Nevertheless, we run a regression analysis on price as DV and attach the result below in Table 12.

Table 12: Survey Experiment Price Regression Results

	Dependent variable:
	unlist(price) price
Z_1	−248.864 (−801.806, 304.078)
Z_2	−303.838 (−877.101, 269.425)
age	−14.167 (−37.173, 8.838)
finance_rel	198.208** (62.681, 333.735)
rain	−3.039 (−214.610, 208.532)
days_reddit	−17.582** (−29.825, −5.338)
hours_media	35.568** (11.955, 59.180)
memeYN	37.654 (−433.234, 508.542)
gender_Woman	658.607** (187.481, 1,129.733)
income_0	−7,539.035*** (−11,564.390, −3,513.680)
income_between0and14999	−6,873.565*** (−8,938.494, −4,808.636)
income_between100000and150000	−7,272.159*** (−9,421.961, −5,122.357)
income_between15000and29999	−7,404.279*** (−9,463.886, −5,344.672)
income_between30000and49999	−7,259.873*** (−9,338.214, −5,181.532)
income_between50000and74999	−6,963.279*** (−9,046.780, −4,879.778)
income_between75000and99999	−6,983.706*** (−9,128.511, −4,838.901)
income_over150000	−7,019.619*** (−9,395.376, −4,643.863)
Constant	7,329.284*** (4,915.310, 9,743.258)
Observations	249
Note:	*p<0.1; **p<0.05; ***p<0.01

Appendix 3. A GME case study (observational) – trying volume as DV rather than price





Appendix 4. Demographic Description of Experimental Study Participants

	gender	n
	<chr>	<int>
1	Man	138
2	Woman	107
3	NA	4

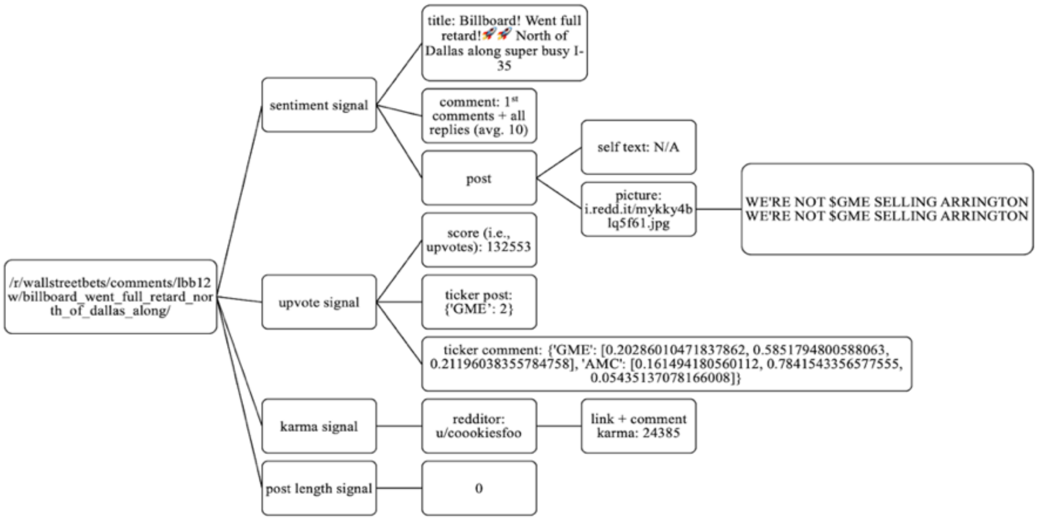
	finance_rel	n
	<dbl>	<int>
1	1	114
2	2	40
3	5	26
4	4	24
5	3	22
6	6	19
7	NA	3
8	7	1

	income	n
	<chr>	<int>
1	Between $15,000 and $29,999	58
2	Between $30,000 and $49,999	47
3	Between $50,000 and $74,999	46
4	Between $0 and $14,999	45
5	Between $100,000 and $150,000	21
6	Between $75,000 and $99,999	21
7	Over $150,000	7
8	NA	3
9	$0	1

	lottery	n
	<dbl>	<int>
1	1	116
2	2	70
3	3	45
4	4	9
5	5	5
6	NA	4

	rain	n
	<dbl>	<int>
1	3	85
2	4	79
3	2	37
4	5	33
5	1	12
6	NA	3

Appendix 5. Illustration about data cleaning process out of one r/WallStreetBets Post



Appendix 6. Illustration about data cleaning process out of one r/WallStreetBets Post

1. Demographic
    a. Gender (categorical)
    b. Age
    c. Annual_Income (categorical)
    d. Finance_rel: how relevant is their job to finance (1 least, 7 most)
    e. Risk tolerance
        i. Chance of rain to prompt you taking an umbrella (1 least, 7 most)
        ii. Lottery worth $1000 with 1% chance of winning, willingness to pay ($1, $5, $15, $20: 1-5)
2. Exposure to the issue
    a. How many days in the past week used Reddit
    b. How many days in the past week used social media
    c. Heard about meme stock before or not
3. Investment Decision
    a. Predicted price per share
    b. Amount of money willing to invest
4. Other reactions to the stimuli
    a. Credibl: how much find @RoaringBunny's post content credible
    b. Hit_like: how likely to hit like under @RoaringBunny's post
5. Validity check question:
    a. What is the name of the Pizza company discussed by @RoaringBunny