Social contagion and asset prices: Reddit's self-organised bull runs*

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Abstract

Does information sharing among investors impact asset returns? We use text data from discussions on WallStreetBets (WSB), an online forum with over eleven million followers as of February 2022, to identify how the coordination of price expectations among retail investors has market impact. We develop a model for strategic complementarities in investor sentiments and extrapolation among investors, and link it to asset returns. We empirically document that sentiments expressed by WSB users about assets' future performances (bullish or bearish) are in part due to sentiments of their peers (strategic complementarities) and past asset returns (extrapolation). Peer influence is estimated in two ways using random, temporal variation in peers and an interaction network approach for different identification strategies. The model predicts a negative relationship between past sentiments and returns, and a positive one between concurrent sentiments and returns. We instrument for average current and past sentiments, and uncover a relationship with returns that is consistent with our model framework. We next expand our approach to incorporate idiosyncratic sentiment shocks among investors. Exploiting the fat tail properties of the popularity of content on WSB, we use a granular instrumental variable strategy to show that idiosyncratic sentiment shocks survive aggregation and can affect returns, driving prices away from equilibrium.

JEL codes: D91, G14, G41.

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1 Introduction

In investigating the stock market crash of May 28, 1962, the Securities and Exchange Commission (SEC) found that: ‘investor “psychology” being what it is, the increasing decline in one or several issues can easily spread to others. Once the process becomes generally operative, the stage is set for a serious market break’ (1963). The SEC concluded that large institutions acted as a balancing force during the collapse. The report pointed at retail traders as the *key players* behind the panic. Over half a century later, we are again confronted with the consequences of investors’ social behaviours. As online discussants on Reddit’s ‘WallStreetBets’ (WSB) forum drove up the price of GameStop shares in January, 2021, retail investors regained a spotlight on the (virtual) trading floor. A key difference between 1962 and today is the internet, which offers both a coordination platform on an unprecedented scale, and a new datasource on investor narratives, interactions and psychology.

This paper sets out to reconcile observed behaviours on social media with economic theory by examining the beliefs and positions of individuals active on WSB. We propose a stylized model for how social and psychological forces – information assimilation from peers and extrapolation – can affect asset prices and result in bubbles. The model’s assumptions are validated and parameters estimated using the WSB dataset. The data is also used to explore several other aspects of investor behaviour, such as their reaction to salient events and the passthrough of beliefs to asset demand. In a final empirical exercise, we estimate the effect of the activity on WSB on asset prices.

Our approach addresses several challenges in the literature. Current research often relies on investor survey data for information on beliefs, and filings (such as 13F filings) to study holdings. This data is reported at a fairly low frequency (quarterly or semi-annually), typically covers high net worth individuals or institutional investors (and only their largest asset holdings) and does not explicitly match holdings to beliefs. The WSB dataset allows us to examine small retail investors and observe their reactions to information at a more granular timescale. We are able to track positions and beliefs of the same individuals over time, as well as the information that they are exposed to on the forum. The rich dataset, in combination with novel econometric techniques and our model framework, allows us to estimate how investors react to information shared by peers as well as large market moves, and to examine how investor behaviours move markets on a daily / weekly timeframe.

We begin with an empirical analysis of the data. First, we examine the extent to which individuals trade based on their expressed beliefs. We manually extract positions from position screenshots on WSB and beliefs using supervised text analysis. The strong, statistically significant link between the expressed sentiment of an investor and their future positions demonstrates that people trade based on their beliefs. Expressing a positive sentiment about an asset on WSB raises the probability of a long investment in the same asset in the future by over six times. The effect is not symmetric - expressing a negative sentiment raises the probability of a short investment only 2.5 times. Neutral sentiments appear to be highly predictive of long positions.

We also perform a preliminary analysis of how beliefs relate to market dynamics. We observe that higher asset returns are associated with high current sentiment, but lower past sentiments. We track the link between returns and sentiments and find that sentiments are positively linked to past returns and negatively linked to returns shortly after. In an estimate with daily fixed effects, we observe that returns are 0.1 log points lower if sentiments expressed on the previous day are twice more likely to be bullish than bearish.

We explain the link between returns and investor beliefs through a stylized model. We build intuition using a simple, dynamic model where investors update their demand for an asset based on the observed demand of their peers, as well as extrapolation. The investor aggregates information from peers in a Bayesian manner. Asset demand and returns are determined simultaneously through market clearing, and returns are accounted for by current and past demand. The model justifies the observed positive relationship between returns and current demand, and a negative one with lagged demand.

In the second part of the paper, we empirically validate the assumptions of our model and perform parameter estimation. Specifically, we document the extent of mechanical extrapolation and information assimilation from peers among investors. We test for how information from peers affects investor decision-making in two ways. In our first approach, we select individuals who express sentiments about an asset multiple times, and observe peers discussing the same asset in-between. We use historic peer sentiment as an Instrumental Variable (IV). This approach mitigates the common shock problem, and draws inspiration from the peer effects in classrooms literature, which gauges future student performance based on entry exams (Duflo et al. 2011). Second, we leverage the network of interactions on WSB to identify which information an individual investor has been exposed to. The network links an older submission about an asset to a new submission if the author of the new submission comments on the older submission. We estimate the degree of information assimilation by regressing the sentiment expressed by the new submission on the average sentiment of older, linked submissions. We instrument the sentiment of linked submissions to control for an author's endogenous choice to comment, and use the timing of our IVs to control for common shocks. We test for mechanical extrapolation through investigating how recent stock returns change sentiments.

The Ordinary Least Squares (OLS) coefficient for the effect of average, predicted peer sentiment is a statistically significant predictor for the change in author sentiment in both approaches, indicating that retail investors. The IV results suggest that a doubling in the odds of peers expressing bullish over bearish sentiments increases the odds of one given user to express bullish over bearish sentiment by 14%, on average. Even though the role that narratives play in investor decision-making has been heavily discussed in the literature, to the best of our knowledge, this is the first work documenting a relationship between an investor's sentiment and that of his peers, outside a controlled experimental setup (Bursztyn et al. 2014).

Our final section ties together our model, and empirical observations of market and WSB data. Our main result centers on predicting variation in sentiments among WSB users unrelated to current price changes. This strategy works well because of the strong temporal persistence of sentiments to specific assets, due to the peer effect channel. Our estimates are economically and statistically significant in predicting changes in weekly average log returns, as well as changes in volatility and trading volumes. These results provide evidence for a relationship between social dynamics, proxied by WSB conversations, and financial markets.

Our model predicts that, in equilibrium, a negative relationship exists between past sentiments and returns, since investors are willing to accept a lower return on an asset that they value more highly. An outstanding question is how to explain the socially-driven price run-ups, such as the GameStop short squeeze. We expand our model to account for idiosyncratic social shocks in sentiments – sentiments that cannot be explained by recent news and stock performance, and are distinct from our overall sentiment metric. This paper leverages the framework of Gabaix & Koijen (2020, 2021) for granular instrumental variables – we propose that 'granular' social shocks (i.e. those that receive a large social following) will not be averaged out across all investor sentiments and can have an outsized impact on returns. Similarly to other content online, our data is heavy-tailed. A few submissions receive a large following, while most go virtually unnoticed.

We propose a granular instrumental variable which compares the average idiosyncratic sentiment in posts and the popularity-weighted idiosyncratic sentiment. The IV is effective at predicting granular social shocks. We observe a statistically significant relationship between our predicted social shock and future returns – the idiosyncratic doubling in the odds of a very popular post expressing bullish over bearish sentiments increases returns in the following week by 0.007, on average. The results are not symmetric, as negative idiosyncratic social shocks have a much greater impact than positive ones. The relationship helps explain the slow run-up and relatively fast collapse of popular stocks on WallStreetBets.

Related literature Economic interest in asset mispricing dates back to Tulipmania - the gradual overheating and subsequent collapse of tulip bulb prices in the Netherlands in the 17th century (Garber 1989). Since then, many frameworks have been proposed which explain the gradual increase and then dramatic drop in financial assets, including psychological models, such as diagnostic expectations (Bordalo et al. 2021), the spread of information (Veldkamp 2006), and extrapolation (Glaeser & Nathanson 2017). A parallel strand of the literature highlights the importance of peers and narratives in forming investor perspectives Shiller (1984), who provides statistical evidence of the greater volatility in stock prices than warranted by that of dividends. Since then, 'narrative economics' has played an increasingly important role in our understanding of investor decision-making and market moves (Shiller 2005, 2014, 2017, Banerjee et al. 2013, Hirshleifer 2020). By leveraging new data, our work provides fresh empirical evidence of how heuristics, and peer effects in particular, affect investor decision-making and can result in asset mispricing.

Several studies in the peer effects literature leverage naturally occurring variation in peers for their identification strategy. An area which pioneered many of these techniques investigates peer effects in the classroom (see Epple & Romano (2011), Sacerdote (2011) for a general overview, and Duflo et al. (2011) for a prominent example). Social networks are also an active area of study (see Bramoullé et al. (2020) for a recent review). Bursztyn et al. (2014) perform a field experiment with a financial brokerage in Brazil, where they study investment decisions made by peer pairs: the peers are offered a ‘high stakes’ investment opportunity (minimum investments were R$2,000 – around 50% of the median investor’s monthly income) in a certain order to identify the effects of ‘social learning’ and ‘social utility’ in financial decision-making. Other related work investigates the diffusion of micro-finance decisions in a social network (Banerjee et al. 2013), the effect of peers on risk taking (Lahno & Serra-Garcia 2015), and the effect of social networks on saving (Breza & Chandrasekhar 2019). By studying a broader set of investors in a natural experiment, our research question is similar to Pool et al. (2015), who demonstrate that socially connected fund managers appear to hold similar stocks. The present paper highlights how to transfer well-established techniques from this literature to social media data, thereby shedding light on investor psychology.

Other works study the interplay between online forums and financial markets, as well as the spread of information in social networks. This paper differs from studies focusing on the spread of information through friend networks, such as Aral et al. (2009), Aral & Nicolaides (2017), since Reddit users are anonymous, without any explicitly defined friendship links. The anonymity within Reddit is crucial to the prominence of WSB: in contrast to the exercise in Banerjee et al. (2013), where information is transmitted via friendship networks, the mechanism by which information dissipates on WSB is much closer to the homogenous mixing conditions popular in traditional epidemiological models, and therefore closer in spirit to Banerjee (1993). Our work complements studies that focus on identifying one direct relationship between social activity and assets, for example Kumar & Lee (2006), Chen et al. (2014). Cookson & Niessner (2020) also use social media data to understand investor social dynamics and demonstrate an impact to the financial markets, but focus on disagreement among investors.

Road map We present our results in five sections. The following section comprehensively describes the data source and relevant variables. Section 3 presents a model for price dynamics in the presence of information sharing among investors. Section 4 presents empirical evidence for our proposed investor dynamics. Section 5 empirically evaluates the effect of retail investors on financial markets. Section 6 concludes.

2 What is *WallStreetBets*?

Reddit, launched in 2005, is a social news aggregation, web content rating, and discussion website. It was ranked as the 19th most visited site globally in April 2021,[1] with over 430 million anonymous users by the end of 2019.[2] The website’s contents are self-organised by subject into smaller sub-forums, ‘subreddits’, which discuss a unique, central topic.

[1] https://www.alexa.com/topsites

[2] https://redditblog.com/2019/12/04/reddits-2019-year-in-review/

Structure of WSB Within subreddits, users publish titled posts (called 'submissions'), typically accompanied with a body of text or a link to an external website. These submissions can be commented and 'upvoted' or 'downvoted' by other users. A ranking algorithm raises the visibility of a submission with the amount of upvotes it receives, but lowers it with age. Therefore, the first submissions that visitors see are i) highly upvoted, and ii) recent, with the precise algorithm considered private intellectual property and discussed further in Appendix A.1.[3] Comments on a submission, visible to anyone, are subject to a similar scoring system, and can, themselves, be commented on.

Features The WSB subreddit was created on January 31, 2012, and reached one million followers in March 2020.[4] As per a Google survey from 2016, the majority of WSB users are 'young, male, students that are inexperienced investors utilizing real money (not paper trading); most users have four figures in their trading account'.[5] Individuals on the forum discuss and express their sentiments about stock-related news. In addition to market discussions, there is ample evidence of users pursuing the investment strategies encouraged in WSB conversations. Users post screenshots of their investment gains and losses, which subreddit moderators are encouraged to verify – a dynamic reminiscent of Shiller's (2005) description of an asset bubble. The discussions are whimsical, but mostly investment-focused.

Available data We downloaded WSB data using the PushShift API.[6] PushShift records all comment and submission data at the time of creation. The full dataset consists of two parts. The first is a total of 1.4 million submissions, with their authors, titles, text and timestamps. The second is comprised of 16.5 million comments, with their authors, text, timestamp, and the identifier of the parent comment or submission. Submission and comment numbers have grown exponentially since 2015 – our Online Appendix displays the forum's exponential growth.

Our dataset spans January, 2012 to July, 2020. Importantly, it does not include the events of the 2021 GameStop (GME) short squeeze. The decision to focus on this timeframe is intentional: before the GME short squeeze, WSB received less attention from institutional investors, as well as less bot-activity. As such, our sample tracks retail investor discussions more precisely, without systematic external influence. Furthermore, ample research has emerged focusing exclusively on the GameStop short squeeze, whereas our goal is to characterise investor behaviour, rather than examine a single event.

Identifying assets The following sections predominantly rely on submissions for text data, since they are substantially richer. Comments are used to trace interactions between discussants. In order to understand how users discuss specific assets, we extract mentions of *tickers* from the WSB submissions' text data. A ticker is a short combination of letters, used to identify an asset on trading platforms. For example, 'AAPL' refers to shares in Apple,

[3] https://www.reddit.com/r/help/comments/717686/order_of_posts/
[4] https://subredditstats.com/r/wallstreetbets
[5] https://andriymulyar.com/blog/how-a-subreddit-made-millions-from-covid19
[6] https://pushshift.io/

Inc. Appendix A.3 documents how tickers are extracted from submissions. Our Online Appendix displays the twenty tickers that feature most prominently in WSB conversations up to July, 2020. These are typically stocks in technology firms, such as AMD or FB. A handful of Exchange Traded Funds (ETF) are also present, notably the S&P 500 (SPY) and a leveraged gold ETF (JNUG).

A small fraction of the 4,650 tickers we extract dominate the discourse on WSB: 90% of tickers are mentioned fewer than 31 times, and more than 60% are mentioned fewer than five times. Our Online Appendix documents the heavy-tailed nature of ticker discussions. In total, we are left with 111,765 submissions that mention one, unique ticker and were posted before July 1st, 2020. These submissions have 1.9 million comments in total.

Sentiment model In addition to extracting tickers, we gauge whether submissions express an expectation for an asset's future price to rise, the *bullish* case, to fall, the *bearish* case, or to remain unpredictable/stable, the *neutral* case. We identify sentiment using a supervised-learning approach, with a hand-labeled dataset of almost five thousand submissions for training, validation and testing (Araci 2019). The sentiment model outputs a probability for each sentiment category, achieving 70% accuracy in categorising the manually labeled test set. Appendix A.4 discusses details of this Natural Language Processing (NLP) model.

Key sentiment variable. The sentiment classifier assigns three probability scores to each submission about a ticker: the probability of a submission being bullish, $P(\phi = +1)$, bearish, $P(\phi = -1)$, neutral, $P(\phi = 0)$. The probabilities sum to one. At the time t when an author i posts about asset j, we use the probability scores above to calculate a continuous sentiment score between $(-\infty, \infty)$:

$$\Phi_{i,j,t} = \frac{1}{2} \log\left(\frac{\mathrm{P}(\phi_{i,j,t} = +1)}{\mathrm{P}(\phi_{i,j,t} = -1)}\right).$$

Submissions labeled as bullish ($\mathrm{P}(\phi = +1) = 1$), or bearish ($\mathrm{P}(\phi = +1) = 1$), are set to $\mathrm{P}(\phi = +1) = 0.98$, or $\mathrm{P}(\phi = -1) = 0.98$, to retrieve a finite value for the log-odds. We also extract three categorical variables (bullish, bearish, neutral) which are encoded with a one if the label received the highest probability from our classifier: the categorical variable $\phi^{+1}_{i,j,t}$ will be equal to one is author i's post about asset j at time t is categorised as bullish; $\phi^{0}_{i,j,t}$ and $\phi^{-1}_{i,j,t}$ will be zero. We leverage these variables to investigate investor sentiment throughout the paper.

2.1 Isn't all of this just talk?

Why should we care about the sentiments people express about assets online? Anecdotally, the GameStop short squeeze demonstrated that the online discussions on the WSB forum have impact on assets. But this does not constitute evidence that people follow through on the investment strategies they discuss online, systematically.

Table 1: Follow-through on WSB Advice

	Dependent variable: Position in Asset j of Author i	
	$B_{i,j}$ - categorical	
	(1)	(2)
	Logistic	Logistic
$\Phi_{i,j}$	1.50 (0.20) ***	
$\phi_{i,j}^{-1}$		-0.97 (0.29) ***
$\phi_{i,j}^{0}$		0.66 (0.21) ***
$\phi_{i,j}^{+1}$		1.84 (0.27) ***
Observations	278	278
Pseudo-R^2	0.13	0.17

Notes: this table presents Logistic regression estimates for the relationship between the sentiment expressed by an investor i about asset j in a post at some point before or simultaneously to time the same author posts the position taken in the same asset. Sentiment estimates are presented in two ways: (1) the continuous log-odds of the author expressing positive over negative sentiment $\Phi_{i,j}$, and (2) as a categorical variable where $\phi_{i,j}^{-}1$ corresponds to the expression of negative sentiment, $\phi_{i,j}^{0}$ - neutral, $\phi_{i,j}^{+}1$ - positive.
*** Significant at 1% level ** Significant at 5% level * Significant at 10% level

To address the concern that WSB sentiment data has limited impact on investment decisions, we utilize the screenshots that people post of their investment positions to test whether WSB users follow through on their expressed sentiments. We extract approximately 9,000 images from WSB – we focus only on image-related URLs (such as ones with the domain name 'imgur', an image-hosting site) mentioned in posts of authors who had posted before about an ticker. We hand-annotate a third of the images. Specifically, we manually annotate the image, if it is a position screenshot, with i) the tickers in the screenshot and ii) the positions (long or short) the author displays.

We subsequently match the ticker screenshot to a submission posted before that screenshot by the same author and ticker. We regress the most recently expressed sentiment by author i about asset j (our key sentiment variable $\Phi_{i,j}$) on the position $B_{i,j}$ extracted from their screenshot:

$$B_{i,j} = \lambda^s \Phi_{i,j} + u_{i,j,t}^{p}, \tag{1}$$

where $u_{i,j,t}^{p}$ is an error term, and λ^s measures the pass-through rate of sentiment into eventual investment positions. We perform several tests by expressing previous sentiment of the author as a categorical variable and estimating $B_{i,j}$ as a categorical variable in a logistic regression.

Results. Table 1 presents the coefficients estimated using a Logistic regression. We observe an author's sentiment is highly correlated to their subsequent holdings of the stock. Let us consider the results in column (2) - an author creating a bullish post about an asset raises the probability of a long versus short investment by over six times. We note that the sample of screenshots is biased. Authors on WSB are socially incentivized to share extreme losses or gains. We, therefore, observe relatively few positions, as compared to sentiments. The positions data, however, gives us confidence that investors do trade based on their discussions and expressed sentiments.

2.2 Predicting stock returns with WSB sentiments

Table 2: Stock returns versus WSB characteristics

	Dependent variable:	
	$r_{j,t}$	
	(1)	(2)
$\bar{\Phi}_{j,t}$	0.60*** (0.04)	
$\bar{\Phi}_{j,t-1}$	−0.16*** (0.02)	−0.07*** (0.02)
$r_{j,t-1}$		−0.06*** (0.004)
$\bar{\Phi}_{j,t-1} \times r_{j,t-1}$		0.01 (0.01)
Day FE	Yes	Yes
Observations	8,287,639	8,287,639
R^2	0.0004	0.003
Note:		*p<0.1; **p<0.05; ***p<0.01

We run a set of simple exercises to motivate what follows: does activity on WSB influence stock market returns? We average the sentiment characteristics in Eq. 1 by stock j and trading day t, denoting these mean sentiments by $\bar{\Phi}_{j,t}$. We merge these daily sentiment observations with US common stock returns reported by CRSP, and transform the reported returns into log returns. Subsequently, we regress daily log returns on current mean sentiments, as well as previous day sentiments:

$$r_{j,t} = \lambda_1 \bar{\Phi}_{j,t} + \lambda_2 \bar{\Phi}_{j,t-1} + \eta_t^r + v_{j,t}^r, \tag{2}$$

where η_t^r is a daily fixed effect, $v_{j,t}^r$ an error term, and λ_1, λ_2 our coefficients of interest.

Results Table 2 reports OLS estimates for these coefficients in Column 1. Perhaps unsurprisingly, returns relate positively to contemporaneous sentiment. The second coefficient implies a negative relationship between WSB activity today and returns tomorrow, which is highly significant for both of our characteristics. However, the implied effects are relatively small; on an average day, returns are 0.1 log points lower if sentiments expressed on the previous day are twice more likely to be bullish than bearish.

In Column 2, we estimate Eq. 2 with the interaction between lagged, average sentiment and lagged returns, to capture a non-linearity for sentiments in stocks that garner exceedingly high amounts of attention. The slight negative relationship between current and past returns could potentially confound the effect of past sentiment, as seen in the smaller coefficient for lagged sentiments. However, there is no clear evidence that the interaction between sentiments and outsized returns produce a significant effect on subsequent returns.

2.3 Motivation

If Table 1 is to be believed, the sentiments expressed in WSB induce trading activity. However, the negative relationship between current returns and past sentiment reported in Table 2 is puzzling in that regard, and would suggest that the authors of those submissions erred in their assessments.

The central argument of our paper is thus precisely that the correlations in Table 2 are not a manifestation of (erroneous) information spreading on WSB. Rather, the trading patterns of these retail investors are responsible for reversals in prices as they seeks to find and follow highly risky strategies. The following section builds a hypothesis on the emergence of bubble-like dynamics as a function of social contagion in investor strategies, whereby return expectations are based on experiences of peers instead of those from the past.

3 Social dynamics and asset prices

Sharing investment strategies appears self-defeating, so what motivates retail investors to do so online, in such unabashed manner? We study their interactions through an asset demand model, by incorporating information complementarities in investment decisions. These give rise to *social contagion* in asset demand; investors buy the asset because others do as well, irrespective of their personal beliefs. This behaviour, if significant, can create reversals in asset price returns.

The mechanism is motivated by a recent literature that studies diagnostic expectations (Bordalo et al. 2021). In doing so, investors trade on the momentum of the stock price, against a supply of shares provided by noise traders. Our inclusion of a social component subsequently induces persistence in asset demand over time, which leads to reversal in future returns.

3.1 General setup

We analyse price for one asset traded by N investors, indexed by i. Each investor derives CARA utility from consuming c, $U_i(c_i) = \exp(-\gamma c_i)$, where γ is the constant absolute rate of risk aversion. We do not include any discounting in their decision-making, but assume they evaluate the asset according to a forward-looking value V with expectation $\mathbb{E}_i(V)$.

For now, we drop the time subscript to study a static version of the model. Shares ϕ_i are purchased at current market price p to optimise the mean-variance objective function

$$\mathcal{L}(\phi_i) = [\mathbb{E}_i(V) - p]\phi_i - \frac{\gamma}{2}\mathbb{E}_i(V-p)^2\phi_i^2, \tag{3}$$

$$\Rightarrow \phi_i^* = \frac{\mathbb{E}_i(V) - p}{\gamma \mathbb{E}_i(V-p)^2}, \tag{4}$$

where an asterisk denotes the value that maximises objective $\mathcal{L}$. In this way, we distinguish between beliefs about value $\mathbb{E}_i(V)$ from investor i's decision to buy amount ϕ_i. Eq. 4 yields a familiar expression for asset demand in equilibrium, namely as a ratio of expected net returns over their variance.

Simple price equilibrium We assume that asset supply originates from noise traders, as in Bordalo et al. (2021), to find a price equilibrium. In effect, equilibrium demands $\sum \phi_i^*$ sum to exogenous supply S. Assuming fixed uncertainty $\sigma^2 = \mathbb{E}_i(V-p)^2$ and averaging expected values $\mathbb{E}(V) = 1/N \sum \mathbb{E}_i(V)$, we can re-arrange Eq. 4 to yield the following expression for the market-clearing price:

$$p = \mathbb{E}(V) - \frac{S}{N}\gamma\sigma^2. \tag{5}$$

Eq. 5 accounts for the price level by investor's average expected value of the asset, in addition to their ability to absorb the exogenous level of assets supplied. This ability depends on the depth of the investor pool – reflected by the number of investors N – as well as their risk appetite $\gamma\sigma^2$. In this simple market, the price increases with expected value, and decreases with supply.

This expression for price ignores heterogeneity and aggregation. Eq. 5 mimics a single representative investor of some size N. However, strategic interactions may give rise to feedback loops in investor demands that do not average out. We also do not consider the effect of heterogeneity in investor wealth, or other size characteristics, although the model can be extended for that purpose. Investors central in a social network are 'indirectly' large by their ability to sway others. We make use of this in our empirical study in Section 5.

Goals The first goal of this section is to endogenise investors' expectation formation for value $\mathbb{E}_i(V)$, and determine a trajectory for prices when aggregating these components. A long literature investigates the link between subjective asset price beliefs and prices, and our contribution is to include a term for social learning. The second goal is to investigate this equilibrium price in a dynamic setting where values are updated under some extrapolation.

3.2 Static model with information complementarities

We study the role of information complementarities in investors' beliefs about the value of an asset. To that end, the model operates in two stages. In the first stage, investors build their expectation for the asset's value, using observed signals from their peers and their expectation of the market-clearing price as a function of the expected, as of yet hidden, supply shock. In the second stage, the asset supply shock is revealed, and investors execute their trades according to their demand curve.

Investor i's maximised payoff from Eq. 3 is

$$\mathcal{L}(\phi_i^*) = \frac{\mathbb{E}_i^2(V-p)}{2\gamma \mathbb{E}_i(V-p)^2} \tag{6}$$

$$= \frac{1}{2}\mathbb{E}_i(V-p)\phi_i^* \tag{7}$$

$$= \frac{1}{2}[\mathbb{E}_i(V) - \mathbb{E}(V)]\phi_i^* + \frac{\gamma\sigma^2}{2}\frac{1}{N}\sum_j^N \phi_j^*\phi_i^*, \tag{8}$$

where $\mathbb{E}(V) = 1/N \sum \mathbb{E}_i(V)$ as before. Here, investors base their price expectations on a form on simple equilibrium in Eq. 5, but uses their personal expectations and constant uncertainty σ^2 to forecast price in the second stage. Further knowledge of other investors' expectations and uncertainties would yield a refined estimate, but work not shown here demonstrates that this expression holds when the first and second moments in expected value are uncorrelated.

Eq. 8 demonstrates that investor's payoff depends on their peers in two regards. First, payoffs increase to the degree that the investor in question can outperform others, in terms of the value they realise in the asset. This is seen in the first component, by which buying(selling) the asset increases the payoff to the extent that i's expected value $\mathbb{E}_i(V)$ is higher(lower) than that of their peers. Second, the payoff increase by the average optimal asset demand of all investors in the economy.

Complementarity in asset demand This asset demand model predicts that social interactions dictate investors' welfare. Eq. 8 is a well-known formulation for strategic interactions between agents acting under quadratic loss (Zenou 2016). Deriving Eq. 8 presents the strategic complementarities in asset demand:

$$\frac{d^2\mathcal{L}(\phi_i^*)}{d\phi_j^* d\phi_i^*} = \frac{\gamma\sigma^2}{2N} \geq 0. \tag{9}$$

The emergence of this strategic complementarity is due to a crowding out effect that investors have on price. The higher asset demand by other investors, the higher the realised price will turn out to be. The acquisition of information under some cost to the investor is an interesting extension, although already studied in detail by Hellwig & Veldkamp (2009). The unweighted average is a consequence of ignoring any mechanism in which information about asset demand is transmitted. In Section 5, we leverage heterogeneity in the importance of certain individuals on WSB discussions for our empirical strategy.

3.3 Price dynamics with peer effects

To study the joint dynamics of an asset's price and demand by social investors, we treat demand ϕ and price p as state variables for a dynamic system, indexed by time t. In doing so, we assume that demands $\phi_{i,t}$ are updated using signals $g(b_{i,t})$ and past demand ϕ_{t-1}. Aggregate asset demand and price are

$$\phi_t = \frac{\mathbb{E}_t[g(b_{i,t})] + \mathbb{E}_t[f(\phi_{i,t})] - p_t}{\gamma\sigma^2}, \tag{10}$$

$$p_t = \mathbb{E}_t[g(b_{i,t})] + f(\phi_{t-1}) - \frac{S_t}{N}\gamma\sigma^2, \tag{11}$$

which demonstrate the importance of signals $b_{i,t}$ in determining the trajectory of demand. Studies in behavioural finance suggest several components that ultimately deviate from rational expectations. In this instance, demand depends on it's lag. We believe this accurately reflects the nature of discussions on WSB specifically, which is characterised by 'leaders' who garner followers to adopt their positions.

Persistent demand The mechanism by which past demand enters current asset demand is by their complementarity in investor payoffs. Investor i's expectation of future returns is linearly increasing in average asset demand by others:

$$f(\phi_{i,t}) = \alpha\phi_{t-1}, \tag{12}$$

where $\phi_{t-1} = 1/N\sum_i \phi_{i,t-1}$ is aggregate asset demand as before. This is in line with the finding that our asset demand model produces strategic complementarities among investor asset demands in Eq. 9.

Mechanical Extrapolation We assume that investors partially trade on the momentum of the asset's price, which Bordalo et al. (2021) term 'mechanical extrapolation'. The functional form of $\mathbb{E}[g(b_i)]$ is specified in Assumption 1.

Assumption 1 (Mechanical Extrapolation)**.** *The average investor projects past price increases into the future using the updating rule:*

$$\mathbb{E}_t[g(b_{i,t})] = p_t + \beta(p_t - p_{t-1}), \tag{13}$$

where β captures a fixed degree of price extrapolation.

Mechanical extrapolation is our preferred way to introduce a relationship between prices and demand (Barberis et al. 2018). A model with mechanical extrapolation has several shortcomings, one of which is the inability to relate expectation updates to psychological underpinnings. However, our assumption is justified by our empirical work in Section 4.2 which demonstrates that individuals update their outlook based on recent asset returns.

System for price and demand Substituting Eqs. 12-13 into Eqs. 10-11 yields demands and returns

$$\phi_t = \frac{\alpha\phi_{t-1} + \beta r_t}{\gamma\sigma^2}, \tag{14}$$

$$r_t = -\frac{\alpha}{\beta}\phi_{t-1} + \frac{S_t\gamma\sigma^2}{\beta N}. \tag{15}$$

In this scenario, asset demand and returns are determined simultaneously. The first mechanism is through market clearing, where demand has to adjust to supply. The second is the adjustment of the expected value for the asset to the realised return through β and the social signal through α. As a result, returns are accounted for by current and past asset demand:

$$r_t = \frac{\gamma\sigma^2}{\beta}\phi_t - \frac{\alpha}{\beta}\phi_{t-1}. \tag{16}$$

This equation for asset demand in equilibrium offers three valuable insights. First, it requires a non-zero degree of extrapolation $\beta > 0$, otherwise demand does not adjust to price. Investors are never compelled to change their purchases since they believe the current price precisely reflects value. Second, higher demand increases current returns, but leads to a subsequent reversal in the following period. This is because the equilibrium price needs to satisfy the value expected both from extrapolation, in addition to the value estimated from the social components. Under exogenous supply, a strong positive signal from peers means that the extrapolated return is *less* important in justifying a higher price. In equilibrium, this results in a negative relationship between returns and the lag in asset demand.

Persistent fluctuations The reversal in returns is an important feature that emerges from social contagion in investors' price expectations. If large enough, these can produce bubbles in asset prices: initial momentum from positive news creates a price run-up, before an absence of news creates a drought of new asset demand. The subsequent price crash carries on its own momentum. We can treat demand as a latent variable to see these oscillations manifest in return data. Substituting lagged demand into the equation for returns, and iterating infinitely yields

$$r_t = -\sum_{T=1}^{\infty}\left(\frac{\alpha}{\gamma\sigma^2}\right)^T r_{t-T} + \frac{S_t\gamma\sigma^2}{\beta N} \tag{17}$$

as long as $\alpha/\gamma\sigma^2 < 1$, so that the contribution of demand fluctuations to returns converges to zero over time. This is an autoregressive model with infinite lags, where the coefficients decrease exponentially with lag size T. Without any knowledge of asset demand, the second term encapsulates an unobservable error term which the model links to exogenous changes in the asset's supply. Eq. 17 demonstrates that an exogenous increase in returns at time t is followed by an smaller decrease in $t+1$. This oscillation persists indefinitely, and would converge to zero rapidly if the social signal $\alpha/\gamma\sigma^2$ is sufficiently small.

3.4 Model predictions

We summarise our asset demand model with social contagion by two prediction, which we seek to validate in our WSB data.

Prediction 1: mechanism for peer effects in asset demand *Given that asset demand across investors are complementary, expressed sentiments react accordingly. A marginal increase(decrease) in peer outlook about an asset will raise(lower) the future outlook of an investor about the asset.*

Besides testing for peer effects among investor sentiments in WSB, we also use the opportunity to test our assumption for mechanical extrapolation. A uniform, marginal increase(decrease) in an asset's returns will raise (lower) the future outlook of an investor about the asset. It will also indirectly increase(decrease) the outlook of an investor through increasing(decreasing) the outlook of his peers.

Prediction 2: return predictability and reversals *Stock returns are lower(higher) when the social component in investor's expected value is large(small).*

Eq. 16 predicts that returns and WSB sentiments correlate positively contemporaneously, but negatively with respect to lagged sentiments. One issue with regard to the positive correlation is that the data will likely reflect the equilibrium outcome, in that sentiments are positive because returns are positive, and vice-versa. One challenge is to find variations in current sentiment that are exogenous with respect to current returns. Stock-specific characteristics will also drive persistent heterogeneity in the expressed sentiments of WSB users.

4 Behaviour and narratives in WSB

This section provides empirical evidence for the existence of the mechanisms underlying bubble formation – namely peer effects and extrapolation – among investors on WSB. We convey our main intuition using a game with strategic complementarities in retail investor decision-making (Zenou 2016, Hellwig & Veldkamp 2009, Bulow et al. 1985). Barlevy & Veronesi (2000) argue, contrary to Grossman & Stiglitz (1980), that learning among investors can become a strategic complement. We propose and test a framework where these complementarities manifest in the sentiments expressed about the future outlook of an asset among investors on WSB.

Testable prediction Prediction 1 in Section 3 establishes the behaviours we expect to see within the WSB community. In this Section, we argue that user sentiment data observed on WSB are consistent with our model: investors are influenced by peer sentiments, and extrapolate past returns. WSB, as a platform, is a venue for 'hype investors' to realise their strategic information complementarities, possibly justifying its exponential user growth.

Estimating equation The target independent variable of interest for studying hype investor sentiment is the log-odds of bullish over bearish sentiment,

$$\Phi_{i,t} = \frac{1}{2}\log\left(\frac{P(\phi_{i,t} = +1)}{P(\phi_{i,t} = -1)}\right) = g(b_{i,t}) + f(\bar{\phi}_{-i,(t-1,t)}) + \varepsilon_{i,t}, \tag{18}$$

derived from our utility framework in Appendix B.1. One key addition is the time subscript, t. An author chooses a bullish over bearish strategy depending on: i) a signal $b_{i,t}$, and ii) the observed sentiments of peers, $\bar{\phi}_{-i,(t-1,t)}$.

4.1 Empirical strategy: consensus formation among investors

We use two approaches to estimate Eq. 18: i) the *Frequent Posters* approach, and ii) the *Commenter Network* approach. Both leverage different features of our data. For the *Frequent Posters* approach, we leverage the fact that certain users post multiple submissions about the same asset (hence, *frequent*). For the *Commenter Network* approach, we use instances in which users comment on others' submissions to more precisely gauge the transmission of sentiments about the same asset.

For the *Frequent Posters* approach, we observe that 8,173 authors create at least two submissions about the same ticker. We quantify peer influence by identifying the impact of other authors who write submissions about the same asset *between* an individual's two submissions. We use an IV of previous, expressed peer sentiments to control for exogenous shocks (see Figure 1 for an illustration). Our approach allows us to control for the author's sentiment prior to exposure to his peers, in addition to market moves. We argue that the peer sentiments that an individual is exposed to have random, temporal variation: the posts that an individual is exposed to on WSB depends on what other anonymous, disconnected users have posted on the forum shortly before the author logs on, and what topic has recently gained popularity (see Section 2 for a detailed description). Users are 'disconnected' in the sense that Reddit does not have friendship/follower ties. Individuals cannot, therefore, filter exposure to certain sentiments over others. We argue that this randomised exposure of users to different opinions (similar in spirit to random assignment of individuals to groups, such as in Weidmann & Deming (2021)) allows us to estimate direct peer effects.

The *Commenter Network* approach considers a submission-to-submission network, with an earlier submission exerting peer influence on a future submission if the author of the later submission commented on the earlier one. The submission-to-submission network helps identify peers an author interacts with more precisely. Here, we also control for market moves, and employ a set of IVs to address endogeneity concerns. As our IVs, we measure: i) sentiments of submissions to which the influencing submission is connected (the 'friends of friends' – detailed in Figure 2b), and ii) the historic sentiment of neighbours. The underlying argument rests on the premise that neighbours of network distance two exert an influence on user sentiments through peer effects (consistently with Bond et al. (2012)), however, allow us to control for a user's endogenous choice to comment on certain posts over others. We use the timing of our IVs to control for common shocks.

4.1.1 Identifying peer influence – Frequent Posters

Within WSB, we observe author i initially express a view about an asset j, $\Phi_{i,j,(t-1)}$ (the continuous log-odds of a post expressing bullish over bearish sentiment, as per Eq. 18), and, subsequently, write a new submission about the same asset at a later time, with an updated sentiment $\Phi_{i,j,t}$ (where time t is in event time). In the time between these posts, the author observes submissions by others on the same asset expressing average sentiment $\bar{\Phi}_{-i,j,(t-1,t)}$, in addition to market moves. Observing $\Phi_{i,j,(t-1)}$ allows us to control for any public and private signal an author receives prior to exposure to his peers. The approach is illustrated in Figure 1.

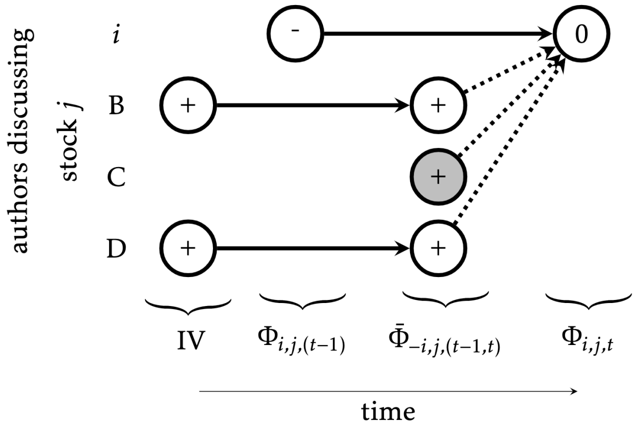


Figure 1: ***Frequent Posters* diagram;** we present a simplified example of our approach – nodes displayed right of a certain author (i, B, C, D) represent the author's submissions, expressing sentiments about stock j, over time. We model author i's sentiment at time t, $\Phi_{i,j,t}$, as a function of their own previous sentiment $\Phi_{i,j,(t-1)}$, as well as the average sentiment expressed by peers between posts $\bar{\Phi}_{-i,j,(t-1,t)}$, as per Eq. 19. The dotted lines denote the peer influence we are trying to estimate; the solid lines denote the persistence of an author's own sentiment. In the Reduced Form we use average expressed peer sentiment to calculate $\bar{\Phi}_{-i,j,(t-1,t)}$; in the IV strategy we use prior peer sentiment as an instrument to estimate $\bar{\Phi}_{-i,j,(t-1,t)}$.

We first estimate the effect of average peer sentiment between an author's two submissions with the following linear model:

$$\Phi_{i,j,t} = \kappa\bar{\Phi}_{-i,j,(t-1,t)} + X_{i,j,t}\beta + \epsilon_{i,j,t}, \tag{19}$$

where the vector of control variables, $X_{i,j,t}$, is composed of stock-specific fixed effects, author i's past sentiment, and stock log-returns, both on day t and the average of the five days preceding t, and the variance in log returns on the five days prior to day t; β is a vector of corresponding coefficients. Even though peers appear randomly on the forum in this formulation (as discussed earlier in this section), an exogenous shock in the period $(t-1,t)$ may affect the views of both peers and the author in question simultaneously. For this reason, the OLS estimates do not enable us to precisely estimate peer influence.

To tackle this issue, we use the historical views of peers as an IV for their views expressed within $(t-1,t)$. Our choice of IV is founded in psychology: Ross et al. (1975) find that 'once formed, impressions are remarkably persevering and unresponsive to new input', with later studies, such as Anderson et al. (1980), supporting these findings. We estimate investor k's sentiment (a peer of investor i) about asset j, $\Phi_{k,j,t}$, based on the sentiment they expressed previously, $\Phi_{k,j,t-1}$:

$$\Phi_{k,j,t} = \kappa^0 \Phi_{k,j,t-1} + \epsilon^0_{k,j,t}, \tag{20}$$

where $\epsilon^0_{k,j,t}$ is an idiosyncratic error, and κ^0 a coefficient. Eq. 20 is estimated using a sample containing submissions by all authors who post multiple times. The F-statistic for this first stage estimate, presented in Table 3, supports our view that this is a strong instrument. Our choice of IV gives a good approximation for author sentiment, while allowing us to control for common shocks affecting the sentiments of peers and investor i in the period $(t-1, t)$. We use the predicted outlook of peers between an author's posts, $\hat{\Phi}_{-i,j,(t-1,t)}$, to estimate peer effects as our Second Stage regression, while keeping all other controls the same. Appendix B provides further details on our variable construction and method. Our Online Appendix describes market variable construction.

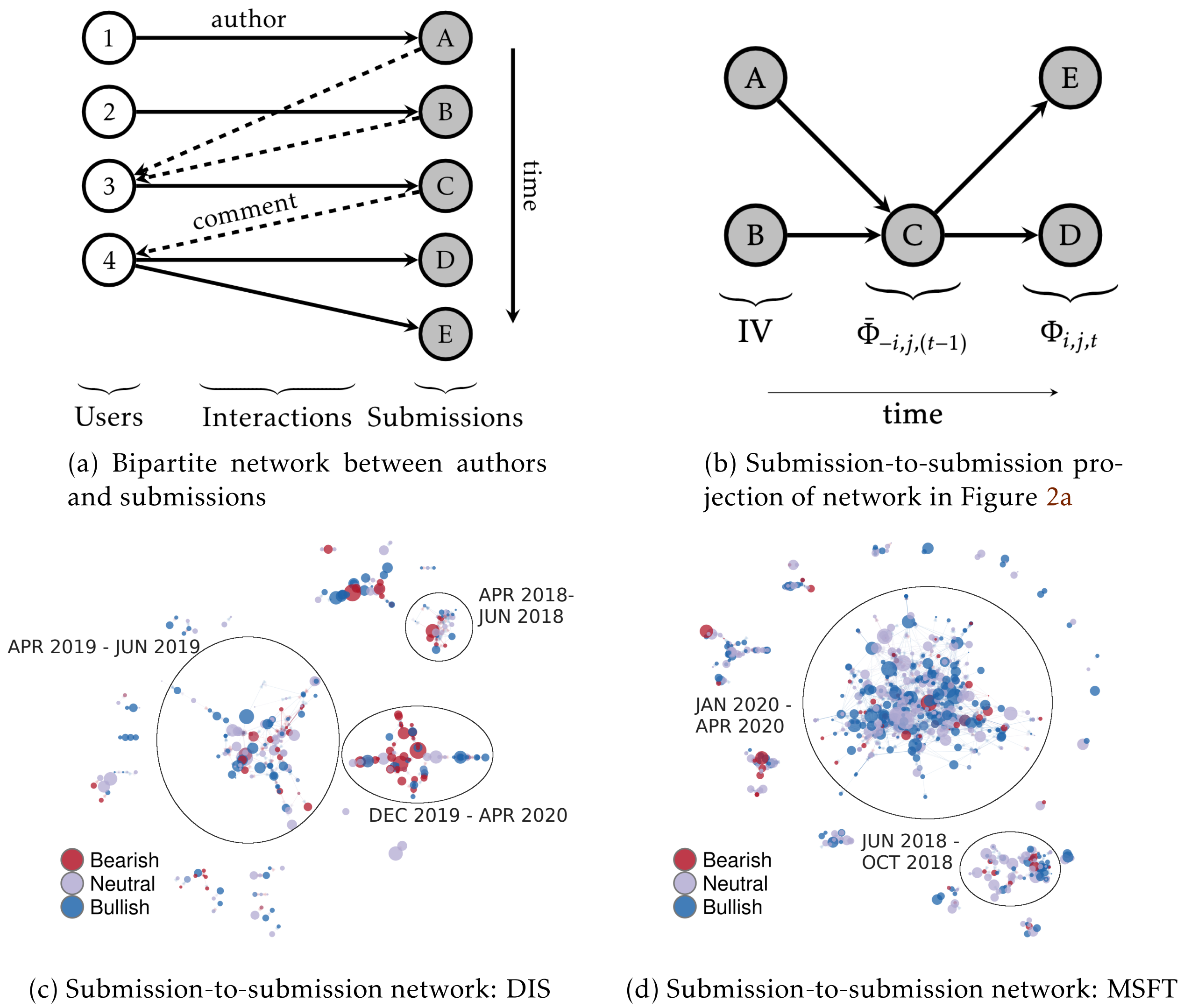
Credible estimation We check whether our estimation strategy is credible, with respect to the three challenges presented by Zenou (2016) and Athey & Imbens (2017) in estimating peer effects. The first lies is in distinguishing peer effects from contextual effects – the tendency of perspectives to vary with some observable characteristics of the group, rather than individuals influencing each other. Controls for asset price movements and ticker specific characteristics – the main sources of exogenous variation – address this concern. Second, the random, anonymous nature of WSB, as well as controlling for ticker-specific fixed effects, address the possibility for correlated effects. The specification with the IV addresses the common shock problem. A more rigorous, statistical analysis of our identification strategy is included with the results.

4.1.2 Identifying peer influence – Commenter Network

WSB allows us to trace the interactions of users through a commenting network, even though there are no user friendship ties. We exploit a submission-to-submission interaction network for each asset, tracking which submissions in the past influence future submissions based on authors' commenting histories. This method offers a more precise way to identify an individual's peers by observing which individuals, and submissions, an author explicitly interacts with. Figures 2a and 2b illustrate the approach.

Two examples of submission-to-submission networks in our data are displayed in Figures 2c and 2d. Distinct temporal clusters emerge, as a certain asset gains and loses prominence on WSB. Some discussions appear fragmented: the DIS discussion in Figure 2c, for example, contains several smaller clusters, with distinct differences in overall sentiments. Others, such as the MSFT discussion in Figure 2d, contain a giant component where investors with different sentiments interact.

Our network approach uses a similar Reduced Form and Second Stage to the *Frequent Posters* approach in Eq. 19. We modify our control for an author's past sentiment about the stock to account for authors who post for the first time: a dummy variable encodes whether



(a) Bipartite network between authors and submissions

(b) Submission-to-submission projection of network in Figure 2a

(c) Submission-to-submission network: DIS

(d) Submission-to-submission network: MSFT

Figure 2: **User networks in WSB conversations**; WSB data is summarised as a bipartite graph, illustrated in Figure 2a, where users (left) are linked to submissions (right) when they author the submission (solid edge) or comment on the submission (dashed edge). The resulting projection of submissions, in Figure 2b, tracks the propagation of sentiments Φ. The submission-to-submission networks for two stocks in Figures 2c and 2d reveal that individuals post more submissions that are bullish(bearish) at times when the price of an asset increases(decreases) dramatically, with some visual evidence that similar sentiments tend to cluster.

the author's most recent previous post is bearish, neutral, bullish or missing.

We use an IV approach to estimate peer influence. As the First Stage, we estimate the sentiments of neighbours to estimate an author's view. As indicated in Figure 2b, the sentiments in submissions **A**, **B** can be used to predict that of submission **C**. The *predicted* sentiment of **C** can then, in turn, be used to predict the sentiments of **D** and **E**. This choice of IV is well-established in the networks literature (Zenou 2016, Patacchini & Zenou 2016, Bifulco et al. 2011), and helps control for the exogenous choice to comment on certain submissions and not others. We also include the neighbour's own historical sentiment as a set of categorical variables, as the second IV (similarly to the *Frequent Posters* approach). Our

Eq. 20, therefore includes a set of author controls $X^0_{i,j,t}$:

$$\Phi_{k,j,t} = \kappa^0 \Phi_{k,j,t-1} + X^0_{i,j,t}\beta^0 + \epsilon^0_{k,j,t},$$

where the superscript denotes the estimation of the First Stage. In the results in Table 3, we display the estimate for our main IV - neighbours of neighbours in the commenting network; the additional IV of author historical sentiment is displayed in Appendix B.

We use the timings of events to mitigate the common shock problem for both our IVs: the neighbor's historical sentiment and the 'friends or friends' posts. For the latter, we calculate the time period of influence for a given post, which ends when the last comment is made on a post. This effectively marks the point when the topic of a post ceases to be of interest to the investor community. We filter for instances where the period of influence for a submission used as an IV for another post ends before the post we are modeling is created. In practice, if post **C** in Figure 2b occurs on July 1st at 2:31PM, the final comments on posts **A** and **B** must occur before, in order to ensure that our IV is not affected by a common shock. We also include an author's own, historical sentiment as an IV only if his previous submission occurs at least two business days before the current one.

The *Commenter Network* offers certain upsides, but also certain shortcomings, as compared to the *Frequent Posters* approach. The network method more precisely identifies the channels of influence between authors. However, the allocation of peers is no longer random, since the network structure is governed by a *choice* to comment.

4.2 Results: Consensus Formation and Peer Effects

In this section, we present the Reduced Form, Second Stage, and First Stage regression estimates for both the *Frequent Posters* and *Commenter Network* approaches. The Reduced Form and Second Stage estimates, across both model specifications, show that peer sentiments directly impact an individual's sentiment about an asset, with users conforming to their peers.

Table 3 presents the results, with Panel A presenting OLS estimates for κ, from Eq. 19, using observed variation in peer sentiments, and Panel B.1 using predicted variation in peer sentiments. We relegate estimated coefficients for control variables to Appendix B. In the *Frequent Posters* approach, the estimated peer effects can be summarised as follows: an average estimate for κ at 0.1, in the Reduced Form case, means that doubling in the odds of peers expressing bullish over bearish sentiments increases the odds of a given submission to be bullish, over bearish, by 7.2%, on average (we raise the log-odds estimate for $\Phi_{i,j,t}$ to an exponent). In the IV setting, an estimate of 0.19 translates to an increase in the corresponding odds for bullish over bearish sentiments by 14.1%. In all cases, the robust standard errors, clustered at the ticker level, produce estimates statistically significant at the 1% level. The *Commenter Network* approach yields a similar result.

The estimated coefficients in columns (1) and (2) of Panel B.1 suggest that an exogenous increase in average peer outlook appears to increase an investor's own future view about an

Table 3: Peer influence in WSB sentiments

	Frequent Posters (1)	Network (2)
Panel A: Reduced Form – peer influence estimated using *observed* average sentiment of peers		
	Independent Variable Average peer sentiment, $\bar{\Phi}_{-i,j,(t-1)}$ (observed)	
Investor Sentiment ($\Phi_{i,j,t}$)	0.10 (0.02) ***	0.05 (0.01) ***
Author & asset controls ($X_{i,j,t}$)	Yes	Yes
Number of obs.	14,396	24,963
F-statistic	71	668
Panel B.1: Second Stage – peer influence estimated using *predicted* average sentiment of peers		
	Independent Variable Average peer sentiment, $\hat{\bar{\Phi}}_{-i,j,(t-1)}$ (predicted)	
Investor Sentiment ($\Phi_{i,j,t}$)	0.19 (0.05) ***	0.19 (0.08) **
Author & asset controls ($X_{i,j,t}$)	Yes	Yes
Number of obs.	11,122	16,521
J-statistic	NA	0.43
F-statistic	77	1,277
Panel B.2: First Stage – estimating peers' sentiments		
	Independent Variable	
	Historical Sentiment of Peers	Sentiment of Neighbours' Neighbours
Sentiment of Peers	0.33 (0.01) ***	0.14 (0.01) ***
Author controls ($X^0_{i,j,t}$)	No	Yes
Number of obs.	19,814	24,013
F-statistic	2,430	118

Notes: this table presents the First Stage, Second Stage and Reduced Form OLS estimates for peer influence on WSB. In column (1), the First Stage is estimated using the initial sentiment expressed by an author about an asset to estimate his sentiment in the following post. In column (2), the First Stage is estimated using the sentiment of previous submissions that an author commented on, regarding the same asset. The Second Stage is estimated using the average predicted sentiment of peers. Ticker-level dummies, asset return and volatility controls, and the intercept are included in the Second Stage and Reduced Form estimates, but not shown here; additional author-specific IVs in the network approach are also included but not shown – the complete estimates are presented in Appendix B. Robust standard errors, clustered at the ticker level for Panels A and B.1, are presented in parentheses. Observations with incomplete data are dropped.
*** Significant at 1% level ** Significant at 5% level * Significant at 10% level

asset. These findings demonstrate that the data are consistent with Prediction 1. As a result, we conclude that the data supports a model where strategic complementarities govern the investment decisions of retail traders on WSB.

Support for identification One potential concern is that individuals who post multiple times about the same asset, or those who comment on others' submissions, may differ from the rest of the population on the forum. If this were the case, our findings would not allow us to draw valid conclusions about the overall population of investors. We provide evidence that sentiments expressed by our samples are similarly distributed to those of the overall user population in Appendix B.

A second concern is whether our proposed independent variables – asset price movements, ticker fixed effects and author historical sentiments – are effective controls for unobserved ticker characteristics. If our controls in the *Frequent Posters* formulation are valid, then a randomly selected cohort of individuals who post on the same ticker *before* the author's first post, should have no effect on the sentiments expressed in dependent submissions. Similarly, if our controls are useful in the *Commenter Network* formulation, a random rewiring of the network should yield no effect. The results are detailed in Appendix B: no statistically significant correlation emerges from the randomly selected cohorts. This provides further evidence that unobserved factors influencing within-ticker variation in both peer composition and author sentiment are not confounding.

A final concern with our *Commenter Network* approach is overidentifying restrictions. A J-statistic of 0.43, and a corresponding p-value of 51%, leads us to believe that our additional instruments are exogenous (see Appendix B for further details). We explore further dynamics observed on WSB, such as whether there is contagion in asset interest among investors online (Banerjee 1993, Shiller 2017), in Appendix B.

5 Has WSB destabilised markets?

Prediction 2 states that sharing of information among investors and trend following can impact asset returns. In Section 4, we focus on identifying the extent to which investors consider information from peers, as well as recent market moves, while updating their beliefs about future asset returns. The evidence for peer effects in asset demand is robust in two, separate estimation strategies we consider. In this section, we conduct a quantitative analysis of asset returns and the data from WSB, in order to validate the link between these behaviours and the markets.

5.1 Return predictability and reversals

Prediction 2 proposes an inverse relationship between asset prices and lagged demand, specifically following a dynamic version of Eq. 16. We are also interested in finding variation in current sentiments that are exogenous with respect to current returns. This may help detect a positive effect carried by retail investor sentiment, proxied through WSB activity.

Independent variable Our independent variable estimated from WSB sentiment data proxies consensus formation $\Delta\Phi_{j,t}$, the first-difference of stock j's mean daily log-returns between calendar weeks t and $t-1$. The purpose is to gauge the stock-specific response to a change in WSB's associated attention and sentiments on a week-by-week basis. This variable gauges the change in asset demand due to changes in intensity of peer sentiments that determine aggregate investment.

Reduced Form First, we formulate the linear relationship between our market variables and social dynamic variables of choice. We then propose a 2SLS empirical strategy to estimate the impact of consensus and contagion on stock market variables. We regress changes in weekly log-returns on consensus formation:

$$\Delta \bar{r}_{j,t} = \beta_{\Omega} \Delta \Phi_{j,t} + \eta_t + \varepsilon_{j,t}, \tag{21}$$

where β_{Ω} is the coefficients of interest, η_t denotes time fixed effects, and $\varepsilon_{j,t}$ an idiosyncratic error. This Reduced Form setup does not allow us to argue that a causal relationship exists between hype investor activity and stock market activity: the narratives discussed and sentiments expressed at a given point in time are often shaped by real-time news, events and stock market moves – resulting in reverse causality. For example, users express positive sentiments in weeks of outsized, positive returns, regardless of past sentiment.

First Stage We use in variation sentiments that can be explained by past activity on WSB and past stock performance to identify our parameters of interest. In doing so, we assume that our target stock market variables are sufficiently uncorrelated between sequential trading weeks. Effectively, this translates to an assumption that the market is sufficiently efficient, such that stocks' weekly returns are uncorrelated to those in the previous week.

We predict consensus formation $\Delta \Phi_{j,t}$ using past stock price behaviour, as well as past sentiments:

$$\Phi^{+}_{j,t} = \log\left(\frac{\mathrm{P}(\phi_{j,t} = +1)}{\mathrm{P}(\phi_{j,t} = 0)}\right) = \lambda^{+}_{r} \bar{r}_{j,t-1} + \lambda^{+}_{\sigma} \sigma^{2}_{j,t-1} + \lambda^{+}_{1} \Phi^{+}_{j,t-1} + \lambda^{+}_{2} \Phi^{-}_{j,t-1} + \eta^{+}_{t} + \varepsilon^{+}_{j,t}, \tag{22}$$

$$\Phi^{-}_{j,t} = \log\left(\frac{\mathrm{P}(\phi_{j,t} = -1)}{\mathrm{P}(\phi_{j,t} = 0)}\right) = \lambda^{-}_{r} \bar{r}_{j,t-1} + \lambda^{-}_{\sigma} \sigma^{2}_{j,t-1} + \lambda^{-}_{1} \Phi^{+}_{j,t-1} + \lambda^{-}_{2} \Phi^{-}_{j,t-1} + \eta^{-}_{t} + \varepsilon^{-}_{j,t}, \tag{23}$$

where superscripts differentiate between the average log-odds of a submission in week t expressing bullish (+) versus negative (−) sentiments, over neutral sentiments. Week fixed effects remain in the sentiment models, so that the full estimation strategy rests on within-week variation in all explaining, as well as explained, variables.

The approach outlined above relies on coarse aggregates for sentiments: the probabilities here are not estimated on data for individual submission sentiments, as is the case in Section 4. Rather, the probabilities are calculated by averaging the probabilities for *all* submissions in week t, discussing ticker j, to be bullish ($\mathrm{P}(\phi_{j,t} = +1)$), bearish ($\mathrm{P}(\phi_{j,t} = -1)$), or neutral ($\mathrm{P}(\phi_{j,t} = 0)$). Predicted values for our sentiment measure follow from the sentiment model predictions:

$$\Delta \widehat{\Phi}_{j,t} = \frac{1}{2}\left(\widehat{\Phi}^{+}_{j,t} - \widehat{\Phi}^{-}_{j,t}\right) - \Phi_{j,t-1}. \tag{24}$$

In all our estimates, we restrict ourselves to a sub-sample spanning January 2016 to July 2020. This choice serves to limit the amount of missing data in times when activity was relatively sparse.

Results Table 4 helps assess the instruments' strength in predicting sentiments on WSB. The high F-statistics justify that the explanatory variables are not weak instruments. In columns (2) and (3), we find that lagged weekly mean and variance in returns, combined with lagged sentiments, are significant predictors for the current log-odds in submissions expressing bullish and bearish sentiments. This is in line with our findings in Section 4.

Table 4: First Stage estimates for consensus and contagion in WSB

	Dependent variable:	
	$\Phi^{+}_{j,t}$	$\Phi^{-}_{j,t}$
$\bar{r}_{j,t-1}$	-0.0002 (0.52)	-1.53^{**} (0.65)
$\sigma^{2}_{j,t-1}$	-3.78^{***} (0.98)	-3.75^{***} (0.68)
$\Phi^{+}_{j,t-1}$	0.09^{***} (0.02)	-0.06^{***} (0.01)
$\Phi^{-}_{j,t-1}$	-0.03^{***} (0.01)	0.16^{***} (0.01)
Week FE	Yes	Yes
Number of obs.	6,711	6,711
F-statistic	17.63	49.53

Notes: the dependent variable in column (2) is the average log-odds of a given submission in week t on stock j to express bullish over neutral sentiment, and in column (3) – bearish over neutral sentiments. Explanatory variables include: the average log-return $\bar{r}_{j,t-1}$, and the variance in log-returns $\sigma^{2}_{j,t-1}$. The logit-transformed sentiments are regressed on the lag of the weekly mean and variance of log-returns, as well as the lag in logit-transformed sentiments. Each specification includes week-specific fixed effects. Accompanying standard errors, displayed in brackets, are clustered at the stock level, and calculated in the manner of MacKinnon & White (1985).
*** Significant at 1% level ** Significant at 5% level * Significant at 10% level

Table 5 presents our main results. Panel A regresses changes in average returns against *observed* measures for sentiment changes $\Delta\Phi_{j,t}$. Panel B in Table 5 presents causal evidence for the impact of consensus formation and contagion among WSB users on stock market variables, using *predicted* and sentiments from the model presented in Table 4. We do not argue that WSB alone affects the markets, but rather that WSB data offers a rich sample of retail investor behaviour.

5.2 Granular social forces

The previous section shows that a negative relationship holds between past sentiments and future returns. The relationship is justified by our model with endogenous sentiments and returns – investors are willing to accept a lower return on an asset that they value more highly.

An outstanding question is how our model framework accounts for the anecdotal run-ups in price, such as the GameStop short squeeze. These run-ups are, arguably, driven by a purely social component, rather than a shift in fundamentals. In order to account for this, we modify our framework from Eq. 14 to suppose that investor sentiments have a noise

Table 5: Market impact of WSB discourse

Panel A: Reduced Form relationship between WSB and market activity	
	Dependent variable:
	$\Delta\bar{r}_{j,t}$
$\Delta\Phi_{j,t}$	0.002*** (0.0003)
Week FE	Yes
Number of obs.	6,671
F-statistic	24.32

Panel B: structural relationship between WSB and market activity	
$\Delta\widehat{\Phi}_{j,t}$	0.004*** (0.001)
Week FE	Yes
Number of obs.	6,671
F-statistic	12.63
J-statistic	8.108

Notes: this table presents OLS estimates for stock j's change in average log-return, $\Delta\bar{r}_{j,t}$, in week t. We filter the sample to stocks mentioned in at least 31 distinct submissions on WSB, and exclude any ETFs. Explanatory variables include a measure for sentiment change, $\Delta\Phi j,t$, which tracks the change in average sentiments on WSB. Each specification includes week-specific fixed effects. Accompanying standard errors, displayed in brackets, are clustered at the stock level, and calculated in the manner of MacKinnon & White (1985). Panel A computes the coefficients using values directly from WSB data, whereas Panel B employs sentiments and stock discussion predicted by past sentiments, stock discussions, as well as returns and return volatility, for which results are in Table 4. The associated J-statistics are recorded at the bottom of Panel B, which are computed by regressing the residuals from the Second Stage on all variables used for predicted $\Delta\widehat{\Phi}_{j,t}$.
*** Significant at 1% level ** Significant at 5% level * Significant at 10% level

component $e_{i,t}$ with mean zero, where i refers to the investor and t is the time period:

$$\phi_{i,t} + e_{i,t} = \frac{\alpha\phi_{t-1} + \beta r_t}{\gamma\sigma^2}, \tag{25}$$

summing across all investors, we observe:

$$\sum_i s_{i,t}\phi_{i,t} + \sum_i s_{i,t}e_{i,t} = \frac{\alpha\phi_{t-1} + \beta r_t}{\gamma\sigma^2},$$

where $s_{i,t}$ is the weight associated with each signal: $\sum_i s_{i,t} = 1$. In an endogenous system, $\sum_i s_{i,t}\phi_{i,t}$ must necessarily equal supply S. This leads to the following relationship with returns:

$$\frac{S\gamma\sigma^2}{\beta} - \frac{\alpha}{\beta}\phi_{t-1} + \frac{\gamma\sigma^2}{\beta}\sum_i s_{i,t}e_{i,t} = r_t. \tag{26}$$

In the case when all information is weighted equally, $\sum_i s_{i,t}e_{i,t} = 0$. However, in the case when hype / social herding might change the distribution of $s_{i,t}$, we might expect idiosyncratic information shocks $e_{i,t}$ to positively influence returns.

Similarly to other online social phenomena, the attention granted to different posts on WSB is heavy tailed - a small fraction attract a high number of comments / upvotes, while most go virtually unnoticed. We exploit this imbalance for our identification strategy: we use the within-week-ticker variation in popularity of posts as a granular instrumental variable to show that idiosyncratic sentiment expressed in popular posts survives aggregation and impacts future asset returns (Gabaix & Koijen 2020, 2021, Galaasen et al. 2020). Consistently with previous sections, we use the log-odds of a bullish over bearish submission $\Phi_{i,j,t}$ as our variables for studying sentiment.

5.2.1 Granularity of the distribution of social attention

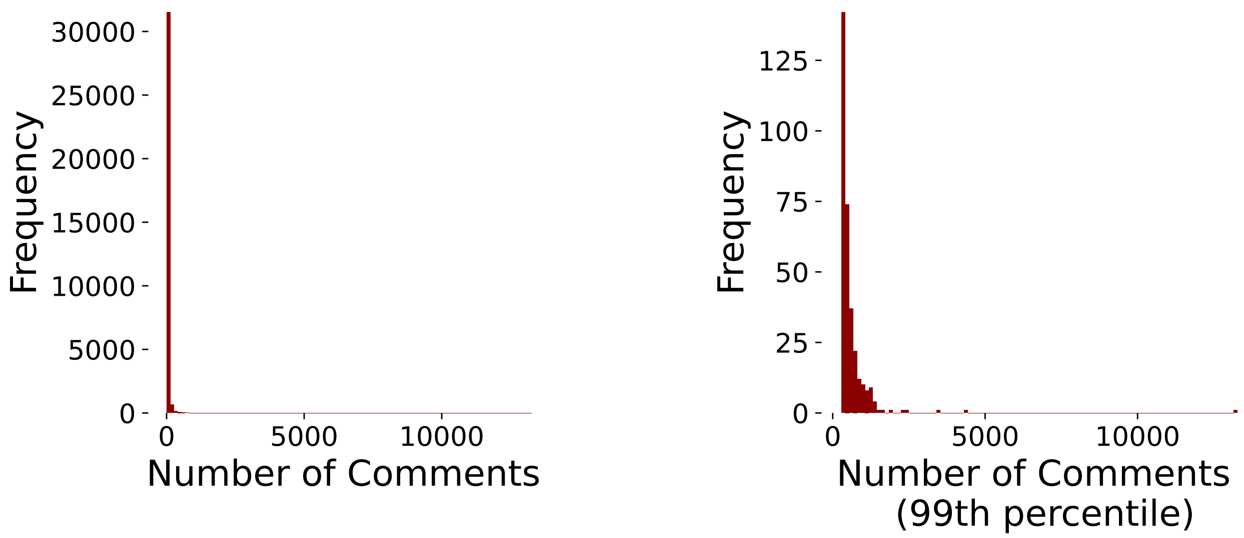


Figure 3: **Heavy tailed attention:** These graphs show the distribution of comments that posts on WSB receive. The left figure plots the full distribution. The right figure zooms in on the 99th percentile of the most popular posts. The Pareto exponent of the 99th percentile is 1.76.

We begin by establishing that the distribution of attention that information shared by investors online receives is heavy tailed. We proxy attention by the number of comments that a particular post receives. The paper exploits within-ticker-week variation in attention; therefore we filter our sample to weeks and tickers where a sufficient number of posts are made - we choose twenty posts for our cutoff. Figure 3 shows the extreme skewness in the distribution of attention - some posts appear to receive a large following, while the majority are of little interest. This implies that idiosyncratic information contained within the most popular posts potentially persists after pooling across all investor's opinions, and may have a disproportionate effect on returns.

5.2.2 Estimates of idiosyncratic social shocks

The next step of our empirical approach consists in extracting idiosyncratic information shocks, measured as unexplained idiosyncratic variation in the sentiments posts. To extract unexplained variation in sentiments, we regress the sentiment expressed in a given post $\Phi_{i,j,t}$ on the return on day t, $r_{j,t}$, the average returns on the week containing t, r_{j,t_w}. The underlying strategy posits that any news that emerges at time t about a company is quickly assimilated by the market and manifests in returns. Any variation in sentiment that is unexplained by market performance at time t is post-specific and is idiosyncratic to news and information more broadly available about that stock at that time. For a post about asset j made by author i at time t, we estimate the idiosyncratic information content of the post as $e_{i,j,t}$ in the following regression:

$$\Phi_{i,j,t} = \beta_1^A r_{j,t} + \beta_2^A r_{j,t_w} + \beta_3^A X_{t_w} + e_{i,j,t}, \tag{27}$$

where X_{t_w} are week fixed effects.

The object of interest, the residual $e_{i,j,t}$, is information shared in the post that is orthogonal to asset j's returns at time t or within week t_w. We, therefore, would expect $e_{i,j,t}$ to have an impact on the market through social forces, rather than through purely informational content (which would have been reflected in the market returns immediately).

Figure 4 plots the idiosyncractic social shocks. We observe that the distribution is asymmetric with a heavy left tail.

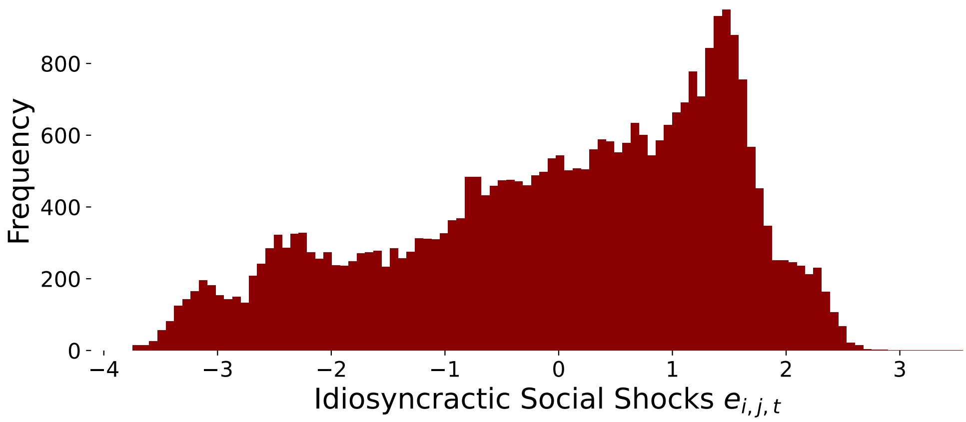


Figure 4: **Iodiosyncractic social shocks:** this graph plots the distribution of idiosyncratic firm shocks from Eq. 27.

5.3 Granular attention: effect on returns - estimation strategy

In order to assess the impact on asset returns of online attention, we proceed by analyzing the following relationship:

$$r_{j,t_w+1} = \beta_1^B \bar{e}_{j,t_w} + \beta_2^B \bar{\Phi}_{j,t_w-1} + \beta_3^B X_{t_w} + v_{j,t_w}, \tag{28}$$

where X_{t_w} are week fixed effects, r_{j,t_w+1} is the total return of stock i in week t_w, $\bar{\Phi}_{j,t_w-1}$ is the average sentiment expressed on the forum about asset j in week t_w-1, $\bar{e}_{j,t_w} = \sum_i s^c_{i,j,t_w} e_{i,j,t_w}$ the popularity-weighted average idiosyncratic sentiment shared about stock i in week t_w ($\sum_i s^c_{i,j,t_w} = 1$), and v_{j,t_w} is a stock-week specific error. s^c_{i,j,t_w} is calculated by summing the total number of comments received across all posts in stock i in week t_w - the comment count for post j is then normalized by the total comment count; comment count is re-indexed so that the minimum number of comments a post receives is one.

A key identification challenge in the specification above stems from the fact that for stock i returns in week t_w+1 may be driven in-part by social forces, but also by asset properties which affect both sentiment and returns simultaneously, which we are unable to control for while estimating idiosyncratic sentiments in Eq. 27. A correlation of these shocks with $\bar{e}_{i,t_w}$ may result for a biased estimator for β^B_1. More formally, outcome variable (after imposing controls from Eq. 28) y^r_{j,t_w+1} may be of the form:

$$y^r_{j,t_w+1} = \beta^B_1 \bar{e}_{j,t_w} + \eta_{j,t_w}, \tag{29}$$

where η_{j,t_w} is the 'common shock' to asset j in period t_w.

We assume that the idiosyncratic social shock from a post can be expressed as having a stock level component, common to all posts about the stock within that time period, and a post-level component:

$$e_{i,j,t_w} = \beta^{cs}_{j,t_w} \eta_{j,t_w} + u_{i,j,t}, \tag{30}$$

where β^{cs}_{j,t_w} is the sensitivity of posts within week t_w to the common shock to stock j. We rely on a Granular Instrumental Variable (GIV) for our identification strategy. The GIV is defined as the difference between popularity-weighted and equally-weighted social shocks, each aggregated for the stock at period t_w:

$$GIV_{i,t_w} = \sum_i s^c_{i,j,t_w} e_{i,j,t_w} - \sum_i \frac{1}{N_{j,t_w}} e_{i,j,t_w}, \tag{31}$$

where N_{i,t_w} is the total number of posts about stock j in week t_w. We subsequently replace $\bar{e}_{j,t_w}$ in Eq. 28 with $\hat{u}_{j,t_w}$, where $\hat{u}_{j,t_w}$ is the predicted values from the regression of the GIV on the social shocks $\bar{e}_{j,t_w}$. The outcome variable $\hat{u}_{j,t_w}$ is driven by the popularity of certain posts over others.

The identification strategy rests on the assumption that the popularity of the idiosyncratic content of posts $s^c_{i,j,t_w} e_{i,j,t_w}$ is not correlated with stock-week shocks η_{j,t_w}. This is not a problem in this setting for several reasons. Firstly, the popularity of a post could potentially be linked to a stock through it's informativeness about the asset's price. However, in the creation of our social idiosyncratic shocks, we extract shocks while controlling for returns on the day and the week of the post. Our social shock time series is, therefore, orthogonal to asset returns at time t and in week t_w and is, therefore, orthogonal to new information available to investors at the time. Second, in WSB we observe data about relatively unsophisticated retail investors where the sentiments of posts at time t about an asset are systematically linked to *negative* future returns (this holds both when we take a raw average and popularity-weighted average average sentiment). Therefore, the investors we observe do not have access to information on stock-level shocks. Finally, both our shock and popularity time series at constructed at time t_w, while the dependent variable is observed at time $t_w + 1$, avoiding contemporaneity issues.

5.4 Granular attention: effect on returns - results

Table 6: Stock returns versus granular social shocks

	Dependent variable: r_{j,t_w+1}						
	Average $\bar{e}_{j,t_w}$	Popularity-weighted $\bar{e}_{j,t_w}$	Instrumented by GIV: $\hat{u}_{j,t_w}$				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Pooled	Pooled	Pooled	Pooled	Pooled	Positive	Negative
Granular Social Shock	0.013	0.035	0.040**	0.044**	0.048**	-0.008	0.112**
	(0.026)	(0.022)	(0.019)	(0.019)	(0.024)	(0.037)	(0.052)
$\bar{\Phi}_{j,t_w-1}$	-0.020	-0.025*		-0.027**	-0.024		
	(0.014)	(0.015)		(0.012)	(0.015)		
Week FE	Yes	Yes	No	No	Yes	No	No
Controls in Eq. 28	Yes	Yes	No	Yes	Yes	No	No
Observations	644	644	644	644	644	161	161
R^2	0.288	0.294	0.007	0.015	0.295	0.000	0.028

Notes: this table presents the OLS estimates for the influence of idiosyncratic social shocks on WSB. Columns (1) and (2) present the effect of average idiosyncratic shocks and popularity-weighted idiosyncratic shocks, respectively. Columns (3), (4) and (5) present various specifications of our instrumented idiosyncratic social shocks $\hat{u}_{j,t_w}$. Columns (6), (7) estimate the effect of social shocks where the instrumented variable is in the top or bottom quartiles (Positive and Negative) of the estimated $\hat{u}_{j,t_w}$. Robust standard errors, clustered at the week level for columns (1), (2), (5), are shown in parentheses. The F-statistic for the first stage regression is 788. Observations with incomplete data are dropped.
*** Significant at 1% level ** Significant at 5% level * Significant at 10% level

In order to study the financial consequences of granular social attention, we run the following regression on weekly returns and posts.

$$r_{j,t_{w+1}} = \beta_1^B \hat{u}_{j,t_w} + \beta_2^B \bar{\Phi}_{j,t_w-1} + \beta_3^B X_{t_w} + v_{i,t_w},$$

where $\hat{u}_{j,t_w}$ are the fitted values of idiosyncratic social shocks on our GIV, r_{j,t_w} is the cumulative weekly return of stock j in week t_w, X_{t_w} are week fixed effects, $\bar{\Phi}_{j,t_w-1}$ is the average sentiment expressed about stock j in the prior week. The formulation closely follows that of our extended model in Eq. 26.

Several patterns emerge from our empirical exercised. Firstly, we observe that the data appears to follow the structure proposed from in our model – idiosyncratic social shocks are positively linked to future returns, while historical sentiments are negatively linked. In the column (5), the estimated effect can be summarised as follows: an estimate for β_1^B at 0.048, means that the idiosyncratic doubling in the odds of a very popular post expressing bullish over bearish sentiments increases returns in the following week by 0.007, on average. The effect is small, but consistent across specifications. Consistently with our model prediction, the average idiosyncratic noise, in column (1), has no effect on returns. The popularity weighted average in column (2) also appears insignificant - we explain this by the fact that the un-instrumented average may contain significant noise, while the instrument helps isolate signal stemming from differnet popularity levels among posts. Finally, we observe that the effect of idiosyncratic social shocks is not symmetric in columns (6), (7): returns respond to negative idiosyncratic social shocks, while positive ones have little effect.

6 Conclusion

Higher asset demand by retail investors does not necessarily entail higher returns when strategic complementarities are at play. This is because investors are willing to hold the asset regardless of its performance. We contribute to the growing literature on asset demand models by documenting the influence of peers on investor opinion formation, using data from WSB as a case study. We specifically observe the existence of strategic complementarities in asset demand among retail investors. User sentiments are, on average, 14% more likely to be bullish rather than bearish, if the odds of peers expressing bullish over bearish sentiments double. These results are consistent with the findings of Pool et al. (2015) and Bursztyn et al. (2014).

In order to validate the structural relationship between sentiment formation and asset returns, we directly investigate the impact of observed investor sentiments, using WSB data. We predict current and past sentiments among WSB users, using historical forum and market data as our IV. Our predicted measure has a statistically significant correlation with market returns.

We leverage the recent work by Gabaix & Koijen (2020) to account for granular social forces – idiosyncratic sentiment shocks (which is not reflective of fundamental news) impact the market due the heavy-tailed nature of the popularity of online content. We use a granular instrumental variable to show how the idiosyncratic sentiments expressed in highly popular posts on WSB can spill-over and impact returns, thereby destabilizing the financial system.

Social dynamics among WSB users are unlikely to drive these results alone, but rather sample broader retail investor sentiments and strategies. The forum offers a window into the minds of an expanding number of retail investors, and it is clear that social media plays a key role in their growing clout on the virtual trading floor. As such, our findings favor the study of narratives in financial markets (Shiller 1984, 2005). The important role that peers and asset returns play in formulating investor opinion points to strategic complementarities in information acquisition among investors, underscoring the importance of work by Barlevy & Veronesi (2000) and Hellwig & Veldkamp (2009). Our conclusions augment the earlier experiments of Bursztyn et al. (2014), showing that information from peers plays a role in a broader investment context than that of the authors' experimental setting. They complement the work of Cookson & Niessner (2020) by tracking a different facet of social dynamics that has tangible impacts on the markets.

With the first publicly acclaimed victory of Main Street over Wall Street, in the form of the GameStop short squeeze, it is an important time to re-evaluate regulatory structures within the financial system, which currently closely monitor financial institutions and large players, but largely overlook smaller investors. The safety of the retail investor is also emerging as a prominent concern. The excitement of potential gains has attracted a greater number of individuals to online forums and new trading platforms, with many offering incentives to lure in the unsophisticated trader. Institutional investors have become alarmingly aware of the ties between retail investor social dynamics and the markets, with profits to be made from influencing online investor discussions.

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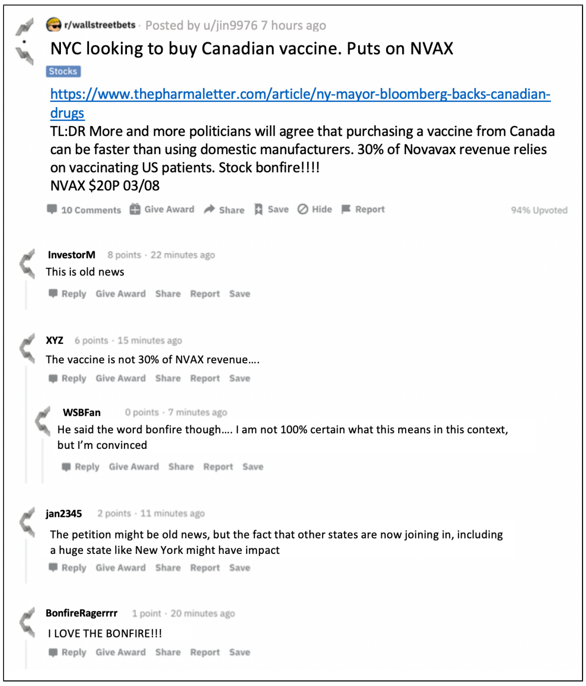
Appendix

A Data appendix

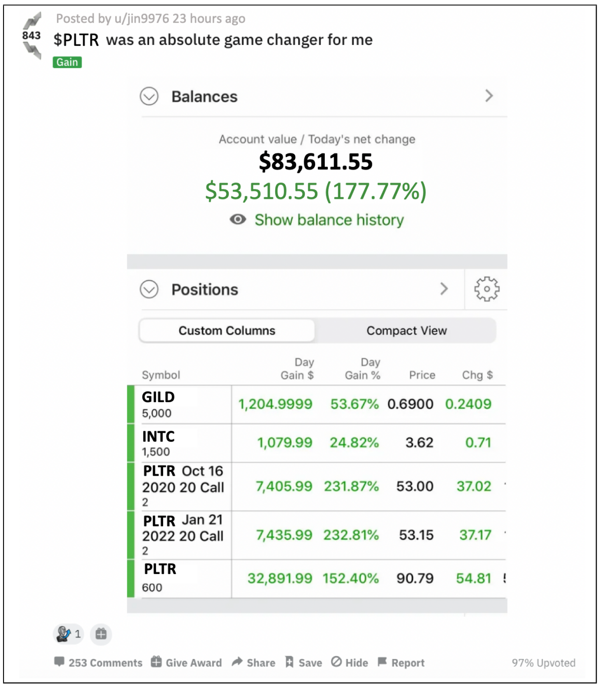
A.1 Extended description of WSB

Figure 5a displays a typical exchange on the WSB forum: individuals discuss stock-related news and their sentiments on whether this will affect stock prices in the future. In addition to market discussions, there is ample evidence of users pursuing the investment strategies encouraged in WSB conversations. Users post screenshots of their investment gains and losses, which subreddit moderators are encouraged to verify, as illustrated in Figure 5b.

Figure 6 displays the evolution of WSB over time. Two jumps are notable: a smaller, seemingly idiosyncratic rise in early 2018, and a sharp spike during the COVID-19 pan-



(a) A typical discussion on WSB



(b) A sample screenshot of user profits

Figure 5: **What does WSB look like?** These snapshots display typical discussions on WSB. The exact text, usernames, and conversation details have been modified to protect user identities.

demic.

A.2 Reddit user content presentation

Our empirical identification strategy in the *Frequent Posters* approach rests on the premises that users are exposed to random variation in peer sentiments. In this section, we discuss the details of how users are presented with content on Reddit.

Upon logging into Reddit, users are presented with a 'home feed'. Historically, the home feed has contained the 'top posts' from the subreddits to which a user has subscribed. More recently, Reddit has implemented an algorithm to try and match users to content based on a machine learning algorithm, via the home feed.[7] However, this change has only taken effect recently, and well after the point when our data were collected.[8] Subreddit top posts are not individually tailored to the specific user. Users have several sort options based on whether they prefer to see most recent or most highly rated content.[9] However, they do not have an option to personalize viewed content beyond this. We, therefore, conclude that individual users were exposed to WSB content based on the content on the forum that was most recent and popular at the time of their logging on, rather than based on personal preference. This, in turn, allows us to assert that users are exposed to random, temporal variation in peer sentiment.

[7] https://reddithelp.com/hc/en-us/articles/4402284777364-What-are-home-feed-recommendations-

[8] https://www.reddit.com/r/help/comments/rrkptm/home_feed_has_changed_drastically/

[9] https://www.reddit.com/r/help/comments/717686/order_of_posts/

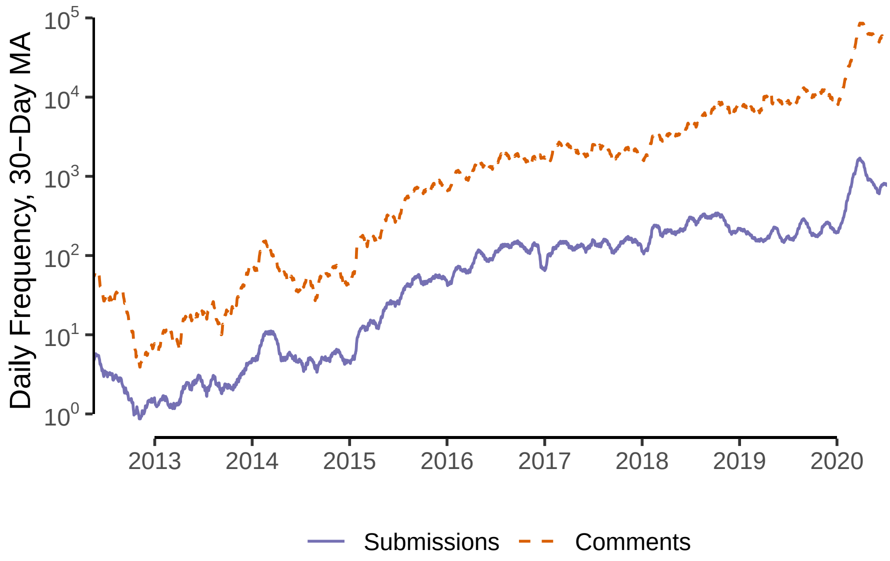


Figure 6: **Daily activity on WSB plotted on a logarithmic scale**; the daily submission and comment counts, averaged over 30 days, demonstrate a persistent exponential increase in activity on the WSB forum from 2015 to 2020, with a substantial jump in early 2020.

A.3 Tickers mentioned on WSB

Conventionally, submissions that mention a ticker will spell it using uppercase letters, or following a dollar sign. However, a challenge is that not all uppercase words are valid tickers. We first match words in WSB submissions to assets by identifying any succession of two to five capital letters. Subsequently, we used a pre-determined list of tickers from the Center for Research in Security Prices (CRSP) to check whether the letters represent a valid ticker. Some abbreviations or capitalised words which are not valid tickers might still show up, such as 'CEO' (*CNOOC Limited*), and 'ALL' (*The Allstate Corporation*). Single characters also appear, such as 'A' (*Agilent Technologies, Inc.*). We manually created a list of such tickers, and removed matches featured in WSB submissions. We refined a second list of candidates by checking whether a collection of one to five letters, lower or uppercase, is preceded by a dollar sign. As a result,'$CEO' or '$a' count as the tickers. These are, again, checked against the list of available tickers.

A.4 Sentiment modeling in WSB posts

Our goal, with regards to the text data in WSB, is to gauge whether discussions on certain assets express an expectation for their future price to rise, the 'bullish' case, to fall, the 'bearish' case, or to remain unpredictable, the 'neutral' case. Among other alternatives, we pursued a supervised-learning approach to identify the sentiment expressed about an asset within a WSB submission. This required a training dataset, for which we manually labelled 4,932 random submissions with unique ticker mentions as either 'bullish', 'bearish' or 'neutral' with respect to the authors' expressed expectations for the future price. We used the FinBERT algorithm for labeling (Araci 2019) - a financially oriented modification of Google's

	Predicted Label		
True Label	**-**	**0**	**+**
-	64%	28%	7%
0	6%	77%	17%
+	6%	27%	67%

Table 7: **Fine-tuned FinBERT confusion matrix:** We use 10% of our hand-labeled data to test the performance of FinBERT on out-of-sample sentiment prediction. The results highlight the model's ability to predict sentiment with reasonably high accuracy.

Bidirectional Encoder Representations from Transformers (BERT) algorithm (Devlin et al. 2018). Work not shown here implements an alternative regression-based approach as a robustness check, but FinBERT performs better out-of-sample.

We trained FinBERT on 75% of the labelled data, and used the remaining 25% for validation and the test set. Table 7 plots the out-of-sample confusion matrix. For the out-of-sample test, we train FinBERT on 75% of the available data and use 15% for validation; we then compute what the algorithm predicts for the remaining 10% of data. We achieve 70% accuracy on the test set. This is better than a LASSO regression's accuracy, which was implemented separately and is not cover here.

A.5 Sentiment variable creation

We begin with the output of our sentiment classifier, detailed in Appendix A.4. It assigns three probability scores to each submission about a ticker: the probability of a submission being bullish, $P(\phi = +1)$, bearish, $P(\phi = -1)$, neutral, $P(\phi = 0)$. The probabilities sum to one. At the time t when an author i posts about asset j, we use the probability scores above to calculate a continuous sentiment score between $(-\infty, \infty)$:

$$\Phi_{i,j,t} = \frac{1}{2}\log\left(\frac{\mathrm{P}(\phi_{i,j,t} = +1)}{\mathrm{P}(\phi_{i,j,t} = -1)}\right).$$

Submissions labeled as bullish ($\mathrm{P}(\phi = +1) = 1$), or bearish ($\mathrm{P}(\phi = +1) = 1$), are set to $\mathrm{P}(\phi = +1) = 0.98$, or $\mathrm{P}(\phi = -1) = 0.98$, to retrieve a finite value for the log-odds.

B Details on testing for consensus and contagion

B.1 Target independent variable

We build a discrete-choice empirical strategy to suit our model. Under the assumption that $u_{i,t}$ is drawn from a standard type-I Extreme Value Distribution, we model the log-odds of expressed investor sentiments ϕ_i by a standard multivariate logistic function,

$$\log\left(\frac{P(\phi_{i,t}=+1)}{P(\phi_{i,t}=0)}\right) = g(b_{i,t}) + f(\bar{\phi}_{-i,(t-1,t)}) - \theta\sigma^2_{i,t} + u^+_{i,t}, \quad (32)$$

$$\log\left(\frac{P(\phi_{i,t}=-1)}{P(\phi_{i,t}=0)}\right) = -g(b_{i,t}) - f(\bar{\phi}_{-i,(t-1,t)}) - \theta\sigma^2_{i,t} + u^-_{i,t}, \quad (33)$$

where t denotes time, and $(t-1,t)$ an interval preceding t. The goal of this paper, in light of Prediction 1, is to test empirically whether $f(\cdot)$ is increasing. To that end, we aggregate bullish and bearish sentiments into one continuous variable, $\Phi_{i,t}$:

$$\Phi_{i,t} = \frac{1}{2}\log\left(\frac{P(\phi_{i,t}=+1)}{P(\phi_{i,t}=-1)}\right) = g(b_{i,t}) + f(\bar{\phi}_{-i,(t-1,t)}) + \frac{u^+_{i,t}-u^-_{i,t}}{2}. \quad (34)$$

In the main body, the error term is expressed as $\epsilon_{i,t}$. Under the assumption that $u^+_{i,t}$ and $u^-_{i,t}$ are independent and identically distributed, $u^+_{i,t}-u^-_{i,t}$ will follow a logistic distribution with finite variance.

B.2 Full regression estimates

Tables 8 and 10 present our full regression estimates. Table 9 presents our First Stage estimates for our *Commenter Network* approach, which has multiple IVs.

Table 8: Peer influence: *Frequent Posters* – full regression estimates

		Dependent Variable: $\Phi_{i,j,t}$	
	Reduced Form (1)	Full Second Stage (2)	Random Peers (3)
Independent Variables $\Phi_{i,j,t-1}$	0.15 (0.01) ***	0.13 (0.01) ***	0.15 (0.01) ***
$\bar{\Phi}_{-i,j,(t-1,t)}$	0.10 (0.02) ***	0.19 (0.05) ***	0.01 (0.02)
$r_{j,t}$	0.85 (0.13) ***	0.95 (0.17) ***	0.89 (0.14) ***
$\bar{r}_{j,t}$	0.80 (0.42) *	0.87 (0.50) *	0.82 (0.44) *
$\sigma^2_{j,t}$	-0.39 (0.61)	0.24 (1.21)	-0.38 (0.61)
Ticker Fixed Effects	Yes	Yes	Yes
No. Observations:	14,396	11,122	14,391
R^2:	0.12	0.08	0.11
R^2_{adj}:	0.08	0.06	0.08

Notes: The dependent variable is individual investor sentiment about an asset, scaled continuously between $(-\infty,\infty)$, is estimated by the individual's previously expressed sentiment about the same asset ($\Phi_{i,j,t-1}$) and a set of market control variables ($r_{j,t}, \bar{r}_{j,t}, \sigma^2_{j,t}$), using OLS. The sentiment of peers ($\bar{\Phi}_{-i,j,(t-1,t)}$) is estimated in several ways. In Column (1), we use observed, average sentiment of peers between an author's two posts. In Column (2), we estimate the sentiment of peers using an IV. In Column (3), we select a random cohort to estimate peer sentiment. Robust standard errors, clustered at the ticker level, are presented in parentheses. Observations with incomplete market data are dropped.
*** Significant at 1% level ** Significant at 5% level * Significant at 10% level

Table 9: First Stage estimates for *Commenter Network* approach

	$\phi^{-1}_{i,j,t-1}$	$\phi^{0}_{i,j,t-1}$	$\phi^{+1}_{i,j,t-1}$	$\bar{\Phi}_{-i,j,t-1}$
Dependent variable:				
Sentiment of Peers	-0.30 (0.04) ***	0.12 (0.03) ***	0.25 (0.03) ***	0.14 (0.01) ***

Notes: The dependent variable is individual investor sentiment about an asset expressed in a single submission, scaled continuously between $(-\infty, \infty)$, modeled using IVs. We estimate it using the individual's previously expressed sentiment about the same asset ($\phi_{i,j,t-1}$) as a categorical variable, with the author not having posted previously ($\phi^{NA}_{i,j,t-1}$) as the baseline, as well as the average sentiment of posts that the author commented on previously ($\bar{\Phi}_{-i,j,t-1}$). We user the timing of IVs to control for common shocks, as discussed in the main text. Our regression has 24,013 observations and an F-statistic of 118.
*** Significant at 1% level ** Significant at 5% level * Significant at 10% level

Table 10: Peer influence: *Commenter Network* – full regression estimates

		Dependent Variable – $\Phi_{i,j,t}$	
	Reduced Form	Full Second Stage	Random Network
	(1)	(2)	(3)
Independent Variables $\phi^{-1}_{i,j,t-1}$	-0.34 (0.04) ***	-0.32 (0.03) ***	-0.35 (0.04) ***
$\phi^{0}_{i,j,t-1}$	0.07 (0.03) **	0.05 (0.03)	0.07 (0.04) **
$\phi^{+1}_{i,j,t-1}$	0.24 (0.04) ***	0.21 (0.05) ***	0.25 (0.04) ***
$\bar{\Phi}_{-i,j,t-1}$	0.05 (0.01) ***	0.19 (0.08) **	0.01 (0.01)
$r_{j,t}$	0.84 (0.12) ***	0.98 (0.24) ***	0.85 (0.12) ***
$\bar{r}_{j,t}$	0.90 (0.42) **	1.31 (0.73) *	0.95 (0.43) **
$\sigma^2_{j,t}$	-0.01 (0.51)	0.57 (0.95)	0.00 (0.53)
Ticker Fixed Effects	Yes	Yes	Yes
No. Observations:	24,963	16,521	25,284
R^2:	0.09	0.07	0.09
R^2_{adj}:	0.06	0.06	0.06

Notes: The dependent variable is individual investor sentiment about an asset expressed in a single submission, scaled continuously between $(-\infty, \infty)$. We estimate it using the individual's previously expressed sentiment about the same asset ($\phi_{i,j,t-1}$) as a categorical variable, with the author not having posted previously ($\phi^{NA}_{i,j,t-1}$) as the baseline. We control for a set of market control variables ($r_{j,t}, \bar{r}_{j,t}, \sigma^2_{j,t}$). The sentiment of posts that the author commented on previously ($\bar{\Phi}_{-i,j,t-1}$) is estimated several ways. In column (1), we present the estimate using the sentiment of posts the author previously commented on. In column (2), we use an IV to predict the sentiment of posts the author comments on. In column (3), we randomly rewire the network, connecting the author to a random set of posts about the same ticker. Robust standard errors, clustered at the ticker level, are presented in parentheses. Observations with incomplete market data are dropped.
*** Significant at 1% level ** Significant at 5% level * Significant at 10% level

B.3 Evidence of identification strategy

A potential concern with our approach is whether the sentiments expressed by individuals who post multiple times or are part of the commenters network follow the same distribution as all submissions on the forum. Figure 7a presents the distribution of sentiments for the second or later post of an author about a ticker and Figure 7b presents the distribution of sentiments for those who comment on other's posts. Figure 7 provides evidence that the sentiment distributions are similar to that of other posters on WSB, which supports the

(a) Frequent Posters Sentiment PDF

(b) Commenters Sentiment PDF

Figure 7: **Density Plot of Sentiments Expressed on WSB**; We present the density plot of the sentiments expressed by users on WSB who post multiple times, labeled as *Multiple Posters*, those who comment on others' posts, labeled as *Network*, and that of all submissions, labeled as *All Posts*.

hypothesis that our analysis offers insight into how all individuals on WSB form opinions.

A second concern is whether we effectively control for unobserved ticker characteristics. Similarly to Patacchini & Zenou (2016), we run 'placebo tests', where we replace the composition of an author's peers with a random cohort of people who post on WSB about the same ticker. The random cohort is chosen as follows. We observe how many peers an individual author has. We then select a random sample of the same number of individuals, without replacement, who do not post between an author's two post but post about the ticker at a different time for the *Frequent Posters* approach (if fewer individuals post before, we select all of those individuals), or through a random network rewiring (we select posts randomly about the same ticker before the current post). The results are presented in Tables 8 and 10, column (3). We observe that all the coefficients remain close to their original values, except for the peer effect, which becomes insignificant. This lends credibility to our peer identification strategy and shows that unobserved factors that influence within ticker variation are not confounding our estimates.

We cannot directly calculate the J-statistic for our *Commenter Network* approach, since we estimate our IV using observations on several neighbours. We, therefore, take an average of the neighbours past sentiments (transforming the categorical variable into a continuous one) and the average across their neighbour's neighbours sentiments. We use this to compute a J-Statistic with two degrees of freedom.

ONLINE APPENDIX

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Contents

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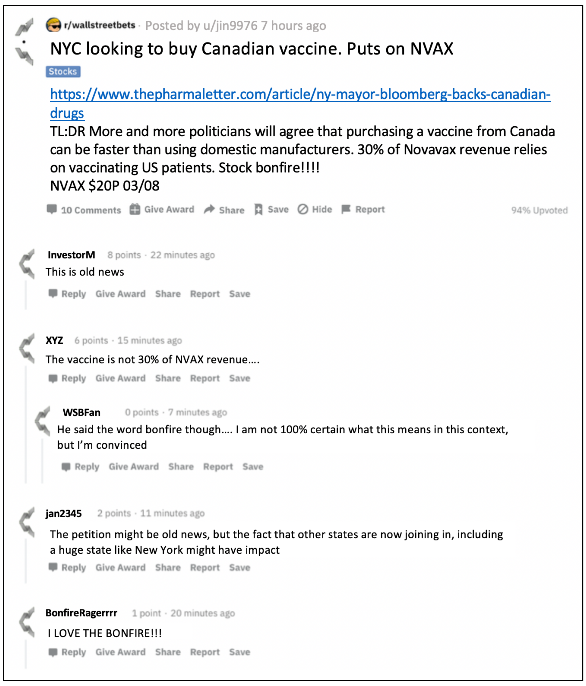
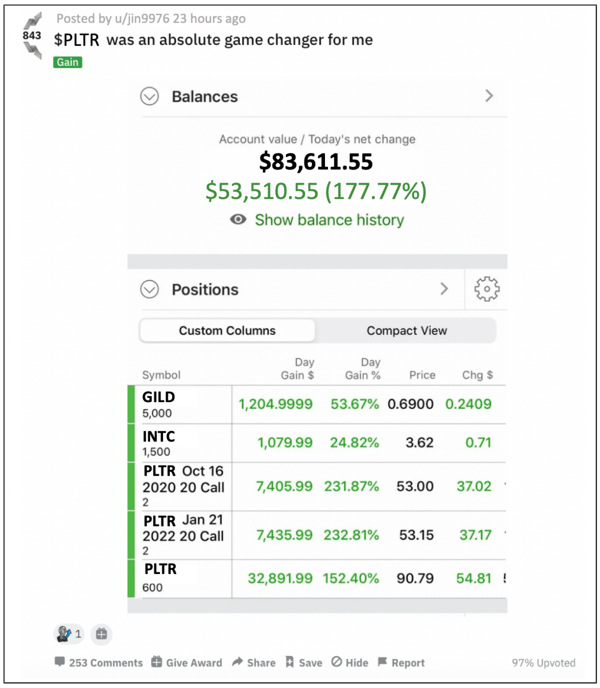
A Extended data appendix

A.1 Extended description of WSB



(a) A typical discussion on WSB



(b) A sample screenshot of user profits

Figure 1: **What does WSB look like?** These snapshots display typical discussions on WSB. The exact text, usernames, and conversation details have been modified to protect user identities.

Figure 1a displays a typical exchange on the WSB forum: individuals discuss stock-related news and their sentiments on whether this will affect stock prices in the future. In addition to market discussions, there is ample evidence of users pursuing the investment strategies encouraged in WSB conversations. Users post screenshots of their investment gains and losses, which subreddit moderators are encouraged to verify, as illustrated in Figure 1b.

Figure 2 displays the evolution of WSB over time. Two jumps are notable: a smaller, seemingly idiosyncratic rise in early 2018, and a sharp spike during the COVID-19 pandemic.

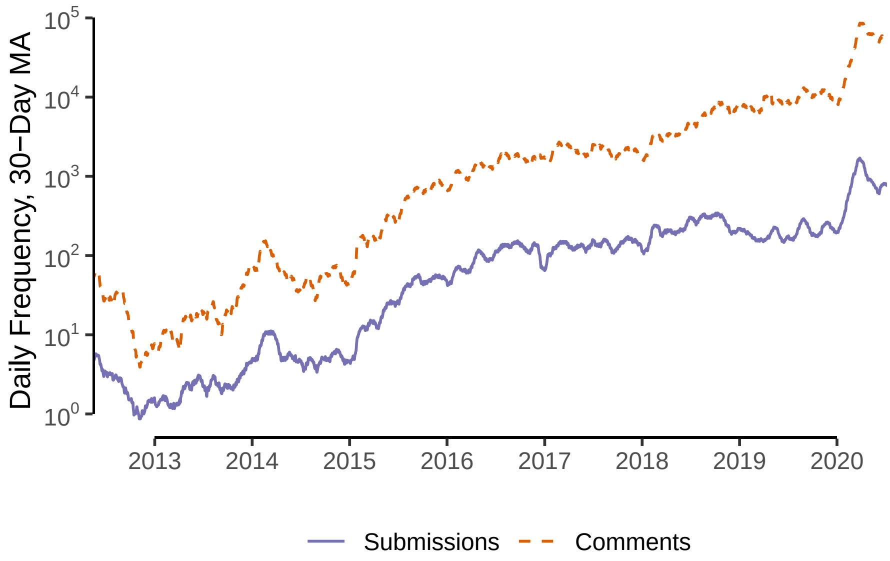


Figure 2: **Daily activity on WSB plotted on a logarithmic scale**; the daily submission and comment counts, averaged over 30 days, demonstrate a persistent exponential increase in activity on the WSB forum from 2015 to 2020, with a substantial jump in early 2020.

A.2 Tickers mentioned on WSB

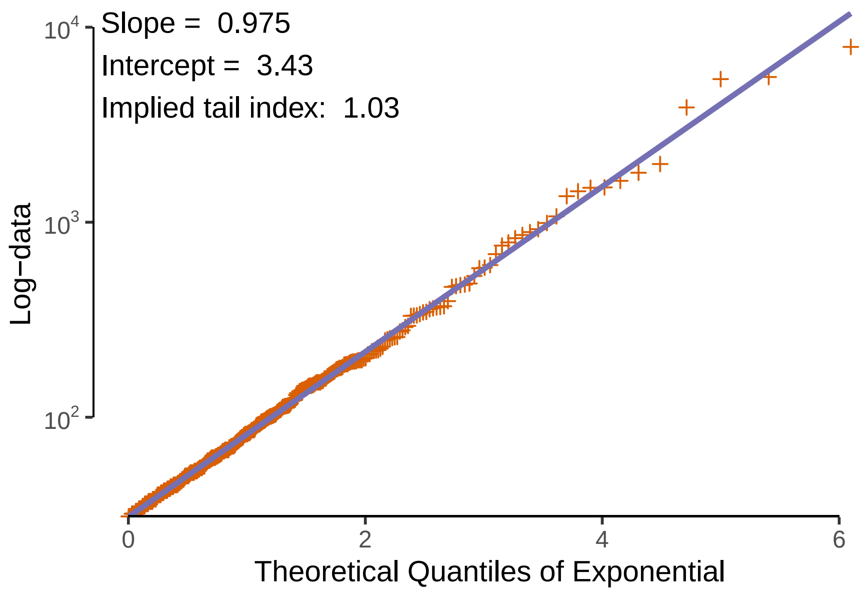


Figure 3: **QQ Plot of the tail in ticker mentions on WSB**; the number of submissions for each ticker (on a log-scale) is plotted against the theoretical quantiles of an exponential distribution. Quantiles are calculated as $q(i) = -\log(1 - i/(N+1)$, where N is the number of observations, and i the order of the statistic, from 1 to N. The linear fit suggests that the data follows a Pareto distribution, with the tail index equal to the inverse of the slope. The threshold for a ticker to be part of the 'tail' is 31 mentions; note the intercept, at $\exp(3.43) \approx 31$.

Conventionally, submissions or comments that mention a ticker will spell it using up-

Table 1: Most frequent ticker mentions

Ticker	Name	Comments	Submissions	Sum
SPY	S&P 500 Index	291,279	9,408	300,687
AMD	Advanced Micro Devices, Inc.	124,685	5,721	130,406
TSLA	Tesla, Inc.	124,222	5,910	130,132
MU	Micron Technology, Inc.	86,611	3,941	90,552
AAPL	Apple Inc.	48,345	1,880	50,225
AMZN	Amazon.com, Inc.	44,426	1,534	45,960
MSFT	Microsoft Corporation	41,152	1,799	42,951
SNAP	Snap Inc.	40,766	2,043	42,809
NVDA	NVIDIA Corporation	38,012	1,556	39,568
SPCE	Virgin Galactic Holdings, Inc.	30,758	1,640	32,398
FB	Facebook, Inc.	26,143	1,446	27,589
DIS	The Walt Disney Company	25,611	1,088	26,699
BYND	Beyond Meat, Inc.	23,299	906	24,205
NFLX	Netflix, Inc.	20,800	936	21,736
JNUG	Direxion Daily Jr Gld Mnrs Bull 3X ETF	15,761	1,095	16,856
GE	General Electric Company	15,730	929	16,659
RAD	Rite Aid Corporation	14,781	839	15,620
SQ	Square, Inc.	14,003	824	14,827
ATVI	Activision Blizzard, Inc.	13,076	674	13,750
USO	United States Oil	12,949	667	13,616

Notes: this table lists the 20 most mentioned assets on WSB, observed by submissions which uniquely mention the related ticker. 'Comments' is the number of comments posted on these submissions, 'Submissions' counts submissions, and 'Total' is the sum of the two. We retrieved the name of the asset corresponding to the identified ticker from *Yahoo Finance*.

percase letters, or following a dollar sign. However, a challenge is that not all uppercase words are valid tickers.

We first match words in WSB submissions to assets by identifying any succession of two to five capital letters. Subsequently, we used a pre-determined list of tickers from CRSP to check whether a match is indeed present in the available financial data. Some abbreviations or capitalised words which are not valid tickers might still show up, such as 'USD' (*ProShares Ultra Semiconductors*), 'CEO' (*CNOOC Limited*), and 'ALL' (*The Allstate Corporation*). Single characters also appear, such as 'A' (*Agilent Technologies, Inc.*). We manually created a list of such tickers, and removed matches featured in WSB submissions, to build a preliminary list of candidate ticker mentions. We refined a second list of candidates by checking whether a collection of one to five letters, lower or uppercase, is preceded by a dollar sign. Any mentions of '$CEO' or '$a' count as the tickers 'CEO' and 'A', respectively. These extracts are, again, checked against the list of available tickers.

A small fraction of the 4,650 tickers we extract dominate the discourse on WSB. 90% of tickers are mentioned fewer than 31 times, and more than 60% are mentioned fewer than five times. The frequency distribution of tail of ticker mentions demonstrates this point, for which Figure 3 displays a QQ-plot. We arbitrarily selected tickers with the number of mentions in the top 10^{th} percentile. Even though threshold of mentions for this top decile is 30 submissions, the most popular, SPY, features in almost 8,000 submissions. The orange crosses in Figure 3 locate the empirical densities, on a log scale, which are plotted against the theoretical quantiles of an exponential distribution on the x-axis. Under the assumption that ticker mentions are heavy-tailed (similarly to vocabulary distributions), the logarithm of the mentions follows an exponential distribution, with the intercept at the threshold, and the slope equal to the inverse of the tail index. Indeed, the linear fit in Figure 3 is close to perfect, supporting the assumption that the popularity of assets in WSB is heavy-tailed, with an estimated tail exponent of approximately 1.03. In what follows, we used submissions for which we identified a single ticker, unless otherwise specified, forming a dataset of 103,205 submissions with unique ticker mentions by our cutoff date.

A.3 Reddit user content presentation

Our empirical identification strategy in the *Frequent Posters* approach rests on the premises that users are exposed to random variation in peer sentiments. In this section, we discuss the details of how users are presented with content on Reddit.

Upon logging into Reddit, users are presented with a 'home feed'. Historically, the home feed has contained the 'top posts' from the subreddits to which a user has subscribed. More recently, Reddit has implemented an algorithm to try and match users to content based on a machine learning algorithm, via the home feed.[1] However, this change has only taken effect recently, and well after the point when our data were collected.[2] Subreddit top posts are not individually tailored to the specific user. Users have several sort options based on whether they prefer to see most recent or most highly rated content.[3] However, they do not have an option to personalize viewed content beyond this. We, therefore, conclude that individual users were exposed to WSB content based on the content on the forum that was most recent and popular at the time of their logging on, rather than based on personal preference. This,

[1] https://reddithelp.com/hc/en-us/articles/4402284777364-What-are-home-feed-recommendations-

[2] https://www.reddit.com/r/help/comments/rrkptm/home_feed_has_changed_drastically/

[3] https://www.reddit.com/r/help/comments/717686/order_of_posts/

in turn, allows us to assert that users are exposed to random, temporal variation in peer sentiment.

A.4 Market variables

We include a set of market return and volatility control variables. The data source for these variables are the daily stock files issued by the Center for Research in Security Prices (CRSP), accessed through Wharton Research Data Services.

Market variables in Section 3.2 The following market variables serve as controls.

$r_{j,t}$: the log return for asset j on trading day t. From CRSP, we calculate it using their 'RET' variable: $r_{j,t} = \log(RET_{j,t} - 1)$, which automatically corrects the percentage change in closing prices for share splits and dividend distributions.

$\bar{r}_{j,t}$: the average log returns for asset j in the five days prior to t (the log return on day t is not included). A minimum of three daily log-return observations is required, otherwise the observation is set as missing.

$\sigma^2_{j,t}$: the variance of log returns for asset j in the five days prior to t (the log return on day t is not included). A minimum of three daily log-return observations is required, otherwise the observation is set as missing.

Matching submission timings to trade timings If a post occurs before 16:00:00 EST on day t, we match it with the log-return on the same day t. If a post occurs after 16:00:00 EST on a given day, we match it with market data for the next trading day, $t+1$. This is done to capture the fact that many news announcements occur after hours and someone posting after the market close may be exposed to these after-hour moves. Instance in which submissions are made on weekends, or holidays, are matched to the next possible trading day. For example, a submission made at 5pm on Friday is paired to the observed log return for the following Monday.

Market variables in Sections 3.4, 5 The following market variables serve as independent variables.

$\bar{r}_{j,t-1}$: the average log returns for asset j in calendar week $t-1$.

$\sigma^2_{j,t-1}$: the variance of log returns for asset j in calendar week $t-1$.

Both variables are constructed from the same daily log returns panel as those described earlier in this appendix.