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YOLO trading: Riding with the herd during the GameStop episode

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Abstract

We explore the 2020 and early 2021 price variation of four stocks: GameStop, AMC Entertainment Holdings, Blackberry and Nokia. The four stocks were subject to a decentralized short squeeze that exploited the short positions of institutional investors. This investor movement was likely initiated by retail investors concentrated mostly around the subreddit r/WallStreetBets (WSB). We demonstrate that part of the next day's price variation can be explained by an increase in activity on the WSB subreddit relative to Google searches (terms related to the event). We discuss implications for future research.

Keywords: GameStop, WallStreetBets, Reddit, short squeeze, volatility.

1. Introduction

The beginning of 2020 witnessed an unprecedented decline in stock markets worldwide, induced by the COVID-19 pandemic and related uncertainty, fear, and extremely high volatility (Ramelli and Wagner, 2020; Baker et al., 2020; Lyócsa et al., 2020; Lyócsa and Molnár, 2020; Ashraf, 2020; Okorie and Lin, 2020; Zhang et al., 2020; Wagner, 2020). Nevertheless, major U.S. market indices recovered swiftly and ended the year 2020 in positive territory. The U.S. stock market subsequently experienced another shock related to herd behavior induced by a social media platform that appears to have culminated in early 2021. A brief and rudimentary description of this event may be found in Chohan (2021). Essentially, small-scale investors concentrated mostly around the subreddit r/WallStreetBets (WSB) initiated a short squeeze of institutional investors betting on declines of several underrated stocks, such as GME (GameStop), AMC (AMC Entertainment), BB (BlackBerry), NOK (Nokia) and a few others. The coordinated effort was accompanied by an increase in the stock price of GME from approximately 5 USD in July 2020 to approximately 10 USD in October 2020 and later from

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17 USD in January up to an intraday maximum of 483 USD on 28 January 2021. Over this period, short sellers – Wall Street giants, such as hedge funds – booked significant losses. This David-vs-Goliath narrative was primarily a driver of a large, unprecedented, crowd-sourced short squeeze.

Regardless of how appealing such a narrative has become for the general public, this type of coordinated behavior may prove to be highly disruptive for financial markets. From the perspective of financial stability, fire sales and price-mediated contagion are of particular interest due to the significant spillovers they might cause, where forced sales by one market participant tighten constraints on others and thereby lead to further forced sales (Geanakoplos, 2010; Stein, 2012; Braouezec and Wagalath, 2019; Chernenko and Sunderam, 2020), a proposition that is supported by a vast amount of research (Coval and Stafford, 2007; Ellul et al., 2011; Shleifer and Vishny, 2011; Jotikasthira et al., 2012; Caballero and Simsek, 2013; Hau and Lai, 2017; Barbon et al., 2019; Fricke and Fricke, 2020). However, it is yet unclear whether such negative spillovers can be initiated from inflated prices of short squeezed stock prices. The decentralized yet similar behavior of investors is also closely related to the strand of literature on herd behavior in financial markets (Scharfstein and Stein, 1990; Avery and Zemsky, 1998; Chang et al., 2000; Bikhchandani and Sharma, 2000; Chiang and Zheng, 2010; Cipriani and Guarino, 2014). The unique aspect of the recent events is the counterhegemonic extensive financial effort, driven by small individual investors collaborating to sabotage the short positions of large Wall Street players such as hedge funds (Chohan, 2021). While such a decentralized people-powered initiative by retail investors might seem tempting, it undoubtedly presents a risky investing strategy, as extremely inflated prices are likely to be followed by sudden price declines, eventually leading to extreme losses for some of the participants. To reflect the emotions and vocabulary of the WSB subreddit, we refer to this type of investing as 'YOLO trading'.[2]

In this study, we provide evidence on how the activity on the WSB subreddit drove daily price variations of GME, AMC, BB, and NOK. Specifically, we create a relative Reddit intensity variable (i.e., our 'YOLO$_1$ trading' variable), which is calculated as a ratio between i) the level of interest in a given stock on the WSB subreddit and ii) the level of interest in events surrounding the short squeeze as indicated by Google searches. If price variations are driven by WSB subreddit activity, an increase in the ratio should lead to higher price variation of the four short squeezed stocks.

[2]YOLO – you only live once – is one of the most frequent terms on the WSB subreddit (apart from standard words such as 'Hold', 'Buy', 'GME' and so forth) and as such well describes the spirit of the entire movement.

The remainder of the paper is structured as follows. The next section describes the data and methodology. Section 3 presents our main results, followed by some robustness checks in Section 4. Section 5 concludes the paper and sketches future research ideas.

2. Data and methodology

2.1. Data sources

To study the price variation of GME, AMC, BB and NOK, we use a daily sampling frequency and restrict our sample to the period from 1 July 2020 to 12 February 2021, i.e., 155 trading days. The date the activity on the WSB subreddit started cannot be established precisely, but our chosen period should be long enough to capture the initial activities on the WSB subreddit. In this study, we use three data sources. First, the prices are retrieved from Datastream. Second, WSB subreddit activity is obtained directly from Reddit and pushshift.io. Third, we use Google search intensity as offered by Massicotte and Eddelbuettel (2018).

2.2. Price variation

In this study, the daily price variation of four stocks of interest is estimated using daily range-based volatility estimators. As the true data generating process (DGP) is unknown and might even change over time, Patton and Sheppard (2009) suggested using composite volatility estimators and thereby diversify against DGP uncertainty. Motivated by Patton and Sheppard (2009) and restricted by our use of daily data, our estimate of daily price variation, V_t for $t = 1, 2, ..., T$, is based on an average of three range-based volatility estimators: PK_t of Parkinson (1980), GK_t of Garman and Klass (1980) and RS_t of Rogers and Satchell (1991) adjusted for overnight price variation[3] J_t:

$$V_t = J_t + 3^{-1}(PK_t + GK_t + RS_t) \tag{1}$$

Specifically, let O_t, H_t, L_t and C_t denote daily opening, high, low and closing prices. Next, define $h_t = ln(H_t) - ln(O_t)$, $l_t = ln(L_t) - ln(O_t)$, $c_t = ln(C_t) - ln(O_t)$, and $J_t = [ln(O_t) - ln(C_{t-1})]^2$. The Parkinson (1980) estimator is given by:

$$PK_t = \frac{(h_t - l_t)^2}{4ln2} \tag{2}$$

[3] The composite range-based estimator was recently used by Lyócsa et al. (2021).

the Garman and Klass (1980) estimator is defined as:

$$GK_t = 0.511\,(h_t - l_t)^2 - 0.019\,(c_t(h_t + l_t) - 2h_t l_t) - 0.383c_t^2 \tag{3}$$

and the Rogers and Satchell (1991) estimator is as follows:

$$RS_t = h_t(h_t - c_t) + l_t(l_t - c_t) \tag{4}$$

2.3. WSB subreddit activity

To capture the intensity of discussions on the WSB subreddit, we use the total number of ticker occurrences in its comments for the day (e.g., 'GME' for GameStop). Let $T_{j,t} \in \mathbb{N}$ denote the number of times a given ticker is found for the j^{th} post on day t. The WSB subreddit activity indicator is:

$$W_t = \sum_{j=1}^{n(t)} T_{j,t} \tag{5}$$

where $n(t)$ is the number of posts on day t. The same approach is applied for the remaining three stocks with tickers 'AMC', 'BB' and 'NOK'. While market prices are quoted only for trading days, WSB subreddit discussions are also recorded for Saturdays and Sundays. To synchronize the data, an average over the consecutive Friday, Saturday, and Sunday is substituted for the Friday value[4].

2.4. Google search volume intensity

Using the R package of Massicotte and Eddelbuettel (2018), we retrieve data on the search volume intensity – SVI_t – for a given term. The SVI_t ranges from 0 to 100, where all values are normalized to the maximum value over the given sample period.

We retrieve two groups of search terms. The first group consists of 19 terms specific for the given event under consideration: GME, AMC, BB, Blackberry, NOK, Nokia, GameStop, short squeeze, short sell, call option, wall street bets, Wallstreet, Melvin Capital, to the moon, Reddit, Keith Gill, DeepF*ckingValue, Dave Portnoy, and Justin Sun[5]. For each trading day, search volume intensity is averaged across these terms, and the resulting variable is denoted as $E_t \in [0, 100]$.

The second group consists of 15 terms that are related to general market conditions, while

[4]In several occasions, missing data were imputed using linear interpolation.

[5]Apart from standard keywords related to the subreddit WSB, given stocks, and short selling, we also added a hedge fund, Melvin Capital, one of the largest short sellers, as well as some 'celebrities' connected to the event and their 'nicknames'.

we also include tickers of stocks that are well known and are from similar industries as the four stocks that were subject to the short squeeze. The terms are SP 500, SPY, VIX, market bubble, stock market, BBY (Best Buy), AMZN (Amazon), TGT (Target), WMT (Walmart), CNK (Cinemark Holdings), IMAX, NFLX (Netflix), DIS (Disney), MSI (Motorola), and APPL (Apple). As before, we average the search volume intensity for each day, and the resulting variable is denoted as $M_t \in [0, 100]$. For both E_t and M_t, weekends are handled in the same way as with W_t.

2.5. Relative Reddit and event intensity: the YOLO variables

Regressing price variation (V_t) on the lagged activity on the WSB subreddit discussion forums (W_{t-1}) might be insufficient, as the discussions might simply be a reaction to the general sentiment. We instead use a ratio of:

$$YOLO_{1,t} = \frac{W_t}{E_t} \tag{6}$$

We refer to this variable as the *relative Reddit intensity.* For days with larger values of $YOLO_{1,t}$, the activity on the WSB subreddit is relatively higher than that found via Google searches. It follows that if discussion on the WSB subreddit has contributed to the price variation of the given stock, the next day's volatility should be associated with today's $YOLO_{1,t}$.

Using the same principle, we also use the following ratio, the *relative event intensity*:

$$YOLO_{2,t} = \frac{E_t}{M_t} \tag{7}$$

For days with larger values of $YOLO_{2,t}$, the intensity of Google searches specifically related to the short squeeze events is relatively higher than the Google search intensity related to general market conditions. Including the variable in our specifications controls for the possible herding effect outside of the WSB subreddit community.

2.6. Model specification

To estimate the role of WSB subreddit discussions, we work within a framework of a linear regression model estimated via OLS of the following form:

$$ln(V_t) = \beta_0 + \beta_1 ln(V_{t-1}) + \beta_2 ln(YOLO_{1,t-1}) + \beta_3 ln(YOLO_{2,t-1}) + \beta_3 ln(M_{t-1}) + \epsilon_t \tag{8}$$

where β are the estimated regression parameters and ϵ_t is the error term. The persistent nature of volatility is reflected by using an autoregressive model framework adjusted with additional variables[6]. Our specification also includes the $ln(M_{t-1})$ term to account for the fact that it was not only the prices of GME, AMC, BB, and NOK that increased, as over the observed time frame, the U.S. market entered a bullish period that led to historical market index maximums (e.g., S&P 500 and NASDAQ). This sentiment might therefore partially explain the volatility levels observed for the four stocks. Finally, we assume that for higher values of $YOLO_{1,t-1}$, we might also observe higher values of V_t, but the absolute size of the effect might change as the volatility level changes. Because volatility levels (for each stock, see Figure 2 and Table 1) changed dramatically over our sample period, we use a log-log specification. All effects are thus expressed in relative terms, i.e., in terms of elasticities.

3. Results

3.1. Data characteristics

We plot the price and return series for the four stocks in Figure 1, along with the SPY ETF to facilitate comparison. There are two key observations. First, all four stocks show a similar pattern of sudden price increases in January. These increases are clearly detached from the development of the otherwise also growing market-wide index. In fact, the average return correlation between the four stocks is 0.614 for the whole sample period and only -0.048 between the four stocks and SPY ETF. However, when excluding January, the average correlation of returns between the two stocks is only 0.149 and that with the market index is 0.306. This clearly suggests a sudden decoupling of the price development of the four stocks from the market.

Second, as opposed to the usual market-wide returns, the daily returns (dashed red line) for the four stocks are of different magnitudes. Note the right axis in Figure 1. Daily returns outside of the $\pm 25\%$ range were not exceptional. These unprecedented return characteristics are also reflected in the volatility, sentiment and WSB Reddit interest variables (see Table 1 and Figure 2). Volatility is still subject to stylized facts of right skewness and persistence, but compared to the period before January 2021, the extreme volatility is of different orders of magnitude. Similar characteristics are visible for the WSB Reddit interest (W_t) and search volume intensity variables (SVI_t). In Figure 2, we plot the relative Reddit intensity (red dashed

[6] An alternative would be to use a range-based HAR model specification that explains future volatility using average weekly and monthly range-based volatility estimates (for application at the market index level see Lyócsa et al., 2021). We elected not to use that specification for three reasons. First, given the event under study, our sample is much shorter, and therefore, the monthly volatility component is unlikely to manifest as a significant predictor. Second, our current model specification seems to sufficiently address residual serial correlation. Third, with a shorter sample, we opt for a simpler model that leads to an estimate of 5 parameters instead of the 7 parameter range-based HAR version of our model.

Table 1: Utilized variables - volatility, interest, Google searches

		Mean	S.D.	$\rho(1)$	min.	max.	DF-GLS
Panel A: Volatility series							
GameStop	V_t^{GME}	0.048	0.164	0.584	0.000	1.280	-3.558
AMC	V_t^{AMC}	0.036	0.196	0.415	0.000	2.161	-4.677
Blackberry	V_t^{BB}	0.008	0.035	0.318	0.000	0.388	-4.073
Nokia	V_t^{NOK}	0.004	0.028	0.339	0.000	0.330	-4.901
Panel B: Interest and sentiment series							
WSB Reddit interest - GME	W_t^{GME}	3 425.21	11 511.46	0.87	1.00	92 855	-3.47
WSB Reddit interest - AMC	W_t^{AMC}	1 423.11	6 192.29	0.91	1.00	41092	-3.61
WSB Reddit interest - BB	W_t^{BB}	893.64	3 107.96	0.90	6.00	22 799	-2.86
WSB Reddit interest - NOK	W_t^{NOK}	742.04	3 902.24	-0.50	1.00	34 917	-4.12
Event related SVI	E_t	10.91	7.89	0.83	5.50	79.50	-3.37
General market SVI	M_t	32.22	5.45	0.25	21.53	52.73	-2.87
Relative Reddit intensity	$YOLO_{1,t}$	158.98	343.62	0.86	0.09	1 739.69	-1.62
Relative event SVI	$YOLO_{2,t}$	0.33	0.17	0.84	0.21	1.51	-2.76

Notes: Descriptive values are calculated over our sample period from 1 July 2020 to 12 February 2021, which leads to 155 trading day observations. $\rho(1)$ is the first-order serial-correlation coefficient. DF-GLS is the t-statistic of the unit-root (in the null) test Elliott et al. (1996) estimated on the residuals of the model, where the 5% critical value is -1.94.

line on the right axis, $YOLO_{1,t}$), which appears to spike before or on the day the volatility spikes. This observation underlines our argument that the price variation of the four stocks was likely exacerbated by activity on the WSB discussion board.

3.2. Model estimates

Our key results can be found in Table 2. We report estimated coefficients, standard errors and corresponding model characteristics. The latter show that despite the nonlinear nature of the event, with highly skewed volatilities, the log-log specification led to residuals that show only mild and insignificant serial dependence, with heteroskedasticity present only for the NOK model. The models, therefore, seem to adequately describe the price variation in our sample period. Interestingly, the autoregressive coefficient is not always the most significant variable, which compared to other studies is unusual (e.g., Patton and Sheppard, 2015) and in contrast to the persistence reported in Table 1. It therefore appears that once our sentiment variables are included, the persistence of volatility declines, which suggests sentiment-driven volatility.

The key variable of interest is the coefficient of the relative Reddit intensity ($YOLO_{1,t}$), which is positive and significant for all four stocks. Therefore, the greater the occurrence of ticker names on the WSB subreddit relative to the Google searches (event-related search volume intensity), the higher the next day's volatility is. Our results suggest that part of the price variation is driven by WSB subreddit discussions.

Interestingly, the coefficient on $YOLO_{2,t}$, which we interpret as the herding effect, is also

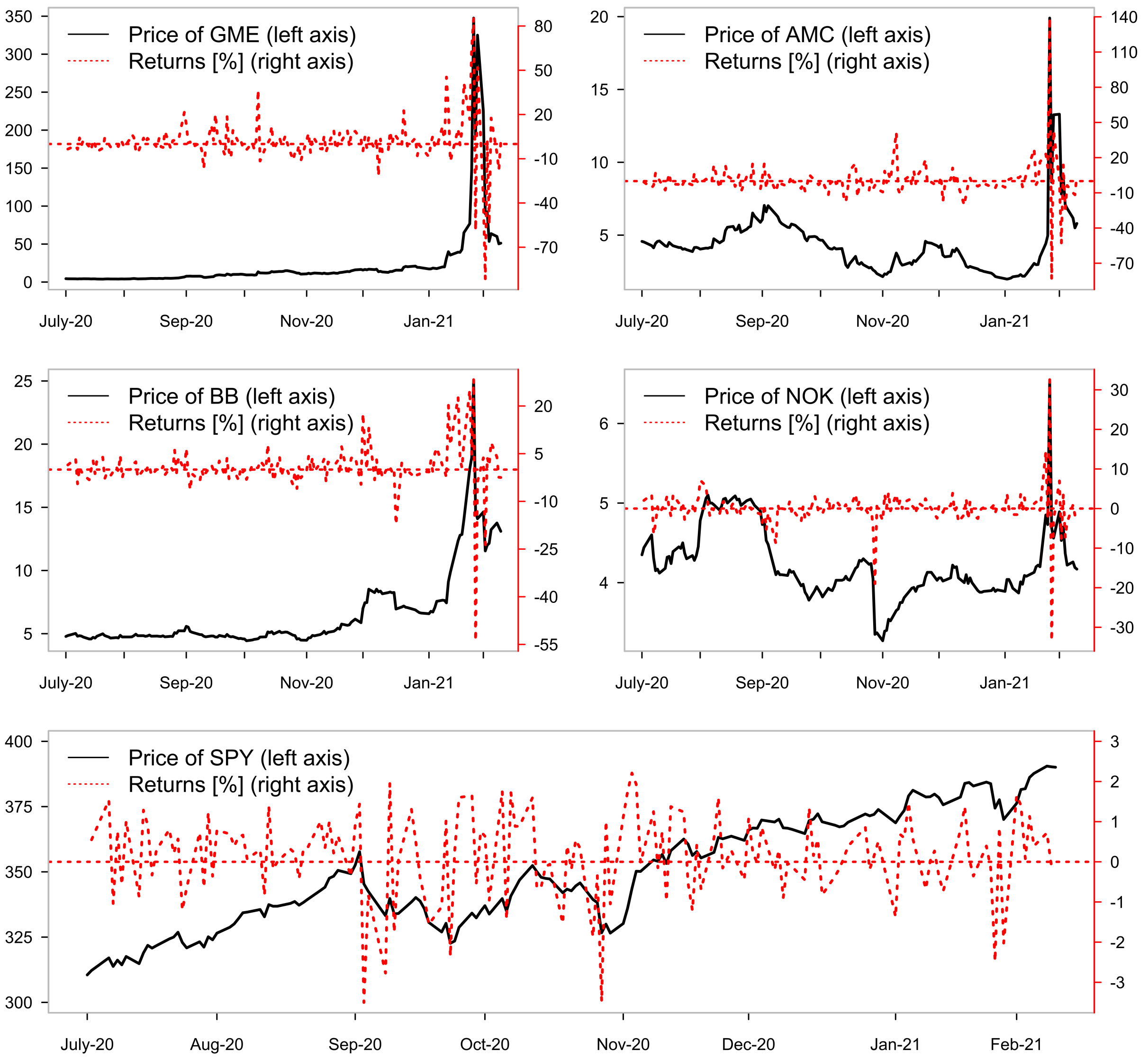

Figure 1: Prices and returns of four stocks and the market ETF - SPY

positive and significant, and the effect seems to be much larger. This is reasonable, given that to generate large price movements, one needs more than a (albeit popular) discussion on the WSB subreddit. This interpretation is supported by the fact that the two variables are not excessively correlated (0.647 in levels and 0.377 after taking the log), nor is the variance inflation factor excessive (see Panel B in Table 2). Moreover, the largest $YOLO_{2,t}$ effect should be found for stocks for which the price variation (reactions) was the highest, which is the case for GME, being subject to both the largest price variation and highest $YOLO_{2,t}$ coefficient. Finally, the general market sentiment variable is (highly) significant only for GME and does not seem to be essential for the remaining stocks.

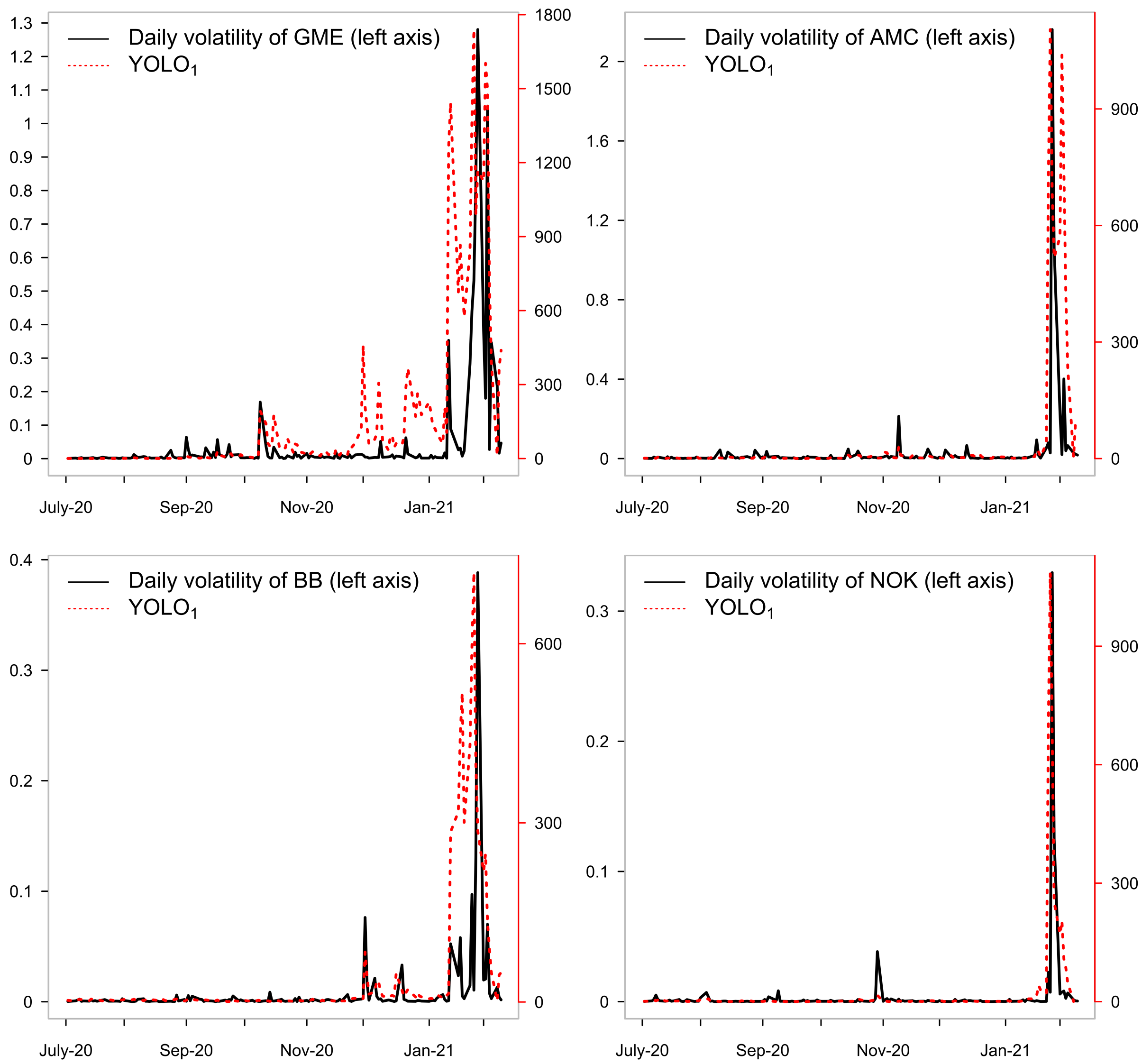

Figure 2: Daily volatility of stocks and YOLO variable

3.3. Robustness checks

We estimate several alternative versions of the model proposed above to better understand our results. First, we used a lin-lin model specification. In these models, heteroskedasticity becomes a larger issue, as indicated by the residual plot[7], with likely leverage points. For AMC and NOK, residual serial dependence was also negative and much stronger (-0.15 and -0.45). For AMC and NOK, the coefficient estimates also had unexpected signs, e.g., the general market SVI (M_t) and relative event SVI ($YOLO_{2,t}$) had negative coefficients. Together, these results indicate that our log-log models are a much better specification.

Second, we estimated the model for a restricted sample that ends at the end of 2020. This subperiod is interesting, as it excludes the most extreme price movements in January,

[7]All results from this section are available upon request.

which are likely to drive our results. Moreover, before January 2021, the short squeezing was much less known but already present. It follows that we should observe much lower model fit and smaller or even insignificant $YOLO_{2,t}$ variables, i.e., less herding outside of the WSB community. Model fit decreased considerably, and $YOLO_{2,t}$ was not significant. Interestingly, relative WSB subreddit intensity $YOLO_{1,t}$ was still significant for GME, while at the 10% level, it was significant for AMC and BB, all with expected signs and a smaller effect at 0.11, 0.16, and 0.25. These results suggest that before January, the WSB discussion forum had a limited, although not irrelevant, direct effect on the price variation of GME, AMC, and BB.

Third, we estimated the model defined in Eq. (8) for other assets that are from similar industries that were clearly not subject to the short squeeze of retail investors but might have been subject to extensive discussions on the WSB subreddit. Specifically, we estimated our model for Best Buy (BBY), Amazon (AMZN), IMAX, Netflix (NFLX), Motorola (MSI), Disney (DIS), and for the broad U.S. market ETF (SPY). Among the seven assets, the results consistently suggested insignificance of the key $YOLO$ variables with few exceptions. For example, for Netflix, $YOLO_{1,t}$ was positive and significant, and $YOLO_{2,t}$ was significant and positive only for Best Buy and Disney. It therefore appears that our results are unique to the short squeeze episodes of 2020 and early 2021.

4. Concluding remarks and agenda for future research

We explore the 2020 and early 2021 decentralized short squeeze strategies executed by retail investors on the stock prices of GameStop, AMC Entertainment Holdings, Blackberry and Nokia. If this strategy is successful, it leads to inflated prices (bubbles) and is therefore very risky. We thus refer to this strategy as '*YOLO trading*'. We study whether the price variation of the four stocks can be explained by the discussion on the WSB subreddit while accounting for Google searches on the topic and the general market sentiment. Our analysis shows that this was indeed the case; as the discussion on the WSB subreddit intensified, the price variation of the four stocks increased. This effect was not observed for other related stocks and was smaller for the pre-January 2021 period. While our results suggest that most of the price variation is not directly related to the discussion on the WSB subreddit, it seems likely that such social network activity can activate other retail investors for the given cause, in this case, to short squeeze institutional investors. This event raises several important questions for future research.

First, the regulatory consequences will be challenging. The manipulation of stock prices was an important issue in the U.S. market up until the 1930s (Allen and Gale, 1992). Although the legal framework outlawed stock-price manipulation, it is difficult to overcome the undesirable behavior of all market participants. Short squeezing belongs to this category of illegal trading practices – if we consider a short squeeze as a price manipulation. However, in the case of WSB, it might be considered 'legal manipulation' protected by the 1st Amendment (i.e., freedom of speech). One of the most recent and extensive short squeeze episodes was the case of Porsche-VW (Allen et al., 2021). Porsche, in a takeover attempt, drove VW's ordinary shares to rise from approximately €200 to over €1,000 in just a few days, making it briefly the most valuable company in the world (for further details, especially about the indictment and legal consequences, see, Möllers, 2015). Such events had significant ramifications in terms of distorting price discovery and overall market efficiency and substantially increased volatility. An attempt to raise or depress stock market prices by making a false statement is illegal — how can a regulator impose high legitimacy standards in a world of easy-to-access mass trading and fast-paced growth of social media? Thus, from a legal perspective, the WSB episode constitutes a new regulatory challenge. Short selling per se might be at the center of such discussions. New studies on justifications for or restrictions on short sales should emerge, as previous research is inconclusive in highlighting all the pros and cons of short-seller participation in stock markets (e.g., Goldstein and Guembel, 2008; Beber and Pagano, 2013; Boehmer and Wu, 2013; Grullon et al., 2015; Chen et al., 2020).

It would be beneficial to further explore all side effects of YOLO trading. For example, further research might provide insights into the following:

- The WSB episode's shock propagation – in the form of return or volatility spillovers among other stocks or even different asset classes. As we presented in Section 3.1, the price development of the four stocks under study exhibited a sudden decoupling from the market. Stock market contagion and comovements both have a direct impact on financial stability and direct implications from the perspective of portfolio allocation (e.g., Forbes and Rigobon, 2002; Bae et al., 2003; Pericoli and Sbracia, 2003; Bekaert et al., 2005; Diebold and Yilmaz, 2009, 2012; Wang et al., 2018; Okorie and Lin, 2021). However, with the short squeeze episode, there was no uncertainty related to whether the prices of the four stocks was close to their fundamental value – they were not. Therefore, this type of price bubble might not propagate to other assets per se.

- Short selling-related costs – as an increase in demand for protection against a short squeeze, the price of the out-of-the-money put options is likely to increase. Perhaps the usual suspects for short squeezing might be identified (e.g., Desai et al., 2006; Boehmer et al., 2008; Diether et al., 2009), which has implications for asset pricing theories and may also lead to the investigation of other financial products and procedures that mitigate investors' short squeeze exposure.

- A more efficient way of settling trades – the clearing of transactions now takes some time to process (usually $T + 2$ settlement cycle applies, i.e., two business days), which might not be a problem during calm periods, but in times of market turmoil, the situation might be different. Hence, the limited ability to fulfill the collateral requirements of brokers, such as Robinhood or Interactive Brokers, forces them to employ trading restrictions. One of the top buzzwords of the 21st century emerges to provide faster and more flexible post-trade processing – blockchain (e.g., Mori, 2016; Chiu and Koeppl, 2019; Ross and Jensen, 2019).

- Sentiment and social media analysis – measuring investors' attention by internet searches (e.g., Google Trends or Wikipedia) or their sentiment by analyzing social media content (e.g., Twitter) – has attracted considerable research interest over the last decade (e.g., Preis et al., 2013; Moat et al., 2013; Hamid and Heiden, 2015; Dimpfl and Jank, 2016; Bento et al., 2020; Audrino et al., 2020). By using word-emotion lexicons (such as EmoLex), we are able to pinpoint the exact sentiment of coordinated small-scale investors' behavior over time. Is it 'joy', 'anticipation', or 'trust' that drive hype and perhaps 'fear', 'anger', and 'sadness' that cause downturns? We believe that this area of research is worth investigating.

Societies worldwide are witnessing polarization and discomposure, amplified by the COVID-19 pandemic and related restrictions. Moreover, since the Global Financial Crisis of 2008, seething rage against the 'machine' of late-stage capitalism is growing. In recent years, we have witnessed how such negative emotions can manifest, with the Capitol Siege being just one example. In reviewing the WSB subreddit, one can easily spot considerable hate and fear, a tendency to latch onto conspiracy theories, and counterhegemonic repercussions. Apart from the direct impact on financial stability, WSB-like people-powered initiatives might dramatically increase the polarization of our societies, providing additional ammunition to both Alt-Right and Alt-Left movements. We should all keep this in mind.

Table 2: Stock price volatility model of interest and sentiment

		GameStop			AMC			Blackberry			Nokia		
		Coef.		S.E.	Coef.		S.E.	Coef.		S.E.	Coef.		S.E.
Panel A: Model estimates													
Constant		**-8.67**	***	[1.74]	-1.65		[2.70]	**-7.62**	***	[1.76]	-2.34		[2.65]
Volatility	V_{t-1}	0.12		[0.10]	**0.16**	*	[0.08]	**0.16**	.	[0.09]	**0.27**	***	[0.07]
Relative Reddit intensity	$YOLO_{1,t-1}$	**0.18**	***	[0.04]	**0.28**	***	[0.06]	**0.43**	***	[0.09]	**0.25**	*	[0.11]
Relative event SVI	$YOLO_{2,t-1}$	**2.06**	***	[0.37]	**1.16**	***	[0.36]	**0.63**	.	[0.37]	**0.73**	*	[0.37]
General market SVI sentiment	M_{t-1}	**1.79**	***	[0.48]	-0.47		[0.75]	0.60		[0.53]	-0.71		[0.73]
Panel B: Model characteristics													
R^2		47.47			39.35			44.98			33.82		
adj. R^2		46.06			37.72			43.51			32.04		
max. VIF		2.26	V_{t-1}		2.58	Y_{t-1}		2.15	Y_{t-1}		2.30	Y_{t-1}	
First-order residual serial-correlation		-0.02			0.01			-0.02			-0.05		
N^{th} order residual serial-correlation	(p-value)	0.85			0.89			0.76			0.60		
Het test	(p-value)	0.31			0.21			0.60			0.02		
Residual DF-GLS	test-stat	-4.24			-2.38			-5.02			-3.9		

Notes: Coefficient significance is derived from a variance-covariance matrix estimated using a quadratic spectral (QS) weighting scheme with prewhitening and adaptively chosen bandwidth of the QS kernel. '. ','', '**', and '***' denote statistical significance at the 10%, 5%, 1% and 0.1% significance levels. Max. VIF reports the maximum variance inflation factor, and we also identify the variable with the maximal VIF value. The N^{th}-order residual serial-correlation test corresponds to the p-value of the Escanciano and Lobato (2009) automatic portmanteau test for serial correlation. Het. test denotes the p-value of the bootstrap version of the White (1980) test of Cribari-Neto (2004), and the residual DF-GLS is the t-statistic of the unit-root (in the null) test of Elliott et al. (1996) run on the residuals of the model, where the 5% critical value is -1.94.*

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