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On the "mementum" of meme stocks

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ABSTRACT

The meme stock phenomenon has yet to be explored. In this note, we provide evidence that these stocks display common stylized facts for the dynamics of price, trading volume, and social media activity. Using a regime-switching cointegration model, we identify the meme stock "mementum" which exhibits a different characterization compared to other stocks with high volumes of activity (persistent and not) on social media. Finally, we show that mementum is significant and positively related to the stock's returns. Understanding these properties helps investors and market authorities in their decisions.

1. Introduction

Recently, the "meme stock" phenomenon has received considerable attention as social media were used as coordination devices to synchronize on buying signals that have significantly affected the price and trading volumes of certain stocks. The most famous episode occurred in January 2021 and involved the U.S. video game retailer GameStop in a short squeeze conceived by users of the *r/wallstreetbets* subreddit on the online social platform Reddit. As a consequence of the coordination mechanism above, the trading strategy caused a significant increase in the stock price which reached approximately 140% in a single market day. However, the strategy has provoked financial losses for several hedge funds that had been pursuing a short position strategy due to the worsening of the firm's fundamentals.[1] The scheme lasted for several days.

The fact that retail investors may be active on several platforms simultaneously and that subreddits, like *r/wallstreetbets*, are directly linked to official profiles in other social media[2] makes the investors' activity natively multi-platform, thus implying that buying signals can be ubiquitous. In summary, the meme stock phenomenon cannot be considered platform specific and its reach far exceeds *r/wallstreetbets* and Reddit itself.

In this letter, we provide a first evidence that meme stocks share common stylized facts for the dynamics of price, trading volume, and social media activity on Twitter. We investigate the "*mementum*", or meme period, of stocks, that is, the momentum when synchronized buying signals that originate on social media have an effect on a stock's price and trading volume.

The main contribution is three-fold. First, we formalize the concept of mementum and provide a characterization based on the pairwise cointegration dynamics of (i) price and (ii) trading volumes with (iii) social media activity. Second, based on this characterization, we use a regime-switching cointegration model to identify the meme period(s) of a stock. The proposed method is general, that is, neither stock nor social platform specific, and allows to infer mementum through a data-driven approach. Finally, we apply the methodology to a set of U.S. stocks, finding that so-called meme stocks experience at least one meme period in the time interval investigated.

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[1] For instance, see https://bloomberg.com/news/articles/2020-12-08/gamestop-declines-after-sales-fall-more-than-analysts-estimated.

[2] For example, see *r/wallstreetbets* on Twitter: twitter.com/Official_WSB, and Discord: discord.com/invite/wallstreetbets.

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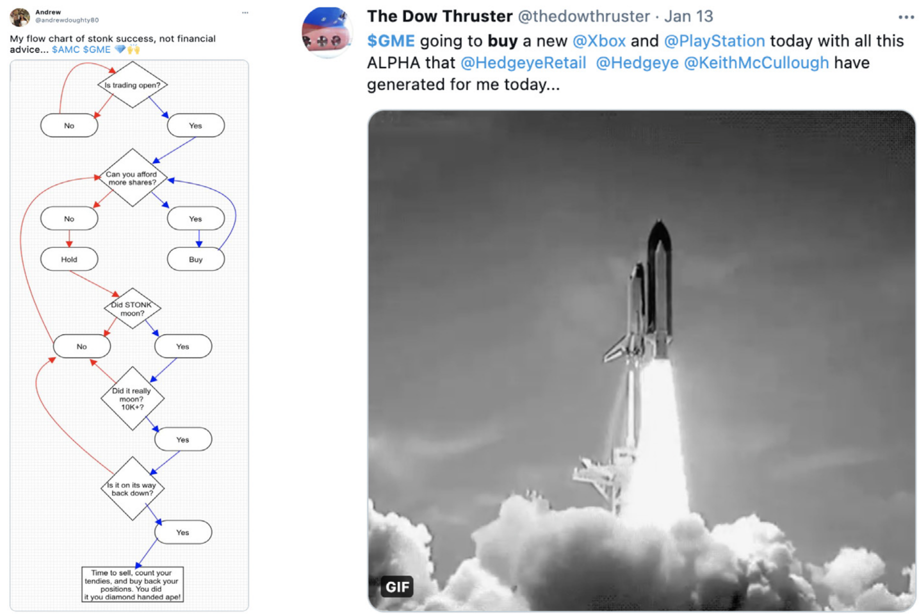

Fig. 1. Examples of stock-related "meme tweets". Left: The tweet mentions GME (i.e., GameStop) and AMC (i.e., AMC Entertainment) and contains an image describing the path toward "stunk success". Tweet link: https://twitter.com/andrewdoughty80/status/1381818643789479936 Right: The tweet mentions GME (i.e., GameStop) and contains an image of a space rocket. Tweet link: https://twitter.com/thedowthruster/status/1349398282842353666.

We identify a state of the stock when the price and social volumes are cointegrated, as well as the trading volume and the social volume. Moreover, this (temporary) equilibrium characterizes a period when the coordination mechanism of investors on social media is the main driver of the dynamics of the stock's price and volumes during that window. Conversely, several popular stocks, also characterized by intense and volatile social activity and price movements, do not exhibit meme periods.

2. Meme stocks and meme periods

Professional and institutional investors monitor stocks through portfolio risk managers and financial analysts' reports. Conversely, many retail investors tend to "feel the mood" of the market by coordinating through – and participating in – online discussions on social media. Those investors are usually viewed as noise traders (De Long et al., 1990). Differently from the growing literature on sentiment analysis and stock returns (e.g., see Baker and Wurgler, 2007; Tetlock, 2007; Kaplanski and Levy, 2010; Donadelli et al., 2017; Arteaga-Garavito et al., 2020), in this work we propose a measure for stock-related meme activity on social media that is not sentiment or emotion-based.

To proxy the meme coordination activity of retail investors on social media, for each selected stock, we construct a daily count time series based on posts explicitly referring to that stock (see examples of tweets in Fig. 1). Specifically, we count the posts containing the official stock ticker symbol preceded by a tag (hash, #, or cash, $).[3] Differently from other works, which use raw daily counts of Twitter posts that include tweets and retweets (e.g., see Umar et al., 2021), we filter out retweets, which are used to share preexisting posts.

Finally, owing to the definition of *meme*, that is, an image with text and/or emojis, we consider only posts that contain images.[4] We do so to clean from the raw series posting activity related to the imitation and diffusion of preexisting stock-related contents. As a result, we obtain a set of pruned count time series at the daily frequency that are coherent with the concepts of "meme stocks" and "mementum", which we aim to investigate and model through this work.

The time-series plots in Fig. 2 show that the social media series for GameStop (GME), AMC Entertainment Holdings Inc. (AMC), and KOSS Corporation (KOSS), which were labeled meme stocks by multiple newspapers,[5] are characterized by abrupt spikes in mid-January 2021. Interestingly, this extreme event does not correspond to any shock to the fundamentals of a stock that may have positively perturbed its price and trading volumes. We hypothesize that this phenomenon originated on social media and produced a synchronized market effect on volumes and prices. On the other side, the social media series for Pfizer (PFE), Moody's (MCO), and Disney (DIS) are more volatile, and most spikes correspond to events related to the COVID-19 pandemic, which can be captured with social media activity, but clearly did not originate on social media.

We now provide a characterization of the concept of "*mementum*" of a stock that relies on the properties of its social and financial time series. The proposed formalization allows to shift the analysis of the phenomenon from a set of loosely defined stylized facts and journalistic intuitions, to a minimal set of mementum-identification requirements, focusing on the cointegration properties of social media activity and financial time series. We focus on Twitter, because it is a popular and generalist social platform, which provides an API for downloading the data.

[3] Tweets were retrieved using the FullArchive endpoint of the Twitter API v2. For each stock, we used the query `($[ACRONYM] OR #[ACRONYM]) -is:retweet has:images`. `[ACRONYM]` stands for the stock's official ticker symbol. `-is:retweet` is used to exclude retweets, and `has:images` is used to include only posts that contain at least one image. See Appendix B for further details on Data collection.

[4] As a robustness check, we also build for each stock a social media time series which, in addition to the post-filtering conditions above, is based only on tweets that also contain at least one emoji (e.g., 🚀, 💎, ⬆️, 📈) related to a meme stock booming. Results obtained with these series are similar to those presented in this letter, and the main findings remain unchanged. These results are available upon request from the authors.

[5] For example, see: https://finance.yahoo.com/news/meme-stocks-roar-back-fueled-by-reddit-inspired-traders-191408799.html and https://www.reuters.com/business/retail-consumer/amc-falls-6-after-second-share-sale-this-week-2021-06-04/.

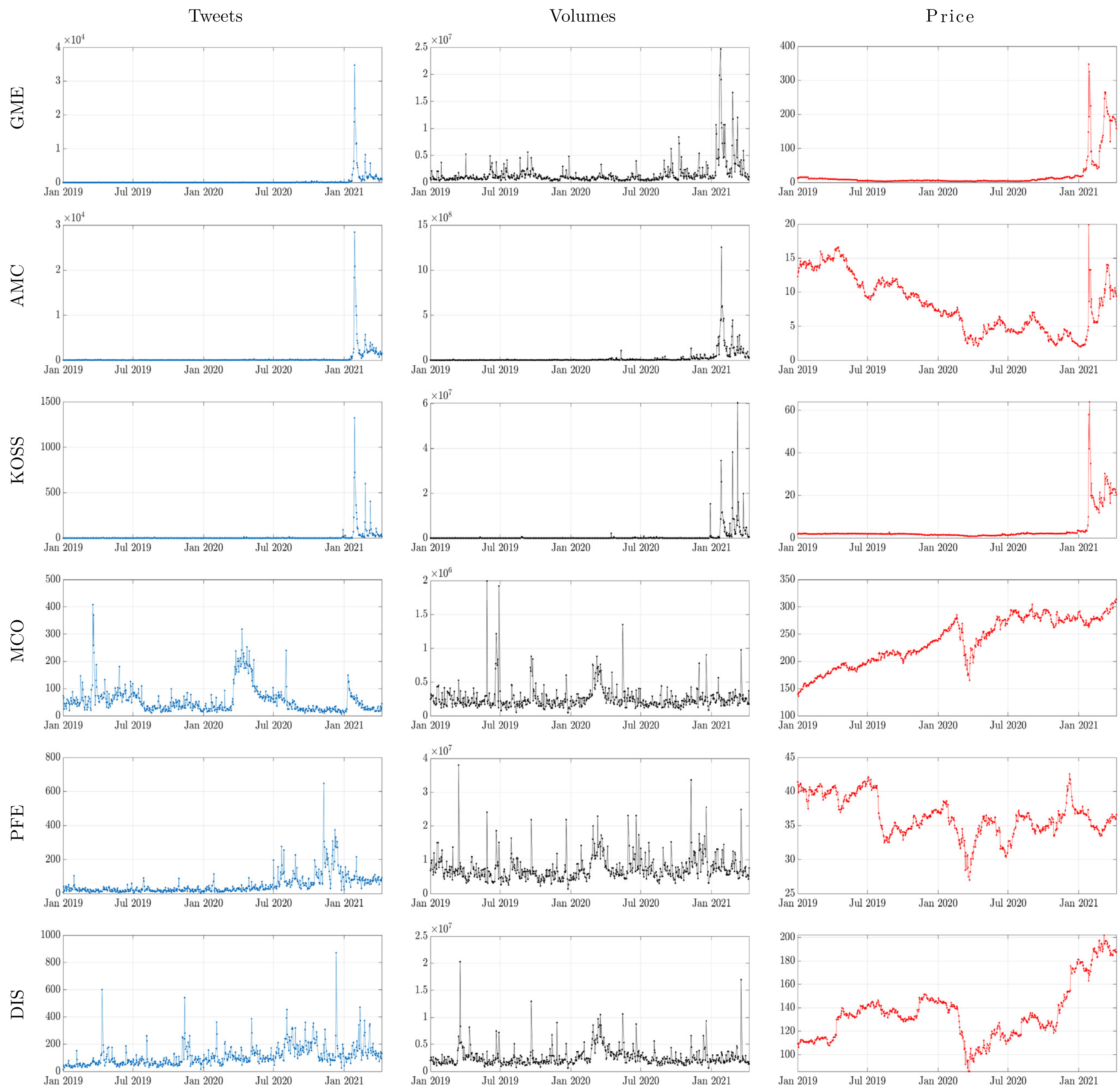

Fig. 2. Time series of tweet counts (first column), traded volume (second column), and stock price (third column) for GameStop (GME), AMC Entertainment (AMC), KOSS Corporation (KOSS), Moody's (MCO), Pfizer (PFE), and Disney (DIS).

However, the following definition and procedure are still valid if other social media are considered.

First, we postulate the contemporaneous existence of a relationship between the series of prices and Twitter posts with images, as well as between the latter and trading volumes. This relationship reflects the effects of buying coordination through social platforms, which, increasing the demand for a stock, is expected to positively affect the prices and trading volumes of the concerned stocks. Second, as these two relationships co-exist during a meme phenomenon, we require them to be synchronized in time. Moreover, as these coordination mechanisms cause structural changes in the social and financial series, we require the relationships to hold after a regime switch. Finally, to account for the persistence of the meme phenomenon, we impose a minimum duration condition that removes isolated and short-lived events. The following definition summarizes these points.

Definition 1 (*Mementum*)**.** We say that a given stock experiences a *mementum* (i.e., a meme period) if there exists a non-empty temporal window such that the following conditions jointly hold:

- *Condition 1:* Coordinated buying signals originated in social media, which are proxied through count time-series, affect the cointegration between (i) price and tweet series, and (ii) volumes and tweet series. This implies that two cointegration relationships occur contemporaneously.
- *Condition 2:* There is synchronicity in the timing when the regime switches to cointegration. The change of just one cointegration relationship does not reflect a common, structural event on social media activity affecting both the price and the trading volume.
- *Condition 3:* For both series, the cointegration regime is persistent, as well as the regime before cointegration.

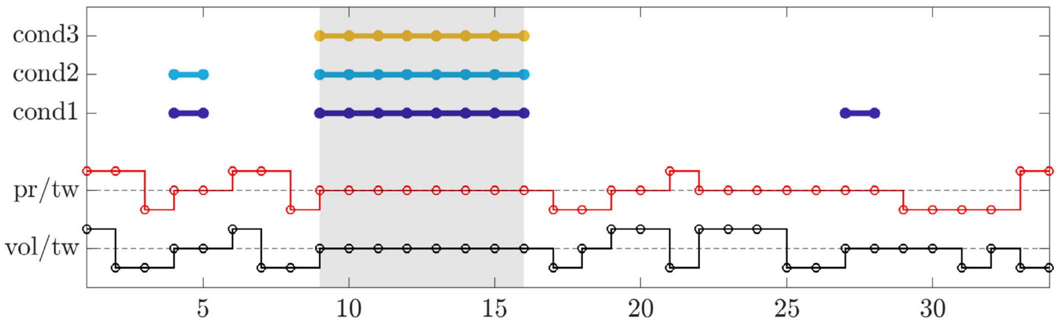

Fig. 3. Example of the method with simulated data. Estimated cointegration regimes for the pairs price/tweets (red line) and volumes/tweets (black line). The dashed lines represent the regime with one cointegrating relationship. The color bars in the top three lines identify the periods when the three conditions in Definition 1 are satisfied (*Condition 1* in dark blue, *Condition 2* in light blue, and *Condition 3* in dark yellow). (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

3. Procedure for identifying the mementum

Cointegration among n time series (either I(0) or I(1)) is defined as the presence of $r < n$ stationary linear combinations of time series (Engle and Granger, 1987; Johansen, 1991). We adopt a time-varying cointegrating framework, which identifies dynamic price-tweet and volume-tweet pairwise cointegrating relationships. Recently, Chua and Tsiaplias (2018) proposed an econometric framework that allows for a time-varying cointegrating matrix and a time-varying cointegrating rank. In this setting, a cointegrating relationship represents a smoothly changing equilibrium toward which the variables are attracted at a specific point in time, but not necessarily at each point. The time-varying rank and parameters vector error correction model (TVR-TVP-VECM) for investigating cointegration is given by

$$\Delta y_t = c + y_{t-1}\Pi_t + \Delta y_{t-1}B + \epsilon_t, \qquad \epsilon_t \overset{iid}{\sim} \mathcal{N}(0, \Sigma), \tag{1}$$

where $y_t = (y_{1,t}, \ldots, y_{n,t})$, Δ is the first difference operator, and Π_t is the $(n \times n)$ time-varying cointegrating matrix. If at time t there exists a non-empty set of cointegrating relationships, then Π_t has rank $r_t < n$ and admits a low rank decomposition as $\Pi_t = \boldsymbol{\beta}_t\boldsymbol{\alpha}_t$, where $\boldsymbol{\beta}_t$ and $\boldsymbol{\alpha}_t$ are $(n \times r_t)$ and $(r_t \times n)$ matrices of cointegrating relationships and loadings, respectively. Specifically, they allow the rows of the loading matrix, $\boldsymbol{\alpha}_t$, and the columns of the cointegrating relationships matrix, $\boldsymbol{\beta}_t$, to vary smoothly over time (similar to the TVP-VECM setting of Koop et al., 2011), independently of each other. Finally, the dynamics of the rank is driven by a homogeneous N-state hidden Markov chain S_t with transition matrix P, with entries $p_{ij} = \mathbb{P}(S_t = j|S_{t-1} = i)$, $i, j = 1, \ldots, n+1$. Defining the indicator $s_{jt} = 1$ if $S_t = j$, the dynamics of Π_t is given by

$$\Pi_t = U_t I(S_t) I(S_t) \Lambda_t V_t' = U_t \kappa_t I(S_t) I(S_t) \kappa_t^{-1} \Lambda_t V_t' \tag{2}$$

where U_t and V_t are orthogonal matrices and Λ_t is a diagonal matrix, stemming from the singular value decomposition of Π_t, and κ_t is an auxiliary diagonal matrix, and $I(S_t)$ is a regime-dependent diagonal matrix with ith diagonal element $I(S_t)_{ii} = (1 - s_{1t})\sum_{j=i+1}^{n+1} s_{jt}$. The assumption of a Markovian process for r_t allows for persistence of the time-varying rank, which is a desirable property in our framework. Notice that, at each point in time the rank of Π_t is fully determined by the chain S_t.

This framework enables the variables to exhibit a common stochastic trend only for specific periods, which is in line with some of the features of mementum, as in Definition 1.[6] As we are interested in pairwise cointegrating relationships, for each stock, we estimate model (1) for the two pairs pr/tw (price and tweets) and vol/tw (volumes and tweets). The estimated regimes allow us to identify the periods where both pairs of variables are cointegrated. This is used as input for the following procedure for identifying the mementum.

For each stock, we take all starting dates of the price-tweet and volume-tweet cointegration regimes, retaining only those that last at least d_c days (*Condition 3*). To reduce the influence of noisy estimates, we impose an additional persistence condition. Specifically, we filter out all dates that were not preceded by at least d_p days of a non-cointegrated regime. For the same reason, we ignore extremely transitory falls (of duration $\leq d_f$) from the cointegration regime, by merging cointegrated intervals that closely follow each other. Thus, we match the starting dates of the price-tweet and volume-tweet cointegrated regimes (*Condition 2*). We allow for d_w days of delay. Once they are matched, we keep only the intersection of dates between the two sets of time intervals (*Condition 1*), keeping, as before, only jointly cointegrated periods that last at least d_c days (*Condition 3*).

Example 1.
Fig. 3 provides a graphical representation of the procedure for a simulated example. A meme period starts when all the conditions are satisfied, at $t = 9$, and lasts until $t = 16$, when at least one condition is violated. Notice that at $t = 4$ conditions 3 is violated (cointegrating relationships are not sufficiently persistent), whereas at $t = 27$ only condition 1 holds.

In the empirical analysis, we impose minimum requirements of persistence and delay by fixing $d_c = 2$, $d_p = 2$, $d_w = 1$, and $d_f = 1$ days. The findings are robust to alternative choices of these parameters.

Fig. 4 shows for each stock the dynamics of the inferred cointegrating relationships, as well as the mementum identified using the conditions in Definition 1. Each of the three selected stocks that were labeled by journalists as meme stocks (GME, AMC, KOSS) experienced at least a meme period. The first stock to exhibit a mementum in 2021 is GameStop, on January 13, followed by AMC, on January 15, and KOSS, on January 25.[7]

Interestingly, a 4-day meme period is identified for KOSS at the end of 2020, but at that time the meme stock label had not yet been used by journalists and analysts in relation to this stock. However, market commentators were questioning which mechanisms, unrelated to fundamentals, could have been at play behind the sharp rise of KOSS' stock price and trading volumes.[8]Moreover, during those days some "meme tweets"

6 We refer to Chua and Tsiaplias (2018) for further details about the properties of the model and the inference procedure. The estimation is performed according to a Bayesian approach relying on a Markov chain Monte Carlo algorithm to approximate the joint posterior distribution.

7 For example, on the first day of GameStop's mementum, the stock's price increased by 57.39% and trading volumes jumped from 7,060,665 to 144,501,736.

8 See https://marketglobalist.com/2020/12/29/is-there-any-reason-behind-the-dramatic-surge-of-koss-corporation-koss-stock/.

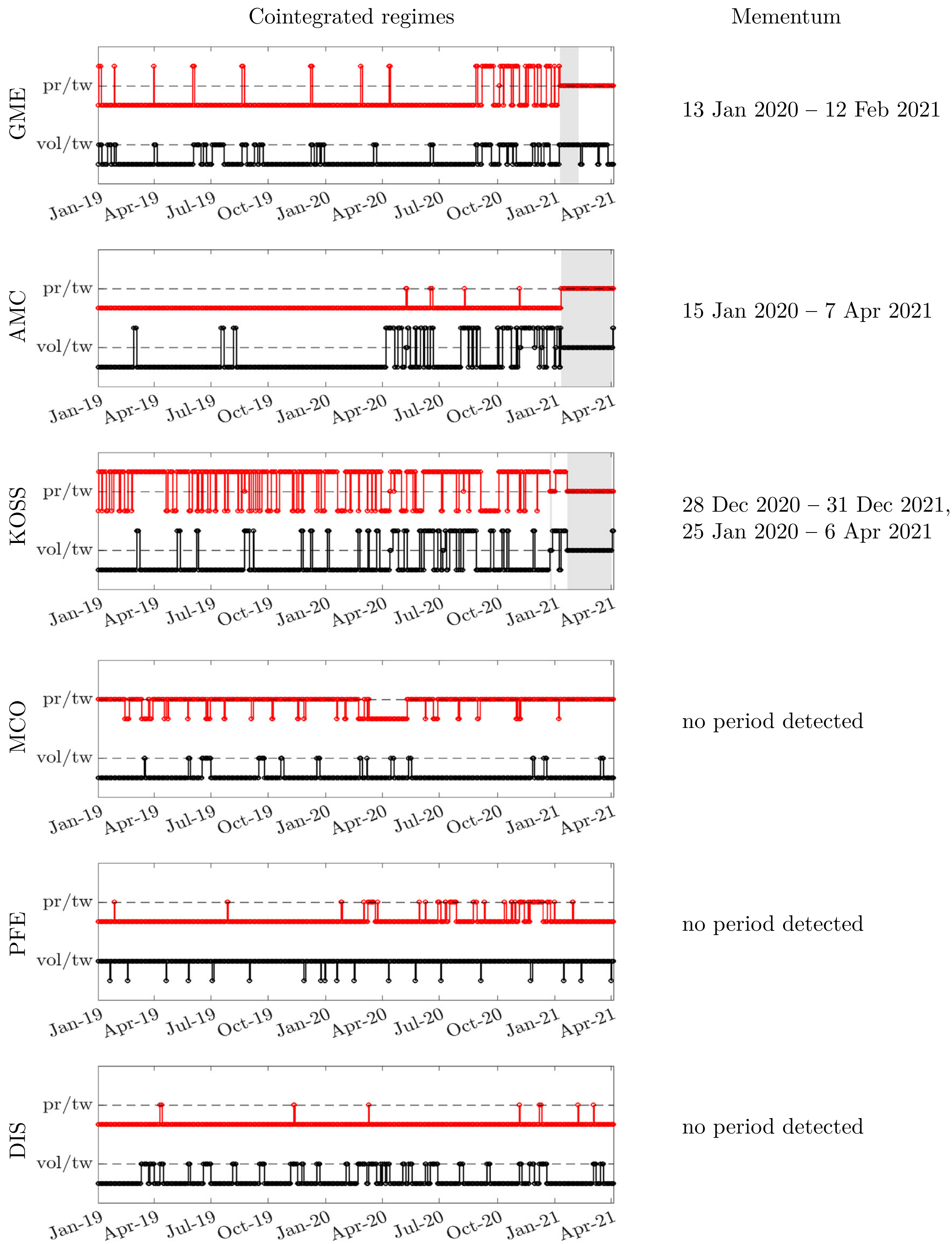

Fig. 4. Estimated time-varying regimes, $\hat{S}_t$, for the price-tweets (pr/tw, red) and volumes-tweets (vol/tw, black) models. The dashed line indicates the cointegration regime; the gray shades represent the meme periods, that is the dates where the conditions in Definition 1 are met, using the parameter values $d_c = 2$, $d_p = 2$, $d_w = 1$, and $d_f = 1$ days. Stocks: GameStop (GME), AMC Entertainment (AMC), KOSS Corporation (KOSS), Moody's (MCO), Pfizer (PFE), and Disney (DIS). (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

instrumental in investor coordination were already observable (see Fig. 5).

Although Moody's, Pfizer, and Disney exhibited multiple transitions between cointegrated and non-cointegrated regimes, the stocks do not have a meme period due to a lack of synchronization and persistence. This confirms that the proposed framework is able to discriminate a mementum from other types of events affecting prices and/or trading volumes.[9]

[9] Additionally, we have also checked for the presence of mementum in other stocks before the COVID-19 era. Our procedure does not detect any mementum.

Fig. 5. Example of "meme Tweet" mentioning $KOSS posted at the end of 2020. Tweet link: https://twitter.com/greenwoodstocks/status/1343690011678486529.

Table 1
Regression results for GameStop (GME), AMC Entertainment (AMC), and KOSS Corporation (KOSS) on the stock *mementum* using the Fama–French three-factor model. Robust standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

	(1) GME	(2) AMC	(3) KOSS
$GME_{mementum}$	0.1084**		
	(0.0442)		
$AMC_{mementum}$		0.0670**	
		(0.0262)	
$KOSS_{mementum}$			0.1206***
			(0.0442)
alpha	0.0071***	−0.0028	0.0024
	(0.0021)	(0.0017)	(0.0021)
MktRF	−0.0172	−0.1690	−1.8458**
	(0.3083)	(0.5970)	(0.9116)
SMB	3.9114***	4.1537***	4.3898***
	(0.5975)	(0.9492)	(1.5014)
HML	1.4944***	1.9639***	1.6024***
	(0.3166)	(0.4200)	(0.5311)
R-squared	0.1110	0.0811	0.0552

Given that the mementum detects buying signal effects resulting from a coordination originated on social media platforms, it can be expressed as a time-varying binary variable, $Stock_{mementum} = \{0, 1\}$. We tested its validity and profitability using the Fama–French three-factor model. The results show that the mementum indicator is significant and positively related to stock returns after controlling for the factors, in all the three considered cases. Table 1 includes the regression results for GME, AMC, and KOSS, for which a mementum has been identified, considering the last 6 months of the sample. Results highlight that the extracted mementum factor is significant and could be used as a buying signal to implement an investment strategy. In particular, there is an excess return of 10.84% for GME, 6.70% for AMC, and 12.06% for KOSS during mementum.

4. Conclusions

The meme stock phenomenon has exerted a significant impact on financial markets, raising new challenges and policy issues that need to be addressed (Warren, 2021).

Our contribution represents an initial attempt in this direction, by providing an econometric characterization of mementum based on regime-switching cointegration and a simple procedure for identifying them from market and social data. In our view, mementum can be counted as a market manipulation strategy as described in Jarrow (1992). The meme-based coordination mechanisms originated in social media allow small investors to act as a single large trader, able to successfully manipulate prices. Similar trading strategies have been also identified in the cryptocurrency markets as "pump-and-dump" schemes where coordinated social trading mechanisms aimed at creating short-term increases in prices (Xu and Livshits, 2019). The potentially destabilizing effect of social investors certainly requires further investigation.

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Appendix A. Supplementary data

Supplementary material containing details on the econometric model and data collection can be found online at https://doi.org/10.1016/j.econlet.2021.110021.

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