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Sentiment-driven price explosiveness in blue-chip stocks: a Clog-log approach

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ABSTRACT

Price explosiveness, typically observed in speculative markets such as cryptocurrencies and meme stocks, can also impact stable, mature stocks like those in the Dow Jones Industrial Average (DJIA). This study explores price explosiveness within the DJIA and examines how textual sentiment from news and social media influences this phenomenon. To identify price explosiveness in DJIA stocks, we employed the SADF and GSADF tests. The SADF test detects short-lived explosive behaviour by varying the endpoint of the sample window while holding the starting point fixed, effectively identifying localised bubbles. The GSADF test extends this approach by varying both the start and endpoint of the window, capturing a broader range of potential bubbles, including overlapping and sustained episodes. Applying these tests to daily closing prices, we calculated right-tailed ADF statistics and determined critical values using Monte Carlo simulations. Despite the DJIA's stability, significant instances of price explosiveness occur, particularly during major events like the COVID-19 pandemic and general elections. Our analysis reveals that social media sentiment is more dominant in driving price explosiveness than news sentiment or broader economic uncertainty indicators.

IMPAT STATEMENT

This study challenges the conventional view that price explosiveness is confined to speculative assets by demonstrating its presence in mature, stable stocks within the Dow Jones Industrial Average (DJIA). Using the SADF and GSADF tests, we find episodes of explosive price behaviour and show that social media sentiment plays a more significant role in triggering these dynamics than traditional news or macroeconomic indicators. These findings have important implications for investors, policymakers, and regulators by highlighting the growing influence of non-traditional information sources on financial stability, even in established markets.

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1. Introduction

In the realm of financial markets, the phenomenon of price explosiveness—characterised by rapid and unsustainable changes in asset prices that significantly deviate from underlying fundamentals—has predominantly been observed in highly speculative assets such as meme stocks and cryptocurrencies (Aloosh et al., 2022; Gronwald, 2021; Shahzad et al., 2022). These assets, often driven by intense social media engagement and speculative trading, have been the focus of numerous studies examining the underlying causes and mechanics of price bubbles. However, the potential for price explosiveness in more mature and stable stocks, such as those comprising the Dow Jones Industrial Average (DJIA), remains underexplored.

The DJIA is a benchmark for blue-chip stocks that are generally considered to be stable and mature. These companies have large market capitalisations and are typically perceived as being less prone to price bubbles (Almansour et al., 2023). The assumption is that in such mature

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markets, prices closely follow fundamentals, and deviations are less frequent and less extreme compared to more volatile asset classes (Ahmed et al., 2022). This is in line with the Efficient Market Hypothesis (Fama, 1965; Malkiel & Fama, 1970), which posits that security prices fully reflect all available information, thereby minimising opportunities for persistent mispricing or speculative bubbles. Moreover, this perception is reinforced by the so-called blue-chip bias—the tendency of investors to assume that blue-chip stocks are inherently less risky and less likely to experience extreme price movements or financial distress compared to smaller or less established companies (Almansour et al., 2023).

Nonetheless, a growing body of research in behavioural finance suggests that even mature and liquid markets are not entirely immune to speculative dynamics. According to the noise trader theory (Shleifer & Summers, 1990), irrational traders driven by sentiment can push prices away from their fundamental values, even when rational arbitrageurs are present. Furthermore, investor sentiment—as captured by media narratives, news coverage, and social media discussions—has been shown to influence asset prices beyond what can be justified by fundamentals alone (Baker & Wurgler, 2007). Importantly, attention-based models (Barber & Odean, 2008) emphasise that when certain stocks attract disproportionate attention, they may experience abnormal trading volumes and prices, irrespective of intrinsic value. Therefore, even blue-chip stocks can occasionally exhibit periods of rapid price appreciation that resemble speculative bubbles, especially when investor sentiment shifts abruptly.

Building on this theoretical foundation, it is reasonable to expect that DJIA stocks may also experience episodes of price explosiveness, particularly during periods of heightened market sentiment or information shocks, leading to the following hypothesis:

H1: Price explosiveness occurs in DJIA stocks despite their mature and stable characteristics.

Research on the dynamics of asset price bubbles has increasingly highlighted the role of textual sentiment, especially from social media platforms, in fuelling episodes of price explosiveness (Lee & Jeong, 2023; Zaman et al., 2023). This is particularly evident in the cryptocurrency space, where assets like Bitcoin and Dogecoin have shown multiple episodes of explosiveness linked directly to public sentiment and high-profile social media activity. For instance, Shahzad et al. (2022) document price bubbles in Bitcoin and Dogecoin, which are linked to Elon Musk's Twitter activity, showing that general crypto-related *tweets* often drive explosiveness in Bitcoin, while Dogecoin-specific *tweets* spur similar behaviour in Dogecoin. These findings demonstrate how market sentiment, particularly from influential individuals, can significantly affect asset pricing beyond traditional fundamentals.

While the literature on cryptocurrencies has established a clear connection between sentiment and price explosiveness, there remains a gap in understanding whether similar dynamics apply to more established and regulated financial assets such as DJIA stocks. Equity markets differ substantially from crypto markets in terms of investor composition, regulatory oversight, and market depth—factors which may influence the sentiment-explosiveness relationship. Nevertheless, with the increasing integration of real-time news and sentiment analytics in algorithmic trading and retail investor platforms (Nyakurukwa & Seetharam, 2025), it is plausible that sentiment also plays a critical role in triggering explosive price movements in traditional stocks. This motivates the following hypothesis:

H2: Textual sentiment significantly influences the likelihood of price explosiveness in DJIA stocks.

These hypotheses extend the existing literature by challenging the conventional wisdom that blue-chip stocks are largely insulated from speculative dynamics. While previous research has demonstrated that sentiment derived from textual data—such as news articles and social media—can significantly impact the price dynamics of meme stocks and cryptocurrencies (Gianstefani et al., 2022), we propose that similar mechanisms may also operate, albeit perhaps less frequently, within the domain of mature blue-chip equities. In doing so, our study broadens the understanding of how behavioural forces interact with price formation, even in traditionally stable segments of the equity market.

We proceed as follows: [Section 2](#) outlines the data and methods, [Section 3](#) presents the results, and [Section 4](#) concludes.

2. Data and methods

2.1. Data

Since we aim to examine price explosiveness among mature blue-chip companies, we chose the DJIA because of the size of constituent companies and also because these companies are frequently mentioned on social media and news media platforms and are, therefore, ideal for the purposes at hand. We use three firm-level variables, daily closing prices, social media sentiment and news media sentiment, all obtained from Bloomberg. Because we include large DJIA constituent stocks, we did not have any missing observations on any of the variables used. News media sentiment and social media sentiment reflect the extent to which investors are optimistic/pessimistic about the prospects of a stock. The sentiment scores are sampled at a daily interval and range from -1 (extreme pessimism) to +1 (extreme optimism). This means that a score of zero reflects that investors are neutral about the prospects of the mentioned stock.

Bloomberg constructs the sentiment scores from machine learning models that rely on data from social media platforms like X and StockTwits, as well as thousands of online news platforms like the Wall Street Journal (Nyakurukwa & Seetharam, 2022). We also use macro-level proxies for textual sentiment reflected by uncertainties about economic policy uncertainty (EPU). These proxies¹ include TV EPU - policy uncertainty estimated from cable news networks (Bergbrant & Bradley, 2022; Hong et al., 2021), EPU - economic policy uncertainty estimated from news articles (Baker et al., 2016) and TV EPU EXP - a variant of TV EPU with additional terms used - risk and risky (Bergbrant & Bradley, 2022; Hong et al., 2021). All these macro-level measures of sentiment are measured at daily granularity. We restrict our sample period to between 1 January 2015 and 30 March 2024 because firm-level sentiment scores gathered from Bloomberg only go as far back as 2015. Ultimately, our dataset consists of 28 stocks and 2325 daily observations² (see Table 1 for details).

2.2. Methods

2.2.1. Price explosiveness

In empirical studies, financial bubbles are often characterised by exponential growth patterns. Such dynamics can be identified using statistical methods like right-tailed unit root tests. Notably, Phillips et al. (2015) developed a single-variable framework to detect bubbles occurring near the end of a dataset, employing an Augmented Dickey-Fuller (ADF) regression model for analysis.

$$y_t = \mu + \phi y_{t-1} + \sum_{i=1}^p \psi \Delta y_{t-1} + \epsilon_t, \epsilon_t \sim N(0, \sigma^2) \quad [1]$$

The Augmented Dickey-Fuller (ADF) regression is typically implemented across the full dataset, where μ represents the constant term, and p denotes the lag order of the first-differenced variable Δy_t , determined through information criteria such as AIC or BIC. In conventional ADF testing, the procedure examines whether the coefficient ϕ equals 1 (suggesting a unit root process) against the alternative hypothesis of stationarity ($\phi < 1$). For detecting explosive trends, Phillips et al. (2015) modified this

Table 1. Results from cloglog.

	GSADF		SADF	
	Coef.	ME	Coef	ME
NEWS	0.5160** (0.2616)	0.0085** (0.0033)	0.2245** (0.1004)	0.02569*** (0.0104)
SOCIAL MEDIA	1.1132*** (0.3655)	0.0182** (0.0110)	0.7473*** (0.1546)	0.0855*** (0.0229)
TV EPU	0.0399 (0.0918)	0.0007 (0.0014)	-0.0429 (0.0529)	-0.0049 (0.0061)
TV EPU EXP	0.0962 (0.0462)	0.0016 (0.0010)	0.0047 (0.0364)	0.0005 (0.0042)
EPU	0.2626 (0.2565)	0.0043 (0.0043)	0.0608 (0.1127)	0.0069 (0.0135)
_cons	-5.4274*** (1.3275)	0.0165** (0.0067)	-2.3296*** (0.4871)	0.1223*** (0.0265)

NB: Coef stands for coefficient. Semi-robust standard errors adjusted for clustering at the firm level are shown in parentheses. ME represents marginal effects.

***, **represents statistical significance at the 1% and 5% levels of significance.

approach into a right-tailed test, retaining the null hypothesis of a unit root ($\varphi = 1$) but testing the alternative $\varphi > 1$, which signals explosive dynamics. This full-sample explosive behaviour test is symbolised as $ADF_0^1(p)$. A key limitation of full-sample testing is its limited sensitivity to transient bubbles due to statistical power constraints. To improve detection, Phillips et al. (2015) introduced a recursive subsampling strategy, where ADF statistics are computed sequentially across expanding or rolling windows. For a subsample spanning observations $t = \lfloor r_1 T \rfloor$ to $\lfloor r_2 T \rfloor$ (with r_1 and r_2 representing the fractional start and end points), the corresponding statistic is labelled $ADF(p)_{r_1}^{r_2}$. Building on this, Phillips and Shi (2019) later formulated a refined test statistic to enhance robustness in identifying episodic bubbles.

$$SADF := \sup_{r_2 \in [r_0, 1]} \{ADF(p)_0^{r_2}\} \quad [2]$$

The Supremum ADF (SADF) test calculates the maximum value (**S**) derived from right-tailed ADF statistics computed over a rolling window of data. This window begins at the first observation and expands incrementally. This recursive approach has been empirically validated as a reliable tool for detecting transient bubbles, such as those prone to abrupt collapses—a phenomenon frequently observed in financial markets (Agosto et al., 2022). The Generalised SADF (GSADF) test extends this methodology by iteratively applying ADF regressions to a broader array of subsamples. Unlike the SADF, which fixes the starting point and incrementally extends the endpoint from a minimum window size to the full sample, the GSADF introduces additional flexibility. It allows both the starting point and the endpoint to vary. Periods where the test statistics exceed the critical values suggest the presence of explosive behaviour or prices.

In examining periods of price explosiveness for blue chip stocks, it is important to note that these instances can be classified as irrational ‘bubbles’, or in certain cases—particularly during major events like COVID-19—they may represent rapid, but potentially rational, adjustments to significant new information or changes in growth expectations. During such events, asset prices may respond quickly to evolving market conditions, and what may appear as explosive behaviour could reflect a market’s attempt to realign with new information rather than a speculative frenzy. This distinction is crucial for understanding the dynamics behind price explosiveness as it highlights the role of market reactions to substantial shifts in economic fundamentals.

2.2.2. Explosiveness and textual sentiment

To model whether textual sentiment affects the odds of price explosiveness, we create a dummy variable (Explosive) that equals 1 in periods of price explosiveness or 0 otherwise, leading to a binary outcome variable. Because we assume that the occurrence of price bubbles in mature companies is a rare event, we use a method that is robust when the probability of an event is low. We use the complementary log-log (cloglog) link function, which is a powerful tool used in generalised linear models. This approach is suited for rare events because it directly addresses the low probability of occurrence, avoiding bias. In the cloglog model, we report robust standard errors clustered at the firm level.

3. Results

We start the presentation of our results by showing the dynamic evolution of price explosiveness for each stock that formed part of the sample. Figure 1 shows the results of the SADF test statistics for various DJIA stocks over time. The blue lines represent the SADF test statistics, while the black dashed lines indicate the sequence of 95% critical values. Periods where the SADF test statistics exceed the critical values are highlighted in red, suggesting the presence of explosive behaviour or prices. The results reveal that several DJIA stocks experienced periods of price explosiveness. Notably, companies like Apple (AAPL) and Amazon (AMZN) have shown significant explosive behaviour, particularly around the year 2020. Boeing (BA) also displays clear explosive periods, especially between 2018 and 2019. Microsoft (MSFT) similarly shows notable explosiveness during the same period.

Conversely, some stocks exhibit minimal or no explosive behaviour, indicated by the absence or sparsity of red areas. For instance, Cisco (CSCO) and Verizon (VZ) show limited instances of explosive behaviour. Temporal patterns indicate that many explosive periods are clustered around significant events, such as the COVID-19 pandemic in 2020. The results also highlight variation in the levels of explosiveness across different sectors, with tech companies like Apple, Amazon, and Microsoft exhibiting more frequent and pronounced explosive behaviour compared to others. Figure 2 reiterates the results

SADF Test statistics (blue) together with the sequence of 95% critical values (black)

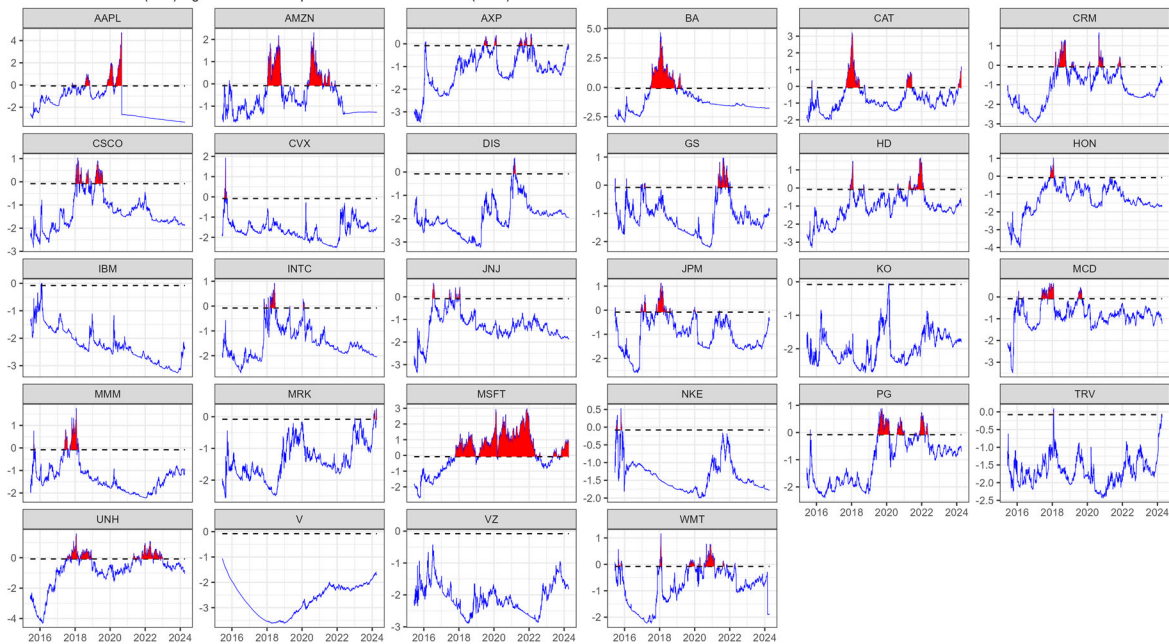


Figure 1. Price explosiveness using the SADF test statistics.
 Note: Explosive periods are coloured in red.

GSADF Test statistics (blue) together with the sequence of 95% critical values (black)

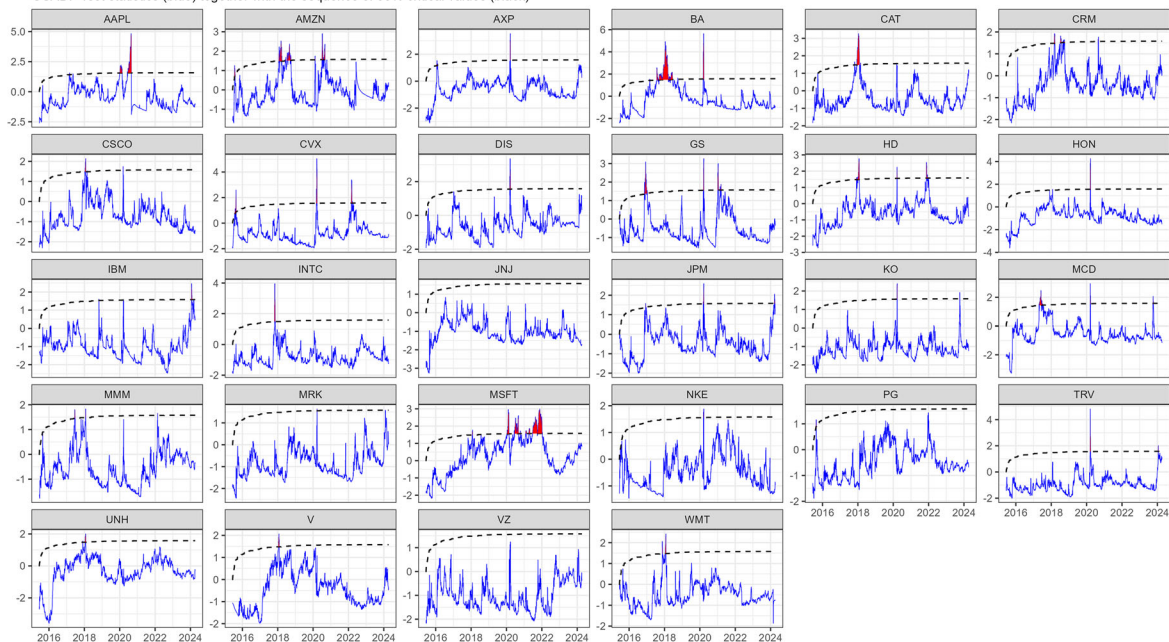


Figure 2. Price explosiveness using the GSADF test statistics.
 Note: Explosive periods are coloured in red.

on price explosiveness explained above, but this time using the GSADF statistics. However, we observe that this time, explosive events are now rarer than before, mainly because the GSADF test has more power compared to the SADF test (Vasilopoulos et al., 2022). Table 2 shows periods of explosive behaviour from a date stamping emanating from the GSADF test³. For each ticker, Table 2 shows the start and end dates of each specific explosive period and the duration of each explosive period.

Finally, we report results from the cloglog model to understand whether our proxies of textual sentiment are associated with the odds of stocks experiencing explosive behaviour in Table 3.

Table 3 shows that in both models, social media sentiment emerges as a significant driver of price explosiveness. In the GSADF model, a one-unit increase in social media sentiment corresponds to a considerable increase

Table 2. Results from the CMP model.

	GSADF		z	SADF		z
	Coef.	Std.Err		Coef.	Std. Err	
EXPLOSIVE						
NEWS	1.6029***	0.1222	13.1100	1.3363***	0.0974	13.7100
SOCIAL MEDIA	1.6876***	0.1172	14.4000	2.3028***	0.1499	15.3600
TV EPU	0.0147	0.0076	1.9200	0.0158***	0.0061	2.6000
TV EPU EXP	0.0166***	0.0040	4.1400	0.0140***	0.0040	3.4800
EPU	0.0316***	0.0067	4.7000	0.0307***	0.0066	4.6700
NEWS						
SOCIAL MEDIA	1.3366***	0.0820	16.3000	1.3123***	0.0788	16.6500
TV_EPU	0.0019	0.0056	0.3400	0.0018	0.0056	0.3200
TV_EPU_EXP	-0.0095***	0.0023	-4.1400	-0.0095***	0.0023	-4.1400
EPU	-0.0085	0.0030	-2.8000	-0.0085***	0.0030	-2.8300
1.EXPLOSIVE	0.0130	0.0128	1.0100	0.0046	0.0065	0.7000
_CONS	0.0453***	0.0154	2.9400	0.0457***	0.0155	2.9500
SOCIAL MEDIA						
NEWS	0.4828***	0.0303	15.9600	0.4739***	0.0292	16.2400
TV_EPU	-0.0025	0.0031	-0.8100	-0.0026	0.0031	-0.8300
TV_EPU_EXP	0.0045***	0.0012	3.5900	0.0044***	0.0012	3.5500
EPU	0.0024	0.0019	1.3100	0.0023	0.0018	1.2300
1.EXPLOSIVE	-0.0032	0.0074	-0.4300	0.0034	0.0037	0.9400
_cons	-0.0105	0.0103	-1.0200	-0.0100	0.0102	-0.9700
/atanhrho_12	-0.4768			-0.4236		
/atanhrho_13	-0.3510			-0.4338		
/atanhrho_23	-0.8557			-0.8165		
rho_12	-0.4437			-0.4000		
rho_13	-0.3373			-0.4085		
rho_23	-0.6940			-0.6731		

Notes: The table shows the results from the CMP models, where the dependent variable for each model is shown in bold, robust standard errors clustered at the firm level are shown in parentheses.

***, **, * shows statistical significance at the 1%, 5% and 10% levels respectively. The variable 1.EXPLOSIVE is a dummy variable with 1 representing explosiveness or 0 otherwise.

Table 3. List of companies used.

	SYMBOL	COMPANY	SECTOR
1	AAPL	Apple Inc.	Technology
2	AMGN	Amgen Inc.	Healthcare
3	AXP	American Express Company	Financials
4	BA	Boeing Company	Industrials
5	CAT	Caterpillar Inc.	Industrials
6	CRM	Salesforce Inc.	Technology
7	CSCO	Cisco Systems Inc.	Technology
8	CVX	Chevron Corporation	Energy
9	DIS	Walt Disney Company	Communication Services
10	GS	Goldman Sachs Group Inc	Financials
11	HD	Home Depot Inc.	Consumer Discretionary
12	HON	Honeywell International Inc.	Industrials
13	IBM	International Business Machines	Technology
14	INTC	Intel Corporation	Technology
15	JNJ	Johnson & Johnson	Healthcare
16	JPM	JPMorgan Chase & Co	Financials
17	KO	Coca-Cola Company	Consumer Staples
18	MCD	McDonald's Corporation	Consumer Discretionary
19	MMM	3M Company	Industrials
20	MRK	Merck & Co. Inc.	Healthcare
21	MSFT	Microsoft Corporation	Technology
22	NKE	NIKE Inc. Class B	Consumer Discretionary
23	PG	Procter & Gamble Company	Consumer Staples
24	TRV	Travelers Companies Inc	Financials
25	UNH	UnitedHealth Group Incorporated	Healthcare
26	V	Visa Inc. Class A	Financials
27	VZ	Verizon Communications Inc	Communication Services
28	WBA	Walgreens Boots Alliance Inc.	Healthcare
29	WMT	Walmart Inc.	Consumer Staples

in the likelihood of price explosiveness, with this effect being highly significant. Similarly, the SADF model also shows a strong positive influence of social media sentiment on price explosiveness, although the effect is slightly less pronounced than in the GSADF model. News sentiment also shows a positive relationship with price explosiveness in both models. Conversely, EPU, TV EPU, and TV EPU EXP do not significantly impact price

explosiveness in either model. This shows the importance of firm-level sentiment in explaining price explosiveness compared to macro-level sentiment indicators like economic policy uncertainty.

In the complementary log-log model, the marginal effects represent the change in the probability of observing a price bubble (i.e. an explosive regime) given a one-unit increase in the explanatory variable, holding other variables constant. Specifically, the results (Table 3) show that a one-unit increase in social media sentiment is associated with an increase of approximately 1.82 percentage points (GSADF) or 8.55 percentage points (SADF) in the probability of a bubble occurring. A one-unit increase in news sentiment increases the probability by approximately 0.85 percentage points (GSADF) and 2.57 percentage points (SADF). These effects are statistically significant and economically meaningful, especially in the case of social media sentiment, where the estimated marginal effects are considerably larger than those for news sentiment.

4. Robustness

The relationship between sentiment and asset price explosiveness is inherently susceptible to endogeneity concerns. While elevated sentiment may lead to a higher likelihood of price explosiveness, it is equally plausible that episodes of sharp price increases could retroactively drive more positive sentiment. This bidirectional feedback loop raises the risk of reverse causality, complicating causal inference. To address this limitation, we implement a robustness check using lagged sentiment variables. Specifically, we model the probability of explosiveness at time t as a function of sentiment measured at time $t - 1$. By introducing a temporal separation between sentiment and explosiveness, we mitigate immediate feedback effects and strengthen the interpretation that sentiment *drives* explosiveness rather than *vice versa*. The results, which are not reported for brevity, show that the lagged values of news and social media have a positive and statistically significant effect on explosiveness.

Further, to more rigorously account for potential endogeneity, we employ the Conditional Mixed Process (CMP) estimator that allows us to estimate recursive multi-equation systems with different types of dependent variables (Nyakurukwa et al., 2025), making it well-suited for our context where explosiveness is modelled as a binary rare event (using the complementary log-log link) and the sentiment is treated as an endogenous regressor. The CMP model addresses potential biases arising from omitted variables or reverse causality by explicitly accounting for endogeneity through its modelling of the selection mechanism (Li et al., 2024; Nguyen et al., 2018). The CMP estimation results (Table 4) indicate that

Table 4. Date stamping price explosiveness using GSADF.

Ticker	Start	Peak	End	Duration
AAPL	2020-01-08	2020-01-29	2020-02-03	17
AAPL	2020-02-04	2020-02-12	2020-02-21	12
AAPL	2020-06-22	2020-08-26	2020-08-31	49
AMZN	2018-02-14	2018-03-12	2018-03-23	25
AMZN	2018-07-12	2018-07-17	2018-07-30	12
AMZN	2018-08-02	2018-09-04	2018-09-17	31
AMZN	2020-08-18	2020-09-02	2020-09-04	13
BA	2017-07-26	2017-07-27	2017-08-10	11
BA	2017-09-14	2018-01-17	2018-03-22	127
BA	2018-04-12	2018-04-18	2018-04-24	8
BA	2018-05-07	2018-06-06	2018-06-19	30
BA	2020-03-11	2020-03-18	2020-03-25	10
CAT	2017-12-13	2018-01-12	2018-02-05	35
CVX	2022-03-02	2022-03-08	2022-03-15	9
GS	2016-11-30	2016-12-08	2016-12-29	20
GS	2021-01-06	2021-01-14	2021-01-20	9
HD	2018-01-05	2018-01-26	2018-02-02	19
INTC	2017-10-27	2017-11-02	2017-11-10	10
MCD	2017-05-03	2017-06-02	2017-06-12	27
MSFT	2020-01-28	2020-02-10	2020-02-24	18
MSFT	2020-06-17	2020-07-09	2020-08-11	38
MSFT	2020-08-12	2020-09-02	2020-09-08	18
MSFT	2021-02-02	2021-02-12	2021-02-22	13
MSFT	2021-04-08	2021-04-16	2021-04-29	15
MSFT	2021-06-22	2021-08-23	2021-09-28	68
MSFT	2021-10-05	2021-11-19	2022-01-07	66
TRV	2020-03-16	2020-03-18	2020-03-26	8

sentiment significantly influences stock price explosiveness. Both news and social media sentiment variables show strong, positive, and highly significant effects on the probability of an explosive regime, as seen from their large coefficients and high *z-values*. In contrast, when examining the reverse relationship—whether explosiveness feeds back into sentiment—the binary explosive variable is statistically insignificant in the sentiment equations. This suggests that while shifts in sentiment can trigger explosive price behaviour, there is no evidence of a feedback loop where price explosiveness, in turn, drives sentiment. Thus, the relationship appears unidirectional: sentiment impacts explosiveness, but explosiveness does not significantly influence sentiment. Finally, though our main model was based on the cloglog model because of the rarity of the explosive effects, we also used the traditional probit model⁴, with results not qualitatively different – news and social media sentiment precede explosive periods.

5. Conclusion

This study investigates price explosiveness in DJIA stocks, revealing that even mature and stable companies are not immune to sudden and significant deviations from fundamentals. Utilising the SADF and GSADF tests, we identified notable instances of price explosiveness among some stocks. Our analysis also highlights the substantial role of textual sentiment in driving price explosiveness. Social media sentiment significantly affects the likelihood of explosive price movements than news sentiment or macro-economic uncertainty indicators like Economic Policy Uncertainty. This finding demonstrates the important influence of firm-level sentiment over macro-level sentiment proxies in explaining price bubbles in mature companies. Traders and investors can incorporate the findings by monitoring social media sentiment as a key indicator of potential price explosiveness and adjusting their positions or risk management strategies accordingly. By integrating sentiment analysis into decision-making, they can identify opportunities for short-term gains or mitigate risks from sudden price movements. Regulators might consider implementing enhanced sentiment monitoring tools to better anticipate and manage potential market disruptions. For instance, regulators could deploy real-time text analytics platforms to continuously track social media and news sentiment using machine learning algorithms, with these signals validated through historical backtesting and ongoing calibration to ensure they reliably flag periods of abnormal sentiment indicative of bubbles. A limitation of this study is the use of proprietary firm-level sentiment scores. Future studies could expand on the findings from the study by using primary data collected from social media platforms to establish whether the results will change using publicly accessible data. Given the complexity of price explosiveness, future research could also benefit from moving beyond the conventional binary classification of explosive versus non-explosive events by exploring the duration and intensity of the explosiveness.

Notes

1. We get these proxies from <https://www.policyuncertainty.com/>.
2. A full list of the companies is shown in Table 4.
3. For brevity we do not show the results from the SADF test but are available upon request.
4. Results are not reported for brevity but are available upon request.

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 K.N – Conceptualization, Formal analysis, Methodology, Writing – original draft.
 All authors have read and approved the final version of the manuscript.

Author contributions

CRedit: **Yudhvir Seetharam**: Conceptualization, Methodology, Supervision, Writing – original draft, Writing – review & editing; **Kingstone Nyakurukwa**: Conceptualization, Formal analysis, Methodology, Writing – original draft.

Disclosure statement

No potential conflict of interest was reported by the author(s).

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Data availability statement

The data associated with the findings of the study is available upon reasonable request.

References

- Agosto, A., Cerchiello, P., & Pagnottoni, P. (2022). Sentiment, Google queries and explosivity in the cryptocurrency market. *Physica A: Statistical Mechanics and Its Applications*, 605, 128016. <https://doi.org/10.1016/j.physa.2022.128016>
- Ahmed, Z., Rasool, S., Saleem, Q., Khan, M. A., & Kanwal, S. (2022). Mediating role of risk perception between behavioral biases and investor's investment decisions. *Sage Open*, 12(2), 21582440221097394. <https://doi.org/10.1177/21582440221097394>
- Almansour, B. Y., Elkrgli, S., & Almansour, A. Y. (2023). Behavioral finance factors and investment decisions: A mediating role of risk perception. *Cogent Economics & Finance*, 11(2), 2239032. <https://doi.org/10.1080/23322039.2023.2239032>
- Aloosh, A., Ouzan, S., & Shahzad, S. J. H. (2022). Bubbles across meme stocks and cryptocurrencies. *Finance Research Letters*, 49, 103155. <https://doi.org/10.1016/j.frl.2022.103155>
- Baker, M., & Wurgler, J. (2007). Investor sentiment in the stock market. *Journal of Economic Perspectives*, 21(2), 129–151. <https://doi.org/10.1257/jep.21.2.129>
- Baker, S. R., Bloom, N., & Davis, S. J. (2016). Measuring economic policy uncertainty. *The Quarterly Journal of Economics*, 131(4), 1593–1636. <https://doi.org/10.1093/qje/qjw024>
- Barber, B. M., & Odean, T. (2008). All that glitters: The effect of attention and news on the buying behavior of individual and institutional investors. *Review of Financial Studies*, 21(2), 785–818. <https://doi.org/10.1093/rfs/hhm079>
- Bergbrant, M. C., & Bradley, D. (2022). *Did they just say that? Using AI to extract economic policy uncertainty from cable news networks* (SSRN Scholarly Paper No. 4059681). <https://doi.org/10.2139/ssrn.4059681>
- Fama, E. F. (1965). The behavior of stock-market prices. *The Journal of Business*, 38(1), 34–105. <https://doi.org/10.1086/294743>
- Gianstefani, I., Longo, L., & Riccaboni, M. (2022). The echo chamber effect resounds on financial markets: A social media alert system for meme stocks. *Papers*, Article 2203(13790), 1–41. <https://ideas.repec.org/p/arx/papers/2203.13790.html>
- Gronwald, M. (2021). How explosive are cryptocurrency prices? *Finance Research Letters*, 38, 101603. <https://doi.org/10.1016/j.frl.2020.101603>
- Hong, J., Crichton, W., Zhang, H., Fu, D. Y., Ritchie, J., Barenholtz, J., Hannel, B., Yao, X., Murray, M., Moriba, G., Agrawala, M., & Fatahalian, K. (2021). Analysis of faces in a decade of US cable TV news. *Proceedings of the 27th*

- ACM SIGKDD Conference on Knowledge Discovery & Data Mining (pp. 3011–3021). <https://doi.org/10.1145/3447548.3467134>
- Lee, K., & Jeong, D. (2023). Too much is too bad: The effect of media coverage on the price volatility of cryptocurrencies. *Journal of International Money and Finance*, 133, 102823. <https://doi.org/10.1016/j.jimonfin.2023.102823>
- Li, Y., Li, J., Li, X., & Lu, Q. (2024). Does participation in digital supply and marketing promote smallholder farmers' adoption of green agricultural production technologies? *Land*, 14(1), 54. <https://doi.org/10.3390/land14010054>
- Malkiel, B. G., & Fama, E. F. (1970). Efficient capital markets: A Review of theory and empirical work. *The Journal of Finance*, 25(2), 383–417. <https://doi.org/10.1111/j.1540-6261.1970.tb00518.x>
- Nguyen, D., Nguyen, H., & Nguyen, K. S. (2018). Ownership feature and firm performance via corporate innovation performance: Does it really matter for Vietnamese SMEs? *Journal of Asian Business and Economic Studies*, 25(2), 239–250. <https://doi.org/10.1108/JABES-10-2018-0078>
- Nyakurukwa, K., & Seetharam, Y. (2022). Can a 280-character message explain stock returns? Evidence from South Africa. *Managerial Finance*, 48(4), 663–686. <https://doi.org/10.1108/MF-12-2021-0598>
- Nyakurukwa, K., & Seetharam, Y. (2025). Investor sentiment networks: Mapping connectedness in DJIA stocks. *Financial Innovation*, 11(1), 4. <https://doi.org/10.1186/s40854-024-00675-7>
- Nyakurukwa, K., Seetharam, Y., & Chipeta, C. (2025). The role of acquaintances' characteristics in shaping digital payment technology. *Finance Research Letters*, 76, 106976. <https://doi.org/10.1016/j.frl.2025.106976>
- Phillips, P. C. B., & Shi, S. (2019). Detecting financial collapse and ballooning sovereign risk. *Oxford Bulletin of Economics and Statistics*, 81(6), 1336–1361. <https://doi.org/10.1111/obes.12307>
- Phillips, P. C. B., Shi, S., & Yu, J. (2015). Testing for multiple bubbles: Historical episodes of exuberance and collapse in the S&P 500. *International Economic Review*, 56(4), 1043–1078. <https://doi.org/10.1111/iere.12132>
- Shahzad, S. J. H., Anas, M., & Bouri, E. (2022). Price explosiveness in cryptocurrencies and Elon Musk's tweets. *Finance Research Letters*, 47, 102695. <https://doi.org/10.1016/j.frl.2022.102695>
- Shleifer, A., & Summers, L. H. (1990). The noise trader approach to finance. *Journal of Economic Perspectives*, 4(2), 19–33. <https://doi.org/10.1257/jep.4.2.19>
- Vasilopoulos, K., Pavlidis, E., & Martínez-García, E. (2022). exuber: Recursive right-tailed unit root testing with R. *Journal of Statistical Software*, 103(10), 1–26. <https://doi.org/10.18637/jss.v103.i10>
- Zaman, S., Yaqub, U., & Saleem, T. (2023). Analysis of Bitcoin's price spike in the context of Elon Musk's Twitter activity. *Global Knowledge, Memory and Communication*, 72(4/5), 341–355. <https://doi.org/10.1108/GKMC-09-2021-0154>