Economics and Business Letters
14(4), 177-192, 2025

The speculative tech bubbles of US artificial intelligence sector

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Received: 22 February 2025
Revised: 03 April 2025
Accepted: 14 May 2025

Abstract
In this study we identify synchronized multiple bubble episodes in leading US artificial intelligence companies during the pandemic market exuberance from 2020 to 2022, and then after the excessive optimism prevailed post 2023. Interestingly, the bubbles are found to be driven by liquidity, financial market stress and economic uncertainty. The investors' sentiment is also found to influence the bubble formation. The results of this letter highlight the importance of fundamentally assessing the longer-term prospects of artificial intelligence companies.

Keywords: speculative bubbles, AI stocks, GSADF test, investor sentiment
JEL Classification Codes: G12, G14, G32, C58

1. Introduction

Over the past few years, the rapid growth of artificial intelligence company valuations has raised concerns about the presence of speculative bubbles in the artificial intelligence markets (AI hereinafter). Major technology firms such as NVIDIA, Microsoft, Alphabet, and Amazon have witnessed an unprecedented stock price appreciation that is driven by advancements in machine learning, cloud computing, and generative AI models. For instance, between 2016 and 2023, NVIDIA's stock price has gone up by 1,000% thus, dwarfing the 45% growth in the S&P500 broader index. The aggregate market of the AI-focused constituents of the S&P 500 has also increased by more than 200% during the same period.

Some analysts have argued that these valuations are genuine and reflect reasonably the longer-term prospects of AI companies. However, others have cautioned that the AI sector

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Citation: Maghyereh, A.I. and B. Awartani (2025) The speculative tech bubbles of US artificial intelligence sector, *Economics and Business Letters*, 14(4), 177-192. DOI: 10.17811/ebl.14.4.2025.177-192.

ISSN: 2254-4380

exhibits characteristics of speculative bubbles, reminiscent of the .com bubble of the late 1990s (Bonaparte, 2024).

Tech bubbles are characterized by unsustainable growth in the market valuation of tech assets. The enthusiasm for the emerging technologies triggers speculative investments and exuberance that drive values away from that justified by actual development, implementation and profitability. This enormous growth is usually accompanied by a surge in IPOs, weak regulations, media hype and high public interest in the sector.

The infamous .com bubble in the late 1990s is one example. It is triggered by internet development and the start of its use in commercial activities. Excited by the new technology, the speculation on all shares that are .com suffix has intensified. The values have enormously increased. The NASDAQ composite index has gone up from 1000 in 1995 to over 5000 in March 2000. Further, IPOs skyrocketed. Even the .com companies with a no-profit history have seen their prices soaring. The bubble starts to deflate in March 2000; by October 2002, the NASDAQ index has lost 78% of its value. The lax regulatory oversight and the lack of investor sophistication have contributed to the formation of the bubble.

Like the .com innovation, AI technology is disruptive and revolutionary. It promises a solution to every problem and hence, investments in AI stocks and AI startups are huge. The bulk of AI valuations are based on the expected future growth as opposed to its current earnings. For instance, Open AI expects to lose $5 billion this year. However, a circulation for funding by the company has valued its own shares at $150 billion. Moreover, regulations are struggling to keep up with the growth of the AI market with many legal and ethical issues involved. The sector has also attracted significant media hype and public interest, much like during the .com era.

The speculative bubbles in AI equities may have adverse repercussions on markets and the economy. According to Roubini (2006), prolonged economic downturns and credit market disruptions can be triggered by the financial instability created by bubbles. Hence, the need arises to assess whether the AI stocks exhibit similar speculative behavior as in other tech bubbles and the .com case.

Despite the potential negative consequences of bubbles in the AI sector, AI is still crucial to the economy. It enhances growth and productivity by revolutionizing industries, optimizing supply chains, and enabling new business models. The automations opportunities created by AI technology has also significant cost savings. Further, AI is related to machine learning and data analytics, which improve decision-making. Moreover, AI creates new markets that range from autonomous vehicles to personalized healthcare. (Kabakova and Plaksenkov, 2018; Guo and Jiang, 2024).

The AI value hinges on scalable infrastructure such as cloud computing and graphics processing units, rather than on consumers facing platforms as in the .com companies. Furthermore, the AI market operates in the context of heightened institutional participation, algorithmic trading, and geopolitical fragmentation between the U.S. and China. All these factors suggest that AI may have a relatively more robust foundation than the .com technology.

Still, the rapid adoption of AI technology, investor enthusiasm, and the fear of missing out (FOMO) can all drive irrational behavior and inflated share prices (Floridi, 2024). This tension between the genuine economic potential of AI and its share speculative behavior underscores the importance of understanding the dynamics of AI markets.

The existing literature examines asset price bubbles in broad technology markets without focusing on the AI sector as we do in this letter. Our aim here is to empirically investigate bubble dynamics in AI stocks and then identify the key drivers contributing to the bubble formation from January 2014 to January 2025.

To sum up, this letter contributes to the literature on potential bubbles in the recent AI boom era. Specifically, we examine whether the surge in AI stocks is a sustainable evolution driven by technological advances, or simply a bubble. In the case of a bubble, the letter date-stamps the start of the bubble and when it is deflated. By bridging the gap in applied research, this letter not only advances the understanding of tech bubbles, but it also provides valuable insights for investors in managing the risks of their AI holdings.

2. Methodology and data

2.1. Methodology

This study implements the GSADF test to detect and stamp the dates of speculative bubbles in AI stocks.[1] The method recursively tests for explosive price behavior, allowing for a precise identification of bubble formations and collapses.

Bubbles are formed when asset prices diverge from fundamental values due to expectations of further price increases (Pindyck, 1993).

Suppose that the intrinsic price is written as the discounted future payoffs:

$$P_t = E_t\left[\sum_{j=1}^{\infty} \frac{D_{t+j}}{(1+r)^j}\right] \tag{1}$$

where P_t represents the asset's price at time t, D_{t+j} denotes future dividends, and r is the discount rate.

Market expectations may drive prices beyond (1) hence, a speculative bubble is formed as:

$$P_t = P_t^f + B_t \tag{2}$$

where P_t^f and B_t are the intrinsic price and the bubble component respectively. If B_t grows persistently, it signals the presence of a speculative bubble.

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[1] The GSADF stands for the Generalized Supremum Augmented Dickey-Fuller test of Phillips et al. (2015). An alternative test is the Log-Periodic Power Law Singularity (LPPLS). However, this test is less robust and relies on strict parameter assumptions and thus, it is sensitive to tuning. The GSADF uses recursive unit root tests to detect multiple bubbles without false signals as the LPPLS test (Zhou and Sornette, 2006). Finally, GSADF is less prone to overfitting, and it is widely adopted by regulators (Shi et al., 2020).

To detect, the GSADF uses price–dividend ratios, the PSY tests for explosive dynamics using recursive right-tailed Augmented Dickey-Fuller (ADF) regressions as:[2]

$$\Delta y_t = \alpha_{r_1,r_2} + \beta_{r_1,r_2} y + \sum_{i=1}^{k} \vartheta_i \Delta y_t + \epsilon_{t,} \quad \epsilon_t \sim N\left(0, \sigma^2_{r_1,r_2}\right) \tag{3}$$

where y_t represents the price–dividend ratio being tested for explosive behavior. For explosive behavior in (3), β_{r_1,r_2} should be significantly greater than 1.

The terms r_1 and r_2 define the start and the end of each subsample within a rolling window of size $r_w = r_2 - r_1$. The supremum ADF (i.e. SADF) test maximizes the ADF statistics over subsamples, while the GSADF test enhances detection by allowing for flexible window sizes:

$$GSADF_{r_0} = \underbrace{sup}_{\substack{r_2 \in [r_0,1] \\ r_1 \in [0, r_2 - r_0]}} \left\{ADF_{r_1}^{r_2}\right\} \tag{4}$$

The critical values are non-standard and derived by either simulations or bootstraps. The bubble periods are then identified when the GSADF test statistic exceeds the critical values. To pinpoint bubble episodes, the Backward Supremum ADF (BSADF) test identifies origination and termination dates as:

$$BSADF_{r_2} = \underbrace{sup}_{r_1 \in [0, r_2 - r_0], r_2 = [r_0, 1]} \left\{ADF_{r_1}^{r_2}\right\} \tag{5}$$

Hence, a bubble starts when the BSADF exceeds its critical value, and it ends when it dips below it. This enables precise stamping of AI stock bubbles dates.

To investigate the determinants of bubble formation, we estimate a panel logit regression as:

$$Pr(y_t = 1 | X_t, \beta, \alpha) = \phi(\alpha + \beta X_t) = \frac{e^{\alpha + \beta X_t}}{1 + e^{\alpha + \beta X_t}} \tag{6}$$

where y_t is the binary limited dependent variable that takes 1 if there is a bubble, and 0 otherwise. X_t is a vector of explanatory variables that are hypothesized to determine bubbles. β is a vector of coefficients to be estimated. Φ is the cumulative distribution function (CDF) of the standard normal distribution. The parameters of the logit model are estimated using maximum likelihood estimator (MLE).

2.2. Data

From the pool of AI stocks in the US, we select all companies that satisfy the following criteria: (1) large market cap, AI-focused, and listed; (2) has industry leadership in terms of spending

[2] For more details see Maghyereh and Abdoh (2022, 2023).

on AI research, development, and implementation; and (3) has significant sectoral influence on the broader technology landscape.

12 companies have satisfied the criteria: Microsoft (MSFT), Apple (AAPL), Tesla (TSLA), NVIDIA (NVDA), Alphabet (GOOG), Amazon (AMZN), Meta (META), Broadcom (AVGO), Netflix (NFLX), Salesforce (CRM), ServiceNow (NOW), and Cisco (CSCO). The data for these companies is only available from January 1, 2014, to January 31, 2025, for 2,870 observations. As customary in the literature, we analyze the natural logarithms of the dividend price ratios. All data are obtained from Refinitiv DataStream.

To ensure that AI bubbles are sector related and do not overlap with market wide trends, we time stamp the bubbles of the S&P500 index using GSADF procedure. The coincidence of the time stamps with those of AI companies implies pronounced market influence as opposed to sectoral bubble episodes.

Multiple factors contribute to bubbles. The fundamental factors include optimistic expectations of earnings growth which tend to push stock prices beyond sustainable levels. Liquidity can also fuel bubbles by reducing effective spreads and encouraging speculative behavior (Nneji, 2015). Lower funding rates increase the appeal of stocks relative to bonds and fuel speculation. The capital markets conditions also play a role. The excess money supply finds its way to the asset markets and inflates prices beyond intrinsic values (Gupta and Subrahmanyam, 2000).

Bubbles are also frequently associated with increases in trading volumes. The investors' enthusiasm and speculative behavior boost trading activity. The collective belief of continued price appreciation creates a sense of urgency to establish positions, and it attracts more participants to the market. (See, Harrison and Kreps, 1978; Scheinkman and Xiong, 2003; Palfrey and Wang, 2012). The other broader macroeconomic conditions, such as GDP growth, further contribute to excessive stock valuations (Asako and Liu, 2013).

In this letter, the empirical analysis of the fundamental factors above is based on proxies. For instance, we use the log leading EPS for expected growth, the bid-ask spread for liquidity, the TED spread for financial stress, and finally the Aruoba-Diebold-Scotti (ADS) and the economic policy uncertainty (EPU) index for the broader macroeconomic conditions.

Besides the fundamental factors, behavioral biases may also trigger speculative bubbles (Shiller, 2015). Feelings such as overconfidence and the fear of missing out (FOMO) can drive irrational buying behavior. Other biases such as recency and confirmation biases may induce investors to disregard warning signals of overbought markets, thus leading to bubbles (Barberis, Shleifer, & Vishny, 1998).

In this letter, we capture these sentiments using bullish and bearish indices obtained from the AAII Investor Sentiment Survey. Further, we use the CBOE Volatility Index (the VIX) as a measure of investors' fear and uncertainty, particularly in the technology sector.

The fundamental and non-fundamental proxies are all sourced from Refinitiv DataStream. In Table A1 of the appendix, we provide detailed definitions for all variables.

3. Empirical findings

3.1. Speculative bubbles

To investigate the presence of speculative bubbles, we apply the GSADF test to the daily dividend–price ratio of the 12 AI stocks. In line with the guidelines of Phillips et al. (2015), we opt for a short lag length ($k = 1$)[3] and establish the minimum window size in the recursive procedure based on a rule-of-thumb method: $0.01 + 1.8/\sqrt{T}$.

To detect the presence of speculative bubbles, we compare the GSADF statistics with the right-tail critical values, which are computed via wild-bootstrap developed by Phillips and Shi (2020).

Table 1 presents the results of the GSADF test statistics. The table reveals strong evidence of speculative bubbles in most AI stocks at the 5% significance level. The GSADF statistics for Tesla (TSLA) and NVIDIA (NVDA), Apple (AAPL) and Alphabet (GOOG) reject the null of no bubbles at the 1% significance level.

Table 1. Bubble detection

Company	Ticker	GSADF - statistic	Diagnostics
Microsoft	MSFT	2.49*	Rejects H0 at the 10% significance level
Apple	AAPL	4.21***	Rejects H0 at the 1% significance level
Tesla	TSLA	7.96***	Rejects H0 at the 1% significance level
NVIDIA	NVDA	9.06***	Rejects H0 at the 1% significance level
Alphabet	GOOG	3.21**	Rejects H0 at the 1% significance level
Amazon	AMZN	3.15**	Rejects H0 at the 5% significance level
Meta	META	2.66**	Rejects H0 at the 5% significance level
Broadcom	AVGO	2.52*	Rejects H0 at the 10% significance level
Netflix	NFLX	3.08**	Rejects H0 at the 5% significance level
Salesforce	CRM	2.05	Cannot reject H0
ServiceNow	NOW	2.73**	Rejects H0 at the 5% significance level
Cisco	CSCO	2.36*	Rejects H0 at the 10% significance level
U.S. stock market	S&PCOMP	3.40***	Rejects H0 at the 1% significance level

Source: own elaboration

Notes: This table presents the GSADF test statistics for the 12 AI stocks and the U.S. stock market. The GSADF test of Phillips et al. (2015) evaluates the null hypothesis of a unit root against the alternative hypothesis of at least one speculative bubble. The minimum window size for the GSADF tests is set to 95 days. Critical values are obtained through 1,000 bootstrap replications outlined by Phillips and Shi (2020). All results assume an autoregressive lag length of 4 selected by the Bayesian information criterion (BIC). For the GSADF test, the critical values are 2.34, 2.58, and 3.17 at the 10%, 5%, and 1% significance levels, respectively. The dataset comprises 2,870 daily observations of the log dividend–price ratio, covering the period from January 1, 2014, to January 31, 2025. Statistical significance at the 10%, 5%, and 1% levels is indicated by *, **, and ***, respectively.

This strong evidence of speculative bubbles can be explained by high investor enthusiasm, technological advancements, and growth expectations. Tesla's dominance in EVs, NVIDIA's AI-driven demand, Apple's innovation, and Alphabet's AI and cloud expansion have fueled

[3] As part of a robustness analysis, lag lengths of 2 and 3 are also tested, and the results are found to be relatively insensitive to lag choices.

speculative surges. These stocks attract heightened market optimism, thus leading to price increases that may have exceeded fundamental values.

The evidence of bubbles in Amazon (AMZN), Meta (META), Netflix (NFLX), and ServiceNow (NOW) is moderate, and it is only significant at the 5% level. A weaker but still notable bubbles are found in Microsoft (MSFT), Broadcom (AVGO), and Cisco (CSCO). The null of no bubbles in these companies' shares is rejected at the 10% significance level.

The stock of Salesforce (CRM) company is the only share that is found without evidence of speculative bubbles. The revenue growth stability and the solid business fundamentals of Salesforce have made its stock less prone to speculation and irrational behavior. The value of the company is closely tied to its enterprise software services and steady expansion in cloud computing. Therefore, the company may not have generated the same level of speculative activity as other companies in the sample.

Figure 1 illustrates the timeline of bubbles in companies that experienced significant bubbles at the 5% significance level or less throughout the sample period. The shaded areas in the figure correspond to each ticker symbol and it highlights the periods during which price bubbles are identified. As can be seen in the figure, there are multiple bubble episodes during the pandemic period that extend from 2020 to 2022 and then after the year 2023.[4]

The figure also shows that GOOG, NOW and TSLA display more frequent bubbles in the pandemic period than those displayed by NVDA and META. The bubble episodes of META and NVDA are more pronounced post 2023 with ongoing bubble episodes in 2024. This can be linked to the optimism following the AI boom, and to the surge in demand for high-performance GPU.[5]

The sustained bubble patterns in the prices of both META and NVDA suggests excessive valuations. Such behavior is consistent with the previous speculative episodes where rapid technological advancements has led to excessive optimism and pricing, as seen in the .com and more recently, in the pandemic-era tech stock bubbles.[6]

The common and synchronized bubble formations among AI stocks indicate the influence of sector-wide trends and probably macroeconomic factors. As mentioned previously, the AI stocks have experienced simultaneous bubble episodes during the pandemic. These have been driven by investor exuberance, low interest rates, increased liquidity, and rapid technological improvements and adoptions.

Similar findings on the NASDAQ and its explosive behavior during the pandemic are recorded by Demmler and Fernández (2024). The ongoing bubbles of NVDA and META stocks post-2024 shows renewed speculative phase that is driven by AI advancements thus, reflecting interconnectedness between investor sentiment across the AI industry.

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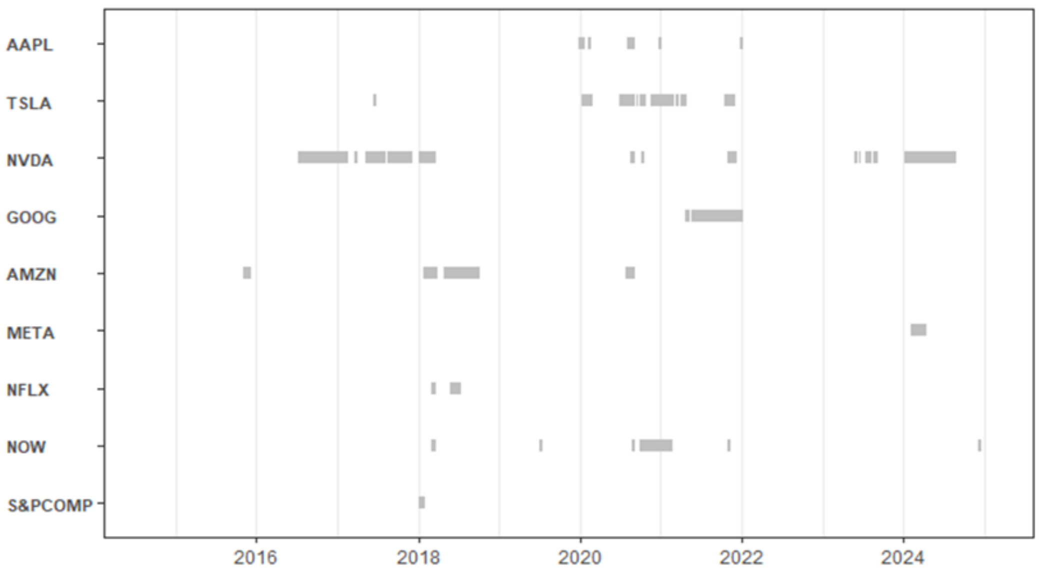
[4] AAPL and NVDA exhibit fewer and shorter bubble episodes than the rest of companies during the pandemic period. AAPL stock have more stable pricing dynamics and hence, it is less prone to extreme speculative cycles. NVDA displays strong speculative behavior with long episodes after 2023.

[5] GPUs are critical for artificial intelligence, machine learning, and data centers.

[6] Figure 2 provides another display for the bubble episodes. It graphs the time series sequence of the BSADF statistics and its 95% critical value. The shaded areas time stamp the start and the end of speculative bubbles. Another representation is Table A2 in the appendix, it time stamps and provide extra information on the bubbles: its start, its peak, its end and the duration of the bubble in days.

In Figures 1 and 2, along with Table A2, we compare the timing of bubbles in AI stocks with the timing of market-wide bubbles as detected in the S&PCOMP.[7] The figures show that the AI stocks exhibit bubbles at times which are significantly different from the times of bubbles in the wider market. This suggests that speculative behavior in the AI sector is independent of the market wide. Only TSLA and AAPL have displayed occasionally some common bubbles with the market. Hence, for these stocks we do not exclude some systematic market influences. However, while the broader market trends contribute to bubble formation, the idiosyncratic factors appear to be the primary drivers of AI bubble episodes.[8]

Figure 1. Timeline of bubble occurrences

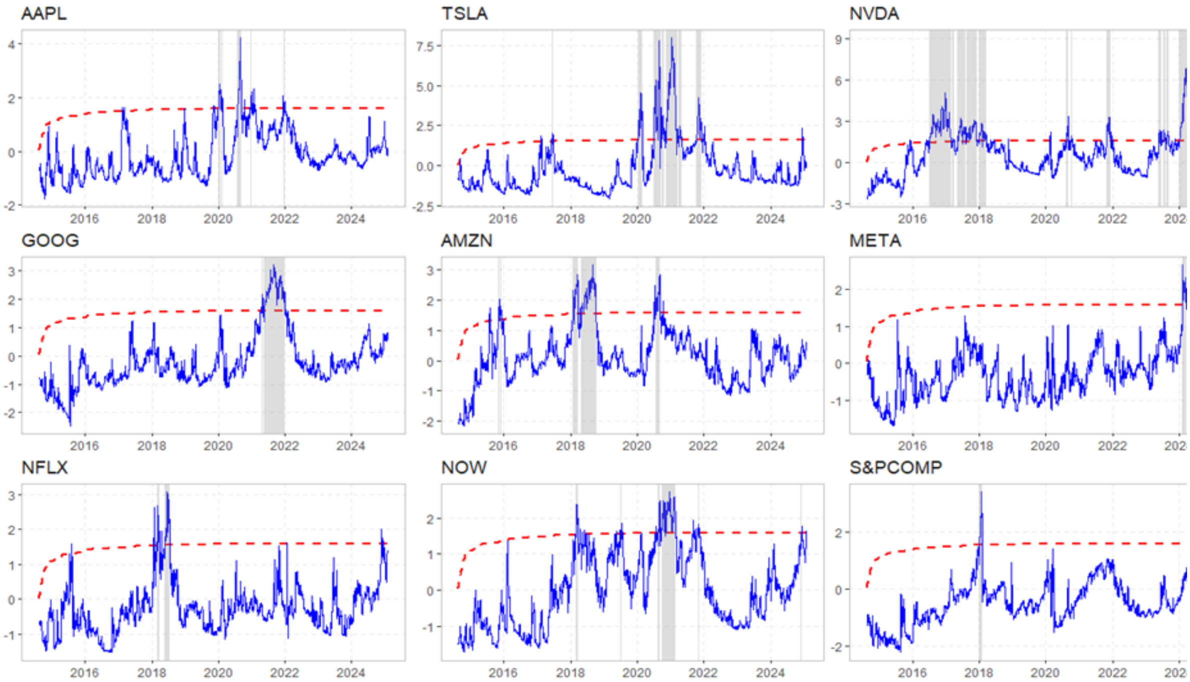


Source: own elaboration
Notes: The shaded areas in the figure highlight the periods during which price bubbles were identified using the GSADF test.

[7] The test detects only one market-wide bubble episode that spans the period from 5/1/2018 to 2/2/2018 for 20 days. It coincides with the US Tax Cuts and Jobs Act. effective in early 2018. The act has come with a revised earning expectations and it triggered stock buybacks thus, driving bullish sentiments. The accompanying strong economic indicators, including low unemployment, GDP growth, and rising consumer confidence, further fueled market optimism.

[8] Furthermore, we analyze rolling correlations between each stock's returns and the market index and find no correlation spikes during bubble periods. This suggests that there is no significant link to market movements during these times. Additionally, we conduct a logistic regression where the dependent variable is the probability of a stock being in a bubble, as identified by GSADF results, and the independent variables include market return and market implied volatility (VIX). The results show an insignificant relationship between these variables and the probability of a bubble, further supporting the conclusion that market-driven factors are not influencing bubble episodes. For conciseness, these additional findings are not reported.

Figure 2. Time-stamping of bubble periods



Source: own elaboration
Notes: This figure illustrates the date-stamping of bubble periods as estimated using the GSADF test. The blue line represents BSADF test statistics, while the red dotted line shows the critical values over the sample period. The shaded gray areas mark the identified bubble episodes, occurring when the BSADF test statistics exceed the critical values. These critical values are derived through 1,000 bootstrap replications.

3.2. Determinants of bubbles

Table 2, columns 1-9 display the parameter estimates of the logistic regression in equation 6 for each company. Column 10 presents the estimates of the fixed effect of the panel that contains eight companies. The table shows that bubble formation in AI stocks is influenced by fundamental and non-fundamental factors.

For example, the leading EPS and the probability of bubble formation are positively related. Higher earnings expectations increase optimism and drive prices beyond intrinsic values. Similar results are found in La Porta et al. (1997) and Brunnermeier and Nagel (2004) where it has been shown that speculative behavior in financial markets tends to overprice growth potential, thus leading to bubbles that deflate when the expected growth is not realized.[9]

The trading volume has a positive and significant effect. During bubbles, the investors' enthusiasm and speculative behavior increase trading activity. The fear of missing out (FOMO) also attracts more investors as prices rise. This creates a self-reinforcing cycle: the rising prices attract more participants, further increasing trading volumes and fueling speculation

[9] In Scheinkman and Xiong (2003) divergent beliefs about expected future earnings fuels speculative trading and increases the likelihood of bubble formation.

(Scheinkman and Xiong, 2003). The surge in trading reflects a collective belief in continued price appreciation, even in the absence of fundamental support.[10]

The bid-ask spread is negatively associated with the probability of speculative bubbles. A narrower spread implies higher liquidity and lower transaction costs. This encourages trading and speculative behavior as entering and exiting positions is not costly. Later and towards the end of the bubble episode, liquidity disappears triggering collapses in the stock price (e.g. Caginalp et al., 2001; Nneji, 2015).

The TED spread proxy credit stress. It has negative association with the likelihood of bubbles. In previous tech bubble episodes, credit conditions were relaxed and investors used to buy on low margins with high leverage. However, the tighter credit environment can deter speculative leverage, thereby reducing the likelihood of bubbles. This conforms with the Minsky (1992) hypothesis that during financial stress, credit tightening reduces speculative behavior.

The ADS Index that reflects economic conditions is positively correlated with bubbles. The robust economic performance fuels overoptimism and leads to excessive capital inflows and to bubble formation. The economic policy uncertainty (EPU) is also positively related to the chances of bubbles. The uncertainty increases market volatility as investors become more risk-averse, potentially causing asset prices to deviate from their intrinsic values. This result aligns well with the findings of Cheng et al. (2021), who suggest that the high exposure to EPU is associated with bubble formation.

The non-fundamental factors are also significant. The VIX index is negatively associated with bubbles as elevated fears suppress speculative behavior (Shiller, 2015). Similarly, the bearish sentiment triggers pessimism among investors which dampens the development of bubbles. The Brown and Cliff (2004) study is similar, and it points out that bearish investor sentiment is associated with lower asset prices and less speculative activity.

On the other hand, bullish sentiments exhibit positive relationship with bubble formation. This is consistent with Scheinkman and Xiong (2003), who find that emotions of overconfidence and optimism that are associated with the bullish sentiment tend to drive asset prices beyond its fundamental values.

The relationship between sentiment and bubble formation may be attributed to herding. For instance, the optimism and overconfidence that accompany the bullish sentiment may cause investors to ignore their own information and to follow the crowd. This reinforces speculative demand and inflates asset prices beyond their intrinsic values. The study by Ju et al. (2020) document herding in Chinese equities during periods of high bullish sentiment. They also illustrate how herding behavior contributes to market inefficiencies and to the deviation of valuations from the fundamentals.

[10] The prior literature in support of this finding indicate that speculative trading occurs alongside temporary overpricing (e.g., Pan et al., 2026; Zhang et al., 2024).

Table 2. Determinants of bubbles

	APPLE	TESLA	NVDA	GOOGLE	AMZN	META	NFLEX	Now	Panel
	(1)	(2)	(3	(4)	(5)	(6)	(7)	(8)	(9)
EPS	0.2631**	0.3979***	1.0983***	0.0806**	0.1648***	0.9215***	0.0465**	0.0841***	0.9023***
	(0.0210)	(0.0000)	(0.0000)	(0.0370)	(0.0000)	(0.0000)	(0.0492)	(0.0050)	(0.0000)
Spread	-1.2636*	-0.9322***	-0.3695***	-0.2102***	-2.5055***	-0.0623	-1.0816	-0.0627***	-1.2313***
	(0.5100)	(0.0090)	(0.0000)	(0.0000)	(0.0000)	(0.4200)	(0.2910)	(0.0022)	(0.0000)
VOL	1.0267**	0.6272***	1.0569**	0.2829***	0.2921**	0.1970**	0.4325***	0.2627**	0.5254**
	(0.0360)	(0.0000)	(0.0348)	(0.0000)	(0.0220)	(0.0300)	(0.0770)	(0.0430)	(0.0456)
TED	-0.0570***	-0.0460***	-0.0326***	-0.0218***	-0.0347***	-0.0510**	-0.0725***	-0.0251***	-0.0010***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0180)	(0.0000)	(0.0000)	(0.0017)
ADS	0.0865	0.0987**	0.0891***	0.1086***	0.1697***	0.6029***	0.1605	0.8918***	0.2071***
	(0.3050)	(0.0110)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.2910)	(0.0018)	(0.0000)
EPU	0.0047*	0.0014**	0.1025***	0.0107***	0.0023***	0.0009	0.0008***	0.0037***	0.0006***
	(0.0540)	(0.0350)	(0.0000)	(0.0000)	(0.0020)	(0.1830)	(0.0049)	(0.0078)	(0.0000)
VIX	-0.0054	-0.0127	-0.0135	-0.0247*	-0.0164*	-0.0188**	-0.0114	-0.0143	-0.0006***
	(0.8040)	(0.1440)	(0.1170)	(0.0830)	(0.0940)	(0.0200)	(0.8940)	(0.0087)	(0.0000)
Bearish	-0.0544***	-0.0631**	-0.0754***	-0.0757***	-0.0796	-0.1511***	-0.0741***	-0.0682***	-0.0146***
	(0.0000)	(0.0140)	(0.0000)	(0.0000)	(0.1940)	(0.0041)	(0.0000)	(0.0000)	(0.0002)
Bullish	0.0233***	0.0758***	0.0308***	0.0424***	0.0468	0.2773	0.0091	0.0505***	0.0234***
	(0.0010)	(0.0010)	(0.0000)	(0.0000)	(0.4908)	(0.1876)	(0.3960)	(0.0008)	(0.0000)
Constant	-1.2175	-2.9665	-1.0830	-1.6602	-2.7658*	-0.9933	-0.8543*	-1.8132**	0.4258***
	(0.8600)	(0.2160)	(0.2004)	(0.1830)	(0.0830)	(0.4060)	(0.0924)	(0.0560)	(0.0000)
Adj. R^2	0.2247	0.3826	0. 2039	0. 3103	0.1933	0.5728	0.2718	0.2436	0.2992
Observations	2,870	2,870	2,870	2,870	2,870	2,870	2,870	2,870	22,960

Note: The table reports the regression results for Equation (7), with columns (1) through (8) presenting company-specific probit model results, while column (9) provides the panel probit model results adopting firm fixed effects. The dependent variable is binary, indicating the presence of a bubble (y_t=1) or its absence (y_t=0). The model includes the explanatory variables (X_t): Forward earnings per share (EPS); Bid-ask spread (Spread); Trading volume (VOL); TED spread for interest rates (TED); ADS Business Condition Index (ADS); Economic Policy Uncertainty Index (EPU); CBOE Volatility Index (VIX); Bearish Index (Bearish); Bullish Index (Bullish). ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

The results that we obtain here underscore the critical role of investor sentiment and thus herding in driving speculative bubbles in the AI sector. It helps investors and policymakers to better assess and mitigate the risks associated with speculative bubbles in the AI-driven markets. For instance, investors should adopt a more disciplined valuation framework to avoid being swept by a herd-driven market euphoria. On the other hand, policymakers should implement measures to enhance market transparency and to reduce information asymmetry.

4. Conclusion

This letter tests whether the recent surge in AI markets is another Tech bubble, or it is more likely to be driven by the future prospect of technological innovations. For that purpose, we investigate 12 leading AI stocks in the US from 2014-2025.

The results that we obtain support bubbles during the pandemic from 2020 to 2022 and then during the euphoria surrounding the AI advancement post 2023. Of the twelve stocks, bubbles are more pronounced in the equities of NVIDIA and Tesla, and least pronounced in Salesforce, which remains relatively stable, probably due to its more grounded business fundamentals.

The bubble formation is found to depend on fundamental and non-fundamental factors. Bubbles in AI stocks are more likely when earnings, liquidity and economic growth expectations are high. The non-fundamental factors, including investor sentiment, fear, and uncertainty play a significant role in amplifying and/or curbing speculative behavior. For instance, bullish sentiment and low fear are positively associated with bubbles, whereas bearish sentiment and financial stress tend to reduce the chances of speculative bubbles. The evidence aligns with existing literature on speculative bubbles and investor psychology, thus, emphasizing the importance of behavioral biases in driving market excesses.

The findings in this study have several important implications. First, bubbles in the AI stocks highlight the need for more disclosures on AI companies, their activities, finances, investments and revenue streams. Measures that enhance transparency and reduce information asymmetry in the AI sector are warranted to prevent excessive risk-taking and potential market crashes.

Second, while speculative bubbles pose risks, they also reflect high expectations that may be realized for some companies. The bubbles do not negate the transformative potential of AI; rather, it underscores the importance of distinguishing between genuine innovation and speculative excesses. Investors should focus on companies with strong fundamentals and sustainable business models, rather than chasing short-term gains driven by market hype.

Finally, the study highlights the interconnectedness of AI stocks and the broader technology sector. The synchronized bubble episodes observed in this study suggest that investor sentiment in the AI industry is highly influenced by the sector-wide trends. As such, policymakers and regulators should adopt a holistic approach to managing risks in AI-driven markets, considering the sector-specific dynamics.

Acknowledgements. The authors would like to thank the editors and the anonymous reviewers for their valuable comments and constructive suggestions, which have greatly improved the quality of this paper.

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Appendix

Table A1. Definitions the bubble determinant variables

Variable	Symbol	Definition	Source
Forward earnings per share	EPS	The estimate of anticipated earnings per share for the upcoming fiscal year. It is calculated by dividing the company's projected net income by the number of outstanding shares. Forward EPS is commonly used by investors to assess the company's future profitability. A higher Forward EPS generally indicates growth expectations, which can positively influence the company's stock price.	Thomson Reuters DataStream
Bid-ask spread	Spread	The difference between the highest price a buyer is willing to pay for a stock (the bid price) and the lowest price a seller is willing to accept (the ask price). This spread serves as an indicator of market liquidity; narrower spreads typically suggest higher liquidity, facilitating easier transactions for investors. Conversely, wider spreads may indicate lower liquidity, potentially deterring speculative trading due to higher transaction costs.	Thomson Reuters DataStream
Trading volume	VOL	The total number of shares transacted daily.	Thomson Reuters DataStream
TED spread for interest rat es	TED	the difference between the interest rates on short-term U.S. government debt (specifically, three-month Treasury bills) and interbank loans (typically measured by the three-month London Interbank Offered Rate, or LIBOR). The TED spread has been a reliable gauge of financial market stress.	Thomson Reuters DataStream
ADS Business Condition In dex	ADS	Developed by economists Aruoba, Diebold, and Scotti, it composes various economic variables that reflect different aspects of economic activity. It provides real-time insight into the current state of the business cycle.	Thomson Reuters DataStream
Economic Policy Uncertaint y Index	EPU	Capture the degree of uncertainty about economic policy, which can arise from various sources, such as changes in government regulations, tax policies, fiscal policies, or political instability. It combines three components (Media mentions, tax code expirations, economic forecast disagreement) into a composite measure of uncertainty, with the media coverage of economic policy uncertainty being the primary driver.	Thomson Reuters DataStream
CBOE Volatility Index	VIX	Measure of market expectations for near-term volatility, often referred to as the "fear gauge." It reflects the market consensus on the expected 30-day volatility, derived from the prices of S&P 500 index options. It gauges market sentiment: Elevated VIX levels indicate increased market uncertainty and potential for higher volatility, suggesting that investors anticipate significant price fluctuations.	Thomson Reuters DataStream
Bearish Index	Bearish	The bullish component index of the AAII Investor Sentiment Survey. It represents the percentage of investors who have a positive outlook on the market, expecting it to rise over the next six months.	Thomson Reuters DataStream
Bullish Index	Bullish	The bullish index component of the AAII Investor Sentiment Survey. It indicates the percentage of investors who anticipate a market decline over the next six months.	Thomson Reuters DataStream

Table A2. Bubble periods

	Start	Peak	End	Duration (Days)	Signal	Ongoing
AAPL	09-01-2020	13-01-2020	27-01-2020	12	positive	FALSE
	31-07-2020	01-09-2020	08-09-2020	27	positive	FALSE
	15-12-2020	28-12-2020	06-01-2021	16	positive	FALSE
	04-02-2021	04-02-2021	16-02-2021	8	positive	FALSE
TSLA	13-06-2017	14-06-2017	27-06-2017	10	positive	FALSE
	07-01-2020	04-02-2020	26-02-2020	36	Positive	FALSE
	30-06-2020	31-08-2020	08-09-2020	50	Positive	FALSE
	09-09-2020	08-01-2021	05-03-2021	127	Positive	FALSE
	09-03-2021	15-03-2021	24-03-2021	11	Positive	FALSE
	31-03-2021	13-04-2021	29-04-2021	21	Positive	FALSE
	12-10-2021	04-11-2021	13-12-2021	44	Positive	FALSE
	22-12-2021	03-01-2022	07-01-2022	12	Positive	FALSE
NVDA	20-05-2016	02-06-2016	24-06-2016	25	positive	FALSE
	06-07-2016	27-12-2016	02-03-2017	171	positive	FALSE
	13-03-2017	20-03-2017	04-04-2017	16	positive	FALSE
	10-05-2017	08-06-2017	13-12-2017	155	positive	FALSE
	15-12-2017	18-12-2017	01-01-2018	11	positive	FALSE
	02-01-2018	29-01-2018	05-02-2018	24	positive	FALSE
	06-02-2018	20-02-2018	27-03-2018	35	positive	FALSE
	01-06-2018	05-06-2018	21-06-2018	14	positive	FALSE
	12-08-2020	02-09-2020	08-09-2020	19	positive	FALSE
	05-10-2020	13-10-2020	19-10-2020	10	positive	FALSE
	29-10-2021	19-11-2021	17-12-2021	35	positive	FALSE
	21-12-2021	27-12-2021	05-01-2022	11	positive	FALSE
	13-06-2023	14-06-2023	23-06-2023	8	positive	FALSE
	12-07-2023	18-07-2023	02-08-2023	15	positive	FALSE
	21-08-2023	31-08-2023	07-09-2023	13	positive	FALSE
	08-01-2024	18-06-2024	29-08-2024	168	positive	FALSE
GOOG	07-04-2021	29-04-2021	12-05-2021	25	positive	FALSE
	20-05-2021	01-09-2021	05-01-2022	164	positive	FALSE
AMZN	13-02-2018	12-03-2018	23-03-2018	28	positive	FALSE
	31-05-2018	20-06-2018	25-06-2018	17	positive	FALSE
	28-06-2018	04-09-2018	08-10-2018	72	positive	FALSE
	06-07-2020	10-07-2020	17-07-2020	9	positive	FALSE
	30-07-2020	06-08-2020	11-08-2020	8	positive	FALSE
	12-08-2020	02-09-2020	08-09-2020	19	positive	FALSE
META	02-02-2024	07-02-2024	28-03-2024	39	positive	FALSE
	02-04-2024	05-04-2024	15-04-2024	9	positive	FALSE
NFLX	15-02-2018	09-03-2018	23-03-2018	26	positive	FALSE
	23-05-2018	20-06-2018	19-07-2018	41	positive	FALSE
NOW	02-03-2018	14-03-2018	23-03-2018	15	positive	FALSE
	17-07-2020	20-07-2020	11-08-2020	17	positive	FALSE
	13-08-2020	02-09-2020	07-09-2020	17	positive	FALSE
	21-09-2020	16-10-2020	10-11-2020	36	positive	FALSE
	11-11-2020	18-12-2020	06-01-2021	40	positive	FALSE
	28-01-2021	11-02-2021	25-02-2021	20	positive	FALSE
	28-10-2021	04-11-2021	10-11-2021	9	positive	FALSE
S&PCOMP	05-01-2018	26-01-2018	02-02-2018	20	positive	FALSE

Notes: This table presents GSADF tests bubble periods. Start indicates the time at which the bubble begins to form, Peak marks the date when the bubble reaches its highest point, End identifies the time at which the bubble bursts, Duration reflects the total length of the bubble, and Signal indicates whether the bubble is positive or negative. Bubble dates are identified using 95% critical values derived from the wild bootstrap. These critical values are calculated through 1,000 bootstrap replications.