Journal of Economics and Financial Researches, 2024, 6(2): 198-220 doi: 10.56668/jefr.1574019

Speculative Bubbles in Artificial Intelligence Investments: Analysis of the "Magnificent Seven" Technology Stocks and Volatility Spillover Effects

Volkan ETEMAN[a]

Abstract

This paper comprehensively analyzes the speculative bubble risks of investments in artificial intelligence (AI) technologies in financial markets. A GSADF test and volatility spillover analysis on the stocks of the so-called "Magnificent Seven," namely Meta, Microsoft, Apple, Amazon, Google, Nvidia, and Tesla is conducted. The test results reveal significant bubbles, especially in Nvidia and Tesla stocks, and these bubbles spread volatility to other technology stocks. The fact that Nvidia plays a central role in volatility spillovers suggests that overpricing in AI investments can create a domino effect across the sector, leading to severe volatility in global markets. Investors should diversify portfolios and adopt long-term strategies against speculative bubble risks. At the same time, policymakers should increase market efficiency by tightening financial regulations.

Keywords: Speculative Bubbles, Frequency Connectedness, Tech Stock, GSADF Test.

JEL Classification: G12, G14, O33

Yapay Zekâ Yatırımlarında Spekülatif Balonlar: "Muhteşem Yedi" Teknoloji Hisse Senetlerinin Analizi ve Volatilite Taşma Etkileri

Öz

Çalışmada finans piyasalarında yapay zeka (YZ) teknolojilerine yapılan yatırımların spekülatif balon risklerini kapsamlı bir şekilde analiz edilmektedir. Meta, Microsoft, Apple, Amazon, Google, Nvidia ve Tesla olmak üzere "Muhteşem Yedili" hisseleri üzerinde bir GSADF testi ve volatilite taşması analizi yapılmıştır. Test sonuçları, özellikle Nvidia ve Tesla hisselerinde önemli balonlar olduğunu ortaya koymakta ve bu balonlar diğer teknoloji hisselerine volatilite yaymaktadır. Nvidia'nın volatilite taşmalarında merkezi bir rol oynaması, YZ yatırımlarında aşırı fiyatlandırmanın sektör genelinde domino etkisi yaratarak küresel piyasalarda ciddi volatiliteye yol açabileceğini göstermektedir. Yatırımcılar portföylerini çeşitlendirmeli ve spekülatif balon risklerine karşı uzun vadeli stratejiler benimsemelidir. Aynı zamanda, politika yapıcılar finansal düzenlemeleri sıkılaştırarak piyasa verimliliğini artırmalıdır.

Anahtar Kelimeler: Spekülatif Balonlar, Frekans Bağlantısı, Teknoloji Hisseleri, GSADF Testi.

JEL Sınıflandırması: G12, G14, O33

---

[a] Ress. Assist. Dr., Munzur University, Faculty of Economics and Administrative Science, Department of International Trade and Business, Türkiye, volkaneteman@gmail.com, ORCID: 0000-0002-3430-7073

Araştırma Makalesi / Research Article
Makale Geliş Tarihi / Received Date: 26.10.2024 Makale Kabul Tarihi / Accepted Date: 09.12.2024

1. Introduction

The rapid development of the Internet in the early 1990s marked a technological revolution, epitomized by the launch of the Mosaic browser in 1993, which opened the Internet to commercial use (Mcenary, 1995). By 1995, Netscape's IPO drove a surge in tech stock investments, especially in NASDAQ-listed companies (Crain, 2014). However, this period's exuberance, grounded in unrealistic expectations, led to the dot-com Bubble, which burst in 2000 with significant financial consequences (Baker and Wurgler, 2007).

Fast forward to today, Artificial Intelligence (AI) has taken center stage, transforming industries like healthcare, finance, and manufacturing. The "Magnificent Seven" tech giants—Meta, Microsoft, Apple, Amazon, Google, Nvidia, and Tesla—have become central players, with a combined market capitalization exceeding $11 trillion (Mitcham, 2024). AI's potential, however, may also carry the same speculative risks observed in past bubbles. Investor enthusiasm over AI's transformative power has led to overvaluations that echo the irrational exuberance seen during the dot-com bubble.

This study seeks to explore these parallels, focusing on the risk of speculative bubbles in AI investments and the potential market instability they may cause. We specifically aim to answer the following questions:

1. How do current AI investment trends compare to the Dotcom Bubble?

2. Does the enthusiasm for AI technologies reflect their true potential, or is it driven by speculative behavior?

3. What impact could a burst AI bubble have on global markets?

In line with these research questions, the motivation of our study is as follows. The rapid increase in investment in Artificial Intelligence (AI) technologies in recent years has generated significant interest in the global financial markets. AI is positioned as a strategic tool to increase operational efficiency and open the door to innovative business models in many sectors, including healthcare, finance, agriculture, and industry. However, this rapid growth risks leading to irrational investment behavior and speculative bubbles, similar to the dot-com bubble of the past. Fluctuations in the market capitalization of AI-based companies such as Nvidia and Tesla could cause severe shocks to the global financial system. This study aims to analyze the risks in current AI investments, assess the risks of bubble formation, and examine the economic consequences that may arise if these bubbles burst. A sound framework for AI investment is critical to maintaining global economic stability.

The introduction outlines the study's basic dynamics, followed by a review of bubble-related research. Theoretical framework, data, and methodology are discussed in the third, fourth and fifth sections, respectively. The sixth section covers the application of methods, while the seventh discusses the results. In the eighth section which is the conclusion summarizes the findings with suggestions for future research.

2. Related Literature

Financial bubbles are periods when asset prices deviate from macroeconomic fundamentals, rising rapidly and then falling sharply. Shiller (2000) emphasizes the impact of irrational investment behavior on bubble formation, while Kindleberger (1978) and Minsky (1986) explain the link between financial bubbles and economic crises. To detect these bubbles, the SADF and GSADF tests developed by Phillips, Wu and Yu (2011) and Phillips, Shi and Yu (2015) are often used to identify explosive price movements in time series.

The dot-com bubble highlighted the devastating effects of bubbles in the technology sector. Johansen and Sornette (2000) study the Nasdaq crash, while Hays and Schreiber (2010) examine the long memory effect in US stock markets during this period. Baker and Wurgler (Baker and Wurgler, 2007) study the impact of investor sentiment on markets, while Brunnermeier and Nagel (2005) examine the role of hedge funds in the technology bubble. Other studies have examined the formation of bubbles in high-tech stocks after 2000. For example, Teti and Maroni (2021) assess modern bubbles in the technology industry, while Zhao et al. (2021) analyze the contagion effects of bubbles in the international oil and Chinese stock markets.

While AI investments have great potential, they are also prone to speculative bubbles. The rapid rise of companies such as Nvidia in AI-based technologies can lead to irrational increases in market capitalization. Kassouri et al. (2021) analyzed the sensitivity of clean energy and high-tech stocks to oil shocks and the formation of bubbles in these sectors, while Kyriazis et al. (2020) investigated bubbles in cryptocurrency markets. Almudhaf (2017) investigated the existence of speculative bubbles in African stock markets and presented important findings on this issue. Giorgis et al. (2024) examine the emergence of a clean technology bubble between 2004 and 2008, which includes solar energy, biofuels, batteries, and other renewable sources; they analyze this bubble through the lens of the Social Bubble Hypothesis, suggesting that such bubbles can expedite technological innovation. The study synthesizes the historical development of the clean-tech bubble, the influence of venture capital and government funding, and provides evidence of its role as an innovation-accelerating phenomenon.

This study fills an important gap in the existing literature by analyzing the detection of speculative bubbles and volatility spillover effects on the stocks of the so-called "Magnificent Seven" technology giants. While most previous studies have focused on financial bubbles, they have not comprehensively addressed the risks posed by AI investments and their impact on technology companies. By examining both the risks of bubbles in AI investments and how these bubbles spread to other companies, this study provides new evidence on the domino effect that sectoral dependencies can create in global markets.

This study makes three important contributions to the existing literature. First, it identifies the relationship between AI investments and speculative bubbles and analyzes the existing bubble risks in this area using a large dataset. Second, an in-depth examination of the interactions between volatility spillover analysis and technology stocks allows us to understand the speed and impact of a potential shock in financial markets. Third, the results provide important implications for policymakers and investors in managing speculative bubble risks in AI and technology stocks.

3. Theoretical Framework

The rapid increase in investments in AI technologies and the assessment of a possible bubble risk in this area are closely related to economic theories and financial market dynamics. The theoretical framework of this study can be categorized under four main headings: Financial Bubble Theory, Speculative Investment Behavior, Technological Innovation Theory, and Efficient Market Hypothesis.

3.1. Theory of Financial Bubbles

Financial bubbles are economic events in which the price of an asset rises rapidly away from rational expectations, followed by a sharp decline. The excessive optimism of investors, speculative behavior, and abundant liquidity in the markets play an important role in the formation of bubbles (Shiller, 2000). Past events such as the dot-com bubble have clearly demonstrated the economic damage caused by financial bubbles. This theory provides a basic reference point for the study to analyze the speculative effects of AI investments. The probability of an AI bubble is based on the divergence of speculative pricing from real values.

3.2. Speculative Investment Behaviors

Speculative investment behavior occurs when investors have irrational expectations and inflate asset prices in search of quick gains (Keynes, 1936). This behavior is often driven by the promise of high returns in an uncertain future and contributes to bubble formation. While AI technologies offer great potential for investors, the rapid increase in investments in this field may also trigger speculative behavior. A similar dynamic was observed during the dot-com bubble (Wheale and Amin, 2003), with many companies rapidly appreciating in value without making a profit. Overvaluations in AI investments could be a sign of similar speculative behavior.

3.3. Technological Innovation Theory

Joseph Schumpeter's Theory of Creative Destruction (1942) suggests that new technologies trigger economic growth by destroying old structures. AI technologies are considered an innovative force with the potential to transform large parts of economies and businesses. While technological innovations create new business models and products in the market, they can also bring the risk of speculative overvaluation. This theory is important in analyzing the long-term economic impacts of AI. The transformative impact of

AI technologies may cause investors to overestimate future potential, which favors speculative bubble formation.

3.4. Efficient Market Hypothesis (EMH)

Eugene Fama's Efficient Market Hypothesis (1970) argues that markets price all available information quickly and accurately and that asset prices are always close to their true value. However, past bubbles and market crashes show that this hypothesis is not fully realized. When market efficiency is poor, irrational investor behavior and speculation come into play. In AI investments, it is argued that markets do not always act rationally and speculative pricing may occur. The effects of market efficiency on AI investments constitute an important part of the study.

In this framework, investments in AI technologies carry bubble risk due to irrational investor behavior and deficiencies in market mechanisms. Investors' belief that AI will enable the entire industrial transformation may cause assets to be overvalued and priced far above their actual market value. The rapid commercialization of AI and the fact that most of the investments are based on speculative expectations overlap with the financial bubble theory.

In this context, the theoretical framework of the study is shaped around the financial bubble theory, speculative investment behavior, technological innovations and efficient market hypothesis to understand the speculative bubble formation in AI investments. In light of these theories, the speculative aspect of investments in AI technologies and the risks that may arise in the event of a possible bubble bursting will be analyzed.

The behavioral finance literature provides a significant framework for understanding how irrational decisions by investors contribute to the formation of market bubbles. In particular, the works of Shiller (2000) and Kahneman and Tversky (1979) demonstrate how cognitive biases and overconfidence lead to deviations of market prices from fundamental values. In this context, behavioral finance offers critical insights into the limitations of market efficiency, complementing the Efficient Market Hypothesis (EMH). Considering that markets often fall short of strong-form efficiency, findings from behavioral finance support the theoretical basis of this study. This perspective is particularly essential in explaining bubble formation in innovative technologies such as AI investments.

4. Data

In this study, daily frequency data covering the period of January 2, 2016 - June 28, 2024, was used. The study period was chosen because it covers important events in which technology stocks experienced increases and fluctuations in global financial markets. This period, especially when AI technologies are rapidly developing and major changes are observed in the financial performances of technology giants such as Nvidia, Tesla, Meta, and Apple, offers rich data in terms of analysis. The data used in this study was obtained from the Investing.com website, ensuring reliability and consistency in tracking the financial metrics of the selected stocks.

AI and technology investments, along with the digital transformation and remote working trends that accelerated with the pandemic in the post-2020 period, have caused significant increases in the stock prices of these companies. Nvidia's success in the production of AI graphics processors and Tesla's advances in electric vehicle technologies have increased volatility by triggering speculative investment behaviors. Therefore, the study examined the existence of bubbles and volatility spillovers on the stocks of these companies.

The selected period covers a period in which technological innovations accelerated, AI investments, and technological transformations had a wide impact on financial markets. In addition, the COVID-19 pandemic in 2020 further increased the demand for technology companies and caused significant fluctuations in the volatility of these stocks. In particular, the market values of AI and advanced technology-based companies such as Nvidia and Tesla showed a significant increase during this period. Therefore, choosing a period between January 2, 2016, and June 28, 2024, which includes such major global developments and technological leaps, is critical for both bubble detection and volatility analysis.

5. Method

5.1. GSADF Test: Testing Explosive Behavior Over Time

The GSADF test is a broader version of the ADF test, which analyzes whether there are explosive roots in different sub-periods of the time series. In the GSADF test, the time series is tested in many sub-windows and the supremum (highest) ADF statistic is selected among these windows. In the GSADF test, ADF statistics are calculated for each sub-period (Phillips et al., 2015):

$$y_t = \alpha + \beta y_{t-1} + \sum_{i=1}^{p} \delta_i \Delta y_{t-i} + \varepsilon_t \tag{1}$$

where the data window varies between r_1 and r_2 (start and end points). r_1 and r_2 are sub-periods in the data set. The GSADF statistic is calculated by taking the supremum of the ADF statistics taken over the different sub-periods:

$$GSADF = \sup_{r_2 \in [r_0, 1]} \left(\sup_{r_1 \in [0, r_2 - r_0]} ADF_{r_1, r_2} \right) \tag{2}$$

This equation takes the maximum (supremum) of the ADF statistics for all sub-periods ranging between r_1 and r_2. Where r_1 and r_2 are the tested sub-periods, ADF_{r_1,r_2} is the ADF statistic for each sub-period, and r_0 is the minimum window width to be tested.

According to this supremum value, it is decided whether there is an explosive unit root in a certain period of the time series.

The test statistic calculated in the GSADF test is compared with the critical values. If the GSADF statistic exceeds the critical values, the presence of an explosive unit root in the time series is detected, indicating the presence of a bubble. This test can be used to determine the rapid rise and subsequent decline in stock prices. In addition, the GSADF test is an effective method for detecting speculative bubbles, especially in financial markets, because bubbles usually appear in certain periods and can burst in a short time. This test analyzes different sub-periods in time to more accurately capture bubble formations. In addition, the test's use of the supremum value detects the presence of bubbles with the highest probability (Phillips et al., 2015).

5.2. Baruník and Křehlík (2018) Frequency Connectedness Approach

The Baruník and Křehlík (2018) method focuses on analyzing volatility spillovers on a frequency basis. This method starts with the Vector Autoregression (VAR) model and then performs variance decomposition. Fourier transform is used to examine spillovers in the frequency domain and the effect of volatility spread by each variable on the other at different time frequencies is measured. The basic model used to examine volatility spillovers is the VAR (Vector Autoregression) model as follows (Baruník and Křehlík, 2018):

$$\mathrm{X_t = A_1X_{t-1} + A_2X_{t-2} + \cdots + A_pX_{t-p} + \varepsilon_t} \qquad (3)$$

where X_t is a vector of variables (returns of each stock) of size $kx1$, A_i is the autoregressive coefficient matrix of size kxk, p is the lag length of the model, ε_t is the error term and is a white noise vector with mean zero.

The variance of the error terms obtained from the VAR model is transformed into the frequency domain to understand volatility spillovers among stocks. In this step, the general effect and frequency-based spillovers are separated. A function $H(h)$ shows the variance decomposition of h −step forecast errors. This reveals how much a time series spills over into another series. However, the feature of the Baruník and Křehlík method is to determine these spillovers by decomposing them according to time-frequency. In order to examine volatility spillovers in the frequency domain, the variance decomposition is decomposed into frequencies with the help of the Fourier transform. As a result, how spillovers occur in the short, medium, and long term is analyzed. Using the Fourier transform, each component is transferred to the frequency domain as follows (Baruník and Křehlík, 2018):

$$\mathrm{F(\omega) = \int_{-\infty}^{\infty} f(t)e^{-i\omega t}dt} \qquad (4)$$

where $F(\omega)$ is the frequency component and $f(t)$ is the time domain component. The Fourier transform enables analysis by transforming the t −time series into the ω −frequency domain. After this transformation, variance decomposition is performed in three frequency ranges:

Short-term spillovers (1-4 days): Situations where financial shocks spread rapidly. Medium-term spillovers (4-10 days): Medium-term interactions in markets. Long-term spillovers (10 days and beyond): Effects of long-term uncertainties and systematic risks. The measure of spillover in frequency shows the share of volatility carried over between stocks. For example, the amount of variance that a stock carries over to another stock is calculated using the formula:

$$\mathrm{Spillover}_{i\rightarrow j}(\omega) = \frac{\mathrm{Variance}_{i,j}(\omega)}{\mathrm{Total\ Variance}(\omega)} \tag{5}$$

where ω represents frequency and is expressed as the percentage of spillover from one stock to another.

6. Empirical Findings

In this study, bubble assets and volatility spillovers of stocks called "Magnificent Seven" were examined. Using the GSADF (Generalized Supremum Augmented Dickey-Fuller) test, it was investigated whether there was a bubble in these stocks. The GSADF test results are shown in Table 1. Bubble assets of less than seven days were not taken into account when calculating bubble periods.

Table 1. GSADF Test Results

		META	MSFT	AAPL	AMZN	GOGGL	NVDA	TSLA
GSADF Test prob		2.19 (0.103)	2.86 (0.007)	4.88 (0.000)	2.91 (0.005)	2.93 (0.005)	8.04 (0.000)	8.83 (0.000)
Criticial Value	%90 level	2.241						
	%95 level	2.460						
	%99 level	2.804						

Note: Monte Carlo simulation for critical values was performed with 5000 replications. The names of the stocks are used with their stock exchange abbreviations.

The test results in Table 1 show the existence of significant bubbles, especially in stocks such as NVDA and TSLA. High GSADF test values , such as 8.04 for NVDA and 8.83 for TSLA, were found, which reject the null hypothesis at the 1% significance level. According to the findings in Table 1, NVDA and TSLA have particularly high GSADF values.

Table 2. H_1: Explosive Unit Root Presence

META	Cannot reject H_0
AAPL	Rejects H_0 at the 1% significance level
AMZN	Rejects H_0 at the 1% significance level
GOGGL	Rejects H_0 at the 1% significance level
MSFT	Rejects H_0 at the 1% significance level
NVDA	Rejects H_0 at the 1% significance level
TSLA	Rejects H_0 at the 1% significance level

Table 2 provides information on the hypotheses for each stock. Table 2 shows the results of the bubble existence research conducted for the "Magnificent Seven" stocks (META, MSFT, AAPL, AMZN, GOOGL, NVDA, TSLA) with the GSADF test. The results confirm the existence of bubbles for AAPL, AMZN, GOOGL, MSFT, NVDA, and TSLA at the 1% significance level, while the null hypothesis could not be rejected for META stock. This result shows that META did not carry an explosive unit root during the examined period, while bubble behavior was observed in other stocks.

Table 3. AAPL Bubble Dates and Durations

Start	Peak	End	Duration	Signal
2017-02-14	2017-03-01	2017-03-08	15	Positive
2020-01-08	2020-01-13	2020-01-27	12	Positive
2020-07-06	2020-07-15	2020-07-23	13	Positive
2020-07-30	2020-09-01	2020-09-18	35	Positive
2020-09-25	2020-10-12	2020-10-23	20	Positive
2020-12-01	2020-12-08	2020-12-14	9	Positive
2020-12-15	2021-01-26	2021-02-17	42	Positive
2021-12-07	2021-12-10	2021-12-20	9	Positive
2021-12-21	2022-01-03	2022-01-06	11	Positive

Table 3 shows the dates and durations of bubble existence of Apple stock. Bubbles detected in Apple stocks are associated with the company's major product launches and market expansions. For example, the bubble period between 2017-02-14 and 2017-03-08 can be related to the strong performance of iPhone 7 sales and new product expectations. The bubble between 2020-01-08 and 2020-01-27 can be associated with the success of the iPhone 11 and the increasing demand in the Chinese market. The bubble observed during the pandemic, especially between 2020-07-06 and 2020-09-18, can be explained by the increased demand for devices such as iPads and MacBooks due to remote working. In addition, Apple's stock split decision also accelerated the price increase during this period. The bubble observed between 2020-12-01 and 2021-02-17 was supported by the strong sales performance of the iPhone 12 and the widespread use of 5G. Finally, the bubble between 2021-12-07 and 2022-01-06 has been attributed to Apple introducing new products to the market despite supply chain issues and the year-end shopping season positively affecting the company's performance.

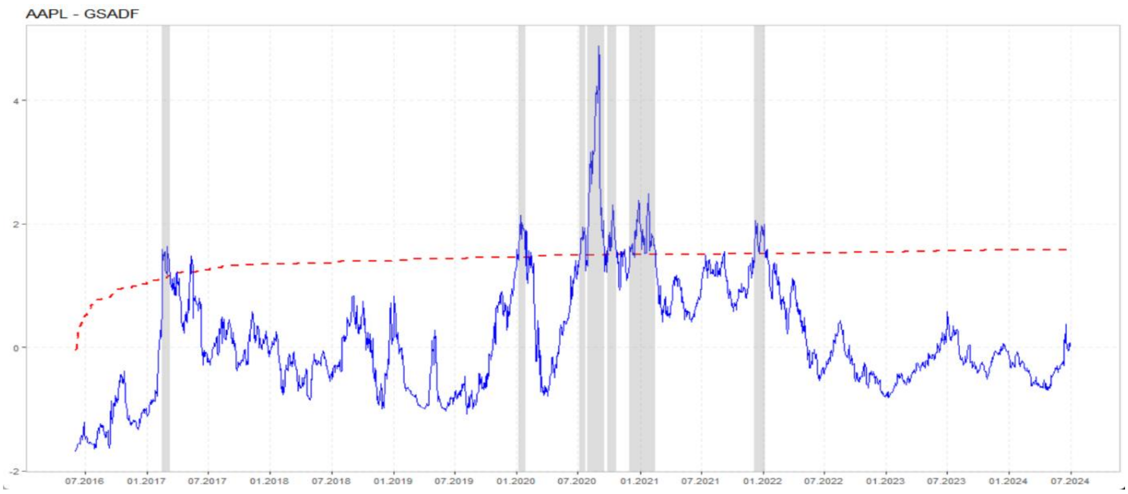


Figure 1. AAPL Bubble Periods

Figure 1, Bubble periods observed in Apple stocks usually coincide with times of major changes in global market dynamics. Bubble periods in 2020, in particular, are linked to the increased interest in technology companies due to the COVID-19 pandemic. The increased demand for remote working and online services during the pandemic increased interest in Apple's products and services, leading to an explosive increase in its stock prices. For example, the new iPhone models launched by Apple in the July-August period of 2020 (2020-07-06/ 2020-09-18) and the increased online shopping during the pandemic caused the bubble to gain momentum during this period.

Table 4. AMZN Bubble Dates and Durations

Start	Peak	End	Duration	Signal
2018-02-14	2018-03-12	2018-03-23	26	Positive
2018-08-06	2018-09-04	2018-09-17	29	Positive
2020-08-18	2020-09-02	2020-09-04	13	Positive

In Table 4, Amazon stocks have exhibited significant bubble behavior, while e-commerce has expanded rapidly. The bubble between 2018-02-14 and 2018-03-23 can be associated with Amazon's investments in Prime services and the expansion of its retail strategies. The bubble between 2018-08-06 and 2018-09-17 coincides with when Amazon consolidated its leading position in e-commerce and increased its sales with events such as Prime Day. The bubble seen during the pandemic between 2020-08-18 and 2020-09-04 can be explained by the increase in online shopping on a global scale and the rapid increase in stock prices due to Amazon's investments in its logistics network. This period also saw cloud computing services significantly contribute to the company's growth.

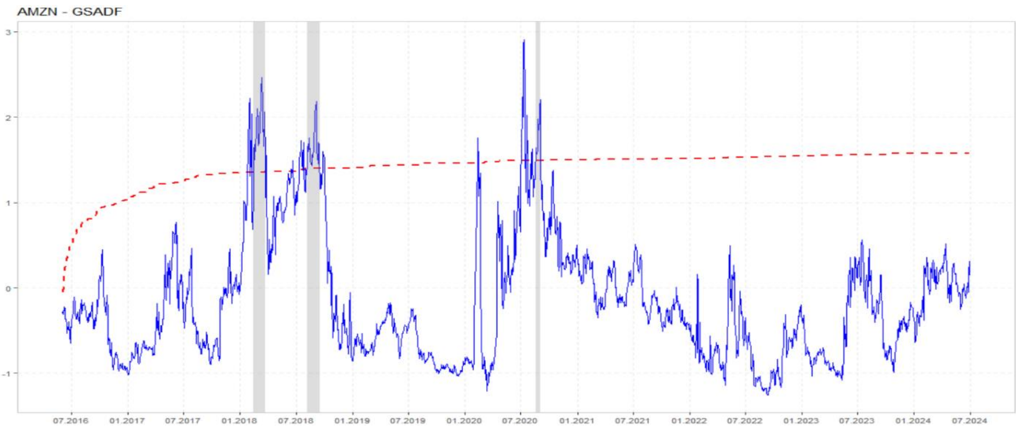


Figure 2. AMZN Bubble Periods

Figure 2 shows that Amazon's bubble periods parallel the demand brought by the pandemic. The bubbles experienced in Amazon stocks in 2020 can be explained by the pandemic's greatly increased e-commerce. With the COVID-19 pandemic shaking the global economy in March 2020, consumers turned to online shopping, and Amazon stocks rose rapidly. In the August-September 2020 period (2020-08-18 - 2020-09-04), the bubble was strengthened by Amazon's revenue reaching a record level during the pandemic. During this period, the intense demand for Amazon's Prime memberships and the increase in e-commerce sales were important factors in the formation of the bubble. In summary, the bubbles seen in Amazon stocks in 2018 and 2020 were due to the rapid spread of e-commerce and cloud computing services globally.

Table 5. GOOGL Bubble Dates and Durations

Start	Peak	End	Duration	Signal
2021-06-04	2021-06-14	2021-06-18	10	Positive
2021-06-21	2021-09-01	2021-12-01	114	Positive
2021-12-02	2021-12-08	2021-12-17	11	Positive

Table 5 shows that Google’s digital advertising and cloud computing expansions have pushed the company’s stock prices upwards. The long-term bubble detected between 2021-06-04 and 2021-12-17 can be associated with a significant increase in digital advertising revenues. The acceleration of digitalization and advertisers’ shift to digital platforms during the pandemic have increased Google’s advertising revenues. In addition, the increase in revenues from platforms owned by Google, such as YouTube, during this period also supported the formation of the bubble. During the same period, the demand for cloud computing services strengthened the company’s performance.

Figure 3. GOOGL Bubble Periods

Figure 3, Alphabet (Google)'s long-term bubbles observed in 2021 are related to the growth of digital advertising during the pandemic period. The bubble experienced, especially in the June-December 2021 period (2021-06-21 – 2021-12-01), can be explained by the significant increase in Google's advertising revenues. In this period, when digitalization accelerated, companies shifted their advertising budgets to digital platforms, and Google's revenues reached record levels. In addition, the demand for Google's cloud services was also effective in this bubble period.

Table 6. MSFT Bubble Dates and Durations

Start	Peak	End	Duration	Signal
2020-01-30	2020-02-10	2020-02-24	16	Positive
2020-06-30	2020-07-09	2020-07-17	12	Positive
2020-08-20	2020-09-02	2020-09-04	11	Positive
2021-07-02	2021-08-23	2021-09-28	60	Positive

In Table 6, bubbles seen in Microsoft stocks are closely related to the increasing demand for remote work solutions and cloud services. The first bubble detected between 2020-01-30 and 2020-02-24, can be attributed to the growth of Microsoft's cloud service Azure and the increasing demand for collaboration tools such as Microsoft Teams before the pandemic. The long-term bubble between 2020-06-30 and 2020-09-28 can be explained by the high demand for digital business solutions during the pandemic, which increased stock prices. During this period, Microsoft's financial results reflected the significant expansion in cloud services and collaboration tools, and investors were positively affected by this growth.

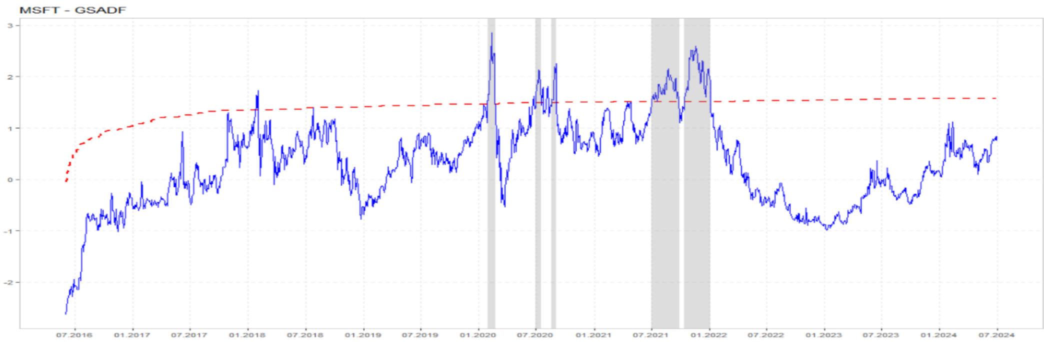


Figure 4. MSFT Bubble Periods

It is observed that the bubbles in Microsoft's share prices in Figure 4 are moving in line with the increasing demand, especially for cloud computing and collaboration solutions.

Table 7. NVDA Bubble Dates and Durations

Start	Peak	End	Duration	Signal
2016-06-02	2016-06-02	2016-06-17	11	Positive
2016-07-08	2016-07-20	2016-07-21	9	Positive
2016-07-22	2016-08-12	2016-08-30	27	Positive
2016-11-11	2016-11-18	2016-12-02	14	Positive
2016-12-14	2016-12-27	2017-01-05	14	Positive
2020-08-12	2020-09-02	2020-09-08	18	Positive
2020-10-05	2020-10-13	2020-10-19	10	Positive
2021-06-17	2021-07-06	2021-07-16	20	Positive
2021-07-21	2021-08-05	2021-08-17	19	Positive
2021-08-19	2021-08-30	2021-09-28	27	Positive
2021-10-14	2021-11-29	2022-01-13	63	Positive
2023-06-13	2023-06-20	2023-06-26	8	Positive
2023-07-12	2023-07-18	2023-08-09	20	Positive
2023-08-21	2023-08-31	2023-09-08	13	Positive
2024-01-09	2024-06-18	2024-06-28	119	Positive

In Table 7, bubbles detected in Nvidia stocks have been associated with demand for AI, data center technologies, and the gaming sector. While early bubbles such as 2016-06-02 and 2016-06-17 pointed to an increase in demand for graphics processors, the bubble in the period 2020-08-12 and 2020-09-08 is directly related to increased remote working, gaming, and data center solutions due to the impact of the pandemic. Demand for Nvidia's graphics cards has increased dramatically, especially in the gaming industry and cryptocurrency mining. The last bubble between 2023-07-12 and 2024-06-28 is still ongoing, and this bubble is associated with AI applications and Nvidia's continued leadership in this field. Global demand for AI and data centers has rapidly increased the company's stock prices during this period. In addition, new product launches and technological developments expected in 2024 may also extend the duration of this bubble.

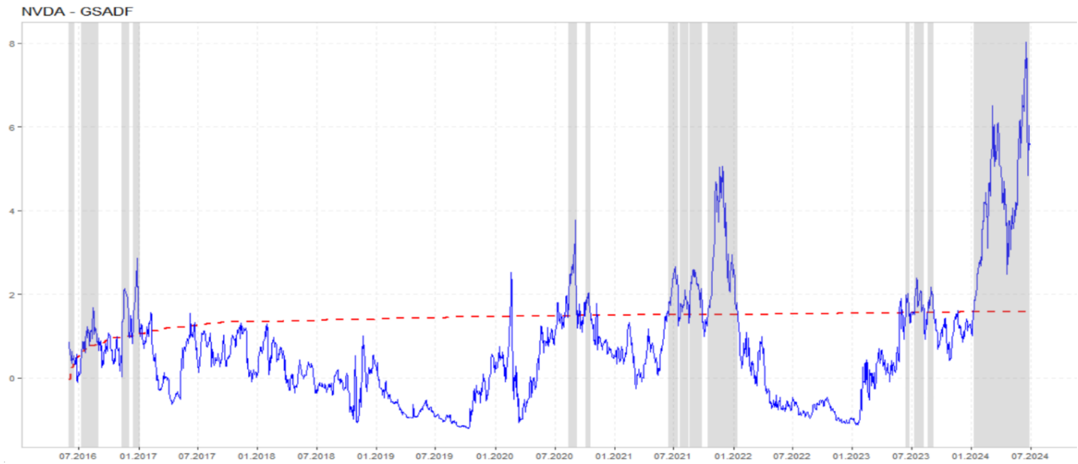


Figure 5. NVDA Bubble Periods

Figure 5, Nvidia has experienced bubble periods, especially during periods when demand for AI, the gaming industry, and data center technologies increased. These bubbles during and after the pandemic in 2020 are associated with a significant increase in demand for Nvidia's graphics processors. The bubble in August 2020 (2020-08-12– 2020-09-08) can be explained by the increased demand for the gaming industry and data center solutions, especially during remote work. In addition, the demand for graphics cards for cryptocurrency mining also affected the bubble periods.

Table 8. TSLA Bubble Dates and Durations

Start	Peak	End	Duration	Signal
2020-01-07	2020-02-04	2020-02-26	34	Positive
2020-06-30	2020-08-31	2020-09-08	48	Positive
2020-09-09	2020-09-15	2020-10-30	37	Positive
2020-11-03	2020-11-05	2020-11-13	8	Positive
2020-11-17	2021-01-08	2021-03-04	72	Positive
2021-04-12	2021-04-13	2021-04-27	11	Positive
2021-10-18	2021-11-01	2021-12-06	34	Positive

In Table 8, The bubbles seen in Tesla stocks are related to innovation in electric vehicle technologies and the company's high expectations for the future. The first bubble between 2020-01-07 and 2020-02-26 can be explained by Tesla's increase in production targets and the market success of its new vehicles such as the Model 3. The bubble between 2020-06-30 and 2020-09-08 gained momentum with Tesla's inclusion in the S&P 500 index, increasing investor expectations. In addition, Tesla's investments in autonomous driving technologies also triggered the price increase in this period.

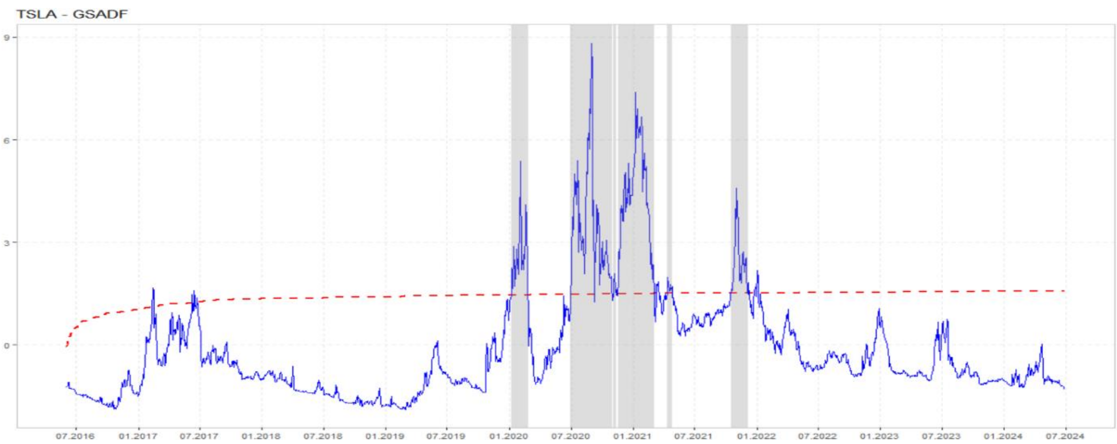


Figure 6. TSLA Bubble Periods

Figure 6, Tesla's bubble periods are linked to its pioneering position in electric vehicle technologies and high expectations for the future. The bubbles observed in Tesla stocks in 2020 can be explained by the company's increased production targets and the increase in market value. In particular, the bubble period that started in June 2020 and ended in August 2020 (2020-06-30- 2020-09-08) is associated with the inclusion of Tesla's stocks in the S&P 500 index and the rapid increase in the company's valuation. In addition, Tesla's bubble periods have accelerated in parallel with the company's ability to maintain market leadership and investors' future expectations.

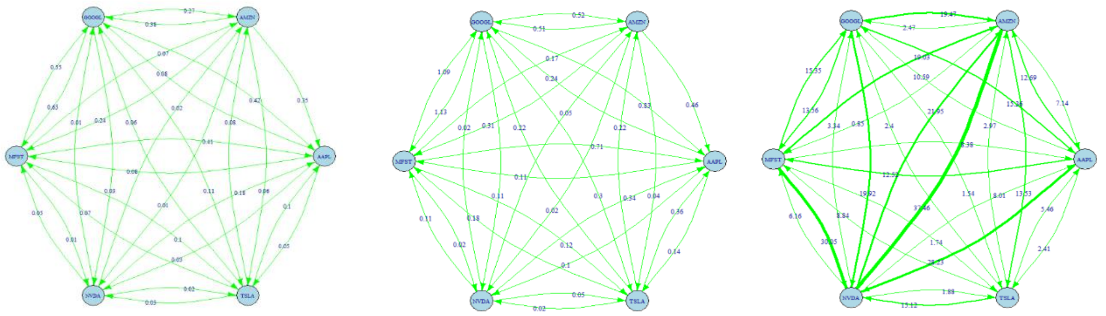
Bubble periods observed in all stocks considered in the study are related to global economic events, sector dynamics, and strategic moves of companies. Each bubble period is a response to important developments in the markets and indicates remarkable market reactions especially for companies operating in technology and innovation areas.

Table 9 shows the volatility spillovers that occurred in the short (1-4 days), medium (4-10 days), and long term (10 days and beyond) among the "Magnificent Seven" stocks where bubble presence was obtained. The spillovers expressed as "From" (which stock receives the spillover) and "To" (which stock spreads the spillover) for each stock allows for an in-depth analysis of the interactions between stocks. When looking at the table, considering that the bubble presence continues according to the GSADF test for NVDA, the effect of the volatility released by this stock on other stocks is extremely critical. NVDA stands out as the stock that receives the most volatility, especially in the long term (10 days and beyond), with a very high ratio of 57.5. This shows that Nvidia is the stock most affected by the uncertainties and volatility in the market. Nvidia is seen to derive its volatility largely from tech giants such as GOOGL (21.56) and MSFT (18.98). This situation reveals how tight the interactions within the tech sector are and the interdependence of these stocks.

Table 9. Baruník and Křehlík (2018) Frequency Connectedness

	AAPL	AMZN	GOOGL	MSFT	NVDA	TSLA	FROM
Roughly corresponds to 1 days to 4 days							
AAPL	0.86	0.00	0.08	0.08	0.03	0.05	2.30
AMZN	0.35	0.58	0.38	0.24	0.01	0.06	9.70
GOOGL	0.42	0.27	1.41	0.65	0.03	0.11	13.86
MSFT	0.41	0.07	0.55	1.29	0.01	0.10	10.67
NVDA	0.18	0.02	0.01	0.05	0.13	0.02	2.59
TSLA	0.10	0.08	0.06	0.07	0.03	1.90	3.26
TO	13.67	4.15	10.19	10.21	0.94	3.23	**42.38**
Roughly corresponds to 4 days to 10 days							
AAPL	1.83	0.00	0.24	0.11	0.10	0.14	2.92
AMZN	0.46	0.97	0.51	0.31	0.02	0.04	6.54
GOOGL	0.83	0.52	2.82	1.13	0.11	0.30	14.03
MSFT	0.71	0.17	1.09	1.93	0.02	0.12	10.28
NVDA	0.34	0.05	0.02	0.11	0.13	0.05	2.78
TSLA	0.36	0.22	0.22	0.18	0.02	4.35	4.85
TO	13.15	4.68	10.13	8.93	1.32	3.17	**41.39**
Roughly corresponds to 10 days to Inf days							
AAPL	30.04	12.69	10.59	12.52	28.23	2.41	11.68
AMZN	7.14	34.61	2.47	0.85	37.46	13.53	10.8
GOOGL	15.36	19.47	21.56	13.56	19.92	1.54	12.28
MSFT	8.38	19.03	15.35	18.98	30.05	1.74	13.11
NVDA	8.01	21.95	3.34	6.16	57.5	1.88	7.27
TSLA	5.46	2.97	2.40	8.84	15.12	57.6	6.12
TO	7.80	13.38	6.01	7.37	22.99	3.71	**61.26**

On the other hand, Nvidia spreads 7.27 percent volatility, which means it significantly affects other stocks. Especially in the long term, GOOGL, AAPL, and MSFT are the leading stocks that receive volatility from Nvidia. This shows the impact of Nvidia's price fluctuations in the technology sector on other giant companies. Nvidia's position in critical areas such as AI, data center technologies, and the gaming sector plays a decisive role in volatility spillovers. It is seen that GOOGL and MSFT both receive and spread volatility in volatility spillovers. Both of these companies are affected by Nvidia and also affect the market with their strong positions in digital advertising, cloud computing, and business software. In the long term, it can be expected that a large part of these spillovers will be concentrated in future growth areas such as AI and data centers.



a. Short term (1 to 4 days) **b.** Medium Term (4 to 10 days) **c.** Long Term (10 day to Inf.)

Figure 7. Baruník and Křehlík (2018) Frequency Volatility Spillover Network Structure

Figure 7 visually presents the volatility spillover network among the "Magnificent Seven" stocks in the short, medium, and long term. While spillovers appear more limited in the short (Figure 7a) and medium (Figure 7b) terms, spillovers are more pronounced and stronger in the long term (Figure 7c). In the long term (10 days and beyond), the effect of the volatility published by NVDA on other technology stocks is seen in the figure. Nvidia spreads the spillovers it receives from other companies widely. This spread shows strong interactions, especially towards big players such as GOOGL, AAPL, and MSFT. The performance of stocks receiving volatility from NVDA becomes more important when the bubble in Nvidia's stock continues. According to the GSADF test, the fact that the bubble in NVDA still exists may mean that uncertainties and volatility in the market will continue in the long term. This situation indicates that other stocks closely related to Nvidia will also be more vulnerable to volatility. Stocks like GOOGL, MSFT, and AAPL could see more volatility due to the spillovers they received from Nvidia.

This analysis reveals that the volatility spillovers concentrated within the tech sector are driven not only by Nvidia's performance but also by global developments in AI and data centers. Figure 7 shows that these spillovers are propagated within a strong network structure and that Nvidia is a central player in this network over the long term.

6.1. Evaluation of Findings

This study detected bubble assets in technology stocks known as the "Magnificent Seven" using the GSADF test. Within the framework of the Financial Bubble Theory, the existence of significant bubbles in Nvidia (NVDA) and Tesla (TSLA) stocks indicates that speculative pricing moves away from the real values of the assets and increases rapidly, followed by a risk of sharp decline. This finding supports how financial bubbles can have destructive effects on markets. The GSADF value for Nvidia was 8.04, and for Tesla was 8.83, and bubbles were detected for both stocks at a significance level of 1%. These results indicate that the market prices of these companies have deviated from macroeconomic fundamentals and reached speculative levels.

Speculative behavior has also been observed in Amazon, Apple, Google, and Microsoft stocks. Speculative Investment Behavior Theory suggests that investors overprice the value of these companies with irrational expectations. For example, bubbles in Apple stocks are often linked to events that create speculative interest, such as the company's new product launches or market expansions. Apple's price increases in 2020 were supported by the increased remote working and high demand for Apple products due to the pandemic. This is a classic example of investors behaving with excessive optimism based on future earnings expectations.

The study results can also be associated with the Technological Innovation Theory. Joseph Schumpeter's Theory of Creative Destruction states that new technologies trigger economic growth by destroying old structures (Wheale & Amin, 2003). The bubbles observed in the stocks of Nvidia and Tesla are due to the innovative potential brought by AI and electric vehicle technologies. Nvidia's leadership in graphics processors and Tesla's pioneering role in electric vehicle technologies have caused these companies to be overvalued by investors with high expectations for the future. These findings show how technological innovation can trigger speculative behavior and contribute to the formation of bubbles.

On the other hand, when considered within the EMH framework, these findings prove that markets do not always behave rationally. As a result of the GSADF test for Meta, no bubble was found and the null hypothesis could not be rejected, suggesting that Meta exhibited a performance closer to market efficiency. However, the same is not true for other technology giants. Bubbles have been detected in companies such as Amazon, Apple, Google, and Microsoft, which reveals that markets do not fully price the true values of these companies and that investors exhibit irrational behavior.

Volatility spillover analyses show how tight the interactions between technology stocks are. According to the Baruník and Křehlík (2018) frequency connectedness approach, Nvidia stands out as the stock with the highest spread of volatility in the market in the long term. It is observed that Nvidia is overpriced, especially with speculative expectations for artificial intelligence and data centers, and these price movements spread to other technology stocks. This situation confirms the spillover effect of speculative investment behaviors on the market. Technology giants such as Apple, Google, and Microsoft, which receive volatility from Nvidia, are directly affected by the fluctuations in Nvidia's performance. This finding clearly shows how speculative investment can chain effect players in an industry.

As a result of these analyses, the findings of the study within the framework of financial bubble theory, speculative investment behavior, technological innovation theory, and market efficiency hypothesis show that the risk of speculative bubbles in AI and technology investments is serious and that when these bubbles burst, they can cause major fluctuations in global markets. Bubbles in companies such as Nvidia and Tesla carry the potential for a large-scale crisis in the technology sector. Volatility spillover analysis shows that such speculative bubbles are not confined to one company but can also affect other technology giants.

7. Discussion

This study examines speculative bubble risks in AI and technology stocks using the GSADF test and volatility spillover analysis. The results show that optimistic investment behavior towards AI technologies causes prices to deviate from rational values, as explained by financial bubble theory. Significant bubbles, especially in giants like Nvidia and Tesla, suggest technological innovations are overpriced, with wide-reaching consequences.

Current speculative investment behavior in AI mirrors the dot-com bubble. During that era, high expectations for internet companies led to a market crash. Similarly, excessive increases in the market values of Nvidia, Tesla, and other tech giants reflect irrational optimism about their innovation capabilities, detached from economic fundamentals.

Nvidia's leadership in AI, particularly in graphics processors, has been overvalued. From an EMH perspective, the prices of companies like Nvidia and Tesla do not reflect all market information, and speculative movements harm market efficiency. Nvidia's volatility also spreads to other stocks, showing how innovative technologies like AI impact broader financial markets.

The findings of this study align with prior research examining speculative bubbles and volatility spillovers in other sectors. For instance, the results are consistent with Kyriazis et al. (2020), who identified speculative bubble dynamics in cryptocurrency markets. Similar to the AI sector, the cryptocurrency market exhibited irrational exuberance and rapid price escalations disconnected from fundamental values. Moreover, Kassouri et al. (2021) demonstrated how clean energy and high-tech stock prices were vulnerable to bubble formations, influenced by external shocks such as oil price volatility. These parallels indicate that sectors driven by innovation and speculative expectations often share common patterns of price deviations and market inefficiencies.

In contrast, studies focusing on traditional sectors, such as Almudhaf (2017) on African stock markets, highlighted that speculative bubbles in these markets tend to arise from macroeconomic uncertainties rather than technological innovation. Comparing these dynamics emphasizes how AI and technology-driven sectors, due to their rapid growth and investor optimism, are uniquely prone to speculative pricing and interconnected volatility spillovers, which may not be as prevalent in less innovative or slower-evolving industries.

This comparative perspective reinforces the need for tailored approaches to managing speculative risks in rapidly evolving sectors like AI while drawing lessons from other markets to enhance financial stability and efficiency.

8. Conclusion

The rapid growth potential of AI technologies has led investors to show great interest in this area, but when evaluated within the framework of the theory of financial bubbles and speculative investment behavior, it has been observed that this investment behavior is characterized by irrational excessive optimism. The bubbles identified show that investors' expectations of innovative AI-based technologies are exaggerated and that this situation carries the risk of disrupting market equilibrium.

The study also found strong interactions between the volatility spillover analysis and technology stocks. Nvidia's central role in the volatility spillover suggests that investment surges in innovative technologies such as AI can spill over to other major technology companies, creating a domino effect in global markets. These findings suggest that speculative bubbles in AI technologies can affect not just one sector, but a broader economic sphere.

This study contributes to the literature by integrating theoretical insights from behavioral finance and emphasizing actionable steps to enhance market efficiency, particularly in the AI and technology sectors. By comparing the findings with studies in other innovative and traditional markets, the research highlights the unique susceptibility of technology-driven sectors to speculative bubbles and volatility spillovers. These insights underscore the importance of tailored regulatory and policy interventions to mitigate risks and improve market stability. The theoretical and practical implications derived from this study provide a comprehensive framework for understanding and managing the dynamics of speculative bubbles in evolving financial landscapes.

To better understand the risks of speculative bubbles in AI and technology investments, the dynamics of bubble bursting and its impact on the global financial system should be studied in more depth. Investigating how bubbles in the AI and technology sectors spread to other industries will contribute to understanding sectoral contagion risks. In addition, comprehensive studies of the effectiveness of financial regulation in preventing bubbles may offer new approaches to managing speculative bubbles in high-risk sectors. Finally, research on the long-term economic and social impacts of artificial intelligence technologies will provide a clearer perspective on the sustainability of innovations in this field.

The results of this study indicate that the risks of speculative bubbles in the technology sector, particularly in AI investments, can reach serious proportions and potentially devastate global financial stability. The following are recommendations for investors, policymakers, and regulators to manage these risks and minimize the impact of excessive speculative behavior in the markets.

Monitoring and warning mechanisms for speculative investments: The findings indicate high risks of speculative bubbles, especially in technology stocks such as Nvidia and Tesla. In this context, regulators should establish advanced bubble monitoring systems and financial early warning mechanisms to detect speculative bubbles in AI investments earlier. Regularly applying methods such as GSADF testing in the markets can help strengthen these systems.

Transparency and disclosure in AI investments: Increasing market transparency is critical to reducing irrational investment behavior in AI technologies. There is evidence that investors overestimate the potential of AI. To address this, companies should strengthen their disclosure policies to investors and be more transparent about AI projects' realistic return expectations and risks.

Guiding Investor Behavior: Speculative investment behavior can lead to market bubbles. Based on the findings, expanding financial education programs can help investors adopt more conscious and long-term strategies. Regulators should develop special programs to educate investors in high-risk areas such as AI investments.

Managing systemic risks in the tech sector: The evidence suggests that volatility in AI investments may spill over to other tech stocks, creating a domino effect across the sector. Therefore, financial authorities should conduct more rigorous stress tests and cross-sector risk analysis to prevent the spread of systemic risks in the tech sector. Tests focused on key companies such as Nvidia and Tesla can prevent these risks from spreading.

To move markets closer to strong-form efficiency, actionable steps should be implemented, particularly focusing on the AI and technology sectors. These steps could include enhancing the transparency of information disclosure, ensuring that all investors have equal access to relevant data, and promoting the adoption of long-term investment strategies over short-term speculation. Policymakers and financial regulators should also establish robust monitoring systems to identify inefficiencies and speculative bubbles early. Strengthening investor education programs specific to innovative and volatile sectors like AI can further reduce irrational behavior and contribute to more stable and efficient markets.

Statement of Research and Publication Ethics

In this study, which did not require ethics committee approval and/or legal/special permission, research and publication ethics were followed.

Researcher's Contribution Rate Statement

I am a single author of this paper. My contribution is 100%

Researcher's Conflict of Interest Statement

There are no potential conflicts of interest in this study.

References

Almudhaf, F. (2017). Speculative Bubbles and Irrational Exuberance in African Stock Markets. *Journal of Behavioral and Experimental Finance*, 13: 28–32. https://doi.org/10.1016/j.jbef.2016.11.002

Baker, M. and 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

Baruník, J. and Křehlík, T. (2018). Measuring the frequency dynamics of financial connectedness and systemic risk. *Journal of Financial Econometrics*, 16(2): 271–296. https://doi.org/10.1093/jjfinec/nby001

Brunnermeier, M.K. and Nagel, S. (2005). Hedge Funds and the Technology Bubble. *SSRN Electronic Journal*. https://doi.org/10.2139/ssrn.423940

Crain, M. (2014). Financial markets and online advertising: Reevaluating the dotcom investment bubble. *Information Communication and Society*, 17(3): 371–384. https://doi.org/10.1080/1369118X.2013.869615

Fama, E.F. (1970). Efficient capital markets: A review of theory and empirical work. *The Journal of Finance*, 25(2): 383–417.

Giorgis, V., Huber, T.A. and Sornette, D. (2024). 'Salvation and profit': Deconstructing the clean-tech bubble. *Technology Analysis and Strategic Management*, 36(4): 827–839. https://doi.org/10.1080/09537325.2022.2060809

Hays, P. and Schreiber, M. (2010). Evidence of long memory in U.S. stock returns : The case of the 1990s bubble. *Quarterly Journal of Finance and Accounting*, 49(1): 5–19.

Johansen, A. and Sornette, D. (2000). The Nasdaq crash of April 2000: Yet another example of log-periodicity in a speculative bubble ending in a crash. *European Physical Journal B*, 17(2): 319–328. https://doi.org/10.1007/s100510070147

Kassouri, Y., Kacou, K.Y.T. and Alola, A.A. (2021). Are oil-clean energy and high technology stock prices in the same straits? Bubbles speculation and time-varying perspectives. *Energy*, 232: 121021. https://doi.org/10.1016/j.energy.2021.121021

Keynes, J.M. (1936). General Theory of employment. *Quarterly Journal of Economics*, 209–223. http://qje.oxfordjournals.org/

Kindleberger, C.P. (1978). Manias, Panics and Crashes. In *Manias, Panics and Crashes*, 4(2): 103-112.

Kyriazis, N., Papadamou, S. and Corbet, S. (2020). A systematic review of the bubble dynamics of cryptocurrency prices. *Research in International Business and Finance*, 54: 101254. https://doi.org/10.1016/j.ribaf.2020.101254

Mcenary, K.W. (1995). The internet, world-wide web, and mosaic: An overview. *American Journal of Roentgenology,* 164(2): 469-473.

Minsky, H.P. (1986). *Stabilizing an unstable economy* (Hyman P. Minsky Archive*,* 144). http://digitalcommons.bard.edu/hm_archive/144

Mitcham, K. (2024). ESG factors and profitability performance for the Dow Jones industrial average stock index. *Available at SSRN 4793201*. https://doi.org/10.2139/ssrn.4793201

Phillips, P.C.B., Shi, S. and 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

Phillips, P.C.B., Wu, Y. and Yu, J. (2011). Explosive behavior in the 1990s Nasdaq: When did exuberance escalate asset values? *International Economic Review*, 52(1): 201–226.

Schumpeter, J. (1942). *Capitalism, Socialism and Democracy* (3rd edition). London: George Allen and Unwin.

Shiller, R.J. (2000). Measuring bubble expectations and investor confidence. *Journal of Psychology and Financial Markets*, 1(1): 49–60. https://doi.org/10.1207/S15327760JPFM0101_05

Teti, E. and Maroni, D. (2021). The new great bubble in the technology industry? *Technology Analysis and Strategic Management*, *33*(5): 520–534. https://doi.org/10.1080/09537325.2020.1828577

Wheale, P.R. and Amin, L.H. (2003). Bursting the dot.com “Bubble”: A case study in investor behaviour. *Technology Analysis and Strategic Management*, 15(1): 117–136. https://doi.org/10.1080/0953732032000046097

Zhao, Z., Wen, H. and Li, K. (2021). Identifying bubbles and the contagion effect between oil and stock markets: New evidence from China. *Economic Modelling*, *94*: 780–788. https://doi.org/10.1016/j.econmod.2020.02.018