Causal Linkages Between Emerging Stocks and the Magnificent Seven*

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Abstract

This study investigates potential causal relationships between leading US technology firms collectively known as the "Magnificent Seven" and a group of innovative, smaller-cap emerging stocks in sectors such as artificial intelligence, space exploration, nuclear energy, and quantum computing. Using Yahoo Finance's hourly stock price over multiple timeframes (30 to 720 days), we applied Granger causality testing to assess whether price movements in one stock could statistically predict movements in another. Time series were pre-processed to ensure stationarity using the Augmented Dickey-Fuller (ADF) test, and optimal lag lengths were selected via the Akaike Information Criterion (AIC). Our results reveal that causal relationships are limited in short-term windows, but increase in complexity and bidirectionality over longer periods. Causal links were found to align with real-world events, such as partnerships and investments, including Microsoft's relationships with C3.ai and Oklo. These findings suggest that Granger causality can capture evolving market dynamics and interdependencies, providing valuable information for investors and researchers monitoring the convergence between dominant and emerging technology players.

1 Introduction

The Magnificent Seven, Apple, Google, Microsoft, NVIDIA, Meta, Amazon, and Tesla are not just the most recognizable names in the technology sector, but also powerful drivers of market sentiment, innovation, and investor behavior. Their stock movements often ripple across industries, influencing investor behavior and shaping macroeconomic narratives.

At the same time, a new generation of smaller, emerging firms is gaining traction in high-impact fields such as artificial intelligence, quantum computing, space exploration, and nuclear energy. Although these companies lack the market capitalization of their larger counterparts, their technological breakthroughs and niche focus make them increasingly relevant in the modern economy.

This study explores whether there are statistically significant causal links between these two groups: the dominant tech giants and emerging disruptors. Using Granger causality analysis, we assess whether historical price patterns from one group can help forecast movements in the other, and how these relationships evolve over various time horizons. The goal is to discover whether emerging firms serve as early indicators of innovation trends or whether established giants continue to lead and influence market behavior. The results offer valuable insights for financial forecasting, portfolio strategy, and a deeper understanding of how technological influence flows through modern capital markets.

2 Literature Review

The study of how stock prices influence each other, particularly in firm size and market visibility, has greatly interested financial researchers. An important concept in this field is the *lead-lag relationship*, where the movements of one stock, typically a large-cap or more liquid security, appear to anticipate those of another. This dynamic is especially prominent in the technology sector, where dominant firms can shape sector-wide performance through innovation, investor sentiment, and market visibility.

Seminal work by Lo and MacKinlay [5] and Hou and Moskowitz [4] demonstrated that large, liquid firms tend to lead smaller or less liquid stocks in terms of price discovery, largely due to asymmetries in information dissemination and trading volume.

This dynamic is particularly relevant in the technology sector, where some dominant firms consistently shape market expectations. Bellew and Chapman [1] analyzed sectoral return spillovers and found that Big Tech stocks, such as Apple and Microsoft, regularly act as influencers across both tech and non-tech industries. Yang and Li [6] further explored this leadership behavior, showing that in tech-heavy markets, a small subset of firms often move first and dictates short-term sentiment.

Granger causality methods have proven to be effective in quantifying these lead-lag relationships. Billio et al. [2] and Diebold and Yilmaz [3] used Granger-based network models to study systemic connectedness in US markets. Their work highlights how influence intensifies during periods of volatility or structural change, conditions frequently observed in the tech industry due to innovation cycles and policy shifts.

Although these studies establish that large-cap tech firms often act as market leaders and that Granger causality is a useful tool to quantify influence, the literature has largely focused on broad market indices or sector-level dynamics. There is limited empirical analysis exploring how influence flows specifically between dominant US tech firms and emerging, innovation-focused small caps over extended time horizons.

This represents a gap, given the growing role of niche, high-growth companies in shaping technological disruption. Emerging firms in areas like artificial intelligence, quantum computing, space technology, and nuclear energy may not yet command large market capitalizations, but their innovations and the investor sentiment they generate could influence or even anticipate broader market moves. Conversely, Big Tech companies may still dominate attention and capital flows, reinforcing top-down influence patterns.

Our study addresses this intersection by applying Granger causality testing across multiple timeframes between the Magnificent Seven and a set of emerging tech stocks. Unlike prior research, we focus on short-term predictive influence and also on how these relationships evolve in the long term. In doing so, we provide a detailed understanding of market dynamics within the innovation economy and offer empirical insight into how leadership and responsiveness co-exist within the modern tech sector.

3 Data

This research analyzes potential causal relationships between emerging stocks and the Magnificent Seven, a group of leading US giants comprising Apple (AAPL), Google (GOOG), Microsoft (MSFT), NVIDIA (NVDA), Meta (META), Amazon (AMZN) and Tesla (TSLA). For the emerging group, we selected a diverse set of smaller-cap stocks with relatively lower market shares known for their innovation and relevance in artificial intelligence, space technology, nuclear energy, and quantum computing. These included BigBear.ai (BBAI), SoundHound AI (SOUN) and Quantum Computing Inc. (QUBT), Oklo (OKLO), Rocket Lab (RKLB), C3.ai (AI), and Akamai Technologies (AKAM).

Price data were obtained using the Yahoo Finance API through the yfinance Python library. For each stock, we extracted the highest hourly prices across multiple timeframes: 30, 60, 90, 180, 360, and 720 days, with the end date fixed at April 28, 2025. This range was chosen to capture both short and medium-term market dynamics that may reflect immediate causal interactions.

Before analysis, raw time-series data were preprocessed, which involved removing any entries with missing values and transforming the series to achieve stationarity, a key requirement for time-series methods such as Granger causality testing. We applied the Augmented Dickey-Fuller (ADF) test iteratively to each stock time series, differentiating the data until we achieved a p-value less than or equal to 0.05.

4 Methodology

We applied Granger causality testing to examine the presence and direction of causality between emerging small-cap stocks and Magnificent Seven, a group of dominant, large-cap US stocks.

4.1 Stationarity and Differencing

For time-series analysis, we need the data to be stationarity, which means that the statistical properties of a series(mean, variance, autocorrelation) should remain constant over time. Since financial price data are typically non-stationary, we first assess stationarity using the Augmented Dickey-Fuller (ADF) test, which checks for the presence of a unit root in each series. A series is considered stationary if the ADF test returns a p-value less than or equal to 0.05. For each stock, we applied the differencing iteratively until its time series was stationary.

4.2 Optimal Lag Selection via AIC

To determine the optimal lag length for Granger causality testing, we applied the Akaike Information Criterion (AIC) to each pair of stocks. The AIC balances model fit and helps avoid overfitting while capturing relevant dynamics. For every combination of a Magnificent Seven stock and an emerging tech stock, we computed the AIC across a range of lag values and selected the lag that minimized the criterion. The optimal lag was then used for the Granger causality testing

4.3 Pairwise Granger Causality Testing

For each pair consisting of a Magnificent Seven stock ($Stock_A$) and an emerging stock ($Stock_B$), Granger causality tests were performed in both directions: A → B: Does $Stock_A$ cause $Stock_B$? B → A: Does $Stock_B$ cause $Stock_A$?

Using the optimal lag determined via AIC (Section 2.3), we computed the p-values for each directional test. A causal link was considered statistically significant if the p-value was less than 0.05. Based on the direction(s) of statistical significance, the results were classified into four types: Unidirectional (Magnificent Seven causes Emerging), i.e., A causes B, but B does not cause A; Unidirectional (Emerging causes Magnificent Seven) i.e., B causes A, but A does not cause B; Bidirectional Causation, i.e., Both directions are statistically significant; No Causation i.e., Neither direction is statistically significant.

5 Results and Discussion

To understand the statistical findings, we reviewed relevant news articles and real-world events to examine whether the known partnerships between the Magnificent Seven stocks and emerging firms align with the observed causality patterns.

Case 1: Microsoft (MSFT) and C3.ai (AI)

On 19 November 2024, Microsoft announced an expanded partnership with C3.ai to provide cloud computing services to the enterprise market, as reported by Investor's Business Daily[1].

Days	Stock_A	Stock_B	P_Value_A_to_B	Causal_A_to_B	P_Value_B_to_A	Causal_B_to_A
30	MSFT	AI	0.9173	No	0.5689	No
60	MSFT	AI	0.4299	No	0.2899	No
90	MSFT	AI	0.1799	No	0.0143	Yes
180	MSFT	AI	0.8384	No	0.2756	No
360	MSFT	AI	0.2576	No	0.008	Yes
720	MSFT	AI	0	Yes	0	Yes

Figure 1: Granger causality analysis between MSFT and AI

In our Granger causality analysis:

[1] https://www.investors.com/news/technology/ai-stock-c3ai-stock-artificial-intelligence-microsoft-cloud-partnership

- In the 90-day window highlighted in yellow in Figure 1, the p-value for AI $\rightarrow$ MSFT falls below 0.05, indicating statistically significant causality, that is, C3.ai causes Microsoft.
- In the 720-day window highlighted in pink in Figure 1, both directions (MSFT $\leftrightarrow$ C3.AI) show significant causality, suggesting a bidirectional relationship. (since the p-value for both are below 0.05)

These results suggest that the announcement coincides with a shift from no causality to first unidirectional, then bidirectional influence, reflecting deepening integration between the companies.

Case 2: Microsoft (MSFT) and Oklo (OKLO)

Microsoft's strategic investment of $40 million in Oklo, a start-up nuclear energy company, was reported in 2022 as part of a larger push into clean energy[2].

Days	Stock_A	Stock_B	P_Value_A_to_B	Causal_A_to_B	P_Value_B_to_A	Causal_B_to_A
30	MSFT	OKLO	0.172	No	0.1332	No
60	MSFT	OKLO	0.0159	Yes	0.1773	No
90	MSFT	OKLO	0.5586	No	0.0652	No
180	MSFT	OKLO	0.2078	No	0.1023	No
360	MSFT	OKLO	0.043	Yes	0.7311	No
720	MSFT	OKLO	0.043	Yes	0.7311	No

Figure 2: Granger causality analysis between MSFT and OKLO.

Our Granger tests reveal:

- From the 60-day window highlighted in green in Figure 2 onward, MSFT $\rightarrow$ OKLO shows significant causality.
- This unidirectional relationship persists across longer windows, aligning with Microsoft's known equity involvement.

This indicates that the Magnificent Seven stocks can act as leading indicators for smaller-cap strategic partners.

Case 3: Emergence of Bidirectional Causality in the Long Term

By the 720-day window, a large number of pairs of stocks, including those without prior significance, exhibit bidirectional Granger causality, as illustrated in Figure 3. This widespread emergence suggests that over longer periods, interdependencies between the Magnificent Seven stocks and emerging firms become more symmetric.

[2] `https://www.ainvest.com/news/oklo-strategic-shift-altman-exit-paves-ai-nuclear-synergy-2504`

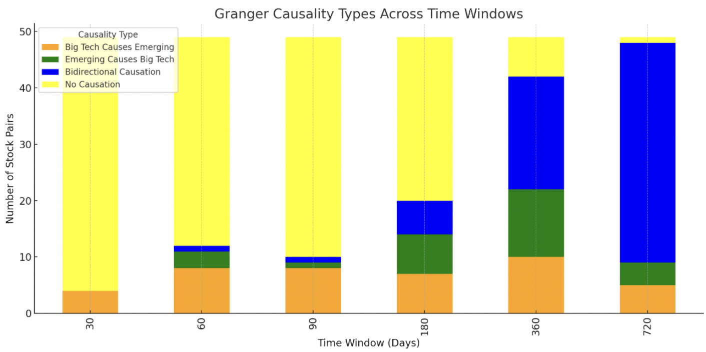

Figure 3: Bidirectional Granger causality analysis when considering long-term periods.

There could be several factors contributing to this pattern. Most of the stocks in our dataset are technology-driven and span domains such as artificial intelligence, space exploration, nuclear energy, and quantum computing. As the technology sector continues to expand and gain market attention, the co-movement of these stocks becomes more likely. In such an environment, innovation adoption, investor sentiment, and macroeconomic changes can increasingly affect both large-cap and small-cap tech firms, leading to stronger mutual influence over time.

6 Conclusion

This research explored causal relationships between emerging stocks and the Magnificent Seven US tech giants through pairwise Granger causality testing over multiple time frames. By transforming the hourly stock price data to achieve stationarity and selecting optimal lags via the Akaike Information Criterion (AIC), we systematically evaluated the presence and direction of predictive influence between each pair of stocks.

Our analysis revealed that causality patterns evolve with time; shorter windows exhibit limited predictive relationships, whereas longer windows (e.g., 720 days) show an increase in bidirectional causality. In addition, real-world partnerships, such as those between Microsoft and C3.ai or between Microsoft and Oklo, align with statistically significant Granger causal relationships in our findings. Furthermore, the emergence of bidirectional causality in the long term suggests growing market interdependencies between established tech firms and their innovative, smaller-cap counterparts.

These results suggest that Granger causality can serve as a useful analytical tool to uncover potential lead-lag dynamics in equity markets, especially in rapidly evolving sectors. Future work could extend this research by incorporating intraday or minute-level data to capture more granular causal shifts and sector-level macroeconomic or sentiment variables to capture causal inference more effectively.

Acknowledgment

We gratefully acknowledge using OpenAI's ChatGPT for proofreading, grammatical checks, and other text editing tasks.

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