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Causal Networks and Risk Contagion of Technology Stocks under Macroeconomic Policies: An Informatics-Driven Study

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Abstract. This paper investigates how macroeconomic policies shape the dynamics of leading technology stocks—Google (GOOGL), Apple (AAPL), and Microsoft (MSFT)—through the lens of advanced informatics and service science. Using daily stock price data (2020–2025) alongside macroeconomic indicators (interest rates, inflation, and GDP growth), the study applies econometric techniques including Granger causality tests, Kalman filtering, causal network analysis, and bootstrap validation. Results reveal that inflation exerts the strongest negative pressure on Apple, while GDP growth most benefits Microsoft. Correlation and contagion indices further show that systemic risks intensify during market turbulence, reducing the diversification potential of technology portfolios. By integrating macroeconomic indicators with dynamic contagion modeling, the study provides an informatics-driven framework for monitoring systemic risk in technology markets. The findings offer both theoretical contributions to the literature on financial informatics and practical implications for risk management, decision support, and policy design in the digital economy.

Keywords: technology stocks, interest rates, inflation, gdp growth, dynamic correlation, risk contagion, granger causality, causal networks; robustness test

1. Introduction

Technology stocks have become a driving force in global financial markets, with giants such as Google (GOOGL), Apple (AAPL), and Microsoft (MSFT) shaping innovation, investment flows, and market sentiment (Deng et al., 2025). These firms not only dominate in terms of market capitalization but also play a strategic role in the resilience of the digital economy (Chishti and Dogan, 2024). Understanding the dynamics of their stock performance under changing macroeconomic policies is therefore essential for investors, policymakers, and service providers seeking to manage risk and allocate resources effectively (Ansari, 2025).

While existing research has examined the effects of macroeconomic variables such as interest rates, inflation, and GDP growth on stock markets, most studies adopt a static or sector-general approach (Ali et al., 2025). Few investigations focus specifically on the technology sector, which is characterized by high growth, sensitivity to innovation, and global interdependencies. Moreover, prior work often neglects the dynamic, systemic (Qiao, 2025), and informatics-driven relationships that emerge under conditions of financial stress. For example, during crises such as the COVID-19 pandemic, correlations among technology stocks intensified, reducing diversification benefits and amplifying systemic risk (Zhang et al., 2024).

This study contributes to bridging this gap by applying an integrated informatics and service science perspective to the analysis of technology stock dynamics. The innovations of the paper are threefold. First, it incorporates macroeconomic variables into a unified econometric framework that captures their causal influence on technology stock returns (Fikriyah and Yuliana, 2025). Second, it employs advanced informatics tools—Granger causality tests, Kalman filtering, contagion indices, and bootstrap validation—to model correlations, volatility, and systemic risk. Third, it uses causal network analysis to map the interdependencies among leading technology stocks, highlighting pathways of contagion and risk propagation (Munyo and Veiga, 2024).

By combining financial econometrics with informatics-based modeling, this research provides both theoretical and practical contributions (Odunaike, 2025). Theoretically, it advances understanding of how macroeconomic conditions interact with systemic dynamics in technology markets. Practically, it offers decision-support insights for portfolio managers, financial regulators, and service providers by identifying conditions under which technology stocks are most vulnerable to macroeconomic shocks and systemic contagion (Camanho et al., 2024). In doing so, the paper positions technology stock dynamics not only as a matter of financial analysis but also as a service science challenge—supporting stability, resilience, and informed decision-making in the digital economy(Zhang et al., 2024) .

The remainder of this paper is organized as follows. Section 2 reviews relevant literature on macroeconomic policy, contagion modeling, dynamic correlations, and causal networks. Section 3 introduces the data and methodology, including econometric and informatics-based techniques (Stanimirovic et al., 2025). Section 4 presents empirical results on correlations, contagion effects, and macroeconomic influences. Section 5 discusses the implications for systemic risk management and service science (Hargyatni et al., 2024). Section 6 concludes with theoretical contributions, practical recommendations, and directions for future research.

2. Literature Review

In order to understand the linkages and risk transmission among leading technology companies, it is necessary to build on established theories such as financial contagion, correlation modeling, causal inference, and statistical robustness (Batuparan et al., 2025). This section reviews foundational work in these areas, which together inform the analytical framework of this study:

2.1. Macroeconomic Policy and Stock Price Dynamics

The influence of macroeconomic factors such as interest rates, inflation, and GDP growth on stock prices is well-documented in financial literature. Fama (1981) emphasized that interest rates have a significant impact on stock prices, affecting the present value of future earnings. High interest rates tend to reduce stock prices, especially in high-growth industries such as technology, where the valuation of future cash flows is critical. Research by Bernanke and Kuttner (2005) supports this view, noting that monetary policy directly affects stock prices by affecting investor expectations and the cost of capital. However, due to the technology industry's reliance on innovation and capital-intensive investment, its sensitivity to interest rate changes may vary. While the relationship between macroeconomic policies and stock prices has been explored in various sectors, its direct impact on technology stocks remains less understood, and studies that examine these macroeconomic variables specifically in relation to the technology sector are more limited. This study builds on these insights by incorporating macroeconomic variables into the analysis of technology stock dynamics.

The study on the Chinese stock market (Tsai et al., 2021) emphasizes that the relationship between innovation indicators (such as patents) and economic performance may be complex and influenced by institutional factors such as patent subsidy programs, which may affect the quality and economic significance of innovation indicators. This complexity suggests that the link between macroeconomic or innovation indicators and market performance in China may be more nuanced and intermittent compared to the more consistent relationships often observed in developed economies. This underscores the challenge of applying unified models across different market contexts.

Barberis et al. (2001) conducted an innovative study that explored how investor sentiment, macroeconomic variables, and especially interest rates, affect the psychological aspects of market behavior. They argue that investor sentiment may play a significant role in stock price dynamics. They point out that interest rates can be considered as signals of future economic conditions. Fluctuations in interest rates affect investors' expectations of corporate earnings, risk, and capital costs. These expectations also shape market sentiment, causing stock prices to deviate from their true value based on more "rational" economic factors.

Furthermore, beyond macroeconomic variables, the microstructural characteristics of the market itself, such as stock liquidity, have been found to significantly impact firms' fundamental risk and valuation. Brogaard et al. (2017) show that higher stock liquidity significantly reduces a firm's default risk through two channels: improving informational efficiency of stock prices and facilitating corporate governance by blockholders. This suggests that market liquidity, as a crucial intermediary variable, may amplify or attenuate the actual impact of macroeconomic policies on stock prices

By incorporating emotion-driven behavior and macroeconomic variables into the model, this study provides a more comprehensive understanding of how investor psychology interacts with macroeconomic factors to further influence the dynamics of technology industry stock prices. Understanding this relationship is very important for us as investors and policymakers because it helps predict how technology stocks will respond to economic shocks or changes in market sentiment.

2.2. Stock Market Contagion

Regarding the "contagion" referred to in this article, it can be understood as the transmission of a shock from one market or asset to another market or asset, especially when the market is under great pressure. Allen and Gale (2000) proposed a theoretical model. Through this model, it shows how liquidity shocks in a certain region spread through the connections between different banks. According to this paper, we can understand the theory of contagion in more detail.

Forbes and Rigobon (2002) designed a "contagion index". By quantifying the degree of change in market correlation during financial stress, it is possible to better analyze how shocks are transmitted between emerging and developed markets. And this paper, by incorporating macroeconomic variables into the contagion model, studies and analyzes the contagion effect of the technology stock market in crisis and stable periods from a more detailed perspective.

The concept of stock market contagion has in fact been widely studied, focusing on understanding how shocks in one market affect other markets. Horváth et al. (2018) studied the phenomenon of stock market contagion in Central and Eastern Europe (CEE). According to the paper, unexpected volatility in the US stock market, especially in periods of negative returns, can lead to extreme resonances between US and CEE markets. Their study highlights that financial contagion occurs not only in times of crisis, but also in more stable periods, although the effect is weaker in stable periods. The researchers designed a contagion measure that quantifies the extreme resonances that markets experience together after a shock (Wang and Rey, 2025).

By studying stock market contagion, we can explore more linkages between technology stocks, linkages in different periods, and understand the overall operation of the economy, so that investors and decision makers can predict how stock markets affect each other when the market fluctuates, and take more effective countermeasures.

2.3. Dynamic Correlation and Smoothing Techniques

According to Durbin and Koopman (2012), the Kalman filter is a recursive state- space method used to smooth estimates and reveal underlying trends. This technique is currently widely used in econometrics and portfolio modeling, mainly because it can improve the detection accuracy of signals.

As detailed by Poncela et al. (2021) , Kalman filtering is an efficient technique. It can effectively extract potential factors in a range of problems such as missing data, mixed-frequency data, non-stationary processes, and time-varying parameters. The main advantage of Kalman filtering in dynamic factor models (DFM) is that it can efficiently and accurately handle nonlinearities and lateral dependencies. By using Kalman filtering, I believe that it can be used to improve the forecast accuracy of empirical applications such as macroeconomic forecasting, and it can provide smooth state estimates that vary over time.

Hamilton (2020) designed a method for handling non-stationary data and variance in time series analysis. This method can better handle anomalies in the data, which provides reinforcement for the application of Kalman filters in this study, and the combination of these two methods can better discover potential stock trends.

Incorporating this technique into my research enhances the modeling framework for more robust analysis of the dynamic relationship between macroeconomic factors and stock returns, especially for technology companies. Kalman filtering is able to smooth data and extract common factors, thereby improving the accuracy and reliability of the correlation between stock prices and economic indicators, especially during times of economic uncertainty.

2.4. Causal Relationships and Network Centrality

Granger (1969) introduced a formal definition of causality in time series: variable X is said to Granger-cause Y if past values of X help predict Y. Bonacich (2007) proposed the eigenvector centrality measure, which accounts for both direct and indirect influence within a network.

Causal network analysis is an important tool for understanding the inter-dependencies between various factors that affect technology stocks. An et al. (2022) introduced causal network analysis to examine the connections and dependencies between entities in a network and highlight how these inter-linkages amplify market shocks and influence stock behavior. In the technology stock market, companies like Google, Apple, and Microsoft can be placed in a causal network, the principle of which is that changes in the stock price of one company can trigger chain reactions among other companies. According to An et al. (2022), a company's position in the network plays an important role in the spread of the entire industry through stock price fluctuations. This centrality measure helps to identify which companies have the greatest impact on overall market behavior.

This approach can better work with feedback loops: stock price fluctuations may affect macroeconomic policies (through changes in consumer behavior or corporate investment), which then affect technology stocks due to changes in macroeconomic policies. This mutual influence between stocks and macroeconomic factors amplifies the analysis based on causal networks and allows us to better understand the importance of complex market dynamics.

Diebold and Yilmaz (2012)'s study on the dynamic network connectivity of financial markets mainly explores the spread of some different shocks to industries that are placed in such causal networks or can be said to be linked to each other. Their study used a connectivity index to assess how financial market shocks in one asset or industry affect other assets or industries. This is important when studying contagion effects in the technology industry, as companies in the technology industry share a network of influences, both direct and indirect.

By applying these principles, this study highlights the role of network centrality in understanding how macroeconomic factors and stock market fluctuations affect the technology industry. This study extends previous research by quantifying the relationships between technology companies and examining how core companies such as Google or Microsoft drive broader market fluctuations, thereby deepening our understanding of systemic risk in the technology industry.

2.5. Bootstrap Techniques in Financial Econometrics

The Stationary Bootstrap method by Politis and Romano (1994) provides a way to generate pseudo-time-series data with preserved dependence structure, suitable for auto- correlated financial data. Bootstrapping has become an indispensable tool in econometrics for estimating the distribution of estimators and test statistics. These methods rely on resampling techniques to generate approximate distributions of statistics, often pro- viding more accurate approximations than traditional asymptotic methods, especially when sample sizes are small. Horowitz (2019) explains that under mild regularity conditions, bootstrapping can improve on first-order asymptotic theory, significantly im- proving the coverage and rejection rates of hypothesis tests. Horowitz further emphasizes that bootstrapping is particularly useful when analytical distribution approximations are difficult or impossible to obtain. The method replaces traditional mathematical analysis with computation, thus providing a practical solution when asymptotic distributions can- not be derived analytically. This article outlines several applications of bootstrapping, demonstrating its usefulness in nonparametric estimation, confidence interval construction, and hypothesis testing.

One of the significant advantages of bootstrapping is its ability to correct for finite, sample errors in statistical tests. Specifically, it provides a way to reduce the large errors that can occur in traditional tests, such as those based on the information matrix test of White (1982), which can be subject to large finite sample biases.

In the context of time series data, Horowitz (1992) showed that bootstrapping can be adjusted to accommodate data dependencies through various methods, including stationary bootstrapping. This approach has become key to analyzing auto correlated data, which is common in econometric models.

3. Data and Methodology

3.1. Data Description and Preprocessing

In this study, the relationship between macroeconomic policies and stock price dynamics of major technology companies is explored, including Google (GOOGL), Apple(AAPL) and Microsoft (MSFT). The data used in the study comes from two sources: one is the stock price data of the three technology companies, and the other is macroeconomic data containing key economic indicators. The following is a detailed description of the data sources and processing methods:

(1)Stock price data: The stock price data is the transaction record from January 1, 2020 to January 1, 2025. The data comes from Yahoo Finance. To ensure data quality, we use a variety of data preprocessing techniques:

Missing value processing: I use a linear interpolation method based on time series to fill in the data, and use forward filling and backward filling to ensure data continuity.

Outlier processing: Outliers were identified and treated using a robust statistical method based on the Hampel filter. This method effectively filters data noise while preserving information about genuine market movements.

The key fields in the dataset include:

Date: Indicates the specific trading day.

Close: The price at the end of the stock trading on that day.

High, Low, Open: Represent the highest price, lowest price and opening price in daily trading respectively.

Volume: The trading volume of stocks on that day, reflecting market liquidity.

Through the above pre-processing steps, we use stock price data to calculate the daily return rate, that is, the percentage change of the daily closing price. The daily return rate is an important indicator for exploring correlation, causality, and volatility under different economic conditions in subsequent analysis, and provides a solid data foundation for understanding the connection between the stock market and macroeconomic variables.

(2)Macroeconomic data: The macroeconomic dataset contains a number of key economic indicators that can affect the performance of financial markets. These data is mainly from authoritative channels such as Federal Reserve Economic Data (FRED) and Yahoo Finance.

The main fields in the dataset include:

Date: The date corresponding to each economic indicator. Interest Rate: represents the current level of financing costs in the economy, directly affecting the borrowing costs of enterprises and the present value of future earnings.

Inflation Rate: measures the rate of increase in the overall price level of goods and services, which has a profound impact on corporate costs and consumption levels.

GDP Growth Rate (GDP): The growth rate of gross domestic product reflects the level of production activities and market vitality of the entire national economy, and is usually closely related to consumer demand and corporate performance.

3.2. Return Computation and Stationarity Testing

Logarithmic returns are computed as:

$$\mathrm{r} = \mathrm{in}\frac{Pt}{Pt-1} \tag{1}$$

Where Pt denotes the adjusted closing price on day t, we perform Augmented Dickey-Fuller (ADF) tests to verify the stationarity of the return series. In addition, Ljung-Box tests are conducted to assess the presence of auto- correlation. All return series are found to be stationary with negligible autocorrelation at lag 5.

3.3. Kalman-Smoothed Rolling Correlation

Pairwise Pearson correlation coefficients are calculated within a 60-day rolling window. To reduce noise, I applied a Kalman filter to smooth the rolling correlation series, which enhances signal extraction and reflects underlying long-term relationships more clearly.

3.4. Risk Contagion Index

A contagion index is constructed as:

$$\mathrm{CIt} = \mathrm{Volt} * \mathrm{Corrt} \tag{2}$$

Where Volt is the exponentially weighted moving average of return volatilities, and Corrt is the average pairwise correlation across the three stocks. The contagion index is nor- malized to the interval [0, 1] using min-max scaling:

$$CI * t - \frac{\mathrm{CIt} - \min(\mathrm{CI})}{\max(\mathrm{CI}) - \min(\mathrm{CI})} \tag{3}$$

3.5. Granger Causality and Causal Network

We perform Granger causality tests in a 60-day rolling window, testing the null hypothesis that stock X does not Granger-cause stock Y. A causal link is drawn if the p-value is below 0.1. We construct a directed graph and compute eigenvector centrality to identify the most influential nodes.

3.6. Bootstrap Robustness Check

To validate the robustness of our correlation estimates, we apply the Stationary Bootstrap procedure by Politis and Romano (1994). We use a blocksize of 60 and perform 2000 resampling iterations. Confidence intervals are derived from the empirical distribution of bootstrap samples using the 2.5th and 97.5th percentiles.

3.7. Robustness Check with Alternative Window Size

To ensure the robustness of our findings regarding dynamic correlations and causality, we repeated the core analyses (sections 3.3, 3.4, and 3.5) using an alternative rolling window size of 90 days. The qualitative conclusions remained unchanged, confirming that our results are not overly sensitive to the specific choice of window length.

4. Results

4.1. Descriptive Statistics

Table 1 shows the mean, standard deviation, skewness, and kurtosis of the daily returns.

Table 1. Descriptive Statistics of Daily Returns

Ticker	Mean Return	Std. Dev.	Skewness	Kurtosis
GOOGL	0.08%	1.72%	0.19	3.12
AAPL	0.10%	1.85%	-0.04	3.28
MSFT	0.09%	1.65%	0.11	2.97

4.2. Dynamic Correlation Results

Fig.1: 60-Day and 90-Day Rolling Correlation (Kalman Smoothed)

Kalman-Smoothed Rolling Correlations illustrates the 60-day and 90-day rolling correlations between stock pairs, smoothed via the Kalman filter. A robustness check using a 90-day rolling window yielded qualitatively identical patterns, confirming the stability of these correlation dynamics, as shown in Figure 1.

4.3. Contagion Index Dynamics

The contagion index plotted in Figure reveals significant spikes during market turbulence. The evolution of the contagion index derived from a 90-day window was markedly similar, reinforcing the finding that systemic risk spikes during periods of market stress, as shown in Figure 2.

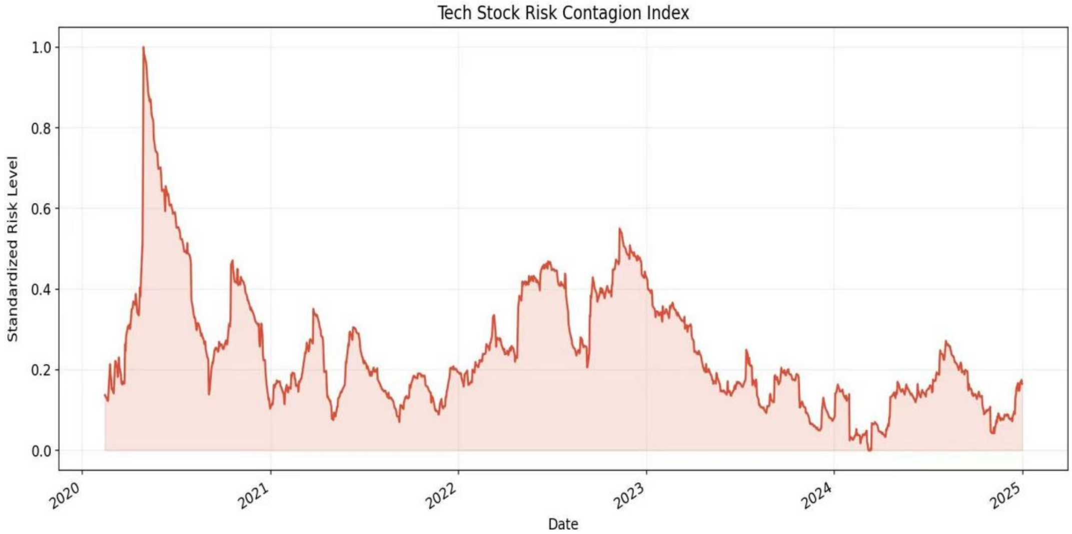

Fig.2: Tech Stock Risk Contagion Index

4.4. Causal Network Results

Figure 3 displays the causal network derived from Granger tests. All nodes are connected bidirectionally.

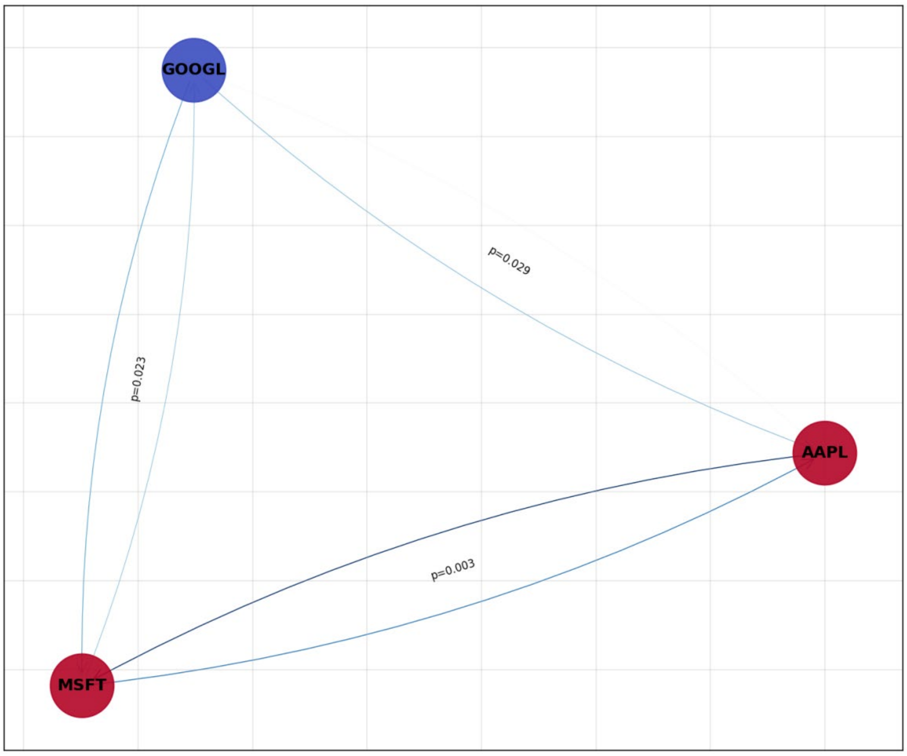

Fig.3: Tech Stock Causal Network

4.5. Bootstrap Validation

Table 2 presents the 95% confidence intervals of pairwise correlations obtained from 2000 bootstrap replications.

Table 2. Bootstrap Confidence Intervals for Correlations

Pair	2.5% CI	97.5% CI
GOOGL-AAPL	0.26	0.53
GOOGL-MSFT	0.09	0.58
AAPL-MSFT	0.26	0.58

4.6. According to the results and in combination with economic indicators

Correlation between Interest Rate and Technology Stocks the correlation between Microsoft (MSFT) and the interest rate is 0.052, indicating that changes in the interest rate have almost no impact on the fluctuations of its stock price. The correlation between Google (GOOGL) and the interest rate is-0.072, showing a slight negative correlation, which means that changes in the interest rate may have a slight impact on its stock price, but the impact is weak, as shown in Figure 4.

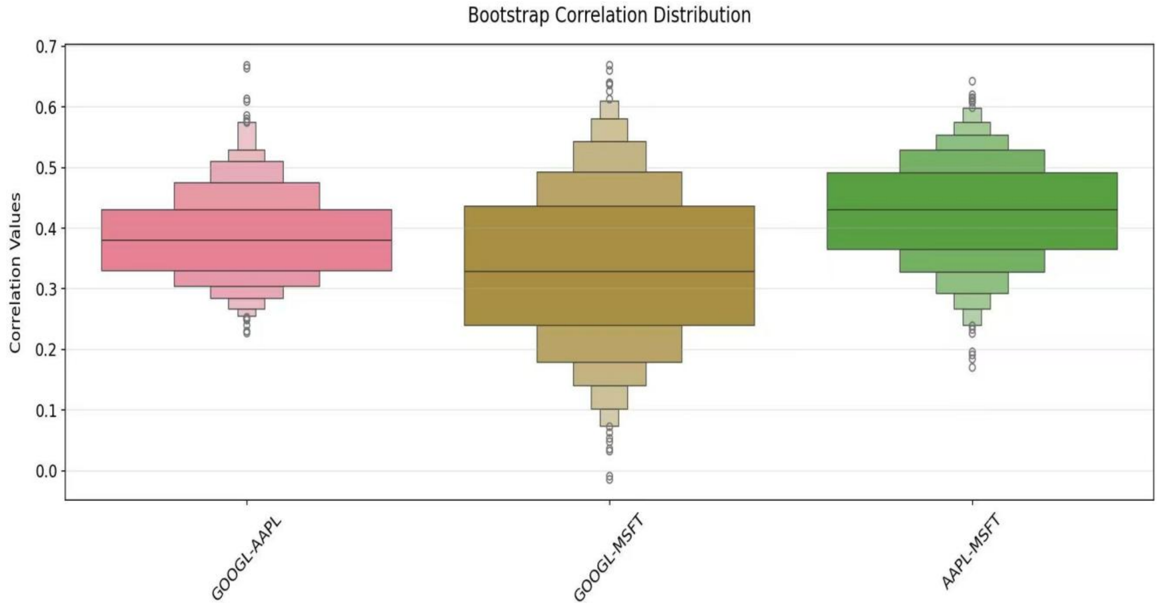

Fig.4: Bootstrap Correlation Distribution

The correlation between Apple (AAPL) and the interest rate is- 0.100, indicating that an increase in the interest rate may have a certain negative impact on its stock price. However, compared with other factors, this impact is not significant.

Correlation between Inflation Rate and Technology Stocks the correlation between Microsoft (MSFT) and the inflation rate is 0.033, indicating that inflation has a relatively small impact on its stock price. The correlation between Google (GOOGL) and the inflation rate is-0.071, showing a slight negative correlation, suggesting that an increase in inflation may have a weak negative impact on its stock price. The correlation between Apple (AAPL) and the inflation rate is-0.151, indicating that in a high-inflation environment, Apple’s stock price may face greater pressure, especially because high costs and low profit margins may limit its profit expectations. This aligns with Apple's business model, which is heavily exposed to global supply chains and consumer discretionary spending, making it particularly vulnerable to cost-push inflation and reduced purchasing power.

Correlation between GDP Growth Rate and Technology Stocks The correlation between Microsoft (MSFT) and the GDP growth rate is 0.228, indicating that technology companies may benefit during periods of economic growth, and their stock prices usually maintain a positive correlation with the trend of economic growth. Microsoft's strong positive correlation with GDP growth likely stems from its diversified enterprise-focused product suite (e.g., Azure cloud services, Office software), which benefits directly from increased business investment and IT expenditure during economic expansions. The correlation between Google (GOOGL) and the GDP growth rate is 0.125, showing a slight positive correlation between its stock price and GDP growth, but the impact is relatively small. The correlation between Apple (AAPL) and the GDP growth rate is-0.000755, showing almost no correlation, which means that the fluctuations of its stock price are not much affected by the economic growth rate, and it may be more related to its industry characteristics and market demand.

5. Discussion

5.1. Dynamic Correlations of Leading Technology Stocks

Analysis of the dynamic correlations between Google, Apple, and Microsoft shows that these companies have consistently maintained strong positive correlations. Notably, this correlation increases significantly during periods of greater market volatility, such as during the COVID-19 pandemic or during economic recessions. This observation is significant because it suggests that the diversification benefits typically enjoyed among technology stocks may be weakened during periods of market turmoil. This finding resonates with the financial contagion literature, demonstrating how idiosyncratic shocks can become systemic during stress periods, reducing the effectiveness of sector diversification. Specifically, when stocks fluctuate synchronously due to macroeconomic or overall market shocks, the diversified returns of holding many similar technology stocks may decrease, which may lead to higher portfolio risks for investors. This increased correlation means that when a technology stock experiences large price fluctuations due to economic events or policy changes, other stock tend to follow, thereby exacerbating overall market risk. This information is important for portfolio managers because it suggests that technology stocks, which are generally considered growth sectors, may not provide sufficient diversified risk protection during periods of heightened uncertainty.

5.2. Risk Contagion Effect

The constructed risk contagion index clearly shows the connection between market risk levels and stock correlations during periods of market stress. The results show that volatility and correlations between stocks rise in tandem during periods of market turmoil, such as the 2020 COVID-19 market crash. This suggests that risks in one stock can quickly spread to other tech stocks, a phenomenon known as the "contagion effect." During such periods of heightened uncertainty, systemic risk escalates, meaning that the entire tech sector is more vulnerable to shocks. The risk contagion index also highlights that as correlations between tech stocks rise, the sensitivity of the entire sector to economic and geopolitical events also increases. This important finding has far-reaching implications for both investors and policymakers. For investors, it emphasizes the need to monitor overall sector risks in addition to focusing on individual stock performance, while policy- makers should recognize that important sectors like technology may face higher financial stability risks during periods of economic stress.

5.3. Bidirectional Causality among Tech Giants

The contagion index I constructed clearly shows the relationship between market risk and stock market correlation. The key point is that especially in times of market stress, during periods of market turmoil (such as the outbreak of COVID-19 in 2020), stock volatility and correlation raise together (Yiming et al., 2024). We can see that the risk of one stock can quickly spread to other technology stocks, a phenomenon known as the "contagion effect". At the same time, during such periods of increased uncertainty, systemic risk is also rising. With the increase in systemic risk, we can see that the entire technology industry be- comes more fragile and more vulnerable to shocks. Through the contagion index, we can also see that when the correlation between technologies stocks increases, the sensitivity of the entire industry to economic and geopolitical events also increases with the increase in correlation. With this finding, it is very important for investors and policymakers (Raza et al., 1983). For investors, it reminds us not only to pay attention to the performance and operation of individual stocks, but also to the risks of the entire industry; at the same time, policy- makers need to be aware that in times of increased economic stress, key and vulnerable industries such as technology may face greater financial stability risks.

5.4. Macroeconomic factors and their impact on stock behavior

The impact of interest rates on technology stocks and the overall economy, Tech stocks and interest rates: When interest rates rise, Apple and Google's stock prices may be suppressed, especially in a market environment with high uncertainty. As high-risk assets, the valuation of technology stocks is susceptible to interest rate effects (Pham et al., 2025). However, there is little significant correlation between Microsoft's stock price and interest rates, which may be attributed to its advantages in capital-intensive industries and a relatively stable revenue model (Abd et al., 2025). The impact of interest rates on the economy:

High interest rates generally lead to slower economic activity, especially in the areas of consumption and corporate investment. High interest rates increase borrowing costs and reduce corporate and consumer spending, thereby affecting overall economic growth. For the technology industry, which relies on financing and innovation investment, rising interest rates may limit its growth potential.

5.5. The impact of inflation on technology stocks and the overall economy

Tech stocks and inflation: The negative correlation between Apple's stock price and inflation reflects that a high inflationary environment may lead to an increase in its production costs, thereby affecting profitability. In particular, when raw material and labor costs rise, Apple may face greater price pressure, which in turn affects its stock performance. Although the impact of inflation on Microsoft and Google is relatively small, a high inflationary environment may still have an impact on their earnings expectations in the long run. The impact of inflation on the economy: Rising inflation will curb consumer spending and increase corporate costs. For technology companies, this may lead to profit compression; for the overall economy, high inflation usually prompts central banks to tighten monetary policy, which further affects market liquidity and economic growth.

5.6. The impact of GDP growth rate on technology stocks and the overall economy

Technology stocks and GDP growth rate: There is a positive correlation between Microsoft and GDP growth rate, indicating that Microsoft can benefit when the economy grows, and the increase in market demand drives its stock price up. In contrast, the correlation between Apple and GDP growth rate is close to zero, indicating that the relationship between its stock price fluctuations and economic growth is weak. This may be because the global demand for Apple products has a certain degree of independence and is not completely dependent on overall economic growth. The impact of GDP growth rate on the economy: GDP growth is an important indicator of economic health. When the economy grows, consumer demand increases, corporate investment rises, and market vitality increases, this growth provides technology companies with greater market demand and development opportunities, promoting their innovation and expansion; conversely, when the GDP growth rate slows down, market demand weakens, corporate investment declines, and technology companies may face growth bottlenecks.

5.7. Policy Recommendations

In an environment of high inflation and high interest rates, policymakers can help the technology industry reduce financing pressure and support its continued growth by pro- viding more fiscal support and innovation incentives. Inflation Control: Policies should focus on controlling inflation, especially reducing production costs and lowering commodity prices to ease the cost pressure faced by technology companies. Economic growth should be supported: When economic growth slows down, the government should stimulate consumption and investment through fiscal policies, support innovation in the technology industry, and ensure growth during economic downturns.

6. Conclusion

This study examines the dynamic impact of macroeconomic policies, particularly interest rates, inflation, and GDP growth, on the stock price behavior of leading technology companies such as Google, Apple, and Microsoft. This study utilizes an information driven econometric framework that integrates Granger causality analysis, Kalman filtering, contagion index, and bootstrap validation, providing quantitative evidence and systematic insights. The results show that inflation places the greatest downward pressure on Apple, while GDP growth strongly benefits Microsoft, reflecting how business models interact differently with macroeconomic environments. At the system level, the contagion index confirms that the correlation between technology stocks intensifies during crises, reducing diversified returns and amplifying sector wide risks. In addition to financial impacts, this study also contributes to service science and informatics by treating the dynamics of technology inventory as a decision support problem. The integration of econometric models with information technology such as causal networks and risk contagion modeling provides a structured approach to monitor systemic risk, explain interdependence, and support policy and investment portfolio decisions in volatile environments. The research highlights that managing systemic risk in technology markets requires not only traditional financial models but also informatics-enabled tools capable of detecting dynamic correlations and contagion pathways in real time.

For practitioners, the findings provide actionable insights. Investors and portfolio managers can use contagion monitoring to recognize when diversification benefits diminish, adjusting strategies accordingly. Policymakers and regulators can leverage systemic indicators to anticipate vulnerabilities in the digital economy, particularly in technology-intensive sectors that are highly exposed to global shocks. For service providers, the study illustrates how informatics-based models can be embedded in risk management platforms to deliver resilience-oriented decision support.

Future research should extend this framework to a broader set of technology firms, apply high-frequency and alternative data sources, and incorporate nonlinear and machine learning models to capture hidden dynamics. Such work would deepen the intersection of financial econometrics with informatics, enabling more adaptive and service-oriented approaches to systemic risk management in the digital economy.

In conclusion, the paper shows that the dynamics of technology stocks under macroeconomic policies are not only a financial phenomenon but also an informatics and service science challenge. By integrating advanced econometric techniques with systemic risk modeling, this study strengthens the foundations for informed decision-making in finance, policy, and digital service management.

References

Deng, Y., Wang, Y., & Zhou, T. (2025). Macroeconomic expectations and expected returns. Journal of Financial and Quantitative Analysis, 60(4), 1760-1796.

Chishti, M. Z., & Dogan, E. (2024). Analyzing the determinants of renewable energy: the moderating role of technology and macroeconomic uncertainty. Energy & Environment, 35(2), 874-903.

Ansari, M. A. (2025). Tourism and economic growth: Evidence from cross-country data with policy insights. Journal of the Knowledge Economy, 16(1), 968-1013.

Ali, A., Umrani, Z., & Jadoon, A. K. (2025). Macroeconomic and Financial Determinants of Equity Market Value: Evidence from the UK Listed Firms. Journal of Social Signs Review, 3(4), 304-320.

Qiao, Y. (2025). Prediction of Macroeconomic indicators in China's Market based on Traditional Time Series model and LSTM Model. In Proceedings of the 2025 International Conference on Digital Economy and Information Systems (pp. 340-350).

Zhang, Q., Wu, P., Li, R., & Chen, A. (2024). Digital transformation and economic growth Efficiency improvement in the Digital media era: Digitalization of industry or Digital industrialization?. International Review of Economics & Finance, 92, 667-677.

Fikriyah, N. F., & Yuliana, I. (2025). Sectoral Market Sensitivities to Macroeconomic Signals and Global Moderators in a Digitally Shifting Investment Landscape. Journal of Social Commerce, 5(2), 136-156.

Munyo, I., & Veiga, L. (2024). Entrepreneurship and economic growth. Journal of the Knowledge Economy, 15(1), 319-336.

Odunaike, A. (2025). Integrating real-time financial data streams to enhance dynamic risk modeling and portfolio decision accuracy. Int J Comput Appl Technol Res, 14(08), 1-16.

Camanho, A. S., Silva, M. C., Piran, F. S., & Lacerda, D. P. (2024). A literature review of economic efficiency assessments using Data Envelopment Analysis. European Journal of Operational Research, 315(1), 1-18.

Zhang, C., Waris, U., Qian, L., Irfan, M., & Rehman, M. A. (2024). Unleashing the dynamic linkages among natural resources, economic complexity, and sustainable economic growth: Evidence from G‐20 countries. Sustainable Development, 32(4), 3736-3752.

Stanimirovic, T., Klun, M., & Kotnik, Z. (2025). Fiscal Measures For Green Transition And Their Influence On Macroeconomic Indicators: Case Of Slovenia. Review of Economic and Business Studies, (35), 61-70.

Hargyatni, T., Purnama, K. D., & Aninditiyah, G. (2024). Impact analysis of artificial intelligence utilization in enhancing business decision-making in the financial sector. Journal of Management and Informatics, 3(2), 282-296.

Batuparan, D. S., Wahyuni, S., & Sudhartio, L. (2025). Business Model Innovation and Digitalization in SME Internationalization: The Mediating Role of Internationalization Process. Journal of Logistics, Informatics and Service Science, 12(4), 18-37.

Fama, E. F. (1981). Stock returns, real activity, inflation, and money. The American economic review, 71(4), 545-565.

Bernanke, B. S., & Kuttner, K. N. (2005). What explains the stock market's reaction to Federal Reserve policy?. The Journal of finance, 60(3), 1221-1257.

Tsai, H. W., Che, H. C., & Bai, B. (2021). Exploring Patent Effects on Higher Stock Price and Stock Return Rate—A Study in China Stock Market. Chinese Business Review, 20(5), 168-180.

Barberis, N., Huang, M., & Santos, T. (2001). Prospect theory and asset prices. The quarterly journal of economics, 116(1), 1-53.

Brogaard, J., Li, D., & Xia, Y. (2017). "Stock liquidity and default risk". Journal of Financial Economics, 124(3), 486–502

Allen, F., & Gale, D. (2000). Financial contagion. Journal of political economy, 108(1), 1-33.

Forbes, K. J., & Rigobon, R. (2002). No Contagion, Only Interdependence: Measuring Stock Market Comovements. Journal of Finance, 57 (5), 2223-2261.

Horváth, R., Lyócsa, Š., & Baumöhl, E. (2018). Stock market contagion in Central and Eastern Europe: unexpected volatility and extreme co-exceedance. The European Journal of Finance, 24(5), 391-412.

Wang, Y., & Rey, W. P(2025). Construction of MEC Task Offloading Strategy and Risk Assessment Model Based on Multi-objective Optimization . Journal of Logistics, Informatics and Service Science, 12(4), 295-315.

Durbin, J., & Koopman, S. J. (2012). Time series analysis by state space methods. Oxford university press.

Poncela, P., Ruiz, E., & Miranda, K. (2021). Factor extraction using Kalman filter and smoothing: This is not just another survey. International Journal of Forecasting, 37(4), 1399-1425.

Hamilton, J. D. (2020). Time series analysis. Princeton university press.

Granger, C. W. (1969). Investigating causal relations by econometric models and cross-spectral methods. Econometrica: journal of the Econometric Society, 424-438..

Bonacich, P. (2007). Some unique properties of eigenvector centrality. Social networks, 29(4), 555-564.

An, W., Beauvile, R., & Rosche, B. (2022). Causal network analysis. Annual Review of Sociology, 48(1), 23-41.

Diebold, F. X., & Yilmaz, K. (2012). Better to give than to receive: Predictive directional measurement of volatility spillovers. International Journal of forecasting, 28(1), 57-66.

Politis, D. N., & Romano, J. P. (1994). The stationary bootstrap. Journal of the American Statistical association, 89(428), 1303-1313.

Horowitz, J. L. (2019). Bootstrap methods in econometrics. Annual Review of Economics, 11(1), 193-224..

White, H. (1982). Maximum likelihood estimation of misspecified models. Econometrica: Journal of the econometric society, 1-25.

Horowitz, J. L. (1992). A smoothed maximum score estimator for the binary response model. Econometrica: journal of the Econometric Society, 505-531.

Yiming, W., Xun, L., Umair, M., & Aizhan, A. (2024). COVID-19 and the transformation of emerging economies: financialization, green bonds, and stock market volatility. Resources Policy, 92, 104963.

Raza, A., Asif, L., Türsoy, T., Seraj, M., & Erkol Bayram, G. (2025). Macro-economic indicators and housing price index in Spain: fresh evidence from FMOLS and DOLS. International Journal of Housing Markets and Analysis, 18(1), 227-248.

Pham, C. T. B., Nguyen, L. H., & Vu, T. T. M. (2025). Audit Quality, Foreign Ownership, and Stock Price Synchronicity: Evidence from Vietnam's Emerging Market. Journal of Logistics, Informatics and Service Science, 12(1): 39-54.

Abd Elghany, M. (2025). Advanced Technologies and International Business: A Comprehensive Review of Digital Transformation in Global Operations. Journal of Logistics, Informatics and Service Science, 12(1), 231-262.