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EXAMINING THE VOLATILITY SPILLOVER BETWEEN THE FEAR INDEX AND THE MAGNIFICENT SEVEN TECHNOLOGY STOCKS

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Abstract

This study investigates the volatility spillover dynamics between the VIX fear index and the Magnificent Seven technology stocks - namely Microsoft, Apple, Nvidia, Amazon, Alphabet, Meta Platforms, and Tesla - over the period of June 2012 to March 2024. To achieve this objective, the variance causality test is employed to detect potential volatility transmissions among the series. Preliminary diagnostic tests confirm the validity of the GARCH (1,1) specification for all individual return series. The results from the variance causality analysis indicate significant volatility spillovers from the VIX to the conditional variances of Microsoft, Alphabet, Meta Platforms, Nvidia, and Amazon stocks. Building on these findings, impulse-response functions and variance decomposition analyses are conducted based on the conditional variance series estimated through the GARCH (1,1) model. The impulse-response analysis reveals that a positive shock in the VIX generates a temporary increase in the conditional volatility of Apple, Alphabet, Nvidia, and Tesla stocks, which gradually diminishes over time. Conversely, a VIX shock induces a negative volatility response in Meta Platforms, Microsoft, and Amazon stocks, although these effects also fade and converge to zero in the long run. Variance decomposition results further show that, in the short term, the volatility of each technology stock is predominantly driven by its own internal dynamics. However, as the forecast horizon extends, the influence of the VIX index becomes increasingly pronounced, underscoring its role as a significant external volatility driver. These findings imply that investors' perceptions of heightened risk - captured by the VIX index - are effectively transmitted to technology stock markets. Accordingly, the incorporation of the VIX index into volatility forecasting models can enhance prediction accuracy. From a practical standpoint, the study underscores the importance of monitoring the fear index when developing portfolio allocation and risk management strategies-oriented equities.

JEL classification: G11, G15, G17
Keywords: Volatility, Volatility Spillover, Technology Stock

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Introduction

Global financial markets are significantly influenced by global events. While globalization has deepened markets and increased transaction volumes, negative events such as wars, natural disasters, and pandemics have also had adverse effects (De la Torre et al., 2007, Shaik et al., 2023; Aksoy & Yilmaz, 2024). These dynamics often lead to shifts in investor risk appetite (Gemici et al., 2023). When risk appetite is high, transaction volumes and stock indices rise; conversely, in low-risk periods, sell-offs dominate (Hoffmann et al., 2015). Various indicators are used to measure investor sentiment, among which the VIX (Volatility) index is frequently referenced (Chiang, 2012; Daniali et al., 2021; Wang et al., 2022). The VIX, developed by Robert E. Whaley, was introduced by the Chicago Board Options Exchange on January 19, 1993, to measure stock market volatility (Mehta, 2015; Moran & Liu, 2020). Initially based on S&P100 option prices (Whaley, 1993), the methodology shifted to S&P500 (SPX) options in 2003 due to rising trading volumes (Whaley, 2009). The index uses the weighted average of call and put options expiring in 23–37 days, forecasting volatility over the next 30 days (Ozair, 2014). VIX values below 20% signal low volatility, and values above 30% reflect high volatility (Taspunar et al., 2016; Iskenderoglu & Akdag, 2020). High volatility implies increased risk and expected market sell-offs, while low volatility indicates reduced investor fear. Therefore, an increase in the VIX usually corresponds to falling stock indices, indicating an inverse relationship (Kao et al., 2020; Russon & Vakil, 2017; Sarıtas & Nazlıoglu, 2019; Whaley, 2000). In this context, the VIX is widely recognized as the "investor fear index" and serves as an important volatility indicator. Its time-varying behavior during uncertainty supports the theory of investor sentiment by reflecting changes in investor attitudes (Nur, 2021).

Fluctuations in financial markets often lead investors to be more selective, prioritizing technology companies with strong future potential. At the forefront of this trend are the Magnificent Seven: Microsoft, Apple, Nvidia, Alphabet, Amazon, Meta, and Tesla. These companies draw significant investor interest as they are seen as leaders in technology and artificial intelligence, demonstrate rapid growth and high profit margins, face limited competition in their sectors, and are widely viewed as safe-haven assets for the future.

This study aims to examine the volatility spillover between the VIX fear index and the stock returns of the Magnificent Seven companies during the period June 2012 to March 2024. Data available for Meta Platforms, one of the Magnificent Seven companies, begins as of June 2012. This date constitutes the first frequency of the study data set. The last date for which data is available during the study period constitutes the last frequency of the data set. However, the main reason for including the companies referred to as the Magnificent Seven in the research sample is their strong financial structures, high growth potential, and the intense interest and expectations they generate among investors. Their role as global trend setters, particularly in the technology sector, makes these companies a meaningful sample for examining systematic risk and volatility dynamics in financial markets. The stocks of the Magnificent Seven have attracted the attention and imagination of investors with their extraordinary performance, but this high level of interest has also brought some challenges. The dominant position of the Magnificent Seven in the market raises important structural issues such as market concentration, reduced competition, the risk of excessive dependence on a few key players, and a tendency to follow popular investment trends (Holder & Almada, 2025). On the other hand, Eteman (2024) states that the rapid increase in investments in Artificial Intelligence (AI) technologies in recent years has played a decisive role in the value gains of these companies and has attracted significant attention in global financial markets. Additionally, he highlights that the fluctuations observed in the market values of AI-focused companies such as Nvidia and Tesla have the potential to cause serious shocks to the global financial system. Given the leading position of these firms in the market, it is important to examine the interaction between these firms and market-based risk indicators such as the VIX, particularly in the context of volatility spillovers.

Volatility spillover refers to the transmission of risk across markets and has become increasingly significant in today's interconnected financial systems, especially during external shocks. Understanding this concept is essential for risk management, portfolio optimization, and forecasting market behavior (Alamaren et al., 2024). The study contributes to the literature by identifying the spillover effect between VIX and the Magnificent Seven. Previous research generally finds a negative relationship between the VIX and stock returns (Chandra & Thenmozhi, 2015; Fountain et al., 2008; Topaloglu, 2019), though some report a positive link (Kanas, 2012; Qadan et al., 2019), suggesting period- and sample-based differences. Thus, this research offers new insights into their interrelation, helping investors assess spillover risk and develop more effective strategies. In sum, the study provides a new perspective on the link between the VIX, and technology companies and provides useful insights for investors, portfolio managers, and market participants on the impact of changes in the VIX index on the risk-return characteristics of their portfolios.

Literature review

The relationship between the VIX index and stock returns has long been a focus of academic research. Many studies have explored this connection across various time frames and markets. Modern portfolio theory, rooted in Markowitz's mean-variance model (1952), assumes that investors are rational and risk-averse - a view also upheld by the CAPM (Sharpe, 1964) and APT (Ross, 1976). Based on this, the VIX, known as a market risk indicator, is often linked to stock performance. For example, Sarwar (2012) found that the VIX significantly and asymmetrically affects the S&P100, S&P500, and S&P600. Similarly, Wang et al. (2014) observed a positive link between the VIX and CSI300 volatility. The fact that the VIX index has a statistically significant effect on particularly indicative indices demonstrates how important this variable is in the investment decision-making process in financial markets. However, depending on the scope and methodology used, some studies have found opposite results. Sarwar (2014) concluded that the VIX had no impact before the European equity crisis but significantly affected both US and European indices afterward, with a stronger effect on European markets. This finding is considered important in that it demonstrates the importance that risk-averse rational investors attach to risk variables. However, Ruan (2018) also found a significant influence on the S&P500. Grima et al. (2021) showed a cointegration relationship between COVID-19 cases, the VIX, and major global indices. The VIX had the strongest negative effect on DAX (-23.26%) and FTSE100 (-22.15%), while the SSEC (-4.45%) was least affected. The findings obtained in this study are considered important from two perspectives. First, it is proven that the importance and impact level of the VIX index may vary on a regional basis. Second, it can be said that the VIX index continues to be sensitive to crises. Another study with findings in the opposite direction by Vartanian and Neto (2023) analyzed Latin America and G7 stock indices and found the VIX impacted returns in all periods except during COVID-19. Therefore, it can be stated that the regional differences observed in the VIX index are also valid for the crisis period. A different perspective by Tran and Vo (2023), analyzing 1985 - 2022 data for 11 Pacific countries, concluded that VIX increases have a stronger effect than decreases. Altinkeski et al. (2024) found that high returns can be achieved when the VIX index is low, and low returns can be achieved when the index is high.

Another key area in the literature is whether the VIX reliably predicts market volatility. Bekaert and Hoerova (2014) found stock variance to be a stronger indicator during crises. Differently, Fu et al. (2016) showed put-based VIX estimates better predict future returns. Therefore, it can be said that the predictive power of VIX may vary depending on scope and period factors. Shu and Chang (2019) confirmed the VIX as a leading volatility measure across US, Europe, and Asia. Likewise, Wang (2019) found the VIX outperformed alternative indicators in explaining global equity volatility. These studies emphasize that the VIX index can be considered an indicator of volatility in the global economy in recent times. On the other hand, Bayramlı et al. (2022) compared VIX and CDS premiums using BIST30 and Participation30 indices. They found the VIX more effective in the post-COVID period, especially for Participation30. This finding demonstrates the importance of measuring different types of risk using the VIX and CDS indices. However, the fact that the VIX index is more sensitive to financial markets strengthens the explanatory power of the findings. Bonaparte et al. (2023) suggested that VIX may not fully capture future volatility due to limitations in option price-based estimations. Bangsgaard and Kokholm (2024) found that VIX futures led S&P500 futures during high volatility periods. Similarly, Aikins and Kurov (2025) found statistically significant relationships between VIX futures and S&P 500 futures. Therefore, it can be stated that the power of the VIX index in predicting volatility in futures may vary depending on the scope of the study and the period. Shah (2024), who investigated the same topic using a different methodology, identified a bidirectional Granger causality relationship between the VIX index and S&P 500 index volatility.

Literature gap

The VIX index is widely accepted as an indicator of global market volatility and is frequently used to assess investor behavior. Additionally, it is frequently included in models for predicting volatility in futures markets. However, when examining previous empirical studies focusing on the relationship between the VIX index and markets, it is notable that findings vary, and no consensus has been reached on this matter. This indicates that the topic remains current and open to discussion. To the best of our knowledge, there are only a limited number of studies examining the relationship between the VIX index and the returns of technology stocks. Furthermore, given the rapid advancement of the technology age and the critical role that companies operating in this sector play in shaping the future, as well as the intense interest they attract from investors, the importance of this topic is increasing. Within this framework, the present study aims to analyze the volatility spillover between the VIX index, and the stock returns of the leading technology companies known as the "Magnificent Seven". In this context, it is anticipated that the study will both fill an important gap in the literature and provide meaningful insights for investors.

Methodology

Data

This study investigates the volatility spillover between the VIX fear index and the stock returns of the Magnificent Seven - namely Microsoft (MSFT), Apple (AAPL), Nvidia (NVDA), Amazon (AMZN), Alphabet (GOOGL), Meta Platforms (META), and Tesla (TSLA). The VIX index is employed as the proxy for market volatility, while individual stock data represent technology sector performance. All data were sourced from www.investing.com. Due to the availability of data for Meta Platforms (META) beginning in June 2012, the analysis period was determined as June 2012 to March 2024. The dataset consists of monthly observations for each variable. There are several fundamental reasons why the data set used in this study consists of monthly observations. Data obtained at daily or weekly frequencies are overly sensitive to short-term market fluctuations and speculative movements. Agrawal et al. (1999) state that when ARCH-GARCH models are estimated in analyses using daily data sets, autocorrelation between error terms causes difficulties in determining the appropriate model, particularly during the model selection stage. Second, from a scope perspective, the use of monthly data allows for a longer analysis period (Baumeister & Guerin, 2021). Additionally, Jacobsen and Dannenburg (2003) tested the extent to which direct estimates made with low-frequency data are consistent with implicit estimates obtained from high-frequency data; their findings indicate that these two estimates are highly consistent with each other in most cases. Table 1 presents the definitions and details of the variables used in the empirical analysis.

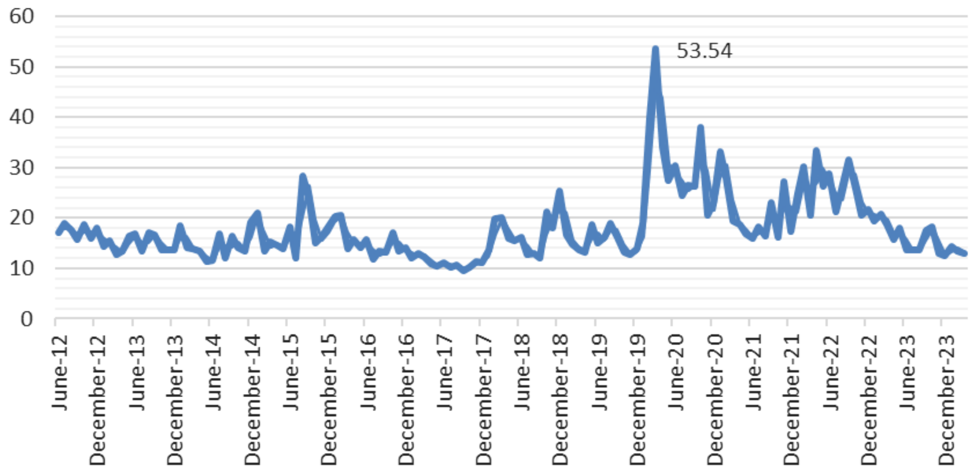
Table 1: Explanatory information on variables

Variables	Acronym	Volatility Calculated	Scope
Dependent Variables	MSFT	GARCH (1,1)	06.2012 - 03.2024
	AAPL		
	NVDA		
	AMZN		
	GOOGL		
	META		
	TSLA		
Independent Variable	VIX		

Source: Author's own work.

The time-series behavior of the VIX index throughout the analysis period is shown in Figure 1. The VIX index peaked at 53.54% in March 2020, coinciding with the World Health Organization's declaration of the COVID-19 pandemic, indicating an increase in market fear and volatility.

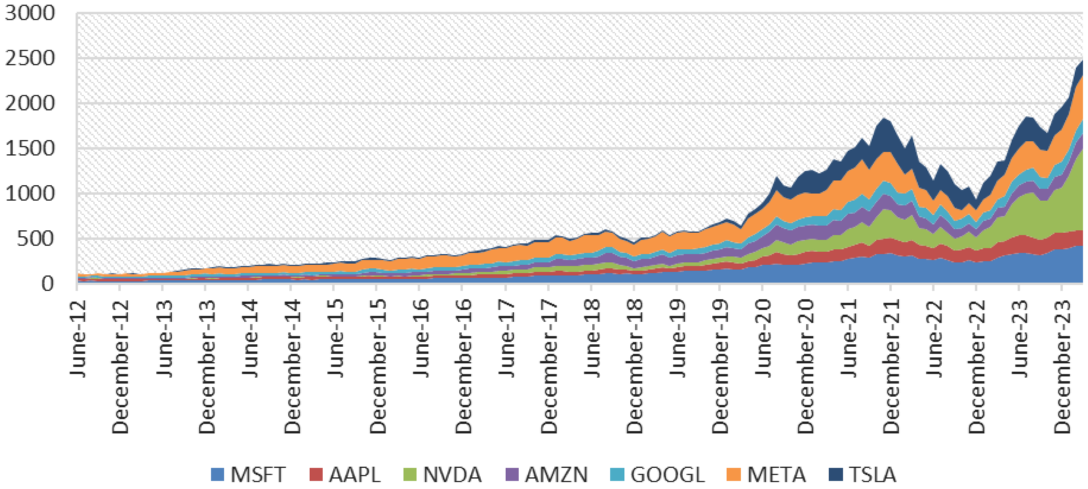
Figure 1: VIX index



Source: Investing.com (2024).

Figure 2 shows the total value trends of the companies known as the Magnificent Seven, ranked according to their market capitalization based on their closing stock prices on March 23, 2024.

Figure 2: Trends in total value of the Magnificent Seven technology companies



Source: Investing.com (2024).

Microsoft leads with a market value of $3.19 trillion, followed by Apple ($2.66 trillion), Nvidia ($2.36 trillion), Alphabet ($1.88 trillion), Amazon ($1.86 trillion), Meta Platforms ($1.30 trillion), and Tesla ($535.29 billion). Since November 2022, Nvidia's market share within the group has notably increased, making it the most heavily weighted stock in February 2024, with Microsoft ranking second. The overall trend in the graph shows that nearly all these companies have experienced a steady increase in total value over time.

Empirical models and estimation strategy

Engle (1982) developed the autoregressive conditional variance model (ARCH) to better understand the dynamic aspect of financial assets and to estimate the time-varying variance. In this model, unconditional variance is assumed constant (Engle, 2001). There are some limitations in the ARCH model because the unconditional variance is assumed constant and long lags are used (Topaloglu, 2020). In addition, numerous parameters are required for forecasting using the ARCH model, which reduces the model's forecasting power and makes it complex (Bollerslev, 1986). Due to these limitations, Bollerslev (1986) developed Engle's ARCH model and created the GARCH model (Engle, 2001). With the GARCH model, conditional variance is expressed as both its own past value and the square of the error term (Ural, 2009). Thus, the predictive power of the model becomes more realistic and is improved. For this reason, the GARCH model was preferred in this study. The equation of the Generalized Autoregressive Conditional Heteroskedastic (GARCH) model developed by Bollerslev (1986) is as follows:

$$r_t = \phi_0 + \sum_{i=1}^{S} \phi r_{t-i} + \varepsilon_t \tag{1}$$

$$\varepsilon_t = \sqrt{h_t} * z_t \tag{2}$$

$$h_t = a_0 + \sum_{i=1}^{q} ai\varepsilon_{t-i}^2 \sum_{i=1}^{p} \beta h_{t-j} \tag{3}$$

The equations above define the stochastic process of the GARCH model. In equation 3, which is the final form of the model, represents the conditional variance series, represents the constant coefficient, represents the ARCH effect, and represents the GARCH effect. Granger's (1969) concept of causality refers to the power of one variable to predict another. In previous variance tests, Granger causality (Cheung & Ng, 1996; Hong, 2001) relied on the cross-correlation functions (CCF) of the standardized residuals of two series. However, these tests suffer from the problem of overdimensionality in small samples. In contrast, Hafner and Herwartz's (2006) LM-based Granger variance causality test, a more robust approach, overcomes these limitations. (Nazlıoglu et al., 2015). The equational representation of Hafner and Herwartz's (2006) test for causality in variance is as follows.

$$\epsilon_{it} = \xi_{it}\sqrt{\sigma_{it}^2}(1 + Z_j^{'}\pi) \tag{4}$$

$$Z_{jt} = (\epsilon_{jt-1}^2, \sigma_{jt-1}^2) \tag{5}$$

Where:
ξ_{it} = standardized residual,
σ_{it}^2 = conditional variance for series i.

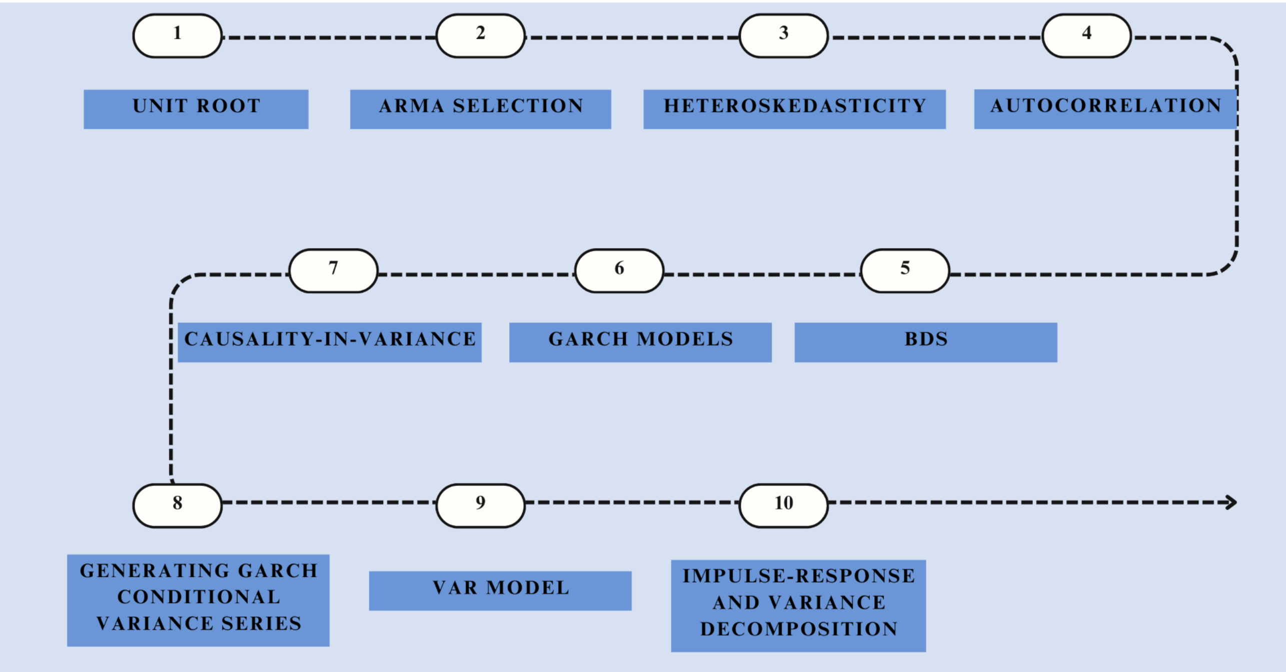
The H_0 hypothesis of the test states that there is no causality (H_0: $\pi = 0$), while the alternative hypothesis states that there is causality (H_1: $\pi \neq 0$). In this context, the econometric equation used for the volatility spillover of the test is as follows.

$$\lambda_{LM} = \frac{1}{4T}\left(\sum_{t=1}^{T}(\xi_{it}^{2}-1)Z'_{jt}\right)V(\theta_j)^{-1}\left(\sum_{t=1}^{T}(\xi_{it}^{2}-1)Z_{jt}\right) \tag{6}$$

$$V(\theta_j) = \frac{K}{4T}\left(\sum_{t=1}^{T} Z_{jt}Z'_{jt} - \sum_{t=1}^{T} Z_{jt}X'_{it}\left(\sum_{t=1}^{T} X_{it}X'_{it}\right)^{-1} \sum_{t=1}^{T} X_{it}Z'_{jt}\right), K = \frac{1}{T}\sum_{t=1}^{T}(\xi_{it}^{2}-1)^{2} \tag{7}$$

The asymptotic distribution of the test statistic in the econometric equation above depends on the specification errors in the Z_{jt} series. In this context, since there are two different Z_{jt} series in the λ_{LM} equation, it can be said that the asymptotic distribution depends on two degrees of freedom. Rejection of the null hypothesis of the test implies that volatility spills over from the j series to the i series, whereas failure to reject the null hypothesis implies the opposite. The analysis process applied in the study is summarized in Figure 3.

Figure 3: The analysis process



Source: Author's own work.

As explained in detail in the methodology section, the analysis process applied in this study consists of unit root tests, volatility analyses, determination of volatility spillover relationships, and impact-response and variance decomposition analyses performed by establishing a VAR model.

Results

Descriptive stats and unit root

According to the descriptive statistics (Table 2), the variable with the highest mean value is VIX (2.83) while the variable with the lowest mean value is AAPL (0.006). However, the variable with the highest median value is VIX (2.78), while the variable with the lowest median value is TSLA (0.004). On the other hand, the null hypothesis of the Jarque-Bera test states that the series express normal distribution, while the alternative hypothesis states the opposite (Sadat & Hasan, 2019). Jarque-Bera probability values indicate that MSFT, AAPL, GOOGL and AMZN series are normally distributed, while the other series are not. Skewness and Kurtosis results also support this finding.

Table 2: Descriptive statistics

Stats	MSFT	AAPL	NVDA	GOOGL	AMZN	META	TSLA	VIX
Mean	0.00	0.00	0.01	0.00	0.00	0.00	0.01	2.83
Median	0.00	0.00	0.01	0.00	0.01	0.00	0.00	2.78
Maximum	0.07	0.08	0.14	0.08	0.10	0.16	0.25	3.98
Minimum	-0.06	-0.08	-0.16	-0.08	-0.11	-0.17	-0.19	2.25

Stats	MSFT	AAPL	NVDA	GOOGL	AMZN	META	TSLA	VIX
Skewness	0.04	-0.27	-0.42	-0.18	-0.10	-0.49	0.48	0.86
Kurtosis	3.22	2.55	3.96	3.35	3.79	5.79	3.74	3.67
Jarque-Bera	0.33	2.89	9.66	1.52	3.93	51.84	8.79	20.13
Probability	0.84	0.23	0.00	0.46	0.13	0.00	0.01	0.00

Source: Author's own work.

Fourier-based tests that take structural breaks into account were used in the unit root test of the study. Of these tests, the Fourier ADF test tests for the presence of a unit root in the series under the null hypothesis, while the Fourier KPSS test tests for the stationarity of the series under the null hypothesis (Cil, 2023). Therefore, it can be said that the hypotheses of the tests were formulated in opposite directions and that both tests confirmed each other's validity. According to the results of Fourier ADF and Fourier KPSS unit root tests (Table 3), all variables used in the study are stationary at I(0) level. Fourier ADF and Fourier KPSS test results support each other, and all variables used in the study do not have unit root at the level.

Table 3: Unit root results

Variables	Fourier ADF		Fourier KPSS	
	Level		Level	
	Constant	+ Trend	Constant	+ Trend
	ADF Statistic Values		KPSS Statistics Values	
MSFT	-13.79***	-13.80***	0.11***	0.06***
AAPL	-9.31***	-9.36***	0.03***	0.06***
NVDA	-11.80***	-11.90***	0.17***	0.07***
GOOGL	-4.83***	-4.86***	0.03***	0.03***
AMZN	-13.31***	-13.32***	0.14***	0.06***
META	-3.70**	-3.80**	0.07***	0.04***
TSLA	-5.03***	-5.27***	0.08***	0.08***
VIX	-4.41***	-4.77***	0.11***	0.06***
Critical Values	Constant Model %1(-3.77) %5(-3.07) %10(-2.71) + Model %1(-4.45) %5 (-3.78) %10(-3.44)		Constant Model %1(0.33) %5(0.44) %10(0.71) + Trend Model %1(0.11) %5 (0.14) %10(0.21)	

***, and ** indicate respectively statistical significance at the 1, and 5 percent levels

Source: Author's own work.

ARMA selection, heteroscedasticity, autocorrelation and BDS test

In order to perform ARCH/GARCH hypothetical tests, the least lagged ARMA model should be selected first (Yıldırım & Bekun, 2023). According to the ARMA results for the variables considering the Schwarz information criterion (Table 4), ARMA (0,0) for the Magnificent Seven stocks and ARMA (1,1) for the VIX fear index are determined as the most appropriate model.

Table 4: ARMA selection

MSFT	0	1	2	3	4	5
0	-4.45	-4.41	-4.39	-4.39	-4.39	-4.38
1	-4.41	-4.38	-4.38	-4.38	-4.37	-4.37
2	-4.39	-4.38	-4.36	-4.36	-4.36	-4.36
3	-4.39	-4.38	-4.36	-4.36	-4.36	-4.36
4	-4.39	-4.37	-4.36	-4.36	-4.40	-4.35
5	-4.38	-4.37	-4.36	-4.36	-4.35	-4.35
AAPL	**0**	**1**	**2**	**3**	**4**	**5**
0	-3.87	-3.81	-3.82	-3.80	-3.80	-3.80
1	-3.81	-3.79	-3.79	-3.77	-3.77	-3.77
2	-3.82	-3.79	-3.78	-3.79	-3.78	-3.78

AAPL	0	1	2	3	4	5
3	-3.80	-3.77	-3.79	-3.77	-3.77	-3.77
4	-3.80	-3.77	-3.78	-3.77	-3.79	-3.77
5	-3.80	-3.77	-3.78	-3.77	-3.77	-3.77
NVDA	**0**	**1**	**2**	**3**	**4**	**5**
0	-3.01	-2.94	-2.94	-2.94	-2.95	-2.94
1	-2.94	-2.91	-2.91	-2.90	-2.92	-2.91
2	-2.94	-2.91	-2.92	-2.91	-2.92	-2.92
3	-2.94	-2.90	-2.91	-2.91	-2.92	-2.91
4	-2.95	-2.92	-2.92	-2.92	-2.92	-2.92
5	-2.94	-2.91	-2.91	-2.91	-2.92	-2.91
GOOGL	**0**	**1**	**2**	**3**	**4**	**5**
0	-4.23	-4.18	-4.16	-4.16	-4.17	-4.16
1	-4.18	-4.15	-4.15	-4.15	-4.16	-4.15
2	-4.16	-4.15	-4.13	-4.12	-4.13	-4.13
3	-4.16	-4.15	-4.12	-4.12	-4.13	-4.13
4	-4.17	-4.16	-4.13	-4.14	-4.14	-4.14
5	-4.16	-4.15	-4.13	-4.13	-4.14	-4.13
AMZN	**0**	**1**	**2**	**3**	**4**	**5**
0	-3.73	-3.67	-3.66	-3.66	-3.66	-3.66
1	-3.67	-3.63	-3.63	-3.63	-3.63	-3.63
2	-3.66	-3.63	-3.62	-3.62	-3.62	-3.62
3	-3.66	-3.63	-3.62	-3.62	-3.62	-3.62
4	-3.66	-3.63	-3.62	-3.62	-3.62	-3.62
5	-3.66	-3.63	-3.62	-3.62	-3.62	-3.63
META	**0**	**1**	**2**	**3**	**4**	**5**
0	-3.19	-3.13	-3.12	-3.12	-3.12	-3.12
1	-3.13	-3.09	-3.09	-3.10	-3.09	-3.09
2	-3.12	-3.09	-3.09	-3.09	-3.09	-3.09
3	-3.12	-3.10	-3.09	-3.09	-3.09	-3.09
4	-3.12	-3.09	-3.09	-3.09	-3.09	-3.09
5	-3.12	-3.09	-3.09	-3.09	-3.09	-3.09
TSLA	**0**	**1**	**2**	**3**	**4**	**5**
0	-2.35	-2.28	-2.27	-2.27	-2.33	-2.27
1	-2.28	-2.25	-2.25	-2.24	-2.31	-2.24
2	-2.27	-2.25	-2.25	-2.24	-2.30	-2.24
3	-2.27	-2.25	-2.24	-2.24	-2.30	-2.24
4	-2.33	-2.31	-2.30	-2.30	-2.30	-2.29
5	-2.27	-2.25	-2.24	-2.24	-2.30	-2.24
VIX	**0**	**1**	**2**	**3**	**4**	**5**
0	0.55	0.24	0.33	0.42	0.49	0.47
1	-0.05	-0.07	-0.03	-0.02	-0.02	-0.03
2	0.17	-0.04	0.18	0.21	0.21	0.20
3	0.33	0.17	0.27	0.33	0.36	0.36
4	0.40	0.17	0.20	0.40	0.41	0.42
5	0.43	0.18	0.28	0.39	0.44	0.46

Source: Author's own work.

Identifying the ARCH-LM effect in the specified ARMA models is important for selecting the tests to be used in the next stage (Epaphra, 2017). For ARMA models (Table 5), there is a problem of heteroscedasticity in all series and autocorrelation in all series except AAPL and TSLA.

Table 5: Test results for heteroscedasticity and autocorrelation

ARMA (0,0)	Heteroscedasticity				Autocorrelation			
MSFT								
	F-stat.	F-stat. P.	Observed R^2	R^2 Significance	AC	PAC	Q-Stat	Prob
Lag 1	33.80	0.00	27.50	0.00	0.44	0.44	28.20	0.00
Lag. 5	6.87	0.00	28.39	0.00	0.03	0.06	36.46	0.00
Lag 10	3.35	0.00	28.58	0.00	-0.08	-0.05	39.03	0.00
Lag 20	1.85	0.02	32.71	0.03	-0.12	-0.01	49.27	0.00
AAPL								
	F-stat.	F-stat. P.	Observed R^2	R^2 Significance	AC	PAC	Q-Stat	Prob
Lag 1	26.62	0.00	22.64	0.00	0.10	0.10	1.41	0.23
Lag. 5	16.62	0.00	53.59	0.00	0.03	0.05	2.73	0.74
Lag 10	9.78	0.00	60.40	0.00	-0.07	-0.08	5.22	0.87
Lag 20	5.32	0.00	66.11	0.00	0.02	-0.04	16.30	0.69
NVDA								
	F-stat.	F-stat. P.	Observed R^2	R^2 Significance	AC	PAC	Q-Stat	Prob
Lag 1	52.52	0.00	38.59	0.00	0.32	0.32	14.84	0.00
Lag. 5	21.24	0.00	61.91	0.00	0.22	0.14	34.81	0.00
Lag 10	10.99	0.00	64.40	0.00	0.04	-0.05	55.90	0.00
Lag 20	6.25	0.00	71.75	0.00	-0.05	-0.09	63.49	0.00
GOOGL								
	F-stat.	F-stat. P.	Observed R^2	R^2 Significance	AC	PAC	Q-Stat	Prob
Lag 1	70.37	0.00	47.28	0.00	0.31	0.31	14.42	0.00
Lag. 5	29.43	0.00	73.28	0.00	0.07	0.12	16.84	0.00
Lag 10	17.19	0.00	79.98	0.00	-0.02	-0.03	21.70	0.01
Lag 20	10.13	0.00	88.19	0.00	0.00	-0.06	23.45	0.26
AMZN								
	F-stat.	F-stat. P.	Observed R^2	R^2 Significance	AC	PAC	Q-Stat	Prob
Lag 1	65.44	0.00	45.03	0.00	0.38	0.38	20.68	0.00
Lag. 5	25.64	0.00	68.45	0.00	-0.05	0.02	25.22	0.00
Lag 10	14.61	0.00	74.36	0.00	0.01	-0.07	28.30	0.00
Lag 20	7.50	0.00	78.10	0.00	-0.08	-0.08	37.82	0.00
META								
	F-stat.	F-stat. P.	Observed R^2	R^2 Significance	AC	PAC	Q-Stat	Prob
Lag 1	40.08	0.00	31.51	0.00	0.25	0.25	9.24	0.00
Lag. 5	12.18	0.00	43.75	0.00	0.08	0.08	12.90	0.02
Lag 10	7.26	0.00	50.45	0.00	0.05	-0.05	30.14	0.00
Lag 20	3.68	0.00	53.53	0.00	-0.02	0.03	33.05	0.03
TSLA								
	F-stat.	F-stat. P.	Observed R^2	R^2 Significance	AC	PAC	Q-Stat	Prob
Lag 1	29.00	0.00	24.31	0.00	0.03	0.03	0.20	0.65
Lag. 5	20.51	0.00	60.69	0.00	0.18	0.18	6.52	0.25
Lag 10	11.00	0.00	64.46	0.00	0.11	0.06	13.02	0.22
Lag 20	5.68	0.00	68.39	0.00	-0.02	-0.02	18.52	0.55

VIX								
ARMA (1,1)	Heteroscedasticity				Autocorrelation			
	F-stat.	F-stat. P.	Observed R^2	R^2 Significance	AC	PAC	Q-Stat	Prob
Lag 1	137.59	0.00	70.14	0.00	0.51	0.51	38.83	0.00
Lag. 5	30.21	0.00	74.45	0.00	0.11	-0.01	64.96	0.00
Lag 10	15.52	0.00	76.74	0.00	0.03	0.12	71.08	0.00
Lag 20	7.97	0.00	80.48	0.00	0.05	0.09	83.78	0.00

Source: Author's own work.

The BDS test results show that there are nonlinearities in the series used in the study (Table 6). Since the variables used in the study have heteroscedasticity and autocorrelation problems and nonlinearities are detected in the series of the variables, ARCH/GARCH models should be used instead of ARMA models in the volatility modeling of the study. In other words, it can be said that the null hypothesis showing equal variance (H_0: $\beta_1 = \beta_2 = \dots = \beta_n = 0$) is rejected and the existence of heteroscedasticity is accepted (Engle 1982).

Table 6: Results for BDS test

Variable	Dimension	BDS Statistic	Std. Error	z-Statistic	Prob.
MSFT	2	0.00	0.00	1.68	0.09
	3	0.00	0.00	2.25	0.02
	4	0.01	0.00	3.71	0.00
	5	0.00	0.00	4.04	0.00
	6	0.00	0.00	5.45	0.00
AAPL	2	0.00	0.00	10.32	0.00
	3	0.00	1.39	12.33	0.00
	4	-7.64	1.40	-5.46	0.00
	5	-3.98	1.23	-3.23	0.00
	6	-2.15	1.01	-2.13	0.03
NVDA	2	0.01	0.00	2.07	0.03
	3	0.02	0.01	2.19	0.02
	4	0.03	0.01	2.35	0.01
	5	0.04	0.01	3.11	0.00
	6	0.05	0.01	3.88	0.00
GOOGL	2	0.00	0.00	1.79	0.07
	3	0.00	0.00	2.80	0.00
	4	4.06	3.46	1.17	0.24
	5	-1.97	6.34	-3.11	0.00
	6	-2.24	1.08	-2.08	0.03
AMZN	2	0.00	0.00	3.45	0.00
	3	0.00	2.79	3.79	0.00
	4	-1.15	3.22	-3.56	0.00
	5	-6.42	3.24	-1.98	0.04
	6	-3.83	3.03	-1.26	0.20
META	2	0.02	0.00	3.41	0.00
	3	0.04	0.01	3.88	0.00
	4	0.07	0.01	4.96	0.00
	5	0.09	0.01	5.98	0.00
	6	0.10	0.01	6.89	0.00
TSLA	2	0.01	0.00	2.57	0.01
	3	0.02	0.00	2.86	0.00
	4	0.03	0.01	3.05	0.00
	5	0.04	0.01	3.60	0.00
	6	0.04	0.01	3.95	0.00

Variable	Dimension	BDS Statistic	Std. Error	z-Statistic	Prob.
VIX	2	0.07	0.00	12.29	0.00
	3	0.13	0.01	13.84	0.00
	4	0.17	0.01	14.71	0.00
	5	0.19	0.01	15.18	0.00
	6	0.19	0.01	15.73	0.00

Source: Author's own work.

GARCH model estimation and causality in variance

GARCH (1,1) model results (Table 7), coefficients α_1 and β_1 are positive and significant. Therefore, it can be said that both past and current period shocks cause the volatility in the indices (Ahmar et al., 2024) Based on the sum of the $\alpha_1 + \beta_1$ coefficients obtained for each series, the values are calculated as 0.95 for MSFT, 0.99 for AAPL, 0.97 for NVDA, 0.99 for GOOGL, 0.99 for AMZN, 0.89 for META, 0.99 for TSLA, and 0.94 for VIX. Therefore, the equality $\alpha_1 + \beta_1 < 1$ holds for all series. The sum of $\alpha_1 + \beta_1$ is less than 1, indicating that the shocks to the indices cause volatility but do not have a permanent effect and do not exhibit long memory properties. For the GARCH (1,1) models to be valid, the problems of heteroscedasticity and autocorrelation in the series are expected to be eliminated.

Table 7: Results for volatility modeling

Variables	Model	Coefficient		
		α_0	α_1	β_1
MSFT	GARCH (1,1)	0.00	0.36*	0.59***
AAPL		0.00	0.03*	0.96***
NVDA		0.00	0.21*	0.76***
GOOGL		0.00	0.02*	0.97***
AMZN		0.00	0.04**	0.95***
META		0.00	0.13**	0.76***
TSLA		0.00	0.11***	0.88***
VIX		0.01	0.72***	0.22*
$h_t = \alpha_0 + \sum_{i=1}^{q} \alpha i \varepsilon_{t-1}^2 + \sum_{i=1}^{p} \beta h_{t-j}$				

***, ** and * indicate respectively statistical significance at the 1, 5 and 10 percent levels

Source: Author's own work.

For the GARCH model to be valid, a series of diagnostic tests must first be applied. In other words, the absence of the problems of changing variance and autocorrelation in the GARCH model indicates that the model is valid (Fenkli et al., 2024). The test results for heteroscedasticity and autocorrelation tested through GARCH (1,1) models (Table 8), there is no problem with heteroscedasticity and autocorrelation in the model, and the model is valid.

Table 8: Results for heteroscedasticity and autocorrelation

GARCH (1,1)	Heteroscedasticity				Autocorrelation			
	F-stat.	F-stat. P.	Observed R^2	R^2 Significance	AC	PAC	Q-Stat	Prob
MSFT	1.64	0.20	1.65	0.19	-0.10	-0.10	1.69	0.19
AAPL	2.43	0.12	2.43	0.11	0.13	0.13	2.48	0.11
NVDA	2.33	0.12	2.32	0.12	0.12	0.12	2.39	0.12
GOOGL	1.12	0.34	11.24	0.33	-0.08	-0.08	12.48	0.25
AMZN	1.35	0.24	1.35	0.24	-0.09	-0.09	1.38	0.23
META	0.00	0.94	0.00	0.94	0.00	0.00	0.00	0.94
TSLA	1.20	0.30	6.04	0.30	-0.03	-0.00	5.06	0.40
VIX	0.00	0.96	0.00	0.96	0.00	0.00	0.00	0.96

Source: Author's own work.

After estimating the volatility of the series, volatility residual series (GARCH conditional variance series) are constructed for each variable through GARCH (1,1) models for volatility spillovers between the series (Nazlıoglu et al., 2015). Then, the spillovers between the series are analyzed using the test for causality in variance. The test for causality in variance is shown in Table 9.

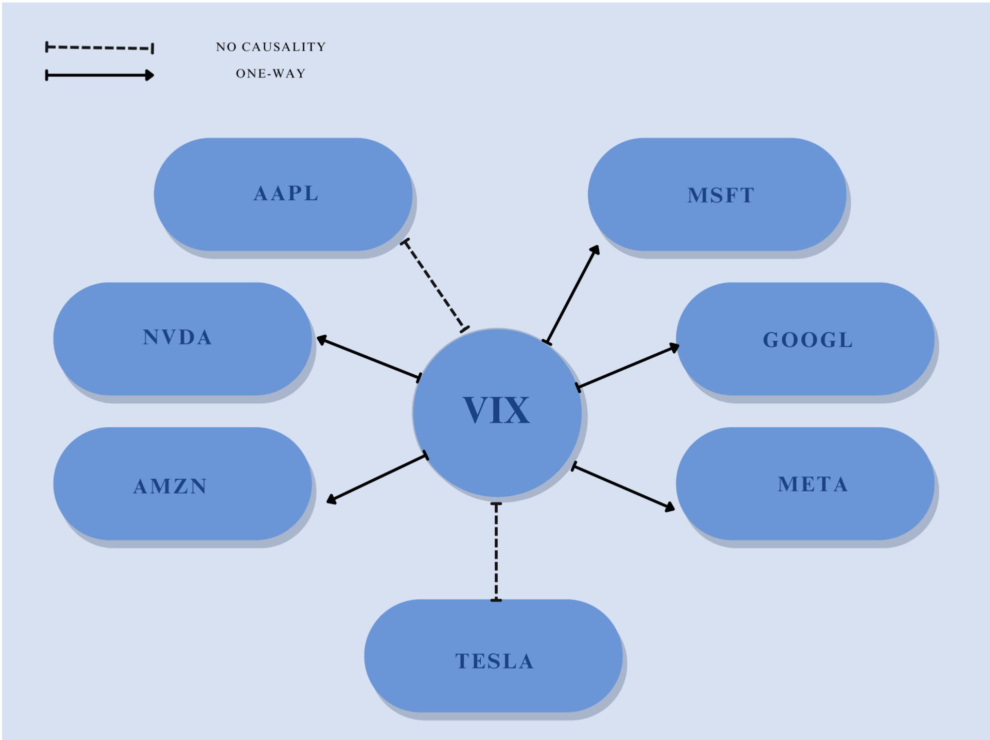
Table 9: Result for causality-in-variance test

Causality			LM stat.	P-value
MSFT	→	VIX	0.27	0.87
VIX	→	MSFT	6.50	0.03
AAPL	→	VIX	0.94	0.62
VIX	→	AAPL	1.63	0.44
NVDA	→	VIX	0.27	0.87
VIX	→	NVDA	6.50	0.03
GOOGL	→	VIX	0.44	0.80
VIX	→	GOOGL	13.39	0.00
AMZN	→	VIX	0.47	0.78
VIX	→	AMZN	13.37	0.00
META	→	VIX	2.80	0.24
VIX	→	META	6.46	0.03
TESLA	→	VIX	1.11	0.57
VIX	→	TESLA	0.32	0.85

Source: Author's own work.

No spillover effect is detected between VIX and AAPL, and VIX and TESLA. On the contrary, a one-way spillover from the variance of VIX to the variance of MSFT, NVDA, GOOGL, AMZN and META is confirmed (Figure 4).

Figure 4: Summary of causality-in-variance result



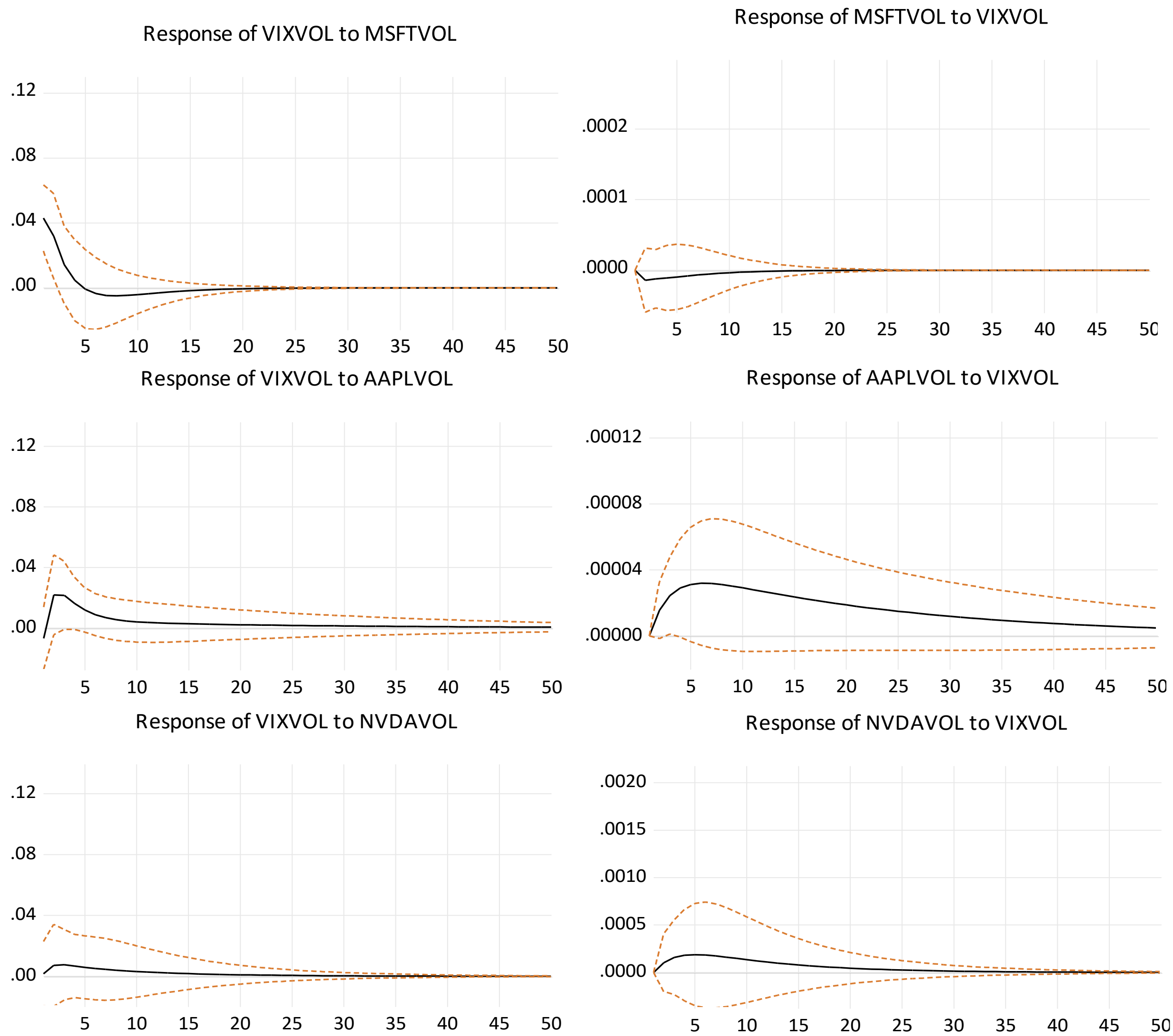
Source: Author's own work.

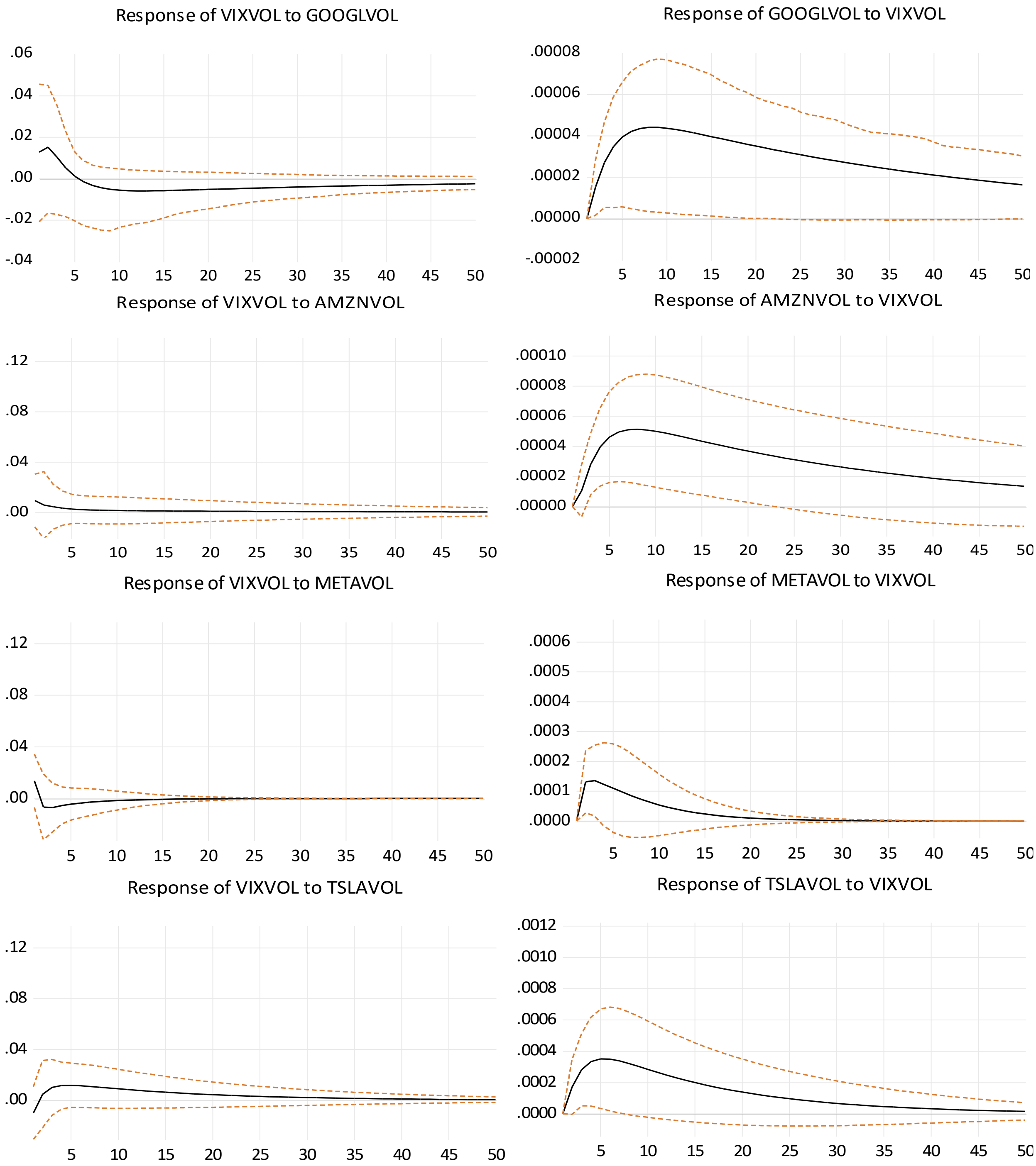
The presence of volatility spillovers from the fear index to the respective technology indices suggests that investors transfer their perception of high risk from the fear index to technology stocks. This suggests that information from the fear index improves the volatility forecast for MSFT, NVDA, GOOGL, AMZN and META stocks. Therefore, investors should consider the fear index in their portfolio construction and hedging strategies.

Impulse-Response and variance decomposition

The appropriate lag length is determined for impulse-response and variance decomposition tests and the VAR model is constructed by considering the minimum lag length according to the Schwarz information criterion. At this point, each of the Magnificent Seven conditional variance series and the VIX conditional variance series have been modeled separately for each company, and separate lag lengths have been determined for each model. Generalized impulse-response functions of the variance series are obtained for a one standard deviation shock in variance from GARCH (1,1) estimates (Figure 5). With impact-response analysis, it is possible to determine the extent to which one variable responds to a shock in another variable, thereby enabling accurate analysis of fluctuations (Daneshvar et al., 2024). According to the findings of the impulse-response analysis, a shock in the variance of the fear index causes a positive shock in the variance of AAPL, NVDA, GOOGL, AMZN, META and TESLA series and their effects disappear after a while and converge to zero. On the contrary, a shock in the variance of the fear index causes a negative shock in the variance of MSFT series and the effect converges to zero after a while. Therefore, it can be said that the fear index is an important shock transmitted to the Magnificent Seven stocks and should be considered in these investments. These findings are consistent with the causality findings in variance.

Figure 5: Impulse-response analysis





Source: Author's own work.

Finally, variance decomposition analysis is performed for the variance series obtained from GARCH (1,1) estimations (Annex 1). Variance decomposition analysis shows how much of a shock in a variable is self-induced and how much is caused by other variables (Mamipour et al., 2019). According to the variance decomposition analysis results, all of the changes in the volatility of the Magnificent Seven indices in the first period are due to their internal dynamics. Based on these results, it can be said that the changes in the volatility of the Magnificent Seven indices in the first period are due to their internal dynamics. Based on these results, it can be said that the changes in the Magnificent Seven indices in the first period were due to their internal dynamics. However, as the number of periods increased, the VIX index had a significant effect.

Discussion

The study examined the volatility spillover between the VIX and the Magnificent Seven technology stocks and obtained various findings. According to the results of the causality-in-variance test, a unidirectional volatility transmission from the VIX index to the stocks of MSFT, NVDA, GOOGL, AMZN, and META was identified, whereas no significant causality-in-variance was detected between the VIX index and the stocks of AAPL and TESLA. This finding is consistent with the studies by Sarwar (2012) and Ruan (2018), which identified the impact of the VIX index on benchmark indices. Considering that the VIX index is widely recognized as a volatility indicator in the global economic environment (Śliwiński & Lobza, 2017; Ahelegbey & Giudici, 2022), our findings suggest that MSFT, NVDA, GOOGL, AMZN, and META stocks are susceptible to uncertainty stemming from the VIX index. On the other hand, no such relationship was identified for AAPL and TSLA, indicating that these two stocks moved relatively independently of volatility in the VIX index during the period under review. This finding suggests that data related to the fear index could enhance the accuracy of volatility forecasts for MSFT, NVDA, GOOGL, AMZN, and META stocks. Therefore, it is important for investors to consider the VIX index when developing portfolio construction and risk hedging strategies.

On the other hand, findings from impulse-response analysis reveal that variance shocks in the VIX fear index led to significant and temporary effects on the stocks of the Magnificent Seven. Positive variance shocks were observed in the AAPL, NVDA, GOOGL, AMZN, META, and TSLA series, with these effects diminishing over time and converging toward zero. In contrast, the VIX-induced variance shock in the MSFT series produced a negative effect, which also dissipated over time and converged toward zero. These findings are consistent with the causality in variance analysis presented earlier in the study and support the role of the VIX index as a volatility transmitter for the Magnificent Seven stocks. In this context, it can be said that volatility in the VIX index is an important risk factor to consider in investment decisions regarding these technology stocks.

Finally, the results obtained from the variance decomposition analysis indicate that volatility changes in the Magnificent Seven companies during the initial period were entirely driven by their own internal dynamics. This finding suggests that the volatility structures of these stocks moved independently in the short term and did not respond immediately to external shocks. However, in later periods, the impact of the VIX index on the volatility components of these stocks increases gradually. This increasing impact of the VIX indicates that macro-level market sentiment indicators should also be considered in assessments of the investment profile of these technology stocks.

Kang et al. (2019) state that portfolio managers and global investors are seeking investment opportunities with an appropriate risk-return balance and, in this regard, attach importance to asset allocation strategies to create well-diversified portfolios. They also highlight the need for knowledge of dispersion dynamics to achieve higher levels of hedging effectiveness and diversification benefits. In this context, the findings of our study are important for investors in terms of distinguishing between stocks that are more sensitive to short-term shocks and those that are more resilient, developing hedging strategies, and time-based portfolio optimization.

Conclusion and policy implications

The study aims to analyze the volatility spillover between the Magnificent Seven stocks Microsoft, Apple, Nvidia, Alphabet, Amazon, Meta Platforms and Tesla and the VIX index over the period 06:2012 to 03:2024 using monthly data. A causality in variance test is applied to detect volatility spillover. In this context, firstly, the appropriateness of the GARCH (1,1) model for the causality test in variance is tested for the series. GARCH (1,1) model is found to be valid in all series. Accordingly, it can be said that both past period volatilities and current period shocks cause the volatility in the indices. However, the sums $\alpha_1 + \beta_1$ are less than one in all series and it can be said that the shocks to the indices cause volatility but do not have a permanent effect and do not exhibit long memory properties. According to the subsequent causality in variance findings, no spillover effect was detected between VIX and Apple and VIX and Tesla. On the contrary, a one-way spillover from the VIX variance to the variance of Microsoft, Nvidia, Alphabet, Amazon and Meta Platforms is confirmed.

Following the causality findings, impulse-response and variance decomposition analyses were performed on the conditional variance series generated by the GARCH (1,1) model. The impulse-response analysis findings show that a shock to the variance of the fear index causes a positive shock to the variance of the Apple, Nvidia, Alphabet, Amazon, Meta Platforms and Tesla series and their effects disappear after a while and converge to zero. In contrast, a shock to the variance of the fear index causes a negative shock to the variance of the Microsoft series and the effect converges to zero after a while. Finally, according to the variance decomposition findings, it is found that the changes in the Magnificent Seven indices in the first period are driven by their internal dynamics. However, as the number of periods increases, the VIX index has a significant effect. It can be said that these findings are similar to the results of Sarwar (2012), Wang et al. (2014), Ruan (2018), Vartanian and Neto (2023) as well as Tran and Vo (2023) in the literature.

Our findings include some policy recommendations for investors and market participants. According to the findings, investors transfer their high-risk perceptions from the fear index to technology stocks. This suggests that the information obtained from the fear index improves the volatility forecasting of the related stocks. Therefore, investors are advised to consider the fear index in their portfolio strategies. In addition, investors should always be prepared for fluctuations in market conditions. According to the study's findings, shocks do not exhibit long memory properties, so investors must act quickly and focus on short-term effects as they will not have much time to make decisions. In sum, the existence and direction of volatility spillover between the fear index and technology stocks are important for investors' long-term portfolio optimization.

This study has some limitations. First, it focuses only on the volatility spillover between the fear index and technology firms. Given that many factors affect market behavior, it is important to include these factors in the analysis to expand policy implications. In addition, factors that affect the volatility of technology firms, such as investor interest and social media news, can be investigated. Moreover, the findings can be replicated by decomposing the effects of positive and negative shocks using asymmetric tests.

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Annex 1: Result for variance decomposition analysis

Period	MSFTVOL	VIXVOL	AAPLVOL	VIXVOL	NVDAVOL	VIXVOL	GOOGLVOL
1	100.00	0.00	100.00	0.00	100.00	0.00	100.00
2	99.89	0.10	99.10	0.89	99.87	0.12	97.77
3	99.72	0.27	97.70	2.29	99.66	0.33	94.46
4	99.55	0.44	96.20	3.79	99.43	0.56	91.08
5	99.40	0.59	94.78	5.21	99.21	0.78	88.03
6	99.29	0.70	93.53	6.46	99.01	0.98	85.40
7	99.21	0.78	92.44	7.55	98.83	1.16	83.19
8	99.16	0.83	91.51	8.48	98.67	1.32	81.35
9	99.12	0.87	90.71	9.28	98.54	1.45	79.80
10	99.10	0.89	90.04	9.95	98.43	1.56	78.50
11	99.08	0.91	89.47	10.52	98.34	1.65	77.41
12	99.08	0.91	88.98	11.01	98.26	1.73	76.48
13	99.07	0.92	88.56	11.43	98.19	1.80	75.69
14	99.07	0.92	88.20	11.79	98.14	1.85	75.00
15	99.07	0.92	87.88	12.11	98.09	1.90	74.41
16	99.07	0.92	87.61	12.38	98.06	1.93	73.90
17	99.07	0.92	87.37	12.62	98.02	1.97	73.45
18	99.07	0.92	87.16	12.83	98.00	1.99	73.05
19	99.07	0.92	86.97	13.02	97.98	2.01	72.70
20	99.07	0.92	86.81	13.18	97.96	2.03	72.39
Period	**VIXVOL**	**AMZNVOL**	**VIXVOL**	**METAVOL**	**VIXVOL**	**TSLAVOL**	**VIXVOL**
1	0.00	100.00	0.00	100.00	0.00	100.00	0.00
2	2.22	98.58	1.41	99.34	0.65	98.73	1.26
3	5.53	96.39	3.60	98.29	1.70	96.77	3.22
4	8.91	94.07	5.92	97.16	2.83	94.71	5.28
5	11.96	91.91	8.08	96.10	3.89	92.81	7.18
6	14.59	90.01	9.98	95.16	4.83	91.15	8.84
7	16.80	88.37	11.62	94.36	5.63	89.75	10.24
8	18.64	86.97	13.02	93.70	6.29	88.57	11.42
9	20.19	85.79	14.20	93.17	6.82	87.59	12.40
10	21.49	84.80	15.19	92.75	7.24	86.78	13.21
11	22.58	83.95	16.04	92.41	7.58	86.10	13.89
12	23.51	83.23	16.76	92.15	7.84	85.53	14.46
13	24.30	82.62	17.37	91.95	8.04	85.05	14.94
14	24.99	82.09	17.90	91.80	8.19	84.65	15.34
15	25.58	81.64	18.35	91.68	8.31	84.31	15.68
16	26.09	81.24	18.75	91.59	8.40	84.02	15.97
17	26.54	80.90	19.09	91.52	8.47	83.77	16.22
18	26.94	80.60	19.39	91.47	8.52	83.55	16.44
19	27.29	80.33	19.66	91.43	8.56	83.37	16.62
20	27.60	80.10	19.89	91.40	8.59	83.21	16.78

Source: Author's own work.