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Investigation of the Relationship between Technology Indices on Selected Stock Markets Using Johansen Cointegration Test

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Abstract

New technological products and methods not only have the potential to increase efficiency but also force business processes to change. Globalization has increased the speed of development and dissemination of current technologies, and their impact has deepened. Business processes and financial assets in the finance sector are significantly affected by these developments. Additionally, the significant increase in the value of technology company stocks in recent years has attracted the attention of investors and researchers. The aim of this study is to investigate whether there is a cointegration relationship among the indices formed by the values of technology company stocks in different markets. The indices selected for examination are the NASDAQ 100 Technology TR (NTTR) from the United States, the iShares STOXX Europe 600 Technology UCITS (SX8PEX) from the European Union markets, and the FTSE TechMARK All Share (FTTASX) from the United Kingdom. Time series have been created based on the monthly closing values of selected indices between December 2018 and February 2024. The unit root test results showed that all series have a degree of stationarity of 1 (I=1). The potential cointegration relationships between the series were investigated using the Johansen Cointegration method, and specification tests were conducted. As a result of the study, it was determined that there is no significant cointegration relationship among the selected technology index series.

Keywords
Global Stock Markets, Technology Indices, Johansen Cointegration Analysis

JEL Classification
G15, G17, C58

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Seçili Hisse Senedi Piyasalarındaki Teknoloji Endeksleri Arasındaki İlişkilerinin Johansen Eşbütünleşme Yöntemiyle İncelenmesi

Öz

Yeni teknolojik ürün ve yöntemler, verimliliği artırıcı etki yaratabilmelerinin yanında iş süreçlerini değişime zorlamaktadırlar. Küreselleşme süreci, güncel teknolojilerin geliştirilmesi ve kullanımının yayılım hızını artmış ve etki alanı derinleşmiştir. Finans sektöründeki iş süreçleri ve finansal varlıklar bu gelişmelerden önemli derecede etkilenmektedirler. Ayrıca teknoloji şirketlerine ait hisse senetlerinin son yıllarda anlamlı derecede değer kazanmaları yatırımcı ve araştırmacıların ilgisini çekmektedir. Bu çalışmanın amacı, farklı piyasalardaki teknoloji şirketlerine ait hisse senetlerinin değerleri üzerinden hesaplanan endeksler arasında eşbütünleşme ilişkisinin var olup olmadığının araştırılmasıdır. Amerika Birleşik Devletleri NASDAQ 100 Technology TR (NTTR), Avrupa Birliği piyasalarından iShares STOXX Europe 600 Technology UCITS (SX8PEX), Birleşik Krallık FTSE TechMARK All Share (FTTASX) endeksleri incelenmek üzere seçilmiştir. Seçili endekslerin 2018 Aralık ile 2024 Şubat arasındaki dönemdeki aylık kapanış değerleri üzerinden zaman serileri oluşturulmuştur. Birim kök testi sonuçları serilerin tamamının durağanlık derecelerinin 1 (I=1) olduğunu göstermiştir. Seriler arasındaki muhtemel eşbütünleşme ilişkileri Johansen Eşbütünleşme yöntemi ile araştırılmış ve sınama testleri gerçekleştirilmiştir. Çalışmanın sonucunda seçili teknoloji endeksleri serileri arasında anlamlı bir eşbütünleşme ilişkisinin var olmadığı tespit edilmiştir.

Anahtar Kelimeler
Küresel Hisse Senedi Piyasaları, Teknoloji Endeksleri, Johansen Eşbütünleşme Testi

JEL Kodu
G15, G17, C58

1. Introduction

Today, the significant appreciation of technology stocks attracts the attention of investors and researchers around the world. The technology sector, consisting of companies in the telecommunications, media, information technology and software, has a structure that can change faster than others. Current developments in the Technology Sector are closely followed by consumers, investors and researchers with the development and spread of web-based communication devices (Sadorsky, 2003).

The technology sector has more potential to create high added value. By spreading positive experiences regarding the use of innovative products and methods, a great number of consumers, investors, and researchers around the world may become interested in these innovations. Factors such as the ability to customize software products according to consumer expectations, their ability to be updated according to needs that arise over time, and their low sales and delivery costs enable companies operating in this sector to grow faster than other companies.

Technology stocks have high price-earnings ratios. This causes the future price valuations to be high. This also affects the current firm value of technology companies. Firm value is a function of a company's current state and expected future returns. As a result, the relationship between the price-earnings ratios of technology companies and the book value of the company weakens (Feltham & Ohlson, 1995).

Another distinctive feature of the technology sector is that it is significantly sensitive to developments in the economy. Technology stocks have higher degrees of volatility than stocks of companies in other sectors. Gharbi Sahut & Teulon (2014) stated that the volatility of the stocks of high technology companies traded on the NASDAQ stock exchange compared to the stocks of companies in other sectors is 4 times higher than the volatility of the S&P 500 and NYSE AMEX indices (Gharbi, Sahut & Teulon, 2014). In addition, there are academic studies showing that technology stocks can gain value despite expectations that stock prices will tend to decline in periods when the rate of variability in the economy increases or economic stagnation occurs (Emsbo-Mattingly, Hofschire, Litvak & Lund-Wilde, 2017). It has been observed that stocks of companies operating in the technology industry exhibited an upward trend during COVID-19 periods when high price volatility was experienced in global financial markets (Mazur, Dang & Vega, 2021).

The global economic crisis in 2008 caused financial investors to turn to alternative investment portfolios with a more stable balance between risk and return (Kinateder, Campbell & Choudhury, 2021). Since this period, with the acceleration of globalization, the degree of mutual diffusion and interaction between asset markets has increased. With the beginning of the 4th Industrial Revolution, financial investors and academics began to turn to green bonds, renewable energy bonds, stocks, and financial technology (Fintech) markets instead of conventional financial assets such as stocks, bonds, gold, and oil (Rejeb & Arfaoui, 2016). Fintech refers to the integration and application of financial services and tools with technology.

Since fintech investment assets have more efficient, transparent, and easy-to-understand structures than traditional financial assets, investors and researchers have begun to show more and more interest in these assets. Therefore, fintech products played an important role in restoring the trust in financial markets that had been damaged during the global economic crisis in 2008. Fintech applications replace traditional financial applications in payment transactions, banking services, and commercial processes, allowing new opportunities to arise in various industries on a global scale (Breidbach, Keating & Lim, 2020).

In recent years, global pandemics, wars and conflicts in certain regions, the increasing effects of global warming, and natural disasters have significantly impacted economic and financial processes worldwide. Additionally, technological developments such as social media, e-commerce, blockchain technology, cryptocurrencies, and artificial intelligence have started to become more widespread and have managed to attract the interest of investors. In light of all these developments, global technology companies have shown faster financial growth and development compared to other companies. This situation can be cited as one of the reasons why individual and institutional investors worldwide prefer technology assets in their portfolio choices more than in the past. This study examines whether these trends are similar in global markets. By conducting cointegration tests among selected technology indices, the existence of a long-term equilibrium among these assets has been investigated. The obtained results will contribute to the literature in terms of determining whether the investment preferences in question show similarities.

2. Literature Review

Rašiová & Árendáš (2023) calculated and compared the volatility degrees of the stocks of technology companies traded in the stock markets in the United States (US) and the market in which these assets are traded. As a result of the study, they argue that they found a strong negative relationship between price changes of technology stocks in the market and market volatility (Rašiová & Árendáš, 2023).

Tiwari, Abakah, Shao, Le, & Gyamfi (2023) examined the connections between technology stocks, green financial assets, and energy sector stocks with non-parametric causality analysis. They investigated whether price changes of technology stocks affect green financial assets and energy markets. According to the results, they argued that the price changes of technology stocks are decisive in predicting the prices of assets other than green financial assets (Tiwari, Abakah, Shao, Le & Gyamfi, 2023).

Adekoya, Oliyide, Akinseye, & Ogunbowale (2022) investigated whether the fear index affects the stocks of oil companies in the US stock markets and whether technology stocks have an effect on predicting the fear indices. As a result of the study, they stated that the fear index of oil stocks was a strongly negative determinant in predicting the fear index of technology companies (Adekoya, Oliyide, Akinseye &, 2022).

Niu (2021) applied a time-dependent internal correlation method by quantitatively establishing the connection between crude oil stocks, renewable energy stocks, and technology stocks. As a result of the study, it was concluded that there is a strong long-term correlation relationship between crude oil prices, renewable energy stocks, and technology stocks in pairs, and that this relationship is stronger than the short-term connection (Niu, 2021).

Chu, Chan, & Zhang (2021) compared the relationship between the returns of Bitcoin and high-performance technology stocks with various global stock markets. As a result of the study, they concluded that there are significant similarities between high technology stocks and Bitcoin in terms of price valuation, but that high technology stocks have a more meaningful relationship than Bitcoin in terms of diversification features in global stock markets (Chu, Chan & Zhang, 2021).

Kocaarslan & Soytaş (2019) used the dynamic conditional correlation method to investigate the possible relationship between clean energy and technology stock prices and oil prices. As a result of the study, they concluded that there is a strong relationship between oil prices and clean energy and technology stock price movements due to dynamic conditional correlation (Kocaarslan & Soytaş, 2019).

Wong & Govindaraju (2012) investigated the R&D investments made by state-owned technology companies in Malaysia and the possible effects of their technological investments on the valuation of the stocks of these companies. As a result of the study, they concluded that the stocks of companies that developed their technological infrastructure gained more value than other companies (Wong & Govindaraju, 2012).

Qiao, Smyth, & Wong (2008) analyzed the volatility change of information technology company stocks in Canada, France, Hong Kong, Japan, Taiwan, and the United States and the Emerging Markets index using SWARCH models. As a result of the study, they concluded that the volatility levels of information technology stocks are affected by the developments in these sectors according to macroeconomic indicators (Qiao, Smyth, & Wong 2008).

Sadorsky (2003) investigated whether there is a relationship between the degree of volatility in the prices of technology stocks in the USA and macroeconomic indicators. In addition, the study conducted research on the possible relationship between price changes of technology stocks and oil prices. According to the results, it is suggested that the conditional volatility in oil prices, period premiums, and changes in the consumer price index have a significant impact on the conditional volatility of the technology stock prices (Sadorsky, 2003).

Kwon (2002) compared the accuracy of the predicted values in predicting the price movements of the stocks of high-technology companies and low-technology companies and calculating risk premiums. As a result of the study, it was concluded that the share movements of high technology companies were predicted more accurately by market analysts (Kwon, 2002).

3. Materials and Methods

In this study, it was investigated whether there is a long-term cointegration relationship between technology indices calculated on the share prices of companies operating in the technology sector and whose shares are traded on stock exchanges. The indices are determined to be distributed according to economic region. It was decided to select and examine the United States (USA) NASDAQ 100 Technology TR (NTTR) index, the European Union (EU) iShares STOXX Europe 600 Technology UCITS (SX8PEX) index, and the United Kingdom (UK) FTSE TechMARK All Share (FTTASX) index. The data set consisting of 63 observations for each index was created with the data of the monthly values of the selected indices between December 2018 and February 2024. Index data was obtained from the Investing Finance Platform and the websites of the stock exchanges to which the indexes belong. Information about the selected indices is given in Table 1.

Table 1

Selected Technology Indices

Indices	Region	Symbol
NASDAQ 100 Technology TR	USA	NTTR
iShares STOXX Europe 600 Technology UCITS	EU	SX8PEX
FTSE TechMARK All Share	UK	FTTASX

Time series analysis will be applied with series created from the monthly values of the indices between December 2018 and February 2024. The degree of stationarity of the series in time series analysis is very important in determining the method to be used in examining the cointegration relationship. In order to determine the degree of stationarity of the series, standard unit root tests, Augmented Dickey-Fuller (ADF) unit root test, and Phillips-Perron (PP) unit root tests were applied. According to the results, all series contain unit roots at level. In other words, series are not stationary at their own levels. ADF and PP unit root tests were applied by taking the first differences of the series, and it was determined that all the series became stationary. This result represents that the degree of integration of the series is 1 (I = 1).

The most appropriate method to be used when examining the cointegration relationship between multiple time series with degrees of stationarity different from zero is the Johansen Cointegration Test. This method is a time series analysis where calculations are made based on eigenvalues and eigenvectors (Johansen, 1991).

In Johansen Cointegration Tests, the significant vector autoregressive model (VAR) must be estimated. Before estimating the VAR model, the appropriate lag length (lag) must be calculated. With the help of Eview's statistical program, the valid lag length of the VAR model was applied to the VAR Lag Order Selection Criteria process, and the lag length was calculated as 1 (lag = 1).

In the VAR model, where the lag length is calculated as 1 (lag = 1), the inverse roots of the AR characteristic polynomials must be examined, and the results must be within the unit circle. In the estimated VAR model, it was determined that the results of the AR Roots of Characteristic Polynomial Analysis of the series were within the unit circle.

In the next stage, the estimated VAR model cointegration test will be performed. To identify the most suitable model and information criterion, the results of the information criteria were calculated on Eview's according to the rank values of 5 models, and the appropriate model was selected. Cointegration analysis was performed with the selected model, and it was concluded that there is no cointegration relationship between the series.

In order to economically interpret the results from the Johansen Cointegration Test, normality tests, autocorrelation tests, and heteroscedasticity tests of the estimated VAR model need to be applied. In the estimated VAR model, it was determined by the tests that the series were normally distributed and that the model did not have autocorrelation and heteroscedasticity problems.

3.1. Unit Root Analysis of NTTR, SX8PEX, FTTASX Series

Unit root tests are analyzes used to test whether the series of variables are stationary in time series analyses. The equation for the unit root test in a time series is as follows.

$$Y_t = D_t + z_t + \varepsilon_t \quad (1)$$

D_t: Deterministic component (trend or seasonality component, etc.)

z_t: Stochastic component

ε_t: Stationary error process

In examining the cointegration relationship in time series analysis, the determining condition in choosing the useful method is the degree of stationarity of the series. Therefore, NTTR, SX8PEX, and FTTASX series Augmented Dickey Fuller (ADF) and Phillips-Perron (PP) standard unit root tests were applied. The results of the ADF and PP unit root tests are in the tables below. Table 2 shows the ADF unit root test results calculated at the level of the series, and Table 3 shows the ADF unit root test results calculated by taking the first differences of the series.

Table 2

ADF Unit Root Test Results of NTTR, SX8PEX, FTTASX Series at Level

		FTTASX	**NTTR**	**SX8PEX**
	t-Statistic	-2.3373	-0.867	-1.3282
With Constant	Prob.	0.1638	0.7923	0.6112
		no	no	no
	t-Statistic	-2.6423	-1.474	-2.0405
With Constant & Trend	Prob.	0.2638	0.8281	0.5679
		no	no	no
	t-Statistic	0.6208	1.5419	1.1797
Without Constant & Trend	Prob.	0.8478	0.9686	0.9373
		no	no	no

Note. (*) Significant at 10% level; (**) Significant at 5% level; (***) significant at 1% level and (no) not significant.

In ADF unit root tests, if the probability values of the t-statistics of the series are greater than 5%, the H0 hypothesis is accepted. In ADF unit root tests, the H0 hypothesis states that the series contain unit roots, which means series are not stationary (Elliott, Rothenberg & James Stock, 1996). According to the ADF unit root test calculated at the series' level in Table 2, the probability values of the t-statistics of all series were calculated to be greater than 5%. According to this result, the H0 hypothesis is accepted. In other words, all series contain unit roots at level according to the ADF unit root test results.

Table 3

ADF Unit Root Test Results in First Differences of NTTR, SX8PEX, FTTASX Series

		d(FTTASX)	d(NTTR)	d(SX8PEX)
With Constant	t-Statistic	-8.0977	-7.8483	-8.402
	Prob.	0	0	0
		***	***	***
With Constant & Trend	t-Statistic	-8.1057	-7.789	-8.3316
	Prob.	0	0	0
		***	***	***
Without Constant & Trend	t-Statistic	-8.0788	-7.543	-8.2011
	Prob.	0	0	0
		***	***	***

Note. (*) Significant at 10% level; (**) Significant at 5% level; (***) significant at 1% level and (no) not significant.

In Table 3, the ADF unit root test was applied in the first differences of the series. According to the results, the probability values of the t-statistics calculated in the model with constant, the model with trend and constant, and the model without trend and constant are less than 5%. According to these results, the H0 hypothesis is rejected and the alternative hypothesis is accepted. In other words, all series become stationary according to the ADF unit root test in first differences for all series. This result represents that the degree of integration of the series is 1 (I = 1).

Phillips-Perron (PP) unit root tests were applied to support the results obtained from the ADF standard unit root test. In PP unit root tests, the H0 hypothesis represents that the series contains unit root. If the probability values of the t-statistics are greater than 5%, the H0 hypothesis is accepted (Phıllıps & Perron, 1988). In other words, it will be concluded that the series contains a unit root.

Table 4

PP Unit Root Test Results of NTTR, SX8PEX, FTTASX Series at Level

		FTTASX	NTTR	SX8PEX
With Constant	t-Statistic	-2.3373	-0.867	-1.3282
	Prob.	0.1638	0.7923	0.6112
		no	no	no
With Constant & Trend	t-Statistic	-2.6423	-1.474	-2.0405
	Prob.	0.2638	0.8281	0.5679
		no	no	no

	t-Statistic	0.6208	1.5419	1.1797
Without Constant & Trend	Prob.	0.8478	0.9686	0.9373
		no	no	no

Note. (*) Significant at 10% level; (**) Significant at 5% level; (***) significant at 1% level and (no) not significant.

The results for Table 4 display the probability values of the t-statistics for all three models of the series: those with a constant, trend, and constant, and those without a constant and trend, all of which exceed 5%. In this case, the H0 hypothesis is accepted. The series contains a unit root.

Table 5

PP Unit Root Test Results for First Differences of NTTR, SX8PEX, FTTASX Series

		d(FTTASX)	**d(NTTR)**	**d(SX8PEX)**
	t-Statistic	-8.2374	-7.8483	-8.402
With Constant	Prob.	0	0	0
		***	***	***
	t-Statistic	-8.4049	-7.789	-8.3316
With Constant & Trend	Prob.	0	0	0
		***	***	***
	t-Statistic	-8.1625	-7.5416	-8.2008
Without Constant & Trend	Prob.	0	0	0
		***	***	***

Note: (*) Significant at 10% level; (**) Significant at 5% level; (***) significant at 1% level and (no) not significant.

According to the results in Table 5, the probability values of t-statistics calculated for all three series, the model with constant, the model with trend and constant, and the model without trend and constant, are less than 5%. According to this result, the H0 hypothesis was rejected and the alternative hypothesis was accepted. In other words, according to the PP test, all series become stationary in first differences. This result represents that the degree of integration of the series is 1 ($I = 1$).

In cases where there are more than two variables and the stationarity degree of the series of the variables is 1 ($I = 1$) in time series analysis, the method that will provide the most significant results in the cointegration tests applied between the variables is the Johansen Cointegration Test. After estimating the VAR model with the valid lag length (lag), it is investigated whether there are cointegration relationships between the series. After the normality test, autocorrelation test, and heteroscedasticity tests of the estimated VAR model are performed, the results of the estimated VAR equation can be interpreted (Johansen, 1995).

3.2. VAR Model of NTTR, SX8PEX, FTTASX Series

Vector Autoregression (VAR) is a statistical stochastic model used to detect the relationship between multiple time-varying variables. VAR models are a statistical method that allows generalization of a univariate autoregressive model to time series with more than two variables (Hatemi, 2004). The equation for a general VAR model is as follows.

$$X_t = \pi_1 X_{t-1} + \cdots + \pi_k X_{t-k} + \varepsilon_t$$

(2)

X_t: n internal variable vectors

k: Lag length

π: n*n dimensional matrix

εt: Errors with a mean of zero

In the VAR model above, the endogenous variable vector Xt has lagged values and is non-stationary. After the first difference of the xt vector, the VAR model is expressed with the following equation.

$$\Delta X_t = \Gamma_i \Delta X_{t-1} + \cdots + \Gamma_{k-1} \Delta X_{t+k-1} + \pi X_{t-k} + \varepsilon_t$$

(3)

$$\Gamma_i = -(I - A_1 - \cdots - A_i)$$

Γ_i: Represents short-term relationships in X_t

$$\pi = -(I - A_1 - \cdots - A_k)$$

Π: Represents long-term relationships in X_t

3.3. Determination of Significant Delay Length for VAR Model of NTTR, SX8PEX, FTTASX Series

In order to perform the Johansen Cointegration Test, a significant lag length needs to be determined. The lag length (lag) of the VAR model to be estimated with the series of FTTASX, NTTR, and SX8PEX variables was performed according to the VAR lag order selection criterion test in Eview's statistical program, and the results are given in Table 6.

Table 6

VAR Lag Length Selection Criteria for FTTASX, NTTR, SX8PEX Internal Variables

Lag	LogL	LR	FPE	AIC	SC	HQ
0	-1052.83	NA	1.30E+12	36.40807	36.51464	36.44958
1	-926.925	234.4516*	2.31e+10*	32.37671*	32.80301*	32.54277*
2	-925.703	2.14854	3.03E+10	32.64493	33.39095	32.93552
3	-921.583	6.819065	3.61E+10	32.81321	33.87896	33.22834
4	-913.699	12.23457	3.80E+10	32.85168	34.23715	33.39135
5	-904.16	13.81503	3.81E+10	32.83309	34.53829	33.4973

Note. LR: Sequential modified LR test statistic (Each test at 5% level), FPE: Last prediction error, AIC: Akaike information criterion, SC: Schwarz information criterion, HQ: Hannan-Quinn information criterion.

Table 6. shows the lag length test statistics values from AIC, SC, and HQ information criteria. The lag length to the smallest values among the results from the selection criteria process represents the most significant lag length (lag) for the estimated VAR model (Hatemi & Hacker 2008). According to the test results, the test statistics values of the information criteria at the 1st lag of the series (lag = 1) are the lag length with the smallest values in the table. Therefore, when estimating the VAR model of the series, the lag length will be 1.

3.4. AR Roots of Characteristic Polynomial

The characteristic polynomial of a square matrix is a polynomial that is invariant under matrix similarity and contains the eigenvalues as roots. The modulus values of the roots of the AR characteristic polynomials in the VAR model must be less than 1 (modulus < 1). In addition, another important criterion in this analysis is that the inverse roots of AR characteristic polynomials should not be outside the unit circle consisting of their upper values. (Forsythe & Motzkin, 1952). Modulus values of 1-lag AR characteristic polynomials of the internal variables FTTASX, NTTR, and SX8PEX series are given in Table 7.

Table 7

1-lag AR Characteristic Polynomials of FTTASX, NTTR, SX8PEX Series

Root	Modulus
0.9698	0.9698

0.83989	0.83989
0.69242	0.69242

The fact that all the modulus values in Table 7 are less than 1 (modulus < 1) represents that the roots of the characteristic polynomial are within acceptable limits. The calculated modulus values support the validity of the VAR model established with the internal variables FTTASX, NTTR, and SX8PEX.

The unit circle showing the positions of the inverse roots of the AR characteristic polynomial of the estimated VAR model is given below.

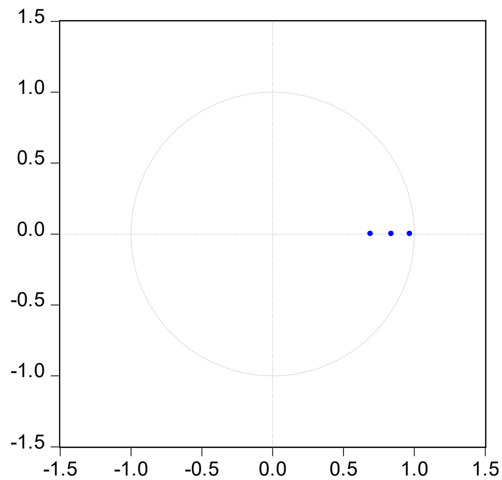

Figure 1. Inverse Roots of AR Characteristic Polynomial

In Figure 1, the fact that the inverse roots of the AR characteristic polynomial of the VAR model established with the internal variables FTTASX, NTTR, and SX8PEX remain within the unit circle representing the upper limits supports the significance of the estimated VAR model.

3.5. Estimating the VAR Model

For the estimated VAR model, it has been determined that the stationarity degree of the series is 1 (I = 1), the valid lag length is calculated as 1 (lag = 1), and the inverse roots of the AR characteristic polynomial are located within the boundaries of the unit circle. As a result of these criteria being suitable, the VAR model of the series belonging to the variables FTTASX, NTTR, and SX8PEX can be estimated. Table 8. shows the results obtained from the VAR model estimation consisting of 62 observations for each variable.

Table 8

Estimated VAR Model for FTTASX, NTTR, SX8PEX Series

	SX8PEX	NTTR	FTTASX
	0.869089	33.55245	6.279422
SX8PEX(-1)	-0.22602	-33.7606	-9.01915
	[3.84522]	[0.99384]	[0.69623]
	0.000649	0.880597	-0.0045
NTTR(-1)	-0.001	-0.14918	-0.03985
	[0.64973]	[5.90289]	[-0.11292]
	-0.00162	-0.584587	0.752424
FTTASX(-1)	-0.0025	-0.37405	-0.09993
	[-0.64680]	[-1.56287]	[7.52973]
	9.795461	1543.678	705.7949
C	-6.15475	-919.341	-245.602
	[1.59153]	[1.67911]	[2.87373]

After the VAR model is estimated, the Johansen Cointegration Test can be performed to determine whether there is a cointegration relationship between the series of variables. In performing this test, a significant model must be determined according to information criteria. After determining the significant model, the results from the Johansen Cointegration Test will be evaluated.

3.6. Johansen Cointegration Test of FTTASX, NTTR, SX8PEX Series

The Johansen Cointegration Test is based on the principle that when there are more than two variables, there is the possibility of more than one cointegration vector. This test is calculated on eigenvalues and eigenvectors. In addition, it is accepted that each series of variables is endogenous. In other words, it is a test calculated under the assumption that each series is the dependent variable. In order to perform the Johansen Cointegration Test, the prerequisite is that the series are not stationary at the level and become stationary at first differences (I = 1) (Johansen, 1991).

Equation (3) The rank of the π matrix in the estimated VAR model represents the number of cointegration vectors in the model. The rank of a matrix is calculated as follows:.

$$A = [a_{ij}]_{mxn} \neq 0 \quad \textbf{(4)}$$

Among the square submatrices of the matrix whose rank formula is given in Equation (4), the one with the highest rank among those whose determinant is different from zero is called the rank of matrix. The rank of an A matrix is represented by rank (A). According to the Johansen Cointegration Test,

Rank (π) = 0 There is no long-term cointegration relationship between the series.

Rank (π) = 1 There is a single long-run relationship between the series.

Rank (π) > 1 There is more than one cointegration relationship between the series (Hatemi & Hacker, 2008).

In the Johansen Cointegration Test, the significant model must be determined by finding the degrees of the information criteria. According to the estimated VAR model with Eview's statistical program, the ranks of all models can be ranked while performing the Johansen Cointegration Test. According to the information criteria in the alignment of models and ranks, the model with the smallest values is the most significant model for the Johansen Cointegration Test. Table 9. shows the values of information criteria according to rank and model.

Table 9

Sorting of Information Criteria by Rank and Model

Trend of Data	None No Intercept No Trend	None Intercept No Trend	Linear Intercept No Trend	Linear Intercept Trend	Quadratic Intercept Trend
Sorting of Akaike Information Criteria by Rank (Rows) and Model (Columns)					
0	32.47602	32.47602	32.52354	32.52354	32.60014
1	32.45497*	32.45555	32.48651	32.49129	32.53609
2	32.61089	32.58285	32.58543	32.60026	32.61458
3	32.80759	32.77792	32.77792	32.78656	32.78656
Sorting of Schwarz Information Criteria by Rank (Rows) and Model (Columns)					
0	32.78746*	32.78746*	32.93879	32.93879	33.11921
1	32.97403	33.00922	33.10939	33.14878	33.26278
2	33.33759	33.37875	33.41594	33.49998	33.5489
3	33.74192	33.81606	33.81606	33.9285	33.9285

The results in Table 9. show that it is seen that the smallest value among the information criteria is the value of model number 1, where the rank of the Akaike information criterion is 1 and there is no constant and no trend. In the Johansen Cointegration Test, the cointegration relationship between the FTTASX, NTTR, and SX8PEX series can be examined by using the model without constants and trends.

Table 10. shows the results obtained from the Johansen Cointegration test, which includes the unconstrained Trace and Max-Eigen rank tests of the FTTASX, NTTR, and SX8PEX series.

Table 10

Johansen Cointegration Test Results of FTTASX, NTTR, SX8PEX Series

Trace	**Eigenvalue**	**Trace Statistics**	**0.05 Critical Value**	**Prob.****
None	0.19569	15.77366	24.27596	0.3962
At most 1	0.039975	2.489635	12.3209	0.9063
At most 2	1.74E-05	0.001061	4.129906	0.9804
Max-Eigen	**Eigenvalue**	**Max-Eigen Statistic**	**0.05 Critical Value**	**Prob.****
None	0.19569	13.28402	17.7973	0.2101
At most 1	0.039975	2.488575	11.2248	0.8626
At most 2	1.74E-05	0.001061	4.129906	0.9804

Note. Trace test indicates no cointegration at the 0.05 level, (*) denotes rejection of the hypothesis at the 0.05 level, (**) MacKinnon-Haug-Michelis (1999) p-values

The results in Table 10. show that there is no cointegration relationship at the 5% level of the trace and maximum eigenvalue (max-eigen) statistics. According to this result, it has been determined that there is no cointegration relationship between the series of FTTASX, NTTR, and SX8PEX variables according to the Johansen Cointegration Test. In other words, based on the results, it can be said that the selected indices do not reach equilibrium in the long term and their volatilities are not synchronized.

3.7. Validity Tests of VAR Model of FTTASX, NTTR, SX8PEX Series

Before interpreting the results from the Johansen Cointegration Test, normality tests, autocorrelation tests, and heteroscedasticity tests of the estimated VAR model of the FTTASX, NTTR, and SX8PEX series must be performed. If the series in the estimated VAR model are normally distributed and there is no autocorrelation or heteroscedasticity problem, the model is considered valid and significant. Thus, the results of the Johansen Cointegration Test can be interpreted from an economic perspective.

Table 11. shows the results obtained from the autocorrelation test of the VAR model of the FTTASX, NTTR, SX8PEX series.

Table 11

Autocorrelation LM Test of VAR Model Residuals

Lag	LRE* stat	df	Prob.	Rao F-stat	df	Prob.
1	2.254278	9	0.9868	0.24595	(9, 129.1)	0.9868
2	6.307183	9	0.7088	0.698788	(9, 129.1)	0.709

In Table 11, the autocorrelation LM test probability values of the VAR models of the FTTASX, NTTR, and SX8PEX series are greater than 5%. According to this result, the H0 hypothesis is accepted. So there is no autocorrelation problem between the series (Breusch, 1978).

Table 12. shows the results from the heteroscedasticity test of the VAR model of the FTTASX, NTTR, and SX8PEX series.

Table 12

Heteroscedasticity Test of the Residuals of the VAR Model

Chi-sq	df	Prob.
43.5677	36	0.1805

Table 12. shows the probability values of the heteroscedasticity test of the VAR model for the FTTASX, NTTR, and SX8PEX series. If the probability value of the heteroscedasticity test is greater than 5%, H_0 is accepted. The probability value of the heteroscedasticity test of the estimated VAR model was calculated to be greater than 5% (0.1805) (White, 1980). According to this result, the H_0 hypothesis cannot be rejected. In other words, there is no heteroscedasticity problem between series.

Table 13. shows the results from the normality test of the VAR model of the FTTASX, NTTR, SX8PEX series.

Table 13

Normality Test of VAR Model

Components	Jarque-Bera	df	Prob.
1	0.305515	2	0.8583
2	1.509394	2	0.4702
3	1.446296	2	0.4852
Joint	3.261205	6	0.7754

In the Jarque-Bera Normality Test, if the probability value of the joint component is greater than 5%, the H_0 hypothesis is accepted (Jarque & Bera, 1980). The probability value of the joint component obtained from the normality test of the VAR model of the FTTASX, NTTR, and SX8PEX series in Table 13 was calculated to be greater than 5% (0.7754). According to this result, the H0 hypothesis cannot be rejected. In other words, the series are normally distributed.

4. Conclusion

Technology-based financial assets protect investors against risks and increase capital gains, as well as providing financial support to reduce the negative effects of global climate change and environmental problems. Since the beginning of Industry 4.0, the technology sector's financial assets, environmentally friendly financial products, and fintech products are considered financial assets with increasing investment volume worldwide. During the global economic crisis in 2008, investors' confidence in financial markets was significantly shaken. Technology-based financial assets have made a significant contribution to restoring this trust.

It is possible for a company that has just entered the technology sector to achieve high capital gains, even though it has low setup capital, thanks to the high-tech products or methods that it can develop over time. The tendency of venture capital companies to invest in technological ventures has been increasing over time around the world.

Software products have different features among technology products and methods. Software that can be shaped as products, methods, and systems has features such as being personalized according to consumer or company needs, being updated according to changing conditions over time, and having very low logistics costs. These products are increasingly used, developed, and spread in real economic processes and the financial sector over time. There are academic studies showing that financial assets belonging to software products tend to behave differently compared to other financial assets. Technology stocks are important financial assets in capital markets. There are numerous academic studies showing that these assets are less sensitive to high market volatility and economic crises than other financial assets. In addition, there are many studies showing that although the technology sector is increasingly sensitive to fluctuations in the economy and markets to which it belongs, it acts contrary to the movements in the global market.

In this study, it was examined whether there is a cointegration relationship between stock market indices that differ regionally and consist of stocks of companies in the technology sector. According to the results, evaluations can be made on whether these assets have similar price and earnings movements globally. For this purpose, indices with high transaction volumes and investor numbers from different regions were selected around the world. It was decided to examine the NASDAQ 100 Technology TR (NTTR) index from the United States (US) stock markets, the iShares STOXX Europe 600 Technology UCITS (SX8PEX) index from the European Union (EU) markets, and the FTSE TechMARK All Share (FTTASX) index from the United Kingdom (UK) markets. Examinations were made using the Johansen Cointegration Test method to determine whether there is a cointegration relationship between the selected indices. According to the results, there was no cointegration relationship between the series of the selected indices. It can be said that technology stocks exhibit price and earnings movements according to the market conditions in which they are traded and the economic position of the region they belong to. The results of the study indicate that the volatilities of global technology indices are shaped by independent factors and do not tend to converge in the long term. Recently, developments such as pandemics, wars, and natural disasters around the world have negatively impacted financial stability. However, during the same period, assets belonging to technology companies have gained more value compared to others. This situation can be attributed to the tendency of investors in global markets to allocate more of their asset preferences to technology stocks. The results obtained from the study are important in terms of whether this trend is similar among selected markets. However, the results obtained from the study indicate that there is no long-term equilibrium among selected technology indices; in other words, there is no significant synchronization among their volatilities. It is expected that the spread of high technology use will increase and the level of awareness of environmental problems will rise globally in the near future. This situation may affect the global similarity of price and earnings movements of financial assets of technological products. For this reason, it may be useful to conduct academic research similar to this study from a broader perspective in the near future.

Declaration of Research and Publication Ethics

This study which does not require ethics committee approval and/or legal/specific permission complies with the research and publication ethics.

Researcher's Contribution Rate Statement

Since the author is the sole author of the article, his contribution rate is 100%.

Declaration of Researcher's Conflict of Interest

There are no potential conflicts of interest in this study.

References

Adekoya, O. B., & Adewuyi, J. (2022). Oil and multinational technology stocks: Predicting fear with fear at the first and higher order moments. *Finance Research Letters, 46*, 102210. https://doi.org/10.1016/j.frl.2021.102210

Ben Rejeb, A., & Arfaoui, M. (2016). Financial market interdependencies: A quantile regression analysis of volatility spillover. *Research in International Business and Finance, 36*, 140–157. https://doi.org/10.1016/j.ribaf.2015.09.022

Breidbach, C. F., & Wirtz, B. (2020). Fintech: Research directions to explore the digital transformation of financial service systems. *Journal of Service Theory and Practice, 30*(1), 79–102. https://doi.org/10.1108/JSTP-08-2018-0185

Breusch, T. S. (1978). Testing for autocorrelation in dynamic linear models. *Australian Economic Papers, 17*(1), 334–355. https://doi.org/10.1111/j.1467-8454.1978.tb00635.x

Chu, J., Chan, S., & Zhang, Y. (2021). Bitcoin versus high-performance technology stocks in diversifying against global stock market indices. *Physica A: Statistical Mechanics and Its Applications, 580*, 126161. https://doi.org/10.1016/j.physa.2021.126161

Elliott, G., Rothenberg, T., & Stock, J. H. (1996). Efficient tests for an autoregressive unit root. *Econometrica, 64*(4), 813–836. https://doi.org/10.2307/2171846

Emsbo-Mattingly, L., & Hofschire, D. (2017, January 13). *The business cycle approach to equity sector investing*. Fidelity Investments. https://www.fidelity.com/webcontent/ap101883-markets_sectors-content/18.01.0/business_cycle/Business_Cycle_Sector_Approach.pdf

Feltham, G. A., & Ohlson, J. A. (1995). Valuation and clean surplus accounting for operating and financial activities. *Contemporary Accounting Research, 11*(2), 661–688. https://doi.org/10.1111/j.1911-3846.1995.tb00462.x

Forsythe, G. E., & Straus, T. (1952). An extension of Gauss' transformation for improving the condition of systems of linear equations. *Mathematics of Computation, 6*(37), 18–34. https://doi.org/10.1090/S0025-5718-1952-0048162-0

Gharb, S., Suret, J.-M., & Siala, M. (2014). R&D investments and high-tech firms' stock return volatility. *Technological Forecasting and Social Change, 88*, 306–312. https://doi.org/10.1016/j.techfore.2013.10.006

Govindaraju, C., & Wong, C.-Y. (2012). Technology stocks and economic performance of government-linked companies: The case of Malaysia. *Technological and Economic Development of Economy, 18*(2), 248–261. https://doi.org/10.3846/20294913.2012.688313

Hacker, R. S., & Hatemi-J, A. (2008). Optimal lag-length choice in stable and unstable VAR models under situations of homoscedasticity and ARCH. *Journal of Applied Statistics, 35*(6), 601–615. https://doi.org/10.1080/02664760801920473

Hatemi-J, A. (2004). Multivariate tests for autocorrelation in the stable and unstable VAR models. *Economic Modelling, 21*(4), 661–683. https://doi.org/10.1016/j.econmod.2003.09.005

Jarque, C. M., & Bera, A. K. (1980). Efficient tests for normality, homoscedasticity and serial independence of regression residuals. *Economics Letters, 6*(3), 255–259. https://doi.org/10.1016/0165-1765(80)90024-5

Johansen, S. (1991). Estimation and hypothesis testing of cointegration vectors in Gaussian vector autoregressive models. *Econometrica, 59*(6), 1551–1580. https://doi.org/10.2307/2938278

Johansen, S. (1995). Likelihood-based inference in cointegrated vector autoregressive models. *Econometric Theory, 14*(4), 517–524. https://doi.org/10.1017/S0266466600007123

Kinateder, H., Campbell, R., & Ratti, R. (2021). Safe haven in GFC versus COVID-19: 100 turbulent days in the financial markets. *Finance Research Letters, 43*, 101951. https://doi.org/10.1016/j.frl.2021.101951

Kocaarslan, B., & Soytas, U. (2019). Dynamic correlations between oil prices and the stock prices of clean energy and technology firms: The role of reserve currency (US dollar). *Energy Economics, 84*, 104502. https://doi.org/10.1016/j.eneco.2019.104502

Kwon, S. S. (2002). Financial analysts' forecast accuracy and dispersion: High-tech versus low-tech stocks. *Review of Quantitative Finance and Accounting, 19*(1), 65–91. https://doi.org/10.1023/A:1015730325706

Mazur, M., Dang, M., & Vega, M. (2021). COVID-19 and the March 2020 stock market crash: Evidence from S&P 1500. *Finance Research Letters, 38*, 101690. https://doi.org/10.1016/j.frl.2020.101690

Niu, H. (2021). Correlations between crude oil and stock prices of renewable energy and technology companies: A multiscale time-dependent analysis. *Energy, 221*, 119800. https://doi.org/10.1016/j.energy.2021.119800

Phillips, P. C. B., & Perron, P. (1988). Testing for a unit root in time series regression. *Biometrika, 75*(2), 335–346. https://doi.org/10.1093/biomet/75.2.335

Qiao, Z., Wong, R., & Kutan, A. M. (2008). Volatility switching and regime interdependence between information technology stocks 1995–2005. *Global Finance Journal, 19*(2), 139–156. https://doi.org/10.1016/j.gfj.2008.01.003

Rašiová, B., & Árvai, P. (2023). Copula approach to market volatility and technology stocks dependence. *Finance Research Letters, 52*, 103553. https://doi.org/10.1016/j.frl.2022.103553

Sadorsky, P. (2003). The macroeconomic determinants of technology stock price volatility. *Review of Financial Economics, 12*(2), 191–205. https://doi.org/10.1016/S1058-3300(02)00071-X

Tiwari, A. K., & Jondeau, E. (2023). Financial technology stocks, green financial assets, and energy markets: A quantile causality and dependence analysis. *Energy Economics, 118*, 106498. https://doi.org/10.1016/j.eneco.2022.106498

White, H. (1980). A heteroskedasticity-consistent covariance matrix estimator and a direct test for heteroskedasticity. *Econometrica, 48*(4), 817–838. https://doi.org/10.2307/1912934