ADAM AKADEMİ / *ADAM ACADEMY*
Sosyal Bilimler Dergisi / *Journal of Social Sciences*

April 2026, *Vol. 16, No. 1, p. 75-92*
https://doi.org/10.31679/adamakademi.1540706

Araştırma Makalesi / *Research Article*

Başvuru / *Received:* 29.08.2024 | **Kabul** / *Accepted:* 31.12.2024

Return and Volatility Spillovers between XU100 and US Stock Markets

BIST100 ile ABD Hisse Senedi Piyasaları Arasında Getiri ve Volatilite Yayılımı

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Abstract

The integration of financial markets means that economic events in one part of the world can have ripple effects globally. A financial crisis in a major economy such as US. economy can lead to reduced investor confidence worldwide, impacting stock markets, currency values, and economic growth in various countries. By using daily closing price, this study aims to examine the time-varying and Spillover effect between the XU100, NASDAQ and Dow Jones indices over the period between 03/13/2015 and 03/13/2024.

The results of BEKK-GARCH model show that volatility shocks of returns in US stock market namely NASDAQ and DOW Jones transferred to Turkish stock markets (XU100). Also, there is spillover effect from US stock market to XU100. This effect in one-side. Based on DCC-GARCH results there is generally positive relationship between returns of US stock market and XU100 return. In additional, although there is not any long run relationship between price of two stock market, there is long run relationship between returns of two markets.

These results can help investors and market participants understand how risks and returns interact in different markets. It can also provide an important source of information for developing effective portfolio management strategies.

Keywords

Volatility Spillover, BIST100, NASDAQ, Dow Jones, DCC-GARCH, BEKK-GARCH

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Öz

Finansal piyasaların giderek artan entegrasyonu, bir ülkede meydana gelen ekonomik gelişmelerin diğer ülkelerin finansal piyasalarını etkilemesine yol açmaktadır. Bu çalışma, Türkiye hisse senedi piyasasını temsil eden BIST100 endeksi ile ABD hisse senedi piyasalarını temsil eden NASDAQ ve Dow Jones endeksleri arasındaki

getiri ve volatilite yayılım ilişkisini incelemeyi amaçlamaktadır. Çalışmada 13 Mart 2015 ile 13 Mart 2024 tarihleri arasındaki günlük kapanış verileri kullanılmıştır.

Analizde volatilite yayılım etkilerini belirlemek amacıyla BEKK-GARCH modeli, zamanla değişen korelasyon yapısını incelemek için ise DCC-GARCH modeli uygulanmıştır. Ayrıca uzun dönem ilişkilerin varlığı ARDL sınır testi ve Johansen eş bütünleşme testi ile analiz edilmiştir. Elde edilen bulgular, ABD hisse senedi piyasalarından BIST100 endeksine doğru tek yönlü volatilite yayılımı olduğunu göstermektedir. Ayrıca piyasalar arasında genel

olarak pozitif yönlü bir getiri ilişkisi tespit edilmiştir. Uzun dönem analiz sonuçları ise fiyat serileri arasında eş bütünleşme bulunmadığını ancak getiri serileri arasında uzun dönemli bir ilişki olduğunu ortaya koymaktadır.

Anahtar Kelimeler
Volatilite Yayılımı, BIST100, NASDAQ, Dow Jones, DCC-GARCH, BEKK-GARCH

Introduction

Globalization, along with the acceleration of economic integration around the world, has significantly increased the dependence between capital markets and strengthened the interaction between these markets. This situation has caused financial connections between countries to become more complex and caused the effects of global economic fluctuations to spread rapidly. In particular, the liberalization of capital flows has facilitated investors' access to markets in different countries, further deepening the dependence between markets (Baele, 2005)as this region has gone through a unique period of economic, financial, and monetary integration. More specifically, I quantify the magnitude and time-varying nature of volatility spillovers from the aggregate European (EU and (Chevallier et al., 2018)2012. Many studies have shown that increased financial integration leads to transmission and volatility spillovers between stock market returns. Many studies such as (Ojaghlou, 2024), (Zorgati & Garfatta, 2021), (Zehri, 2021), (Ben-Saïda et al., 2018) and (Mukherjee & Mishra, 2010) have shown that increased financial integration leads to transmission and volatility spillovers between stock market returns. These studies reveal that volatility spillovers between stock markets are generally associated with volatility in stock returns and investment risks in stock markets.

Identifying the source of volatility is vital to the healthy functioning of financial markets. Accurately analyzing the timing of volatility spillovers and understanding the effects of these spillovers on international stock markets is a critical step in preventing or mitigating potential crises in global markets. These analyzes allow investors to create risk management strategies more effectively, while also providing a better understanding of the expectations and reactions of market participants (Shen et al., 2022)especially under the current situation of the China–US trade conflicts. In this paper, we aim to uncover the risk spreading channels by means of volatility spillovers within the Chinese sectors using stock market data. By applying the generalized variance decomposition framework based on the VAR model and the rolling window approach, a set of connectedness matrices is obtained to reveal the overall and dynamic spillovers within sectors. We find that 17 sectors (mechanical equipment, electrical equipment, utilities, and so on.

Financial networks contain various channels that can increase the spread and risk of contagion of volatilities occurring in global markets. These networks cover a wide spectrum, from relationships between financial institutions to the behavior of investors. Factors such as rumors, especially those spread on social media, can lead to rapid and unexpected movements in markets, which can have serious consequences on the stability of the international financial system. In this context, understanding the structure and dynamics of financial networks is an important requirement to minimize the risk of contagion and ensure global financial stability. These analyzes are among the key elements to be considered when making strategic decisions for regulators, investors and market participants.

Various studies in the literature focus on a deeper understanding of stock market volatility because volatility refers to the risk and uncertainty of financial assets. Volatility spillover is defined as a change in volatility in one market having a lagged effect on the volatility of other stock markets (Milunovich & Thorp, 2006)weekly, and monthly rebalancing horizons when volatility spillovers are included in covariance forecasts. We estimate the conditional second moment matrix of (synchronized. Volatility spillover is of great importance for risk management and therefore, it is a critical necessity to investigate the sources of volatility in financial markets around the world. According to a generally accepted view, excessive financial market volatility in general and stock market volatility in particular can harm the smooth functioning of the economic system (Nikmanesh & Mohd Nor, 2019). This makes it difficult for investors to cope with uncertainty, increases uncertainty in financial decision-making, and can threaten market stability. Therefore, understanding the volatility dynamics of financial markets stands out as an indispensable element for both academic research and applied risk management strategies. Examining volatility spillovers in stock markets is also of great importance in predicting and mitigating the effects of global financial crises. Such studies can help regulatory authorities and market participants develop more effective strategies to maintain financial stability.

Trade liberalization increases economic integration, which strengthens the interdependence of exchanges. In this context, changes and shocks in global markets may create more widespread and profound effects in integrated economies (Baele, 2005) as this region has gone through a unique period of economic, financial, and monetary integration. More specifically, I quantify the magnitude and time-varying nature of volatility spillovers from the aggregate European (EU and (Akhtaruzzaman et al., 2021). It means reducing or eliminating barriers to trade between countries, tariffs, quotas and other protectionist measures. This type of liberalization increases the volume of trade between countries. Trade liberalization strengthens economic integration between countries. This integration creates greater interconnection of countries' economies and increases interdependence. A more integrated economy encourages the free movement of goods and services, capital flows and investment opportunities. In this context, increasing economic integration may also increase the interdependence of countries' stock markets. This means that economic events in one country can affect the stock markets of other countries. For example, an economic fluctuation or crisis in one country may also affect the stock markets of other countries that have a high trade volume with this country. Volatility in one market or sector is likely to affect others, so exploring spillover effects is important for understanding the risk transmission pathway" emphasizes a critical point in understanding how the interdependencies and connections between financial markets and sectors work (Shen et al., 2022)especially under the current situation of the China–US trade conflicts. In this paper, we aim to uncover the risk spreading channels by means of volatility spillovers within the Chinese sectors using stock market data. By applying the generalized variance decomposition framework based on the VAR model and the rolling window approach, a set of connectedness matrices is obtained to reveal the overall and dynamic spillovers within sectors. We find that 17 sectors (mechanical equipment, electrical equipment, utilities, and so on. Global shocks, sudden events both from within and outside the financial system, create significant volatility in markets. Therefore, investors, financial institutions and policy makers must have a deep understanding of the causes of volatility and inter-market correlations. Trade liberalization supports financial development by encouraging capital flows and creates more momentum in markets. This liberalization contributes to making financial markets more dynamic and accessible by increasing international investment opportunities (D.-H. Kim et al., 2010).

The difference in volatility between stock markets can indirectly determine the degree of openness of the markets. Volatility differences between markets may reflect the levels of economic and financial integration of countries or regions. More open and integrated markets generally show lower volatility spreads because these markets can have greater capital flows and higher liquidity (Majdoub & Mansour, 2014)namely Turkey, Indonesia, Pakistan, Qatar, and Malaysia. The empirical design uses MSCI (Morgan Stanley Capital International. However, the direct relationship of volatility differences to market openness is complex and depends on many factors. For example, if a market exhibits high volatility, it may mean that the market is more closed or more sensitive to external risks. Moreover, the degree of openness of markets is shaped not only by volatility but also by other factors such as trade barriers, capital mobility and the regulatory environment.

The integration of financial markets has significantly increased the interconnectedness of economies worldwide, making it crucial to understand how economic events in one part of the world can have ripple effects globally. A financial crisis in a major economy, such as the US economy, can trigger a chain reaction that impacts investor confidence, stock markets, currency values, and economic growth in various countries. This study aims to explore the time-varying and spillover effects between the XU100, NASDAQ, and Dow Jones indices by analyzing daily closing prices over a specific period. Understanding these dynamics is essential for investors, policymakers, and financial analysts to make informed decisions in an increasingly interconnected global financial system.

Understanding time-varying and spillover effects among major stock market indices such as the XU100, NASDAQ, and Dow Jones is critical for several reasons. First, in today's interconnected global economy, events in one market can quickly impact others, leading to potential financial instability. By examining these effects, we can gain important insight into how shocks propagate across markets and develop strategies to mitigate their effects. Additionally, investors can use this research to make more informed decisions, effectively manage risks and optimize their portfolios. Policymakers can also benefit from this research by taking measures to increase market stability and prevent contagion effects during periods of economic turbulence. Consequently, this study has the potential to provide valuable contributions to financial market analysis and can help stakeholders better manage the complexities of the global financial environment.

Literature Review

Research on return and volatility movements between international stock markets reveals complex connections that create significant impacts on global financial dynamics. These studies show that the US stock market is often the main source of congestion and provides a significant influence on other markets. In particular, studies by (Mohammadi & Tan, 2015) and (Hwang, 2023) reveal that the US market creates unidirectional effects, that is, changes and volatility in the US market are transferred to other markets, but the opposite situation is rarely observed.

The influence of the US market is particularly strong on developed economies such as Canada and Germany. Research by (Hwang, 2023) shows that these developed markets are highly sensitive to fluctuations in the US market, and changes in the US market create large harmonics between stock market returns and volatility. This high degree of dependence highlights the central role of the US market in shaping global financial conditions.

In contrast, changes in the US market have a more limited impact on emerging markets, such as China. Research by (Mohammadi & Tan, 2015) and (Qarni & Gulzar, 2018) reveals that emerging markets are less sensitive to convection effects from the US market. This limited impact offers potential diversification benefits for international investors to include emerging market assets in their portfolios, as these markets may not generally move in parallel with developed markets.

Geographic proximity also plays an important role in market integration. For example, higher integration and convection effects are observed between geographically close markets such as China and Hong Kong. Studies by (Mohammadi & Tan, 2015) and (Qarni & Gulzar, 2018) show that these stronger

Table 1. Literature Summary

Study	Abstract Summary	Methodology	Main Findings
(J. S. Kim & Ryu, 2015)	Examines return spillover, volatility transmission, and column behavior between the U.S. and Korean stock markets.	- Analyzed return spillover effects - Examined volatility transmission - Investigated column behavior	- The U.S. stock market causes return spillovers in the Korean market. - Significant volatility transmission between the U.S. and Korean markets. - Stronger column magnitude between the U.S. and Korean markets.
(Qarni & Gulzar, 2018)	Analyzes return and volatility spillover effects between the Shanghai Stock Exchange and its major trading partners, including the US.	- Covariance stationary N-variable VAR(p) model - KPPS H-step ahead forecast error variance - Spillover index calculation	- Increased return and volatility spillovers between SSE and major trading partners. - Low spillovers from SSE to U.S. and Germany. - High integration between SSE and Hong Kong.
(Mohammadi & Tan, 2015)	Examines return and volatility spillovers across equity markets in Mainland China, Hong Kong, and the United States.	- Daily data analysis - ARCH and GARCH models - Dynamic Conditional Correlation (DCC) model	- Unidirectional return spillover from the U.S. to Hong Kong, Shanghai, and Shenzhen. - High correlation within Chinese markets. - Lower correlations with Hong Kong and the U.S., suggesting diversification benefits.
(Hwang, 2023)	Investigates the influence of the U.S. stock market on return and volatility spillovers to its major trading partners.	- Diebold and Yilmaz (2012) spillover index approach - Weekly stock market returns analysis (2011-2019)	- The U.S. stock market is most influential in terms of spillovers to major markets, especially Canada and Germany. - The U.S. and Chinese markets are least vulnerable to foreign shocks.
(Mulyadi & Anwar, 2012)	Examines return and volatility spillovers between the U.S., UK, and Greek stock markets during American and European crises.	- GARCH (1, 1) and GARCH-X models - Data from January 2006 to July 2010	- Significant return spillover between the U.S., UK, and Greece. - No volatility spillover from the U.S. to Greece or between the U.S. and European markets during crises.
(Li & Giles, 2015)	Analyzes volatility spillover effects between developed markets (U.S., Japan) and Asian emerging markets.	- Asymmetric multivariate GARCH model - Data from January 1993 to December 2012	- Significant unidirectional volatility spillovers from the U.S. to Japanese and Asian emerging markets. - Stronger bidirectional spillovers during the Asian financial crisis.
(Bissoondoyal-Bheenick et al., 2018)	Examines volatility spillovers between the U.S., China, and Australian stock markets.	- Industry-level data analysis - Causality analysis	- Significant two-way volatility spillover among the U.S., Chinese, and Australian stock markets. - One-way spillover from the U.S. to China in specific industries.
(Chow, 2017))	Investigates volatility spillovers and linkages between Asian stock markets and the U.S. and UK stock markets.	- Diebold-Yilmaz spillover index - Rolling regressions	- Increased volatility spillovers in Asian markets post-crisis. - Susceptibility linked to market openness. - Asian markets have become significant emitters of financial shocks.
(Zhang & Mao, 2022)	Analyzes spillover effects between Chinese and U.S. stock markets during the COVID-19 pandemic.	- Comparison of periods before, during, and after COVID-19 - Analysis of RMB/US exchange rate and gold prices	- Asymmetric spillover effect with stronger impact from Chinese to U.S. market during COVID-19. - Highest risk correlation during COVID-19 spread. - RMB/US exchange rate and gold as macro spillover channels.
(Y. A. Liu & Pan, 1997)	Investigates U.S. stock market influence on returns and volatilities in four Asian stock markets.	- Two-stage GARCH approach - ARMA (1)-GARCH (1,1)-in-mean model	- U.S. market has a greater impact than Japan on Asian markets. - Increased spillover effects after the 1987 stock market crash.
(Chan, 2010)	Examines volatility spillovers among ASEAN-5 stock markets and between ASEAN-5 and U.S. and Japanese markets.	- EGARCH model	- ASEAN-5 markets are highly autocorrelated and interconnected. - U.S. market has a greater impact on ASEAN-5 compared to Japan. - Philippines and Thailand are more susceptible to spillovers.
(Joshi, 2011)	Analyzes return and volatility spillovers among Asian stock markets, excluding XU100 and US markets.	- Six-variable GARCH-BEKK model	- Bidirectional spillovers among most Asian markets. - Low magnitude of spillovers indicating weak integration. - Higher own volatility spillovers compared to cross-market spillovers.
(Le & Kakinaka, 2010)	Investigates mean and volatility spillover effects from major markets (U.S., Japan, China) to Indonesia and Malaysia.	- GARCH models - Comparison of mean spillover effects	- Significant mean return spillovers from U.S., Japan, and China to Indonesia and Malaysia. - U.S. market has the most significant effect. - Greater volatility spillover from U.S. to Indonesia compared to Malaysia.
(Diebold & Yilmaz, 2009)	Provides measures of return and volatility spillovers between global equity markets, including XU100 and U.S. markets.	- VAR models - Variance decomposition - Spillover index formulation	- Spillovers account for approximately 30% of forecast error variance across 16 global markets. - Return spillovers show a gently increasing trend. - Volatility spillovers respond to major and minor crises.

Table 1. Literature Summary

(Umer et al., 2018)	Examines return and volatility spillovers among EAGLEs stock markets, with a focus on the influence of developed markets.	- Multivariate GARCH BEKK model - Dynamic Conditional Correlation (DCC) model	- Persistent spillovers during pre-crisis and post-crisis periods. - Significant impact of external markets, especially the U.S., on EAGLEs markets. - Variation in spillovers over time.
(Sunoto & Dewi, 2020)	Finds no volatility spillover between U.S. (NASDAQ) and Chinese (SSE) stock markets during 2016-2018.	- GARCH methodology - Daily stock return data analysis	- No volatility spillover between U.S. and Chinese stock markets during 2016-2018. - No effect of U.S. market fluctuations on Chinese market volatility, and vice versa.

interactions in regional markets lead to more pronounced and immediate movements in stock market returns and volatility. The 2007-2008 financial crisis further increased these convection effects and increased the correlations between global stock markets. Studies by Mohammadi and Tan (2015) and Kim and Ryu (2015) reveal how the crisis intensified market linkages and increased the compliance of returns and volatility between different regions during these periods. Increased correlation during periods of financial stress highlights the interconnected nature of global markets and the challenges faced by investors.

(H.-H. Liu & Lin, 2021)futures and NASDAQ stock index futures as the main research objects, and applies the ARJI (autoregressive jump intensity model find evidence of volatility spillover and time-varying correlation between the S&P500 and NASDAQ indices, with Liu specifically noting two-way spillovers between the S&P500 index cash and futures. Ghorbel (2012) extends this analysis to include crude oil, finding strong evidence of volatility spillovers from crude oil to stock markets, and a significant impact of oil price shocks on the relationship between oil and stock indices returns. However, Xiao (2010) focuses on the European stock markets, finding volatility spillover and time-varying conditional correlation between the CAC, DAX, FTSE100, and S&P indices. These studies collectively highlight the complex and dynamic nature of the relationships between stock market indices and the factors that influence them.

Studies in the literature highlight the complexity and variability of return and volatility spillovers in international stock markets. The central location of the US market, combined with diverse influences on developed and emerging markets, reflects the complex and evolving nature of global financial interconnections. This helps us understand how events in international financial markets interact with each other and what role they play in global economic balances. In this context, the complexity and variability in financial markets illustrate the complex structure of the global economic system and how financial risks can spread on a global scale. Research on return and volatility movements between international stock markets highlights the complex dynamics and significant impacts on global financial stability. Key findings include:

U.S. Market Influence: The U.S. stock market is a major source of return and volatility spillovers to other markets. Studies by Mohammadi & Tan (2015) and Hwang (2023) show that changes and volatility in the U.S. market often propagate to developed markets like Canada and Germany, while the reverse is less common. This underscores the U.S. market's dominant role in global financial dynamics.

Impact on Developed vs. Emerging Markets: The influence of the U.S. market is more pronounced on developed economies than on emerging markets. Research indicates that developed markets are highly sensitive to U.S. fluctuations, whereas emerging markets, such as China, exhibit limited spillovers from the U.S. This difference suggests potential diversification benefits for investors considering emerging markets.

Geographic Proximity: Proximity affects market integration. Stronger spillovers are observed between geographically close markets, such as China and Hong Kong. The 2007-2008 financial crisis further intensified regional spillovers and increased correlations among global stock markets.

Sector-Specific Spillovers: Beyond equities, spillovers also occur between stock markets and other asset classes. Ghorbel (2012) found notable spillovers from crude oil to stock markets, highlighting the interconnectedness of commodities and equities.

Crisis and Extraordinary Events: Significant global events, such as the 2007-2008 financial crisis and the COVID-19 pandemic, have amplified spillovers. During the pandemic, Zhang & Mao (2022) observed stronger spillovers from the Chinese to the U.S. market, driven by macroeconomic variables.

The literature reveals a complex web of financial linkages, with the U.S. market playing a central role in influencing global stock market returns and volatility. The varying impacts on developed and emerging markets, as well as the effects of geographic proximity and major financial crises, illustrate the dynamic nature of international financial markets.

Data and Methodology

The main purpose of this study is to investigate the relationship between XU100, NASDAQ and Dow Jones indices between 03/13/2015 and 03/13/2024. we use daily closing data. Table 1 represents the main index of those countries. The letter R represents the return of index. The daily return of each series is calculated as the logarithmic difference with respect to the corresponding market index. Returns were calculated with the following formula:

$$R_t = 100 \times \ln\left(\frac{p_t}{p_{t-1}}\right)$$

Statistics such as mean, median, maximum, minimum and standard deviation describe the different characteristics of each index. For example, the average of the XU100 index is 1991.75, while the average return of

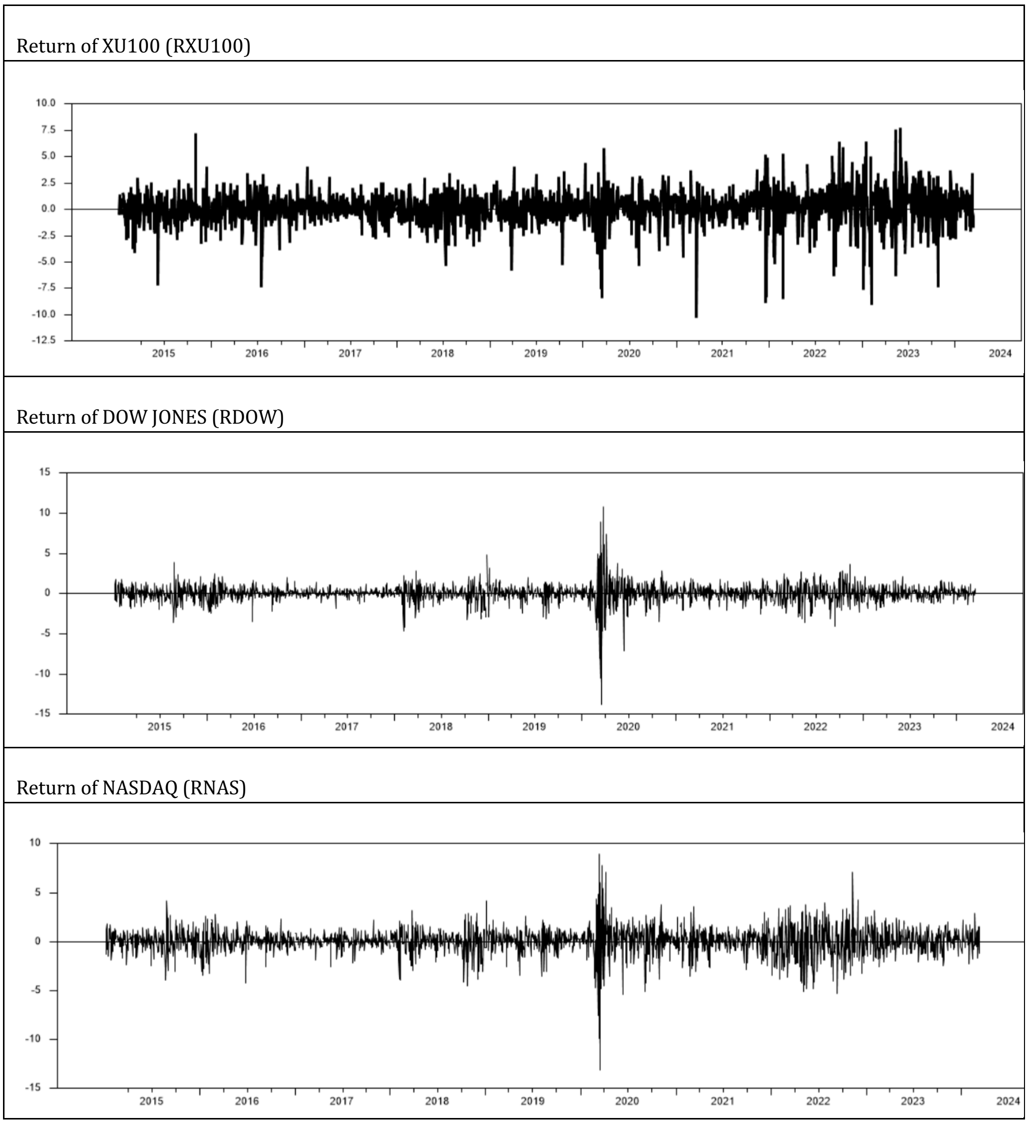
Table 2. Descriptive statistics

	XU100	RXU100	DOW	RDOW	NAS	RNAS
Mean	1991.75	0.1016	26571.03	0.0346	9184.29	0.0540
Median	1074.01	0.1398	26106.77	0.0568	8017.90	0.1111
Maximum	9374.20	7.7814	39131.53	10.764	16274.9	8.9346
Minimum	685.680	-10.306	15660.18	-13.841	4266.84	-13.149
SD	2056.44	1.5536	6431.50	1.1335	3541.83	1.346
Skewness	2.0878	-0.7149	0.0140	-0.9605	0.3428	-0.686
Kurtosis	6.2203	8.4817	1.751347	25.45993	1.718665	11.619
Jarque-Bera (Probability)	2682.25 (0.00)	3095.74 (0.00)	150.467 (0.00)	49014.2 (0.00)	203.708 (0.00)	7348.34 (0.00)

the XU100 (RXU100) index is 0.1016. Similarly, various statistics of indices provide information about the distribution and variability of returns of each.

The Jarque-Bera statistic and probability value can be used to evaluate how well each index fits a normal distribution. According to the Jarque-Bera test results in the table, the Jarque-Bera statistics of all series are quite high (2682.25 for XU100, 3095.74 for RXU100, 150.467 for DOW, 49014.2 for RDOW, 203.708 for NAS, 7348.34 for RNAS). This indicates that not all series follow a normal distribution exactly and probably deviate significantly from the normal distribution. The following graph shows the returns of the series:

In the period before COVID-19 pandemic, financial markets generally showed stable growth and there were no major economic shocks, and therefore, as seen in the graphs, there are not many fluctuations in the returns of the series. However, the COVID-19 pandemic affected the whole world in early 2020 and caused serious fluctuations in financial markets. In the first months of the pandemic, there were sharp declines in the markets due to its rapid and uncertain spread and the harsh quarantine measures taken by governments. During this period, significant value losses have been observed in the XU100, Dow Jones, and Nasdaq, leading to significant fluctuations in returns as depicted in the graph. In addition, the impact of the Pandemic on financial markets has been characterized by sharp changes in supply and demand conditions, uncertainties in the business world, and fiscal and monetary policy interventions implemented by governments. Sectors such as tourism, aviation and retail have been among those most affected by the pandemic. In contrast, some areas, such as the technology and healthcare sectors, have gained value during the pandemic process. In the post-pandemic period, a recovery trend was observed in the markets with the development and distribution of vaccines. However, this



Graph 1. Plots of Return Series

recovery process has varied across sectors and geographical regions. In the long term, the effects of the COVID-19 pandemic on financial markets will continue to be evaluated together with economic structures and policy decisions.

Unit root

Unit root tests are vital in economics and finance because they determine whether a time series is stationary or non-stationary and according to (Wolters & Hassler, 2006)unit root tests are nowadays the starting point of most empirical time series studies. The oldest and most widely used test is due to Dickey and Fuller (1979, unit root tests are nowadays the starting point of most empirical time series studies. (Herranz, 2017) highlights the potential for misleading results in linear regressions with unit root processes and addresses the risk of misleading cointegration relationships with those with close unit roots. (Wolters & Hassler, 2006)unit root tests are nowadays the starting point of most empirical time series studies. The oldest and most widely used test is due to Dickey and Fuller (1979 emphasizes the importance of modelling the determinant component in unit root tests and discusses the need for tests that take structural shifts into account. We use (Dickey & Fuller, 1979) and (Phillips & Perron, 1988)" methodology for testing unit root test. The results are summarized in table 2.

Table 2 shows unit root test results of our series. Tests such as ADF (Augmented Dickey-Fuller) and PP (Phillips-Perron) are used to determine whether a time series is stationary or not. When we look at the ADF and PP test results for the XU100 index, it has been determined that the series is not stationary in both cases, while ΔXU100 obtained because of the first difference process have revealed that the series has become stationary (). Similarly, for the NASDAQ index, the series is not stationary in cases of Intercept and Intercept and trend, but the ADF and PP test results for Δ NASDAQ obtained because of first difference show that the series are stationary (). However, it has been observed that the DOW series is stationary within the 95% confidence interval. As for the return series, it was determined that all three series

Table 3. Unit Root Results

	Augmented Dickey–Fuller test (ADF)		Phillips–Perron test (PP)	
Variables	intercept	Intercept and trend	intercept	Intercept and trend
XU100	2.312(26)	0.551(26)	3.944(18)	1.45(19)
Δ XU100	-7.77(26) ***	-8.308(26) ***	-50.25(13) ***	-49.93(10) ***
R XU100	-21.59(3) ***	-21.78(3) ***	-47.66(4) ***	-47.843(3) ***
DOW	-0.61(10)	-3.538(10) **	-0.564(20)	-3.514(27) **
R DOW	-14.95 (9) ***	-14.956(9) ***	-55.76 (13) ***	-55.75(12) ***
NAS	-0.040(23)	-1.987 (23)	-0.184(12)	-2.19(11)
Δ NAS	-50.14(0) ***	-50.144(0) ***	-51.578(8) ***	-51.588(7) ***
R NAS	-15.70(13) ***	-15.711(11) ***	-53.78(18) ***	-53.78(21) ***

Note: ** represent α %95 confidence level, and *** represent α %99 confidence level. The number between parentheses shows optimum lags. R shows return of indexes and Δ represent first difference of indexes.

were stationary within the 99% confidence interval at I (0).

To examine this relationship, we have analyzed the Spillover effect with the BEKK-GARCH model, and the time-varying correlation with the DCC-GARCH model. Also, for long run relationship we use cointegration analyses such as Johansen cointegration test and ARDL bound methodology. The BEKK-GARCH model was developed by Baba, Engle, Kraft and Kroner (1990) and (R. F. Engle & Kroner, 1995). BEKK-GARCH model is used to evaluate the spillover effects between financial data by analyzing the time-varying variance structures. The model is an effective tool for determining volatility relationships in multi-variable time series. The BEKK Model is specifically focused on capturing the conditional covariance matrix of a vector of variables. It is suitable for analyzing volatility and correlation dynamics between multiple assets or variables. The model assumes that the conditional covariance matrix fits a multivariate autoregressive process. In the BEKK Model, the conditional covariance matrix at time *t* depends on the lagged conditional covariance matrix, the lagged error squared, and sometimes other external variables. The model allows estimating both diagonal and off-diagonal elements (covariances) of the conditional covariance matrix.

$$H_t = CC' + \sum_{j=1}^{q}\sum_{k=1}^{k} A'_{kj}\varepsilon_{t-j}\varepsilon'_{t-j}A_{kj} + \sum_{j=1}^{p}\sum_{k=1}^{k} B'_{kj}H_{t-j}B_{kj}$$

Where, C is N x N the parameter matrices, C is the lower triangular matrix, and ARCH and GARCH are obtained by creating a sandwich term with a coefficient matrix around a symmetric matrix. The first order BEKK model is as follows:

$$H_t = CC' + A'u_{t-1}u'_{t-1}A + B'H_{t-1}B$$

In the BEKK-GARCH model, the coefficients C, B, and A are used to explain how the volatility of the time series changes over time. Matrix C represents the constant part of the model and determines the constant component of the conditional variance matrix. Matrices B and A measure the effect of past errors and past conditional variances on the current conditional variance, respectively. These coefficients are important for understanding volatility clustering in financial time series and how shocks propagate over time. Table H shows the results of the four-dimensional GARCH-BEKK model. These results demonstrate the complexity of the relationships between the returns of different stocks and the effectiveness of the model in the analysis. Table 3 shows results of GARCH-BEKK model.

Based on table 3, the μ coefficients (mean returns) are positive and statistically significant for NASDAQ, DOW and BIST100. This indicates that the average returns of the indices are positive. As motioned before, the C matrix coefficients represent the constant component of the conditional variance, and all coefficients are statistically significant. This indicates that a constant component of volatility exists and does not change over time. The A matrix coefficients measure the impact of past errors

Table 4. GARCH-BEKK

Parameters	Coefficient	Standard Error	t-statistics	Probability (Signify.)
$\mu_{R\ NASDAQ}$	0.10715	0.01693	6.3291	0.0000
$\mu_{R\ DOW}$	0.07143	0.01330	5.3704	0.0000
$\mu_{R\ BIST100}$	0.10827	0.0315	3.4293	0.0006
$C_{(1,1)}$	0.19488	0.0149	13.030	0.0000
$C_{(2,1)}$	0.19019	0.0173	10.941	0.0000
$C_{(2,2)}$	0.07056	0.0090	7.7606	0.0000
$C_{(3,1)}$	0.1411	0.0381	3.6942	0.0002
$C_{(3,2)}$	0.07748	0.0414	1.8714	0.06128
$C_{(3,3)}$	0.14076	0.0421	3.339	0.0008
$A_{(1,1)}$	0.25267	0.02958	8.5412	0.0000
$A_{(1,2)}$	0.0239	0.0277	0.864	0.3872
$A_{(1,3)}$	-0.07018	0.03302	-2.1249	0.03359
$A_{(2,1)}$	0.1114	0.0361	3.0802	0.0020
$A_{(2,2)}$	0.3748	0.03653	10.261	0.0000
$A_{(2,3)}$	0.13008	0.04104	3.1695	0.00152
$A_{(3,1)}$	0.01760	0.01308	1.345	0.1785
$A_{(3,2)}$	0.01142	0.01174	0.9722	0.3309
$A_{(3,3)}$	0.1657	0.0206	8.0463	0.0000
$B_{(1,1)}$	0.9661	0.0093	103.101	0.0000
$B_{(1,2)}$	-0.00087	0.0093	-0.0928	0.92602
$B_{(1,3)}$	0.0253	0.01021	2.4793	0.0131
$B_{(2,1)}$	-0.0506	0.0138	-3.645	0.0002
$B_{(2,2)}$	0.89781	0.0154	58.011	0.00000
$B_{(2,3)}$	-0.0532	0.01434	-3.7100	0.0002
$B_{(3,1)}$	-0.0076	0.0049	-1.525	0.1272
$B_{(3,2)}$	-0.00620	0.00464	-1.337	0.1809
$B_{(3,3)}$	0.97753	0.00566	72.528	0.00000

(shocks) on current volatility. For example, the coefficient of $A_{(1,1)}$ is quite high and significant, indicating that past shocks in the NASDAQ index significantly affect own current volatility. On the other hand, some coefficients such as $A_{(1,2)}$ is not statistically significant. this indicate that past errors (shocks) of NASDAQ dose not effect DOW_J current return. $A_{(3,1)}$ and $A_{(3,2)}$ are not statistically significant that shows past errors (shocks) of RBİST100 has not any impact on both NASDAQ and DOW_J current return.

The B matrix coefficients measure the impact of past conditional variances on current volatility or spillover effect. The coefficients of ($B_{(1,1)}$), ($B_{(2,2)}$), and ($B_{(3,3)}$) are quite high and significant, indicating that past volatility greatly effects on own current volatility. On the other hand, some coefficients such as ($B_{(1,2)}$),($B_{(3,1)}$) and ($B_{(3,2)}$) are not statistically significant. That indicates that there is not spillover effect from RBİST100 to both RNASDAQ and RDOW_J and also there is no any spillover effect from RNASDAQ to RDOW_J. while the coefficient of ($B_{(2,1)}$),($B_{(1,3)}$) and ($B_{(2,3)}$) are statistically significant that show both RNASDAQ and RDOW_J have spillover effects on RBİST100 and also RDOW_J has spillover effects on RNASDAQ.

The DCC-GARCH method was used to detect time-varying correlations of return series and to analyze how volatility changes over time. DCC-GARCH model is developed by (R. Engle, 2002b). This model is used for dynamic conditional correlation models. In this way, it is possible to understand how the correlation between financial data changes over time and how it is affected by periods. The DCC-GARCH model plays an important role in areas such as risk management and portfolio diversification and ARDL limit test is developed by Pesaran, Shin and Smith (2001). This test is used to analyze the relationship between each other and causal relationships. It is an effective tool to determine the existence and direction of long-term relationships. ARDL limit test is widely used in the understanding of macroeconomic relations and market dynamics. The models used in your work are important tools for understanding financial market relationships and predicting future price movements. This model can be used in areas such as risk management, portfolio management, and economic policy creation to help make sound decisions.

Based on (R. Engle, 2002), Constant Correlation model are used to form the overall covariance matrix by using:

$$H_{ij,t} = R_{ij}\sqrt{H_{ii,t}H_{jj,t}}$$

Where R is the constant correlations and default variance model is:

$$H_{ii,t} = c_i + a_i u_{i,t-1}^2 + b_i H_{ii,t-1}$$

And R_t is taken as follows:

$$R_t = diag\left(q_{11,t}^{\frac{1}{-2}} \ldots q_{NN,t}^{\frac{1}{-2}}\right) Q_t \, diag\left(q_{11,t}^{\frac{1}{-2}} \ldots q_{NN,t}^{\frac{1}{-2}}\right)$$

were.

$$Q_t = (1-\alpha-\beta)\overline{Q} + \alpha u_{t-1} u'_{t-1} + \beta Q_{t-1}$$

According to (R. Engle & Sheppard, 2001), if we have positive definite Q_t, it implies R_t to have positive sign and $\overline{Q}$ is an $N \times N$ unconditional variance matrix of u_t. according to the estimation results of the DCC model, α and β (parameters of the DCC model) are non-negative and their sum is less than one ($\alpha+\beta<1$).

$$\rho_{12,t}=\frac{(1-\alpha-\beta)\overline{q_{12}}+\alpha u_{1,t-1}u_{2,t-1}+\beta q_{12,t-1}}{\sqrt{(1-\alpha-\beta)\overline{q_{11}}+\alpha u_{1,t-1}^2+\beta q_{11,t-1})(1-\alpha-\beta)\overline{q_{22}}+\alpha u_{2,t-1}^2+\beta q_{22,t-1})}}$$

ρ values represent correlation coefficients, while α and β coefficients represent variance model parameters and $\alpha \geq 0$ and $\beta \geq 0$ and $\alpha+\beta<1$. The results of DCC-GARCH are summarized in the table 5. The conditions set for the estimated parameters and ensure the conditional correlation matrix. If these parameters are positive, it indicates that an increase in the conditional correlation is expected for the next period

Table 5. Results of DCC-GARCH

	Augmented Dickey–Fuller test (ADF)		Phillips–Perron test (PP)	
Variables	intercept	Intercept and trend	intercept	Intercept and trend
XU100	2.312(26)	0.551(26)	3.944(18)	1.45(19)
Δ XU100	-7.77(26) ***	-8.308(26) ***	-50.25(13) ***	-49.93(10) ***
R XU100	-21.59(3) ***	-21.78(3) ***	-47.66(4) ***	-47.843(3) ***
DOW	-0.61(10)	-3.538(10) **	-0.564(20)	-3.514(27) **
R DOW	-14.95 (9) ***	-14.956(9) ***	-55.76 (13) ***	-55.75(12) ***
NAS	-0.040(23)	-1.987 (23)	-0.184(12)	-2.19(11)
Δ NAS	-50.14(0) ***	-50.144(0) ***	-51.578(8) ***	-51.588(7) ***
R NAS	-15.70(13) ***	-15.711(11) ***	-53.78(18) ***	-53.78(21) ***

Note: *** indicates significance at the 1% level.

The estimation results of the GARCH (1, 1) model show that it satisfies the condition $\alpha+\beta<1$ when $\alpha \geq 0$ and $\beta \geq 0$ (non-negative). Moreover, after a shock in the return series. The beta parameter (β) in the DCC model also expresses the effect of the conditional correlation of the previous

Table 6. Diagnostics of DCC-GARCH model

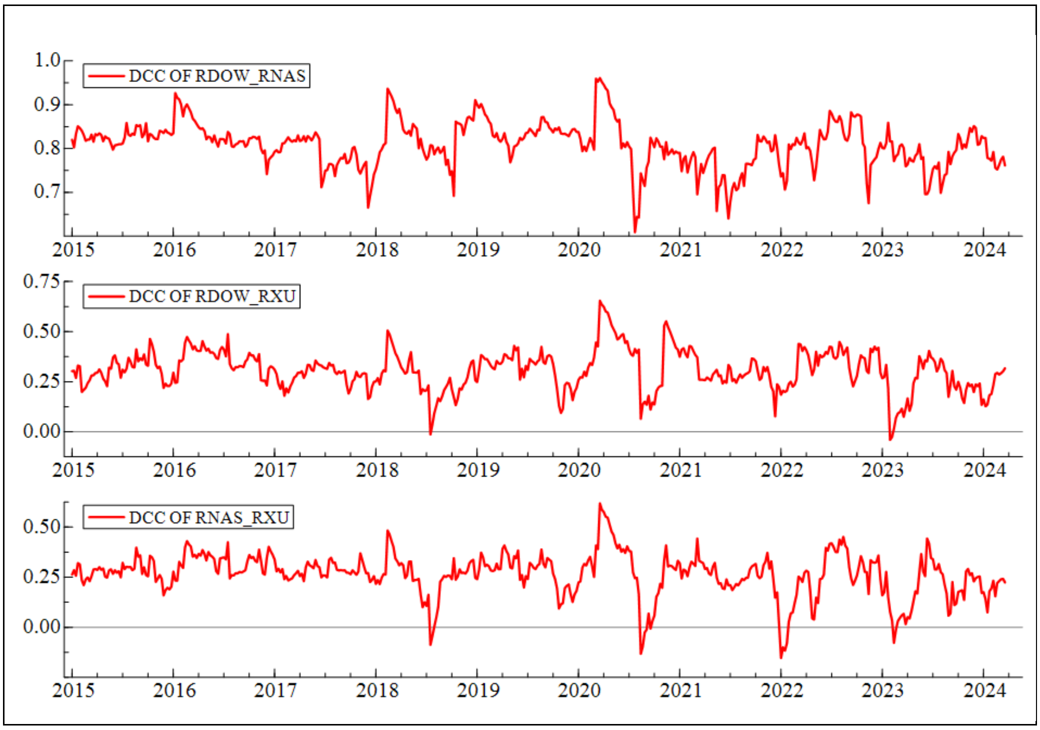
```
Q-Statistics on Standardized Residuals

 Series: RDOW
  Q (5) = 6.77940 [0.2375703]
  Q (10) = 21.2600 [0.0193520]
  Q (20) = 27.0592 [0.1336073]
  Q (50) = 62.1066 [0.1169709]

 Series: RNAS
  Q (5) = 2.15640 [0.8271084]
  Q (10) = 7.69222 [0.6588719]
  Q (20) = 23.1609 [0.2809650]
  Q (50) = 50.6665 [0.4470912]

 Series: RXU
  Q(  5) =  12.4029   [0.0296650]
  Q (10) = 17.1807 [0.0704594]
  Q (20) = 24.6256 [0.2161299]
  Q (50) = 65.7032 [0.0673442]
H0: No serial correlation ==> Accept H0 when prob. is High [Q < Chisq(lag)]
---------------
Hosking's Multivariate Portmanteau Statistics on Standardized Residuals
  Hosking (5) = 53.7113 [0.1751042]
  Hosking (10) = 104.607 [0.1392040]
  Hosking (20) = 182.245 [0.4392220]
  Hosking (50) = 469.874 [0.2498060]
---------------
Li and McLeod's Multivariate Portmanteau Statistics on Standardized Residuals
  Li-McLeod (5) = 53.6652 [0.1762193]
  Li-McLeod (10) = 104.467 [0.1413085]
  Li-McLeod (20) = 182.372 [0.4366100]
  Li-McLeod(50) = 468.094   [0.2684903]
```

period on the conditional correlation of the current period. If β approaches 1 and is larger, this indicates that the conditional relationships of the current period will be close to the conditional relationships of the previous period. Diagnostic tests of the DCC model are given in the table 5.

DCC-GARCH Diagnostic test results are used to analyze dynamic conditional correlations between multiple time series with the DCC-GARCH model. Hosking and Li-McLeod Multivariate Portmanteau Statistics are tests to check the adequacy of vector autoregressive models used in the analysis of standardized residuals (residuals) obtained from GARCH models. Hosking's Multivariate Portmanteau Statistics on Standardized Residuals tests the null hypothesis that there is no autocorrelation in the standardized residuals. A high p-value (usually above 0.05) suggests that there is no significant autocorrelation in that lag pattern and that the model is adequate.

Hosking's Multivariate Portmanteau Statistics on Squared Standardized Residuals: like above, but this time the test is applied to squared standardized residuals. This is a test for autocorrelations in variances (volatility). Again, high p-values indicate no significant autocorrelation. Li and McLeod's Multivariate Portmanteau Statistics: These are alternative versions of the Hosking test that may have better properties in certain situations. Interpretation is the same as the Hosking test. The results show that p-values for standardized and squared standardized residuals are generally above the 0.05 threshold, especially at higher lag patterns, indicating that the model does not show significant autocorrelation and captures the dynamics of the data well.

In summary, diagnostic tests suggest that the DCC-GARCH model fits the data appropriately, there is no significant autocorrelation in the residuals or their squares, and the volatility dynamics of the model are well specified. Graph 2 shows for the DCC between variables:



Graph 2. DCC Between Variables

Dynamic conditional correlations between RDOW, RNAS and RXU series were examined and when the graphs between these were examined, it was understood that there was generally a positive dynamic conditional correlation (DCC) between RDOW and RXU and was generally around 0.25. Between RNAS and RXU, it has been observed that DCC is generally positive, like RDOW-RXU, and is negative only in the short term in the 2022 and 2020 periods. However, DCC between RDOW and RNAS was determined to be very strong.

After time-varying and spillover analyses in this section, long run relationship between the returns are investigated. For this goal, ARDL bound model has been used. As mentioned before The ARDL (Auto-Regressive Distributed Lag) model is a powerful econometric tool used to analyze long-run equilibrium relationships between variables in time series data. This model allows researchers to examine how variables interact in the short and long term. The ARDL model aims to reveal the equilibrium relationships between variables that may show uncertain behavior in the short term but act together predictably in the long term. This plays a critical role in separating long- and short-term effects to understand economic dynamics. The general form of the ARDL model is as follows:

where, $\beta_{i(i=1,2)}$ represents the long-run multiplier, α_0 is the constant term. Lagged values of ΔY_t and current and delayed values of ΔX_t are used in modeling the short-term dynamic structure. To ensure that there is no level relationship between ΔY_t and ΔX_t the bounds test procedure is performed by excluding the lagged level variables ΔY_{t-1} and ΔX_{t-1} in equation (1). Thus, we test using the F-test the null hypothesis of no long-run relationship between the levels of the variables: $\beta_1=0$ and $\beta_2=0$, versus the alternative hypothesis H_1 of $\beta_1\neq 0$ and $\beta_2\neq 0$. There are two sets of critical values: one set is estimated under the assumption that all variables in the model are), while the other is estimated under the assumption that the variables are $I(0)$. If the calculated F statistics fall outside the inclusive band, an inference can be made without prior knowledge of the order of integration of the variables. However, if the estimated test statistic is higher than the upper bound critical value, the null hypothesis of no long-run relationship between the levels of the variables is rejected. If the estimated test statistic is lower than the lower bound critical value, the null hypothesis of no long-run relationship between the levels of the variables cannot be rejected. The following models (price and return) are summarized in Table

$$\Delta Y_t = \alpha_0 + \sum_{i=1}^{p} \alpha_{1i}\Delta Y_{t-i} + \sum_{q=0}^{p} \alpha_{2i}\Delta X_{t-i} + \beta_1 Y_{t-1} + \beta_2 X_{t-1} + u_t$$

D using ARDL and Johansen methods based on unit root test results:

$$XU = \beta_0 + \beta_1 DOW + e_t \quad \text{Model (1)}$$

$$XU = \beta_0 + \beta_1 NAS + e_t \quad \text{Model (2)}$$

$$R\,XU = \beta_0 + \beta_1 RDOW + e_t \quad \text{Model (3)}$$

$$RXU = \beta_0 + \beta_1 RNAS + e_t \quad \text{Model (4)}$$

level	countries	Methodology	ECT	Result
Price	Model 1	ARDL (7,1)	ECT= 0.001 F-statistic=6.43	no cointegrated
		Johansen cointegration	ECT= 0.942	no cointegrated
	Model 2	ARDL (10,2)	ECT= 0.0012*** F-statistic=8.14	no cointegrated
		Johansen cointegration	ECT= 0.0015***	no cointegrated
Return	Model 3	ARDL (5,3)	ECT= -0.953*** F-statistic=159.9***	cointegrated
		Johansen cointegration	ECT= -0.877**	cointegrated
	Model 4	ARDL (4,4)	ECT= -0.878*** F-statistic=156.4***	cointegrated
		Johansen cointegration	ECT= -0.934***	cointegrated

This is the result of ARDL bound and Johansen cointegration test. ECT is the error correction term, which must be between -1 and 0. F-statistic represents the F-bound Test value. None of ECT of model 1 and Model 2 is negative. Therefore, there is no long-run relationship between XU and NAS and DOW in either the ARDL or Johansen methodologies (model 1 and model 2). However, in term of returns ECT are in accepted rage of -1 and 0 and all of them are statistically significant. Therefore, there is a long-run relationship in terms of returns (model 3 and model 4).

Conclusion

The integration of financial markets explains the global impact of worldwide economic events. For instance, a financial crisis in a major economy, such as the US, can shake global investor confidence and negatively affect stock markets, currencies and economic growth in various countries. This research aims to examine the time-varying interaction and Spillover effect between the XU100, Dow Jones and NASDAQ indices over the period from 13/03/2015 to 13/03/2024.

Based on the results of the BEKK-GARCH model, the return volatility in NASDAQ and Dow Jones, are transmitted to the XU100. However, there is a one-way effect from the US stock market to the XU100. According to the DCC-GARCH results, there is generally a positive relationship between the US stock market returns and the XU100 returns over the time. In addition, for the examining long run relationship between the selected stock market, Johansen cointegration and ARDL bound test are employed. The ARDL bounds test results show that there is a long-run relationship between the US stock market returns and the XU100 returns. The Johansen cointegration test also confirms the existence of a long-term relationship between return of the two stock markets. While there is not any long run relationship between them in term of prices.

The results show that there is a certain relationship between indices and that this relationship provides significant benefits to investors and market participants in areas such as risk management, return forecasting, strategy development and risk allocation. This study is valuable as a resource for understanding how risks and returns interact in different markets and for making more informed investment decisions.

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