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Analysis of the interaction of Participation 30 Index with Dow Jones Islamic Markets Index and CBOE Volatility Index

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Abstract

This study aims to examine the dynamic relationship between Islamic markets and global financial risk factors using the Dow Jones Islamic Markets World Index (DJIM), Participation 30 Index (KATLM 30), and the CBOE Volatility Index (VIX). The analysis applies the DCC-GARCH model to the daily return series from January 3, 2014, to December 31, 2021. The results reveal a negative interaction between VIX and the Islamic indices throughout the study period. Furthermore, the dynamic correlation coefficient between VIX and DJIM (-0.755040) was higher than that between VIX and KATLM 30 (-0.180328), while the dynamic correlation coefficient between KATLM 30 and DJIM (0.26989) was weak and positive. These findings suggest that KATLM 30 is less affected by global risks, exhibits less integration into the global financial system, and serves as a better diversifier for international investment portfolios than DJIM. This study provides valuable insights for investors and portfolio managers and contributes to enhancing portfolio management strategies.

Keywords:
DJIMI, VIX, Islamic Index, Volatility, DCC-GARCH

JEL Codes:
C23, F36, G11, G15

Katılım 30 Endeksi'nin Dow Jones İslami Piyasalar Endeksi ve CBOE Volatilite Endeksi ile etkileşiminin analizi

Öz

Bu çalışma, Dow Jones İslami Piyasalar Dünya Endeksi (DJIM), Katılım 30 Endeksi (KATLM 30) ve CBOE Oynaklık Endeksi'ni (VIX) kullanarak İslami piyasalar ile küresel finansal risk faktörleri arasındaki dinamik ilişkiyi incelemeyi amaçlamaktadır. Analiz, DCC-GARCH modelini 3 Ocak 2014 - 31 Aralık 2021 günlük getiri serisine uyguluyor. Sonuçlar, çalışma dönemi boyunca VIX ile İslami endeksler arasında negatif bir etkileşim olduğunu ortaya koyuyor. Ayrıca VIX ile DJIM arasındaki dinamik korelasyon katsayısı (-0,755040), VIX ile KATLM 30 arasındakinden (-0,180328) daha yüksek, KATLM 30 ile DJIM arasındaki dinamik korelasyon katsayısı (0,26989) ise zayıf ve pozitiftir. Bu bulgular, KATLM 30'un küresel risklerden daha az etkilendiğini, küresel finansal sisteme daha az entegrasyon sergilediğini ve uluslararası yatırım portföyleri için DJIM'den daha iyi bir çeşitlendirici olarak hizmet ettiğini göstermektedir. Bu çalışma, yatırımcılar ve portföy yöneticileri için değerli bilgiler sağlamakta ve portföy yönetimi stratejilerinin geliştirilmesine katkıda bulunmaktadır.

Anahtar Kelimeler:
DJIMI, VIX, İslami Endeks, Volatilite, DCC-GARCH

JEL Kodları:
C23, F36, G11, G15

Introduction

Advances in technology and communication networks have accelerated the integration of financial markets, fostering increased information transmission and interconnectedness. Moreover, significant global financial events such as the 2008 Global Financial Crisis, the 2009 European debt crisis, the 2020 Covid-19 pandemic, and the 2022 Ukraine-Russia War have further highlighted the heightened correlation among markets (Duncan & Kaburdi, 2013; Majdoub & Mansour, 2014; Haddad et al., 2020; Mensi et al., 2022).

The correlation among financial assets plays a crucial role in investment portfolio construction and risk management strategies, as recognized by market experts (Mensi et al., 2016). Diversification of portfolios can effectively reduce risk and enhance returns, especially when assets exhibit weak or negative correlations (Kandemir & Gökgöz, 2022). However, the increased correlation among financial assets has introduced challenges in investment decision-making, leading to reduced portfolio diversity and elevated portfolio risk (Forbes & Rigobon, 2002; Bekaert et al., 2003; Mensi et al., 2022). Consequently, individual and institutional investors seek alternative financial assets to navigate these complexities and maintain their portfolio performance.

In recent years, Islamic financial markets have gained prominence as potential alternatives for portfolio diversification and risk reduction, particularly in the aftermath of the 2008 global financial crisis (Ahmad et al., 2018; Haddad et al., 2020; Mensi et al., 2022). Scholars have identified Islamic financial assets as safe havens during financial turmoil that provide stability and resilience to investors' portfolios (Hammoudeh et al., 2014; Mensi et al., 2015; Foglie & Panetta, 2020). This attractiveness stems from fundamental factors that set Islamic markets apart, including the prohibition of interest (usury), adherence to a non-greedy investment approach, and investment philosophy aligned with ethical principles that avoid unethical industries.

Especially after the 1990s, depending on the globalization of the markets, the economic interaction and the integration between Islamic and conventional markets have increased (Haddad et al., 2020). There are a number of studies (Majdoub & Mansour, 2014; Naifar, 2016; Ahmad et al., 2018; Haddad et al., 2020; Canbaz & Baykut, 2021) underlining the impact of global events on the economic consequences of this integration. The relationship of Islamic markets with global risk factors can also guide investors in diversifying their international portfolios. However, uncertainty about which Islamic market may constitute a better alternative for investors will pave the way for further studies (Adekoya et al., 2022).

Exploring the interaction between different Islamic indices and global risk factors is important, providing valuable insights for investors and portfolio managers. By comprehensively examining the dynamics and interdependencies between these Islamic indices and global risk factors, we gain a deeper understanding of their underlying relationships and implications for investment decision-making. This exploration is crucial in assisting investors in diversifying their portfolios and effectively managing risk within the constantly evolving global financial landscape. By uncovering these interactions, investors and portfolio managers can make well-informed decisions and develop strategies that align with their investment objectives and risk tolerance.

In light of the background mentioned above, the primary objective of this study is to shed light on the evolving interactions between different Islamic indices and global risk factors over time. This study contributes to the existing literature by comparing various Islamic indices in terms of diversification and examining the relationship between Islamic indices and global risk factors. Furthermore, this research aims to reduce uncertainties surrounding which Islamic indices offer better investment opportunities, thereby adding value to the literature. Additionally, this study investigates the volatility spillover effects between Islamic markets and global risk factors while providing alternative suggestions for portfolio investors and managers. To achieve these objectives, we employ the dynamic volatility model DCC-GARCH to analyze the interactions among the following indices: the widely recognized Dow Jones Islamic Market World Index (which serves as a reference index for international investors), the Türkiye Participation 30 Index, and the widely used CBOE Volatility Index (a global uncertainty indicator). By unveiling the dynamics and interdependencies between these indices, our study aims to provide valuable insights and actionable recommendations that can enhance portfolio management practices and improve investment decision-making within the context of Islamic markets and global risk factors.

1. Literature Review

The research exploring the interaction between Islamic indices and global risk factors has garnered significant attention in recent years, leading to three strands of literature. The first group studies examine the interaction between Islamic and Conventional indices whereas the second group compares the performances of Islamic and Conventional indices. Lastly, the third group investigates the reactions of Islamic and Conventional indices during periods of global events with economic impact (Ajmi et al., 2014; Ahmad et al., 2018; Haddad et al., 2020).

The first group studies also document various results (Girard & Hassan, 2008; Ajmi et al., 2014; Hammoudeh et al., 2014; Nazlıoğlu et al., 2015; Naifar, 2016; Baykut & Çonkar, 2020; Kahyaoğlu & Akkuş, 2020; Mensi et al., 2022; Uçar & Kandemir, 2022). The negative (Antar & Alahouel, 2020) and positive correlations (Dania & Malhotra, 2013; Seçme et al., 2016; Ahmad et al., 2018) have been documented by scholars. Furthermore, a group of researchers (Hanif & Bhatti, 2018; Bayram & Othman, 2019) conclude no relationship between Islamic and conventional indices. Overall, the results of this strand of research demonstrate the complexity of the relationship between Islamic and conventional indices. The second group of research comparing the performances of Islamic indices and conventional indices has shown mixed results. Whilst there are scholars indicating that Islamic indices are better diversifiers than conventional indices in general (Hammoudeh et al., 2014; Shamsuddin, 2014; Mensi et al., 2015; Şensoy et al., 2015; Ali et al., 2018; Foglie & Panetta, 2020), there are also others stating vice versa (Jawadi et al., 2014; Al-Khazali et al., 2016). These varying findings highlight the importance of considering different factors and contexts when evaluating the performance of Islamic and conventional indices.

The third group of literature examines the relationship between Islamic indices and global risk factors. Whereas some have found that Islamic indices are negatively related to global risk factors (Mensi et al., 2016; Raza et al., 2019; Arfaoui & Raggad, 2021; Sial et al., 2022), others indicate a weak correlation (Ajmi et al., 2014; Haddad et al., 2020). For example, investigating the interaction between Gulf markets and the Dow Jones Islamic World Emerging Equity Index, VIX, crude oil, gold, and US treasury bill rate, Mensi et al. (2016) analyze daily data covering 3 June 2005 to 18 March 2016 through quantile regression. Their findings point out a negative relationship between Dow Jones Islamic World Emerging Equity Index and VIX. Ajmi et al. (2014) analyzed the relationship among the Dow Jones Islamic Market Index (DJIM), various stock indices, crude oil markets, bond indices, MOVE, VIX, and economic policy uncertainty (EPU). Their analysis, covering the period from January 4, 1999, to October 8, 2010, indicated a causal relationship between DJIM and all variables except VIX.

Studies focusing on the interaction between different Islamic indices have documented a positive relationship between them. For instance, Bezgin & Karaçayır (2022) investigated the volatility spillover relationship between the Dow Jones Sukuk Index and different Islamic stock indices using the DCC-GARCH model. Their findings revealed a positive volatility spillover among various Islamic stock indices. Similarly, other studies (Majdoub & Mansour, 2014; Najeeb et al., 2015; Mensi et al., 2016) have also indicated a positive relationship among different Islamic indices.

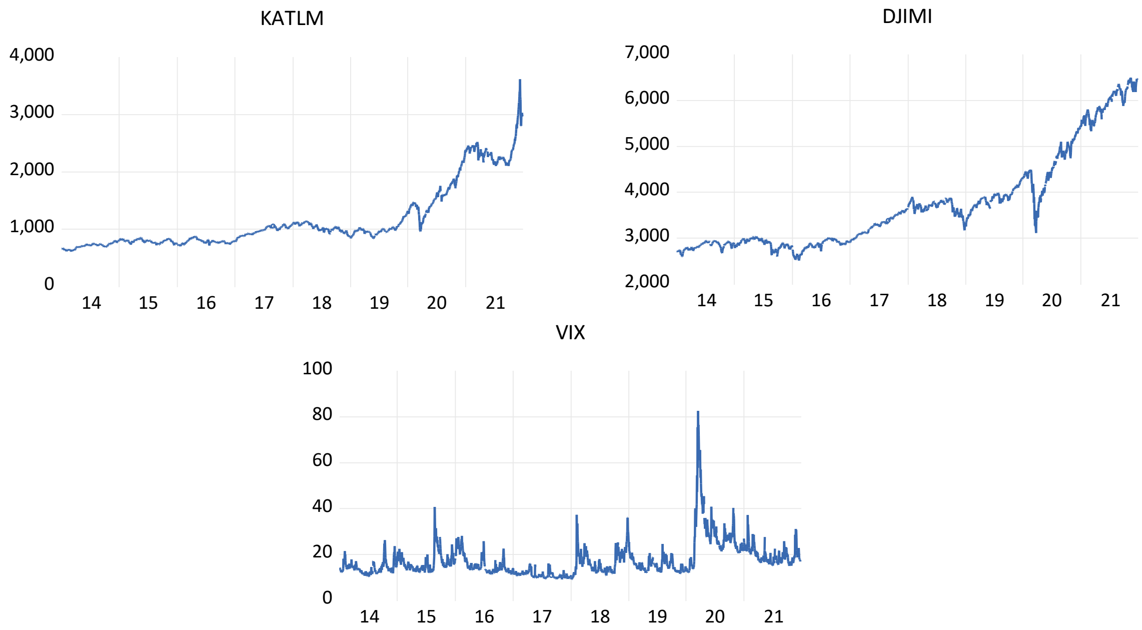
Existing literature on the interaction between Islamic indices and global risk factors primarily considers the CBOE Volatility Index (VIX) as a global risk factor. The VIX measures the volatility of the Standard and Poor's (S&P) index, with increases in VIX corresponding to declines in the S&P. Additionally, studies investigating the effects of global risk factors on Islamic stock indices also incorporate other indices such as the MOVE index (which measures the return volatility of US Treasury options) and the Economic Policy Uncertainty index (EPU) as global risk factors. Furthermore, studies examining the impact of global risk factors on Islamic stock indices consider worldwide issues, such as the 2008 financial crisis and the COVID-19 pandemic, as global risk factors. Consequently, in this study, we adopt the VIX as a global risk factor, considering its widespread usage in the existing literature, and employ a dynamic model to account for worldwide issues.

The comprehensive literature review indicates that the current studies have primarily focused on examining the interaction between Islamic and conventional indices. In contrast, the relationship between global risk factors and Islamic indices still needs to be explored. Therefore, investigating the relationship between global risk factors and different Islamic indices is crucial for providing valuable insights into portfolio investments. The effects of global risk factors on Islamic indices may vary based on regional, national, or developmental factors. Thus, this study aims to fill this gap in the existing literature.

2. Data and Methodology

The study examines the interaction between the Participation 30 Index, the Dow Jones Islamic Markets World Index, and the CBOE Volatility Index by analyzing daily closing price data from January 2, 2014, to December 31, 2021. The data for the study were sourced from the "investing.com" website. Figure 1 illustrates the graphical representation of the daily price changes for the variables under investigation.

Figure 1. Daily Closing Prices Change Graphs



Source: Authors.

Upon reviewing Figure 1, it is evident that the Dow Jones Islamic Markets World Index (DJIMI) demonstrates a more consistent upward trend than the other variables. Particularly, during the initial phase of the COVID-19 pandemic in the first quarter of 2020, all variables experienced significant price fluctuations. The observed variations over time and occasional outliers highlighted the importance of employing dynamic models in the analysis. Before analyzing the interactions of the variables, they were transformed into a daily logarithmic return series. The definitions and uses of these variables are summarized in Table 1.

Table 1. Variable Definitions

Variables	Definition of Variables	Use of Variables
KATLM	Participation 30 Index	It was used by calculating the daily logarithmic return. [100*LN($KTLM_T/KTLM_{T-1}$)]
DJIMI	Dow Jones Islamic Markets World Index	It was used by calculating the daily logarithmic return. [100*LN($DJIMI_T/DJIMI_{T-1}$)]
VIX	CBOE Volatility Index	It was used by calculating the daily logarithmic return. [100*LN(VIX_T/VIX_{T-1})]

Source: Authors.

The interaction between the variables has been analyzed via the multivariate GARCH model. BEKK or DCC-derived models can be applied for multivariate GARCH analysis. However, while DCC models have no variable number limitation, BEKK models have. In this respect, the DCC-GARCH model has been applied in the analysis, depending on the studies considering that DCC-derived models may be superior to BEKK-derived models (Tsay, 2013; Do et al., 2019; Kandemir et al., 2022).

The DCC-GARCH model Engle (2002) developed tests the dynamic correlations between variables in two steps. In the first step of the analysis, the univariate GARCH model developed by Bollerslev (1986) is applied to the variables:

$$\gamma_t^2 = x + \alpha\, \theta_{t-1}^2 + \beta\, \gamma_{t-1}^2 \qquad (1)$$

$$\theta_t = \gamma_t l_t, l_t \sim (0,1) \qquad (2)$$

Equation 1 is the GARCH (1,1) model. In Equation 1, "x" represents the conditional variance, "α" represents the shock coefficient of the past news (ARCH), and "β" represents the coefficient indicating the persistence of the shock effect (GARCH). The "l_t" in the second equation is calculated from the standardized errors of the first equation.

The DCC coefficients between the series are calculated in the second step of the analysis. For this, the lagged values of the residuals and covariance matrices in the first step of the analysis are used:

$$K_t = G_t C_t G_t \quad (3)$$

"K_t" refers to the conditional covariance matrix, and "C_t" refers to the time-varying correlation matrix. "G_t" is the "m x m" diagonal matrix of dynamic standard deviations in the univariate GARCH model.

$$Gt = \begin{bmatrix} \sqrt{\gamma_{0,t}^2} & 0 \\ 0 & \sqrt{\gamma_{f,t}^2} \end{bmatrix} \quad (4)$$

$$Ct = \begin{bmatrix} \theta_{oo,t} & \theta_{os,t} \\ \theta_{fo,t} & \theta_{ff,t} \end{bmatrix} = \begin{bmatrix} 1 & \theta_{of,t} \\ \theta_{fo,t} & 1 \end{bmatrix} \quad (5)$$

"C" is defined as positive and other parameters must be less than or equal to 1. To achieve this, "C_t" is modeled as follows:

$$C_t = \phi_{of,t}^{*-1} \phi_{of,t} \phi_{of,t}^{*-1} \quad (6)$$

Where "$\phi_{of,t}$" indicates the unconditional variance between f and j after GARCH execution.

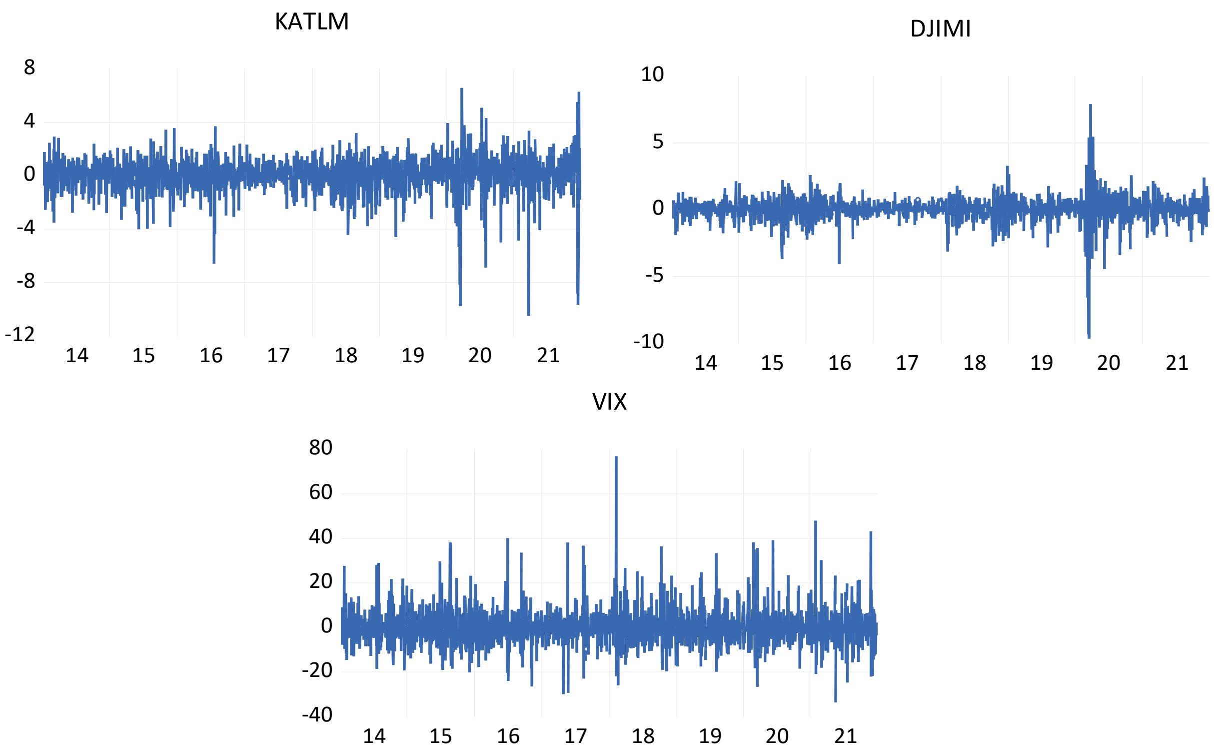
$$\phi_{of,t} = (1 - \delta_1 - \delta_2) \cdot \phi^* + \delta_1 (\theta_{o,t-1} \theta_{f,t-1}) + \delta_2 (\phi_{of,t-1}) \quad (7)$$

In Equation 7, "ϕ" refers to the unconditional covariances between the series estimated in the first step of the analysis. In addition, the "δ_1" and "δ_2" parameters provide the condition of being non-negative and being "$\delta_1 + \delta_2 < 1$".

3. Findings

Figure 2 displays the time path graphs of the daily logarithmic return series for each variable used in this study. Before applying the DCC-GARCH model, the variables are transformed into their daily logarithmic returns. The graphs visually represent the changes in the logarithmic returns over time for each variable. These time series graphs offer insights into the volatility and fluctuations exhibited by the variables throughout the study period.

Figure 2. Time Series Graphs of Return Series



Source: Authors.

Upon examining the graphs, it is evident that all of the series exhibit high volatility and display clusters in specific periods. The presence of volatility indicates fluctuations and variations in the values of the variables over time. These fluctuations can be attributed to various factors, such as market dynamics, economic events, and investor sentiment. Overall, the presence of volatility and clusters in specific periods underscores the importance of considering the dynamic nature of the variables in the subsequent analysis and interpretation of the study's findings. The descriptive statistics of the variables are summarized in Table 2 illustrate:

Table 2. Descriptive Statistics

	KATLM	DJIMI	VIX
Mean	0.07533	0.039654	0.01453
Media	0.173087	0.064478	-0.43481
Maximum	6.599596	7.913372	76.8245
Minimum	-10.4589	-9.6319	-33.582
Std. Dev.	1.296266	0.903828	8.29497
Skewness	-1.31253	-1.14904	1.24343
Kurtosis	12.12148	22.37128	10.19715
Jarque-Bera	7522.717***	31774.07***	4841.621***
LB-Q^2 (5)	410.119***	1295.88***	99.1851***
LB-Q^2 (10)	480.019***	2105.46***	109.039***
LB-Q^2 (20)	514.126***	2449.83***	110.4***
LB-Q^2 (50)	528.853***	2512.28***	124.146***

Source: Authors.

Descriptive statistics show that the series with the highest standard deviation is VIX; not all are normally distributed. In addition, it has been revealed that there is an autocorrelation problem in the squares of the residuals of the series, so the series have heteroscedasticity (ARCH). It is understood that using the GARCH derivative model would be appropriate for solving the ARCH problem in series. At the next stage of the analysis, unit root analyses of the series are shown in Table 3:

Table 3. Unit-Root Tests

Unit-Root Tests		KATLM	DJIMI	VIX
ADF	Intercept	-27.3806***	-14.5021***	-47.885***
	Trend and Intercept	-27.4199***	-14.5276***	-47.8732***
PP	Intercept	-41.2751***	-45.5439***	-50.9176***
	Trend and Intercept	-41.285***	-45.5479***	-50.901***

Source: Authors.

As evident from Table 3, it is seen that all of the return series are stationary in level (I_0). The DCC-GARCH model was applied to the stationary return series at level, and the univariate GARCH model estimation, which is the first step of the application, is summarized in Table 4 illustrate:

Table 4. Univariate GARCH Model Estimation

	KATLM	DJIMI	VIX
Cs (M)	0.100421***	0.069433***	-0.085172
Cst (V)	0.178569*	0.026875***	17.326491***
ARCH (Alpha)	0.128334**	0.225127***	0.209596***
GARCH (Beta)	0.760671***	0.751435***	0.545087***

Source: Authors.

In Table 4, the terms “Cs (M),” “Cs (V),” “ARCH (Alpha),” and “GARCH (Beta)” are used to describe specific aspects of the analysis. The “Cs (M)” represents the mean coefficient of variance, quantifying the average magnitude of price changes relative to their mean values. The "Cs (V)" refers to the coefficient of variance equation, providing additional information about the variability of the series. The "ARCH (Alpha)" focuses on the effect of past shocks, while the “GARCH (Beta)” examines the persistence of these shocks over time.

Upon reviewing Table 4, it becomes evident that the influence of past shocks is significant across all series, and this influence is enduring. Positive or negative news events and past shocks in the Participation 30 Index (KATLM), Dow Jones World Islamic Markets Index (DJIMI), and CBOE Volatility Index (VIX) have a substantial impact on the future price movements of these series, and this effect is deemed permanent. This indicator is essential for comprehending and elucidating the global interaction between markets and the indices that serve as market indicators.

Table 5 presents descriptive statistics of model residuals:

Table 5. Descriptive Statistics of Model Residuals

	KATLM	DJIMI	VIX
JB	4048.0***	58.011	3361.4***
LB-Q^2 (5)	1.11764	7.31841	0.938862
LB-Q^2 (10)	2.14199	9.48436	3.64067
LB-Q^2 (20)	8.10905	15.9859	9.81053
LB-Q^2 (50)	53.4384	60.8163	28.1803

Source: Authors.

When Table 5 is examined, the residues of KATLM and VIX after the GARCH model application are not normally distributed; DJIMI was observed to be normally distributed. It is seen that there is no autocorrelation problem at the 5th, 10th, 20th, and 50th lag lengths in the squares of the model residuals. Thus, the ARCH effect disappears. This finding shows that the DCC-GARCH model is viable for detecting volatility in variables and dynamic conditional correlation between variables. In step 2 of the DCC-GARCH model, the DCC coefficients between the series will be estimated. Table 6 illustrates DCC between variables:

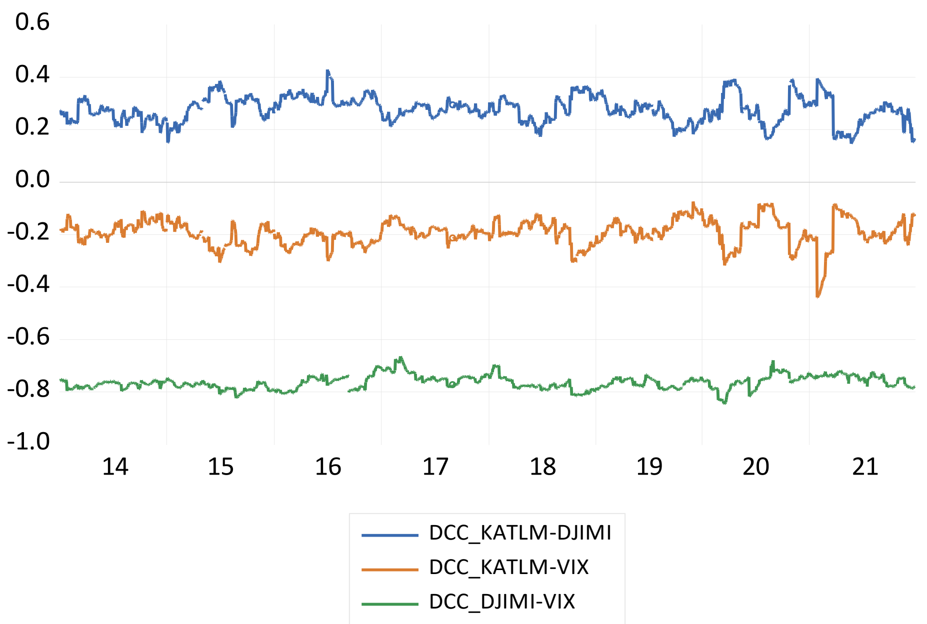
Table 6. DCC Coefficients Between Variables

	DJIMI	VIX
KATLM	0.269891***	-0.180328***
DJIMI		-0.755040***
Alpha	0.011392***	
Beta	0.962129***	
df	5.606278***	

Source: Authors.

DCC coefficients between series show that DCCs between series are significant. The DCC coefficient between the VIX and other series is negative and is -0.755040 with DJIMI and -0.180328 with KATLM. The DCC coefficient between KATLM and DJIMI is 0.269891. The strongest correlation relationship is between VIX and DJIMI, and the correlation relationship of the KATLM series with other series is weak, both positive and negative. This may be because the KATLM series is a newer indicator than DJIMI, and the investor profile is more limited. This relationship is expected to become widespread and usable in the coming periods, and the coefficient will increase. This increase may be due to the market itself, its globalization, and the investor profile development. In Table 6, "Alpha" denotes the effect of past correlations, "Beta" denotes the persistence of the impact of past correlations, and "df" is the distribution parameter. Accordingly, past correlations between series affect subsequent correlations, and this effect is permanent. The time series graphs of the correlations between the series are illustrated in Figure 3.

Figure 3. Time Series Graphs of Dynamic Conditional Correlations Between Series



Source: Authors.

When examining dynamic correlation graphs, it is observed that the correlation coefficient of VIX with the other series varies over time but remains consistently negative throughout the entire period. Moreover, the correlation coefficient of VIX with DJIMI is higher than the correlation coefficient with KATLM over the entire period. The correlation between KATLM and DJIMI is weak and positive throughout the period. Notably, the relationship between the KATLM index and both VIX and DJIMI is weaker than that between DJIMI and VIX, indicating a higher potential for portfolio diversification. Regarding portfolio diversification, the relationship between the KATLM index and VIX exhibits a more pronounced structure than the DJIMI index. Additionally, it is observed that the relationship between KATLM and VIX experiences significant fluctuations, particularly during the Covid-19 period. This finding suggests that global events and market conditions influence the integration of the KATLM index with the global financial system. The negative relationship between Islamic indices and VIX aligns with previous studies conducted by Raza et al. (2019), Haddad et al. (2020), Arfaoui & Raggad (2021), and Sial et al. (2022). However, it differs from the study by Ajmi et al. (2014) which indicates a weak relationship between Islamic indices and VIX. On the other hand, the positive relationship between Islamic indices themselves (Najeeb et al., 2015; Mensi et al., 2016) and the finding that Islamic indices serve as effective diversifiers (Raza et al., 2019) align with the results of some studies.

In summary, the findings provide valuable insights into the relationships among the variables, highlighting the importance of considering these dynamics for portfolio diversification and risk management strategies. Furthermore, it sheds light on integrating the KATLM index into the global financial system and its potential as a diversification tool, particularly during the Covid-19 pandemic.

Conclusion

This study aims to dynamically examine the relationship among Dow Jones Islamic Markets World Index, Turkey Participation 30 Index, and CBOE Volatility Index. In addition, we attempt to provide suggestions to financial advisors, investors, and policymakers through our findings. Our findings provide useful information for creating a portfolio investment strategy, risk management, and asset allocation. Moreover, the results indicate that Islamic indices are integrated into the global financial system over time. After the review of existing literature, we have observed that the majority of studies analyze the relationship of Islamic indices with global risk factors. However, research investigating the relationship of different Islamic indices with global risk factors is scarce. This is one of the main motivations for our study. We utilized VIX as a global risk indicator to examine the relationship between different Islamic indices and global risk factors. Furthermore, analyzing the interaction between the series with the dynamic DCC-GARCH model contributes to revealing the effect of global risks in different periods on the interaction.

In the study, firstly, we have converted the daily closing series into the daily return series. Afterward, we applied the unit-root test to the daily return series and reported that all series were stationary at level. In the last stage, we analyzed the dynamic relationship between different Islamic indices and VIX via DCC-GARCH. Our results document that the relationship of VIX with Islamic indices is negative throughout the entire period, although there are changes in the coefficient over time. The correlation coefficient of VIX with DJIM (-0.755040) is higher than the correlation coefficient with KATLM (-0.180328) throughout the entire period. This finding shows that the KATLM index is less affected by global risks than DJIM, is less integrated into the global financial system, and is a better diversifier than DJIM. In addition, the correlation coefficient of KATLM with DJIM (0.26989) is positive and weak throughout the entire period. The weak relationship of KATLM with DJIM supports the previous finding.

The negative relationship between the VIX and Islamic indices is in line with the following studies Mensi et al. (2016), Raza et al. (2019), Haddad et al. (2020), Arfaoui & Raggad (2021), Sial et al. (2022). On the other hand, the increase-decrease in the correlation coefficient of KATLM with VIX during the Covid-19 period is also in line with some studies (Naifar, 2016; Canbaz & Baykut, 2021) stating that Islamic indices are related to global risks. In addition, there is a weak relationship between Islamic indices, according to the findings of the study by Majdoub & Mansour (2014). The positive relationship between Islamic indices suggested by Najeeb et al. (2015) and Mensi et al. (2016) is similar to their results.

Including different Islamic index stocks in an investment portfolio already containing Islamic stocks contributes to hedging and diversification. Therefore, Islamic stocks from different countries can serve as complementary diversifiers. The weak correlation between the KATLM index and the VIX implies that KATLM can also act as a good diversifier for other global assets. Considering these findings, policymakers should recognize the increasing integration of Islamic indices into the global financial system. Policymakers should acknowledge the significance of Islamic indices and establish appropriate regulatory frameworks to ensure their stability and resilience. This includes implementing robust risk management practices and promoting transparency in Islamic financial markets. Thus, policymakers can enhance investor confidence and support the growth of Islamic financial markets.

The current study examined the relationship among KATLM, DJIM, and VIX. Yet, we cannot conclude that our findings are valid for different Islamic indices. Therefore, in future studies, the relationship between different Islamic indices might be considered together with global risk indicators, considering regional and level of development factors, and similar assessments may be examined with various risk indicators. While this study's findings reveal the positive-negative relationship between the series, they do not document the series affecting each other. We suggest that future studies examine the relationship of different Islamic indices with global risk indicators with models that reveal causal relationships.

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