Journal of Islamic Economics and Finance
İslam Ekonomisi ve Finansı Dergisi

204-239 ISSN 2149-3820
e-ISSN 2651-5342
2026 12(1)

journal homepage: http://dergipark.gov.tr/jief

PETROL FİYATLARI VE VIX'İN DOW JONES İSLAMİ PİYASALAR (DJIM) SEKTÖREL GETİRİLERİ ÜZERİNDEKİ ETKİSİ: QARDL YAKLAŞIMI İLE BİR ANALİZ

Ali Osman ÖZTOP[a]
Muğla Sıtkı Koçman Üniversitesi, Muğla, Türkiye

Tuna KÖSE[b]
Bağımsız Araştırmacı, Muğla, Türkiye

MAKALE BİLGİSİ

Makale Geçmişi:

Başvuru: 17 Mart 2026
Kabul: 11 Haziran 2026

Makale Türü:
Araştırma Makalesi

JEL Sınıflandırma:
G15;
Q43;
C21;

Anahtar Kelimeler:
İslami hisse senedi piyasaları,
QARDL,
Petrol fiyatları,
VIX,
Asimetrik etki

ÖZ

Bu çalışmada petrol fiyatları ve küresel belirsizliğin İslami sektör getirileri üzerindeki etkisi incelenmiştir. Bu amaçla Brent petrol fiyatları ve Volatilite Endeksi'nin (VIX) Dow Jones İslami Piyasalar Endeksi (DJIM) bünyesindeki 10 sektörel endeks getirisini, 4 Ocak 2016 – 12 Ocak 2026 dönemi haftalık verileriyle Kantil ARDL (QARDL) yaklaşımıyla ele alıyoruz. Çalışmamızın ilk bulgusu, Brent petrol fiyatlarının sektörel getiriler üzerindeki etkisinin kantiller arasında asimetrik bir örüntü izlediğidir. Buna göre ayı piyasası koşullarında gözlenen pozitif ilişki, boğa piyasası koşullarında negatife dönmektedir ve kantiller arasındaki asimetrik geçişler tüm 10 sektör için Wald testi sonuçları tarafından doğrulanmaktadır. Bununla birlikte, bireysel uzun vadeli Brent katsayıları enerji bağlantılı sektörler dışında çoğunlukla istatistiksel olarak anlamsız kalmaktadır. VIX tarafında ise tüm sektörlerde negatif ve istatistiksel olarak anlamlı bir etki tespit ediyoruz. En duyarlı sektörler Teknoloji ve Sanayi iken, Petrol ve Gaz ile Telekomünikasyon sektörleri en düşük hassasiyeti göstermektedir. Bulgular, İslami piyasaların küresel belirsizlik şoklarından tamamen yalıtılmış olmadığını açıkça ortaya koymaktadır. Ayrıca COVID-19 dönemi, özellikle yüksek kantillerde getiri tepkisini güçlendirerek volatiliteyi artırmış; bu etki en güçlü Petrol ve Gaz sektöründe gözlenmiştir.

https://doi.org.tr/ 10.54863/jief.1911644

[a] **Sorumlu Yazar:** " *Ekonomi ve Finans Bölümü, Muğla Sıtkı Koçman Üniversitesi, Muğla, Türkiye,* aliosmanoztop@mu.edu.tr, *ORCID: 0000-0002-7568-5927*
[b] *"Bağımsız Araştırmacı, Muğla, Türkiye,* tunakose48@gmail.com , *ORCID:0000-0002-8703-0215."*

Kaynak göster: Öztop, A.O., Köse, T.(2026). Petrol Fiyatları Ve VIX'in Dow Jones İslami Piyasalar (Djım) Sektörel Getirileri Üzerindeki Etkisi: Qardl Yaklaşımı İle Bir Analiz , *İslam Ekonomisi ve Finansı* Dergisi, *12(1*), 169-212, https://doi.org.tr/ 10.54863/jief.1911644

JIEF Journal of Islamic Economics and Finance
İslam Ekonomisi ve Finansı Dergisi

ISSN 2149-3820 e-ISSN 2651-5342 2026 12(1)

journal homepage: http://dergipark.gov.tr/jief

THE IMPACT OF OIL PRICES AND VIX ON DOW JONES ISLAMIC MARKETS (DJIM) SECTORAL RETURNS: AN ANALYSIS WITH THE QARDL APPROACH

Ali Osman ÖZTOP[a]

Muğla Sıtkı Koçman University, Muğla, Türkiye

Tuna KÖSE[b]

Independent Researcher, Muğla, Türkiye

ARTICLE INFO

Article History:

Received: 17 March 2026

Accepted: 11 June 2026

Article Type:

Research Article

JEL Classification:

G15;

Q43;

C21;

Keywords:

Islamic stock markets,

QARDL,

Oil prices,

VIX,

Asymmetric impact

ABSTRACT

In this study, the effects of oil prices and global uncertainty on Islamic sector returns were examined. For this purpose, we address Brent crude oil prices and Volatility Index (VIX) on 10 sectoral index returns within the Dow Jones Islamic Markets Index (DJIM) using the Quantile ARDL (QARDL) approach with weekly data for the period January 4, 2016 – January 12, 2026. The first finding of our study is that the point estimates of the Brent oil price effect on sectoral returns follow an asymmetric pattern across quantiles. According to this, the positive relationship observed under bear market conditions shifts to negative under bull market conditions, and asymmetric transitions across quantiles are confirmed by Wald test results for all 10 sectors. However, the individual long-run Brent coefficients remain largely statistically insignificant outside energy-linked sectors. On the VIX side, we identify a negative and statistically significant effect across all sectors. The most sensitive sectors are Technology and Industrials, while Oil & Gas and Telecommunications sectors exhibit the lowest sensitivity. The findings clearly demonstrate that Islamic markets are not completely insulated from global uncertainty shocks. Additionally, the COVID-19 period increased volatility by amplifying return responses, particularly in the higher quantiles, with this effect being most pronounced in the Oil & Gas sector.

https://doi.org.tr/ 10.54863/jief.191

[a] **Corresponding Author:** " *Department of Economy and Finance, Muğla Sıtkı Koçman University, Muğla, Türkiye,* aliosmanoztop@mu.edu.tr, ORCID: 0000-0002-7568-5927.*"*

[b] "*Independent Researcher, Muğla, Türkiye,* tunakose48@gmail.com , ORCID:0000-0002-8703-0215."

To cite this article: Öztop, A.O., Köse, T.(2026). The Impact of Oil Prices And VIX On Dow Jones Islamic Markets (Djım) Sectoral Returns: An Analysis wıth the Qardl Approach, *Journal of Islamic Economics and Finance*, *12*(1), 169-212, https://doi.org.tr/ 10.54863/jief.1911644

INTRODUCTION

With the process of globalization, the liberalization of financial markets and the acceleration of technological innovations have strengthened the interaction between stock markets and macroeconomic and financial indicators. These developments have facilitated access to financial information and increased market integration. Consequently, stock market indices have become more responsive and sensitive to changes in macroeconomic and financial variables. From a general perspective, many stock exchanges around the world have established Islamic stock market systems alongside conventional stock markets, thereby ensuring diversity in this field. Islamic finance differs from conventional financial markets due to the strict criteria that firms must meet in order to qualify for inclusion in Shariah-compliant indices (Hoe et al., 2025). The Islamic finance system is a system established to meet the needs of individuals and institutions that operate in activities other than those considered haram in Islam (Şarkaya İçellioğlu, 2018). In other words, this system does not include companies involved in alcohol, tobacco, pork-related products, gambling, entertainment, weapons, and conventional financial services (Arfaoui and Rejeb, 2020). Furthermore, in these markets, firms are required to meet Sharia requirements regarding acceptable products, commercial activities, debt levels, and interest income and expenses of Islamic companies (Marashdeh et al., 2020).

Considering the characteristics of Islamic finance, studies on Islamic finance particularly examine the relationships between conventional financial markets through returns and/or volatility (Nazlıoğlu et al., 2015; Majdoub et al., 2016; Şarkaya İçellioğlu, 2018; Yarovaya et al., 2021). In addition, the relationships of Islamic finance with macroeconomic and financial variables such as exchange rates (Majid and Yusof, 2009; Hussin et al., 2012), interest rates (Hammoudeh et al., 2014; Ülev and Özdemir, 2015), inflation rate (Marashdeh et al., 2020; Yahya, 2020) and commodity prices such as gold, natural gas, etc. (Hussin et al., 2013; Nagayev et al.,

2016) have also been investigated. Furthermore, the Volatility Index and oil prices also have a significant impact on Islamic indices. The Volatility Index (VIX), calculated by the Chicago Board Options Exchange (CBOE), measures the degree of fear in the markets. The VIX index is determined by investors and expresses their consensus view on expected future stock market volatility. If the expected VIX increases (decreases), investors demand higher (lower) rates of return from stocks, and therefore stock prices decrease (increase) (Whaley, 2009). On the other hand, sharp movements in oil prices can lead to stock market fluctuations (Zhu et al., 2016). Indeed, the extent to which stock prices are affected by changes in world oil prices is explained by stock valuation theory. Accordingly, the stock price is defined as the sum of the discounted values of expected future cash flows from different investment perspectives (Arouri & Nguyen, 2010). When examining the relationship between oil prices and stock markets, it is observed that an increase in oil prices negatively affects real output, which in turn leads to a decline in aggregate stock prices (Jouini, 2013). Furthermore, volatile oil prices can cause a reduction in the risk premium, which in turn can have a negative impact on cash flows and consequently on stock returns (Chang et al., 2020). On the other hand, high oil prices may increase expected inflation, which will increase interest rates and consequently stock returns (Ftiti and Hadhri, 2019).

In global markets, energy costs and financial uncertainty constitute the two most fundamental factors affecting investment decisions. Therefore, this study examines the impact of changes in oil prices (Brent) and the VIX, known as the global fear index, on Dow Jones Islamic Markets Index (DJIMI) sectoral returns, using weekly data from January 4, 2016 to January 12, 2026. The relationship between variables at different quantile levels is examined using the Quantile Autoregressive Distributed Lag (QARDL) model. Thus, not only average effects but also the dynamics during periods of extremely low or extremely high returns in the market could be analyzed. Our main motivation is to reveal how these effects differ depending on the market condition (bear, bull, or normal market conditions) and the asymmetric responses of sectors to these shocks.

Therefore, the study contributes to the literature from several perspectives. First, the vast majority of existing studies examine the aggregate Islamic stock index. This study takes into account 10 different sectoral stock indices. Thus, the study contributes to the limited literature on sectoral indices. Furthermore, while considering sectoral stock indices, the study aims to understand the global phenomenon by taking into account global sectoral indices rather than country-level indices. Indeed, our selection of sectors due to the differing impact of oil prices and VIX on each sector constitutes the main motivation of the study. Second, the QARDL method is used in the study. This method analyzes asymmetric and heterogeneous effects by revealing whether the relationships between variables differ at different quantile levels.

LITERATURE REVIEW

Although the Islamic finance literature has shown a notable development over the last decade, it is observed that empirical studies examining the relationships between Islamic finance markets and macroeconomic and financial variables have remained relatively limited. When the existing literature is reviewed, it is noteworthy that there are numerous studies analyzing the impact of VIX and oil prices on conventional stock markets (Arouri and Rault, 2012; Sarwar, 2012; Fernandes et al., 2014; Basher et al., 2018; Tursoy and Faisal, 2018; Sarıtaş and Nazlıoğlu, 2019; Dai et al., 2020; İskenderoğlu and Akdağ, 2020; Altınöz and Umut, 2022; Pazarcı et al., 2022). In contrast, studies addressing the effects of these variables on Islamic stock markets are situated within a more limited literature framework. In this context, Ajmi et al. (2014) examined the relationship between the Dow Jones Islamic Market Index (DJIM) and VIX through linear and nonlinear Granger causality tests. While the findings do not indicate a significant causal relationship within the linear framework, nonlinear test results show a unidirectional causality from VIX to DJIM. This result suggests that nonlinear methods may be more appropriate for modeling Islamic indices. Similarly, Hammoudeh et al. (2014) analyzed the dependence structure between DJIM and VIX and identified a significant and negative dependence between the variables. It is stated that the relationship fluctuates over time but generally exhibits a symmetric structure. Naifar (2016) examined the relationship between VIX and DJIMI returns using a quantile regression approach and found negative and statistically significant results across all quantiles. Furthermore, it is stated that the dependence increases from lower quantiles to higher quantiles, meaning that the relationship strengthens during periods when the market is in an upward trend. Paltrinieri et al. (2019) revealed that Islamic indices respond negatively to VIX, while Arfaoui and Rejeb (2020) showed that there is a time-varying and significant relationship between DJIM volatility and VIX. It is emphasized that the impact of VIX on DJIM volatility becomes more pronounced especially during periods of financial fragility and crises. Özçelebi and Pérez-Montiel (2023) examined the relationship between DJIMI and VIX using quantile-based methods and wavelet coherence analysis. The findings show that the relationship between the two variables may hold in the long run and is particularly negative and statistically significant at the 5th and 50th quantiles. The quantitative autoregressive model results reveal that large-scale shocks in VIX do not create a significant impact on DJIMI in the short run; however, the quantile regression model allowing for regime changes shows that VIX increases reduce DJIMI performance. Studies conducted on the Turkish case also present similar findings. Essayem et al. (2022) examined the impact of global risk factors on the Participation 30 Index (KAT30) using the quantile regression method and found that VIX has a negative effect across all quantiles except Q0.75 and Q0.95. This finding suggests that the effect of VIX is stronger under bearish market conditions. Kazak (2023) analyzed the impact of VIX on the Participation 50 Index (KAT50) using the Fourier Toda–Yamamoto causality test and revealed a unidirectional causal relationship from VIX to the KAT50 index. Finally, Gürbüz (2024) examined the relationship between the KAT50 Index and VIX using the ARDL bounds test approach with monthly data for the 2014–2021 period and found that VIX has a negative and significant effect on the KAT50 index.

Although studies examining the relationship between oil prices and Islamic stock markets are increasingly growing in the literature, it is observed that the findings vary depending on differences in country, period, and methodology. In the Malaysian case, Hussin et al. (2012) analyzed the relationship between oil prices and the FBMES and found a positive and statistically significant relationship between the variables. Furthermore, causality analyses point to a unidirectional relationship from oil prices to Islamic stock returns. Hussin et al. (2013) reported a bidirectional causality finding between oil prices and the Malaysian Islamic stock market. Similarly, Ajmi et al. (2014) examined the relationship between DJIM and Brent oil prices using linear and nonlinear Granger causality tests; they found unidirectional causality from the index to oil prices in the linear model and bidirectional causality in the nonlinear model. Studies focusing on volatility and dependence structures show that the impact of oil price shocks on Islamic indices is significant in most cases. Ghorbel et al. (2014) revealed that oil price volatility affects the volatility of 11 Islamic indices, with Malaysian and Indonesian markets being particularly more sensitive to these shocks. Hammoudeh et al. (2014) found a positive dependence between DJIM and oil prices but emphasized that sharp declines in oil prices create a stronger negative impact on Islamic index returns. Examining long-run relationships, Abdullah et al. (2016) showed that there is a cointegration relationship between selected Southeast Asian Islamic indices and oil prices, and that short-run dynamics differ across countries. Naifar (2016) determined that the impact of crude oil prices on DJIMI returns is particularly positive and significant at lower quantiles (bear market conditions). Studies employing nonlinear and asymmetric approaches reveal that the impact of oil prices is not homogeneous. Badeeb and Lean (2018), within the framework of the nonlinear ARDL model, found a generally weak relationship between oil price changes and the Islamic composite index, but showed that responses differ markedly across sectors. Ftiti and Hadhri (2019) investigated the causal relationship between Brent oil prices and nine Dow Jones Islamic Market Indices and stated that significant causal relationships exist between Brent oil prices and DJIM, DJIDEV, DJIGCC, DJIUS2, particularly in the short and medium term, but that this relationship weakens in the long run. Furthermore, it was stated that oil prices may enhance the predictability of Islamic stock returns. Paltrinieri et al. (2019) also revealed that Islamic indices generally respond positively to increases in oil prices. Sectoral and quantile-based analyses also support the heterogeneous nature of the relationship. Chang et al. (2020) examined the relationship between oil prices and DJIM and its sub-sectors within the quantile cointegration framework; they found that low (high) oil price quantiles adversely affect the high (low) quantiles of the index. While results consistent with the general index were obtained in many sectors such as finance, healthcare, consumer, and industrials, more different and often positive relationships were found in basic materials, technology, and telecommunications sectors. Lin and Su (2020) showed that there is generally a negative and asymmetric relationship between oil market uncertainty and Islamic stock returns. In the Turkish case, Essayem et al. (2022) analyzed the impact of the Oil Volatility Index on the KAT30 Index using the quantile regression method and stated that the effect is particularly positive and significant at upper quantiles. Gürbüz (2024) found that oil prices have a positive and significant impact on the KAT50 Index within the ARDL bounds test approach. Beyond financial markets, the indirect effects of oil prices on Islamic financial institutions are also being investigated. Hidayat and Sakti (2020), in their dynamic GMM analysis conducted on 81 Islamic banks, showed that the direct impact of oil price changes on the profitability of banks is limited (4.2%–4.8%), but the indirect effect through macroeconomic channels reaches quite high levels (46%–60%).

Overall, existing findings indicate that VIX creates a predominantly negative and periodically varying effect on Islamic stock markets, while the relationship between oil prices and Islamic stock markets, although predominantly positive, exhibits an asymmetric, quantile-dependent, and periodically variable structure. Therefore, the diversity of methods used and the periodic differences in findings demonstrate the need for more comprehensive and comparative empirical analyses on the subject.

This study contributes to the limited literature building on the aforementioned body of work. Additionally, it is observed that sectoral Islamic stock analyses regarding oil-Islamic stock and VIX-Islamic stock relationships are largely limited. This study contributes to the literature by using the QARDL model to examine the impact of changes in global oil prices and the VIX variable on global aggregate and sectoral Islamic stock returns at different quantile levels. Indeed, the study will be useful for portfolio managers and investors in understanding how the relationships differ depending on the market condition and the asymmetric responses of sectors to these shocks.

DATA AND METHODOLOGY

Dataset

In this study, we used weekly data covering the period from January 4, 2016 to January 12, 2026. The dependent variables of the study are the 10 sectoral indices within the Dow Jones Islamic Market Index (DJIMI): Basic Materials (BM), Consumer Goods (CG), Consumer Services (CS), Financials (FIN), Healthcare (HC), Industrials (IND), Oil & Gas (OG), Technology (TECH), Telecommunications (TEL), and Utilities (UTL). Brent crude oil price (BRT), representing global oil prices, and the CBOE Volatility Index (VIX), representing global financial uncertainty, were used as independent variables. The Brent and VIX series are also measured as weekly log changes ($\Delta ln \times 100$), consistent with sectoral indices. Changes in the VIX represent shocks to market uncertainty, and this usage is consistent with the literature (Sarwar, 2012; Naifar, 2016). Dow Jones Islamic sector index data were obtained from the S&P Global database (spglobal.com), while Brent oil and VIX data were obtained from the CBOE Volatility Index: Federal Reserve Economic Data (FRED) database.

In the study, in order to eliminate low-frequency noise in the raw daily data and in order to mitigate the impact of non-synchronous trading, $r_t =$

$\ln\left(\frac{P_t}{P_{t-1}}\right) \times 100$ we converted to weekly frequency1. As a result of this transformation, 521 weekly return series were obtained. While weekly returns exhibit limited serial dependence in most sectors, autocorrelation is observed in the Oil & Gas, Financials, Brent, and VIX series, and a distinct clustering of volatility is observed in the squared returns of all series (Ljung-Box statistics are reported in Table 1). These dynamics are accounted for through the ARDL lag structure and bootstrap-based inference. Additionally, the impact of the COVID-19 pandemic during the March 2020 - June 2021 period was included in the model with a dummy variable. Figure 1 displays the trends of the sectoral return series.

Figure 1: Weekly DJIM Sectoral Return Series

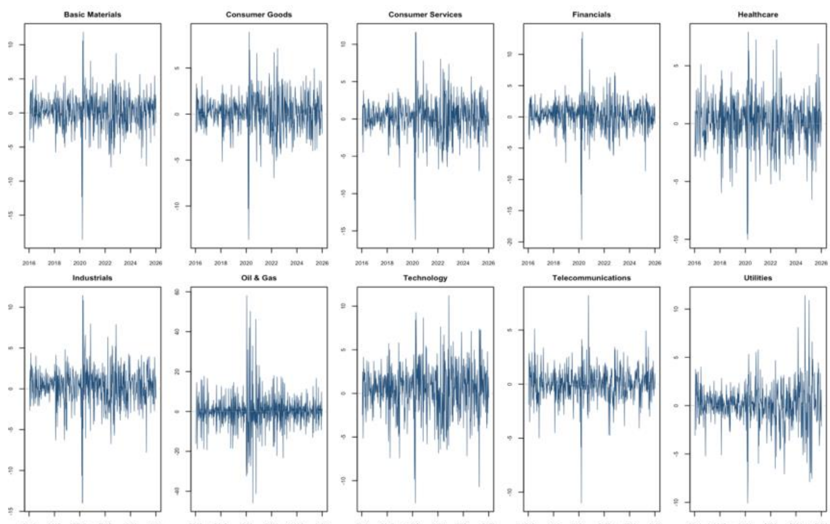


Table 1 presents the descriptive statistics used in the study.Accordingly, the Technology sector provides the highest average return at 0.377%, while the Telecommunications sector produces the lowest return at 0.013%. VIX, with its volatility at 15.824%, represents the most extreme volatility value in the sample. Additionally, the highest standard deviation at the sectoral level was recorded in the Oil & Gas sector at 9.296%. All

[1] Weekly series are constructed using the closing values from each Friday, where P_t represents the closing value for that Friday.

sectors except Oil & Gas (0.596) and VIX (0.622) are observed to have negative skewness, indicating that downward extreme movements occur more frequently. This skewness is statistically significant in all series except Utilities (|z| > 2.99), and excessive kurtosis is evident in all series. On the other hand, the positive skewness in Oil & Gas and the VIX indicates that sharp upward movements dominate these series. All variables have high kurtosis values and are leptokurtic. The JB test indicates that the variables do not exhibit a normal distribution; this finding supports the application of quantile-based methods. The pronounced leptokurtosis and fat tails observed in the series, along with the fact that the effects may vary depending on the market regime (bull/bear), necessitate a quantile-based approach. The Koenker-Xiao slope equality test, which reveals this heterogeneity across quantiles, is presented in Table 5.

Table 1: Descriptive Statistics for Weekly Return Series

	Mean	Mdn	SD	Min	Max	Skew.	Kurt.	JB	Q(4)	$Q^2(4)$
BM	0.139	0.257	2.631	-18.598	11.875	-0.821	9.690	1030.18[a]	9.2[c]	172.6[a]
CG	0.115	0.240	2.135	-13.661	8.911	-0.699	8.154	619.06[a]	7.9[c]	224.3[a]
CS	0.163	0.238	2.574	-16.194	11.653	-0.598	8.673	729.65[a]	8.0[c]	292.4[a]
FIN	0.227	0.261	2.527	-19.654	13.575	-0.871	13.433	2428.67[a]	12.4[b]	211.1[a]
HC	0.125	0.294	2.143	-10.035	7.917	-0.408	5.594	160.51[a]	4.6	170.7[a]
IND	0.206	0.284	2.468	-14.001	11.448	-0.663	8.767	760.03[a]	6.1	300.5[a]
OG	0.016	0.277	9.296	-45.970	58.218	0.596	11.324	1535.06[a]	106.4[a]	99.4[a]
TECH	0.377	0.584	2.932	-12.579	11.239	-0.320	4.416	52.41[a]	5.0	112.0[a]
TEL	0.013	0.019	1.530	-11.021	8.214	-0.587	10.118	1129.79[a]	1.6	33.4[a]
UTL	0.093	0.197	2.235	-10.088	11.416	-0.154	7.019	352.76[a]	9.0[c]	59.1[a]
BRT	0.127	0.536	5.506	-34.639	26.912	-0.497	8.430	661.62[a]	15.2[a]	230.5[a]
VIX	-0.114	-0.965	15.824	-55.622	85.372	0.622	6.230	260.05[a]	17.1[a]	10.2[b]

Note. a:p < .01, b:p < .05, c: p < .10, Q(4) and $Q^2(4)$ are the Ljung-Box statistics for returns and squared returns, respectively (4-lag). The asymptotic standard error of skewness is ≈0.107; skewness is statistically significant in all series except UTL, while kurtosis is statistically significant in all series (|z|>2).

The results of the ADF, PP, and KPSS tests conducted to determine whether the variables are stationary are presented in Table 2. The fact that the return series are I(0) (stationary) implies that the long-run coefficients should be interpreted not as a cointegrating vector but as cumulative (steady-state) multipliers of a stationary dynamic model (Pesaran et al., 2001; De Boef and Keele, 2008; Philips, 2018), while also ensuring the standard validity of quantile regression inference (Koenker and Xiao, 2006). The findings show that all return series are I(0) at their level values, meaning they are stationary. The stationarity of return series is a well-established stylized fact in the financial economics literature (Cont, 2001; Campbell et al., 1997). This property ensures that long-run terms are interpreted not as a spurious cointegrating relationship but as cumulative multipliers of a stationary model, while also supporting the validity of quantile regression inference (Granger and Newbold, 1974). While the ADF, PP and ZA tests reject the unit root at the 1% level, the KPSS test falls below the critical values, confirming that the series are stationary. The Zivot-Andrews test rejects the null hypothesis of a unit root in all series even when a single internal structural break is allowed, meaning that stationarity is preserved even under a break. The identified break dates are determined internally by the test, do not rely on any external assumptions, and vary across sectors; in one group of series (BM, IND, OG, with explanatory variables Brent and VIX), the break occurs in the March-May 2020 period, while in other sectors, it falls in different periods of the sample. The fact that the identified breaks for the core driving variables (Brent, VIX) and the sector most sensitive to oil (OG) coincide with the World Health Organization's March 11, 2020, pandemic declaration and the March-April 2020 oil price war period independently supports the defined window of the COVID-19 dummy variable in the model.

Table 2: Unit Root Test Results for Return Series

Variable	ADF	PP	KPSS	ZA
BM	-11.427***	-536.259***	0.055	-11.874***
CG	-11.296***	-537.763***	0.067	-11.626***

CS	-10.956***	-556.381***	0.048	-11.204***
FIN	-11.367***	-571.764***	0.112	-11.566***
HC	-12.205***	-507.323***	0.042	-12.492***
IND	-11.077***	-537.730***	0.060	-11.402***
OG	-14.880***	-566.091***	0.046	-15.544***
TECH	-11.140***	-559.113***	0.050	-11.494***
TEL	-10.005***	-544.168***	0.099	-10.385***
UTL	-10.056***	-452.894***	0.077	-10.575***
BRT	-9.108***	-500.092***	0.098	-10.266***
VIX	-12.847***	-510.998***	0.029	-13.162***

Note. ****p* < .01. The KPSS critical values at the 5% and 1% levels are 0.146 and 0.216, respectively. The ZA critical values at the 1% and 5% levels are −5.34 and −4.80, respectively. The null hypothesis for the KPSS test is stationarity, while that for the ADF and PP tests is the presence of a unit root. ZA break dates: BM 27.03.2020; CG 07.01.2022; CS 26.11.2021; FIN 03.11.2023; HC 10.09.2021; IND 10.04.2020; OG 03.04.2020; TECH 25.04.2025; TEL 25.11.2016; UTL 11.04.2025; Brent 01.05.2020; VIX 03.04.2020.

Table 3 presents the pairwise Pearson correlation matrix among the variables. Generally strong positive correlations are observed among sectoral indices, and nearly all pairwise correlations are statistically significant at the 1% level. Given the large sample size (n=521), the analysis focuses on the magnitude and sign of the coefficients. The nonparametric Spearman correlation also reveals the same pattern; for example, the relationship between Oil & Gas and Brent is stronger in the Spearman correlation (0.326) than in the Pearson correlation (0.224) (see Table A1). In contrast, VIX return has a negative correlation with all sectors, significant at the 1% level, with the strongest negative relationship observed in the IND (−0.667) and TECH (−0.655) sectors. Brent oil price return is positively but weakly to moderately correlated with all sectors, and all correlations are significant at the 1% level (ranging from 0.138 to 0.303). The IND-CS (0.871), IND-BM (0.844), and CS-CG (0.808) pairs have the highest correlations. The OG sector having the lowest correlation with other sectors (ranging from 0.074 to 0.224) reflects the sector’s unique dynamics. The OG-TECH pair is the weakest pairwise correlation, significant only at the 10% level $(r = 0.074, p < 0.10)$. Each sectoral index is treated as the dependent variable in a separate model, with only Brent and the VIX included as explanatory variables. The correlation between these two variables is low (r = −0.21), and the VIF values are close to one (≈1.06–1.09).

Table 3: Pairwise Correlation Matrix of Weekly Return Series

	BM	CG	CS	FIN	HC	IND	OG	TECH	TEL	UTL	BRT	VIX
BM	1.000											
CG	0.733***	1.000										
CS	0.714***	0.808***	1.000									
FIN	0.664***	0.738***	0.795***	1.000								
HC	0.650***	0.678***	0.682***	0.714***	1.000							
IND	0.844***	0.827***	0.871***	0.826***	0.737***	1.000						
OG	0.213***	0.114***	0.126***	0.155***	0.115***	0.169***	1.000					
TECH	0.623***	0.725***	0.822***	0.736***	0.641***	0.796***	0.074*	1.000				
TEL	0.611***	0.566***	0.465***	0.474***	0.484***	0.557***	0.169***	0.389***	1.000			
UTL	0.566***	0.483***	0.478***	0.446***	0.436***	0.557***	0.193***	0.463***	0.440***	1.000		
BRT	0.303***	0.163***	0.184***	0.172***	0.146***	0.236***	0.224***	0.173***	0.138***	0.159***	1.000	
VIX	-0.562***	-0.580***	-0.627***	-0.585***	-0.592***	-0.667***	-0.115***	-0.655***	-0.357***	-0.363***	-0.213***	1.000

Note. Lower triangle of the Pearson correlation matrix is reported. Significance is based on the two-tailed *t*-test with $n - 2$ degrees of freedom.
***$p < .01$, **p < .05, *$p < .10$.

Methodology

In this study, we use the Quantile Autoregressive Distributed Lag (QARDL) model developed by Cho et al. (2015) to examine the relationships between variables at different quantile levels. While the traditional ARDL focuses only on the conditional mean, the QARDL model allows testing for parameter heterogeneity at quantiles $\tau \in \{0.05, 0.10, 0.25, 0.50, 0.75, 0.90, 0.95\}$. Thus, it was examined whether the effects of oil prices and VIX on sectoral returns change according to market regimes. The leptokurtic structure and rejection of normality observed in the descriptive statistics necessitate quantile methods (see Table 1). Since the variables I(0) (stationary), the QARDL model is specified as a quantile-based dynamic distributed-lag model. In this framework, the long-run coefficients (L) are long-run multipliers that measure the cumulative (steady-state) response of a permanent shock to the conditional quantile.

The QARDL model is defined as follows (Equation 1):

$$Q_{y_t}(\tau \mid \mathcal{F}_{t-1}) = \alpha(\tau) + \rho(\tau) y_{t-1} + \beta_1(\tau) Brent_t + \beta_2(\tau) Brent_{t-1} + \beta_3(\tau) VIX_t + \beta_4(\tau) VIX_{t-1} + \gamma(\tau) COVID_t \quad (1)$$

Here $Q_{y_t}(\tau \mid \mathcal{F}_{t-1})$, y_t's τth conditional quantile function; $\alpha(\tau)$ the quantile-specific intercept; $\rho(\tau)$ the lagged coefficient of the dependent variable; $\beta_1(\tau)$ and $\beta_2(\tau)$ the short-run effects of Brent oil price; $\beta_3(\tau)$ and $\beta_4(\tau)$ the short-run effects of VIX; $\gamma(\tau)$ the coefficient of the COVID-19 dummy variable. The analysis was conducted for quantile values $\tau = \{0.05, 0.10, 0.25, 0.50, 0.75, 0.90, 0.95\}$. Lower quantiles ($\tau = 0.05, 0.10$) represent bear market conditions, higher quantiles ($\tau = 0.90, 0.95$) represent bull market conditions, and the median quantile ($\tau = 0.50$) represents normal market conditions.

Long-run coefficients from the QARDL model were calculated with the following formula (Equation 2 and Equation 3):

$$L_{Brent}(\tau) = \frac{\beta_1(\tau) + \beta_2(\tau)}{1 - \rho(\tau)} \quad (2)$$

$$L_{VIX}(\tau) = \frac{\beta_3(\tau) + \beta_4(\tau)}{1 - \rho(\tau)} \quad (3)$$

These coefficients reflect the long-run effects of oil and VIX changes. In order to measure the level of uncertainty regarding the long-run effects of the coefficients and to increase the statistical reliability of the estimates, 95% confidence intervals were derived using a bootstrap method with 1,000 replications.[2] The error-correction representation of the model is given in Equation 4. The adjustment speed coefficient $(\rho(\tau) - 1)$ ranges from −0.66 to −1.44 across all sectors and quintiles and is consistently and significantly negative. This indicates that the return to equilibrium in weekly returns occurs rapidly (Table A4). The Ljung-Box test on the QARDL residuals at the median lag ($\tau = 0.5$) shows no residual autocorrelation in 7 out of 10 sectors; limited dependence is observed in Oil & Gas (where strong dynamics persist even at a 5-lag), Industrials, and Basic Materials. The fact that the estimation is not sensitive to this dependence is confirmed by the calculation of long-term confidence intervals using the moving-block bootstrap method, which yielded results nearly identical to the case results (Tables A2 and A3).

$$\begin{aligned} \Delta y_t(\tau) = \alpha(\tau) + (\rho(\tau) - 1) \cdot [y_{t-1} \\ -L_{Brent}(\tau) \cdot Brent_{t-1} - L_{VIX}(\tau) \cdot VIX_{t-1}] \\ +\beta_1(\tau) \cdot \Delta Brent_t + \beta_3(\tau) \cdot \Delta VIX_t + \gamma(\tau) \cdot COVID_t + \varepsilon_t(\tau) \end{aligned} \quad (4)$$

[2] Confidence intervals were calculated using case (pairs) bootstrap (1,000 iterations) and the percentile method, in which the observations were resampled. To ensure robustness against potential serial correlation, the same intervals were also calculated using the moving-block bootstrap method (block length 8) and were found to be nearly identical (Tables A2 and A3); significance differs in only 4 out of 140 cells.

FINDINGS

Preliminary Test Results

Table 4 reports the ARDL bounds-test F-statistics for all sectoral models. As the variables are stationary I(0), these statistics gauge the joint significance of the lagged level terms (a stable dynamic linkage) rather than cointegration. The F-statistics exceed the Pesaran et al. (2001) upper critical values for all sectors at the 1% level, with the strongest linkage in the OG sector ($F = 210.292, p < 0.01$). Overall, the results point to a robust dynamic linkage between each sectoral index and Brent and VIX, and support the application of the QARDL model. On the other hand, the Bayesian Information Criterion (BIC) determined 1 lag as optimal in all sectors and only 5 lags in Oil & Gas. The lag length was selected using the BIC (Schwarz) criterion, with an emphasis on parsimony; the longer lag (5) in the Oil & Gas series reflects the strong serial correlation in that series.

Table 4: Optimal Lag Selection and Joint Significance of the Dynamic Terms

Sector	**Lag (BIC)**	***F-Statistic***	**Decision**
BM	1	56.299***	Significant
CG	1	58.671***	Significant
CS	1	53.912***	Significant
FIN	1	61.783***	Significant
HC	1	60.804***	Significant
IND	1	51.521***	Significant
OG	5	210.292***	Significant
TECH	1	50.362***	Significant
TEL	1	50.958***	Significant
UTL	1	55.111***	Significant

Note. Lag (BIC) = optimal lag length selected by the Schwarz (1978) Bayesian Information Criterion. Because all series are stationary I(0), these F-statistics test the joint significance of the lagged dynamic terms rather than cointegration; all are significant at the 1% level. The Pesaran et al. (2001) bounds (k = 2) are shown only as a reference threshold: $I(0) = 4.13$

and $I(1) = 5.00$. The dependent variable in each model is the DJIM sectoral index return; the independent variables are Brent crude oil and VIX returns.
***$p < .01$.

Table 5 reports the Koenker-Xiao (2002) quantile slope equality test results. The Brent effect differs significantly across quantiles only in the IND ($F = 2.919, p < 0.01$) and CS ($F = 1.962, p < 0.10$) sectors, while homogeneity cannot be rejected in the remaining 8 sectors. Our findings therefore indicate that Brent crude oil prices generally exhibit a homogeneous structure across the DJIM sectoral breakdowns. The relationship between oil prices and returns is observed to operate relatively stably across different market regimes. In addition, we determine that sensitivity to oil price volatility in most DJIM sectors does not show a significant increase in extreme market regimes.

In contrast, on the VIX side, significant quantile-variation is confirmed in the CG ($F = 3.380, p < 0.01$), CS ($F = 2.571, p < 0.05$), FIN ($F = 3.430, p < 0.01$), HC ($F = 7.660, p < 0.01$), OG ($F = 3.880, p < 0.01$), and TECH ($F = 1.960, p < 0.10$) sectors. This pervasive heterogeneity implies that the distribution of DJIM sectoral returns also differentiates depending on different VIX decline or rise regimes. The strongest evidence emerges in the HC sector ($F = 7.660, p < 0.01$), which demonstrates that anxiety-driven repricing is particularly quantile-sensitive in defensive sectors. Finally, we determine that in the BM, TEL and UTL sectors, the effects of both Brent and VIX variables remain largely homogeneous.

Table 5: Quantile Slope Equality Test Results

	Brent		VIX		
Sector	F-stat	p	F-stat	p	Decision
BM	1.630	0.133	0.490	0.816	Both Homogeneous
CG	1.730	0.110	3.380***	0.003	VIX: Heterogeneous
CS	1.960*	0.068	2.570**	0.017	Both heterogeneous
FIN	0.730	0.628	3.430***	0.002	VIX: Heterogeneous

HC	0.990	0.433	7.660***	<.001	VIX: Heterogeneous
IND	2.920***	0.008	1.260	0.272	Brent: Heterogeneous
OG	0.360	0.907	3.880***	0.001	VIX: Heterogeneous
TECH	1.200	0.305	1.960*	0.068	VIX: Heterogeneous
TEL	1.710	0.116	1.190	0.310	Both Homogeneous
UTL	1.750	0.105	1.590	0.145	Both Homogeneous

Note. The Koenker and Xiao (2002) quantile slope equality test examines whether the effect of each regressor is constant across quantiles ($\tau = 0.05, 0.10, 0.25, 0.50, 0.75, 0.90, 0.95$). The null hypothesis is that slope coefficients are equal across all quantiles. Rejection of H_0 implies heterogeneous (quantile-varying) effects, justifying the QARDL specification.
***p < .01. **p < .05. *p < .10.

Sectoral Effects of Brent Oil Price

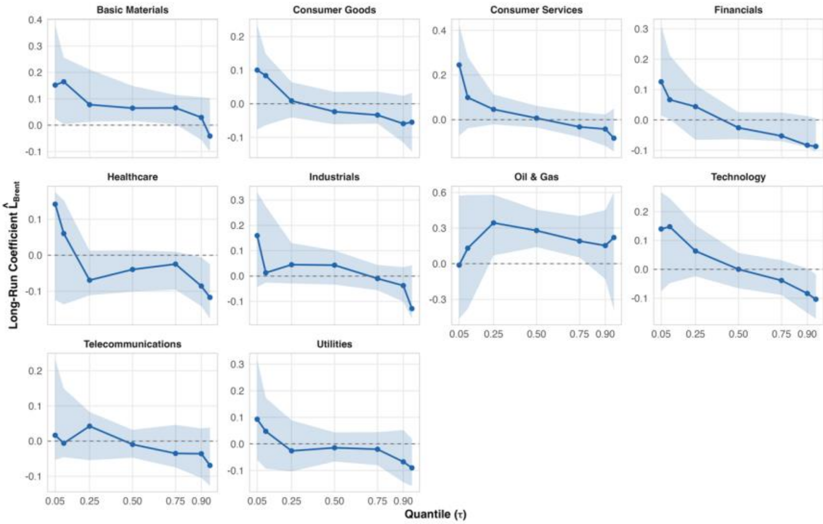
Table 6 reports the short-run and long-run QARDL effects of Brent oil price on DJIM sectoral returns at seven different quantile levels. Figure 2 visually presents the variation of long-run coefficients across quantiles. The most notable finding of the results is that the point estimates of the Brent oil price effect systematically decreases from lower quantiles (bear market) to higher quantiles (bull market), and even changes sign in most sectors. However, it should be noted that the majority of long-run Brent coefficients are individually statistically insignificant; the bootstrap confidence intervals encompass zero in most sectors and quantiles. This finding reveals that while oil price shocks exhibit a directional pattern across quantiles, the economic magnitude of this effect remains uncertain in most sectors.

Table 6: QARDL Short-Run and Long-Run Brent Crude Oil Effects on DJIM Sectoral Returns

Sector		$\tau = 0.05$	$\tau = 0.10$	$\tau = 0.25$	$\tau = 0.50$	$\tau = 0.75$	$\tau = 0.90$	$\tau = 0.95$
BM	$\hat{\beta}$	0.166***	0.121***	0.068***	0.080***	0.079***	0.059**	-0.012
	$\hat{L}$	0.152**	0.165**	0.078**	0.065**	0.066**	0.029	-0.041
CG	$\hat{\beta}$	0.035	0.024	0.010	-0.031**	-0.024**	-0.043*	-0.013
	$\hat{L}$	0.100	0.084	0.009	-0.024	-0.034	-0.059	-0.055
CS	$\hat{\beta}$	0.064	0.019	0.033*	0.012	-0.013	-0.028	-0.078**
	$\hat{L}$	0.245	0.099	0.046	0.007	-0.032	-0.042	-0.083
FIN	$\hat{\beta}$	0.081	0.054**	0.037*	0.005	-0.027	-0.062***	-0.065*
	$\hat{L}$	0.126**	0.067**	0.044	-0.026	-0.053	-0.083	-0.087
HC	$\hat{\beta}$	0.074*	0.041	-0.021*	0.000	0.004	-0.015	-0.038**
	$\hat{L}$	0.142	0.060	-0.069	-0.040	-0.025	-0.086**	-0.117**
IND	$\hat{\beta}$	0.102**	0.017	0.051***	0.036***	0.005	-0.036	-0.093***
	$\hat{L}$	0.160	0.013	0.045	0.043	-0.010	-0.038	-0.129
OG	$\hat{\beta}$	0.219	0.409***	0.414***	0.355***	0.315***	0.388**	0.437**
	$\hat{L}$	-0.012	0.131	0.344**	0.279**	0.190**	0.152	0.220
TECH	$\hat{\beta}$	0.072	0.043	0.046*	0.023	-0.006	-0.075**	-0.087***
	$\hat{L}$	0.140	0.148	0.063	0.000	-0.039	-0.084	-0.104**
TEL	$\hat{\beta}$	0.025	0.004	0.037***	0.002	-0.015	-0.024	-0.032
	$\hat{L}$	0.017	-0.006	0.043	-0.009	-0.035	-0.036	-0.069
UTL	$\hat{\beta}$	0.112***	0.037	0.009	-0.004	-0.011	-0.025	-0.041
	$\hat{L}$	0.093	0.047	-0.026	-0.015	-0.020	-0.068	-0.090

Note. $\hat{\beta}$ = short-run coefficient; $\hat{L}$ = cumulative long-run multiplier from the QARDL model of Cho et al. (2015). Significance of $\hat{\beta}$ is based on *t*-statistics. For $\hat{L}$, ** indicates the 95% bootstrap confidence interval (1,000 replications) excludes zero.
****p* < .01. ***p* < .05. **p* < .10.

Figure 1: Long-Run Oil Price (Brent) Effects Across Quantiles



Under bear market conditions ($\tau = 0.10$), the long-run point estimates of Brent oil price (L_{Brent}) are positive and at their highest levels in the BM (0.165), OG (0.131), TECH (0.148), CS (0.099), and CG (0.084) sectors. However, among these, only BM and OG yield statistically significant long-run coefficients; the remaining sectors' estimates fall within the bootstrap confidence intervals that include zero. The OG sector is the only sector that exhibits a consistently positive directional response to oil prices, with statistically significant long-run coefficients at the middle quantiles ($\tau = 0.25\ through\ 0.75$). It has the highest long-run coefficient (0.279) at the median quantile ($\tau = 0.50$). This is consistent with expectations and stems from the fact that increases in oil prices directly increase the revenues of energy companies.

Under bull market conditions ($\tau = 0.90$), the Brent point estimates turn negative in the HC (-0.086), FIN (-0.083), TECH (-0.084), UTL (-0.068), and CG (-0.059) sectors. Yet, of these long-run coefficients, only HC yields individually significant estimates at this quantile; the remaining sectors' negative coefficients are not statistically distinguishable from zero. This finding suggests that during periods when the market is in an upward trend, increases in oil prices may adversely affect the returns of these sectors through the cost increase channel, although the statistical evidence for this channel remains limited outside the energy-linked sectors. Indeed, the adverse impact of oil price increases on non-energy-intensive sectors such as HC and TECH can be explained by the pressure of oil prices on production costs and indirectly on discount rates.

Sectoral Effects of VIX

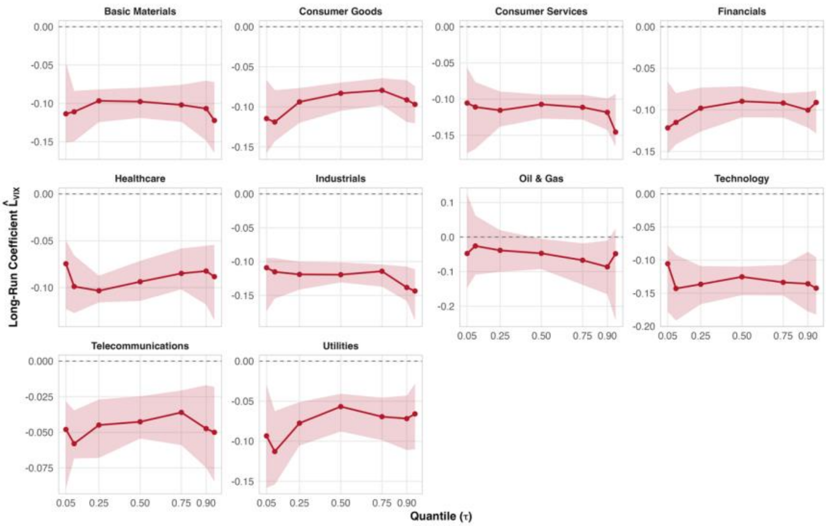
Table 7 reports the QARDL effects of VIX on DJIM sectoral returns at quantile levels. VIX has a negative and statistically significant effect across nearly all sectors and all quantiles. This finding reveals that increases in global financial uncertainty adversely affect Islamic stock returns regardless of market conditions. Unlike the Brent oil price, the VIX effect is observed to exhibit a relatively stable structure across quantiles, although the Wald test results (see Table 9) indicate that the quantile differences are statistically significant in all sectors. The economic magnitude of these differences, however, is considerably smaller than that observed for Brent.

Table 7: QARDL Short-Run and Long-Run VIX Effects on DJIM Sectoral Returns

Sector		$\tau = 0.05$	$\tau = 0.10$	$\tau = 0.25$	$\tau = 0.50$	$\tau = 0.75$	$\tau = 0.90$	$\tau = 0.95$
BM	$\hat{\beta}$	-0.087***	-0.093***	-0.084***	-0.076***	-0.087***	-0.092***	-0.107***
	$\hat{L}$	-0.114**	-0.111**	-0.097**	-0.098**	-0.102**	-0.107**	-0.122**
CG	$\hat{\beta}$	-0.082***	-0.092***	-0.079***	-0.075***	-0.067***	-0.075***	-0.074***
	$\hat{L}$	-0.115**	-0.119**	-0.094**	-0.083**	-0.079**	-0.091**	-0.097**
CS	$\hat{\beta}$	-0.105***	-0.102***	-0.095***	-0.096***	-0.100***	-0.110***	-0.130***
	$\hat{L}$	-0.105**	-0.111**	-0.116**	-0.107**	-0.111**	-0.118**	-0.145**
FIN	$\hat{\beta}$	-0.097***	-0.102***	-0.094***	-0.083***	-0.084***	-0.086***	-0.088***
	$\hat{L}$	-0.122**	-0.115**	-0.098**	-0.090**	-0.092**	-0.100**	-0.091**
HC	$\hat{\beta}$	-0.074***	-0.083***	-0.084***	-0.075***	-0.075***	-0.070***	-0.065***
	$\hat{L}$	-0.074**	-0.099**	-0.103**	-0.094**	-0.085**	-0.082**	-0.088**
IND	$\hat{\beta}$	-0.094***	-0.098***	-0.098***	-0.099***	-0.097***	-0.118***	-0.115***
	$\hat{L}$	-0.109**	-0.115**	-0.119**	-0.119**	-0.114**	-0.138**	-0.144**
OG	$\hat{\beta}$	-0.013	-0.004	-0.050**	-0.044***	-0.043***	-0.040	-0.015
	$\hat{L}$	-0.048	-0.026	-0.038	-0.047**	-0.067**	-0.086**	-0.048
TECH	$\hat{\beta}$	-0.098***	-0.124***	-0.125***	-0.114***	-0.121***	-0.127***	-0.128***
	$\hat{L}$	-0.105**	-0.143**	-0.137**	-0.125**	-0.134**	-0.136**	-0.142**
TEL	$\hat{\beta}$	-0.043***	-0.044***	-0.034***	-0.033***	-0.030***	-0.035***	-0.035***
	$\hat{L}$	-0.048**	-0.058**	-0.045**	-0.043**	-0.036**	-0.047**	-0.050**
UTL	$\hat{\beta}$	-0.047***	-0.060***	-0.050***	-0.041***	-0.052***	-0.058***	-0.060***
	$\hat{L}$	-0.093**	-0.113**	-0.077**	-0.057**	-0.069**	-0.072**	-0.066**

Note. $\hat{\beta}$ = short-run coefficient; $\hat{L}$ = cumulative long-run multiplier from the QARDL model of Cho et al. (2015). Significance of $\hat{\beta}$ is based on *t*-statistics. For $\hat{L}$, ** indicates the 95% bootstrap confidence interval (1,000 replications) excludes zero.
****p* < .01. ***p* < .05. **p* < .10.

Figure 2: Long-Run VIX Effects Across Quantiles



The strongest negative effect of VIX was observed in the TECH (L_{VIX}: ranging from -0.105 to -0.143) and IND (L_{VIX}: ranging from -0.109 to -0.144) sectors. In the CS sector, the VIX effect is relatively stable across quantiles, ranging from -0.105 to -0.145. The OG sector has the weakest VIX effect, yielding statistically insignificant results at lower quantiles ($\tau = 0.05, 0.10$). The TEL sector also exhibits relatively low VIX sensitivity, with L_{VIX} coefficients ranging from -0.036 to -0.058. These findings indicate that the sectors most sensitive to uncertainty shocks are those with high growth potential (TECH) and those strongly linked to the real economy (IND).

Although the variation of VIX effect across quantiles is limited, a strengthening effect at higher quantiles (bull market) is observed in some sectors. In the IND sector, the VIX effect increases from -0.115 at $\tau = 0.10$ to -0.138 at $\tau = 0.90$; this indicates that the industrials sector becomes more sensitive to uncertainty during bull market periods. A similar trend is observed in the CS sector, where the VIX effect strengthens from -0.107 at $\tau = 0.50$ to -0.145 at $\tau = 0.90$. In contrast, in the HC sector, the VIX effect eases at higher quantiles (from -0.099 to -0.082), which is consistent with the defensive nature of the sector.

Impact of COVID-19

The quantile-based coefficients ($\gamma(\tau)$) of the COVID-19 dummy variable are presented in Table 8. In the upper quantiles (bull market), the coefficients are mostly positive and significant, while in the lower quantiles (bear market), they are negative. However, we found that the significance of the lower quantiles was particularly pronounced in the Oil & Gas and Healthcare sectors (22 out of 70 sector-quantile combinations were significant at the 5% level). This pattern suggests that the upper-quartile (bull market) response strengthened particularly during the pandemic period, while the two-tailed (both lower and upper) expansion was most pronounced in the Oil & Gas sector. The core findings hold when the COVID period is excluded from the sample (Table A5). The window selected for the dummy variable covers the acute pandemic-disruption period, spanning from the World Health Organization's declaration of the pandemic (March 2020) to mid-2021, when markets had largely normalized and vaccination had become widespread.

Table 8: COVID-19 Dummy Coefficients γ(τ) by Sector and Quantile

Sector	**τ=0.05**	**τ=0.10**	**τ=0.25**	**τ=0.50**	**τ=0.75**	**τ=0.90**	**τ=0.95**
BM	-1.50	-0.77	0.12	0.32	0.64*	0.92	1.46
CG	-0.68	-0.87	0.30	0.64**	1.07***	1.31***	1.51***
CS	-1.81*	-0.60	0.22	0.65***	0.48**	1.54***	1.91***
FIN	-0.99	-0.85*	-0.68	0.16	0.67*	1.31***	1.67***
HC	0.12	-0.61***	0.02	0.05	0.25	1.43***	1.57***
IND	-2.78	-0.03	0.20	0.24	0.60**	1.47	2.99**
OG	-18.80***	-8.46**	-3.12	-1.16	2.78**	6.32	17.47*
TECH	-0.63	-0.72	0.12	0.38	0.69	1.64***	1.35***
TEL	-0.69	0.11	0.00	0.02	0.33	0.70***	0.49
UTL	-0.40	-0.37	0.26	0.03	0.20	0.67**	0.21

Note. The cells represent the cantilever regression coefficients ($\gamma(\tau)$) of the COVID-19 model; ****p* < .01. ***p* < .05. **p* < .10.

Asymmetry Tests

Table 9 presents the Wald test results that test the statistical significance of long-run coefficient differences between bear market ($\tau = 0.10$) and bull market ($\tau = 0.90$) quantiles. For Brent oil price, asymmetry was found to be statistically significant in all 10 sectors ($p < 0.01$). The strongest Brent asymmetry was observed in the TECH ($L_{diff} = 0.187, t = 55.95$), CS ($L_{diff} = 0.161, t = 40.93$), and FIN ($L_{diff} = 0.168, t = 51.87$) sectors. Although the OG sector also exhibits statistically significant Brent asymmetry ($p < .001$), the magnitude of the difference is the smallest among all sectors, indicating that oil prices affect this sector more symmetrically relative to others. It is important to note that the Wald test evaluates whether the long-run coefficients differ between quantile regimes, not whether each coefficient is individually different from zero. Given that the majority of individual long-run Brent coefficients are statistically insignificant, the detected asymmetry reflects a directional shift in point estimates across quantiles rather than a transition between two individually well-identified effects. This distinction should be considered when interpreting the economic implications of the asymmetry findings. For VIX, asymmetry was found to be statistically significant in all 10 sectors.

Table 9: Wald Test for Long-Run Asymmetry

	Brent				**VIX**			
Sector	**Δ**	**t**	**p**	**Asym.**	**Δ**	**t**	**p**	**Asym.**
BM	0.0991	27.370***	<.001	Yes	-0.0111	-10.604***	<.001	Yes
CG	0.1116	40.091***	<.001	Yes	-0.0213	-23.224***	<.001	Yes
CS	0.1606	40.925***	<.001	Yes	0.0033	3.191***	.002	Yes
FIN	0.1677	51.874***	<.001	Yes	-0.0107	-12.672***	<.001	Yes
HC	0.0897	21.617***	<.001	Yes	-0.0091	-10.128***	<.001	Yes
IND	0.1011	24.792***	<.001	Yes	0.0130	14.515***	<.001	Yes
OG	0.0593	4.902***	<.001	Yes	0.0689	26.600***	<.001	Yes
TECH	0.1865	55.953***	<.001	Yes	-0.0088	-6.426***	<.001	Yes
TEL	0.0382	13.778***	<.001	Yes	-0.0094	-12.428***	<.001	Yes

UTL	0.0886	23.227***	<.001	Yes	-0.0357	-27.255***	<.001	Yes

Note. The Wald test, following Cho et al. (2015), examines the null hypothesis of equal long-run effects across bear and bull quantiles (H_0: $L(0.10) = L(0.90)$) for each regressor. Δ = difference between bear-market and bull-market cumulative long-run multipliers; Asym. = asymmetry detected at the 5% significance level.
***p < .01. **p < .05. *p < .10.

CONCLUSION

In this study, we examined the impact of Brent oil prices and VIX on the returns of 10 sectoral indices within the DJIM sectors during the period January 4, 2016 – January 12, 2026 using the Quantile ARDL (QARDL) approach. Our main motivation in this study is to investigate how oil prices and VIX differently affect Islamic sectoral returns depending on market conditions. Indeed, oil price is an indicator variable pointing to the cash flow channel, while VIX points to the discount rate channel (Arouri and Nguyen, 2010; Whaley, 2009). These channels summarize the theoretical mechanisms underlying the observed relationships; the analysis reveals the co-movement among the variables.

According to the QARDL analysis results, the point estimates suggest that the effect of Brent oil price on sectoral returns follows an asymmetric pattern depending on market conditions. The positive effect observed under bear market conditions turns negative under bull market conditions. The Wald test results reveal that asymmetric transitions across quantile regimes are statistically significant in all 10 sectors. Nevertheless, the individual long-run Brent coefficients are statistically insignificant in the majority of sectors and quantiles, indicating that the detected asymmetry reflects a systematic directional pattern in point estimates rather than transitions between individually well-identified effects. OG exhibits a consistently positive Brent effect, with statistically significant long-run coefficients at the middle quantiles; this result is consistent with the sector's revenue dependence on oil. BM is the other sector where the long-run Brent effect is significant across multiple quantiles. However, this significance at the BM level is not as robust in the robustness checks (moving-block bootstrap and non-COVID subsample) as it is for Oil & Gas.

On the VIX side, we observe a negative and statistically significant effect across all sectors. Our analysis results show that the TECH and IND sectors exhibit the highest sensitivity to VIX fluctuations; conversely, OG and TEL sectors respond at the lowest level. In addition to sectoral heterogeneity, we must say that DJIM sectors, despite their Shariah-compliant structures, are not independent from global uncertainty shocks. However, while the VIX effect shows statistically significant differences across different quantiles, we must also emphasize the uniform structure of VIX's negative effect. The findings are also consistent with studies in the literature (Naifar, 2016; Arfaoui and Rejeb, 2020; Özçelebi and Pérez-Montiel, 2023). It was found that the COVID-19 period increased volatility by amplifying the return response, particularly in high-volatility segments, especially within the robust Oil & Gas sector (Table 8); these key findings hold even when this period is excluded and under a moving-block bootstrap analysis.

We demonstrate that the effect of oil prices on sectoral returns becomes heterogeneous across quantiles in a manner consistent with prior literature (Chang et al., 2020). However, the economic magnitude of regime-dependent asymmetric effect differences is limited (Badeeb and Lean, 2018).

Finally, our study has some limitations. The analysis is confined to DJIM sectors only. Therefore, comparative evaluation of Shariah-compliant DJIM sectors with conventional sectors presents an important future research area. Additionally, the weekly frequency used in the study limits the capture of intraday or daily dynamics. Brent and the VIX are global and largely exogenous variables and can be considered exogenous relative to a single sector index; the lagged regressors in the model also partially limit potential cointegration. However, the potential endogeneity between oil prices and returns poses a constraint, and instrumental variable (IV) or GMM-based approaches are left for future studies. Future studies that examine how relationships change over time using methods such as

Quantile-on-Quantile regression or TVP-QARDL (Time-Varying Parameter QARDL) could contribute to the literature.

APPENDIX

Table A1: Spearman Rank Correlation Matrix

	BM	CG	CS	FIN	HC	IND	OG	TECH	TEL	UTL	BRT	VIX
BM	1.000											
CG	0.670***	1.000										
CS	0.620***	0.749***	1.000									
FIN	0.584***	0.688***	0.696***	1.000								
HC	0.548***	0.586***	0.575***	0.645***	1.000							
IND	0.788***	0.780***	0.817***	0.751***	0.637***	1.000						
OG	0.267***	0.145***	0.151***	0.139***	0.151***	0.215***	1.000					
TECH	0.555***	0.689***	0.764***	0.673***	0.544***	0.756***	0.094**	1.000				
TEL	0.554***	0.525***	0.432***	0.459***	0.421***	0.511***	0.161***	0.358***	1.000			
UTL	0.526***	0.498***	0.467***	0.430***	0.424***	0.546***	0.175***	0.418***	0.444***	1.000		
BRT	0.278***	0.076*	0.108**	0.095**	0.074*	0.171***	0.326***	0.136***	0.087**	0.077*	1.000	
VIX	-0.550***	-0.582***	-0.634***	-0.625***	-0.541***	-0.695***	-0.129***	-0.653***	-0.342***	-0.387***	-0.170***	1.000
Note. ***p<.01, **p<.05, *p<.10.												

Table A2: Long-Run Brent Multiplier

Sector	$\tau = 0.05$	$\tau = 0.10$	$\tau = 0.25$	$\tau = 0.50$	$\tau = 0.75$	$\tau = 0.90$	$\tau = 0.95$
BM	0.152 [-0.003, 0.376]	0.165 [-0.016, 0.267]	0.078* [0.018, 0.241]	0.065* [0.019, 0.136]	0.066* [0.007, 0.098]	0.029 [-0.065, 0.101]	-0.041 [-0.143, 0.103]
CG	0.1 [-0.109, 0.245]	0.084 [-0.076, 0.149]	0.007 [-0.047, 0.067]	-0.024 [-0.068, 0.014]	-0.033 [-0.078, 0.006]	-0.059 [-0.115, 0.026]	-0.055 [-0.16, 0.026]
CS	0.245 [-0.112, 0.343]	0.099 [-0.077, 0.295]	0.046 [-0.038, 0.114]	0.009 [-0.052, 0.041]	-0.034 [-0.081, 0.026]	-0.04 [-0.125, 0.002]	-0.083 [-0.165, 0.032]
FIN	0.126 [-0.018, 0.369]	0.093 [-0.031, 0.24]	0.046 [-0.086, 0.1]	-0.025 [-0.074, 0.01]	-0.055 [-0.094, 0.009]	-0.083* [-0.119, -0.023]	-0.087* [-0.155, -0.019]
HC	0.142 [-0.142, 0.189]	0.06 [-0.156, 0.159]	-0.069 [-0.116, 0.027]	-0.036 [-0.103, 0.002]	-0.025 [-0.093, 0.009]	-0.086* [-0.127, -0.002]	-0.117* [-0.15, -0.02]
IND	0.153 [-0.073, 0.306]	0.013 [-0.074, 0.289]	0.045 [-0.044, 0.143]	0.041 [-0.02, 0.09]	-0.009 [-0.058, 0.032]	-0.038 [-0.099, 0.019]	-0.128 [-0.168, 0.003]
OG	-0.012 [-0.388, 0.572]	0.13 [-0.29, 0.558]	0.35* [0.023, 0.559]	0.283* [0.106, 0.475]	0.187* [0.051, 0.348]	0.152 [-0.146, 0.499]	0.22 [-0.504, 0.674]
TECH	0.141 [-0.099, 0.253]	0.148 [-0.017, 0.226]	0.063 [-0.031, 0.139]	0 [-0.071, 0.042]	-0.039 [-0.096, 0.016]	-0.084 [-0.144, 0.013]	-0.104* [-0.172, -0.009]
TEL	0.017 [-0.06, 0.239]	-0.006 [-0.046, 0.167]	0.036 [-0.047, 0.084]	-0.008 [-0.046, 0.03]	-0.036 [-0.076, 0.039]	-0.036 [-0.096, 0.039]	-0.069 [-0.105, 0.046]
UTL	0.093 [-0.127, 0.356]	0.047 [-0.115, 0.189]	-0.026 [-0.105, 0.09]	-0.014 [-0.061, 0.034]	-0.02 [-0.088, 0.036]	-0.067 [-0.15, 0.042]	-0.09 [-0.179, 0.046]

Note. Each cell: estimate and 95% moving-block bootstrap CI [lower, upper], reported as a robustness check against the case-bootstrap results in Table 6 (* = CI excludes zero; 1,000 iterations, block length 8).

Table A3: Long-Run VIX Multiplier

Sector	$\tau = 0.05$	$\tau = 0.10$	$\tau = 0.25$	$\tau = 0.50$	$\tau = 0.75$	$\tau = 0.90$	$\tau = 0.95$
BM	-0.114* [-0.148, -0.046]	-0.111* [-0.147, -0.079]	-0.095* [-0.125, -0.08]	-0.098* [-0.122, -0.08]	-0.102* [-0.123, -0.078]	-0.107* [-0.135, -0.067]	-0.122* [-0.163, -0.072]
CG	-0.115* [-0.154, -0.068]	-0.119* [-0.143, -0.071]	-0.092* [-0.121, -0.078]	-0.082* [-0.105, -0.068]	-0.079* [-0.097, -0.067]	-0.091* [-0.11, -0.066]	-0.097* [-0.117, -0.074]
CS	-0.105* [-0.155, -0.063]	-0.111* [-0.161, -0.078]	-0.115* [-0.138, -0.09]	-0.106* [-0.128, -0.093]	-0.112* [-0.128, -0.091]	-0.117* [-0.148, -0.095]	-0.145* [-0.161, -0.092]
FIN	-0.122* [-0.161, -0.061]	-0.113* [-0.142, -0.076]	-0.099* [-0.139, -0.07]	-0.09* [-0.11, -0.071]	-0.092* [-0.114, -0.082]	-0.1* [-0.119, -0.079]	-0.091* [-0.13, -0.069]
HC	-0.074* [-0.129, -0.043]	-0.099* [-0.128, -0.069]	-0.102* [-0.118, -0.087]	-0.093* [-0.114, -0.071]	-0.085* [-0.102, -0.063]	-0.082* [-0.112, -0.064]	-0.088* [-0.12, -0.058]
IND	-0.11* [-0.152, -0.09]	-0.115* [-0.146, -0.092]	-0.119* [-0.145, -0.099]	-0.119* [-0.132, -0.099]	-0.114* [-0.138, -0.103]	-0.138* [-0.161, -0.107]	-0.144* [-0.184, -0.109]
OG	-0.047 [-0.134, 0.108]	-0.024 [-0.114, 0.052]	-0.031 [-0.107, 0.005]	-0.047* [-0.092, -0.011]	-0.066* [-0.139, -0.024]	-0.086* [-0.168, -0.017]	-0.048 [-0.215, 0.009]
TECH	-0.106* [-0.172, -0.081]	-0.143* [-0.182, -0.095]	-0.137* [-0.166, -0.11]	-0.125* [-0.157, -0.112]	-0.134* [-0.154, -0.108]	-0.136* [-0.169, -0.095]	-0.142* [-0.174, -0.102]

TEL	-0.048* [-0.078, -0.021]	-0.058* [-0.068, -0.034]	-0.046* [-0.066, -0.026]	-0.042* [-0.052, -0.026]	-0.036* [-0.055, -0.021]	-0.047* [-0.068, -0.018]	-0.05* [-0.073, -0.014]
UTL	-0.093* [-0.165, -0.018]	-0.112* [-0.154, -0.059]	-0.077* [-0.104, -0.048]	-0.057* [-0.085, -0.042]	-0.069* [-0.094, -0.049]	-0.072* [-0.098, -0.041]	-0.066* [-0.105, -0.028]

Note. Each cell: estimate and 95% moving-block bootstrap CI [lower, upper], reported as a robustness check against the case-bootstrap results in Table 7 (* = CI excludes zero; 1,000 iterations, block length 8).

Table A4: Error-Correction Adjustment Speed (rho(t) minus 1) by Sector and Quantile

Sector	$\tau = 0.05$	$\tau = 0.10$	$\tau = 0.25$	$\tau = 0.50$	$\tau = 0.75$	$\tau = 0.90$	$\tau = 0.95$
BM	-1.079***	-1.024***	-1.105***	-1.094***	-1.165***	-1.255***	-1.188***
CG	-0.921***	-0.865***	-1.038***	-1.150***	-1.159***	-1.287***	-1.360***
CS	-0.948***	-0.923***	-0.982***	-1.090***	-1.156***	-1.332***	-1.344***
FIN	-0.972***	-1.011***	-1.068***	-1.173***	-1.197***	-1.357***	-1.324***
HC	-0.814***	-0.876***	-1.003***	-1.042***	-1.122***	-1.166***	-1.128***
IND	-0.947***	-0.915***	-0.954***	-1.029***	-1.210***	-1.197***	-1.163***
OG	-1.344***	-1.367***	-1.294***	-1.308***	-1.424***	-1.403***	-1.443***
TECH	-1.034***	-0.918***	-0.942***	-1.054***	-1.056***	-1.216***	-1.161***
TEL	-1.038***	-1.083***	-0.993***	-0.993***	-0.935***	-1.001***	-0.850***
UTL	-0.659***	-0.720***	-0.860***	-0.901***	-0.986***	-0.901***	-0.888***

Note. H_0: rho(t) minus 1 = 0; a significant negative value of the coefficient implies error correction. ***p<.01, **p<.05, *p<.10.

Table A5: Robustness: Long-Run Multipliers Excluding the COVID-19 Period

Sector	L_{Brent} $q.10$	$q.50$	$q.90$	L_{VIX} $q.10$	$q.50$	$q.90$
BM	0.057	0.078*	0.071	-0.112*	-0.089*	-0.096*
CG	-0.069	-0.040	-0.023	-0.103*	-0.083*	-0.091*
CS	-0.015	-0.014	-0.031	-0.117*	-0.105*	-0.116*
FIN	0.010	-0.033	-0.086*	-0.115*	-0.094*	-0.104*
HC	-0.133	-0.074*	-0.045	-0.105*	-0.092*	-0.086*
IND	-0.006	0.040	-0.036	-0.116*	-0.115*	-0.137*
OG	0.313	0.342*	0.340*	-0.068	-0.037	-0.064
TECH	0.026	-0.053	-0.022	-0.152*	-0.128*	-0.144*
TEL	0.036	0.006	0.013	-0.059*	-0.043*	-0.052*
UTL	0.048	0.007	-0.045	-0.110*	-0.055*	-0.070*

Note. * indicates that the 95% case-bootstrap confidence interval does not include zero (1,000 replications; non-COVID subsample).

REFERENCES

Abdullah, A. M., Saiti, B., & Masih, M. (2016). The impact of crude oil price on Islamic stock indices of South East Asian countries: Evidence from MGARCH-DCC and wavelet approaches. *Borsa Istanbul Review*, *16(4),* 219-232. http://dx.doi.org/10.1016/j.bir.2015.12.002

Ajmi, A. N., Hammoudeh, S., Nguyen, D. K., & Sarafrazi, S. (2014). How strong are the causal relationships between Islamic stock markets and conventional financial systems? Evidence from linear and nonlinear tests. *Journal of International Financial Markets, Institutions and Money, 28, 213-227*. http://dx.doi.org/10.1016/j.intfin.2013.11.004

Altınöz, B., & Umut, A. (2022). Döviz kuru ve petrol fiyatlarındaki dalgalanmaların hisse senedi getirileri ile ilişkisi: Borsa İstanbul sektör endeksleri için bir uygulama. *İstanbul İktisat Dergisi*, 72(1), 385-405. https://doi.org/10.26650/ISTJECON2021-1026350

Arfaoui, M., & Rejeb, A. B. (2020). Modeling the volatility of DJIM equity indices: A fundamental analysis using quantile regression. *International Journal of Islamic and Middle Eastern Finance and Management, 14(3),* 482-505. https://doi.org/10.1108/IMEFM-09-2019-0418

Arouri, M. E. H., & Nguyen, D. K. (2010). Oil prices, stock markets and portfolio investment: Evidence from sector analysis in Europe over the last decade. *Energy policy, 38(8),* 4528-4539. https://doi.org/10.1016/j.enpol.2010.04.007

Arouri, M. E. H., & Rault, C. (2012). Oil prices and stock markets in GCC countries: Empirical evidence from panel analysis*. International Journal of Finance & Economics, 17(3),* 242-253. https://doi.org/10.1002/ijfe.443

Badeeb, R. A., & Lean, H. H. (2018). Asymmetric impact of oil price on Islamic sectoral stocks. *Energy Economics, 71,* 128-139. https://doi.org/10.1016/j.eneco.2017.11.012

Basher, S. A., Haug, A. A., & Sadorsky, P. (2018). The impact of oil-market shocks on stock returns in major oil-exporting countries. *Journal of International Money and Finance, 86,* 264-280. https://doi.org/10.1016/j.jimonfin.2018.05.003

Campbell, J. Y., Lo, A. W., & MacKinlay, A. C. (1997). The econometrics of financial markets. *Princeton University Press.*

Chang, B. H., Sharif, A., Aman, A., Suki, N. M., Salman, A., & Khan, S. A. R. (2020). The asymmetric effects of oil price on sectoral Islamic stocks: New evidence from quantile-on-quantile regression approach. *Resources Policy, 65, 101571.* https://doi.org/10.1016/j.resourpol.2019.101571

Cho, J. S., Kim, T., & Shin, Y. (2015). Quantile cointegration in the autoregressive distributed-lag modeling framework. *Journal of Econometrics, 188(1),* 281–300. https://doi.org/10.1016/j.jeconom.2015.05.003

Cont, R. (2001). Empirical properties of asset returns: stylized facts and statistical issues. *Quantitative Finance, 1(2),* 223–236. https://doi.org/10.1080/713665670

Dai, Z., Zhou, H., Wen, F., & He, S. (2020). Efficient predictability of stock return volatility: The role of stock market implied volatility. *The North American Journal of Economics and Finance, 52,* 101174. https://doi.org/10.1016/j.najef.2020.101174

De Boef, S., & Keele, L. (2008). Taking time seriously. *American Journal of Political Science, 52(1),* 184–200. https://doi.org/10.1111/j.1540-5907.2007.00307.x

Dickey, D. A., & Fuller, W. A. (1979). Distribution of the estimators for autoregressive time series with a unit root. *Journal of the American Statistical Association, 74(366a),* 427–431. https://doi.org/10.1080/01621459.1979.10482531

Essayem, A., Görmüş, Ş., & Güven, M. (2022). Testing the effect of local macroeconomic indicators and global risk factors on the Turkish participation stock market: Evidence from quantile regression approach. *Trends in Business and Economics, 36(3),* 258-267. https://doi.org/10.5152/TBE.2022.1018360

Fernandes, M., Medeiros, M. C., & Scharth, M. (2014). Modeling and predicting the CBOE market volatility index. *Journal of Banking & Finance, 40,* 1-10. http://dx.doi.org/10.1016/j.jbankfin.2013.11.004

Ftiti, Z., & Hadhri, S. (2019). Can economic policy uncertainty, oil prices, and investor sentiment predict Islamic stock returns? A multi-scale perspective. *Pacific-Basin Finance Journal, 53,* 40-55. https://doi.org/10.1016/j.pacfin.2018.09.005

Ghorbel, A., Abdelhedi, M., & Boujelbene, Y. (2014). Assessing the impact of crude oil price and investor sentiment on Islamic indices: Subprime crisis. *Journal of African Business, 15(1),* 13-24. http://dx.doi.org/10.1080/15228916.2014.881222

Granger, C. W. J., & Newbold, P. (1974). Spurious regressions in econometrics. *Journal of Econometrics, 2(2),* 111–120. https://doi.org/10.1016/0304-4076(74)90034-7

Gürbüz, A. (2024). BIST 100 ve katılım 50 endekslerinin döviz kuru, CDS risk primi, CBOE oynaklık endeksi (VIX) ve petrol fiyatları arasındaki ilişkinin incelenmesi. *Kahramanmaraş Sütçü İmam Üniversitesi Sosyal Bilimler Dergisi, 21(2),* 769-782. https://doi.org/10.33437/ksusbd.1400787

Hammoudeh, S., Mensi, W., Reboredo, J. C., & Nguyen, D. K. (2014). Dynamic dependence of the global Islamic equity index with global conventional equity market indices and risk factors. *Pacific-Basin Finance Journal, 30,* 189-206. https://doi.org/10.1016/j.pacfin.2014.10.001

Hidayat, S. E., & Sakti, M. R. P. (2020). Oil prices and Islamic banks performance in the OIC countries: Evidence from the Dynamic GMM approaches. *Journal of Economic Cooperation & Development, 41(2).* 113-140. https://doi.org/10.30711/utead.938982

Hoe, K. K., Zaidi, N. S. B., Kadri, N., & Abdul Karim, B. bin. (2025). The impact of macroeconomic variables on Islamic stocks market performance in Malaysia. *Unimas Review of Accounting and Finance, 9(1),* 220-250. https://doi.org/10.33736/uraf.11625.2025

Hussin, M. Y. M., Muhammad, F., Hussin, M. A., & Razak, A. A. (2012). The relationship between oil price, exchange rate and Islamic stock market in Malaysia. *Research Journal of Finance and Accounting, 3(5),* 83-92. https://www.iiste.org/Journals/index.php/RJFA/article/view/2127#:~:text=The%20findings%20showed%20that%20Islamic,to%20the%20exchange%20rate%20variable.

Hussin, M. Y. M., Muhammad, F., Razak, A. A., Tha, G. P., & Marwan, N. (2013). The link between gold price, oil price and Islamic stock market: Experience from Malaysia. *Journal of Studies in Social Sciences, 4(2).* https://www.infinitypress.info/index.php/jsss/article/view/228

İskenderoğlu, Ö., & Akdağ, S. (2020). Comparison of the effect of VIX fear index on stock exchange indices of developed and developing countries: The G20 case. *The South East European Journal of Economics and Business, 15(1),* 105-121. https://doi.org/10.2478/jeb-2020-0009

Jouini, J. (2013). Return and volatility interaction between oil prices and stock markets in Saudi Arabia. *Journal of Policy Modeling, 35(6),* 1124-1144. http://dx.doi.org/10.1016/j.jpolmod.2013.08.003

Kazak, H. (2023). Korku endeksi etkisinde İslami ve konvansiyonel pay piyasa endeksleri arasındaki ilişki: Türkiye örneği. *Journal of Emerging Economies and Policy, 8(2)*, 196-208. https://izlik.org/JA64BR37KU

Koenker, R., & Xiao, Z. (2002). Inference on the quantile regression process. *Econometrica, 70(4),* 1583–1612. https://doi.org/10.1111/1468-0262.00342

Koenker, R., & Xiao, Z. (2006). Quantile autoregression. *Journal of the American Statistical Association, 101(475),* 980–990. https://doi.org/10.1198/016214506000000672

Lin, B., & Su, T. (2020). The linkages between oil market uncertainty and Islamic stock markets: Evidence from quantile-on-quantile approach. *Energy Economics, 88,* 104759. https://doi.org/10.1016/j.eneco.2020.104759

Majdoub, J., Mansour, W., & Jouini, J. (2016). Market integration between conventional and Islamic stock prices. *The North American Journal of Economics and Finance, 37,* 436-457. http://dx.doi.org/10.1016/j.najef.2016.03.004

Majid, M., & Yusof, R. M. (2009). Long-run relationship between Islamic stock returns and macroeconomic variables: An application of the autoregressive distributed lag model. *Humanomics, 25(2),* 127-141. http://dx.doi.org/10.1108/08288660910964193

Marashdeh, H., Ashraf, S., & Muhammad, N. (2020). Impact of macroeconomic variables on Islamic and conventional stock market returns: A panel data approach. *Global Business and Economics Review, 23(4),* 390-411. https://doi.org/10.1504/GBER.2020.110685

Nagayev, R., Disli, M., Inghelbrecht, K., & Ng, A. (2016). On the dynamic links between commodities and Islamic equity. *Energy Economics, 58,* 125-140. https://doi.org/10.1016/j.eneco.2016.06.011

Naifar, N. (2016). Do global risk factors and macroeconomic conditions affect global Islamic index dynamics? A quantile regression approach. *The Quarterly Review of Economics and Finance, 61,* 29-39. http://dx.doi.org/doi:10.1016/j.qref.2015.10.004

Nazlıoğlu, S., Hammoudeh, S., & Gupta, R. (2015). Volatility transmission between Islamic and conventional equity markets: Evidence from causality-in-variance test. *Applied Economics, 47(46),* 4996-5011. http://dx.doi.org/10.1080/00036846.2015.1039705

Özçelebi, O., & Pérez-Montiel, J. A. (2023). Examination of the impacts of the immediate interest rate of the United States and the VIX on the Dow Jones Islamic Market Index. *Bulletin of Economic Research, 75(4),* 1157-1180. https://doi.org/10.1111/boer.12399

Paltrinieri, A., Floreani, J., Kappen, J. A., Mitchell, M. C., & Chawla, K. (2019). Islamic, socially responsible, and conventional market comovements: Evidence from stock indices. *Thunderbird International Business Review, 61(5),* 719-733. https://doi.org/10.1002/tie.22027

Pazarcı, Ş., Kar, A., Kılıç, E., & Umut, A. (2022). Türkiye'de borsa, döviz kuru, CDS primi ve VIX endeksi ilişkisinin ampirik analizi. Afyon Kocatepe Üniversitesi *Sosyal Bilimler Dergisi, 24(3),* 1090-1103. https://doi.org/10.32709/akusosbil.1084718

Pesaran, M. H., Shin, Y., & Smith, R. J. (2001). Bounds testing approaches to the analysis of level relationships. *Journal of Applied Econometrics, 16(3),* 289–326. https://doi.org/10.1002/jae.616

Philips, A. Q. (2018). Have your cake and eat it too? Cointegration and dynamic inference from autoregressive distributed lag models. *American Journal of Political Science, 62(1),* 230–244. https://doi.org/10.1111/ajps.12318

Sarıtaş, H., & Nazlıoğlu, E. H. (2019). Korku endeksi, hisse senedi piyasası ve döviz kuru ilişkisi: Türkiye için ampirik bir analiz. *Ömer Halisdemir Üniversitesi İktisadi ve İdari Bilimler Fakültesi Dergisi, 12(4),* 542-551. https://doi.org/10.25287/ohuiibf.538592

Sarwar, G. (2012). Is VIX an investor fear gauge in BRIC equity markets?. *Journal of Multinational Financial Management, 22(3),* 55-65. https://doi.org/10.1016/j.mulfin.2012.01.003

Şarkaya İçellioğlu, C. (2018). Sermaye piyasalarında İslami endeksler ve geleneksel endeksler arasındaki ilişkiler: Katılım 30 endeksi ve BİST 100 endeksi. *Cumhuriyet Üniversitesi İktisadi ve İdari Bilimler Dergisi, 19(2),* 132-144. https://izlik.org/JA44ZA97UA

Schwarz, G. (1978). Estimating the dimension of a model. *The Annals of Statistics, 6(2),* 461–464. https://doi.org/10.1214/aos/1176344136

Shin, Y., Yu, B., & Greenwood-Nimmo, M. (2014). Modelling asymmetric cointegration and dynamic multipliers in a nonlinear ARDL framework. *In R. C. Sickles & W. C. Horrace (Eds.), Festschrift in Honor of Peter Schmidt* (pp. 281–314). Springer. https://doi.org/10.1007/978-1-4899-8008-3_9

Tursoy, T., & Faisal, F. (2018). The impact of gold and crude oil prices on stock market in Turkey: Empirical evidences from ARDL bounds test and combined cointegration. *Resources Policy, 55,* 49-54. http://dx.doi.org/10.1016/j.resourpol.2017.10.014

Ülev, S., & Özdemir, M. (2015). Katılım endeksi ile piyasa faiz oranları arasındaki nedensellik ilişkisi. *International Congress on Islamic Economics and Finance, 21-23 October 2015, Sakarya/TURKEY,* 47-54. https://makale.isam.org.tr/handle/123456789/316525

Whaley, R. E. (2009). Understanding the VIX. *Journal of Portfolio Management, 35(3),* 98-105. https://www.pm-research.com/content/iijpormgmt/35/3/98.abstract

Yahya, T. (2020). The effect of macro variables on the Jakarta Islamic index. *Asian Journal of Islamic Management, 2(1),* 36-45. https://doi.org/10.20885/ajim.vol2.iss1.art4

Yarovaya, L., Elsayed, A. H., & Hammoudeh, S. (2021). Determinants of spillovers between Islamic and conventional financial markets: Exploring the safe haven assets during the COVID-19 pandemic. *Finance Research Letters, 43,* 101979. https://doi.org/10.1016/j.frl.2021.101979

Zhu, H., Guo, Y., You, W., & Xu, Y. (2016). The heterogeneity dependence between crude oil price changes and industry stock market returns in China:

Evidence from a quantile regression approach. *Energy Economics, 55,* 30-41. https://doi.org/10.1016/j.eneco.2015.12.027

ARAŞTIRMACILARIN KATKI ORANI

Yazarların mevcut araştırmaya katkı oranları aşağıda belirtildiği gibidir:

Birinci yazarın çalışmaya katkı oranı %60, ikinci yazarın çalışmaya katkı oranı %40’tır.

ÇATIŞMA BEYANI

Bu araştırmada herhangi bir kişi veya kurumla finansal ya da kişisel bir ilişki bulunmamaktadır. Çalışma kapsamında herhangi bir çıkar çatışması mevcut değildir.

ARAŞTIRMANIN ETİK İZNİ

Bu çalışmada “Yükseköğretim Kurumları Bilimsel Araştırma ve Yayın Etiği Yönergesi” kapsamında öngörülen tüm ilke ve kurallara riayet edilmiştir. Söz konusu Yönerge’nin ikinci bölümünde “Bilimsel Araştırma ve Yayın Etiğine Aykırı Eylemler” başlığı altında tanımlanan eylemlerden hiçbiri gerçekleştirilmemiştir.

HAKEM DEĞERLENDİRMESİ

En az iki dış hakem / Çift Taraflı Körleme.

YAPAY ZEKA BEYANI

Bu çalışmanın hazırlanması sırasında yazar, metin düzeltmesi için ChatGPT-5.2 ve DeepL araçlarını kullanmıştır. Bu araçları kullandıktan sonra, yazar içeriği gerektiği gibi gözden geçirmiş ve düzenlemiş olup, yayının nihai içeriğinden tamamen sorumludur.

AUTHORS' PERCENTAGE-BASED CONTRIBUTIONS

The contributions of the authors to the study by percentages, are as follows:

The first author's contribution to the study is 60%, the second author's contribution to the study is 40%.

DECLARATION OF COMPETING INTERESTS

This study has not received any specific funding from public, commercial, or non-profit organizations. There are no competing interests to declare.

ETHICAL APPROVAL OF THE STUDY

This study was conducted in full compliance with the principles set forth in the “Instruction on Scientific Research and Publication Ethics for Higher Education Institutions.” None of the actions described under the second chapter of the Instruction, titled “Actions Against Scientific Research and Publication Ethics,” were carried out during any stage of this research.

PEER REVIEW

Reviewed by at least two external referees / Double-Blind Review.

DECLARATION OF GENERATIVE AI AND AI-ASSISTED TECHNOLOGIES IN THE WRITING PROCESS

During the preparation of this work, the author used ChatGPT-5.2 and DeepL for proofreading. After using these tools, the author reviewed and edited the content as needed and takes full responsibility for the final content of the publication.