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Stochastic and Dynamic Interaction between Islamic Volatility Index and Volatility Indices

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Abstract: Integration in financial markets offers opportunities for free flow of information and capital for international investments. However, this also poses challenges for maintaining effective international portfolio diversification due to heightened market correlations. This study aims to analyze the diversifying potential of Islamic financial assets and undertake a dynamic analysis of their correlation with volatility indices. In this context, the study explores the interaction between the Dow Jones Islamic Market Developed Markets Quality and Low Volatility Index (DJIDVI) and such volatility indices including the CBOE Volatility Index (VIX), CBOE Oil Volatility Index (OVX), CBOE Gold Volatility Index (GVZ), and Euro Currency Volatility Index (EVZ). The Dynamic Correlation-Multivariate Stochastic Volatility (DC-MSV) model is employed to assess of how volatility shocks in one asset influence the volatility of others. The findings reveal that DJIDVI demonstrates the highest volatility clustering among the considered series. Moreover, DJIDVI exhibits mutual interactions with VIX and EVZ, and shocks increasing DJIDVI volatility also contribute to heightened volatility in VIX and OVX. Notably, the correlation between DJIDVI and volatility indices is influenced by global events. The study emphasizes the enhanced predictability of DJIDVI and its negative correlation with other series establishing its potential as a diversifier. The findings of this study contribute to advancing the understanding of international portfolio diversification emphasizing the importance of incorporating Islamic financial assets.

Keywords: Portfolio Diversification, Islamic Market Volatility Index, Multivariate Stochastic Volatility, Time- Varying Correlation

Jel Codes: C11, C15, C32, G11, G15

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Introduction

Globalization has facilitated the information flow between financial markets promoting market integration and enabling international investments. International diversification in investors' portfolios offers opportunities for higher risk-adjusted returns and superior rates of return across different markets. However, the increased inter-market integration poses challenges for maintaining international portfolio diversity due to heightened market correlations. The reason is that the increase in integration between financial markets causes thecorrelation between markets to increase, and the high correlation between markets makes international portfolio diversification difficult. The efficacy of portfolio diversification relies on the weak or negative correlation between financial assets. Consequently, the growing dependency on financial markets underscores the importance of alternative assets for international portfolio diversification (Karim, Majid & Karim, 2009; Khan, 2011; Raza, Ali,Shahzad, Rehman & Salman, 2019; Kandemir & Gökgöz, 2022).

The emergence of Islamic financial markets has introduced a new dimension to portfolio diversification (Abbas, Sharif, Song, Ali, Khan & Amin, 2022). Empirical evidence from several studies (Ashraf & Mohammed,2014; Muteba Mwamba, Hammoudeh & Gupta, 2017; Ng, Chin & Chong, 2020; Bossman, 2021) highlights the significance of Islamic stocks in portfolio diversification. Islamic stocks differ from conventional stocks in terms of their risk-return profile, lower financial leverage, and restrictions on non-sharia-compliant investments (Raza et al., 2019). Moreover, Islamic stocks undergo rigorous reviews for trading activities, dividends, and financial ratios (Karim & Masih, 2021). Consequently, it is theoretically expected that the performance of Islamic and conventional indices will vary.

During times of crisis, Islamic markets have emerged as a distinct asset class (Abbas et al., 2022). Severalstudies (Al-Khazali, Lean & Samet, 2014; Jawadi, Jawadi & Louhichi, 2014; Mehdi & Mghiaeth, 2017; Shahzad,Arreola-Hernandez, Bekiros, Shahbaz & Kayani, 2018a; Hassan, Hoque, Wali & Gasbarro, 2020; Godil, Sarwat, Khan, Ashraf, Sharif & Ozturk, 2022) demonstrate the advantages of Islamic indices over traditional indices in crisis situations. The low volatility of Islamic indices serves as a key reason for their better performance in portfolio diversification, particularly during financial crises (Shahzad, Ferrer, Ballester & Umar, 2017). It is crucial to dynamically examine the interaction among alternative assets, as the diversification benefits of such assets may differ during crises compared to other periods.

This study aims to dynamically investigate the relationship between Islamic financial assets and other financial assets providing recommendations for investors and fund managers based on the findings. Specifically, we analyse the interaction between the Dow Jones Islamic Market Developed Markets Quality and Low Volatility Index and various volatility indices including the CBOE Volatility Index, CBOE Oil Volatility Index, CBOE Gold Volatility Index, and Euro Currency Volatility Index using the DC-MSV (Dynamic Correlation-Multivariate Stochastic Volatility) model. Numerous models, such as DCC-GARCH derivative models, DC-MSV, TVS, DY derivative models, and Dynamic ARDL, can illustrate the dynamic interaction between financial assets. However, correlation analysis provides more insightful findings regarding the benefits of asset diversification. Therefore, it is essential to employ a model that calculates the dynamic correlation between assets. Although DCC-GARCH derivative models are widely used to examine the dynamic correlation between Islamic assets and other assets (Raza et al., 2019; Hamma, Ghorbel & Jarboui, 2021; Hachicha, Ghorbel, Feki, Tahi & Dammak, 2022), they cannot determine the directional impact or common shocks affecting the assets. In contrast, the DC-MSV model not only reveals the dynamic correlation between asset pairs but also explains how volatility shocks in one asset affect the volatility of the other asset. Therefore, the application of the DC-MSV model to analyse the relationship between Islamic assets and other financial assets is expected to make a significant contribution to the existing literature. Moreover, this paper distinguishes itself by utilizing volatility indices as representations of financial assets. Volatility indices serve as measures of market volatility for the respective financial markets they represent. We gain advantages in assessing the reactions of these indices to shocks during periods of uncertainty and exploring potential volatility interactions among them using volatility indices. Notably, there is a lack of research utilizing the Dow Jones Islamic Market Developed Markets Quality and Low Volatility Index, as the available data for this index is limited to November 2, 2020. This paper fills this gap, thereby contributing to the literature. The subsequent sections of the paper comprise a comprehensive literature review, an outline of the methodology employed, presentation of the findings, and a conclusive discussion.

Literature Review

The literature on the relationship between Islamic financial assets and other financial assets has witnessedsignificant growth, particularly following the 2008 financial crisis. Researchers have extensively explored the potential of Islamic financial assets for portfolio diversification and have sought to ascertain whether these assets exhibit distinct characteristics compared to traditional assets during times of crisis. Notably, recent studies have increasingly employed dynamic models and volatility models to capture the evolving nature of this relationship. Table 1 provides a summary of selected studies conducted in a similar context to the present paper.

Table 1

Summary of Related Studies on the Relationship between Islamic Financial Assets and Other Financial Assets

Author(s)	Variables	Data	Method	Findings
Ghorbel, Abdelhedi & Boujelbene (2014)	Islamic stock indices of 11 countries, S&P 500, crude oil, and VIX	April 2007 - April 2012 (Daily)	BEKK-GARCH (Engle & Kroner, 1995)	Price shocks that occur in all variables are effective in their volatility in the next period and these effects are permanent. Oil price shocks and the volatility in the VIX are influential in the volatility of Islamic stocks. Global financial events have an effect on the interaction between the variables. The correlation between Islamic indices and crude oil and VIX varies over time.
Nazlıoğlu, Hammoudeh & Gupta (2015)	DJIM, S&P 500, SPY, SPAS, 50TR, Brent Oil, US Political Uncertainty Index, Federal Funds Rate (FFR), and VIX	4.1.1999 - 20.9.2013 (Daily)	GARCH (Bollerslev, 1986), Causality in Variance (Hafner & Herwatz, 2006)	DJIM has lower volatility than other variables. While the correlation between DJIM and oil is positive, it is negative with VIX. The volatility of variables is affected by global events. While there is a mutual volatility spillover between DJIM and brent oil, there is a one-way volatility spread from VIX to DJIM.
Naifar (2016)	DJIM, S&P 500, SPEU, SPAS50, VIX, Crude Oil, America, Asia and European CDS Premiums, and World-sentix economic sentiement indicator	January 2003 - October 2014 (Monthly)	Quantile Regression (Koenker & Bassett, 1978)	The interaction between DJIM and VIX is negative, while it is positive with crude oil. The interaction between DJIM and variables is not the same throughout the entire period. Especially after the 2008 financial crisis, DJIM's interaction with global and macroeconomic factors has increased.
Mensi, Hammoudeh, Al-Jarrah, Sensoy, & Kang (2017)	Gold, Crude Oil, Dow Jones Global index (W1DOW), World Sustainability Index (W1SG1), and DJIM Sectoral Islamic Indices	9.11.1998 - 5.3.2015 (Daily)	DECO-FIAPARCH (Engle & Kelly, 2012) DY (Diebold &Yılmaz, 2016)	The correlation of Islamic indices with oil and gold are generally positive. Islamic indices are generally net volatility emitters, although their net volatility nature against oil and gold varies by sector.

Author(s)	Variables	Data	Method	Findings
Shahzad, Mensi, Hammoudeh, Rehman & Al-Yahyaee (2018b)	Dow Jones Islamic Indices (World, Financials, USA, UK, Japan), and Crude Oil	1.1.1996 - 31.12.2015 (Daily)	CoVAR (Reboredo & Ugolini, 2015)	There is a weak-positive interaction between oil and Islamic indices. The strongest interaction is with DJIM. Islamic indices of developed markets are effective on oil prices. The relationship between oil and Islamic indices changed significantly during the 2008 financial crisis. In times of crisis, the diversifying aspect of Islamic indices may show instability.
Ftiti & Hadri (2019)	DJIM, DJIDEV, DJIEMG, DJIEU, DJIAP, DJIGCC, DJIUK, DJIJP, EPU, Oil, and FSI	January 2002 – February 2018 (Monthly)	Nonlinear Granger Causality (Dolado & Lütkepohl, 1996)	There is no causal relationship between EPU and Islamic indices. Oil is correlated with Islamic indices other than DJIUK. The financial stress index is associated with DJIM, DJIDEV, DJIEU, DJIUS and DJIDJP.
Mishra, Sharif, Khuntia, Meo & Rehman Khan (2019)	DJIM and Crude Oil	1.1.1996 - 13.04.2018	Quantile-on-quantile regression (Sim & Zhou, 2015)	While oil prices positively affect the Islamic index in the short term, they affect it negatively in the long term. There is an asymmetrical relationship between oil and the Islamic index. Different investment horizons should be considered in terms of portfolio diversification.
Raza et al. (2019)	Dow Jones Traditional and Islamic Indices (Global, Developed, Emerging, Europe and Asia Pacific), US Government Bonds, Oil, Gold, and VIX	1.1.1996 – 31.12.2015 (Daily)	DCC (Engle, 2002), ADCC (Cappiello et al., 2006), cDCC (Aielli et al., 2013), GO-GARCH (Van Der Weide, 2002), Rolling Window (Basher & Sadorsly, 2016)	Traditional and Islamic Stock Indices has a strong negative correlation with U.S bonds, a positive correlation with gold, a weak and positive correlation with oil, and a negative-strong correlation with the VIX. The correlations between assets have also exhibited variations during periods such as the European debt crisis and the 2011 U.S. debt ceiling crisis. Islamic indices offer better diversification compared to traditional indices.

Author(s)	Variables	Data	Method	Findings
Godil, Sarwat, Sharif & Jermsittiparsert (2020)	DJIM, DJCM, EPU, Oil, Gold, and Geopolitical Risk (GPR)	January 1997 - July 2019 (Monthly)	QARDL (Cho, Kim & Shin, 2015)	DJIM is negatively correlated with EPU, GPR, and oil and positively correlated with gold. Adding oil to Islamic stocks in a bull market and economic policy uncertainty in a bear market can be an effective strategy for diversifying an investment portfolio.
Lin & Su (2020)	Dow Jones Islamic indices (Canada, Japan, Turkey, Kuwait), and OVX	25.4.2013 – 15.4.2019 (Daily)	Quantile-on-quantile regression (Sim & Zhou, 2015)	OVX has asymmetric and negative relationship with Islamic indices. Increases in OVX have a greater impact on Islamic indices than decreases. Uncertainty in the oil market raises the OVX which is instrumental in the declines in Islamic indices. The decline in OVX, on the other hand, is less effective than the rise in Islamic indices.
Hamma et al. (2021)	Islamic and Conventional Emerging Markets Indices, Gold, Crude Oil, VISTOXX, VIX, CDSEU (Credit Default Swap European index), and DJCOM	27.12.2007 - 30.9.2016 (Daily)	DCC (Engle, 2002) and ADCC (Cappiello et al.., 2006)	While the Islamic emerging markets index has a positive correlation with gold and oil, it has a negative correlation with VIXSTOXX and VIX. Past price shocks in all variables affect future prices and this effect is permanent. VISTOXX is a good diversifier for Islamic and traditional assets.

Author(s)	**Variables**	**Data**	**Method**	**Findings**
Kaarim & Masih (2021)	DJIM, DJIEM, DJIEU, DJIAP, DJIUS, DJIUK, OVX, and Crude Oil	17.5.2007 - 4.5.2017 (Weekly)	Wavelet Time-Frequency Analysis (Rua & Nunes, 2009)	The correlation between Islamic stocks and crude oil is positive, while it is negative with OVX. OVX negatively affects Islamic Stock returns. There is a mutual volatility transmission between Islamic stocks and crude oil.
Bahloul & Khemakhem (2021)	S&P GSCI, Total Commodities, Energy, Precious Metals, Industrial Metals, Livestock, Agriculture, and MSCI Islamic World and Emerging Markets	30.8.2007 - 30.6.2020 (Daily)	DY (Diebold & Yılmaz, 2014)	The interconnectedness between commodities and Islamic indices changes over time and is influenced by global events. Islamic indices are net receivers of volatility versus commodities. There is a positive correlation between Islamic indices and commodities.
Suleman, McIver & Kang (2021)	DJIM, Crude Oil, Gold, and Silver	4.01.2010 - 30.11.2020 (Daily)	DY (Diebold & Yılmaz, 2012), SAM (Barunik et al., 2017)	There is a mutual volatility spillover between DJIM and commodities. DJIM is a net spreader of volatility against commodities. Volatility spillover changes over time. Negative volatility spillover between DJIM and commodities is more effective than the positive one. Therefore, bad news in the market is more effective on volatility and spillover than good news.
Abbass et al. (2022)	DJCM, DJIM, Geopolitical Oil Price Risk Index (GPOPR), Global Gold Price, Global Interest Rate (GIR), and Global Exchange Rate	January 2000 - November 2020 (Monthly)	QARDL (Cho et al., 2015)	DJIM's relationship with the global exchange rate is stronger than its relationship with the global gold price and geopolitical oil price risk index. DJIM's interaction with the variables considered is generally positive.

Author(s)	Variables	Data	Method	Findings
Adekoya, Akinseye, Antonakakis, Chatziantoniou, Gabauer & Oliyide (2022)	Sectoral Islamic Indices, and Brent Oil	25.04.2013 - 2.09.20221 (Daily)	Asymmetric TVP-VAR (Antonakakis, Cunado, Filis, Gabauer & de Gracia, 2020)	Connectedness based on negative returns is higher than connectedness based on positive returns. Negative connectedness tends to increase in global events with economic impact. Brent oil is a net receiver of volatility.
Godil et al. (2022)	Dow Jones Islamic and Conventional Stock Index, Gold, Silver, Platinum, Crude Oil, Gasoline, and Natural Gas	June 2002 – September 2019 (Monthly)	Dynamic ARDL (Jordan & Philips, 2018)	While gold affects the Islamic index negatively, the effect of oil on the Islamic index is meaningless. In terms of diversifying Islamic stocks, gold is a better diversifier than oil.
Hachicha et al. (2022)	Dow Jones Islamic and Traditional Stock Indices, VSTOXX, Oil, Gold, and Sectoral CDS Indices (Raw Materials, Industry, Health Care, and Telecommunications)	January 2000 - April 2019 (Daily)	DCC (Engle, 2002), ADCC (Cappiello, Engle & Sheppard, 2006), GO-GARCH (Van Der Weide, 2002)	The correlation between the variables differs according to the models. The relationship of the Islamic index with VSTOXX and oil is generally negative, while it is positive with gold.
Jawadi, Cheffou & Jawadi (2023)	DJIDEV, DJIEMG, VIX, Crude Oil, and Covid-19 News (as Dummy)	January 2000 - July 2022 (Daily)	ARDL (Pesaran, Shin & Smith, 2001)	The volatility of Islamic indices is affected by global events. There is a positive interaction between Islamic indices and crude oil, and a negative interaction with VIX. Crude oil affects DJIDEV more than DJIEMG.
Kang, Arreola Hernandez, Rehman, Shahzad & Yoon (2023)	S&P Dow Jones US Sector Indices, MSCI US Islamic, Crude Oil, Gold, VIX, and OVX	31.05.2007 - 4.11.2022 (Daily)	DY (Diebold & Yılmaz, 2014)	The Islamic stock index has reciprocal volatility spillover with industry stocks, gold, oil, OVX, and VIX. Islamic stocks are a net spreader of volatility across variables.

Several papers in Table 1, including Mensi et al. (2017), Shahzad et al. (2018b) (Islamic Index for Developed Markets), Suleman et al. (2021), Adekoya et al. (2022), and Kang et al. (2023) suggest that Islamic indices act as net volatility spreaders against commodities and the VIX. However, other studies, such as Ghorbel et al. (2014), Nazlıoğlu et al. (2015), Bahloul & Khemakhem (2021), Kaarim & Masih (2021), Godil et al. (2022),and Jawadi et al. (2023) (Developed Markets Islamic Index), indicate that Islamic indices are net volatility receivers.Furthermore, it has been observed that some papers, such as Ftiti and Hadri (2019), demonstrate a mutual volatilityspillover between Islamic indices and oil, while others, like Raza et al. (2019), show a weak correlation. The positive relationship between Islamic indices and commodities (Nazlıoğlu et al., 2015; Mensi et al., 2017; Shahzadet al., 2018b; Raza et al., 2019; Godil et al., 2020; Hatciacha et al., 2022), as well as the positive relationship with exchange rates (Abbas et al., 2022), is supported by multiple papers. Conversely, the negative relationship with VIX and OVX (Naifar, 2016; Raza et al., 2019; Hamma et al., 2021; Jawadi et al., 2023) is also evidenced. Nevertheless, some studies (Mishra et al., 2019; Godil et al., 2020; Hatciacha et al., 2022) have identified a negative relationship between Islamic indices and oil. It is apparent that there is no consensus regarding the relationship between Islamic indices and other financial assets examined. Therefore, conducting this paper is deemed important in providing recommendations on contentious issues.

Several papers (Nazlıoğlu et al., 2015; Naifar, 2016; Shahzad et al., 2018b; Raza et al., 2019; Bahloul &Khemakhem, 2021; Jawadi et al., 2023) indicate that the interaction between Islamic indices and commodities, exchange rates, and volatility indices is influenced by global events. Additionally, it is observed that variables discussed in some papers (Ghorbel et al., 2014; Hamma et al., 2021) are affected by past price shocks. Thus, conducting a dynamic examination of the relationship between Islamic financial assets and other financial assets would contribute to assessing the impact of crises and past shocks.

Most of the reviewed papers (Ghorbel et al., 2014; Nazlıoğlu et al., 2015; Mensi et al., 2017; Raza et al.,2019; Hamma et al., 2020; Bahloul & Khemakhem, 2021; Suleman et al., 2021; Adekoya et al., 2022; Hachicha et al., 2022; Kang et al., 2023) utilize GARCH and DY (Diebold and Yılmaz)-based volatility models. To the best of our knowledge, there has been no study utilizing the DC-MSV model. The use of the DC-MSV model in this paper would not only reveal the dynamic correlation between series but also provide advantages in terms of detecting the impact of shocks in the volatility of one series on the volatility of other series. Therefore, the utilization of the DC-MSV model in this paper can be considered a contribution to the existing literature. Additionally, the examined papers did not consider the Islamic volatility index as a representation of Islamic assets.

Examining the interaction between the Islamic volatility index and other volatility indices can be seen as anotherdistinguishing aspect of this paper compared to previous literature.

Methodology and Data

Methodology

The concept of volatility refers to the deviations in the return and price of a financial asset over a specific period. Financial assets with high volatility often experience frequent price changes. Predicting the future prices of highly volatile financial assets is more challenging compared to assets with low volatility (Gökgöz & Kandemir, 2023). Consequently, accurate predictions of future prices and volatility play a crucial role in investment decision-making. This necessity has led to the widespread use and continuous advancement of volatility models.

Robert Engle, a Nobel Prize-winning author, has discovered that the variances of error terms exhibit temporal variation when analyzing UK inflation data. He has also observed this phenomenon in other financial assets, such as interest rates, option prices, and exchange rates. In 1982, Engle introduced the ARCH (Autoregressive Conditional Heteroskedasticity) model which considers the varying variance when calculating volatility (Kula & Baykut, 2017). Since its inception, the ARCH model has been extensively employed in volatilityprediction. However, subsequent developments in finance and the identified limitations of ARCH-type models paved the way for the development of alternative volatility models.

Stochastic volatility models were first introduced by Taylor (1986) as an alternative to ARCH-type models. In stochastic volatility models, volatility is treated as an unobserved and latent variable, in contrast to ARCH-type models where volatility is modeled as an observable variable. Stochastic volatility models offer the ability to predict the volatility connectedness between multiple financial assets. Moreover, they provide more robust findings in cases of excessive kurtosis compared to ARCH-type models (Broto & Luiz, 2004; Das, Ghoshal & Basu, 2009; Göktaş, 2019).

The dynamically correlated multivariate stochastic volatility (DC-MSV) model has been developed by Yu and Meyer (2006) not only analyzes the volatility clustering in assets univariately, but also reveals the dynamic correlation and the volatility interaction between assets[1]:

$$r_t = A + Br_{t-1} + Z_t \qquad (1)$$

Equation 1 expresses the bivariate VAR (1) model.

$$Z_{X,t} = \exp(G_{X,t}/2)\varepsilon_{X,t} \qquad (2)$$

$$Z_{Y,t} = \exp(G_{Y,t}/2)\varepsilon_{Y,t} \qquad (3)$$

In equations 2 and 3, "$G_{X,t}$" and "$G_{Y,t}$" represent the volatility of variables X and Y, respectively.

$$\rho_t = \mathrm{cov}(\varepsilon_{X,t}, \varepsilon_{Y,t}) = (\exp(q_t)-1) / (\exp(q_t)+1) \qquad (4)$$

The symbol, "ρ_t" represents the time-varying dynamic correlation between the variables.

$$q_{t+1} = \psi_0 + \psi_1(q_t - \psi_0) + \sigma_q v_t \qquad (5)$$

In equation 5, the symbol "ψ" represents the relationship between the variables, while the symbol "σ" represents the standard deviation of volatility. The higher the value of "σ," the greater the level of uncertainty in the volatility of the asset2.

$$G_{X,t+1} = \mu_X + \phi_X(G_{X,t} - \mu_X) + \phi_{XY}(G_{Y,t} - \mu_Y) + \eta_{X,t} \qquad (6)$$

$$G_{B,t+1} = \mu_Y + \phi_Y(G_{Y,t} - \mu_Y) + \phi_{YX}(G_{X,t} - \mu_X) + \eta_{Y,t} \qquad (7)$$

In equations 6 and 7 "μ_X" and "μ_Y" refer to the fixed parameters of the volatility model created for X and Y. "ϕ_X" and "ϕ_Y" are parameters that measure the persistence of the volatility of X and Y. The closer these parameters are to 1, the higher the persistence of volatility. There is an inverse relationship between the parameters "ϕ_X" and "ϕ_Y" and the standard deviation of the volatility "σ". When the volatility persistence is high (ϕ is close to 1), the volatility of the variable is more predictable (σ is closer to 0). "ϕ_{XY}" indicates the effect of the change in the volatility of Y on the volatility of X. Similarly, "ϕ_{YX}" represents the effect of the change in the volatility of X on the volatility of Y.

Data

The daily data for the study was collected for the period from November 2, 2020, to April 28, 2023. The Dow Jones Islamic Market Developed Markets Quality and Low Volatility Index, CBOE Volatility Index (VIX), CBOE Oil Volatility Index (OVX), CBOE Gold Volatility Index (GVZ), and Euro Currency Volatility Index were obtained from the website “investing.com.” On the other hand, the Islamic Volatility Index data was obtained from the “Bloomberg” database. Definitions of the series are provided in Table 2.

Table 2

Series Definitions

Series	Definitions	Usage of the Series	Number of Observation
DJIDVI	Dow Jones Islamic Market Developed Markets Quality and Low Volatility Index	$100 \text{ X } \ln\left(\frac{DJIDVI_t}{DJIDVI_{t-1}}\right)$	625
VIX	CBOE Volatility index	$100 \text{ X } \ln\left(\frac{VIX_t}{VIX_{t-1}}\right)$	625
OVX	CBOE Oil Volatility Index	$100 \text{ X } \ln\left(\frac{OVX_t}{OVX_{t-1}}\right)$	625
GVZ	CBOE Gold Volatility Index	$100 \text{ X } \ln\left(\frac{GVZ_t}{GVZ_{t-1}}\right)$	625
EVZ	Euro Currency Volatility Index	$100 \text{ X } \ln\left(\frac{EVZ_t}{EVZ_{t-1}}\right)$	625

Source: Created by authors.

The study employed the DC-MSV (Dynamically Correlated Multivariate Stochastic Volatility) model toassess the persistence of volatility, volatility spillover, and dynamic correlation within the series. To begin with, the original series were transformed into logarithmic return series, and their stationarity was tested. Subsequently, as indicated in Table 3, the stationary series (in pairs) were subjected to analysis using the DC-MSV model. The estimation of the DC-MSV model was conducted using the “Markov Chain Monte Carlo” (MCMC) method, and the analysis involved 100,000 samples using the “Winbugs” package program[3].

Findings

Figure 1 illustrates the time path graphs of the daily logarithmic return series for the analysed variables.

The figure shows the fluctuations in the daily returns of the series over the observation period.

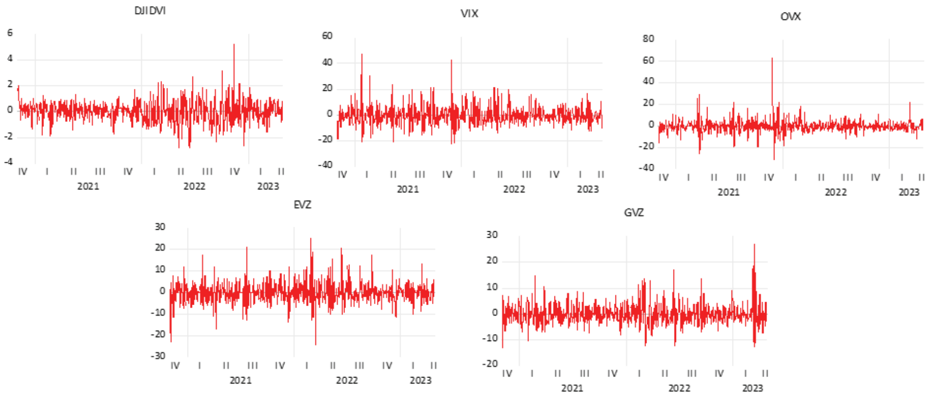

Figure 1: Time Series Graphs of Daily Return Series

The time path graphs of the daily return series in Figure 1 depict the volatility of each series over the entire observation period. It is evident that all series exhibit significant volatility, and the volatility levels vary throughout the period. The graphs illustrate that the dynamics influencing the volatility of the series may differ, as indicated by the fluctuations and jumps in volatility observed in different periods. Notably, certain periods, such as the end of 2021, exhibit common patterns of increased volatility across multiple series.

Table 3

Descriptive Statistics

	DJIDVI	VIX	OVX	GVZ	EVZ
Mean	0.022156	-0.13691	-0.1004	-0.0585	-0.01427
Maximum	5.275498	48.02141	63.60733	27.27553	25.21622
Minimum	-2.8054	-22.0352	-31.1237	-12.9374	-24.3256
Std. Dev.	0.856769	7.567381	6.402998	4.243944	5.130378
Skewness	0.269628	1.059923	1.757789	0.939798	0.352147
Kurtosis	5.62427	7.663064	21.02972	7.15853	6.560194
Jarque-Bera	186.9164*	683.279*	8787.241*	542.3503*	342.9951*
ADF	-20.7490*	-27.1085*	-20.6514*	-26.8626*	-21.4305*

"*"indicates significance at 1%.

Table 3 presents the descriptive statistics for the series. The statistics indicate that none of the series exhibit a normal distribution, and they are found to be stationary at level (I_0). Among the series, DJIDVI (Dow Jones Islamic Market Developed Markets Quality and Low Volatility Index) has the lowest standard deviation suggesting that it has relatively lower volatility compared to the other series.

Table 4 presents the averaged values of “μ” (constant term), “ϕ” (volatility persistence), and “σ” (volatilitypredictability) for the series analysed using the DC-MSV model. Since the model was performed in pairs, these values were calculated multiple times. By averaging these values and presenting them in a single table, it allows for a comprehensive evaluation of the volatility persistence across the series.

Table 4

Averaged Values of Volatility Persistence and Predictability of Series

	Average	Standard Deviation	MC Error	Confidence Interval (%95)	
μ_{DIJDVI}	-0.45763*	0.235725	0.019735	-0.8745	0.073465
μ_{VIX}	3.732*	0.136425	0.007374	3.472	4.00875
μ_{OVX}	3.1*	0.1825	0.009333	2.747	3.476
μ_{GVZ}	2.64025*	0.150575	0.007797	2.36425	2.9605
μ_{EVZ}	2.8975*	0.1333	0.007906	2.63875	3.16375
ϕ_{DJIDVI}	0.984525*	0.00889	0.00062	0.96325	0.997575
ϕ_{VIX}	0.877675*	0.046083	0.004277	0.7768	0.9513
ϕ_{OVX}	0.850125*	0.052335	0.004864	0.72835	0.93385
ϕ_{GVZ}	0.895475*	0.04909	0.004935	0.775175	0.965025
ϕ_{EVZ}	0.72355*	0.083063	0.007956	0.532475	0.8583
$\sigma\eta_{DJIDVI}$	0.118825*	0.021973	0.002357	0.085768	0.175575
$\sigma\eta_{VIX}$	0.347925*	0.06667	0.007081	0.228875	0.481125
$\sigma\eta_{OVX}$	0.4829*	0.08558	0.008894	0.329425	0.673925
$\sigma\eta_{GVZ}$	0.276825*	0.068048	0.007452	0.170475	0.432125
$\sigma\eta_{EVZ}$	0.56255*	0.09759	0.010165	0.3872	0.7666

“*”indicates significance at 5%.

It is observed in Table 4 that all parameter estimates have low Markov Chain (MC) errors and are significant at the 5% level. The series with the highest volatility persistence, as indicated by the parameter ϕ, is DJIDVI (ϕDJIDVI = 0.984525), while the series with the lowest volatility persistence is EVZ (ϕEVZ = 0.72355). Therefore, DJIDVI exhibits the highest volatility persistence among the series, while EVZ has the lowest.

Additionally, it is expected that series with higher volatility clustering will have more predictable volatility. This expectation is supported by the fact that DJIDVI has the lowest σ value (σDJIDVI = 0.118825), indicating higher predictability of volatility. On the other hand, EVZ has the highest σ value (σEVZ = 0.56255), suggesting lower predictability of volatility.

Table 5

Volatility Interaction Between Series

	Average	Standard Deviation	MC Error	Confidence Interval (%95)	
$\phi_{DJIDVI-VIX}$	0.02208*	0.01241	0.001092	-0.00133	0.04716
$\phi_{VIX-DJDVI}$	-0.05274*	0.02572	0.001962	-0.1123	-0.0099
$\phi_{DJDVI-OVX}$	0.002789	0.008709	6.62E-04	-0.01423	0.01992
$\phi_{OVX-DJDVI}$	-0.1343*	0.058	0.004206	-0.2594	-0.03253
$\phi_{DJIDVI-GVZ}$	-0.00622	0.01369	0.00105	-0.03456	0.02082
$\phi_{GVZ-DJDVI}$	0.02288*	0.02858	0.002206	-0.0246	0.09032
$\phi_{DJIDVI-EVZ}$	-0.00119*	0.0145	0.001298	-0.02989	0.02571
$\phi_{EVZ-DJIDVI}$	0.01483*	0.05285	0.003798	-0.08903	0.1202
$\phi_{VIX-OVX}$	0.05831*	0.04007	0.003432	-0.0094	0.146
$\phi_{OVX-VIX}$	0.05411*	0.05356	0.004394	-0.04005	0.169
$\phi_{VIX-GVZ}$	-0.0502*	0.03325	0.002251	-0.115	0.01715
$\phi_{GVZ-VIX}$	0.07925*	0.03253	0.003113	0.02554	0.1496
$\phi_{VIX-EVZ}$	-0.00842*	0.04499	0.004028	-0.09277	0.0858
$\phi_{EVZ-VIX}$	0.1509*	0.07028	0.006145	0.03175	0.3093
$\phi_{OVX-GVZ}$	0.002307*	0.03979	0.002786	-0.07279	0.08448
$\phi_{GVZ-OVX}$	0.01762*	0.01807	0.001274	-0.01979	0.05291
$\phi_{OVX-EVZ}$	-0.00756*	0.05463	0.004542	-0.1158	0.1075
$\phi_{EVZ-OVX}$	0.08345*	0.05261	0.004254	-0.0068	0.2055
$\phi_{GVZ-EVZ}$	0.06556*	0.06991	0.007236	-0.03479	0.2479
$\phi_{EVZ-GVZ}$	0.1305*	0.08705	0.008448	-0.01389	0.3501

"*"indicates significance at 5%.

Table 5 shows the volatility interaction between the series. It is observed that there is a mutual volatility interaction in all series except for DJIDVI. Specifically, DJIDVI exhibits a mutual volatility interaction with VIXand EVZ, while the volatility interaction with OVX and GVZ is unidirectional[4].

For DJIDVI and VIX, the volatility interaction is asymmetrical. A 1% increase in VIX volatility leads toa 0.022% increase in DJIDVI volatility, while a 1% increase in DJIDVI volatility results in a 0.053% decrease in VIX volatility. This indicates that positive shocks in VIX volatility positively affect DJIDVI volatility, while positive shocks in DJIDVI volatility negatively affect VIX volatility.

On the other hand, for DJIDVI and EVZ, the volatility interaction is also asymmetrical. A 1% increase inEVZ volatility leads to a 0.001% decrease in DJIDVI volatility, whereas a 1% increase in DJIDVI volatility resultsin a 0.015% increase in EVZ volatility. This indicates that positive shocks in EVZ volatility decrease DJIDVI volatility, while positive shocks in DJIDVI volatility increase EVZ volatility.

The volatility interaction between DJIDVI and OVX, as well as DJIDVI and GVZ, is unidirectional fromDJIDVI to OVX and GVZ. DJIDVI acts as a volatility emitter against OVX and GVZ. A 1% increase in DJIDVIvolatility leads to a 0.134% decrease in OVX volatility, and a 1% increase in DJIDVI volatility results in a 0.023%increase in GVZ volatility.

There is a mutually positive volatility interaction between VIX and OVX. A 1% increase in OVX volatilityleads to a 0.58% increase in VIX volatility, while a 1% increase in VIX volatility results in a 0.054% increase in OVX volatility.

The volatility interaction between VIX and GVZ, as well as VIX and EVZ, is asymmetrical. A1% increase in GVZ and EVZ volatility leads to a decrease in VIX volatility. Specifically, a 1% increase in GVZ volatility decreases VIX volatility by 0.05%, and a 1% increase in EVZ volatility decreases VIX volatility by 0.01%.

There is a mutual volatility interaction between OVX and GVZ, as well as OVX and EVZ. A 1% increasein OVX volatility results in a 0.018% increase in GVZ volatility and a 0.083% increase in EVZ volatility. Similarly, a 1% increase in GVZ volatility leads to a 0.002% increase in OVX volatility, while a 1% increase in EVZ volatilityresults in a 0.08% decrease in OVX volatility.

The findings indicate a mutually positive volatility interaction between GVZ and EVZ. A 1% increase inEVZ volatility leads to a 0.066% increase in GVZ volatility, and a 1% increase in GVZ volatility results in a 0.131% increase in EVZ volatility.

The non-reciprocity of DJIDVI's volatility interaction with all other series suggests that DJIDVI may have a unique behaviour compared to the other series. This characteristic makes DJIDVI potentially valuable as a diversifier for the portfolio. However, it is important to note that the diversification benefits of an asset for anotherasset are not solely determined by the absence of a reciprocal relationship. The effectiveness of diversification depends on the nature of the relationship between the assets. Ideally, assets that are unrelated or negatively correlated tend to provide better diversification benefits. A weak positive relationship in the same direction between two assets can still offer some diversification benefits, but the extent of diversification may be limited. On the other hand, if two assets have a strong negative relationship, they may exhibit more than just diversification benefits, potentially providing additional risk mitigation advantages (Kandemir and Gökgöz, 2022). In this context, the mean of the dynamic correlations between the series calculated using the D C-MSV model is presented in Table 6.

Table 6

The Mean of Dynamic Correlation Between Series

Series	VIX	OVX	GVZ	IEVZ
DJIDVI	-686075*	-0333296*	-0.366499*	-0427087*
VIX		0.374160*	0.457231*	0.445268*
OVX			0.339595*	0.29638*
GVZ				0.453811*

"*"indicates significance at 5%.

Table 6 reveals that DJIDVI has a negative mean correlation with all other series. The strongest correlation is observed between DJIDVI and VIX with a coefficient of -0.686. The VIX index reflects market volatility in the S&P 500 tending to increase during periods of market uncertainty and decrease during periods of reduced uncertainty. In contrast, DJIDVI represents low volatility in the DJ Developed Countries Islamic Index. Therefore, as DJIDVI increases, the Islamic indices of developed countries decrease. The strong negative correlation between DJIDVI and VIX suggests that DJIDVI serves as a hedging tool during times of heightened market uncertainty.

Similar to the correlation between DJIDVI and VIX, DJIDVI also has negative correlations with OVX, GVZ, and EVZ. These negative correlations indicate that DJIDVI diverges from the overall market trends and can act as a good diversifier for these markets. On the other hand, the positive mean correlations among the other series suggest that DJIDVI may be a better diversifier compared to the other series. However, it is important to examine the dynamic nature of these relationships over time to understand the effectiveness of DJIDVI as a diversifier may vary. Figure 2 illustrates the time-varying correlation between the series.

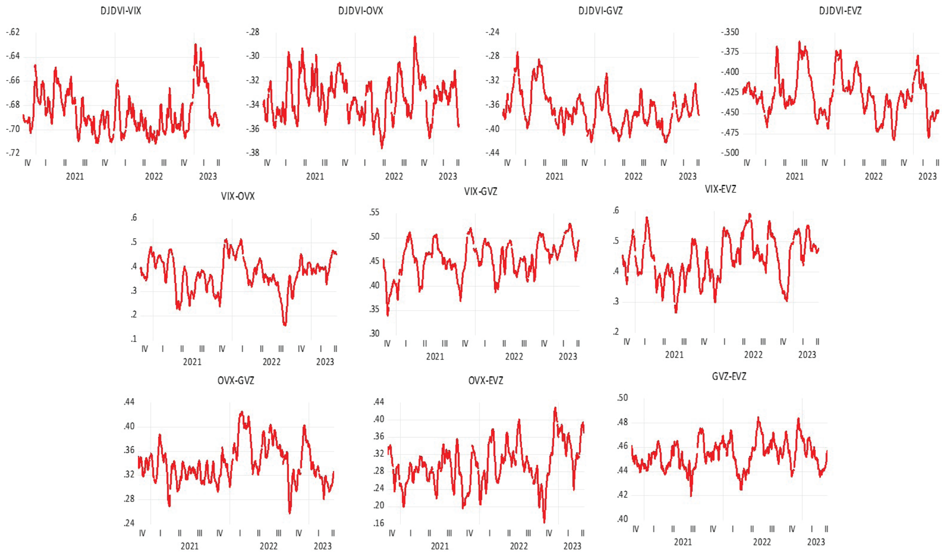

Figure 2: Dynamic Correlation Between Series

The results, show that correlation between DJIDVI and other series remains consistently negative throughout the entire period. However, the varying correlation coefficients indicate that the strength of this negative correlation may fluctuate over time, particularly during significant global events such as the Covid- 19 pandemic (January 2020-November 2021 and new variants), oil price shocks (April 2020), geopolitical conflicts (beginning of the Russia-Ukraine War, February 2022 and sanctions against Russia, March 2022), and financial disruptions (bankrupt of the Silicon Valley Bank, March 2023). These observations suggest that global events have an impact on the interaction between DJIDVI and other volatility series.

Additionally, it is worth noting that the correlations among the other series, excluding DJIDVI, exhibit positive coefficients that change throughout the entire period. This indicates a general similarity in their volatilitydynamics. In contrast, DJIDVI stands out as the best diversifier among the series showcasing its unique characteristics compared to the other series.

Conclusion

The paper investigates the volatility spillover and predictability of the Developed Markets Islamic Volatility Index (DJIDVI) in relation to the S&P 500, crude oil, gold, and EURO exchange rate volatility indices. The study period covered from November 2, 2020, to April 28, 2023, and utilized the DC-MSV model to analyse the volatility indices. The unique contribution of the paper lies in its use of different variables and methods to test topics that lack consensus in the literature highlighting its significance.

The paper is first calculated the volatility series and conducted stationarity analyses. It is found that all series have been influenced by past price shocks with a permanent effect. Among the series, DJIDVI has exhibitedthe highest volatility clustering indicating that its future values is more predictable compared to other series. While most series have exhibited mutual volatility interactions, DJIDVI has showed mutual interactions with VIX and EVZ setting it apart from other markets. The paper is found that shocks increasing DJIDVI volatility has also increased the volatility of VIX and OVX, while reducing the volatility of GVZ and EVZ. Conversely, shocks increasing the volatility of VIX has reduced the volatility of DJIDVI, and shocks increasing the volatility of EVZincreased the volatility of DJIDVI. The volatility interaction between DJIDVI, VIX, and EVZ is asymmetric. Notably, global events has influenced the correlation between DJIDVI and volatility indices.

The findings of the paper align with several previous studies indicating a consistent pattern. Ghorbel et al. (2014) and Hamma et al. (2021) also found that DJIDVI is influenced by past price shocks with a permanent effect that support the paper's findings in this regard. The interaction between DJIDVI and volatility indices is consistent with the findings of Abbas et al. (2022). The unidirectional volatility interaction from DJIDVI to OVX and GVZ, as well as the positive correlation between DJIDVI and OVX and GVZ, align with the findings of Mensi et al. (2017), Shahzad et al. (2018), and Bahloul & Khemakhem (2021). However, our findings diverge from the results of Raza et al. (2019), Godil et al. (2020), and Hatciacha et al. (2022) who have determined a negative relationship between Islamic indices and commodities. On the other hand, our finding that the relationship between DJIDVI and volatility indices is influenced by global events is similar with the findings of Nazlıoğlu et al. (2015), Naifar (2016), Shahzad et al. (2018), and Jawadi et al. (2023). This suggests that global events play a significant role in shaping the dynamics of connectedness between DJIDVI and volatility indices.

The paper's results highlight DJIDVI's higher volatility clustering, predictability, and negative correlation with other series suggesting that it as a good diversifier. DJIDVI's lower volatility and divergence from other seriesmake it a less risky option. Therefore, adding assets from developed markets Islamic indices to portfolios can provide international diversification benefits and effective risk management strategies.

It should be noted that Islamic indices may vary depending on the market's level of development and internal dynamics of the country. Emerging markets, for example, may be more susceptible to global shocks potentially impacting diversification aspects during times of global uncertainty. Hence, the findings of the paper may not be universally applicable to all Islamic indices. Future research can explore the interconnectedness between volatility indices and other alternative financial assets providing further insights for investors and financial decision-makers.

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Footnotes

1 To examine multivariate stochastic volatility models more comprehensively. https://doi.org/10.1080/07474930600713564

2 “ψ” was determined in the paper, but “ψ_0” and “ψ_1” were not reported.

3 For the estimation of the DC-MSV model, the initial values were determined using the package program, and a total of 90,000 samples were considered. The first 10,000 samples were excluded as burn-in samples.

4 The second variable is the volatility emitter, and the first variable is the volatility receiver. For example, in “ϕDJIDVI–VIX”, VIX is the volatility emitter, and DJIDVI is the volatility receiver.