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Full Length Article

Emerging market portfolios and Islamic financial markets: Diversification benefits and safe havens

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Abstract

We examine the relationship between Islamic and conventional stock market returns to see if Islamic financial markets provide portfolio diversification benefits and safe havens during turbulent times. Using daily data from January 1996 through September 2020 we consider conventional emerging stock market returns and some Islamic stock market returns and examine their interactions using causality-in-variance, dynamic conditional correlations, optimal hedge ratios, and causality-in-risk tests. Causality-in-variance test results show causality between Islamic stock returns and all emerging stock returns which indicates Islamic markets provide limited safe havens. Results from both time-varying conditional correlations and the hedge ratios show that there are positive and significant correlations between emerging stock markets and Dow Jones Islamic Market Index, which implies limited portfolio diversification benefits afforded by Islamic stock markets.

JEL classification: G2; G23; G15; C12

Keywords: Portfolio allocation; Islamic stocks; Risk spillovers

1. Introduction

At the beginning of the 1990s, most emerging economies started to adopt financial liberalization policies removing many of the barriers to international financial flows, which made them portfolio investment destinations for international investors (Bilson et al., 2001). Bekaert and Harvey (1997) emphasized four basic characteristics of investments in emerging markets: (i) higher average returns, (ii) low correlations with developed countries' stock markets, (iii) more predictable returns, and (iv) high volatility. On the other hand, some studies show that volatility in emerging stock markets has decreased due to financial liberalization, which contributed to economic development in these countries (Ben Rejeb & Boughrara, 2015). Although emerging markets benefited from financial liberalization, the increase in short-term international financial flows made them vulnerable to external shocks. Bekaert and Harvey (2002) argued that the same financial liberalization increased the correlation between emerging markets and the rest of the world market returns, which reduced potential portfolio diversification benefits between developed and emerging markets.

There is increasing evidence that emerging markets cannot provide significant diversification benefits for international investors due to the increase in financial market integration (Cevik et al., 2012) and similar effects of the global shocks on different financial markets (El-Alaoui et al., 2015). This was more evident during the Global Financial Crisis (henceforth GFC) of 2007–2009 with the synchronized collapse in

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developed and emerging stock markets and hence international investors started to seek alternative investment vehicles (Jawadi et al., 2014). It is precisely at this point that Islamic Financial instruments came to the fore providing an alternative to existing conventional financial instruments with potential diversification benefits (Ghorbel et al., 2014; Jawadi et al., 2014; El-Alaoui et al., 2015). Indeed, some recent studies show that GFC had less of an impact on Islamic financial markets compared to conventional ones (Dewandaru et al., 2014, 2015, Al-Khazali et al., 2014) and if true, this suggests Islamic financial markets can be considered safe havens during financial distress. Moreover, Ghorbel et al. (2014) suggested the widespread use of Islamic financial instruments would reduce the excessive use of derivatives and credit default swaps (which are not allowed in Islamic Finance) that were implicated in the GFC.

Islamic stock markets involve issuing and trading in shares of firms that are compliant with Islamic principles. The compliance of these firms depends on their fulfillment of the qualitative and quantitative criteria established by Shairah Committees per directives of Islamic law. Firms that fail to meet qualitative criteria during the process are considered to be ineligible. While qualitative criteria cover the suitability of sectors in which the firms operate, quantitative criteria cover the eligibility of the firms' income and profits, according to certain rules and thresholds.

According to Islamic jurisprudence, certain financial endeavors and gains thereof such as interest (riba), gharar (uncertainty or hazard regarding transactional outcome), and gambling are prohibited. Therefore, companies that engage in these and other prohibited activities such as alcoholic beverages, some disallowed entertainment, conventional financial services, conventional insurance, pork products, alcoholic restaurants and bars, tobacco, and weapons are considered ineligible. Indexes formed by international firms such as Dow Jones (Dow Jones Islamic Market Index, DJIM), Financial Times Stock Exchange Group (FTSE) Global Equity Shariah Index, and Morgan Stanley Capital International (MSCI) World Islamic Index are representatives of recent developments that gained traction after the widespread trade in Sharia-compliant instruments. However, the eligibility criteria applied by these institutions vary (Charfeddine et al., 2016; Derigs & Marzban, 2008). Due to the low number of observations and lack of comparison with other indexes, Islamic indexes formed by individual countries are rarely used.

The primary objective of this paper is to answer some hypotheses regarding the relationship between Islamic and conventional markets, namely whether Islamic markets provide portfolio diversification benefits, or whether Islamic markets provide safe havens during turbulent times. To that end, we examine time-varying conditional correlations and volatility spillovers between Islamic and emerging stock markets. We examine causality between conventional financial returns and Islamic financial returns via causality-in-variance tests as there is scant attention paid to these volatility spillover effects in the literature. In doing so, we improve on the existing literature in several ways. First, we consider structural change by allowing a time-varying relationship between conventional and Islamic returns. In order to capture these effects, we use time-varying causality-in-variance tests and rolling subsamples. The issue is germane since the relationship has important implications for investors in terms of optimal portfolio selection. Second, we use the causality-in-risk test suggested by Hong et al. (2009) to examine whether Islamic markets are safe havens during turbulent times.

This study offers contributions to the existing literature in two different ways. First, extant studies that focus on the relation between Islamic stock markets and conventional stock markets generally consider developed countries' conventional stock markets or a regional index. We examine the relation between Islamic stock markets and emerging countries' stock markets. We investigate the relation between Islamic and conventional markets by using country by country stock market data for emerging countries that provide more insights on portfolio diversification benefits for international investors. Moreover, we offer additional econometric methods for testing volatility spillovers between Islamic and conventional stock markets. We consider time-varying tests suggested by Hafner and Herwartz (2006).

Our paper proceeds as follows: Section 2 of the paper presents a brief literature review. Section 3 presents the econometric framework and empirical results. Section 4 contains a concluding discussion.

2. A brief review of the literature

The recent growth in Islamic Finance has attracted the attention of academics and practitioners alike; as such, there has been an increase in the number of studies with a focus on Islamic financial instruments and markets. Many studies focus on examining the relation between Islamic and conventional markets; yet, there is scant attention on volatility spillover effects between conventional and Islamic financial markets (Hammoudeh et al., 2016). The issue is germane because investors can always potentially benefit from alternative financial instruments. Hence it is important to examine if Islamic markets offer alternative instruments for investment with portfolio diversification benefits, or whether Islamic markets are safe havens during turbulent times (Ibrahim, 2015).

There is a growing literature that focuses on the relationship between Islamic and conventional stock markets. Ajmi et al. (2014) examined the relationship between Islamic markets and conventional equity markets using linear and nonlinear models and found no evidence in favor of the 'decoupling' hypothesis. Dewandaru et al. (2014) and Abbes and Trichilli (2015) found the diversification benefits of Islamic markets may vary over regions. Saiti et al. (2014) found evidence in favor of decoupling between Islamic compliant equities in the US and developing countries. Majdoub and Mansour (2014) argued that the correlation between the Islamic equity index of the US and emerging countries such as Turkey, Indonesia, Pakistan, Qatar, and Malaysia are low with no volatility spillover effects from the US to developing countries. This suggests Islamic markets in these countries provide diversification opportunities. Majdoub et al. (2016) examined the diversification possibilities of the Islamic and conventional markets of Indonesia, an emerging market, and developed countries such as France, the UK, and the USA and found co-integration between the Islamic and conventional markets for all countries except for the UK.

Cevik and Bugan (2018) analyzed the regime-dependent relation between Islamic and conventional stock markets using a Markov Switching VAR model. The Granger causality and impulse-response analysis indicated that Islamic stock markets are affected by conventional stock markets in both bear and bull market regimes. These findings are not supportive of the safe-haven hypothesis. Ahmed (2019) investigated causality among Islamic stock markets and regional conventional indexes using causality-in-mean and causality-in-variance suggested by Hong (2001). The empirical results suggest conventional stock markets Granger cause Islamic stock markets. Usman et al. (2019) examined whether there is tail dependence between Islamic and conventional stock markets (USA, UK, Japan, Malaysia, and Pakistan) via the copula CoVaR methodology. Empirical results showed that the comovement between Islamic stock markets and conventional stock markets is generally in the right tail.

Paltrinieri et al. (2019) analyzed data from 78 MSCI Islamic and conventional stock markets from 2005 to 2015 and concluded that investors can attain portfolio diversification benefits through Islamic stock indices, particularly in post-crisis periods. In the same vein, Antar and Alahouel (2019) suggested that the MENA index provides diversification benefits for the US, Canada, and Emerging Markets. On the other hand, Jawadi et al. (2020) examined the relationship between Islamic and conventional stock markets and found positive and significant correlations between Islamic and conventional stock markets. They concluded that the comovement between the two types of markets has increased significantly in the aftermath of the GFC.

Islamic market interactions in different geographical regions are also often the subject of empirical work. Shamsuddin (2014) examined the relation between Islamic stock markets and interest rates by using Dow Jones geographical and sectoral Islamic indices for the 1996−2011 period. Empirical results show that the Shariah rules are not sufficient to decrease interconnectedness between the Islamic stock market indices and interest rates. Dewandaru et al. (2015) compared Dow Jones's Islamic and conventional indices of 11 countries and 10 sectors and found no significant difference in their betas, returns, or volatilities. Nevertheless, the authors still vouch for sectoral diversification as being more efficient than regional diversification. Balcılar et al. (2015) found evidence that raw materials and industrial sectors of the Islamic markets do not provide diversification opportunities. They show that during a crisis, sectors such as services, energy, and technology provide a safe-haven for investors. Studying Islamic sectoral indices in terms of risk and return, Charles et al. (2015) concluded that Islamic markets carry more risk than conventional markets for similar return levels and that Islamic sectors such as raw materials, industry, and technology have the highest levels of risk. Kenourgios et al. (2016) investigated the contagion effects of the recent financial crisis on Islamic equity and bond markets and failed to find strong contagion evidence between conventional and Islamic equities. Consequently, they concluded that Islamic emerging stock indices in the BRICS provide the most effective international portfolio diversification benefits.

The ‘safe-haven’ hypothesis recently has gained some traction in the Islamic Finance literature. Does Islamic finance provide a safe-haven during a crisis? Muteba Mwamba et al. (2017) found that conventional markets have a higher probability for price falls during a crisis hence Islamic markets seem to be less risky than conventional ones, especially during a crisis. Ho et al. (2014) emphasized that while Islamic markets perform better during a crisis, they do not perform as well in other periods. Ashraf and Mohammad (2014) found that, not just during a crisis, but in general Islamic indices perform better and have less systematic risk. However, Boujelbène Abbes (2012) could not validate performance advantages for Islamic indices, during crises or otherwise. Accordingly, investing in Islamic indices makes sense for religious motivations rather than financial performance per se. Kılıç and Buğan (2016) also found reactions of Islamic financial markets to financial shocks is not different from conventional markets.

3. Econometric framework

The role of an Islamic stock market as a hedge or safe-haven within emerging market stock markets depends on how the changes in these stock markets are linked under different market conditions. Reboredo (2013) defined hedge as if an asset is uncorrelated or negatively correlated with another asset or portfolio. The definition of a safe haven depends on extreme market comovements and suggests uncorrelated or negatively correlated asset returns during financial distress. In this context, we examine whether Islamic stock markets provide portfolio diversification benefits (or hedging) for international investors by investigating return and volatility spillovers between Islamic and emerging stock markets.[1] The safe-haven hypothesis for Islamic stock markets will be examined by the causality-in-risk test suggested by Hong et al. (2009).

[1] We estimate the corrected Dynamic Conditional Correlations DCC (*c*DCC) model suggested by Aielli (2013) to obtain dynamic conditional correlations and optimal hedge ratios between the Islamic stock market and emerging stock markets. The test procedures of the *c*DCC model are not elaborated here to save space.

3.1. Volatility spillover tests

Conditional correlations give the link between the first moments of stock returns. On the other hand, volatility spillover effects measured by relationships between second moments of returns cannot be ignored, particularly in financial markets. The volatility spillover effects indicated by causality-in-variance between different financial markets are of paramount importance for investors as they reveal limits of diversification benefits afforded by financial markets in constructing optimal portfolios.

Hafner and Herwartz (2006) proposed a Lagrange Multiplier (LM) test for causality-in-variance and showed that the LM test performs reasonably. Hafner and Herwartz defined the null hypothesis of no causality-in-variance as follows:

$$H_0 = Var\left(\varepsilon_{it}\middle|\mathrm{I}_{t-1}^{(j)}\right) = Var(\varepsilon_{it}|I_{t-1}) \tag{1}$$

where $i, j = 1, 2, \ldots, N$, $i \neq j$ and $\mathrm{I}_t^{(j)} = \mathrm{I}_t\middle|\sigma(\varepsilon_{j\tau}, \tau \leq t)$. Since Hafner and Herwartz (2006) testing procedure depends on residuals of a GARCH model, the test can proceed by estimating a GARCH model suggested by Bollerslev (1986) for return series in Islamic and conventional stock markets:

$$\begin{aligned} r_{it} &= \mu_{it} + \varepsilon_{it}, \\ \varepsilon_{it}/(\varepsilon_{it-1}, \varepsilon_{it-2}, \ldots, r_{it-1}, r_{it-2}, \ldots) &\sim GED\left(0, \sigma_{it}^2\right) \\ \sigma_{it}^2 &= \omega + \alpha_i \varepsilon_{it-1}^2 + \beta_i \sigma_{it-1}^2 \end{aligned} \tag{2}$$

$$\begin{aligned} r_{jt} &= \mu_{jt} + \varepsilon_{jt}, \\ \varepsilon_{jt}/\left(\varepsilon_{jt-1}, \varepsilon_{jt-2}, \ldots, r_{jt-1}, r_{jt-2}, \ldots\right) &\sim GED\left(0, \sigma_{jt}^2\right) \\ \sigma_{jt}^2 &= \omega + \alpha_j \varepsilon_{jt-1}^2 + \beta_j \sigma_{jt-1}^2 \end{aligned} \tag{3}$$

where μ_{it} and μ_{jt} are the means and ε_{it} and ε_{jt} are the innovation processes of returns in Islamic and conventional stock markets respectively. In order to test the null hypothesis of no causality-in-variance, the LM test statistic can be formulated as follows:

$$\lambda_{LM} = \frac{1}{4T}\left(\sum_{t=1}^{T}\left(\xi_{it}^2 - 1\right)z_{jt}'\right)V(\theta_i)^{-1}\left(\sum_{t=1}^{T}\left(\xi_{it}^2 - 1\right)z_{jt}\right) \xrightarrow{d} \chi^2(2) \tag{4}$$

where ξ_{it} is standardized residuals obtained from a GARCH model, $V(\theta_i) = \frac{\kappa}{4T}[\sum_{t=1}^{T} z_{jt}z_{jt}' - \sum_{t=1}^{T} z_{jt}x_{it}'(\sum_{t=1}^{T} x_{it}x_{it}')^{-1} \sum_{t=1}^{T} x_{jt}z_{jt}']$ and $\kappa = \frac{1}{T}\sum_{t=1}^{T}(\xi_{it}^2 - 1)^2$. Also $z_{jt} = (\varepsilon_{jt-1}^2, \sigma_{jt-1}^2)'$, $x_{it} = \sigma_{it}^{-2}(\partial\sigma_{it}^2/\partial\theta_i)$ and $\theta_i = (\omega_i, \alpha_i, \beta_i)'$.

The Hafner and Herwartz (2006) procedure can be implemented using the following steps:

1. Estimate a GARCH (1,1) model for ε_{it} and ε_{jt} and obtain standardized residuals ξ_{it}, partial derivatives x_{it}, and the volatility process σ_{jt}^2 entering z_{jt}.
2. Regress $\xi_{it}^2 - 1$ on x_{it}' and the misspecification indicators in z_{jt}'.
3. λ_{LM} is equal to T times the coefficient of explanation (R^2) of the latter regression.

The asymptotic distribution of λ_{LM} will depend on the number of misspecification indicators in z_{jt}. In our case, λ_{LM} test statistic follows a $\chi^2(2)$ distribution.

A number of studies show that structural breaks lead to an overestimation of GARCH parameters (Galeano & Tsay, 2010; Hillebrand, 2005; Javed & Mantalos, 2011; Rodrigues & Rubia, 2007; Van Dijk et al., 2005). Hence, we use a structural-break-in-variance test suggested by Sanso et al. (2004) to account for structural breaks in the unconditional variance of stock returns series.

There is well-documented literature emphasizing causality relations in financial markets changes over time; hence, a time-varying causality between stock markets cannot be ruled out. For example, the causal link between financial variables tends to change over periods of bear and bull markets. The issue is germane since examining time-varying causality between Islamic and conventional stock markets allows us to test whether Islamic financial markets can provide safe havens during financial distress episodes. To that end, we calculate time-varying LM statistics by using rolling samples in the GARCH model. The first step here in accounting for a time-varying causality-in-variance test is to determine the appropriate rolling sample size. Too small a rolling sample size leads to convergence problems in the GARCH model because the GARCH model estimation requires a large sample size. However, a large size of rolling sample may cause a long delay in detecting changes in causality. As a compromise, we consider a rolling sample size of 1000 observations (corresponding to 5 years) in estimating the rolling sample for the GARCH model.[2] Then, the time-varying LM test is calculated by using Hafner and Herwartz (2006) procedure explained in step 1 through step 3 above for each rolling sample.

3.2. Causality-in-risk test

The Granger causality-in-risk suggested by Hong et al. (2009) allows us to examine comovements in the left tail of the return series that is closely related to the safe-haven hypothesis. A causal link in risky situations between Islamic and emerging stock markets suggests that the Islamic stock market can be predicted by using past information of the conventional stock market in financial distress periods or vice versa. Since the left tail of probabilities of the return series is considered in the test procedure, it requires estimation of the time-varying

[2] There is still no consensus on choosing the appropriate sample size for the rolling window estimation in the literature. Ng and Lam (2006) examined the impact of sample sizes on the GARCH model estimation. They found that if the sample size is less than 700, the maximum likelihood estimation procedure provides wrong optimal solutions; as such, they recommended using 1000 observations for the GARCH model estimation.

Value at Risk (VaR) for returns series to ascertain any downside risk.

In the finance literature, VaR has been widely used to gauge extreme market risk quantitatively (Atukeren et al., 2015; Cevik et al., 2021). For a certain period and given a level of statistical confidence (1-α), VaR gives the maximum amount that can be lost with probability α. For returns series (r_t), the downside VaR (V_t (down)) can be calculated as follows:

$$P(r_{l,t} < -V_t(\text{down})|I_{1(t-1)}) = \alpha \tag{5}$$

where $r_{l,t}$ is stock returns series, $I_{t-1} \equiv \{r_{t-1}, r_{t-2}, \ldots\}$ is the information set available at time t-1.

Note that V_t (down) represents the conditional probability distribution of returns series for the lower α-quantile with 5% risk levels, the latter is a commonly considered level for α. Here we use the GARCH model to estimate time-varying downside risk levels. Hong et al. (2009) showed the null and alternative hypotheses for downside causality in risk as follows:

$$H_0 : P(Y_{1t} < -V_{1t}|I_{1(t-1)}) = P(Y_{1t} < -V_{1t}|I_{t-1})$$

$$H_1 : P(Y_{1t} < -V_{1t}|I_{1(t-1)}) \neq P(Y_{1t} < -V_{1t}|I_{t-1})$$

where I_{t-1}b$(I_{1(t-1)}, I_{2(t-1)})$, $I_{t-1} = \{Y_{1(t-1)}, \ldots Y_{11}\}$, $I_{2(t-1)} = \{Y_{2(t-1)}, \ldots Y_{22}\}$. The null hypothesis implies the time series $\{Y_{2t}\}$ does not Granger cause the time series $\{Y_{1t}\}$ in risk at a given α level for I_{t-1}. On the other hand, the alternative hypothesis indicates the presence of Granger causality running from the time series $\{Y_{2t}\}$ to the time series $\{Y_{1t}\}$ at a risk level given by α for I_{t-1}. Then, the downside risk indicator used in testing for Granger-causality can be defined as follows:

$$Z_{lt}\text{b}1(Y_{lt} < -V_{lt}), l = 1, 2 \tag{6}$$

where $\mathbf{1}(.)$ is the indicator function and Z_{lt} takes value 1 when the actual loss exceeds VaR and 0 otherwise. Here, we can restate the null and alternative hypotheses for the downside indicator as follows:

$$H_0 : P(Z_{1t}|I_{1(t-1)}) = P(Z_{1t}|I_{t-1})$$

$$H_1 : P(Z_{1t}|I_{1(t-1)}) \neq P(Z_{1t}|I_{t-1})$$

Note that the downside Granger causality between $\{Y_{1t}\}$ and $\{Y_{2t}\}$ can be considered as Granger-causality-in-mean between $\{Z_{1t}\}$ and $\{Z_{2t}\}$. If we have a random sample for $\{Y_{1t}\}$ and $\{Y_{2t}\}$ of size T and given the estimator $\widehat{\beta}_l$, the estimates of the downside risk indicator can be obtained from:

$$\widehat{Z}_{lt}\text{b}Z_{lt}\left(\widehat{\beta}_l\right), l = 1, 2, \ldots \tag{7}$$

where $\widehat{Z}_{lt}(\widehat{\beta}_l)b1[Y_{lt} < -V_{lt}(\widehat{\beta}_l)]$. Then the sample cross-covariance function between $\widehat{Z}_{1t}$ and $\widehat{Z}_{2t}$ can be defined as:

$$\widehat{C}(j) = \begin{cases} T^{-1}\sum_{t=1+j}^{T}\left(\widehat{Z}_{lt} - \widehat{\alpha}_1\right)\left(\widehat{Z}_{2(t-j)} - \widehat{\alpha}_2\right), & 0 \le j \le T-1 \\ T^{-1}\sum_{t=1+j}^{T}\left(\widehat{Z}_{l(t+j)} - \widehat{\alpha}_1\right)\left(\widehat{Z}_{2t} - \widehat{\alpha}_2\right), & 1-T \le j \le 0 \end{cases} \tag{8}$$

where $\widehat{\alpha}_1 \equiv T^{-1}\sum_{t=1}^{T}\widehat{Z}_{lt}$. The sample cross-correlation between $\widehat{Z}_{1t}$ and $\widehat{Z}_{2t}$ is given by

$$\widehat{P}^2(j)\widehat{C}(j) \Big/ \widehat{S}_1\widehat{S}_2, \quad j = 0, \pm 1, \tag{9}$$

where $\widehat{S}_l = \widehat{\alpha}_l(1 - \widehat{\alpha}_l)$ is the sample variance of $\widehat{Z}_{lt}$. Then, the Q_r-statistic for the downside causality test is defined as:

$$Q_r(M) = \frac{T\sum_{j=1}^{T-1}k^2\left(\frac{j}{M}\right)\widehat{\rho}^2(j) - C_T(M)}{\sqrt{2D_T(M)}} \tag{10}$$

Here $C_T(M)$ and $D_T(M)$ in the numerator and the denominator in Eq. (10) are defined as:

$$\begin{aligned} C_T(M) &= \sum_{j=1}^{T-1}(1 - j/T)k^2(j/M) \\ D_T(M) &= 2\sum_{j=1}^{T-1}(1 - j/T)\{1 - (j+1)/T\}k^4(j/M) \end{aligned} \tag{11}$$

where M is a predetermined lag level and $k(j/M)$ is a weight function. Hong et al. (2009) show that the non-uniform weighting method (such as Daniel kernel) outperforms others in Monte Carlo simulations; as such we use the Daniel kernel $k_D = \sin(\pi z)/\pi z$ as a weighting method.

Since Q_r statistics are one-sided, the upper tailed normal distribution critical values should be used. The asymptotic critical value at the 5% level is 1.645. If the computed Q_r statistic exceeds the asymptotic critical value at the desired confidence level, the null hypothesis of no downside causality at all lags can be rejected.

4. Data and empirical results

We use daily data for the Islamic and emerging stock markets from January 1st, 1996 through September 18, 2020, where the number of observations is 6448.[3] We consider the Dow Jones Islamic Stock Market Index (DJIM) as a measure of the Islamic stock market, which is a common practice in the literature. We consider 13 major emerging stock markets for conventional stock markets, namely: Argentina, Brazil China, the Czech Republic, India, Indonesia, South Korea, Malaysia, Mexico, Poland, Russia, South Africa, and Turkey.[4] Daily

[3] Using daily stock indices from different continents causes asynchronous data problems because the trading hours of these stock markets are not synchronized. Hence, as in Burns et al. (1988) and BenSaida (2018), we use a simple correction method that depends on the estimation of the first-order vector moving average (VMA) model.

[4] The countries are selected based on the classification of Morgan Stanley Capital International (MSCI).

Table 1
Descriptive statistics.

	DJIM	Argentina	Brazil	China	Czechia	India	Indonesia
Mean	0.022	0.018	0.039	−0.008	0.002	0.028	0.013
Median	0.056	0.020	0.050	−0.010	0.018	0.045	0.021
Max	8.6555	16.318	24.158	13.407	12.076	16.543	14.979
Min	−9.0809	−51.221	−15.24	−12.263	−13.569	−12.891	−18.269
Std. Dev.	0.9512	2.3294	1.7919	1.7265	1.2991	1.4327	1.7362
Skewness	−0.436	−1.772	0.030	0.224	−0.383	−0.225	−0.140
Kurtosis	8.423	41.017	12.61	6.015	8.988	8.719	10.336
J-B	19,268	455,370	42,725	9777.3	21,861	20,479	28,724
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
ARCH (5)	396.85	11.94	202.3	228.67	235.79	119.86	93.212
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
***Q* (20)**	56.291	43.368	55.901	52.774	55.021	95.555	53.235
	[0.000]	[0.001]	[0.000]	[0.000]	[0.000]	[0.018]	[0.000]
Q_s (20)	7719.73	110.437	3135.45	4069	4841.47	1845.66	2151.4
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
ADF	−13.675***	−23.279***	−17.416***	−17.835***	−18.152***	−18.064***	−12.993***
PP	−80.253***	−80.515***	−80.444***	−80.169***	−80.378***	−81.087***	−80.851***
KPSS	0.099***	0.056***	0.034***	0.086***	0.077***	0.043***	0.116***
	S. Korea	**Malaysia**	**Mexico**	**Poland**	**Russia**	**S. Africa**	**Turkey**
Mean	0.005	−0.005	0.034	−0.002	0.028	0.018	0.072
Median	0.000	−0.010	0.046	−0.019	0.032	0.037	0.045
Max	11.223	21.609	11.904	7.7049	19.904	7.2152	18.188
Min	−11.614	−24.786	−12.791	−11.929	−29.338	−10.983	−19.079
Std. Dev.	1.669	1.211	1.345	1.458	2.491	1.183	2.227
Skewness	0.140	0.799	0.060	−0.095	−0.342	−0.349	0.073
Kurtosis	5.9644	74.091	6.7745	3.211	14.543	4.8318	6.9044
J-B	9578.6	1,475,500	12,334	2779.8	56,949	6403.2	12,813
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
ARCH (5)	206.66	409.26	137.41	152.9	233.27	275.97	149.45
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
***Q* (20)**	55.916	140.824	28.942	32.084	95.797	46.804	46.921
	[0.001]	[0.000]	[0.088]	[0.042]	[0.001]	[0.000]	[0.015]
Q_s (20)	4695.48	2842.91	2805.81	2305.64	4304.78	3682.26	1904.59
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
ADF	−39.668***	−13.870***	−38.098***	−25.432***	−12.523***	−18.882***	−15.123***
PP	−81.214***	−81.028***	−80.478***	−80.297***	−80.572***	−81.221***	−80.753***
KPSS	0.096***	0.106***	0.050***	0.031***	0.040***	0.081***	0.075***

Notes: The figures in square brackets show the probability (p-values) of rejecting the null hypothesis. ARCH (5) is the LM conditional variance test statistic. $Q(20)$ and $Q_s(20)$ are the Box-Pierce serial correlation test statistics for return and squared return series respectively. *** indicate the series in question is stationary at the 1% significance level.

closing prices for all stock exchange markets are collected from DataStream. We use the logarithmic return series (first differences of logarithm of price series) as a measure of returns.

The descriptive statistics for all the synchronous returns series are given in Table 1. The mean returns are positive for all stock markets during the sample except for China, Malaysia, and Poland. While the highest mean returns are observed in Turkey, the lowest mean returns are seen in China. Moreover, the Russian stock market shows higher volatility as measured by the standard deviation. All return series exhibit strong negative and positive skewness and excess kurtosis, which point to a leptokurtic distribution for returns. The normal distribution assumption for the returns series is rejected at the 1% level according to the Jarque-Bera normality test. The Box-Pierce Q statistics show the existence of autocorrelation in the returns for all countries except for the DJIM Index, Argentina, China, and Mexico. On the other hand, the Box-Pierce Q statistics for the squared returns series imply the presence of autocorrelations. The LM test results suggest that all returns series exhibit ARCH effects. Finally, all returns series seem to be stationary in levels according to Augmented Dickey-Fuller (ADF), Phillips-Perron (PP), and Kwiatkowski, Phillips, Schmidt, and Shin (KPSS) tests.

We first test for structural breaks in variance suggested by Sanso et al. (2004) and the results are given in Table 2. According to the results in Table 2, we cannot ascertain any structural breakpoints in the variance of returns in DJIM or South Africa. On the other hand, a sudden regime shift point can be seen in Argentina. The Brazilian stock market has three regime shift points between 1997 and 1999. The Polish stock market has four regime shifts in 2003, 2005, 2008, and 2009, the last two structural change points corresponding to the global financial crisis. We find five sudden change points in

Table 2
Variance break tests results.

Series	No. of Breaks	Break Dates									
DJIM	0										
Argentina	1	April 24, 2018									
Brazil	3	July 11, 1997	August 25, 1998	February 8, 1999							
China	8	August 11, 1997	November 3, 1998	November 15, 2001	July 4, 2003	April 13, 2004	May 21, 2004	July 31, 2007	August 19, 2009		
Czechia	5	June 19, 1998	December 19, 2002	September 4, 2008	November 24, 2008	July 16, 2009					
India	5	June 4, 1998	April 30, 2001	October 2, 2007	March 20, 2008	August 24, 2009					
Indonesia	7	August 20, 1997	January 8, 1999	July 8, 2004	July 30, 2007	September 8, 2008	December 16, 2008	April 20, 2020			
S. Korea	7	July 12, 1996	October 21, 1997	January 30, 1998	November 1, 2000	April 29, 2003	December 21, 2011	January 20, 2020			
Malaysia	5	October 9, 2001	June 7, 2004	November 8, 2006	June 25, 2009	February 21, 2020					
Mexico	7	October 22, 1997	January 5, 2001	November 27, 2002	August 29, 2005	September 12, 2008	December 8, 2008	May 18, 2009	December 1, 2009	February 21, 2020	June 12, 2020
Poland	4	November 25, 2003	December 30, 2005	September 12, 2008	May 4, 2009						
Russia	7	May 22, 1996	March 6, 2001	August 7, 2008	November 24, 2008	April 9, 2009	November 9, 2009				
S. Africa	0										
Turkey	9	March 4, 1996	January 22, 1997	April 14, 2003	June 14, 2004	May 9, 2006	September 10, 2008	December 3, 2008	August 12, 2016	April 24, 2018	

the Czech Republic, India, and Malaysia where the structural breaks coincide with the Asian crisis and the Global Financial Crisis. Tests point to seven structural change points in the variance for Indonesia, South Korea, and Russia. The Chinese stock market has eight sudden change points between 1997 and 2009. The highest regime shifts in the variance of returns are in the Turkish stock market where nine sudden change points can be statistically detected. Most of the structural break dates are either during the GFC crisis or country-specific economic crises; hence in a sense, these dates are not surprising. Furthermore, test results suggest that the stock markets of Indonesia, South Korea, Malaysia, and Mexico were affected by the global Covid-19 pandemic because we find regime shift points at the beginning of 2020 in these stock markets.

Econometric work on the effects of structural breaks on GARCH parameters shows that structural breaks in the variance of a series lead to an upward bias in the GARCH parameters. This is important for causality-in-variance tests because testing procedures critically depend on the GARCH parameters. To account for structural breaks, we include dummy variables corresponding to structural breaks in the variance equation of the GARCH model.

The presence of ARCH effects in the returns series suggests a GARCH model is appropriate. Diagnostics show a GARCH (1,1) model is adequate for modeling volatility. We use the Akaike information criterion (AIC) for setting the optimal lag length of the autoregressive parameters in the mean equation. The GARCH model results presented in Table S1 (See the Supplementary Material, available online) show that the GARCH parameters (α and β) are statistically significant at the 1% level. Note that the α estimates indicate the persistence of shocks, and β parameter estimates point to persistence in volatility clustering. In order to show the effects of structural breaks on the GARCH model, we present results with and without dummy variables in Table 3 for all countries. With these results, we confirm that structural breaks in variance lead to an upward bias in GARCH parameters. Specifically, with structural breaks taken into account, the sum of *alpha* and *beta* parameters declines substantially. We also confirm that the GARCH model with dummy variables provides a better fit for all return series according to the log-likelihood value. A likelihood ratio (LR) test confirms these results as the null hypothesis of GARCH without dummy variables can be rejected at the 1% significance level against a GARCH model with dummies for all returns. Needless to say, taking into account structural breaks increases the explanatory power of the GARCH model.

Next, we estimate the *c*DCC model to estimate time-varying correlations and optimal hedge ratios and present the results in Table S2 (See the Supplementary Material, available online). According to the results in Table S2, parameter a shows the effect of shocks on conditional correlations and parameter b indicates the persistence in the conditional correlations. Both parameters happen to be positive and statistically significant. These findings indicate that persistence in the correlations is fairly high and past shocks in the markets affect conditional correlations.

Then, we calculate time-varying conditional correlations and time-varying hedge ratios between the Islamic stock market and emerging stock markets by using conditional variance and covariances obtained from the *c*DCC model. We present time-varying conditional correlations in Fig. S1 (See the Supplementary Material, available online). We also report descriptive statistics for time-varying conditional correlations in Table 3. The results in Table 3 show that conditional correlations between DJIM and emerging stock markets are generally positive for all countries. According to full sample results, although the highest mean correlation is obtained from Mexico, the lowest mean correlation is between DJIM and Indonesia. Also, we find that stock markets in Argentina, Brazil, and Mexico have higher correlations with the DJIM than other stock markets, which indicates limited regional diversification benefits.

In order to examine the effects of the Covid-19 outbreak on conditional correlations, we split the sample into two parts as pre-Covid-19 and Covid-19 period. The Covid-19 period can start from December 1, 2019, because the first Covid-19 case

Table 3
Descriptive statistics for the time-varying conditional correlations.

Stock Markets	Full Sample			Pre COVID-19			COVID-19		
	Mean	Min.	Max.	Mean	Min.	Max.	Mean	Min.	Max.
DJIM & Argentina	0.451***	−0.195	0.848	0.447***	−0.195	0.848	0.565***	0.185	0.797
DJIM & Brazil	0.532***	0.144	0.865	0.533***	0.144	0.865	0.519***	0.331	0.761
DJIM & China	0.286*	−0.166	0.624	0.276*	−0.166	0.607	0.588***	0.531	0.624
DJIM & Czechia	0.144*	−0.146	0.571	0.139*	−0.146	0.458	0.291**	0.083	0.571
DJIM & India	0.195*	−0.120	0.441	0.193*	−0.120	0.441	0.238***	0.115	0.327
DJIM & Indonesia	0.129**	−0.042	0.289	0.126**	−0.042	0.289	0.206***	0.098	0.279
DJIM & S. Korea	0.254**	−0.002	0.445	0.249**	−0.002	0.445	0.389***	0.322	0.434
DJIM & Malaysia	0.145***	−0.013	0.273	0.143***	−0.013	0.273	0.194***	0.122	0.233
DJIM & Mexico	0.588***	0.220	0.861	0.588***	0.220	0.861	0.580***	0.343	0.798
DJIM & Poland	0.325***	0.073	0.591	0.320***	0.073	0.591	0.479***	0.335	0.572
DJIM & Russia	0.352**	0.000	0.732	0.351**	0.000	0.732	0.378***	0.236	0.493
DJIM & S. Africa	0.338***	−0.053	0.641	0.336***	−0.053	0.641	0.403***	0.207	0.538
DJIM & Turkey	0.238*	−0.183	0.597	0.234*	−0.183	0.575	0.351***	0.099	0.597

Notes: ***, ** and * indicate significant correlation at the 1%, 5% and 10% significance level respectively.

Table 4
Descriptive statistics for the time-varying hedge ratio.

Stock Markets	Full Sample			Pre COVID-19			COVID-19		
	Mean	Min.	Max.	Mean	Min.	Max.	Mean	Min.	Max.
DJIM & Argentina	1.197	−0.752	4.719	1.189	−0.752	4.719	1.442	0.684	2.373
DJIM & Brazil	1.067	0.206	4.284	1.073	0.206	4.284	0.898	0.417	1.378
DJIM & China	0.516	−0.342	1.843	0.503	−0.342	1.608	0.919	0.344	1.843
DJIM & Czechia	0.205	−0.321	1.270	0.201	−0.321	1.270	0.307	0.056	0.636
DJIM & India	0.296	−0.526	1.799	0.296	−0.526	1.799	0.286	0.123	0.486
DJIM & Indonesia	0.244	−0.088	0.996	0.242	−0.088	0.996	0.310	0.145	0.562
DJIM & S. Korea	0.404	−0.004	0.993	0.399	−0.004	0.993	0.564	0.228	0.884
DJIM & Malaysia	0.154	−0.019	0.965	0.154	−0.019	0.965	0.174	0.074	0.295
DJIM & Mexico	0.892	0.237	2.232	0.896	0.237	2.232	0.764	0.376	1.470
DJIM & Poland	0.555	0.089	1.493	0.551	0.089	1.493	0.689	0.406	1.043
DJIM & Russia	0.822	0.002	3.903	0.832	0.002	3.903	0.530	0.279	1.000
DJIM & S. Africa	0.474	−0.087	1.337	0.471	−0.087	1.337	0.549	0.331	0.950
DJIM & Turkey	0.559	−1.065	2.525	0.562	−1.065	2.525	0.492	0.174	0.794

appeared on this date. The results in Table 3 indicate that the conditional correlations between DJIM and various stock markets have significantly increased for all countries except for Brazil and Mexico during the Covid-19 outbreak.

We calculate the time-varying hedge ratios by using time-varying variances and covariances and present results for emerging stock markets in Fig. S2 (See the Supplementary Material, available online). Descriptive statistics for the hedge ratios are given in Table 4. The results in Table 4 show that the required amount of investment in DJIM for hedging when a $ 1 long position is taken in an emerging country stock market. For example, the time-varying hedge ratio for Brazil varies between 0.206 and 4.282 which implies that a $1 long position in the Brazilian stock market can be hedged for between 20 cents and $ 4 in DJIM with a mean hedge ratio of 1.067. The average hedge ratio for emerging country stock markets varies between 0.154 cents (Malaysia) and $ 1.197 (Argentina). In addition, the mean hedge ratios seem to have increased during the global Covid-19 pandemic for all countries except for Brazil, India, Mexico, Russia, and Turkey.

Overall, both time-varying conditional correlations and the hedge ratios show that there are positive and significant correlations between emerging stock markets and DJIM, which implies limited portfolio diversification benefits for Islamic stock markets.

In order to examine whether there are significant relationships in the second moments of the return series, we use causality-in-variance tests and the test results are presented in Table 5. The results in Table 5 show causality-in-variance running from DJIM returns to all conventional emerging stock returns at the 5% significance level except for Mexico where the null hypothesis of no causality cannot be rejected. These results suggest volatility spillover effects running from the Islamic stock returns to emerging conventional stock market returns. On the other hand, all conventional emerging stock returns Granger cause-in-variance DJIM except for Malaysia and South Africa where the null hypothesis of no causality in variance cannot be rejected at the 5% significance level. These results show that there are significant bidirectional volatility spillovers between conventional emerging stock returns and Islamic stock returns. This again shows limited diversification benefits afforded by Islamic stock market instruments.

The presence of volatility spillovers from the DJIM to the emerging stock markets may be expected because the DJIM consists of 2909 Sharia-compliant firms across 31 developed markets and 29 emerging markets. Furthermore, the weight of firms traded in G7 countries' stock markets in the DJIM is approximately 78% with firms traded in the US stock market having the largest share (63%). There is well-documented literature that finds volatility spillovers from advanced stock markets to emerging stock markets. As such our results are not surprising and are consistent with expectations.

Recent studies in the literature emphasize dynamic relationships among stock markets where these relationships change over time. Several studies show that conventional stock markets exhibit time-varying behavior (Aloui et al., 2011, 2013; Kang et al., 2015; Kenourgios et al., 2011; Samarakoon, 2011). There is also a number of studies presenting evidence in favor of time-varying behavior in Islamic stock markets

Table 5
Causality-in-variance test results.

Causality Direction	Test Statistic	Causality Direction	Test Statistic
DJIM → Argentina	12.787***	DJIM → Malaysia	20.117***
Argentina → DJIM	6.580**	Malaysia → DJIM	4.971
DJIM → Brazil	6.449**	DJIM → Mexico	2.491
Brazil → DJIM	4.484**	Mexico → DJIM	8.312**
DJIM → China	29.339***	DJIM → Poland	23.714***
China → DJIM	13.458***	Poland → DJIM	20.586***
DJIM → Czechia	9.878***	DJIM → Russia	7.487**
Czechia → DJIM	11.458***	Russia → DJIM	20.172***
DJIM → India	12.521***	DJIM → S. Africa	23.713***
India → DJIM	13.646***	S. Africa → DJIM	5.499
DJIM → Indonesia	20.281***	DJIM → Turkey	6.316**
Indonesia → DJIM	9.276***	Turkey → DJIM	15.586***
DJIM → S. Korea	45.844***		
S. Korea → DJIM	6.926**		

Notes: → indicates the direction of causality. *** and ** show a statistically significant causality relation at 1% and 5% level respectively.

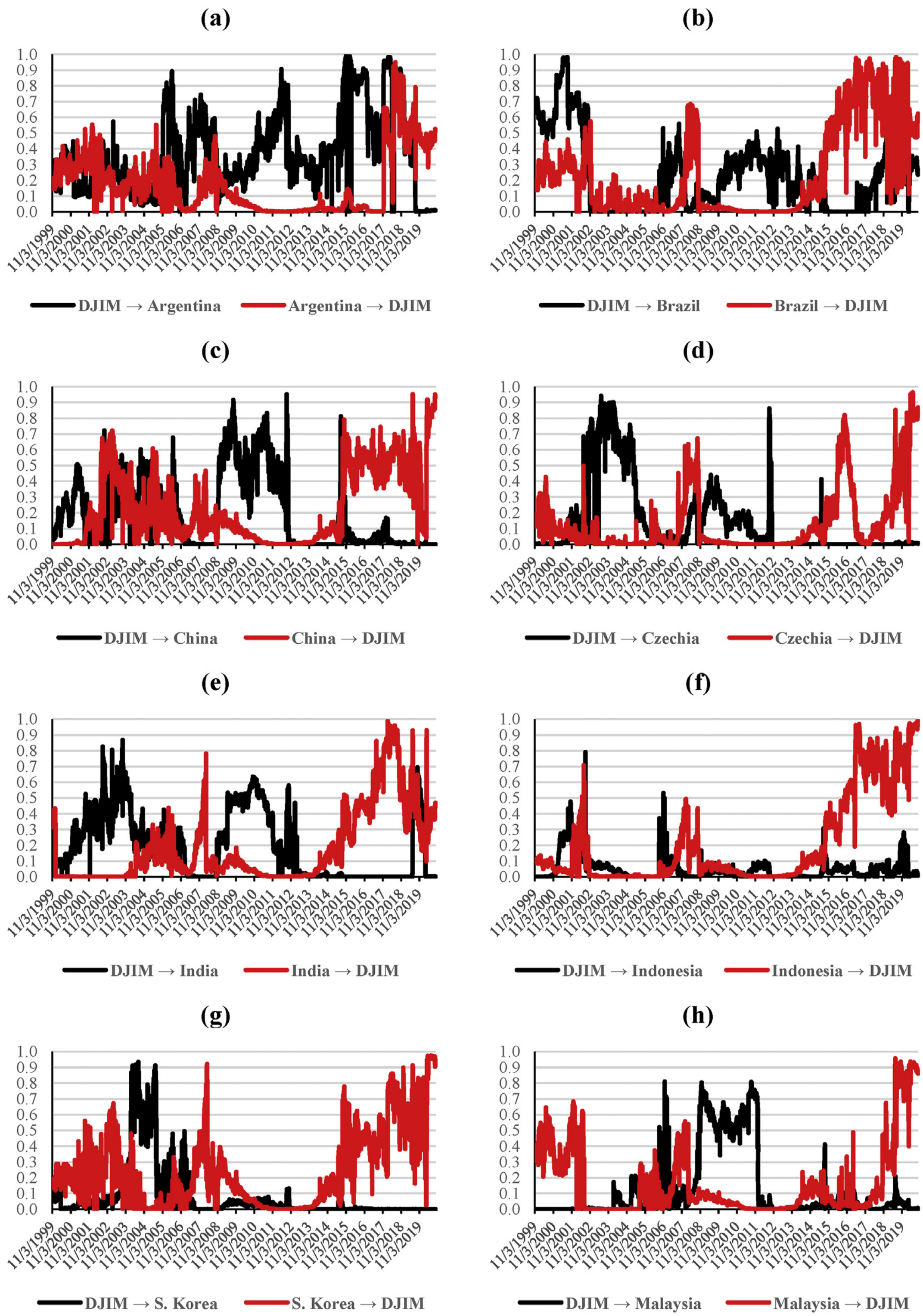

Fig. 1. Time-Varying Causality-in-Variance Test Results, Notes: → indicates the direction of causality relation.

(Ahmad et al., 2018; Ben Nasr et al., 2014; Cevik & Bugan, 2018; Haddad et al., 2020, p. 100760). There are several reasons the relationships among stock markets change over time. It is well known that stock markets generally exhibit sustained increases or decreases over time, with relationships among them that also tend to change over time. Also, financial crises cause structural breaks in stock markets, and hence the relationship between markets can evolve over pre-crisis, crisis, and post-crisis periods. Finally, investor behavior may exhibit limited rationality which can produce relationships between stock markets that can be time-varying. Hence investigating time-varying relationships between stock markets is important

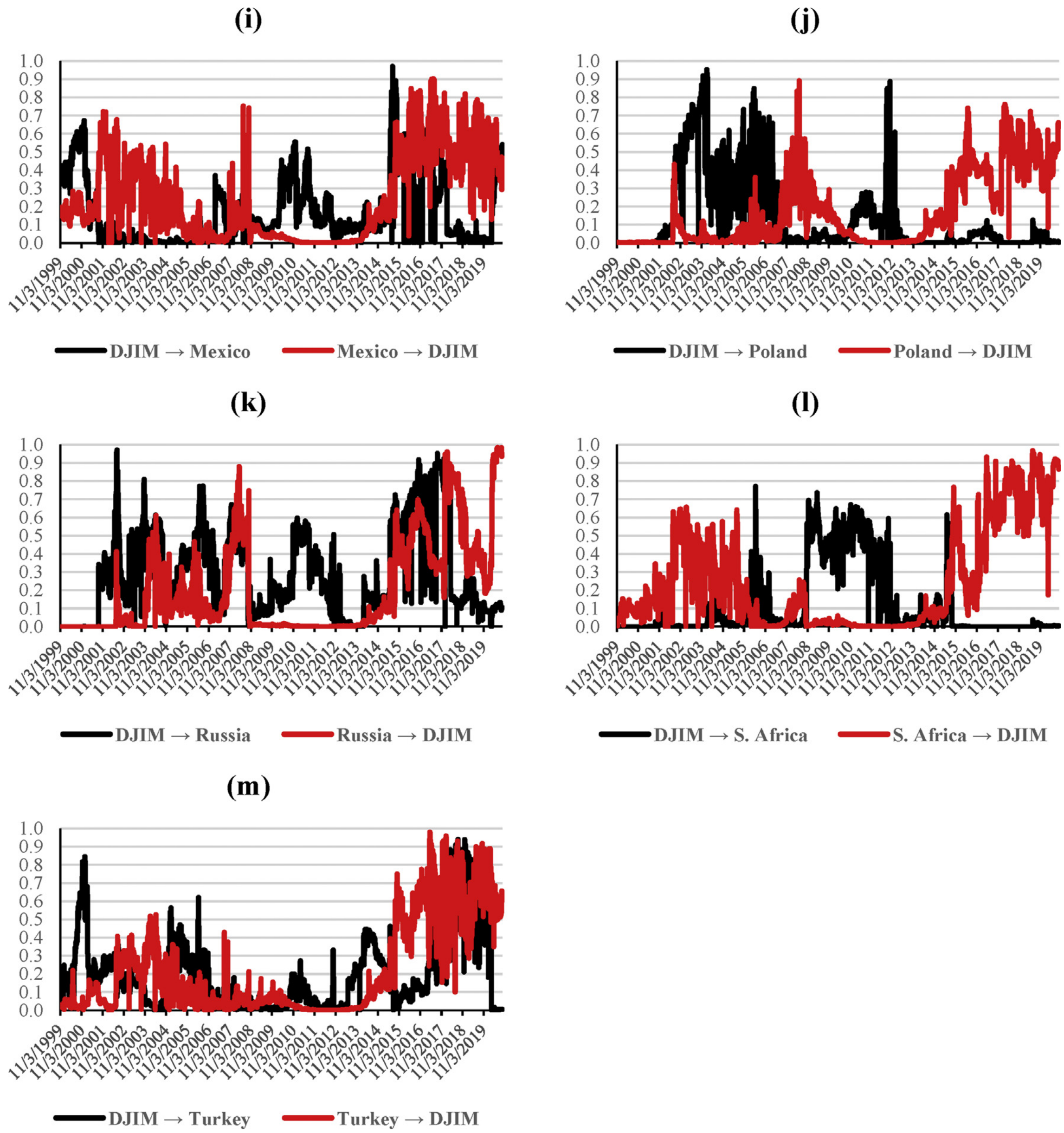

Fig. 1. (*continued*)

and this requires estimation methods that take into account time-varying relationships. This provides a strong motivation for modeling time-varying volatility spillover effects between emerging and Islamic stock markets.

To that end, we use time-varying causality-in-variance tests to better understand the dynamic interactions between Islamic and emerging conventional stock returns by using rolling subsamples. The probability (p-values) of rejecting the null hypothesis of no volatility spillovers is presented in Fig. 1, panels (a) - (m).

Even though the DJIM Granger causes (in-variance) all emerging stock markets except for Mexico per results in Table 5, the time-varying causality-in-variance tests provide a different picture. For example, although we cannot detect a causal link from DJIM to Mexico per results in Table 5, the results in Fig. 1 Panel (i) indicate there are volatility spillovers from DJIM to Mexico between 2001 and 2007 and in 2018−2019. Similar results are obtained for South Africa as we could not validate causality from South African stock markets to DJIM in Table 5. However, in Fig. 1 panel (l) there seems to be time-varying causality in variance from South Africa to DJIM between 2006 and 2015. These results confirm that the dynamic interactions between financial markets are time-varying and causality can change depending on tranquil or distressed episodes in financial markets.

The results in Fig. 1 (a) indicate volatility spillovers from DJIM to Argentina in 2004−2006, 2008, 2016, and 2018 but the null hypothesis can be seldom rejected as causality is generally borderline in these periods. We find causality from Argentinian stock markets to DJIM in 2006−2007 and between 2010 and 2017. Time-varying test results show that there is a causal link running from DJIM to Argentina during the recent Covid-19 outbreak. According to the results in Fig. 1 (b), we find bidirectional volatility spillovers between DJIM and Brazilian markets between 2002 and 2006. After the GFC, the causality between DJIM and Brazil seems to have changed and we find unidirectional volatility spillovers from Brazil to DJIM between 2009 and 2014. Even if DJIM Granger causes Brazilian markets in 2016–2017, there is no causal link in either direction during the recent Covid-19 outbreak between DJIM and Brazil.

The time-varying causality-in-variance test results for China in Fig. 1 (c) favor volatility spillovers from China to the DJIM at the beginning of the sample. Also, we find volatility spillovers from China to DJIM between 2011 and 2015. The time-varying test results provide weak evidence in favor of volatility spillovers from China to DJIM because the null hypothesis can be seldom rejected and the test statistics are generally borderline. On the other hand, DJIM is the Granger cause of Chinese markets in 2002, and 2007–2008. The results also indicate volatility spillovers from DJIM to China after 2012. Notice that during the recent global Covid-19 pandemic, we find a significant volatility spillover from the DJIM to the Chinese stock market. The results in Fig. 1 Panel (d) indicate bidirectional volatility spillovers between DJIM and the Czech stock market in specific periods such as 2001, 2006–2007, 2013–14, and 2017–18. However, there seems to be a change in 2012 as the null hypothesis of no causality-in-variance going from the DJIM to the Czech stock market is rarely rejected before 2012 when it is strongly rejected after 2012. We also find unidirectional volatility spillovers from DJIM to the Czech stock market during the recent global Covid-19 pandemic.

Results in Panel (e) show volatility spillovers running from the Indian stock market to the DJIM at the beginning of the sample. On the other hand, the DJIM Granger causes the Indian stock market during the GFC. We also find volatility spillovers from the Indian stock market to the DJIM between 2010 and 2014. As in the Czech Republic, the null hypothesis of no volatility spillovers from the DJIM to the Indian stock market is strongly rejected after 2012. Although there is no causal link in either direction at the beginning of the recent Covid-19 outbreak between DJIM and India, we find a volatility spillover effect from DJIM to the Indian stock market after the World Health Organization (WHO) declared Covid-19 as a global pandemic in March 2020.

The results in Panel (f) show volatility spillovers from the Indonesian stock market to DJIM between 2000 and 2013 except for 2002 and the GFC period. On the other hand, we cannot detect volatility spillovers from the Indonesian stock market to the DJIM after 2013. DJIM is the Granger cause-in-variance Indonesian stock market returns within the sample except for specific periods such as 2001–2002, 2006, and 2015. As in India, DJIM is the Granger cause of the Indian stock market after the WHO declared Covid-19 a global pandemic.

Time-varying causality-in-variance test results for South Korea indicate volatility spillovers from the DJIM to the South

Table 6
Causality-in-risk test results.

Causality Direction	M = 1	M = 2	M = 3	M = 4	M = 5
DJIM → Argentina	−0.561	0.205	0.901	1.359	1.626
Argentina → DJIM	−0.230	0.392	1.080	1.123	1.168
DJIM → Brazil	−0.466	0.441	1.025	1.315	1.703**
Brazil → DJIM	−0.519	3.553***	7.143***	8.699***	9.308***
DJIM → China	8.889***	9.592***	9.833***	9.253***	9.122***
China → DJIM	0.087	0.554	1.074	1.207	1.263
DJIM → Czechia	1.704**	2.947***	3.835***	4.354***	4.676***
Czechia → DJIM	−0.206	0.620	0.786	1.294	1.912**
DJIM → India	4.099***	4.568***	5.096***	5.815***	7.118***
India → DJIM	6.367***	5.987***	5.695***	5.569***	5.605***
DJIM → Indonesia	7.947***	7.930***	8.526***	8.921***	9.075***
Indonesia → DJIM	−0.423	0.343	1.040	1.376	1.532
DJIM → S. Korea	10.862***	11.120***	11.169***	11.235***	11.695***
S. Korea → DJIM	0.089	0.147	0.855	1.241	1.635
DJIM → Malaysia	4.723***	4.500***	4.148***	4.602***	5.237***
Malaysia → DJIM	4.731***	3.341***	4.581***	5.977***	7.171***
DJIM → Mexico	0.259	1.071	1.699***	2.306**	2.553***
Mexico → DJIM	2.890***	3.000***	3.278***	3.525***	3.498***
DJIM → Poland	11.436***	12.563***	15.337***	17.169***	18.110***
Poland → DJIM	5.197***	5.601***	5.994***	5.999***	6.002***
DJIM → Russia	1.940**	5.553***	10.049***	12.487***	13.720***
Russia → DJIM	−0.565	0.350	0.788	1.208	1.750
DJIM → S. Africa	11.958***	12.089***	11.826***	11.866***	12.169***
S. Africa → DJIM	0.787	0.993	2.342**	3.500***	4.295***
DJIM → Turkey	0.305	2.536***	4.497***	5.710***	6.502***
Turkey → DJIM	−0.625	1.056	2.441***	2.978***	3.164***

Notes: *** and ** indicate statistically significant causal link at the 1% and 5% level, respectively. M denotes the maximum lag.

Korean stock market in the sample except for 2004–2007. More interestingly, we find unidirectional volatility spillovers from the South Korean stock market to the DJIM before the GFC and bidirectional volatility spillover in 2011–2014. The results also show a unidirectional causality from DJIM to the South Korean stock market during the Covid-19 outbreak. Similarly, the results in Panel (h) indicate volatility spillovers from DJIM to the Malaysian stock market within the sample except for 2008–2011. On the other hand, we only detect causality-in-variance running from the Malaysian stock market to the DJIM in 2002–2005, and 2009–2017.

The results in Panel (j) indicate bidirectional volatility spillovers between DJIM and the Polish stock market in specific periods such as 1999–2001, and 2012–2013. Although the volatility spillovers tend to be from the Polish stock market to the DJIM before the GFC, causality was reversed after the GFC. We also find unidirectional volatility spillovers from DJIM to the Polish stock market during the recent global Covid-19 pandemic. According to results in panel (k), there is some evidence in favor of a causal link between the Russian stock market and DJIM: DJIM causes the Russian stock returns in 1999–2001 and 2013 whereas the causality runs from the Russian stock market to the DJIM in 1999–2002 and 2009–2015. We find weak evidence in favor of volatility spillovers from the DJIM to the Russian stock market during the Covid-19 outbreak because test statistics are generally borderline. Empirical results for the Turkish stock market indicate unidirectional or bidirectional volatility spillover between the DJIM and the Turkish stock market until 2017. On the other hand, the time-varying test results show that the link between the DJIM and the Turkish stock market has weakened after 2017. However, there is a significant spillover from the DJIM to the Turkish stock market after the declaration of Covid-19 as a global pandemic.

Overall, the time-varying test results show that the link between DJIM and emerging stock markets was generally strong in the period surrounding the GFC. Also, the volatility spillover effects between Islamic markets and emerging markets increased towards the end of the sample as we detect significant volatility spillovers from DJIM to emerging stock markets during the recent global Covid-19 pandemic. These results do not lend support to the 'safe heaven' hypothesis. Moreover, the decoupling hypothesis is rejected after the GFC as there are significant causality relationships between DJIM and conventional emerging markets in at least one direction in all countries.

Finally, we employ a causality-in-risk test to ascertain whether there is a relation between DJIM and emerging stock markets during financial distress periods. To that end, we use a GARCH model with dummy variables and calculate VaR at the 5% level. Then we calculate the test statistic in Eq. (10) and present downside causality test results in Table 6. The results in Table 6 show causality in risk situations from DJIM to all emerging stock markets except for Argentina. This finding suggests that unexpected losses in emerging stock markets can be predicted by unexpected losses in DJIM. More specifically, while the risk spillovers from DJIM to most emerging stock markets happen immediately, it happens with a time delay for some stock markets such as Brazil, Mexico, and Turkey because the causal link is statistically significant at higher lag lengths in these countries.

Results in Table 6 indicate risk spillovers from Brazil, the Czech Republic, India, Malaysia, Mexico, Poland, South Africa, and Turkey to DJIM which indicates unexpected losses in DJIM can be predicted via sudden past losses in these countries. This also suggests that there is weak evidence favoring DJIM as a safe-haven for these countries because there are risk spillovers between DJIM and the countries in question. However, we cannot ascertain risk spillovers from Argentina, China, Indonesia, South Korea, and Russia to DJIM which lends partial support for the safe-haven hypothesis. Overall, risk spillover test results show all emerging stock markets except for Argentina provide limited safe-haven properties for DJIM because there are significant downside causality links from DJIM to all emerging countries except for Argentina. On the other hand, DJIM can provide investment alternatives for Argentina, China, Indonesia, South Korea, and Russia because no risk spillovers from the emerging stock markets in question to DJIM can be detected.

5. Concluding discussion

During the global financial crisis, the synchronized collapse of developed and emerging stock markets demonstrated the limited ability of significant diversification benefits afforded by emerging markets for international investors, which prompted international investors to seek alternative investment vehicles. The growing Islamic financial instruments and portfolios emerged as a serious alternative to existing financial instruments with potential diversification benefits. Preliminary empirical evidence demonstrated that the global financial crisis had less of an impact on Islamic financial markets compared to the conventional ones, which lent credence to the idea that Islamic financial markets can be considered as safe havens during financial crises.

The growth in Islamic financial markets sped up recently and the total assets of the Islamic financial services industry has exceeded $2 trillion worldwide by 2017. The fast growth of the Islamic financial system has attracted the attention of academics and practitioners with an increasing number of studies examining different aspects of investment opportunities afforded by the Islamic financial instruments. A number of studies documented interactions between Islamic and conventional markets, yet scant attention has been paid to volatility spillover effects and their time-varying nature.

This study examined the relationship between Islamic and conventional stock market returns and whether Islamic financial markets provide portfolio diversification benefits and safe havens during turbulent times. We consider 13 major conventional emerging market stock returns and the Dow Jones Islamic Stock Market Index (DJIM) and examine the dynamic interactions between Islamic stock returns and emerging market returns via causality-in-variance and dynamic conditional correlations tests. We also estimate the time-varying causality-in-variance test in rolling subsamples to better understand the evolving nature in the relationship between the Islamic and emerging stock markets. Finally, we use causality in risk tests to assess time-varying Value at Risk (VaR) for returns to ascertain any downside risk.

The causality-in-variance test results show causality between Islamic stock returns and all emerging stock returns in the sample in at least one direction. On the other hand, the time-varying causality-in-variance test results indicate there is causality between Islamic stock returns and emerging stock returns in at least some subsamples. Evidence of volatility spillovers indicates Islamic markets provide limited safe havens during distress periods with some contagion between Islamic and conventional stock returns. Results from both time-varying conditional correlations and the hedge ratios show there are positive and significant correlations between emerging stock markets and DJIM, which implies limited portfolio diversification benefits afforded by Islamic stock markets.

Unlike (El-Alaoui et al., 2015; Ghorbel et al., 2014; Jawadi et al., 2014), and Kenourgios et al. (2016), our results provide limited evidence that Islamic Finance instruments serve as alternatives to existing conventional financial instruments with potential diversification benefits. Even though some studies found out that Global Financial Crisis had impacted Islamic financial markets less compared to the conventional ones (Dewandaru et al., 2014, 2015, Al-Khazali et al., 2014), our results have evidence that Islamic financial instruments provide little safe havens during financial market distress. Our results are more in line with Boujelbène (2012), and Umar (2017) where Islamic equities provide desirable attributes for the faith-based investors not necessarily from a portfolio allocation point of view. Our results also broadly corroborate work by Jawadi et al. (2020) who examined the relation between Islamic and conventional (world and the US) stock markets and found positive and significant correlations between Islamic and conventional stock markets.

Overall, our empirical findings imply that international investors facing different markets and instruments will have limited diversification benefits and performance improvements in their investment portfolios if they include Islamic financial instruments. Portfolios formed in this fashion will not have superior performance or hedge ratios in crisis and calm periods. Finally, future work on Islamic financial markets and instruments can compare different portfolios returns and contagion across periods based on trading strategies that compare portfolios' returns across stable and crisis periods using volatility forecasting models. Additionally, it would be interesting to add whether gold and other commodities provide safe-haven for returns of Islamic stock markets. These would add to the body of evidence regarding the interrelationships between Islamic, commodities, and conventional markets.

Declaration of competing interest

There is no conflict of interest.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.bir.2021.01.007.

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