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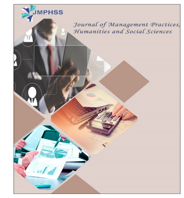

ORIGINAL CONTRIBUTION

Dynamic Linkages among Stocks and Commodities: A Switching Copula Approach

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Abstract— The fluctuating behavior of financial markets has significant impact on economic variables. A relatively new modeling technique, "switching dependence copula" is employed to characterize conditional dependence among stock indices (Islamic/conventional stocks) and commodities. As the dependence may switch in between negative and positive correlation regimes with the passage of time where the copula captures dependence structure more conveniently and portrays pictures most relevantly then a single copula regime. The sample period ranges from 2011 to 2021. All the data sourced from Thomson Reuters. Overall, the results are in favor of commodities phenomenon of providing better hedging and diversification benefit to stock indices. Fluctuating behavior is observed for Islamic stocks and commodities pairs. According to the results, commodities are suitable as cousin during crisis period, especially during negative correlation regime; commodities perform better, providing hedging and diversification benefits.

Index Terms— Commodities, Islamic stock, Conventional stock, Copula, Diversification.

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Introduction

This world is global village at present, as countries are more and more interconnected. Changes in the conditions of one country impact the conditions in other countries. Countries trade with other countries to fulfill their needs of physical goods and services. Changes in the conditions in one country impact it's neighboring countries and the economies of its trading partners actively or passively. These changes include all types of physical and economical changes like law-in-order situation, political environment, economic policies, climatic conditions etc. The inter dependence between economies has increased their financial dependence also (Azimli et al., 2022; Chang et al., 2022; Khalfaoui et al., 2021; Kumar et al., 2021). Countries are investing or purchasing from different countries to get competitive edge, they want to get best at lowest prices to make profit and prosperity. There's nothing like "perfect investment" exist, but designing a strategy which can offers maximum returns and relatively low risk is main concern for all investors. This strategy evolved in latter half of 20th century. In 1952, Harry Markowitz wrote his dissertation on "Portfolio Selection", contained theories caused transformation in the field of portfolio management. Markowitz demonstrated that, risk of portfolio needed to be focused and addressed instead of focusing risk or volatility of individual asset. He also stated that a diversified portfolio is less volatile than the total sum of its individual parts, where each asset might be quite volatile itself. According to Prospect theory, formulated initially in 1979 and developed later in 1992 by Amos Tversky and Daniel Kahneman, how individuals take decisions, when compared with the expected utility theory. Losses and gains are valued differently, and consequently individuals formulate decisions based upon these perceived values. It describes how individual investor makes a selection among probabilistic alternatives where risk is implicated and the probability of different outcome is not known. According to Tversky and Kahneman, losses cause greater emotional impact on individual than an equivalent amount of gain.

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The relation between equity markets and asset classes reveal a safe measure for policy makers during uncertainty and improves the stability of financial markets (Azimli et al., 2022; Shahzad et al., 2018). The interdependence of global commodity classes and equity markets is significantly reported high in short term (Bossman et al., 2022). Tiwari et al. (2020) investigate local dependence among different markets e.g., agriculture, energy and metal using the copula model. The findings highlight strong dependence between commodity markets and energy stocks at the lower tail. Co-movements exist in and between bear and bull markets. In today's competitive and interconnected world, diversification plays an important role for fund managers to get potential benefits (Tiwari et al., 2018).

This research concentrated on the various traits of Conventional and Islamic stock indices at various scales. First, it is examined whether or not any investor can profit from diversification by combining several Islamic and traditional stock indices with GSCI. The next step is to discuss how stock indices react to volatile market conditions. Considering that they are thought to offer hedging or safe haven benefits in times of crisis, combining equities with alternative assets and their combined behaviour is also investigated. Islamic stock indexes are thought to be more resilient to financial crises than traditional conventional stock indices (Charles et al., 2015; Kolid & Sukmana, 2012). Financial integration between equities was demonstrated by Wang et al. (2010); they discovered that it has lately grown globally. Only the visibility of co-movement between stocks and assets may make portfolios diversifiable. It is stated that the ability to distinguish between conventional stock markets and their Islamic analogues is mostly a result of avoiding fundamental risk concerns. Islamic securities can be distinguished from conventional markets by either of these segmentation features, and they can also provide important diversification advantages to investors in international markets. The contrast between Islamic and non-Islamic (conventional) markets is now clearly in the spotlight. This essay will aid in comparing the actions of Islamic and Conventional markets. This will aid in understanding the market when making investment decisions.

The Islamic financial markets are expanding quickly. The size of Islamic financial services business increased from $150bn in 1990 to $2 trillion to 2015 and was expected to be at $3.5 trillion by 2021 (McKenzie, 2009; Thomson Reuters, 2014-15; 2016). Stock markets have gone through numerous downturns since the start of this millennium, and significant unfavorable changes in financial markets impacted significantly. Policy makers and investors will better grasp the connections between different market players and their potential consequences on the global economy. Multiple econometric approaches, such as GARCH and copula-based methodologies, are able to capture dependence and impacts of spillover for extreme movement, and to examine linkages between stock indexes. Tail dependency for random variables can be handled with copula-based models, which are suitable and effective (Patton, 2006). The dependence-switching copula model was developed by Wang et al. (2013) to reveal tail dependence among stock indexes and alternative assets. Changes in dependence structure between negative and positive correlation regimes across stock indices and other asset markets can be reflected by using the dependence-switching copula model. As far as we are aware, no research has previously examined the relationship between stock indexes and alternative assets as well as their integration via switching copula. For the period of March 2011 to March 2021, daily data are used for empirical study of two stock indices (Islamic stock and conventional stock) and the GSCI. Estimates of the dependence and tail dependence reveal that the regime-switching model is sensitive to the tail-risk dependence. Tail dependency in the data results is used to identify an asymmetric influence. When dependency is permitted to transition between distinct regimes, dependence structure is particularly helpful for improving pricing, portfolio hedging, and downside risk spillover predictions (Chollete et al., 2009; Wang et al., 2013).

Objective of the research was to study traits of Conventional/Islamic stock indices in different market situation. Firstly to examine, whether an investor can get diversification benefit by combining Islamic/conventional stock indices with GSCI. The next step was to discuss how stock indices react to volatile market conditions, considering that they offer hedging or safe haven benefits in times of crisis, combining stocks with GSCI and their combined behavior is also investigated.

The remainder of the paper is organized as follows: Section 2 reviews literature. Empirical models are demonstrated in Section 3. Results and debates are presented in Section 4, and conclusion in Section 5.

Literature Review

The interdependence between economies has increased their financial dependence also (Azimli et al., 2022; Khalfaoui et al., 2021; Kumar et al., 2021). Countries are investing or purchasing from different countries to get competitive edge, they want to get best at lowest prices to make profit and prosperity. The relation between equity markets and asset classes reveal a safe measure for policy makers during uncertainty and improves the stability of financial markets (Azimli et al., 2022; Shahzad et al., 2018). The interdependence of global commodity classes and equity markets is significantly reported high in short term (Bossman et al., 2022). Tiwari et al. (2020) investigate local dependence among different markets e.g., agriculture, energy and metal using the copula model. The findings highlight strong dependence between commodity markets and energy stocks at the lower tail. Co-movements exist in and between bear and bull markets. In today's competitive and interconnected world, diversification plays an important role for fund managers to get potential benefits (Tiwari et al., 2018).

Ocal and Oztek (2017) also looked at the time-varying relationships between the equities and commodity markets during the global financial crisis and its immediate aftermath. They found that commodities offer superior prospects for hedging effectiveness. In 2016, Dimitris, K. Nader, N. Dimitrios, studied effects of global financial crisis (GFC) and the Eurozone Sovereign Debt Crisis (ESDC) on Islamic stock indices. Their findings imply that Islamic securities, particularly during volatile times, can serve as a buffer against market risks and instabilities. Rizvi et al. (2015) made a study and recommended using Islamic stocks and their makeup as financial stability buffers. Mghaieth's and El Mehdi's (2017) made analysis of the correlations between volatility in conventional and Islamic markets and supports using Islamic stocks as effective hedging instruments. Wajahat et al. (2019) looked at the benchmarks of the world equity market and compared them to Islamic sustainability equity indices. They discovered that investors should not put their money into Islamic or sustainable equity indices. An investor can gain greater benefits by combining Islamic equities indices with sustainable investment strategies, particularly during economic boom times, bullish market times, and during the subprime crisis. Erb and Harvey (2016), has studied the commodity futures returns differ overtime from traditional asset classes. the conditional correlations between commodity futures and equity returns fell in periods of market turbulence. The institutional investors can use commodity futures as cousin in high market volatility periods and that the major events (e.g, rise in unexpected inflation) do not impact commodity futures and equities prices in the similar ways.

In the examination of securities and tail risks, copula has become widely used. The method's simplicity drew researchers' and market practitioners' attention to the valuation hazards. The first person to apply Gaussian copula models for collateralized pricing debt obligations was Li (1999). In-depth research by Das and Geng (2004) evaluated the mutual default mechanism of issuers using a variety of copula functions and the conventional Clayton, Gumbel, and Student t copula. Copula functions were used by Ghorbel et al. (2017) to examine the relationship between oil and agricultural commodities. Jiang et al. (2017) studied the dynamic connection between the oil market, agricultural raw material markets, and metal markets using copula. Many techniques, including co integration, VECM, Granger causality, structural VAR, multivariate GARCH, wavelets, graph theory, regime-switching VECM, quantile regression, and copula, were used in research to examine the link between stocks and alternative assets. This work varies from other research in that it emphasizes reliance over linear correlation, concentrating in particular on regime switching dependence rather than time-varying, single regime dependence. Additionally, it includes the negative spillover risks from/to alternative assets to stock indices.

Methodologies

The dynamic dependences between stock indices (Islamic and conventional) and alternative (GSCI) are modeled by using a time-varying copula model with a switching dependence. The joint distribution of stock indices and alternative assets is obtained to estimate risk spillover measures across markets. The data consist of two types of stocks indices (Islamic stocks and conventional stocks) and Global Commodity Index as alternative assets. The selected sample countries includes Belgium, France, Germany, Hong Kong, India, Ireland, Italy, Japan, Malaysia, Mexico, Nether Land, Norway, New Zealand, Poland, South Africa, Singapore, Spain, Turkey, UK, and USA. The sample period ranges from 2011 to 2021, yielding a total of 2501 daily observations. All the data sourced from Thomson Reuters.

Copula modeling

copula is a multivariate distribution function with uniform distribution margins with the interval (0,1). According to Sklar's (1959) theorem, for bivariate time series

$r_t = (r_{1,t}, r_{2,t})$, their joint distribution F can be expressed in terms of a copula function, and the marginal distribution functions of these two random variables are as follows:

"$F(r_1, r_2;) = C_t(F_1(r_1;_1), F_2(r_2;_2);)$"

where parameter $\theta = (\theta_1', \theta_2', \theta c')'$, C_t is the copula dependence structure, and F_1 and F_2 are marginal distribution functions of returns r_1 and r_2, respectively.

Accordingly, the joint density:

"$(r_1; r_2; |_t - _1) = c_t(F_1(r_1;_1), F_2(r_2;_2); c)\cdot_1(r_1;_1)\cdot_2(r_2;_2)$"

where c_t is the copula density, and f_1 and f_2 are the marginal densities of r_1 and r_2, respectively.

Dependence-switching modeling

Markov-switching copula model proposed by Wang et al. (2013) to capture these two regimes, state-varying copula is designed as follows:

$$C_{st}\left(u_{1,t}, u_{2,t}; \theta^{p}c; \theta^{n}c\right) = \begin{cases} C^{1}\left(u^{1}\cdot t^{m}u^{2}\cdot t^{1}; \theta^{1}c\right), & \text{if } s_t = P \\ C^{0}\left(u^{1}\cdot t, u^{2}\cdot t^{2}; \theta^{o}c\right), & \text{if } s_t = N \end{cases}$$

Where $u_{1,t}$, $u_{2,t}$ are probability integral transforms of $r_{1,t}$, $r_{2,t}$ based on marginal distribution functions. St is the state variable, $S_t \in$ P, N. P and N denotes positive and negative dependence regime, respectively. $C_o(\cdot)$ and $C_1(\cdot)$ are two mixed copulas with positive and negative dependence structures, respectively. The state variable St follows an order-one Markov chain parameterized by a transition probability matrix, as shown in Eq:

$$P = \begin{Vmatrix} Pnn, & 1 - Pnn \\ 1 - Ppp, & Ppp \end{Vmatrix}$$

where Pij = Pr[S_t= j|S_t = i] for i, j=N, P. P_{nn} is the probability of being in the negative dependence regime at time t that is conditional on being in the same regime at t−1. Whereas P_{pp} is probability of positive dependence regime. To capture the asymmetric tail dependence, the Clayton copula and its transformational copulas are chosen. Therefore, the Clayton copula and 180-degree Clayton copula are mixed as $C_1(.)$ to model positive dependence, while the 90-degree rotated Clayton and 270-degree rotated Clayton are mixed as $C_o(.)$ to model negative dependence (Liu et al., 2017b; Wang et al., 2013).

C_1 ($u_{1,t}$, $u_{2,t}$; θ^1C) = 0.5 Cc ($u_{1,t}$, $u_{2,t}$; α_1) + 0.5 CSC ($u_{1,t}$, $u_{2,t}$; α_2)

C_o ($u_{1,t}$, $u_{2,t}$; θ^1C) = 0.5 Cc (1−$u_{1,t}$, $u_{2,t}$; α3) + 0.5 CSC (1− $u_{1,t}$, $u_{2,t}$; α4)

where Cc (u, v; α) = (u- + v-−1)$^{-1}$/œ, CSC (u, v; α) = u + v−1 + Cc(1− u,1− v; α) and α ∈ (0, ∞). $C_1(\cdot)$ can measure two positive cases where both markets are bearish or bullish, and $C_o(\cdot)$ can measure two negative cases where one market is bullish while the other one is bearish. Furthermore, the Kendall's τi, the correlation coefficient ρi and the tail dependence φi can be obtained by transforming the copula parameters αi with τi = αi/(2 + αi), ρi= sin (π*τi/2) and φi = 0.5∗2ˉ1/αi for i = 1, 2, 3, 4 (Wang et al., 2013). Therefore, the joint density function considering the unobserved regime variable s_t is as follows:

$$f\left(\mathrm{r}_{1,t}, \mathrm{r}_2, \mathrm{t}; \theta^{\mathrm{p}}\mathrm{c}, \theta^{\mathrm{n}}\mathrm{c}, \theta^{\mathrm{p}}, \theta^{\mathrm{k}}\right) = \left\{\sum \mathrm{j} \in (\mathrm{p} = \mathrm{N}) \,\mathrm{Pr}\left(\mathrm{S_t} = \mathrm{j}\right) \mathrm{cj}\left(\mathrm{u}_{1,t}, \mathrm{u}_{2,t}; \theta^{\mathrm{j}}\mathrm{c}\right)\right\} \mathrm{X}$$
$$\Pi^2{}_{\mathrm{k}=1}\left\{\sum \mathrm{j} \in (\mathrm{p} = \mathrm{N}) \,\mathrm{Pr}\left(\mathrm{S_t} = \mathrm{j}\right) f_{\mathrm{k}}\left(\mathrm{r}_{\mathrm{k},t}, \theta^{\mathrm{j}}, \mathrm{S_t} = \mathrm{j}\right)\right\}$$

where cj(·) is the copula under regime j, θ^jc is its parameter set, and θ^j is the parameter set of the marginal distribution under regime j.

Marginal distribution modeling

Referring to most of the previous literature (Liu et al., 2017a, 2017b; Patton, 2006;) and considering the autocorrelation and volatility persistence, we employ an ARMA(m, n) GARCH(p, q)-skewed Student-t model to construct the following marginal distributions:

$$\mathrm{r}_{\mathrm{i},2} = \varphi + \sum_{\mathrm{j}=1}^{\mathrm{m}} \varphi \mathrm{r}_{\mathrm{i},t-\mathrm{j}} + \varepsilon_{\mathrm{i,t}} + \sum_{\mathrm{n}=1}^{\mathrm{n_j}} \Psi\mathrm{j}\varepsilon_{\mathrm{i,t-j,i}} = 1, 2$$

$$\varepsilon_{i,t} = \sigma_{i,t} Z_{i,t}, Z_{i,t} \sim \text{ i.i.d.skst }_{vi},$$

$$\sigma^2_{\mathrm{i,a}} = \alpha_0 + \sum \mathrm{p}_{\mathrm{j}=1} \alpha \mathrm{j} \varepsilon^2 \mathrm{i}, \mathrm{t}-\mathrm{j} + \sum_{\mathrm{j}=1} \varphi_{\mathrm{j}} \sigma^2_{\mathrm{i,t-j}}$$

where εi, t is the error term, and $\sigma^2{}_{i,\ t}$is the conditional variance of returns. zi, t denotes the standardized residual following the skewed Student-t distribution, which allows for non-zero skewness and excess kurtosis. υ_i is the degree of freedom for the skewed-t distribution. The details of the skewed Student-t density distribution are defined as follows (Hansen, 1994):

$$\int (\mathrm{z_t}, \quad \mathrm{v}, \quad \eta) = \begin{cases} bc\left(1 + \frac{1}{v-2}\left(\left(bz_t + \alpha\right)/(1-\gamma)\right)^2\right) - \frac{v+1}{2} & , zt < -\frac{a}{b} \\ bc\left(1 + \frac{1}{v-2}\left(\left(bz_t + \alpha\right)/(1-\gamma)\right)^2\right) - \frac{v+1}{2} & , zt < -\frac{a}{b} \end{cases}$$

where v and η are the degree of freedom parameters (2 < v ≤ ∞) and the symmetric parameter (−1 < η < 1), respectively. The constants a, b and c are given by a = 4ηc(v−2/v-1), b^2 = 1-3η−a^2 and c = Γ(v+1/2)/ Γπ(v−2)Γ (v/2), respectively.

Model estimation

Following the estimations strategy proposed by Li (2005), copula density and marginal densities are estimated individually. Inference for Margins (IFM) is applied for the estimations of mixed copula model proposed by Joe and Xu (1996). This IFM approach is a two-step procedure, the parameters of marginal models are estimated at first, after that copula parameters are estimated by marginal parameters. The marginal ARMA(m,n)-GARCH(p,q) models, with each having skewed Student-t distribution, are estimated using combinations of lag parameters m,n,p and q for values of lags ranging from zero to three. AIC is used to select best lag combination for each marginal model.

Theoretically, we can use a specific distribution to transform the standardized residuals is known. The exact distribution of the standardized residuals is unknowable empirically, and thus, applying a specific distribution to transform the standardized residuals may not result in a uniform distribution. The Canonical Maximum Likelihood (CML) approach highlights that transforming standardized residuals, regardless of the specifications of the marginal models, based on an empirical CDF will always result in a uniform distribution asymptotically. To avoid misspecification in the marginal models, we follow the CML approach to transform the standardized residuals into a uniform distribution using the following empirical marginal cumulative distribution function:

$F^\wedge k(\omega) = (1/\mathrm{T}+1) \sum \mathrm{T}_{\mathbf{t=1}} I\ (\eta^\wedge \mathrm{k} \leq \omega)$

Where I(.) is an indicator function that is one if $\hat{\eta}k; t \leq \omega$ and zero otherwise. Next, we obtain cumulative probability for each observation of $\eta^k; tbyu^k; j =^F\ k(\eta^k; j)$, k = 1,2, j = 1, 2,..., T. Given the estimated marginal parameters, we estimate the copula parameters ψ by maximizing the log-likelihood function Lc(ψ1). Because the dependence structure follows a Markov-switching process, we use Hamilton's filtered system to transform the log-likelihood function of the model as follows:

$Lc(\psi 1) = log(\hat{\xi}' t/t{-}1\eta t)$

$\psi 1 = arg\psi_1 max \sum_{\mathbf{t=1}} T Lc(1)$

Optimal Portfolios

Following Reboredo (2012), Reboredo and Rivera-Castro (2017), Hammoudeh et al. (2014) and Mensi et al. (2015b), this paper compare the risks of three mixed asset portfolios (II, III, IV) with the risk of benchmark portfolio.

Benchmark Portfolio

The benchmark stock index of each country traded at their respective stock exchange is considered as the benchmark portfolio (Portfolio I) which is composed of stocks indices (Islamic and conventional) only. The usefulness of alternative assets (GSCI) is evaluated to assess the potential reduction in the risk of the benchmark equity portfolio.

Risk Minimized Portfolio

without reducing the expected returns, a risk-minimizing (e.g., stock indices and alternative assets) Portfolio (II), is formed following to Kroner and Ng (1998) where the optimal weights are given as:

$$Wt^{\mathrm{AA}} = \frac{h_t^s - h_t^{AAs}}{h_t{}^A - 2h_t{}^{Ads} + h_t^s} \text{with} Wt^{\mathrm{AA}} = \begin{cases} 0 & Wt^{\mathrm{AA}} < 0 \\ Wt^{\mathrm{AA}} 0 \leq & Wt^{\mathrm{AA}} \\ 1 & Wt^{\mathrm{AA}} > 1 \end{cases}$$

The conditional volatility of an alternative asset is represented by ht^{AA}, the conditional volatility of a stock by ht^{s} and the conditional covariance between the alternative asset and a stock at time t by ht^{AAs}. The optimal weight of the stock (i.e., (1 - Wt^{AA})) and for each pair, the information on wt^{AA} is obtained from the rolling window analysis.

Variance Minimized Portfolio

In Portfolio III the weights are determined using the variance-minimizing strategy, e.g., having a long position in a stock market and a short position in an alternative asset, given as:

$\beta_t = \frac{h_t^{AAs}}{h_t^{AA}}$

Equally Weighted Portfolio

Finally, Portfolio IV is composed of equal weights of a stock and an alternative asset is considered similar to that in DeMiguel et al. (2009). This implies that the wealth is distributed equally between stock index and each of the alternative assets.

Risk and Downside Risk Measures

Different risk and downside risk measures are applied to compare the performance of optimal portfolios following Reboredo (2013), Hammoudeh et al. (2014), Chkili (2016) and Harrathi et al. (2016).

Risk Reduction Effectiveness

The Risk-reduction Effectiveness (RE) of a multi asset portfolio P_j is assessed by comparing the percentage reduction in the variance of the multi asset portfolio relative to the variance of the benchmark Portfolio I which is the only stock portfolio:

$$REvar = \frac{1-(Var(Pj))}{(Var(PI))}$$

where P_j indicates the three different portfolios (II, III, IV) and $Var(Pj)$ and $Var(PI)$ denotes the variance of the jth multi asset portfolio and the variance of Portfolio I, respectively. The $REVar$ values lie between 0 and 1 and a higher value indicates a higher variance reduction.

Value-at-Risk Reduction Effectiveness

The rolling conditional correlations and volatilities are used to explore portfolio diversification effects of GSCI, while using different analytical measures such as Value-at-risk reduction, expected shortfall, Semivariance and Regret reduction. The VaR provides information about the maximum loss in a portfolio at a given time t with a confidence level (1-p) with the expected return Rt on a given portfolio. That is, Pr ($Rt \leq VaRt|\psi t{-}1$) = p However, the VaR of a given portfolio can be computed as:

$$VaRt\ (p) = \mu t - t_v^{-1}\ (p)\ \sqrt{ht}$$

where the conditional mean and standard deviation of asset is denoted by μt and $\sqrt{ht}$, respectively, along with the $tv{-}1(p)$, the pth quartile of the t-distribution and the v degrees of freedom.

Expected Shortfall

The expected size of loss because of exceeding VaR is described as the expected short fall (ES) as under: $ES = E$ (Rt|Rt<VaRt(p))

Semi Variance

The returns variability which is below a specific threshold are measured by the Semivariance (SV) approach unlike the variance measure that use equal weights for positive and negative returns and it is given as:

SV=E[min0,Rt– E(Rt)]2

Regret Reduction Effectiveness

Finally, the values of expected returns which are below zero are by the regret reduction (Re) given as under:

$R = -[min 0, Rt]$

Descriptive statistics reported in table1 shows that average daily mean returns of all stock indices and alternative assets ranged from 0.001 to 0.024. Average returns for Islamic stock indices ranges from 0.001 to 0.024 and from 0.002 to 0.024 for conventional stock indices, and for GSCI is 0.024. However, the standard deviation ranges from 0.006 to 0.024. The highest standard deviation is reported for Ireland for Islamic stocks 0.017, and Malaysia reported lowest standard deviation with a value of 0.006 for conventional stocks. Islamic stock markets have the larger range for the maximum and minimum then conventional stock market, and their behavior is more volatile. The return distributions for the stock indices (Islamic and conventional) and alternative assets (GSCI) are positively skewed. The mass of the distribution is concentrated on left. All the return series exhibit excess kurtosis and are rejected following a normal distribution. The kurtosis coefficient and Jarque-Bera test statistics show that the return series are not normally distributed. The null hypothesis of normality is rejected at 1% significance level. The unit root tests of ADF are calculated. These tests show consistent results: each variable is stationary by significant ADF.

Table I
Descriptive statistics

		Mean	St. Dev	Kurtosis	Skewness	Min	Max	J-B	ADF
BEL	ISL	0.001	0.012	138	31.91	-0.128	0.071	198	-100.69
	CON	0.002	0.011	233	47.45	-0.142	0.076	567	-270.75
FRA	ISL	0.002	0.012	239	48.4	-0.117	0.095	597	-345.1
	CON	0.003	0.012	244	49.21	-0.123	0.084	624	-490.31
GER	ISL	0.003	0.012	246	49.43	-0.116	0.091	632	-579.3
	CON	0.004	0.012	247	49.64	-0.122	0.11	639	-731.06
HON	ISL	0.004	0.008	249	49.85	-0.072	0.047	646	-20.82
	CON	0.005	0.011	248	49.83	-0.058	0.056	645	-19.93
IND	ISL	0.006	0.011	248	49.84	-0.116	0.097	646	-21.18
	CON	0.007	0.01	249	49.89	-0.128	0.077	647	-21.23
IRE	ISL	0.007	0.017	249	49.89	-0.132	0.119	647	-970.18
	CON	0.008	0.012	249	49.9	-0.099	0.069	648	-19.82
ITA	ISL	0.008	0.016	249	49.85	-0.169	0.145	646	-51.61
	CON	0.009	0.015	249	49.88	-0.169	0.089	647	-53.93
JAP	ISL	0.009	0.012	249	49.92	-0.073	0.08	648	-18.94
	CON	0.01	0.013	249	49.93	-0.079	0.08	648	-52.4
MAL	ISL	0.01	0.007	249	49.96	-0.052	0.058	650	-22.38
	CON	0.011	0.006	249	49.97	-0.053	0.069	650	-18.74
MEX	ISL	0.011	0.011	249	49.95	-0.068	0.077	649	-18.38
	CON	0.012	0.01	249	49.96	-0.064	0.049	650	-18.56
N.LAND	ISL	0.013	0.012	249	49.95	-0.09	0.101	649	-20.52
	CON	0.014	0.011	249	49.96	-0.108	0.09	650	-20.02
New Zealand	ISL	0.014	0.011	249	49.96	-0.084	0.09	650	-20.8
	CON	0.015	0.007	249	49.97	-0.076	0.072	650	-47
	ISL	0.015	0.012	249	49.96	-0.085	0.058	650	-19.76
NOR	CON	0.016	0.011	249	49.97	-0.094	0.06	650	-19.45
POL	ISL	0.016	0.014	249	49.96	-0.106	0.085	649	-27.32
	CON	0.017	0.01	249	49.97	-0.127	0.058	650	-27.32
SIN	ISL	0.017	0.009	249	49.96	-0.073	0.073	649	-21.14
	CON	0.018	0.008	249	49.97	-0.074	0.061	650	-22.02

Notes: J-B is Jarque Bera normality test. Denotes the rejection of null hypotheses of normality no autocorrelation, unit root, non-stationarity, and conditional homoscedasticity at 1% significance level. "ISL" denotes Islamic stocks and "CON" conventional stocks.

Marginal model's estimations

Table II presents results of parameters estimation for marginal specification of ARMA-GARCH skewed-t model. The optimal lagged order for each return of model is determined by different combination of AIC, ranging from 0 to 3, each return follows different ARMA(m,n) type of mean equations, but most coefficients are significant at 1% level. The sum of ARCH and GARCH terms is close to one for each equation of votality, indicating persistence of high volatility. The values for degree of freedom of skewed-t distribution ranged from 2 to 8, representing non normal and heavy tails for error terms. The asymmetry coefficient is positive and significant at 1% level for all series, further indicating that the heavy tail is skewed to the right. This means large positive returns are more likely than large negative returns.

The Ljung-Box statistics of Q(20) and $Q^2(20)$ and the ARCH-LM tests fail to reject the null hypothesis that there is no serial correlation and conditional heteroscedasticity at significant level of 1%. Comparing these test results with descriptive statistics shows that the marginal distributions are well specified by the constructed ARMA-GARCH skewed-t models, presented in table below.

Table II
Marginal estimation using ARMA-GARCH skewed-*t*-model

Country	Belgium		France		Germany		Hong Kong		India	
	ISL	CON	ISL	CON	ISL	CON	ISL	CON	ISL	CON
Panel A : Mean equation										
Constant	0.001 (0.000)	0.001 (0.000)	0.001 (0.000)	0.001 (0.000)	0.001 (0.000)	0.001 (0.000)	0.000ˆ (0.000)	0.000* (0.000)	0.001* (0.000)	0.001 (0.000)
AR(1)					0.142 (0.000)		0.076 (0.005)	0.066 (0.000)	0.062 (0.001)	0.055 (0.000)
AR(2)										
MA(1)	0.000 (0.020)	0.005 (0.021)	-0.054 (0.020)	-0.041* (0.020)	-0.178 (0.019)	-0.025 (0.019)	-0.065 (0.020)		-0.004 (0.019)	0.007 (0.020)
MA(2)	-0.029 (0.021)	-0.003 (0.023)	-0.005 (0.022)	-0.011 (0.022)		-0.001 (0.022)				0.003 (0.022)
MA(3)	0.0015 (0.0203)									
Panel B : Variance equation										
Constant	0.103 (0.033)	0.104 (0.028)	0.096 (0.024)	0.117 (0.0324)	0.023 (0.008)	0.193 (0.053)	0.014 (0.006)	0.017* (0.008)	0.047 (0.017)	0.033 (0.010)
ARCH (Alpha1)	0.129 (0.027)	0.207 (0.031)	0.240 (0.032)	0.266 (0.039)	0.069 (0.015)	0.260 (0.039)	0.052 (0.013)	0.052 (0.011)	0.061 (0.013)	0.044 (0.016)
ARCH (Alpha2)	0.795 (0.043)									0.037 (0.024)
GARCH (Beta1)		0.716 (0.040)	0.721 (0.030)	0.695 (0.038)	0.917 (0.016)	0.665 (0.042)	0.926 (0.020)	0.936 (0.014)	0.893 (0.026)	0.883 (0.025)
Asymmetry	-0.035 (0.025)	-0.037 (0.025)	-0.041 (0.025)	-0.046ˆ (0.025)	-0.071 (0.022)	-0.033 (0.022)	-0.050 (0.023)	-0.042ˆ (0.022)	-0.056 (0.023)	-0.103 (0.025)
Tail	5.174 (0.756)	4.748 (0.614)	4.259 (0.474)	4.019 (0.412)	4.765 (0.546)	3.577 (0.332)	5.070 (0.541)	5.127 (0.540)	5.560 (0.656)	5.600 (0.6858)
Panel C : Diagnostic tests										
LL	7811.52	8065.42	7905.59	7848.01	7822.03	7761.40	8646.69	7888.64	8039.62	8283.85
AIC	-6.240	-6.441	-6.313	-6.267	-6.246	-6.198	-6.905	-6.300	-6.420	-6.614
ARCH LM(10)	[0.438]	[0.151]	[0.062]	[0.164]	[0.486]	[0.056]	[0.104]	[0.484]	[0.363]	[0.834]
Q(20)	[0.891]	[0.973]	[0.986]	[0.993]	[0.183]	[0.996]	[0.413]	[0.672]	[0.348]	[0.330]
$Q^2(20)$	[1.000]	[1.000]	[1.000]	[1.000]	[0.999]	[1.000]	[0.999]	[0.405]	[0.800]	[0.5910]

Notes: table reports ML estimates and standard deviations in parenthesis for the parameters of marginal distribution model defined in equations. The lags m,n,p and q are selected by using AIC for different combinations of values, ranging from 0 to 3. L jung-Box statistics for serial correlation in model residuals and squared residuals is presented by Q(20) and $Q^2(20)$ respectively, computed with 20 lags. ARCH is the Engle LM test for the ARCH effect in residuals up to 10th order. The *p*-values in the square brackets[] below 0.05 indicates rejection of null hypothesis. Bold numbers represents significance at the 1% level. ˆat 5% level and * Represents 10% significance level.

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Country	Ireland		Italy		Japan		Malaysia		Mexico	
	ISL	CON	ISL	CON	ISL	CON	ISL	CON	ISL	CON
Panel A: Mean equation										
Constant	0.001 (0.000)	0.001 (0.000)	0.000 (0.000)	0.000 (0.000)	0.001 (0.000)	0.001 (0.000)	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)	0.000̂ (0.000)
AR(1)	0.052 (0.000)	0.047 (0.000)			0.208 (0.442)	0.012 (0.314)			-0.229 (0.179)	-0.289 (0.233)
AR(2)										
MA(1)			-0.047* (0.021)	-0.077 (0.020)	-0.224 (0.435)	-0.049 (0.314)	0.019 (0.019)	0.027 (0.021)	0.244 (0.187)	0.341 (0.224)
MA(2)			0.015 (0.020)	0.009 (0.020)		0.021 (0.026)		0.006 (0.020)		
MA(3)										
Panel B : Variance equation										
Constant	0.095 (0.030)	0.051 (0.020)	0.042 (0.018)	0.031 (0.014)	0.036* (0.016)	0.047* (0.021)	0.326ˆ (0.190)	0.476* (0.204)	0.014* (0.005)	1.577 (0.650)
ARCH (Alpha1)	0.081 (0.017)	0.040 (0.029)	0.068 (0.018)	0.083 (0.018)	0.123 (0.036)	0.117 (0.037)	0.054 (0.017)	0.077 (0.016)	0.054 (0.011)	0.068 (0.026)
ARCH		0.061ˆ (0.036)			-0.017 (0.044)	-0.006 (0.047)				0.008 (0.030)
(Alpha2)										
GARCH	0.879 (0.026)	0.854 (0.035)	0.913 (0.023)	0.905 (0.021)	0.876 (0.033)	0.870 (0.038)	0.942 (0.018)	0.912 (0.018)	0.935 (0.013)	0.906 (0.020)
(Beta1)										
Asymmetry	0.047* (0.024)	-0.011 (0.025)	-0.047ˆ (0.026)	- 0.075 (0.026)	-0.043* (0.023)	-0.017 (0.022)	0.005 (0.020)	-0.060 (0.023)	0.011 (0.022)	-0.023 (0.023)
Tail	6.800 (0.900)	6.959 (0.909)	6.167 (0.797)	5.453 (0.579)	4.576 (0.441)	4.275 (0.410)	4.384 (0.416)	5.152 (0.560)	6.082 (0.740)	7.119 (0.925)
Panel C : Diagnostic tests										
LL	7033.34	7972.32	7185.37	7300.23	7863.96	7714.76	9236.74	9532.37	7920.47	8363.35
AIC	-5.617	-6.366	-5.742	-5.834	-6.284	-6.164	-7.384	-7.619	-6.33	-6.683
ARCH LM(10)	[0.459]	[0.159]	[0.063]	[0.000]	[0.7988]	[0.522]	[0.015]	[0.295]	[0.020]	[0.002]
Q(20)	[0.189]	[0.611]	[0.108]	[0.642]	[0.501]	[0.818]	[0.425]	[0.262]	[0.197]	[0.665]
$Q^2(20)$	[0.334]	[0.0785]	[0.002]	[0.000]	[0.458]	[0.407]	[0.010]	[0.188]	[0.050]	[0.014]

Notes: table reports ML estimates and standard deviations in parenthesis for the parameters of marginal distribution model defined in equations. The lags m,n,p and q are selected by using AIC for different combinations of values, ranging from 0 to 3. L jung-Box statistics for serial correlation in model residuals and squared residuals is presented by Q(20) and $Q^2(20)$ respectively, computed with 20 lags. ARCH is the Engle LM test for the ARCH effect in residuals up to10th order. The *p*-values in the square brackets[] below 0.05 indicates rejection of null hypothesis. Bold numbers represents significance at the 1% level. ât 5% level and * Represents 10% significance level.

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Country	Netherland		New Zealand		Norway		Poland		Singapore	
	ISL	CON	ISL	CON	ISL	CON	ISL	CON	ISL	CON
Panel A: Mean equation										
Constant	0.001	0.001	0.000	0.000	0.000*	0.001	0.000	0.000	-0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
AR(1)		-0.008	0.025	-0.038	-0.055	-0.066	0.306		0.049	0.761
		(0.020)	(0.020)	(0.701)	(0.020)	(0.020)	(0.507)		(1.385)	(0.096)
AR(2)					-0.057					0.019
										(0.021)
					-0.02					
MA(1)	-0.013			0.115			-0.303	0.025	-0.074	-0.760
	(0.020)			(0.688)			(0.509)	(0.019)	(1.413)	(0.093)
MA(2)	-0.020						-0.032	-0.026		
	(0.021)						(0.026)	(0.020)		
MA(3)										
Panel B : Variance equation										
Constant	0.015*	0.020*	0.005	0.987	0.021	0.023	0.048*	0.022	1.122*	1.217
	(0.007)	(0.009)	(0.004)	(0.623)	(0.007)	(0.007)	(0.021)	(0.007)	(0.523)	(0.465)
ARCH	0.076	0.110	0.024*	0.076	0.068	0.090	0.060*	0.058	0.084	0.083
	(0.017)	(0.030)	(0.012)	(0.027)	(0.011)	(0.018)	(0.026)	(0.011)	(0.020)	(0.017)
(Alpha1)										
ARCH		0.003		-0.021			-0.012			
		(0.041)		(0.039)			(0.032)			
(Alpha2)										
GARCH	0.915	0.871	0.971	0.918	0.916	0.888	0.925	0.920	0.902	0.897
	(0.019)	(0.033)	(0.0163	(0.038)	(0.014)	(0.022)	(0.023)	(0.015)	(0.024)	(0.021)
(Beta1)										
Asymmetry	-0.033	-0.099	-0.036	-0.105	-0.030	-0.081	-0.011	-0.026	-0.056*	-0.034
	(0.029)	(0.026)	(0.025)	(0.026)	(0.027)	(0.025)	(0.025)	(0.023)	(0.026)	(0.024)
Tail	5.729	5.697	7.405	6.813	7.823	6.190	6.570	4.992	6.873	6.570
	(0.643)	(0.609)	(1.186)	(0.876)	(1.092)	(0.758)	(0.846)	(0.514)	(0.951)	(0.868)
Panel C : Diagnostic tests										
LL	7849.45	8232.75	8006.56	9345.06	7757.88	8195.76	7312.14	8208.84	8614.1	8868.67
AIC	-6.273	-6.579	-6.4	-7.469	-6.2	-6.551	-5.842	-6.561	-6.888	-7.091
ARCH LM(10)	[0.772]	[0.494]	[0.000]	[0.371]	[0.239]	[0.029]	[0.907]	[0.463]	[0.392]	[0.025]
Q(20)	[0.278]	[0.189]	[0.318]	[0.280]	[0.518]	[0.358]	[0.246]	[0.488]	[0.517]	[0.2096]
$Q^2(20)$	[0.571]	[0.441]	[0.131]	[0.607]	[0.050]	[0.007]	[0.705]	[0.064]	[0.284]	[0.0695]

Notes: table reports ML estimates and standard deviations in parenthesis for the parameters of marginal distribution model defined in equations. The lags m,n,p and q are selected by using AIC for different combinations of values, ranging from 0 to 3. L jung-Box statistics for serial correlation in model residuals and squared residuals is presented by Q(20) and $Q^2(20)$ respectively, computed with 20 lags. ARCH is the Engle LM test for the ARCH effect in residuals up to 10th order. The *p*-values in the square brackets[] below 0.05 indicates rejection of null hypothesis. Bold numbers represents significance at the 1% level. ât 5% level and * Represents 10% significance level.

Cont......

Country	South Africa		Spain		Turkey		United Kingdom		USA		GS CI
	ISL	CON	ISL	CON	ISL	CON	ISL	CON	ISL	CON	
Panel A : Mean equation											
Constant	-0.000	0.000	0.000	0.000	0.001	0.001	0.000	0.000*	0.001	0.001	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
AR(1)	-0.030	-0.022				0.300		-0.009	-0.078		-0.364
	(0.020)	(0.019)				(0.417)		(0.020)	(0.020)		(0.457)
AR(2)		-0.033									
		(0.020)									
MA(1)			-0.016	0.011	0.015	-0.320	0.010			-0.063	0.337
			(0.020)	(0.020)	(0.020)	(0.416)	(0.020)			(0.020)	(0.456)
MA(2)			0.004	-0.006	-0.031	0.025	-0.011			0.026	0.001
			(0.021)	(0.021)	(0.020)	(0.021)	(0.022)			(0.024)	(0.025)
MA(3)											
Panel B : Variance equation											
Constant	0.016	0.019	0.033*	0.027	0.110	0.088	0.018*	2.386	0.023	0.026	0.016
	(0.005)	(0.006)	(0.015)	(0.010)	ˆ(0.061)	(0.033)	(0.008)	(0.900)	(0.006)	(0.005)	(0.006)
ARCH	0.061	0.076	0.089	0.081	0.070	0.062	0.082	0.121	0.161	0.183	0.064
	(0.010)	(0.013)	(0.025)	(0.017)	(0.024)	(0.015)	(0.021)	(0.027)	(0.022)	(0.025)	(0.010)
(Alpha1)											
ARCH											
(Alpha2)											
GARCH	0.930	0.903	0.894	0.903	0.879	0.890	0.904	0.854	0.819	0.799	0.926
	(0.010)	(0.017)	(0.030)	(0.019)	(0.049)	(0.029)	(0.024)	(0.033)	(0.023)	(0.023)	(0.011)
(Beta1)											
Asymmetry	-0.042	-0.098	-0.021	-0.061*	0.002	-0.058*	-0.080	-0.083	-0.098	-0.059*	-0.093
	ˆ(0.023)	(0.026)	(0.023)	(0.025)	(0.023)	(0.026)	(0.025)	(0.025)	(0.025)	(0.024)	(0.024)
Tail	6.452	7.363	5.827	5.673	5.072	5.107	6.073	5.383	5.941	4.979	5.305
	(0.843)	(1.014)	(0.736)	(0.664)	(0.542)	(0.533)	(0.730)	(0.552)	(0.709)	(0.514)	(0.576)
Panel C : Diagnostic tests											
LL	7525.29	8265.18	7532.17	7627.78	7207.55	7361.71	8014.33	8579.8	8596.8	8687.6	7779.3
AIC	-6.017	-6.608	-6.022	-6.098	-5.76	-5.882	-6.405	-6.858	-6.872	-6.944	-6.216
ARCH LM(10)	[0.2063]	[0.362]	[0.016]	[0.088]	[0.851]	[0.914]	[0.363]	[0.382]	[0.753]	[0.561]	[0.735]
Q(20)	[0.068]	[0.222]	[0.492]	[0.656]	[0.852]	[0.691]	[0.071]	[0.200]	[0.050]	[0.138]	[0.151]
$Q^2(20)$	[0.346]	[0.050]	[0.046]	[0.125]	[0.970]	[0.909]	[0.225]	[0.216]	[0.493]	[0.661]	[0.878]

Notes: table reports ML estimates and standard deviations in parenthesis for the parameters of marginal distribution model defined in equations. The lags m,n,p and q are selected by using AIC for different combinations of values, ranging from 0 to 3. L jung-Box statistics for serial correlation in model residuals and squared residuals is presented by Q(20) and $Q^2(20)$ respectively, computed with 20 lags. ARCH is the Engle LM test for the ARCH effect in residuals up to10th order. The *p*-values in the square brackets[] below 0.05 indicates rejection of null hypothesis. Bold numbers represents significance at the 1% level. ât 5% level and * Represents 10% significance level.

Switching copula estimation between stock indices and alternative assets

Referring Wang et al. (2013), six single-copula models including normal, t and four other types of Clayton copula are first applied for the estimation of dependence between stocks and alternative assets. The coefficient estimations for each pair of stock indices and GSCI are presented in table.

The results show that the parameters estimated by the normal, t, Clayton and 180-degree Clayton are significant at 1%, 5%, and 10% level for each pair. It is also significant for all pairs of GSCI and Islamic stock indices for all countries on rotated copula types. While comparing values of log likelihood, AIC and BIC of different copulas for each pair, there is no copula that can better perform than any other. the normal copula and t-copula can capture both symmetric positive and negative dependence, but the normal copula has no tail dependence, and the t-copula has symmetric tail dependence, Liu et al. (2017a). Therefore, to capture the asymmetric tail dependence, the mixed Clayton copulas are applied further for dependence-switching copula model.

Table III
Estimation of single –copula models

Country	Belgium		France		Germany		Hong Kong	
	ISL	CON	ISL	CON	ISL	CON	ISL	CON
Normal copula								
ρ	0.258	-0.014	0.319	0.001	0.260	-0.000	0.133	0.023
	(0.019)	(0.020)	(0.018)	(0.020)	(0.019)	(0.020)	(0.020)	(0.020)
LL	-86.475	-0.228	-134.405	-0.001	-87.906	0	-22.419	-0.676
AIC	-170.949	1.543	-266.81	1.998	-173.812	2	-42.837	0.648
BIC	-165.125	7.368	-260.985	7.822	-167.987	7.824	-37.013	6.472
Student's t copula								
ρ	0.254	-0.016	0.322	-0.001	0.256	-0.005	0.126	0.021
	(0.020)	(0.021)	(0.019)	(0.021)	(0.019)	(0.021)	(0.021)	(0.021)
DOF	10.555	21.602*	13.005	34.132	10.281	22.009*	13.168	17.590*
	(2.649)	(9.631)	(3.712)	(24.98)	(2.467)	(10.177)	(4.102)	(7.002)
LL	-95.757	-3.35	-141.934	-1.217	-98.427	-2.741	-28.289	-4.249
AIC	-189.515	-4.699	-281.868	-0.433	-194.854	-3.481	-54.578	-6.498
BIC	-183.691	1.125	-276.044	5.391	-189.03	2.343	-48.753	-0.673
Clayton (u, v)								
α	0.313	0.000	0.417	0.001	0.344	0.008	0.152	0.018
	(0.029)	(0.019)	(0.030)	(0.020)	(0.029)	(0.020)	(0.025)	(0.021)
LL	-78.174	0.001	-124.128	-0.001	-91.822	-0.08	-23.366	-0.416
AIC	-154.347	2.002	-246.256	1.998	-181.645	1.839	-44.731	1.168
BIC	-148.523	7.827	-240.432	7.822	-175.821	7.664	-38.907	6.992
Clayton (1-u, 1-v)								
α	0.277	0.009	0.344	0.016	0.255	0.017	0.126	0.042*
	(0.028)	(0.019)	(0.029)	(0.019)	(0.028)	(0.019)	(0.024)	(0.021)
LL	-62.954	-0.122	-87.677	-0.363	-53.117	-0.413	-16.733	-2.298
AIC	-123.907	1.755	-173.353	1.274	-104.233	1.175	-31.466	-2.597
BIC	-118.083	7.58	-167.529	7.098	-98.409	6.999	-25.642	3.228
Clayton (1.u, v)								
α	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	(0.026)	(0.021)	(0.026)	(0.021)	(0.025)	(0.021)	(0.023)	(0.020)
LL	0.046	0	0.056	0.001	0.045	0.002	0.023	0.004
AIC	2.093	2	2.112	2.003	2.09	2.003	2.046	2.007
BIC	7.917	7.825	7.937	7.827	7.915	7.828	7.871	7.832
Clayton (u, 1-v)								
α	0.000	0.033	0.000	0.010	0.000	0.014	0.000	0.000
	(0.021)	(0.022)	(0.029)	(0.021)	(0.027)	(0.021)	(0.024)	(0.020)
LL	0.047	-1.297	0.06	-0.111	0.048	-0.239	0.026	0.002
AIC	2.094	-0.593	2.119	1.779	2.097	1.521	2.051	2.005
BIC	7.918	5.231	7.943	7.603	7.921	7.346	7.876	7.829

Notes: LL, AIC and BIC are estimates for log likelihood, Akaike information criterion and Bayes information criterion, respectively. ρ represents correlation coefficient of the series in Gaussian or Student-t copula. Dof shows degree of freedom of Student-t distribution. α is shape parameter of Clayton copula. Values shown in parentheses are standard deviations. Bold-faced numbers represent significance at 1 % level, ât 5% and * at 10% significance level. ISL & CON denotes Islamic and conventional stocks respectively.

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Country	India		Ireland		Itlay		Japan	
	ISL	CON	ISL	CON	ISL	CON	ISL	CON
Normal copula								
P	0.127 (0.020)	0.030 (0.020)	0.214 (0.019)	-0.023 (0.019)	0.412 (0.017)	-0.012 (0.020)	0.094 (0.020)	0.026 (0.020)
LL	-20.538	-1.189	-58.79	-0.661	-233.354	-0.169	-11.309	-0.877
AIC	-39.075	-0.378	-115.58	0.678	-464.708	1.663	-20.619	0.247
BIC	-33.251	5.446	-109.756	6.502	-458.884	7.487	-14.795	6.071
Student's t copula								
P	0.122 (0.021)	0.029 (0.021)	0.217 (0.020)	-0.023 (0.021)	0.415 (0.017)	-0.012 (0.021)	0.091 (0.021)	0.025 (0.021)
DOF	17.034 (6.50)	26.938^ (13.97)	12.111 (3.363)	50.006 (47.940)	12.692 (3.441)	66.383 (84.953)	27.339 (17.41)	34.553 (27.50)
LL	-24.46	-3.05	-66.336	-1.197	-241.954	-0.46	-12.624	-1.736
AIC	-46.921	-4.099	-130.672	-0.394	-481.908	1.079	-23.248	-1.472
BIC	-41.096	1.725	-124.848	5.43	-476.084	6.903	-17.424	4.352
Clayton (u, v)								
α	0.164 (0.025)	0.037 (0.021)	0.277 (0.028)	0.000 (0.019)	0.559 (0.032)	0.005 (0.020)	0.128 (0.024)	0.041^ (0.022)
LL	-27.091	-1.687	-63.643	0.002	-201.285	-0.041	-17.862	-1.985
AIC	-52.183	-1.374	-125.286	2.005	-400.569	1.919	-33.724	-1.971
BIC	-46.359	4.45	-119.462	7.829	-394.745	7.743	-27.9	3.853
Clayton (1-u, 1-v)								
α	0.099 (0.024)	0.031 (0.021)	0.198 (0.027)	0.000 (0.020)	0.489 (0.031)	0.000 (0.021)	0.060 (0.023)	0.017 (0.020)
LL	-10.392	-1.228	-32.766	0.005	-160.859	0.005	-3.844	-0.37
AIC	-18.783	-0.456	-63.533	2.011	-319.718	2.009	-5.687	1.261
BIC	-12.959	5.369	-57.709	7.835	-313.894	7.833	0.137	7.085
Clayton (1.u, v)								
α	0.000 (0.023)	0.000 (0.022)	0.000 (0.023)	0.000 (0.020)	0.000 (0.030)	0.002 (0.021)	0.000 (0.023)	0.000 (0.022)
LL	0.021	0.009	0.036	0	0.072	-0.005	0.019	0.008
AIC	2.042	2.017	2.073	2.001	2.144	1.99	2.038	2.016
BIC	7.867	7.842	7.897	7.825	7.968	7.814	7.862	7.84
Clayton (u, 1-v)								
α	0.000 (0.025)	0.000 (0.020)	0.000 (0.025)	0.047* (0.021)	0.000 (0.032)	0.021 (0.021)	0.000 (0.023)	0.000 (0.022)
LL	0.026	0.002	0.041	-2.661	0.076	-0.56	0.018	0.002
AIC	2.053	2.003	2.082	-3.323	2.151	0.879	2.036	2.003
BIC	7.877	7.828	7.906	2.501	7.975	6.703	7.86	7.828

Cont.......

Country	Malaysia		Mexico		Nether Land		Norway	
	ISL	CON	ISL	CON	ISL	CON	ISL	CON
Normal copula								
ρ	0.067 (0.020)	0.045* (0.020)	0.238 (0.019)	-0.013 (0.020)	0.181 (0.020)	-0.001 (0.020)	0.415 (0.017)	-0.009 (0.020)
LL	-5.635	-2.579	-73.426	-0.228	-41.852	-0.002	-237.001	-0.115
AIC	-9.269	-3.157	-144.851	1.544	-81.704	1.997	-472.002	1.771
BIC	-3.445	2.667	-139.027	7.368	-75.88	7.821	-466.178	7.595
Student's t capula								
ρ	0.065 (0.021)	0.044* (0.021)	0.238 (0.019)	-0.014 (0.021)	0.184 (0.021)	-0.000 (0.021)	0.415 (0.016)	-0.011 (0.021)
DOF	36.476 (29.69)	38.254 (27.29)	30.545 (22.49)	99.451 (230.23)	9.550 (2.184)	40.226 (34.73)	16.157 (5.57)	23.92^ (12.60)
LL	-6.453	-3.376	-74.452	-0.336	-53.157	-0.767	-241.694	-2.204
AIC	-10.906	-4.752	-146.904	1.329	-104.315	0.465	-481.389	-2.409
BIC	-5.081	1.072	-141.08	7.153	-98.491	6.289	-475.565	3.415
Clayton (u, v)								
α	0.101 (0.023)	0.037 ^ (0.022)	0.284 (0.028)	0.000 (0.020)	0.238 (0.028)	0.001 (0.020)	0.555 (0.032)	0.003 (0.020)
LL	-11.444	-1.574	-67.431	0.004	-48.663	-0.001	-199.57	-0.008
AIC	-20.887	-1.148	-132.862	2.007	-95.326	1.998	-397.141	1.984
BIC	-15.063	4.676	-127.038	7.832	-89.502	7.822	-391.317	7.808
Clayton (1-u, 1-v)								
α	0.027 (0.022)	0.052* (0.022)	0.233 (0.027)	0.000 (0.020)	0.163 (0.026)	0.004 (0.020)	0.495 (0.031)	0.000 (0.019)
LL	-0.82	-3.161	-45.344	0	-23.564	-0.022	-165.765	-0.001
AIC	0.361	-4.322	-88.689	2	-45.128	1.956	-329.53	1.999
BIC	6.185	1.502	-82.865	7.824	-39.304	7.78	-323.706	7.823
Clayton (1.u, v)								
α	0.000 (0.022)	0.000* (0.022)	0.000 (0.026)	0.000 (0.021)	0.000 (0.023)	0.000 (0.020)	0.000 (0.032)	0.011 (0.021)
LL	0.013	0.011	0.043	0	0.032	0.002	0.074	-0.159
AIC	2.025	2.021	2.086	2	2.064	2.004	2.149	1.681
BIC	7.849	7.845	7.91	7.824	7.888	7.828	7.973	7.505
Clayton (u, 1-v)								
α	0.000 (0.022)	0.000 (0.021)	0.000 (0.028)	0.022 (0.022)	0.000 (0.023)	0.019 (0.021)	0.000 (0.033)	0.015 (0.021)
LL	0.013	0.006	0.047	-0.567	0.031	-0.456	0.076	-0.289
AIC	2.026	2.012	2.094	0.866	2.063	1.088	2.151	1.422
BIC	7.85	7.836	7.919	6.69	7.887	6.912	7.975	7.246

Cont.....

Country	New Zeland		Poland		South Africa		Singapore	
	ISL	CON	ISL	CON	ISL	CON	ISL	CON
Normal copula								
ρ	0.047* (0.020)	0.052 (0.020)	0.226 (0.019)	0.024 (0.020)	0.267 (0.019)	-0.003 (0.020)	0.159 (0.019)	0.021 (0.020)
LL	-2.811	-3.44	-65.712	-0.742	-92.922	-0.019	-32.06	-0.552
AIC	-3.623	-4.879	-129.424	0.516	-183.844	1.961	-62.121	0.896
BIC	2.201	0.945	-123.6	6.34	-178.02	7.785	-56.297	6.72
Student's t capula								
ρ	0.041* (0.020)	0.052 (0.020)	0.223 (0.002)	0.017 (0.021)	0.264 (0.019)	-0.004 (0.021)	0.157 (0.020)	0.016 (0.021)
DOF	14.828 (5.21)	41.608 (38.81)	20.477 (5.76)	18.178* (7.52)	16.666* (6.60)	83.979 (141.81)	27.375 (17.41)	29.812 (19.85)
LL	-7.267	-4.228	-68.322	-4.02	-96.52	-0.209	-33.394	-1.875
AIC	-12.533	-6.456	-134.645	-6.041	-191.041	1.583	-64.789	-1.75
BIC	-6.709	-0.632	-128.821	-0.217	-185.217	7.407	-58.965	4.074
Clayton (1-u, 1-v)								
α	0.078 (0.022)	0.069 (0.023)	0.281 (0.028)	0.039^ (0.021)	0.374 (0.029)	0.000 (0.019)	0.172 (0.026)	0.037^ (0.021)
LL	-7.377	-5.54	-67.608	-2.059	-110.413	0	-28.075	-1.765
AIC	-12.754	-9.08	-133.216	-2.117	-218.826	2.001	-54.15	-1.53
BIC	-6.93	-3.256	-127.392	3.707	-213.002	7.825	-48.326	4.294
α	0.029 (0.021)	0.029 (0.022)	0.206 (0.027)	0.027 (0.021)	0.226 (0.028)	0.003 (0.020)	0.154 (0.026)	0.018 (0.020)
LL	-1.044	-0.943	-37.07	-0.959	-42.145	-0.014	-22.137	-0.496
AIC	-0.088	0.113	-72.14	0.081	-82.291	1.973	-42.274	1.007
BIC	5.736	5.937	-66.316	5.905	-76.467	7.797	-36.45	6.831
Clayton (1.u, v)								
α	0.000 (0.022)	0.000 (0.022)	0.000 (0.026)	0.000 (0.023)	0.000 (0.029)	0.000 (0.021)	0.000 (0.024)	0.000 (0.022)
LL	0.01	0.01	0.042	0.009	0.051	0.002	0.029	0.006
AIC	2.02	2.019	2.084	2.018	2.103	2.005	2.058	2.012
BIC	7.844	7.843	7.908	7.843	7.927	7.829	7.882	7.836
Clayton (u, 1-v)								
α	0.000 (0.022)	0.000 (0.021)	0.000 (0.027)	0.004 (0.021)	0.000 (0.027)	0.015 (0.021)	0.000 (0.025)	0.000 (0.021)
LL	0.007	0.01	0.042	-0.016	0.048	-0.283	0.032	0.003
AIC	2.013	2.019	2.084	1.968	2.095	1.435	2.063	2.005
BIC	7.837	7.843	7.908	7.792	7.919	7.259	7.887	7.829

Cont......

Country	Spain		Turkey		UK		USA	
	ISL	CON	ISL	CON	ISL	CON	ISL	CON
Normal copula								
ρ	0.212 (0.019)	-0.015 (0.020)	0.111 (0.020)	0.028 (0.020)	0.430 (0.016)	-0.011 (0.020)	0.418 (0.016)	-0.008 (0.020)
LL	-57.756	-0.289	-15.628	-1.016	-256.625	-0.147	-241.126	-0.085
AIC	-113.511	1.422	-29.255	-0.031	-511.249	1.706	-480.251	1.831
BIC	-107.687	7.246	-23.431	5.793	-505.425	7.53	-474.427	7.655
Student's t capula								
ρ	0.213 (0.020)	-0.016 (0.021)	0.113 (0.021)	0.028 (0.021)	0.432 (0.016)	-0.012 (0.021)	0.421 (0.017)	-0.008 (0.019)
DOF	11.194 (2.97)	37.535 (64.18)	21.596* (10.22)	86.906 (163.48)	12.381 (3.59)	63.754 (110.33)	12.425	61.326
LL	-66.005	-1.243	-18.105	-1.192	-263.683	-0.464	-248.934	-0.379
AIC	-130.01	-0.487	-34.209	-0.384	-525.367	1.072	-495.867	1.241
BIC	-124.186	5.337	-28.385	5.44	-519.543	6.896	-490.043	7.065
Clayton (u, v)								
α	0.275 (0.028)	0.005 (0.019)	0.123 (0.025)	0.018 (0.021)	0.596 (0.033)	0.000 (0.019)	0.568 (0.032)	0.012 (0.021)
LL	-64.226	-0.036	-14.478	-0.399	-222.732	0	-211.29	-0.189
AIC	-126.452	1.929	-26.956	1.202	-443.465	2.001	-420.581	1.622
BIC	-120.628	7.753	-21.132	7.026	-437.641	7.825	-414.757	7.446
Clayton (1-u, 1-v)								
α	0.194 (0.027)	0.000 (0.020)	0.101 (0.024)	0.036 (0.022)	0.520 (0.032)	0.000 (0.019)	0.494 (0.032)	0.000 (0.021)
LL	-31.833	0.004	-10.593	-1.518	-175.158	0.001	-160.598	0.005
AIC	-61.666	2.008	-19.187	-1.036	-348.316	2.003	-319.197	2.01
BIC	-55.842	7.832	-13.363	4.788	-342.492	7.827	-313.373	7.834
Clayton (u, v)								
α	0.000 (0.024)	0.000 (0.021)	0.000 (0.022)	0.000 (0.021)	0.000 (0.032)	0.006 (0.021)	0.000 (0.020)	0.000 (0.020)
LL	0.037	0.002	0.019	0.007	0.077	-0.036	0.074	0.001
AIC	2.075	2.003	2.037	2.014	2.154	1.927	2.147	2.003
BIC	7.899	7.827	7.861	7.838	7.978	7.752	7.971	7.827
Clayton (1.u, v)								
α	0.000 (0.025)	0.036 (0.022)	0.000 (0.022)	0.000 (0.021)	0.000 (0.033)	0.013 (0.021)	0.000 (0.034)	0.024 (0.021)
LL	0.039	-1.543	0.022	0.004	0.087	-0.194	0.086	-0.726
AIC	2.078	-1.086	2.043	2.008	2.174	1.611	2.172	0.548
BIC	7.902	4.738	7.867	7.833	7.998	7.436	7.996	6.372

Switching copula estimation between global commodity index and stock indices

Islamic stocks

Table IV, presents estimated results of dependence switching copula models for each pair of stocks and GSCI. Firstly, alternative asset (GSCI) is paired with Islamic stock indices and then conventional counterparts. It is used to depict dependence and tail dependence in positive and negative correlation regimes. Where positive correlation regime shows that both stock indices and GSCI are in bearish market state or both stock indices and GSCI are in bullish market state. Negative correlation regime shows that stock indices are in bearish market state and GSCI in bullish market state, and stock indices are in bullish market state and GSCI in bearish market. The parameter ρ measures and φ measures tail dependence among stocks and GSCI. Tail dependence is measure of probability for simultaneous large profits and large losses in both markets, is a good indicator for systemic risk under extreme conditions in market. However, estimated transition probabilities are shown by Pnn and Ppp. The value of estimated transition probabilities near to 1, indicates high persistence of same dependence regime in all estimated pairs. When GSCI is paired with Islamic stock indices, both are in bullish markets under positive correlation regime, the copula parameters are significant for India, Japan, Malaysia, New Zealand, Singapore, and Turkey with tail significant dependence ranges from 0.000 to 0.473. Positive dependence is found for India, Japan, Singapore, and Turkey with value ranges 0.004 to 0.238. This may lead to earn additional profits. Negative dependence is found among the pairs of GSCI and Islamic stocks for Malaysia and New Zealand with values ranges -0.061 to -0.062. The negative correlation between combination of Islamic stocks and GSCI can lower the losses during market downturn, as losses in one market can be off stetted by profits in other market. GSCI can be used by portfolio manager of Islamic stocks in these countries for hedging. Oztek (2017) examined association among equity and commodity markets during the period of financial crisis and aftermath also. Their study revealed provision of better opportunities by commodities for hedging during non-crisis then crisis period. In 3rd case, negative correlation regime is studied, where Islamic stock index is in bearish market state (lower tail) and GSCI in bullish state (upper tail). Findings show a significant dependence between lower tails of Islamic stock with the upper tail of GSCI for maximum sample countries except Italy, Mexico, Norway, South Africa, and UK. Positive dependence found for Germany, Hong Kong, Ireland, Malaysia, Netherland, Spain, Turkey, and USA, value ranged 0.002 to 0.265, and tail dependence ranged 0.000 to 0.125. It indicates that at the same time losses in Islamic stock index can be offset by investment in GSCI. Daskalaki et al. (2017) also found that commodities provide higher diversification benefits. Singha et al. (2016) also examined hedging performance for commodities indices and concluded that they can be used for hedging and diversification. Negative significant dependence is found for Belgium, France, India, Japan, New Zealand, Poland, and Singapore. The value ranged -0.007 to -0.119, interpreting no hedging and diversification benefit for portfolio managers of these countries for Islamic stocks. The negative dependence is documenting that the diversification benefits of GSCI is market and country specific. In 4th case, when Islamic stock index is bullish and GSCI is bearish, significant dependence is reported for all sample countries other than Italy, Mexico, Norway, and UK. Negative dependence found for Belgium, France, Germany, India, Ireland, Malaysia, South Africa, Singapore, Spain, and Turkey ranged -0.002 to -0.148, tail dependence lies within 0.000 to 0.837. Negative dependence means that bearish market state of GSCI will not impact Islamic stock portfolio. On the other hand, positive dependence is found between GSCI and Islamic stock pairs in Hong Kong, Japan, Netherland, New Zealand, Poland, and USA, ranged 0.000 to 0.325. This positive dependence is inferred as; lower tail of GSCI will impact the upper tail of Islamic stock in these countries. So for the investors of these countries, GSCI are not a viable choice to include in their portfolio, as its losses will decrease portfolio profits.

Conventional stock

The estimated transition probabilities shown by Pnn and Ppp are close to 1 indicating high persistence of same dependence regime in all estimated pairs except 0.433 for India in Ppp, showing same regime do not persists for India. In 1st case, when GSCI are paired with conventional stock indices, both stock indices and GSCI are in bearish markets state, significant dependence is reported for all countries except India and New Zealand. Significant negative dependence is documented for Belgium, France, Germany, Hong Kong, Mexico, Netherland, and Turkey, ranged from -0.076 to -0.109. While significant positive dependence is reported for Ireland, Italy, Japan, Malaysia, Norway, Poland, South Africa, Singapore, Spain, UK, and USA, ranges from 0.013 to 0.310. Tail dependence ranged from 0.000 to 0.998. Arouri et al. (2013) also found that financial crisis impacted conventional stock more strongly. When both stock index and GSCI are in bullish market under positive correlation regime, results for majority countries are significant except Germany, Hong Kong, India, Italy, Japan, Poland, and Turkey. Positive dependence is found for Belgium, France, Malaysia, Netherland, Norway, and South Africa, with dependence value ranged 0.006 to 0.217 and tail dependence 0.000 to 0.850. Positive dependence shows that, both stock indices and alternative asset are earning profit at the same time. Investor of these countries can get benefits. Negative dependence is found among GSCI and conventional stocks in bullish market in Ireland, Mexico, New Zealand, Singapore, Spain, UK, and USA with range -0.006 to -0.122, indicating that no benefit can be earned by investors of conventional stock portfolio. Öcal and Oztek (2017) also reported that commodities provide better opportunities for hedging during non-crisis period then crisis period. Findings show significant dependence between lower tail of conventional and upper tail of GSCI for all countries except Belgium, Poland, and Spain. Positive dependence is found for only Norway with value 0.015, indicating that losses in conventional stock index can be off set with investment in GSCI. Daskalaki et al. (2017) also examined diversification benefits of commodity indices and found that commodities provide diversification benefits. Negative significance dependence is found for France, Germany, India, Ireland, Hongkong, Italy, Japan, Malaysia, Mexico, NetherLand, New Zealand, South Africa, Singapore, Turkey, UK, and USA ranged -0.005 to -0.136 and tail dependence ranged 0.000 to 0.894. In case of negative correlation regime, conventional stocks index is bearish market and GSCI is bullish, negative dependence shows negative down turn of stock markets cannot be safeguarded by investment in GSCI, They donot provide hedging benefit, as boom in GSCI market cannot be used to get some benefit in Islamic stock portfolio losses. When conventional stock index is bullish and GSCI is bearish, significant dependence is reported for all countries. Negative dependence found for HongKong and Malaysia, with values -0.005 and -0.053 respectively. This means that bearish market state of GSCI will not impact conventional stock portfolio. Singha et al. (2016) also concluded from their research that emerging markets equities indices can be mixed with commodities indices for hedging and diversification. Positive dependence is found between GSCI and conventional stock pairs in Belgium, France, Germany, India, Ireland, Italy, Japan, Mexico, NetherLand, Norway, New Zealand, Poland, South Africa, Singapore, Spain, Turkey, UK, and USA with values ranges from 0.005 to 0.293. The value of tail dependence ranged 0.000 to 0.293. This dependence is inferred as; lower tail of GSCI will impact upper tail of conventional stock of these countries. For investors of these countries, GSCI is not viable choice, its losses will decrease portfolio revenues.

Table IV
Estimation of the dependence-switching copula model

Country	Belgium		France		Germany		Hong Kong	
	ISL	CON	ISL	CON	ISL	CON	ISL	CON
Panel A: Positive correlation regime								
Both markets are bearish								
α1	0.690	-0.093	0.793	-0.114	0.833	-0.100	0.274	-0.128
	(0.108)	(0.063)	(0.098)	(0.349)	(0.113)	(0.441)	(0.064)	(0.236)
ρ1	0.392	-0.076	0.431	-0.095	0.445	-0.082	0.188	-0.107
	(0.043)	(0.055)	(0.035)	(0.307)	(0.039)	(0.382)	(0.038)	(0.210)
ϕ1	0.183	0.880	0.208	0.215	0.217	0.509	0.039^	0.111
	(0.028)	(0.450)	(0.022)	(0.400)	(0.024)	(0.155)	(0.023)	(0.111)
Both markets are bullish								
α2	0.586	0.086	0.526	0.324	0.363	0.813	0.205	1.255
	(0.101)	(0.077)	(0.098)	(0.202)	(0.082)	(0.000)	(0.062)	(0.700)
ρ2	0.348	0.065	0.321	0.217^	0.239	0.438	0.145	0.569
	(0.044)	(0.055)	(0.045)	(0.114)	(0.045)	(0.000)	(0.040)	(0.170)
ϕ2	0.153	0.000	0.134	0.059	0.074*	0.213	0.017	0.287
	(0.031)	(0.001)	(0.032)	(0.078)	(0.032)	(0.000)	(0.017)	(0.088)
Panel B: Negative correlation regime								
Stock market is bearish, asset market is bullish								
α3	-0.042	-0.133	-0.142	-0.034	0.002	-0.033	0.225	-0.007
	(0.074)	(0.000)	(0.091)	(0.045)	(0.114)	(0.047)	(0.201)	(0.044)
ρ3	-0.034	-0.112	-0.119	-0.027	0.001	-0.026	0.158	-0.005
	(0.061)	(0.000)	(0.082)	(0.036)	(0.089)	(0.038)	(0.126)	(0.035)
ϕ3	0.738	0.906	0.657	0.242	0.000	0.585	0.023	0.176
	(0.217)	(0.000)	(0.205)	(0.630)	(0.000)	(0.176)	(0.063)	(0.501)
Stock market is bullish, asset market is bearish								
α4	-0.068	0.374	-0.093	0.050	-0.038	0.065	0.003	-0.006
	(0.066)	(0.460)	(0.073)	(0.050)	(0.079)	(0.052)	(0.112)	(0.046)
ρ4	-0.055	0.245	-0.076	0.038	-0.030	0.049	0.003	-0.005
	(0.055)	(0.248)	(0.063)	(0.037)	(0.065)	(0.038)	(0.088)	(0.037)
ϕ4	0.124	0.078	0.837^	0.000	0.397	0.000	0.000	0.293
	(0.122)	(0.178)	(0.489)	(0.000)	(0.151)	(0.000)	(0.000)	(0.533)
Regime switching								
Ppp	0.9962	0.9982	0.9984	0.9304	0.9974	0.9110	0.998	0.922
Pnn	0.9957	0.9955	0.9947	0.9995	0.9949	0.9995	0.993	0.999
LL	-5314.82	-5426.85	-5275.13	-5425.08	-5309.67	-5423.31	-5399.51	-5421.54
AIC	10669.64	10893.70	10590.26	10890.15	10659.35	10886.62	10839.03	10883.09
BIC	10786.13	11010.18	10706.74	11006.64	10775.83	11003.11	10955.52	10999.58

Note: αi is shape parameter of dependence-switching copula, ρi is dependence measure and φi is measure of tail dependence. The values in parentheses are standard deviations. The numbers with bold-face shows significance at 1% level, and ^significance at 5% and * at 10% level. LL, AIC and BIC represents estimates log likelihood, Akaike information criterion and Bayes information criterion, respectively. Ppp and Pnn are transition probabilities.

Cont.....

Country	India		Ireland		Italy		Japan	
	ISL	CON	ISL	CON	ISL	CON	ISL	CON
Panel A: Positive correlation regime								
Both markets are bearish								
α1	0.482 (0.120)	2.950 (3.323)	0.755 (0.112)	0.138 (0.142)	0.903 (0.091)	0.039 (0.093)	0.413 (0.115)	0.085 (0.063)
ρ1	0.300 (0.058)	0.805 (0.252)	0.417 (0.042)	0.101 (0.096)	0.469 (0.030)	0.030 (0.070)	0.265 (0.059)	0.064 (0.045)
ϕ1	0.118 (0.042)	0.395 (0.104)	0.199 (0.027)	0.003 (0.017)	0.232 (0.018)	0.000 (0.000)	0.093* (0.043)	0.000 (0.001)
Both markets are bullish								
α2	0.164* (0.081)	2.461 (2.113)	0.285 (0.085)	-0.145 (0.138)	0.522 (0.075)	-0.141 (0.000)	0.006 (0.078)	-0.061 (0.000)
ρ2	0.118* (0.054)	0.762 (0.215)	0.195 (0.050)	-0.122 (0.125)	0.319 (0.035)	-0.119 (0.000)	0.004 (0.061)	-0.049 (0.000)
ϕ2	0.007 (0.015)	0.377 (0.091)	0.044^ (0.031)	0.594* (0.271)	0.132 (0.025)	0.670 (0.003)	0.000 (0.000)	0.450 (0.543)
Panel B: Negative correlation regime								
Stock market is bearish, asset market is bullish								
α3	-0.032 (0.108)	-0.061 (0.047)	0.076 (0.085)	-0.018 (0.074)	-0.088 (0.000)	-0.155 (0.114)	-0.048 (0.111)	-0.148 (0.143)
ρ3	-0.025 (0.088)	-0.049 (0.040)	0.058 (0.062)	-0.014 (0.059)	-0.072 (0.000)	-0.132 (0.104)	-0.039 (0.091)	-0.125 (0.130)
ϕ3	0.113 (0.825)	0.387 (0.338)	0.000 (0.001)	0.277 (0.763)	0.125 (0.294)	0.434 (0.413)	0.752 (0.244)	0.536 (0.243)
Stock market is bullish, asset market is bearish								
α4	-0.047 (0.064)	0.048 (0.051)	-0.040 (0.067)	0.117^ (0.067)	-0.179 (0.000)	0.085 (0.114)	0.006 (0.078)	0.006 (0.077)
ρ4	-0.038 (0.052)	0.037 (0.038)	-0.032 (0.055)	0.087^ (0.046)	-0.154 (0.000)	0.064 (0.082)	0.005 (0.061)	0.005 (0.060)
ϕ4	0.101 (0.196)	0.000 (0.000)	0.139 (0.397)	0.001 (0.004)	0.237 (0.002)	0.000 (0.001)	0.000 (0.000)	0.000 (0.000)
Regime switching								
Ppp	0.9967	0.433	0.9958	0.9973	0.9992	0.9984	0.9975	0.9985
Pnn	0.9972	0.9877	0.9934	0.997	0.9931	0.9953	0.9968	0.9947
LL	-5399.02	-5420.70	-5343.12	-5423.86	-5196.24	-5425.13	-5407.97	-5424.99
AIC	10838.05	10881.40	10726.23	10887.72	10432.48	10890.25	10855.94	10889.99
BIC	10954.54	10997.89	10842.71	11004.20	10548.96	11006.73	10972.42	11006.47

Cont.....

Country	Malaysia		Mexico		Netherland		New Zeland	
	ISL	CON	ISL	CON	ISL	CON	ISL	CON
Panel A: Positive correlation regime								
Both markets are bearish								
α1	0.377	0.017	0.767	-0.131	0.697	-0.110	0.433*	0.175
	(0.119)	(0.115)	(0.206)	(0.197)	(0.112)	(0.466)	(0.202)	(0.063)
ρ1	0.247	0.013	0.421	-0.109	0.395	-0.091	0.276	0.126
	(0.064)	(0.088)	(0.076)	(0.176)	(0.044)	(0.408)	(0.103)	(0.041)
ϕ1	0.079^	0.000	0.202	0.998	0.185	0.269	0.101	0.009
	(0.046)	(0.000)	(0.049)	(0.799)	(0.029)	(0.718)	(0.075)	(0.013)
Both markets are bullish								
α2	-0.075	0.094	0.373	-0.007	0.342	0.178	-0.076	-0.050
	(0.074)	(0.133)	(0.125)	(0.107)	(0.105)	(0.439)	(0.089)	(0.076)
ρ2	-0.061	0.071	0.244	-0.006	0.227	0.128	-0.062	-0.040
	(0.062)	(0.095)	(0.067)	(0.085)	(0.059)	(0.288)	(0.075)	(0.062)
ϕ2	0.473	0.000	0.078	0.136	0.066	0.010	0.447	0.433
	(0.424)	(0.003)	(0.048)	(0.121)	(0.041)	(0.098)	(0.476)	(0.889)
Panel B: Negative correlation regime								
Stock market is bearish, asset market is bullish								
α3	0.016	-0.160	-0.139	-0.087	0.179	-0.041	-0.026	-0.156*
	(0.123)	(0.177)	(0.043)	(0.108)	(0.123)	(0.044)	(0.076)	(0.067)
ρ3	0.012	-0.136	-0.117	-0.071	0.128	-0.033	-0.021	-0.132*
	(0.095)	(0.163)	(0.039)	(0.093)	(0.081)	(0.036)	(0.061)	(0.062)
ϕ3	0.000	0.377*	0.732	0.142	0.010	0.974	0.112	0.421
	(0.000)	(0.181)	(0.115)	(0.141)	(0.027)	(0.177)	(0.719)	(0.811)
Stock market is bullish, asset market is bearish								
α4	-0.025	-0.065	-0.172	0.064	0.097	0.082	0.076	0.034
	(0.087)	(0.136)	(0.044)	(0.084)	(0.086)	(0.064)	(0.109)	(0.184)
ρ4	-0.020	-0.053	-0.147	0.049	0.072	0.062	0.057	0.026
	(0.070)	(0.114)	(0.041)	(0.061)	(0.061)	(0.046)	(0.079)	(0.140)
ϕ4	0.447	0.200	0.278	0.000	0.000	0.000	0.000	0.000
	(0.840)	(0.441)	(0.291)	(0.000)	(0.002)	(0.000)	(0.000)	(0.000)
Regime switching								
Ppp	0.9911	0.9985	0.9946	0.9976	0.9939	0.9616	0.9866	0.9985
Pnn	0.9868	0.9948	0.997	0.9979	0.9896	0.999	0.9879	0.9946
LL	-5414.28	-5423.73	-5350.03	-5426.08	-5350.80	-5425.76	-5416.71	-5421.23
AIC	10868.56	10887.46	10740.05	10892.17	10741.59	10891.51	10873.43	10882.46
BIC	10985.04	11003.94	10856.53	11008.65	10858.07	11007.99	10989.91	10998.94

Cont.....

Country	Norway		Poland		South Africa		Singapore	
	ISL	CON	ISL	CON	ISL	CON	ISL	CON
Panel A: Positive correlation regime								
Both markets are bearish								
α1	0.887	0.160	0.579	0.258	0.699	0.503	0.510	0.133
	(0.088)	(0.177)	(0.086)	(0.196)	(0.086)	(1.782)	(0.182)	(0.106)
ρ1	0.464	0.116	0.345	0.178	0.395	0.310	0.313	0.097
	(0.029)	(0.118)	(0.038)	(0.119)	(0.034)	(0.849)	(0.086)	(0.073)
ϕ1	0.228	0.006	0.151	0.034	0.185	0.126	0.128*	0.002
	(0.017)	(0.031)	(0.026)	(0.069)	(0.022)	(0.615)	(0.062)	(0.011)
Both markets are bullish								
α2	0.523	0.008	0.296	-0.119	0.146	0.031	0.362^	-0.102
	(0.069)	(0.149)	(0.070)	(0.038)	(0.052)	(0.602)	(0.216)	(0.097)
ρ2	0.319	0.006	0.201	-0.099	0.107	0.024	0.238*	-0.084
	(0.032)	(0.116)	(0.041)	(0.033)	(0.035)	(0.458)	(0.118)	(0.084)
ϕ2	0.132	0.000	0.048^	0.167	0.004	0.000	0.073	0.439
	(0.023)	(0.000)	(0.027)	(0.312)	(0.007)	(0.000)	(0.084)	(0.284)
Panel B: Negative correlation regime								
Stock market is bearish, asset market is bullish								
α3	0.015	0.020	-0.015	-0.133	0.256	-0.041	-0.009	-0.062
	(0.000)	(0.064)	(0.141)	(0.0322	(0.000)	(0.044)	(0.095)	(0.083)
ρ3	0.012	0.016	-0.012	-0.112	0.177	-0.032	-0.007	-0.050
	(0.000)	(0.049)	(0.112)	(0.028)	(0.000)	(0.036)	(0.076)	(0.069)
ϕ3	0.000	0.000	0.834	0.894	0.033	0.105	0.968	0.312
	(0.000)	(0.000)	(0.147)	(0.111)	(0.000)	(0.192)	(0.105)	(0.459)
Stock market is bullish, asset market is bearish								
α4	-0.176	0.078	0.011	0.055	-0.173	0.061	-0.098	0.026
	(0.000)	(0.080)	(0.107)	(0.052)	(0.116)	(0.050)	(0.064)	(0.092)
ρ4	-0.151	0.059	0.008	0.042	-0.148	0.046	-0.081	0.020
	(0.000)	(0.058)	(0.083)	(0.038)	(0.108)	(0.037)	(0.055)	(0.070)
ϕ4	0.252	0.000	0.000	0.000	0.272	0.000	0.557*	0.000
	(0.005)	(0.000)	(0.000)	(0.000)	(0.725)	(0.000)	(0.254)	(0.000)
Regime switching								
Ppp	0.9995	0.9772	0.9985	0.9831	0.9988	0.9457	0.9252	0.9952
Pnn	0.9936	0.9931	0.9968	0.9956	0.9943	0.9998	0.9405	0.9961
LL	-5194.03	-5426.11	-5348.84	-5422.46	-5319.27	-5426.21	-5391.89	-5425.44
AIC	10428.07	10892.22	10737.68	10884.92	10678.54	10892.42	10823.78	10890.87
BIC	10544.55	11008.70	10854.16	11001.40	10795.02	11008.90	10940.26	11007.35

Cont.....

Country	Spain		Turkey		UK		USA	
	ISL	CON	ISL	CON	ISL	CON	ISL	CON
Panel A: Positive correlation regime								
Both markets are bearish								
α1	0.620	0.092	0.412	-0.114	1.043	0.046	0.743	0.073
	(0.094)	(0.073)	(0.114)	(0.296)	(0.094)	(0.083)	(0.083)	(0.074)
ρ1	0.363	0.069	0.265	-0.095	0.512	0.035	0.413	0.055
	(0.040)	(0.052)	(0.059)	(0.261)	(0.027)	(0.062)	(0.032)	(0.053)
ϕ1	0.163	0.000	0.093*	0.215	0.257	0.000	0.196	0.000
	(0.027)	(0.002)	(0.043)	(0.339)	(0.015)	(0.000)	(0.020)	(0.000)
Both markets are bullish								
α2	0.429	-0.136*	0.252^	2.082*	0.542	-0.026	0.673^	-0.118^
	(0.102)	(0.058)	(0.131)	(0.905)	(0.077)	(0.063)	(0.087)	(0.062)
ρ2	0.274	-0.115*	0.175*	0.718	0.328	-0.021	0.385^	-0.098^
	(0.052)	(0.052)	(0.079)	(0.118)	(0.035)	(0.050)	(0.035)	(0.055)
ϕ2	0.099*	0.794	0.032	0.358	0.139	0.850	0.178	0.175
	(0.038)	(0.172)	(0.045)	(0.051)	(0.025)	(0.592)	(0.024)	(0.545)
Panel B: Negative correlation regime								
Stock market is bearish, asset market is bullish								
α3	0.136	-0.145	0.057	-0.057	-0.112	-0.039	0.412	-0.139
	(0.125)	(0.000)	(0.081)	(0.046)	(0.000)	(0.119)	(0.396)	(0.386)
ρ3	0.100	-0.123	0.043	-0.046	-0.093	-0.031	0.265	-0.117
	(0.086)	(0.000)	(0.059)	(0.039)	(0.000)	(0.097)	(0.206)	(0.348)
ϕ3	0.003	0.585	0.000	0.787	0.243	0.182	0.093	0.723
	(0.014)	(0.000)	(0.000)	(0.761)	(0.036)	(0.950)	(0.150)	(0.996)
Stock market is bullish, asset market is bearish								
α4	-0.002	0.172	-0.049	0.002	-0.226	0.167	0.534	0.117
	(0.083)	(0.127)	(0.062)	(0.046)	(0.085)	(0.229)	(0.639)	(0.191)
ρ4	-0.002	0.124	-0.039	0.002	-0.199*	0.121	0.325	0.087
	(0.065)	(0.084)	(0.051)	(0.036)	(0.083)	(0.152)	(0.295)	(0.133)
ϕ4	0.799	0.008	0.664	0.000	0.106	0.008	0.136	0.001
	(0.984)	(0.026)	(0.119)	(0.000)	(0.122)	(0.045)	(0.212)	(0.013)
Regime switching								
Ppp	0.9942	0.9984	0.9971	0.9726	0.999	0.9964	0.9985	0.9984
Pnn	0.9898	0.9951	0.998	0.9989	0.9938	0.9944	0.9342	0.995
LL	-5344.62	-5423.88	-5403.72	-5424.55	-5168.38	-5426.53	-5194.37	-5424.66
AIC	10729.25	10887.76	10847.44	10889.10	10376.76	10893.05	10428.75	10889.32
BIC	10845.73	11004.24	10963.92	11005.58	10493.24	11009.53	10545.23	11005.80

The GSCI (global commodity index) are paired with the stock indices and their conventional counterparts subsequently. GSCI have positive dependence with Islamic stock portfolio, providing them opportunity to earn additional returns in boom market. For negative market regime, when GSCI is moving upward, and Islamic stock moving downward, significant dependence is reported for Islamic stocks, making GSCI good hedger for Islamic stock portfolio in downturn. These findings are supported by Elfakhani et al. (2006) Ho et al. (2014), Rizvi et al. (2015) Daskalaki et al. (2017), Dewandaru et al. (2016), Mansur Masih (2016), Wajahat et al. (2019), and Razaet et al. (2019).

Potential Diversification Benefits of Islamic/Conventional Stock Indices with Alternative Assets and Their Risk Exposure

Negative correlation is found between Global Commodity Index Return (GSCI) and Islamic stock portfolio and positive correlation among Global Commodity Index Return (GSCI) and Conventional stock portfolio for Japan, Malaysia, Mexico, New Zealand, Singapore, India, and

Hong Kong. Negative correlation between Islamic stocks and GSCI will provide diversification benefits to portfolio investors. Although values of correlation are positive for majority of countries in both conventional and Islamic stocks, but intensity of correlation is more among conventional stocks and Global Commodity Index Return (GSCI) then Islamic and Global Commodity Index Return (GSCI). A negative correlation between GSCI and Islamic stocks is reported for Malaysia, New Zealand, Singapore, Japan, Mexico, India and Hong Kong. While it is positive for all other countries and values of correlation ranges from 0.002 (Turkey) to 0.056 (Norway). On the other hand, correlation between conventional stocks and GSCI is positive for all countries ranges from 0.062 (Belgium) to 0.900 (France), making them highly correlated and risky. Inclusion of conventional stock in GSCI portfolio will not be a wise decision due to similar pattern of movement is followed by both securities. The overall results of correlation show high correlation between GSCI and conventional stocks. For correlation between GSCI and Islamic stocks, nine countries reported negative correlation and others give low level of correlation, making Islamic stocks a feasible and viable option for diversification. In case of Belgium, risk-reduction effectiveness for Commodity Index Return (GSCI) and stock's are higher for Islamic stock portfolio as the co-efficient values is 0.511, while risk reduction value for conventional stock and Global Commodity Index return is 0.402, which shows existence of better reduction benefits for Islamic investor. As long as Risk-reduction measures how significant results with respect to reduction in risk, it is considered better. As in the case of Islamic stock portfolio and GSCI, better results are witnessed as compared to conventional stock portfolio and GSCI for all countries. The values of GSCI returns and Islamic stock portfolio is 0.510, 0.526, 0.495 for France, Germany, and India respectively, values of their conventional counterparts are 0.128, 0.145 and 0.230 respectively for portfolio type II based in risk minimization strategy. The values ranges from 0.509, 0.524, and 0.495 for Islamic stocks and (GSCI) of France, Germany and India respectively for portfolio type IV based upon equally weighted portfolio, and 0.126, 0.141, and 0.227 for their conventional counterparts respectively, clearly indicating benefits of Islamic stocks in combination with Commodity Index Return (GSCI). Then numeric range of risk reduction measure shows greater reduction benefit for Islamic stocks and global commodity index return (GSCI) portfolio. Overall results of risk reduction show addition of Islamic stocks with Commodity Index Return (GSCI) for diversification is a viable option. Similar results were reported by Naveed et al. (2019), when Islamic stock indices are combined with alternative assets, they provide significant risk and downside risk-reduction.

Table V
Diversification strategies for stock markets

Country	Belgium		France		Germany		Hong Kong		India		Ireland		Italy	
	CON	ISL	CON	ISL	CON	ISL	CON	ISL	CON	ISL	CON	ISL	CON	ISL
Correlation	0.063	0.02	0.9	0.026	0.873	0.026	0.383	-0.06	0.422	-0.01	0.776	0.016	0.83	0.042
RR PII	0.402	0.512	0.13	0.51	0.145	0.526	0.304	0.389	0.231	0.495	0.134	0.667	0.337	0.644
RR PIV	0.396	0.511	0.126	0.509	0.142	0.524	0.304	0.35	0.228	0.495	0.134	0.629	0.305	0.611
VaR Red PII	0.22	0.305	0.067	0.304	0.074	0.315	0.168	0.224	0.121	0.292	0.066	0.425	0.188	0.408
VaR Red PIV	0.215	0.305	0.065	0.303	0.072	0.314	0.168	0.2	0.119	0.292	0.066	0.394	0.168	0.381
ES Red PII	0.777	0.71	0.492	0.75	0.476	0.717	0.666	0.823	0.558	0.804	0.439	0.765	0.512	0.721
ES Red PIV	0.296	0.28	0.109	0.354	0.1	0.329	0.263	0.219	0.034	0.291	-0.031	0.403	0.145	0.325
SV Red PII	0.217	0.279	0.055	0.278	0.058	0.294	0.137	0.225	0.107	0.284	0.054	0.382	0.179	0.387
SV Red PIV	0.214	0.279	0.053	0.279	0.057	0.294	0.137	0.192	0.105	0.284	0.054	0.36	0.16	0.363
Re Red PII	0.205	0.321	0.071	0.306	0.077	0.32	0.191	0.21	0.123	0.277	0.08	0.427	0.2	0.414
Re Red PIV	0.199	0.32	0.069	0.306	0.075	0.318	0.191	0.196	0.121	0.277	0.08	0.395	0.178	0.384

Cont.....

Country	Japan		Malaysia		Mexico		Netherland		New Zealand		Norway		Poland	
	CON	ISL	CON	ISL	CON	ISL	CON	ISL	CON	ISL	CON	ISL	CON	ISL
Correlation	0.296	-0.048	0.266	-0.005	0.482	-0.01	0.873	0.052	0.243	-0.048	0.697	0.056	0.593	0.049
RR PII	0.428	0.553	-0.024	0.273	0.136	0.508	0.017	0.505	0.033	0.5	0.107	0.516	0.139	0.591
RR PIV	0.423	0.552	-0.245	0.17	0.123	0.508	0.016	0.503	-0.138	0.5	0.106	0.514	0.136	0.575
VaR Red PII	0.244	0.335	-0.005	0.154	0.074	0.304	0.006	0.296	0.015	0.297	0.052	0.309	0.074	0.366
VaR Red PIV	0.241	0.334	-0.107	0.097	0.067	0.304	0.006	0.296	-0.072	0.297	0.051	0.307	0.073	0.353
ES Red PII	0.62	0.724	0.812	0.772	0.566	0.779	0.486	0.737	0.897	0.78	0.466	0.819	0.464	0.695
ES Red PIV	0.242	0.328	-0.044	0.05	0.052	0.284	0.074	0.319	-0.076	0.274	-0.006	0.397	-0.06	0.248
SV Red PII	0.22	0.322	-0.026	0.132	0.045	0.254	-0.009	0.255	-0.003	0.28	0.026	0.276	0.045	0.332
SV Red PIV	0.218	0.322	-0.137	0.06	0.035	0.255	-0.01	0.256	-0.091	0.278	0.025	0.277	0.043	0.326
Re Red PII	0.237	0.317	0.008	0.117	0.099	0.315	0.013	0.302	0.037	0.295	0.074	0.336	0.098	0.384
Re Red PIV	0.235	0.316	-0.092	0.06	0.095	0.315	0.013	0.301	-0.054	0.296	0.074	0.333	0.097	0.366

Cont.....

Country	Singapore		South Africa		Spain		Turkey		UK		USA	
	CON	ISL	CON	ISL	CON	ISL	CON	ISL	CON	ISL	CON	ISL
Correlation	0.439	-0.059	0.612	0.018	0.833	0.016	0.396	0.002	0.838	0.023	0.588	0.044
RR PII	0.041	0.425	0.122	0.635	0.241	0.591	0.438	0.62	-0.078	0.542	0.157	0.435
RR PIV	-0.016	0.405	0.119	0.609	0.228	0.578	0.423	0.601	-0.094	0.538	0.155	0.432
VaR Red PII	0.026	0.25	0.063	0.402	0.134	0.363	0.252	0.385	-0.036	0.329	0.079	0.251
VaR Red PIV	-0.002	0.238	0.061	0.38	0.126	0.353	0.242	0.37	-0.043	0.326	0.078	0.249
ES Red PII	0.569	0.844	0.468	0.818	0.517	0.687	0.561	0.678	0.529	0.773	0.518	0.8
ES Red PIV	-0.112	0.223	-0.034	0.418	0.123	0.289	0.178	0.291	0.063	0.347	0.067	0.354
SV Red PII	-0.012	0.233	0.03	0.374	0.119	0.323	0.242	0.371	-0.049	0.288	0.07	0.241
SV Red PIV	-0.046	0.212	0.028	0.355	0.113	0.319	0.234	0.363	-0.057	0.286	0.069	0.238
Re Red PII	0.054	0.241	0.091	0.387	0.152	0.358	0.269	0.372	-0.025	0.312	0.017	0.218
Re Red PIV	0.031	0.232	0.089	0.368	0.143	0.348	0.256	0.354	-0.033	0.311	0.013	0.215

Conclusion

In this study, dependence structure between stock indices and alternative asset was allowed to switch by the application of dependence-switching copula approach. Further, the frame work for portfolio management is quantified by three measure, risk minimization strategy, return maximization strategy and equally weighted strategy was studied. The empirical results of the study revealed regarding risk spillovers from GSCI to stock indices; For the case of Islamic stock indices and GSCI, both dependence and tail dependence between Islamic stock indices and GSCI are stronger in a negative correlation regime than in positive correlation regime. It implies that the comovement between Islamic stock indices and GSCI can be used for hedging and diversification. For the case of conventional stock and GSCI, mixed results are reported. Overall, the market dependences of conventional stock and GSCI are greater than of Islamic stock indices and GSCI. This finding highlighted heterogeneity between the movements between conventional stock and GSCI, leading to a mixed evidence for link with GSCI. Based on the measures of risk spillovers, it is concluded that GSCI can be used for Hedging of crisis and diversification of portfolio based on Islamic stocks and conventional stock indices. It is also computed that the systematic risk measures and risk spillovers of the regime switching model capture the pronounced features useful for financial risk of commodity market.

Research Implications

To represent the conditional dependency between traditional stock indexes and Islamic stock indices and alternative assets in a more realistic way than the previous studies, a relatively new modeling technique, time-varying copula with a switching dependence was used. A dependence-switching copula represents a reliance structure more accurately and realistically than a single copula regime because the dependence may alter between positive and negative correlation regimes with time. These findings have important implications for investors seeking a higher risk-returns trade-off from the global stock markets by diversifying a stock portfolio with commodity index. The results show that the risk-minimizing and equally weighted portfolios outperform the benchmark portfolio (stock only). It highlighted the importance of constructing mixed asset portfolios for diversification purposes, although the benefits would vary and depend upon the inclusion of hedging assets and portfolio composition. That is, the Islamic stock markets are creating enormous investment and trading opportunities for investors to earn higher returns, compared to the returns normally earned from investing in conventional stock markets, and they are also opening avenues for investors of ethical and religious beliefs. The outcomes of the financial implications i.e., the extent of dependence/contagion effects have significant implications for funds managers, individual, institutional, and group investors. Results of the study expose several risk management indications for the pair series (Islamic/conventional stock and GSCI) with mix exposure of diversification/un-diversification.

Future Research Directions

The behavior of more alternative assets, along with more countries needed to be considered for examination to determine the factors helpful in portfolio diversification, hedging benefits and safe haven dynamics. A combined portfolio comprising of conventional stocks, Islamic stock and alternatives assets can also be taken for future research. The used copula families are not only families to describe dependence patterns and dependence structure among pairs, other copula families with their distinguish characteristics also need to be tested.

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