Islamic Equity Investments and the COVID-19 Pandemic

Abstract

Global equity markets experienced a substantial downfall with the outbreak of the COVID-19 as a pandemic. At the peak of the downfall, S&P Dow Jones reported that their Islamic equity indexes (IEIs) continue to outperform their conventional counterparts in the first quarter of 2020. The equity markets have since recovered and have touched historical peaks. This study empirically investigates how Islamic equity investment weathered the trough and peak of equity markets during the COVID-19 pandemic by using a sample consisting of global, US, European, and Asian IEIs, and daily data for the period starting from 01 May 2018 to 30 April 2021. We find evidence that IEIs do provide resistance/hedging during the extreme downfalls of the markets albeit only those following the Shariah screening criteria that follow the market value of equity (MVE) approach. During the COVID-19 period, IEIs exhibit significant excess returns without any extra cost to investors. While examining the impact of varying Shariah screening standards, we find that performance differential is more pronounced for those IEIs that follow the market-value-of-equity-based Shariah screening criteria. As a caution to investors, the hedging benefit associated with IEIs is observed only when there is a big swing in the market.

Keywords: COVID-19; Islamic equity investments; hedging; Downmarket beta; Logistic smooth transition autoregressive model

1. Introduction

After the outbreak of the COVID-19 pandemic, global equity markets experienced a sharp decline in market values. The global market levels in mid-February 2020 reached a full-blown crisis, and the panic mode was as dramatic as anything seen during the Global Financial Crisis (GFC) 2008–09 period (Quinsee, 2020). Nonetheless, the S&P and Dow Jones reported that their Islamic indexes outperformed their conventional benchmarks in the first quarter of 2020 (Welling, 2020). The equity markets have since recovered and reached the historical peaks due to the interventions introduced by the governments, regulators, and multilateral financial institutions to reduce the impact of the pandemic-related restrictions on the real economic sectors and optimism with the availability of vaccines to the global population.

Investment vehicles following Islamic finance principles have specific characteristics such as debt avoidance (low risk), linkages with the real economy, and risk sharing that may provide a buffer to such economic shocks (Abedifar, Ebrahim, Molyneux, & Tarazi, 2015; Chapra, 1985; Ebrahim, 2009; Ibrahim, 2016). Empirical literature supports this argument by showing better performance of Islamic indexes in the immediate aftermath of the GFC (Alam & Rajjaque, 2016; Ashraf, 2013; Hoepner, Rammal, & Rezec, 2011; Masih, Kamil, & Bacha, 2018; Saiti, Bacha, & Masih, 2014). However, the GFC was an endogenous shock resulting from the actions of market players, bankers, and speculators that led to excessive buildup of debt and risk-taking, resulting in the credit bubble (Roy & Kemme, 2020). In contrast, the COVID-19 pandemic crisis is due to exogenous factors directly affecting the real economy.

During a macroeconomic environment where about 5% decline (see Figure 1) is observed in real GDP for developed economies during 2020 (IMF, 2021), stocks from entertainment-related industries, the financial services industry, and highly leveraged firms (in Islamic finance terminology, these are called ‘sin’ stocks) may experience a steeper decline while companies offering an online business, or their support services are expected to perform better than the overall market. We argue that due to exclusion of sin stocks from the Shariah-compliant universe of equities and overweighting of tech-related growth stocks, Islamic portfolios may experience a lower downfall during the COVID-19 crisis and faster recoveries when the markets return to growth and thus offer hedging[1] (disaster resilience) benefits. This paper aims to empirically investigate whether Islamic equity investments provide any resilience/hedging benefits to investors during different stages of exogenous shocks such as the ongoing COVID-19 pandemic.

There are at least two types of Shariah screening standards.[2] One is those Shariah screening standards that follow the market value of equity (MVE) and is considered as following a momentum strategy where stocks with declining price trends (losers) are screened out while stocks with the rising pricing trends (winners) are included in the Islamic portfolio (Ashraf, 2016; Obaidullah, 2005). Meanwhile, the second type of Shariah screening standards uses book value of total assets (BVTA) and relies on the financial strength of the balance sheet. Given the extreme movements during the COVID-19 pandemic, we expect the MVE approach to provide better returns and hedging benefits.

Since the objective of this paper is to document the returns of Islamic equity investment during different stages of the still ongoing pandemic crisis and relate them to differences in Shariah screening criteria and various global regions, we provide empirical analysis based on ten Islamic equity indexes (IEIs)[3] and their benchmark equity indexes (BEIs) during the period starting from 01 May 2018 to 30 April 2021. To account for Shariah screening criterion differences, we use three mainstream Shariah screening criteria from Standard & Poor's (S&P), Morgan Stanley Capital International (MSCI), and Dow Jones (DJ). To capture regional differences, we used global, US, European, and Asian indexes. The severity of pandemic guides the geographic selection in addition to the selected indexes and covers most of the investible universe.

[1] Hedging benefits in this context refers to the phenomenon that during adverse market movement, portfolios following Islamic investment principles will not lose as much as conventional portfolios (Ashraf & Khawaja, 2016a). In the CAPM context, this implies that investments offering hedge either offer higher abnormal returns or lower systematic for the crisis period or both. It is pertinent to note that such a hypothesis is in contravention to the belief that lower diversification may lead to lower risk-adjusted return.

[2] The difference in Shariah screening standards may result in completely different portfolios although obtained from the same universe of equities (Wajid & Ashraf, 2019). Among the major differences is the calculation of leverage, cash holdings, and investments. In the case of MSCI, the standard uses the book value of equity as the denominator in the calculation of these ratios while for S&P and DJ, the trailing market value of equity is used as the denominator. For a detailed discussion on the differences in various Shariah screening standards and how they affect performance, please see Derigs & Marzban, 2009, Ashraf (2016) and Ashraf & Khawaja (2016b). Appendix A provides detailed guidelines for Shariah screening.

[3] We use equity indices as the unit of analysis since these do not account for transaction costs or management skills (Ashraf & Mohammad, 2014).

To capture the performance differentials during the different phases of the pandemic, we follow the recent empirical studies such as Hasaj & Scherer (2021) and Pagano, Wagner, and Zechner (2020). We define five stages of the pandemic as it unfolded for empirical analysis. Specifically, these stages are incubation, outbreak, fever, treatment, and (a new) inoculation period. We employ cumulative return performance, Value-at-Risk (VaR), and drawdown analysis, for the relative risk-return analysis. We use the Capital Asset Pricing Model (CAPM) framework, after incorporating dummy variables for each stage of the pandemic, to analyze the performance differentials with pre-COVID-19 and various stages of the pandemic. To capture the possible hedging benefit during the intertemporal market movements, we employ dual beta and logistic smooth transition autoregressive (LSTAR) models. The dual beta model captures the market movement in up and down markets while the LSTAR model allows a smooth transition between the states of capital markets like 'bull' and 'bear' over the whole sample period (Teräsvirta, 1994).

The empirical findings suggest that IEIs do provide hedging benefits during the severe macroeconomic shock related to the COVID-19 pandemic. IEIs exhibit positive abnormal returns during the COVID-19 period without any increase in systematic risk. Furthermore, such a performance appraisal is more pronounced for those IEIs that follow the MVE-based Shariah screening criterion. In addition, IEIs exhibit comparatively better performance during normal market conditions. However, the excess performance comes at the cost of higher systematic risk and higher VaR. Overall, the empirical findings suggest that IEIs do not generally provide hedging benefits during regular market downfalls. However, when there is a big swing in the market, the risk-averse nature of IEIs pays off resulting in better performance than unrestricted BEIs.

The empirical findings have policy implications for investors and fund managers. First, IEIs earn competitive abnormal returns for faith-driven investors without any additional cost during severe exogenous macroeconomic shocks. Second, for Islamic portfolio construction, the MVE-based approach is more suitable during volatile market conditions as it adjusts to market conditions more proactively. Third, conventional portfolio investors may develop different trading strategies by going short in conventional portfolios and long in Islamic portfolios during severe market downfalls to capitalize on the differential in performance of IEIs and BEIs.

The remainder of the paper is organized as follows; Section 2 provides the empirical methodology used in this paper. Section 3 describes the data sources and presents the univariate analysis. The estimation results are reported and discussed in Section 4. Section 5 summarizes and concludes the paper.

2. Methodology

This section describes the risk measures used for the performance appraisal of IEIs versus BEIs and presents empirical methodologies used for the analysis.

2.1. Value-at-Risk (VaR)

VaR is a simple measure of risk, which is the amount of loss that is exceeded with a probability of μ. Formally, if the log return of the ith index is R_i, then VaR, for the loss probability μ, can be stated as follows:

$$Prob(-R_i > VaR) = \mu \tag{1}$$

Let R_{it} be the daily log return for the ith index in period t. The Risk-Metrics (RM) model can be used to provide the VaR for the index. Let $VaR_{i,t+1}^{\mu}$ represent the VaR for the 1-day ahead return with loss probability μ. If the daily log returns are normally distributed with zero mean and standard deviation $\sigma_{i,t+1}$ for the ith index, then:

$$Prob\left(-R_{i,t+1} > VaR_{i,t+1}^{\mu}\right) = \mu \tag{2}$$

Equation (2) can be rewritten as follows:

$$Prob\left(z_{i,t+1} < -\frac{VaR_{i,t+1}^{\mu}}{\sigma_{i,t+1}}\right) = \mu \tag{3}$$

In equation (3), $z_{i,t+1} = \frac{R_{i,t+1}}{\sigma_{i,t+1}}$ since the daily log returns are normally distributed with zero mean and standard deviation $\sigma_{i,t+1}$. Since $z_{i,t+1}$ follows a standard normal distribution, we have the following:

$$\Phi\left(-\frac{VaR_{i,t+1}^{\mu}}{\sigma_{i,t+1}}\right) = \mu \tag{4}$$

Therefore, $VaR_{i,t+1}^{\mu}$ can be calculated in the following manner:

$$VaR_{i,t+1}^{\mu} = -\sigma_{i,t+1}\Phi^{-1}(\mu) \tag{5}$$

If $\mu = 0.01$ (the loss is greater than $VaR_{i,t+1}^{\mu}$ with a probability of 1%), then we get $VaR_{i,t+1}^{\mu} = 2.33\sigma_{i,t+1}$ which is interpreted as follows: there is a 1% chance of losing more than $2.33\sigma_{i,t+1}$% of the portfolio's value today.[4]

2.2. Maximum Drawdown

The maximum drawdown (MDD) is an alternative to VaR that can assess the tail risk and is commonly used as a risk indicator among investors (de Melo Mendes & Lavrado, 2017). Let P_{it} represent the daily log of asset price of index i in period t. Consider the rolling window of size T_w, then MDD at time t, in percentage terms, is defined as:

$$MDD_{it} = \begin{cases} 0; & if\ P_{it_2} \geq P_{it_1} \\ \max\limits_{t-T_w+1 \leq t_1 < t_2 \leq t} \left(\frac{P_{it_1} - P_{it_2}}{P_{it_1}} \right); & otherwise \end{cases} \quad (6)$$

MDD shows the worst loss in the period $\{t - T_w + 1, \cdots, t\}$ and the duration of the loss is $t_2 - t_1$. If the asset price depicts a non-decreasing trend over the concerned period, then MDD is zero. For the calculation of MDD, we take the window size as 30-days i.e. $T_w = 30$.

2.3. Capital Asset Pricing Model (CAPM)

VaR, presented in the previous subsection, is a measure of a portfolio's stand-alone risk. It does not consider the relative riskiness of the portfolio as compared with the overall market movement. CAPM provides the relative risk/return payoff of an IEI compared to BEIs and is calculated using the standard Constant Risk Model (CRM). The specification of this model is as follows:

$$R_{it} = \alpha_i + \beta_i R_{jt} + \epsilon_{it};\ \forall\ i \in \{1, \cdots, n\}, j \in \{1, \cdots, m\}, t \in \{1, \cdots, T\} \quad (7)$$

In equation (7), R_{it} and R_{jt} are the daily log-returns of the ith IEI and jth benchmark, respectively. The intercept term α_i, Jensen's alpha, measures the ith IEI's excess daily log returns adjusted to the jth benchmark. The coefficient β_i measures the ith IEI's relative riskiness in comparison to the jth benchmark which is the systematic risk and is calculated as:

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[4] We have the VaR in percentage because we are using log returns.

$$\beta_i = \frac{Cov(R_{it}, R_{jt})}{\sigma_j^2} \tag{8}$$

where σ_j^2 is the variance of the return of the jth benchmark. The coefficient β_i is interpreted as follows: $\beta_i = 1$ means that the ith IEI is neutral to the jth benchmark, $\beta_i > 1$ means that the ith IEI is riskier compared to the jth benchmark, and $\beta_i < 1$ means that the ith IEI is safer than the jth benchmark. The error term in equation (7), ϵ_{it}, has zero mean and we assume it to be homoscedastic and serially independent.

The CRM model, presented in equation (7), assumes that β_i is stable over the investment horizon, and under 'bull' and 'bear' market conditions. However, the stability condition is quite restrictive (Ashraf & Mohammad, 2014). Several studies have provided evidence of varying β_i overtime under various market conditions (De Bondt & Thaler, 1985; Faff, 2001; Hodoshima, Garza–Gómez, & Kunimura, 2000; Howton & Peterson, 1998; Lunde & Timmermann, 2004; Pettengill, Sundaram, & Mathur, 1995). Most of these papers used a Dual-Beta Market (DBM) model to estimate the effect of a single market condition on β_i (Ashraf & Mohammad, 2014). This model is specified as follows:

$$R_{it} = \alpha_i + \beta_i R_{mt} + (\alpha_i^D + \beta_i^D R_{mt}) S_t + \epsilon_{it} \tag{9}$$

In equation (9), S_t is a dummy variable representing the two phases of the market and is defined as follows:

$$S_t = \begin{cases} 1; M_t > c_t \\ 0; M_t \leq c_t \end{cases} \tag{10}$$

where M_t is the indicator of the market state and c_t is a critical value for the market state. So, $S_t = 1$ when the market is down - a 'bear' market ($M_t > c_t$), and $S_t = 0$ when the market is up - a 'bull' market ($M_t \leq c_t$). Generally $M_t = R_{mt}$, where R_{mt} is the market return, and the critical value c_t is either set as zero or the mean/median of the market return.[5] However, following Ashraf and Mohammad (2014), we take M_t as the moving average of daily market returns, R_{mt}. The use of the moving average is preferred to account for the noise in the market data, as suggested by Teräsvirta (1994), in the case of monthly returns. In our case, returns may pose even more noise due to daily observations. For this study, the transition function considers the moving average of

[5] We take c_t as the mean of the market returns using a 20-day rolling window.

market returns for the last 20 days, as above or below the daily return to call the state of the market as bull or bear, respectively.

In our setting, in addition to the 'bull' and 'bear' market conditions, we are also interested in the variation in β_i due to COVID-19. As such, we redefine the model of equation (9) as follows:

$$R_{it} = \alpha_i + \beta_i R_{mt} + \sum_{k=1}^{5} C_{kt}\,(\alpha_{ik} + \beta_{ik} R_{mt}) + (\alpha_i^D + \beta_i^D R_{mt}) S_t + \epsilon_{it} \tag{11}$$

In equation (11), C_{kt} are dummy variables that identify different stages of the pandemic following the taxonomy of Pagano et al. (2020) and Hasaj & Scherer (2021); incubation ($k = 1$), outbreak ($k = 2$), fever ($k = 3$), treatment ($k = 4$), and inoculation ($k = 5$). Therefore, the model presented in equation (11) allows variation in systematic risk (β_i) during the various sub-periods of the pandemic (through β_{ik}'s) along with 'bull' and 'bear' market conditions. Ordinary-least-squares (OLS) is not appropriate for the estimation of β_i in equation (7) and equation (9) because of the time-varying nature of β_i and heteroskedasticity of ϵ_{it} (Brooks, Faff, & McKenzie, 1998). Since we expect similar concerns with the estimation of the model presented in equation (11), we rely, following Ashraf and Mohammad (2014), on the generalized autoregressive conditional heteroskedasticity (GARCH) model. The general multivariate GARCH model, proposed by Bollerslev, Engle, & Wooldridge (1988), is given as:

$$Y_t = CX_t + e_t \tag{12}$$

$$e_t = \boldsymbol{H}_t^{1/2} v_t \tag{13}$$

$$\boldsymbol{h}_t = vech(\boldsymbol{H}_t) \tag{14}$$

$$\boldsymbol{h}_t = s + \sum_{i=1}^{p} A_i vech(e_{t-i} e'_{t-i}) + \sum_{j=1}^{q} B_j \boldsymbol{h}_{t-j} \tag{15}$$

In equation (12), Y_t is a $n \times 1$ vector of dependent variables which are daily log-returns of IEIs, C is a $n \times k$ matrix of parameters, X_t is a $k \times 1$ vector of independent variables which contain log-returns of the benchmark. In equation (13), $\boldsymbol{H}_t^{1/2}$ is the Cholesky factor of $\boldsymbol{H}_t$ (the time-varying conditional covariance matrix of IEI log returns), and v_t is a $n \times 1$ vector of independent and identically distributed innovations. In equation (15), s is a $\frac{n(n+1)}{2} \times 1$ vector of parameters while A_i and B_i are $\frac{n(n+1)}{2} \times \frac{n(n+1)}{2}$ matrices of parameters. The $vech(\cdot)$ function converts a symmetric matrix into a column vector of its lower diagonal elements.

Due to many unknown parameters, estimation of the parameters of the general multivariate GARCH model can be difficult. Following Ashraf and Mohammad (2014), we rely on the diagonal-vech GARCH model which replaces equation (15) with the following:

$$\boldsymbol{H}_t = S + \sum_{i=1}^{p} A_i \odot vech(e_{t-i}e'_{t-i}) + \sum_{j=1}^{q} B_j \odot \boldsymbol{H}_{t-j} \tag{16}$$

In equation (16), S is a $n \times n$ symmetric matrix of parameters, $\odot$ represents the Hadamard product which is the element-wise product of the matrices, whereas A_i and B_i are $n \times n$ symmetric matrices of parameters. For estimation purposes, we determine the lags p by minimizing Akaike's Information Criterion (AIC).

2.4. Logistic Smooth Transition Autoregressive (LSTAR) model

Since S_t is a dichotomous variable, the DBM model assumes abrupt jumps between 'bull' and 'bear' market states. Teräsvirta (1994) proposed a model that allows for smooth transitions referred to as the Smooth Transition Autoregressive (STAR) model. Following Ashraf and Mohammad (2014), we consider the LSTAR model which is specified below with K lags:

$$R_{mt} = a_0 + \sum_{l=1}^{K} a_l R_{m,t-l} + F(M_t)\left[b_0 + \sum_{l=1}^{K} b_l R_{m,t-l}\right] + u_{it} \tag{17}$$

$$F(M_t) = \frac{1}{1 + e^{-\gamma(M_t - c_t)}} \tag{18}$$

$F(M_t)$ is the first order logistic function which provides a smooth transition replacement for S_t in equation (11), and γ is a smoothness parameter. Before the LSTAR model can be incorporated in the model presented in equation (11), the non-linear form of equation (17) needs to be justified.

For this purpose, we tested the LSTAR model against a linear autoregressive model (Enders, 2014; González, Teräsvirta, & Dijk, 2005; Woodward & Brooks, 2009). Smooth transitioning between market states can be achieved by rewriting equation (11) as follows:

$$R_{it} = \alpha_i + \beta_i R_{mt} + (\alpha_i^D + \beta_i^D R_{mt})F(M_t) + \sum_{k=1}^{5} C_{kt}\,(\alpha_{ik} + \beta_{ik} R_{mt}) + \epsilon_{it} \tag{19}$$

Note that even though C_{kt}'s are dummy variables, we have kept these unchanged because the subperiods of COVID-19 are exogenously defined.

3. Data sources and univariate analysis

The sample includes ten IEIs and their corresponding BEIs following Shariah screening guidelines of S&P, DJ, and MSCI. [6] The selected IEIs include three global (S&P, DJ, and MSCI), three US (S&P, DJ, and MSCI), two European (S&P and MSCI), and two Asian (DJ and MSCI) IEIs. The daily price data from 01 May 2018 to 30 April 2020 is obtained from Capital-IQ for the MSCI and DJ indexes, while the data for S&P indexes are obtained from the S&P Global website. Appendix B provides information on the IEIs and their respective BEIs from where the Islamic index usually draws its equities and basis of shariah screening that standard follows i.e. MVE or BVTA.

Our main analysis is focused on the performance differential of IEIs with BEIs from various regions and following different Shariah screening criteria during various stages of the COVID-19 pandemic. Consistent with the latest research on equity market performance, we follow the taxonomy of Pagano et al. (2020) and Hasaj & Scherer (2021). The sample period covers the period starting from 01 May 2018 to 30 April 2021 and is divided into six subperiods: pre-COVID-19 period (01 May 2018 to 31 December 2019), the incubation (02 January 2020 to 17 January 2020), outbreak (18 January 2020 to 21 February 2020), fever (24 February 2020 to 20 March 2020), recovery (21 March 2020 to June 30, 2020) and inoculation (01 July 2020 to 30 April 2021).[7]

[6] Appendix A shows the differences between Shariah screening standards. Qualitatively, the main difference in Shariah screening criteria is the denominator of financial ratios and their tolerance levels while determining the 'Shariah-compliance status' of equities. The market value of equity (MVE) is used as a denominator for calculating financial ratios in S&P and DJ, while MSCI uses the book value of total assets (BVTA). MVE-based screening criteria requires the rebalancing of portfolios more often, have fewer equities, and have better return performance than those using BVTA (Ashraf, 2016).

[7] The COVID-19 pandemic is still ongoing. Our sample, however, covers the period till 30 April 2020.

Using the chronological ordering of events in the initial phase of the pandemic, Ramelli & Wagner (2020) categorized the incubation, outbreak, and fever periods while Hasaj & Scherer (2021) introduced treatment as the fourth period. We introduced two sub-periods: pre-COVID-19 and inoculation period. The inoculation period covers the announcement of efficacy results of COVID-19 related vaccines, and their efficacy followed by the mass vaccination. The initial success reports of candidate vaccines from human trials started pouring in early July which builds a positive momentum among the investors.[8]

Daily returns are calculated as the natural logarithmic difference between the daily price and its corresponding lag. Figure 2 exhibits the return performance of both IEIs and BEIs based on US$100 investment on 01 May 2018. It is evident from Figure 2 that all the indexes have recovered from the steep downfall of the markets in the early phase of the pandemic. However, there are interesting differences among the performance of different IEIs from different regions or following different Shariah screening standards. On one side, the IEIs following MVE-based Shariah screening criteria outperform their benchmark index in all the regions and indicate a faster recovery than their BEIs. On the contrary, IEIs following the BVTA-based Shariah screening standard lag the benchmark except for the European market (IEI7) and Asian market (IEI8), indicating that the Shariah screening standard affects return performance. The resistance of IEIs during the extreme downfall as reflected by a lower dip during the outbreak and early recovery during the fever and recovery phase highlight possible hedging benefits of the IEIs.

Table 1 reports the descriptive statistics for the annualized returns, standard deviation, Sharpe ratios, differences in means test (IEI – BEI), and beta coefficients estimated from the standard CRM of the sample IEIs and BEIs for the subperiods. In our analysis, we use the excess of risk-free returns[9] for both IEIs and BEIs. To understand how different the relative riskiness of IEIs is from that of BEIs, we provide test results of the null hypothesis: $\beta=1$. A rejection of the null hypothesis would imply that the riskiness of an IEI is significantly different from the BEI.

[8] On July 14, 2020 Moderna Inc reported Data from phase 1/2 trials of COVID-19 vaccine with two doses administered 28 days apart produced immune responses in all 3 groups of 15 volunteers with very mild adverse effects include injection site pain and chills. (https://www.ajmc.com/view/a-timeline-of-covid19-developments-in-2020)

[9] Risk-free return has been collected from the Kenneth R. French's Data Library: http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/index.html

In terms of returns performance, a considerable deviation can be observed during various stages of the COVID-19 period among indexes (IEI versus BEI) and Shariah screening (MVE versus BVTA). All IEIs and BEIs, on average, show positive returns during the pre-COVID-19 period except for IEI of MSCI Asia and BEIs from Europe and Asia. The average returns of IEIs are above BEIs except for the MSCI Global (IEI3) and MSCI US (IEI6). The trend continues in the incubation period. The positive return performance of IEIs and BEIs turns negative during the outbreak of the pandemic and stayed negative during the fever stage of the pandemic albeit the downfall of IEIs is generally lower than that of the BEIs as can be observed from the differences in means analysis. During the fever period, the returns difference is statistically significant for those IEIs following the MVE approach. We observe a robust recovery during the treatment phase where both IEIs and BEIs showed positive returns albeit with some regional and screening standard differences. Regarding comparative performance, S&P and DJ IEIs outperform their corresponding BEIs irrespective of region or sample period both on annualized and risk-adjusted (see Sharpe ratio) basis except during the inoculation stage. However, the story is different for the MSCI IEIs. Global and US MSCI IEIs underperform their corresponding BEIs during all sub-sample periods. The difference in nominal returns performance is in line with Ashraf (2016) and can be attributed to the difference in Shariah screening standards.

To further understand the return performance of IEIs and whether excess returns of IEIs are associated with higher risk-taking, we compare the risk-adjusted performance of IEIs and BEIs using the Sharpe ratio. Like nominal returns, S&P and DJ IEIs outperform their corresponding BEIs, on a risk-adjusted basis, irrespective of region or sample period, suggesting that better performance in nominal as well on a risk-adjusted basis is associated with indexes following the MVE approach. The performance of IEIs following the BVTA approach lags their BEI except for European and Asian indexes, where it outperforms the BEI both on a nominal and risk-adjusted basis.

Regarding the systematic risk of IEIs, we observe that β coefficients of pre-covid and inoculation periods are very similar for most of the IEIs. Regarding the null hypothesis of similar risks of IEIs versus BEIs for the pre-COVID and inoculation periods, we reject the null hypothesis: β=1 for all IEIs except for the IEIs from Europe and Asia following BVTA-approach for Shariah screening. The rejection of the null hypothesis of similar systematic risk suggests that IEIs do not exhibit similar systematic risk profiles as that of BEIs. However, the scenario changes during the intermediate stages: incubation, fever, and recovery where we fail to reject the null hypothesis of similar risk suggesting that during the extreme downfall and recovery therefrom periods, the performance of IEIs can be explained with the systematic risk.

An interesting trend is the general shrinkage of CRM β coefficients from outbreak to fever and treatment stage. The general shrinkage of CRM β coefficients may reflect the relative risk-averse nature of Islamic investments and suggest potential hedging benefits. Overall, return performance, both nominal and risk-adjusted, and CRM results indicate the dynamism in the relative performance of IEIs during the sample period.

Figure 3 exhibits the 1-day 1% Value-at-Risk (VaR) trend for IEIs and BEIs during the sample period. The VaR started to increase from the incubation stage (shaded yellow) and reached a peak during the treatment period (shaded purple). In contrast to the return performance, there is no significant observable difference in the VaR IEIs versus BEIs. The VaR of IEIs is either similar or lower than that of the BEIs' VaR.

To further understand the relative riskiness of IEIs versus BEIs, Figure 4 depicts downside risk as measured by the maximum losses a portfolio can suffer, estimated as the percentage loss from peak to trough monthly, adjusted on a rolling basis for daily returns. Interestingly, the maximum drawdown of IEIs is comparable with BEIs in a tight range. However, at the peak of drawdown during the recovery period, the maximum drawdown of IEIs is lower than that of the BEIs, suggesting that Shariah restrictions help in reducing the drawdown for Islamic equity investments. Furthermore, European indexes have shown lower maximum drawdown as compared to the US and global indexes.

4. **Multivariate analysis: Results and discussion**

The univariate analysis discussed above shows apparent differences in the performance and relative riskiness of IEIs-vs-BEIs and IEIs following different Shariah screening standards from different regions. The general trend is that IEIs following the MVE approach show higher resistance during the various stages of the pandemic. While considerable differences exist in regional IEIs, but they generally followed the same patterns. However, formal inferences can only be drawn using multivariate analysis capable of capturing the intertemporal differences in the capital market. Below we present the estimation results based on the dual beta and LSTAR models.

4.1. Base model

Table 2 reports the estimation results of our base model after incorporating the subperiod dummies. Panel A reports the abnormal returns while Panel B reports the systematic risk associated with subperiods: pre-COVID-19, incubation, outbreak, fever, recovery, and inoculation. The overall abnormal return and systematic risk would be an additive function of abnormal returns and systematic risks reported for each of the subperiod. Regarding the β coefficients, β_i coefficients are reported against the test of unit-equality; the magnitude of the β_i-to-one shows the relative riskiness of an IEI relative to its BEI.[10] We use the Bollerslev et al., (1988) diagonal vech GARCH model for empirical estimations. The bottom part of the table reports the selected lags, lag (p) of the autoregressive model obtained from Akaike's information criterion (AIC). For all indexes, significant test statistics reported in the row titled χ^2 that affirms that all coefficients of the independent variables are not zero.

Abnormal return performance, reported in Panel A of Table 2, for the global IEIs shows that IEI1 and IEI2, which follow the MVE approach, outperform their respective benchmarks during the pre-COVID-19 period. However, both IEIs also exhibit systematic risk higher than their benchmark as shown by significantly higher β_i than one. Although abnormal returns are insignificant, similar behavior is shown by MVE-based IEIs in terms of systematic risk which is significantly higher than unity for IEI4, IEI5, and IEI9. The IEI7 (European IEI) shows significant abnormal return performance and systematic risk below unity. In comparison, IEIs following the BVTA approach for Shariah screening do not reflect any significant abnormal returns during the pre-COVID-19 period. However, the coefficients of β_i are below unity and statistically significant for the BVTA-IEIs except for IEI8 where it is slightly significant and above unity. Overall, results of the pre-COVID-19 period suggest that the Shariah screening criterion potentially has an impact on the performance of IEIs.

Moving on to the first sub-period of the COVID-19 shock, labeled as incubation period, all MVE-based IEIs reflect hedging potential suggested by the significantly positive coefficient for abnormal return, $\alpha_i^{\text{incubation}}$ except for the European (IEI7) where it is insignificant albeit positive.

Regarding the contribution to systematic risk, $\beta_i^{\text{incubation}}$, the coefficients are insignificant for the IEIs following the MVE approach except for the European (IEI7) where it is positive and significant. While during the same period IEIs following the BVTA approach do not reflect any statistically significant coefficients for both abnormal returns and the systematic risk during this period. Overall, the abnormal returns associated with the MVE-based IEIs are in line with the claims of S&P index services that during the initial stage of the pandemic, IEIs did provide hedging benefits.

During the outbreak phase, we do not observe any statistically significant $\alpha_i^{\text{outbreak}}$ while contribution to systematic risk is positive and significant in the case of IEIs following the MVE approach especially the S&P criteria suggesting that any abnormal return during this phase is associated with high-risk taking.

The most interesting results emerge from the third phase of the COVID-19 shock: the fever period. During this phase, all MVE-based IEIs irrespective of the region show significantly positive abnormal returns without any associated significant increase in the systematic risk hinting towards the hedging benefits of investing in Shariah-compliant equity portfolio albeit following the MVE approach. We observe similar trends during the treatment phase for IEI1 (global), and IEI4 (the US). In contrast, BVTA based IEIs do not show any significant contribution to the abnormal return or the systematic risk during fever or treatment phases except for the IEIs from Asia and the US where it is showing a significantly higher systematic risk.

During the inoculation phase, as the markets recovered from the extreme downfall, we find that the overall performance of IEIs align with their corresponding BEIs except for IEI10 reporting positive and significant coefficient for $\alpha_i^{\text{inoculation}}$ and IEI5 reporting positive and significant $\beta_i^{\text{inoculation}}$.

At this stage, performance differential is more obvious as we note that during the extreme market swings, MVE-based Islamic equity indexes provide hedging benefits through abnormal returns without any additional systematic risk. While IEIs following the BVTA approach, offer any additional returns, it can be explained with higher systematic risk. Overall, the empirical results in Table 2 indicate that IEIs did provide resistance/hedging during the sharp decline and early recovery period of the COVID-19 pandemic however, the potential resistance is limited to IEIs following the MVE approach for equity screening.

4.2. Dual Beta model

As shown by the results of the baseline model, IEIs do perform well during the downward market swing, we extended our model to see if the hedging benefits observed during the pandemic extend to general bearish market trends. Table 3 reports the estimation results based on equation (11) by incorporating the impact of the down market and various phases of the COVID-19 pandemic. Similar to the base model, we use the Bollerslev et al., (1988) diagonal vech GARCH model for empirical estimations and the lag (p) shows the selected lags of the autoregressive model obtained from Akaike's information criterion (AIC) and the significant χ^2 test results confirming that all coefficients of the independent variables are not zero.

In Table 3, Panel A reports abnormal returns for down-market (α_i^{down}) and for the subperiods. Interestingly, significant abnormal return performance for global indexes, IEI1 and IEI2, during the pre-COVID-19 period as reported in Table 2 is picked by the α_i^{down} suggesting that during the normal period, the abnormal performance of global IEIs is linked with the bearish market conditions. Other than these two indexes, none of the remaining eight IEIs show any abnormal performance during the general bearish trends, however, IEI3 (global), IEI7, and IEI8 (Europe) show a significant increase in the systematic risk.

The results for the pandemic period are generally in line with the previous findings in Table 2 whereas, MVE-based IEIs show significant positive abnormal return performance especially during the peak of pandemic (fever and treatment phases). Regarding COVID-19 related subperiod results for the systematic risk, we observe a general shrinkage in systematic risk as reflected by negative signs of the most of coefficients albeit statistically insignificant, indicating the risk-averse nature and resistance of IEIs during the sharp downfall in the market. Among other notable difference is that the β_i coefficients of all the IEIs, except for those following the BVTA approach for Shariah screening in the US (IEI6), Europe (IEI8), and Asia (IEI9), are significantly different from unity, suggesting that the performance of these IEIs is independent of their BEIs, among which BVTA-based IEI3 (global), show significantly lower systematic risk than its benchmark.

The insignificant β_i coefficients for the Asian and European BVTA-based IEIs suggest synchronicity with their benchmarks.

Overall, we do not observe a general trend of the lower systematic risk or abnormal returns of IEIs during the COVID period or during the general bearish trends of the markets except for IEIs following the MVE-based Shariah screening approach followed by S&P and Dow Jones. This signifies that during the exogenous shocks, selected Islamic equity investments do provide hedging benefits however, these results cannot be generalized.

4.3. LSTAR model

As discussed in the methodology section, the dual beta model assumes that variation in the performance of IEIs is linear over time. However, it assumes an abrupt jump between the state of markets from bull to bear or vice versa. To control for the abrupt jump, we estimate the LSTAR model. Since the transition variable M in the LSTAR model is the moving average of the past values of market returns, nonlinearity arises in the model.

To check for the nonlinearity and suitability of an LSTAR model against the presence of a linear autoregressive model, we performed the Lagrange Multiplier (LM) test. In the event of the failure to reject the nonlinearity, an LSTAR model is more appropriate. We provide χ^2 value of the LM test results along with significance in column 2 of Table 4. The statistically significant test results provide evidence of nonlinearity, and therefore, we estimated a logistic smooth transition autoregressive (LSTAR) model. We report the parameter estimates for c_t and γ_i in the last two columns of Table 4. The values of c_i and γ_i indicate a smooth transition between narrow ranges of γ_i from around 2 to 12. This range is sufficient to support the smooth transition from 'down market' to 'upmarket' and vice versa.

Table 5 reports the estimation results of equation (19), in which $F(M_t)$ is used as a down-market indicative variable based on the LSTAR model.[11] Results are estimated using the Diagonal Vech-GARCH model, as suggested by Bollerslev et al., (1988), with optimal ARCH lags selected using AIC, reported at the bottom of Table 5. As estimated values from the LSTAR model are used in the diagonal vech multivariate GARCH model, the entire estimation was bootstrapped,

[11] As $F(M_t)$ is an estimated value from LSTAR, bootstrap process has been used to estimate robust standard errors.

with at least 1000 replications, for appropriate standard errors. However, the diagonal vech multivariate GARCH model did not converge for all replications, as such, the standard errors are based on the replications that converged.

The results are directionally in line with the results provided in Table 3. However, there are few notable differences in terms of the statistical significance and size of the coefficient estimates. Regarding abnormal return performance during the pre-COVID-19 period, only MVE-based indexes: IEI1 (global) and IEI7 (Europe) show significant results. In terms of α_i^{down}, IEI1 show significantly negative abnormal performance. Other than that, all the indexes show no hedging benefits during the normal bearish market.

In terms of the IEIs performance during different phases of the COVID-19 shock, MVE-based indices reflect positive abnormal returns albeit in different stages on the pandemic showing the resistance of IEIs to the extreme downfalls in the market except for the inoculation phase. Interestingly, the systematic risk coefficients of most of the IEIs shrink during the different phases of the COVID-19, especially during the fever and treatment phases. The systematic risk of IEI1, IEI2, IEI4, IEI5, and IEI8 decreased significantly.

Overall, LSTAR model results are in line with our overall conclusion drawn from the previous sections showing that excess return performance of IEIs is associated with higher systematic risk assumed by IEIs during normal market conditions. The hedging benefits are only available during the severe market declines and only from those IEIs that follow the MVE approach for equity screening.

5. Summary and Conclusion

Earlier literature on Islamic equity investments' performance outlines the hedging benefits received during severe capital market downfalls such as during the GFC. The resilience of Islamic equity investments was attributed to Shariah screening criteria, accrued to the exclusion of sin stocks and inclusion of low leveraged and non-financial stocks. Since the GFC was caused by financial market failure, an endogenous shock, Islamic equity investments grounded in real economic activities had offered hedging opportunities to Islamic investors. However, the COVID-19 pandemic is different from the GFC as the financial losses emanate from the real economy.

This paper investigates whether Islamic equity investments provide any hedging benefits to investors during the COVID-19 pandemic relative to the Pre-COVID-19 period. For this purpose, we use a sample of ten IEIs from the Global, US, Europe, and Asia. Besides the regional coverage, we analyzed the performance of IEIs following Shariah screening standards using the MVE and BVTA approaches. The comprehensive coverage helps us avoid cherry-picking. We compared the performance of IEIs and BEIs using both univariate (excess returns, Sharpe ratio, VaR, and maximum drawdown) and multivariate analysis. The LSTAR model is preferred due to its ability to account for capital market movements.

The empirical findings suggest that during extreme bearish market trends, such as the COVID-19 pandemic, IEIs provide hedging benefits by providing positive excess returns without increasing systematic risk. Indexes built using MVE-based Shariah screening criteria show more pronounced hedging benefits as compared to BVTA-based IEIs. During normal market conditions, IEIs also provide excess performance; however, it is mainly associated with higher systematic risk suggesting that extra performance comes with an additional cost of higher non-diversifiable risk.

These findings have policy implications for Shariah-based investors specifically, and equity investors and fund managers in general. Future research avenues are available to research Islamic equity portfolios' performance evaluation using a smart beta methodology (factor-based strategies).

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Appendix A: Shariah Screening Criteria: This appendix provides a comparison of Shariah screening guidelines for equity investments approved by the Shariah boards of Morgan Stanley Capital International (MSCI), Dow Jones (DJ), and Standard & Poor's (S&P). Panel A is a list of impermissible business activities. Panel B provides the list of financial ratios, calculation methodology, and tolerance levels of these ratios for financial screening. BVTD is the book value of total debt, BVTA is the book value of total assets, MVE is the market value of equity, IBS is interest-bearing securities, and AR is accounts receivable.

Panel A: Business Screening

Standard	Impermissible activities*
MSCI	Alcohol, tobacco, pork-related products, financial services excluding Islamic banking and insurance practices, gambling, casinos, music, hotels, cinemas, and adult entertainment.
DJ	Alcohol, tobacco, pork-related products, financial services excluding Islamic banking and insurance practices, entertainment, hotels, casino/gambling, cinema, pornography, and music.
S&P	Alcohol, tobacco, pork-related products, financial services excluding Islamic banking and insurance practices, advertising and media, gambling, pornography, cloning, and the trading of gold and silver as cash on a deferred basis.

* *Up to 5% of total revenue is allowed from impermissible activities. However, an investor should cleanse their income by giving the impermissible income as a donation to charity.*

Panel B: Financial Screening

Standard	Leverage ratio	Interest-bearing liabilities ratio	Quick assets ratio
MSCI	BVTD / BVTA < 33.33%	(Cash + IBS) / BVTA < 33.33%	(Cash + AR) / BVTA < 33.33%
DJ	BVTD / $MVE_{\text{trailing 24-month-average}}$ < 33%	(Cash + IBS) / $MVE_{\text{trailing 24-month-average}}$ < 33%	AR / $MVE_{\text{trailing 24-month-average}}$ < 33%
S&P	BVTD / $MVE_{\text{trailing 36-month-average}}$ < 33%	(Cash + IBS) / $MVE_{\text{trailing 36-month-average}}$ < 33%	AR / $MVE_{\text{trailing 36-month-average}}$ < 49%

Source: (Ashraf, 2016)

Appendix B: Names and Codes and corresponding Islamic Equity Indexes (IEIs) and Benchmark Equity Indexes (BEIs).

Code	Shariah screening basis	Islamic Equity Index	Code	Benchmark Equity Index
IEI1	The market value of equity	S&P Global 1200 Shariah	BEI1	S&P GLOBAL 1200
IEI2	The market value of equity	Dow Jones - Islamic Market	BEI2	Dow Jones - World Index
IEI3	Book value of total assets	MSCI ACWI Islamic Index	BEI3	MSCI ACWI Index
IEI4	The market value of equity	S&P 500 Shariah Index	BEI4	S&P 500
IEI5	The market value of equity	Dow Jones - Islamic Market US Large-cap	BEI5	Dow Jones U.S. Large-Cap Total Stock Market Index
IEI6	Book value of total assets	MSCI AC Americas Islamic Index	BEI6	MSCI AC Americas Index
IEI7	The market value of equity	S&P Europe 350 Shariah Index	BEI7	S&P EUROPE 350
IEI8	Book value of total assets	MSCI AC Europe Islamic Index	BEI8	MSCI AC Europe Index
IEI9	The market value of equity	Dow Jones - Pan Asia Shariah	BEI10	Dow Jones - Pan Asia BMI
IEI10	Book value of total assets	MSCI AC Asia Islamic Index	BEI9	MSCI AC Asia Index

Period		Islamic equity indexes			Benchmark equity indexes			Differences in Means	CRM β
		$\bar{R}_i$	δ_i	Sharpe Ratio	$\bar{R}_i$	δ_i	Sharpe Ratio		
Pre-Covid	IEI1	0.0981	0.1232	0.8	0.0511	0.1103	0.46	0.0470*	1.10*
	IEI2	0.0827	0.1197	0.69	0.0373	0.1061	0.35	0.0454*	1.10*
	IEI3	0.0173	0.1077	0.16	0.0426	0.1083	0.39	-0.0253	0.96*
	IEI4	0.1230	0.1496	0.82	0.0984	0.1385	0.71	0.0246	1.07*
	IEI5	0.1273	0.1507	0.84	0.0972	0.1389	0.7	0.0301	1.07*
	IEI6	0.0487	0.1335	0.36	0.0909	0.135	0.67	-0.0422	0.95*
	IEI7	0.0634	0.1253	0.51	-0.0193	0.1278	-0.15	0.0827*	0.94*
	IEI8	0.0114	0.1314	0.09	-0.0176	0.1263	-0.14	0.0290	1.02
	IEI9	0.0069	0.1573	0.04	-0.0368	0.113	-0.33	0.0437	1.12*
	IEI10	-0.0400	0.1252	-0.32	-0.0341	0.1201	-0.28	-0.0059	1.02
Incubation	IEI1	0.7262	0.1232	10.8	0.4856	0.1103	8.53	0.2406*	1.16
	IEI2	0.7155	0.1197	10.49	0.4750	0.1061	8	0.2405*	1.13
	IEI3	0.3743	0.1077	7.24	0.5044	0.1083	8.29	-0.1301	0.80
	IEI4	0.8407	0.1496	9.51	0.6251	0.1385	7.77	0.2156*	1.09
	IEI5	0.8875	0.1507	9.59	0.6434	0.1389	8.2	0.2441*	1.16
	IEI6	0.3598	0.1335	5.79	0.6230	0.135	8.14	-0.2632	0.71
	IEI7	0.4227	0.1253	7.13	0.1586	0.1278	4.12	0.2641*	1.42
	IEI8	0.2484	0.1314	5.46	0.2115	0.1263	3.95	0.0369	0.78
	IEI9	1.0699	0.1573	6.93	0.3918	0.113	3.41	0.6781	1.09
	IEI10	0.5644	0.1252	4.75	0.4286	0.1201	3.45	0.1358	0.93
Outbreak	IEI1	-0.0669	0.1232	-0.55	-0.1039	0.1103	-0.98	0.0370	1.13*
	IEI2	-0.0777	0.1197	-0.66	-0.1452	0.1061	-1.41	0.0675	1.12
	IEI3	-0.3506	0.1077	-3.06	-0.1314	0.1083	-1.25	-0.2192*	1.04
	IEI4	-0.0248	0.1496	-0.17	0.0096	0.1385	0.08	-0.0344	1.13*
	IEI5	0.0421	0.1507	0.29	0.0389	0.1389	0.31	0.0032	1.13
	IEI6	-0.1914	0.1335	-1.5	0.0194	0.135	0.16	-0.2108	0.98
	IEI7	-0.0514	0.1253	-0.4	-0.1898	0.1278	-1.51	0.1384	1.00
	IEI8	-0.3632	0.1314	-2.6	-0.2244	0.1263	-1.8	-0.1388	1.10
	IEI9	-0.4373	0.1573	-2.19	-0.5128	0.113	-4.13	0.0755	1.36
	IEI10	-0.6208	0.1252	-4.15	-0.5270	0.1201	-3.98	-0.0938	1.10
Fever	IEI1	-4.2269	0.1232	-6.16	-4.7066	0.1103	-6.99	0.4797*	1.01
	IEI2	-4.1413	0.1197	-6.3	-4.7524	0.1061	-7.37	0.6111*	1.01
	IEI3	-4.5099	0.1077	-8.03	-4.6716	0.1083	-7.1	0.1617	0.84*
	IEI4	-4.4539	0.1496	-5.1	-4.7245	0.1385	-5.41	0.2706*	1.00
	IEI5	-4.2136	0.1507	-4.83	-4.8386	0.1389	-5.54	0.6250*	1.00
	IEI6	-4.8208	0.1335	-5.83	-4.9187	0.135	-5.64	0.0979	0.94
	IEI7	-3.9292	0.1253	-7.94	-5.0227	0.1278	-8.45	1.0935*	0.82*
	IEI8	-4.8615	0.1314	-8.11	-5.0401	0.1263	-8.19	0.1786	0.96
	IEI9	-2.6465	0.1573	-5.9	-3.6672	0.113	-10.75	1.0207	1.19
	IEI10	-3.2501	0.1252	-9.55	-3.2353	0.1201	-10.01	-0.0148	1.04
Treatment	IEI1	1.1058	0.1232	3.46	0.9920	0.1103	3.04	0.1138	0.96
	IEI2	1.1292	0.1197	3.75	0.9987	0.1061	3.2	0.1305	0.93
	IEI3	0.9489	0.1077	3.24	0.9881	0.1083	3.16	-0.0392	0.91*
	IEI4	1.1492	0.1496	3.06	1.0499	0.1385	2.79	0.0993	0.99
	IEI5	1.1422	0.1507	3.11	1.0892	0.1389	2.88	0.0530	0.94
	IEI6	1.0070	0.1335	2.7	1.0864	0.135	2.89	-0.0794	0.97
	IEI7	0.9126	0.1253	3.04	0.8919	0.1278	2.52	0.0207	0.82*
	IEI8	0.9795	0.1314	2.9	0.8804	0.1263	2.53	0.0991	0.95
	IEI9	0.7941	0.1573	2.93	0.8488	0.113	3.51	-0.0547	0.97
	IEI10	0.7611	0.1252	3.03	0.7554	0.1201	3.14	0.0057	1.02
Inoculation	IEI1	0.3094	0.1232	2.1	0.3345	0.1103	2.53	-0.0251	1.06*
	IEI2	0.3253	0.1197	2.27	0.3472	0.1061	2.78	-0.0219	1.08*
	IEI3	0.3008	0.1077	2.48	0.3398	0.1083	2.67	-0.0390	0.89*
	IEI4	0.3252	0.1496	1.86	0.3499	0.1385	2.24	-0.0247	1.08*
	IEI5	0.3371	0.1507	1.84	0.3657	0.1389	2.31	-0.0286	1.11*
	IEI6	0.2881	0.1335	1.9	0.3604	0.135	2.29	-0.0723	0.89*
	IEI7	0.2521	0.1253	1.61	0.2998	0.1278	1.82	-0.0477	0.86*
	IEI8	0.2698	0.1314	1.66	0.2403	0.1263	1.47	0.0295	0.91*
	IEI9	0.3652	0.1573	1.81	0.3201	0.113	2.36	0.0451	1.19*
	IEI10	0.3426	0.1252	2.27	0.2519	0.1201	1.98	0.0907	0.99

Table 1: This table shows the descriptive statistics of Islamic Equity Indexes (IEIs) and their corresponding Benchmark Equity Indexes (BEIs). $\bar{R}_i$is the annualized mean return, δ_i is the annualized standard deviation of returns, and the Sharpe ratio is the risk-adjusted return as measured by $\frac{(R_i-R_f)}{\delta_i}$. Daily data is pooled over the sub-sample periods: pre-COVID-19 period (01 May 2018 to 31 December 2019), the incubation (2 January 2, 2020, to 17 January 2020), outbreak (18 January 2020 to 21 February 2020), fever (24 February 2020 to 20 March 2020), recovery (21 March 2020 to June 30, 2020) and inoculation (01 July 2020 to 30 April 2021). β coefficients are obtained from the standard constant risk model (CRM). Names and Codes of corresponding Islamic Equity Indexes (IEIs) and Benchmark Equity Indexes (BEIs) are available in Appendix B. Asterisks *** denotes if the null hypothesis: β=1 (two-tail test) is statistically different from zero, at 1% level, ** 5% level; * 10% level.

Regions	Global			US			Europe		Asia	
Islamic Index	**IEI1**	**IEI2**	**IEI3**	**IEI4**	**IEI5**	**IEI6**	**IEI7**	**IEI8**	**IEI9**	**IEI10**
Panel A: Abnormal returns										
α_i	0.0002***	0.0002***	0.0000	0.0001	0.0001	-0.0001	0.0004***	0.0001	0.0002	0.0000
$\alpha_i^{\text{incubation}}$	0.0004*	0.0005**	-0.0001	0.0005*	0.0005*	-0.0002	0.0005	0.0002	0.0029**	0.0006
$\alpha_i^{\text{outbreak}}$	-0.0002	0.0000	-0.0006	-0.0002	-0.0003	-0.0005	0.0002	-0.0005	0.0006	0.0002
α_i^{fever}	0.0019***	0.0016***	-0.0002	0.0016***	0.0013*	-0.0002	-0.0015	0.0009	0.0065***	0.0007
$\alpha_i^{\text{treatment}}$	0.0008***	0.0001	0.0000	0.001***	0.0000	-0.0007	0.0004	0.0001	0.0000	-0.0001
$\alpha_i^{\text{inoculation}}$	-0.0001	-0.0001	0.0001	-0.0001	-0.0007	-0.0001	0.0000	0.0000	0.0001	0.0007**
Panel B: Systematic risk										
β_i	1.0879***	1.0993***	0.9787*	1.0678***	1.058***	0.9597***	0.9329***	1.0193*	1.130***	1.0091
$\beta_i^{\text{incubation}}$	0.0796	0.0313	-0.1843	0.0430	0.1184**	-0.2527	0.4983***	-0.2568	-0.0429	-0.0856
$\beta_i^{\text{outbreak}}$	0.0555*	0.0312	0.0574	0.0722***	0.0534	-0.0100	0.0777*	0.0540	0.1100	0.0639
β_i^{fever}	-0.0569	-0.0887	-0.0857	-0.0493	-0.0770	0.0050	-0.1187	-0.0094	0.0133	0.0381*
$\beta_i^{\text{treatment}}$	-0.1385	-0.1626	-0.0395	-0.1153	-0.0866	0.0506**	-0.1022	-0.0896	-0.173	0.046**
$\beta_i^{\text{inoculation}}$	-0.0525	-0.0390	-0.0891	-0.0114	0.0611***	-0.0598	-0.0913	-0.0623	0.043	0.0006
Lag(p)	10	12	4	10	6	5	11	9	14	12
L(p).ARCH	0.1649***	0.063**	0.2339***	0.1909***	0.1762***	0.0804*	0.0808**	0.1044**	0.1208***	0.0836**
Wald Test	2273.84***	17066. 9***	12541.94***	53187.84***	26549.87***	15321.07***	10203.26***	19393.17***	1680***	13724.44***

Table 2: This table reports the results capital assets pricing model using a Diagonal Vech-GARCH model. Panel A reports the excess return: α_i, $\alpha_i^{\text{incubation}}$,$\alpha_i^{\text{outbreak}}$, α_i^{fever}, $\alpha_i^{\text{treatment}}$ and $\alpha_i^{\text{inoculation}}$ and Panel B reports the systematic risk: β_i, $\beta_i^{\text{incubation}}$,$\beta_i^{\text{outbreak}}$,$\beta_i^{\text{fever}}$,$\beta_i^{\text{treatment}}$ and $\beta_i^{\text{inoculation}}$ corresponding to the pre-COVID-19 period (01 May 2018 to 31 December 2019), the incubation (2 January 2, 2020, to 17 January 2020), outbreak (18 January 2020 to 21 February 2020), fever (24 February 2020 to 20 March 2020), recovery (21 March 2020 to June 30, 2020) and inoculation (01 July 2020 to 30 April 2021) respectively. Lag(p) shows optimal lags of ARCH selected using the AIC criterion. A Wald test shows χ^2 value testing the null hypothesis that all the coefficients of independent variables are zero. Names and Codes of corresponding Islamic Equity Indexes (IEIs) and Benchmark Equity Indexes (BEIs) are available in Appendix B. Asterisks *** show significance at 1% level, ** 5% level, and * 10% level.

Regions	Global			US			Europe		Asia	
Islamic Index	**IEI1**	**IEI2**	**IEI3**	**IEI4**	**IEI5**	**IEI6**	**IEI7**	**IEI8**	**IEI9**	**IEI10**
Panel A: Abnormal returns										
α_i	0.0000	0.0000	0.0004***	0.0001	0.0002	-0.0003	0.0008***	0.0004**	0.0003	0.0001
α_i^{down}	0.0003*	0.0003**	-0.0006	-0.0001	-0.0001	0.0001	-0.0005	-0.0003	-0.0001	0.0000
$\alpha_i^{\text{incubation}}$	0.0003	0.0004*	-0.0001	0.0005*	0.0005*	-0.0002	0.0005	0.0001	0.0029**	0.0006
$\alpha_i^{\text{outbreak}}$	-0.0002	0.0000	-0.0007	-0.0003	-0.0003	-0.0005	0.0003	-0.0005	0.0006	0.0003
α_i^{fever}	0.0019***	0.0015**	0.0002	0.0017***	0.0014*	-0.0008	0.0028**	0.0010	0.0065***	0.0007
$\alpha_i^{\text{treatment}}$	0.0008***	0.0000	0.0002	0.001***	0.0001	-0.0009	0.001*	0.0002	0.0000	0.0001
$\alpha_i^{\text{inoculation}}$	-0.0001	-0.0001	0.0001	-0.0001	-0.0007	-0.0001	0.0001	0.0000	0.0001	0.0007**
Panel B: Systematic risk										
β_i	1.107***	1.1294***	0.9218***	1.0592***	1.0443*	0.9845	0.8785***	0.9861	1.1296*	0.9943
β_i^{down}	-0.0055	-0.0223	0.0403*	0.0092	0.0132	-0.0376	0.0591**	0.0439**	-0.0139	0.0336
$\beta_i^{\text{incubation}}$	0.0919	0.0392	-0.2111	0.0441	0.1209**	-0.2521	0.4437**	-0.2644	-0.0437	-0.0856
$\beta_i^{\text{outbreak}}$	0.056*	0.0302	0.0234	0.073***	0.0558	-0.0081	0.0708*	0.0421	0.1123	0.0661
β_i^{fever}	-0.0670	-0.1011	-0.0802	-0.0466	-0.0701	0.0033	-0.0659	-0.0191	0.0222	0.0262
$\beta_i^{\text{treatment}}$	-0.1546	-0.1790	-0.0197	-0.1122	-0.0810	0.0457**	-0.0979	-0.0839	-0.1723	0.0441**
$\beta_i^{\text{inoculation}}$	-0.0549	-0.0458	-0.0686	-0.0094	0.0641***	-0.0601	-0.0948	-0.0519	0.0452	-0.0050
Lag(p)	10	12	10	10	6	5	8	9	14	9
L(p).ARCH	0.1687***	0.0527*	0.1269***	0.1892***	0.1942***	0.075*	0.0949**	0.1132**	0.1216***	0.2253***
Wald Test	22804.74***	17098.96***	12792***	55520.27***	26295.03***	17513.43***	8378.59***	18977.59***	1683.05***	13681.08***

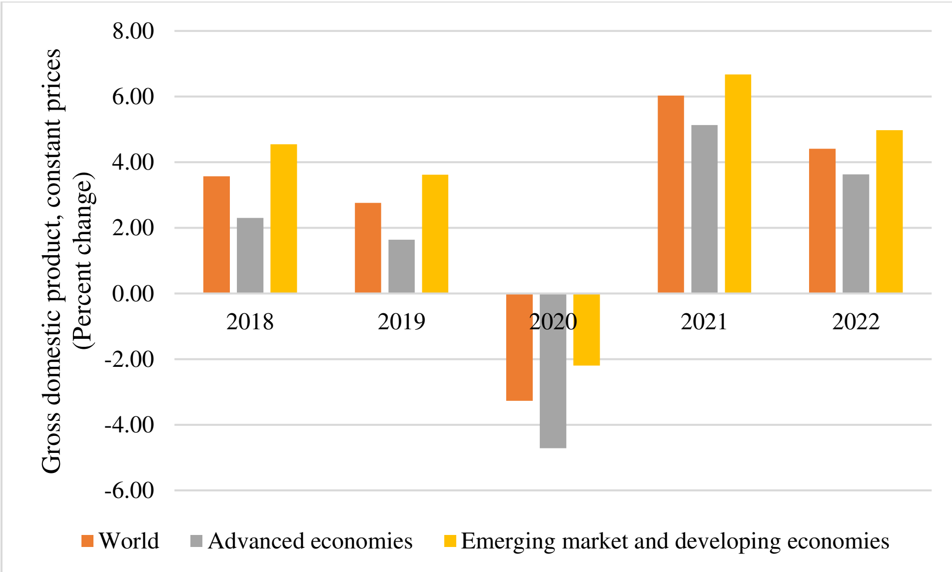
Table 3: This table reports the results of Equation (10) using a Diagonal Vech-GARCH model. Panel A reports the excess return: α_i, $\alpha_i^{\text{incubation}}$,$\alpha_i^{\text{outbreak}}$, α_i^{fever}, $\alpha_i^{\text{treatment}}$ and $\alpha_i^{\text{inoculation}}$ and Panel B reports the systematic risk: β_i, $\beta_i^{\text{incubation}}$, $\beta_i^{\text{outbreak}}$, β_i^{fever}, $\beta_i^{\text{treatment}}$ and $\beta_i^{\text{inoculation}}$ corresponding to the pre-COVID-19 period (01 May 2018 to 31 December 2019),. incubation (2 January 2, 2020, to 17 January 2020), outbreak (18 January 2020 to 21 February 2020), fever (24 February 2020 to 20 March 2020), recovery (21 March 2020 to June 30, 2020), and inoculation (01 July 2020 to 30 April 2021) respectively. Lag(p) shows optimal lags of ARCH selected using the AIC criterion. A Wald test shows χ^2 value testing the null hypothesis that all the coefficients of independent variables are zero. Names and Codes of corresponding Islamic Equity Indexes (IEIs) and Benchmark Equity Indexes (BEIs) are available in Appendix B. Asterisks *** show significance at 1% level, ** 5% level, and * 10% level.

Islamic Index	χ^2	Lag(p)	c_t	γ_i
IEI1	270.25***	13	-0.256	13.435
IEI2	306.5***	15	-0.096	2.471
IEI3	265.8***	12	-0.329	8.953
IEI4	226.69***	9	-0.008	1.461
IEI5	261.73***	11	-0.085	5.825
IEI6	229.13***	9	-0.005	1.452
IEI7	180.94***	14	-0.05	2.732
IEI8	175.23***	14	-0.122	2.721
IEI9	164.15***	10	-0.07	3.843
IEI10	151.9***	10	-0.091	4.281

Table 4: This table shows the Lagrange Multiplier (LM) test for the presence of LSTAR. χ^2shows the value of the LM test. Lag(p) shows optimal lags used in LSTAR, selected using the AIC criterion. *Ct* is the critical value parameter, and γ_i is a smoothness parameter of index *i*. Names and Codes of corresponding Islamic Equity Indexes (IEIs) and Benchmark Equity Indexes (BEIs) is available in Appendix B.Asterisks *** shows significance at 1% level, ** 5% level, and * 10% level

Regions	Global			USA			Europe		Asia	
Islamic Index	**IEI1**	**IEI2**	**IEI3**	**IEI4**	**IEI5**	**IEI6**	**IEI7**	**IEI8**	**IEI9**	**IEI10**
Panel A: Abnormal returns										
α_i	0.0414***	0.0213	-0.0531	0.0018	0.0021	0.0111	0.0113**	0.0023	0.0217	0.0042
α_i^{down}	-0.0425***	-0.0378	0.0558	-0.0035	-0.0032	-0.0223	-0.0205	-0.0038	-0.0380	-0.0071
$\alpha_i^{\text{incubation}}$	0.0004*	0.0005*	-0.0001	0.0005*	0.0005	-0.0002	0.0004	0.0002	0.0029	0.0006
$\alpha_i^{\text{outbreak}}$	-0.0002	0.0000	-0.0006	-0.0002	-0.0003	-0.0004	0.0000	-0.0005	0.0009	0.0002
α_i^{fever}	0.0017	0.0023**	-0.0005	0.0015***	0.0021	-0.0020	-0.0011	0.0005	0.0062**	0.0007
$\alpha_i^{\text{treatment}}$	0.0008**	-0.0002	0.0001	0.001**	0.0001	-0.0007	0.0000	0.0001	-0.0001	-0.0001
$\alpha_i^{\text{inoculation}}$	-0.0001	-0.0001	0.0000	-0.0001	-0.0007*	-0.0001	0.0000	0.0000	0.0004	0.0007
Panel B: Systematic risk										
β_i	1.1698	1.5285	1.7894	1.1148***	1.2239	1.6889	1.4679**	1.8796	1.8055	1.2394
β_i^{down}	-0.0839	-0.7581	-0.8585	-0.0921	-0.2717	-1.4575	-0.9961	-1.4806	-1.1718	-0.3865
$\beta_i^{\text{incubation}}$	0.0675	0.0176	-0.1732***	0.0414	0.1194	-0.2564**	0.4821**	-0.2599*	-0.0919	-0.0935
$\beta_i^{\text{outbreak}}$	0.0608	0.0367	0.0565	0.0711***	0.0608	-0.0088	0.0796*	0.0666	0.1006	0.0603
β_i^{fever}	-0.0583	-0.0694*	-0.0822	-0.0503***	-0.0375	-0.0199	-0.1045	-0.0154	-0.0456	0.0305
$\beta_i^{\text{treatment}}$	-0.1450***	-0.1614***	-0.0488	-0.1156***	-0.0835**	0.0397	-0.0897	-0.0813*	-0.1688	0.0465
$\beta_i^{\text{inoculation}}$	-0.0551	-0.0419	-0.0810***	-0.0121	0.0596	-0.0615	-0.1018***	-0.0615	0.0278	0.0019
Lag(p)	10	12	4	10	6	5	10	9	14	12
L(p).ARCH	0.1857***	0.0614	0.2803***	0.1907***	0.2067***	0.0698	0.078	0.1076	0.1184***	0.0842
Wald Test	25145.42***	17803.28***	13468.53***	53499.62***	18765.81***	12944.7***	10277.53***	20556.68***	1817.06***	14290.08***

Table 5: This table reports the results of Equation (18) using the Diagonal Vech-GARCH model with Logistic Smooth Transition Autoregressive (LSTAR) model's $F(M_t)$ as an indicator of the down market. Panel A reports the excess return: α_i, $\alpha_i^{\text{incubation}}$,$\alpha_i^{\text{outbreak}}$, α_i^{fever}, $\alpha_i^{\text{treatment}}$ and $\alpha_i^{\text{inoculation}}$ and Panel B reports the systematic risk: β_i, $\beta_i^{\text{incubation}}$,$\beta_i^{\text{outbreak}}$,$\beta_i^{\text{fever}}$,$\beta_i^{\text{treatment}}$ and $\beta_i^{\text{inoculation}}$ corresponding to the pre-COVID-19 period (01 May 2018 to 31 December 2019),. incubation (2 January 2, 2020, to 17 January 2020), outbreak (18 January 2020 to 21 February 2020), fever (24 February 2020 to 20 March 2020), recovery (21 March 2020 to June 30, 2020), and inoculation (01 July 2020 to 30 April 2021) respectively. Lag(p) shows optimal lags of ARCH selected using the AIC criterion. Wald Test shows χ^2 value testing the null hypothesis that all coefficients of independent variables are zero. Names and Codes of corresponding Islamic Equity Indexes (IEIs) and Benchmark Equity Indexes (BEIs) are available in Appendix B. Asterisks *** show significance at 1% level, ** 5% level, and * 10% level.



Source: International Monetary Fund, World Economic Outlook Database, April 2021
Figure 1: World Economic Outlook Growth Projections

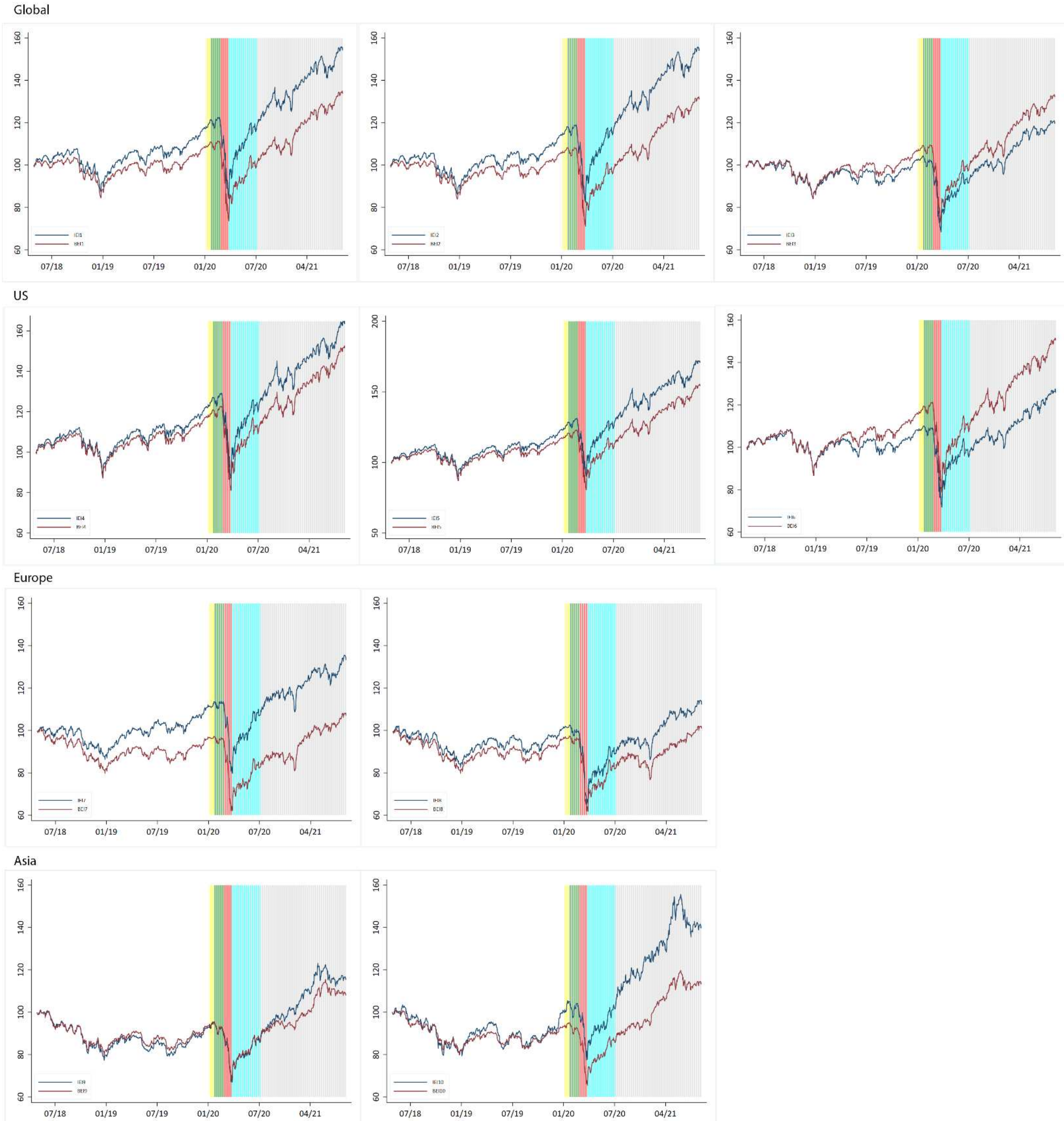


Figure 2: Return performance of IEIs and BEIs during the sample period. Daily data is pooled over the sub-sample periods: pre-COVID-19 period (01 May 2018 to 31 December 2019), the incubation (2 January 2, 2020, to 17 January 2020), outbreak (18 January 2020 to 21 February 2020), fever (24 February 2020 to 20 March 2020), recovery (21 March 2020 to June 30, 2020) and inoculation (01 July 2020 to 30 April 2021) shaded white, yellow, green, red, cyan, and gray respectively. Names and Codes of corresponding Islamic Equity Indexes (IEIs) and Benchmark Equity Indexes (BEIs) are available in Appendix B.

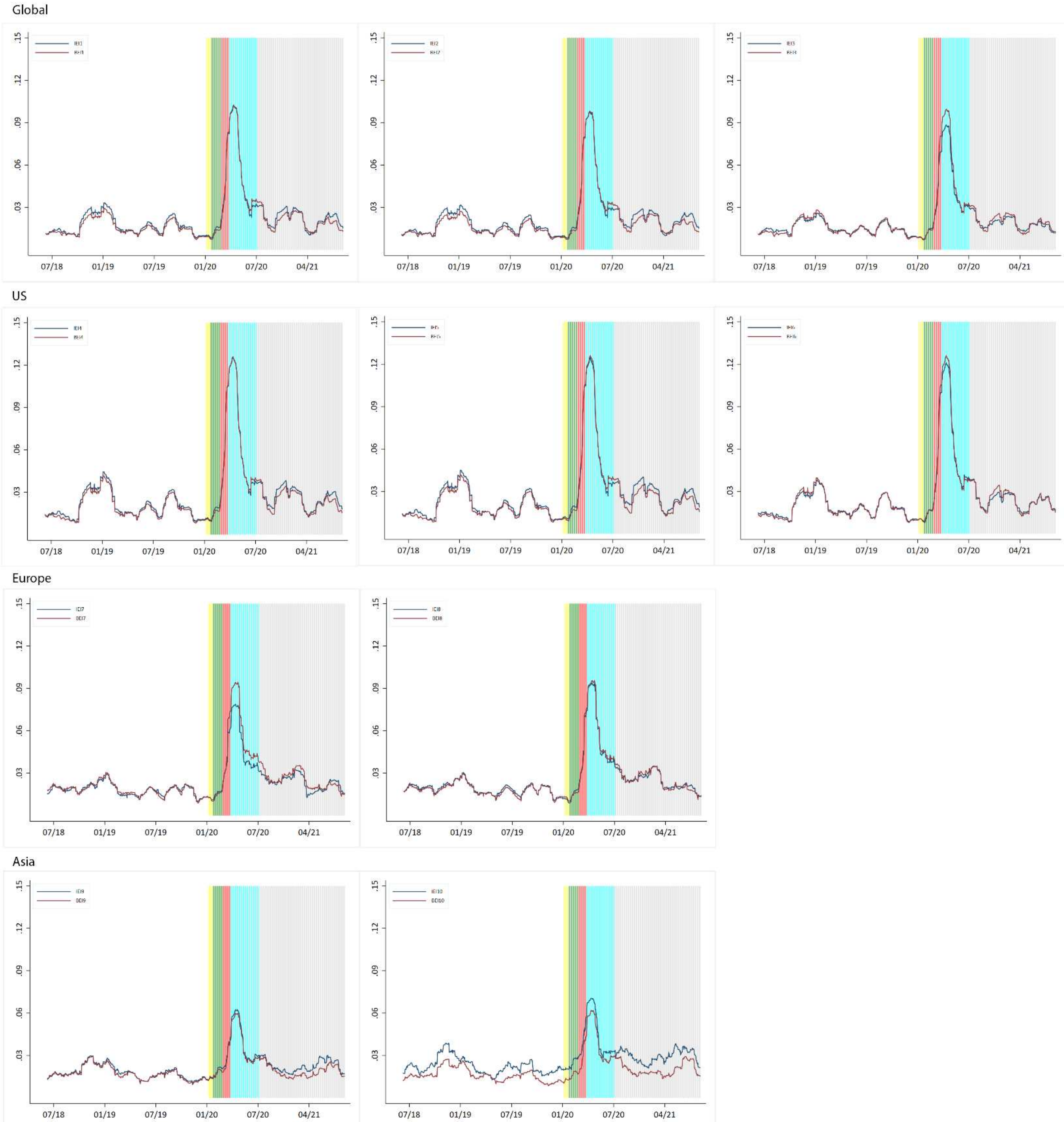


Figure 3: 1-day 1% Daily Value-at-Risk IEIs versus BEIs. Daily data is pooled over the sub-sample periods: pre-COVID-19 period (01 May 2018 to 31 December 2019), the incubation (2 January 2, 2020, to 17 January 2020), outbreak (18 January 2020 to 21 February 2020), fever (24 February 2020 to 20 March 2020), recovery (21 March 2020 to June 30, 2020) and inoculation (01 July 2020 to 30 April 2021) shaded white, yellow, green, red, cyan, and gray respectively Names and Codes of corresponding Islamic Equity Indexes (IEIs) and Benchmark Equity Indexes (BEIs) is available in Appendix B.

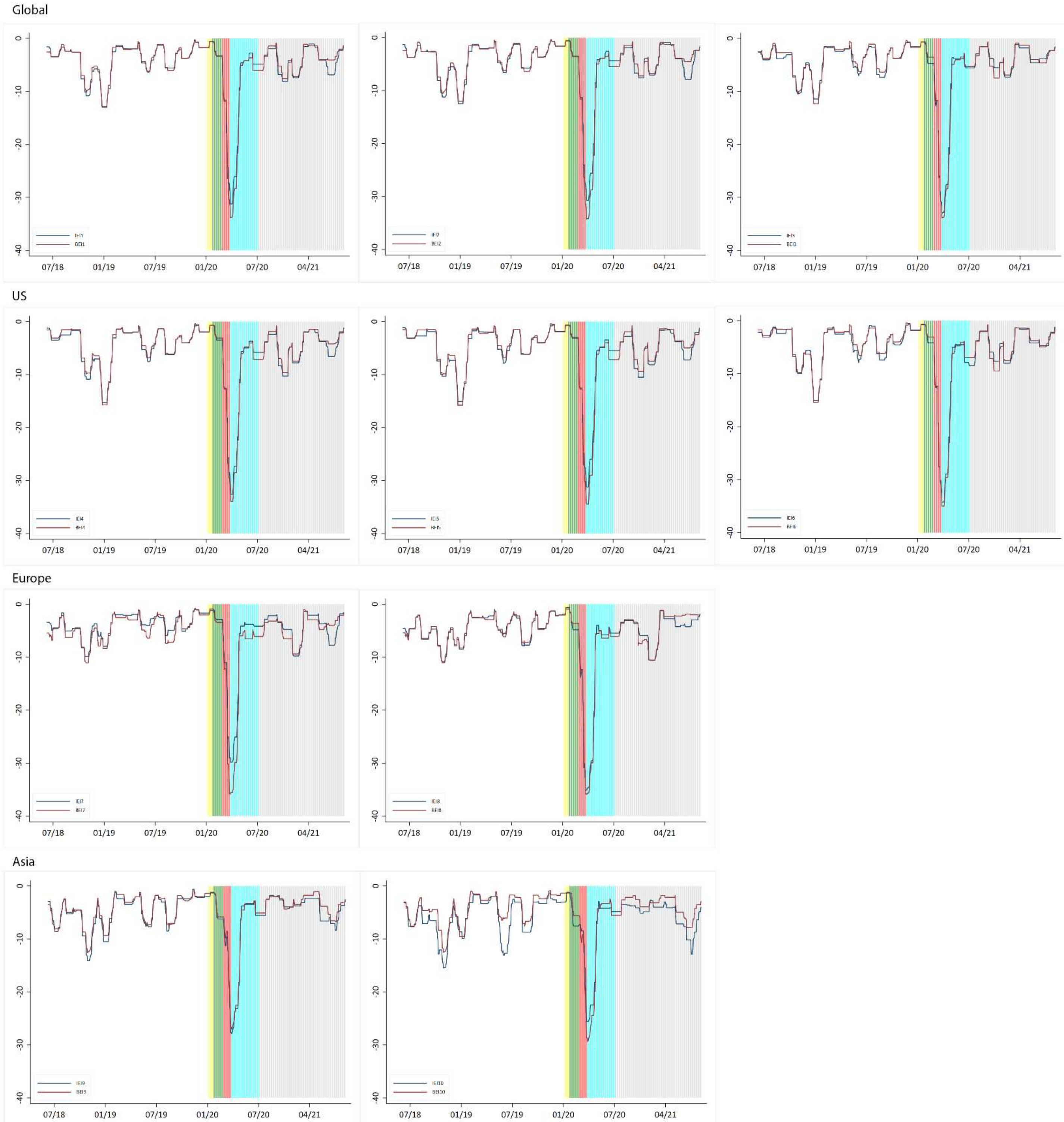


Figure 3: Maximum drawdowns of IEIs versus BEIs. Daily data is pooled over the sub-sample periods: pre-COVID-19 period (01 May 2018 to 31 December 2019), the incubation (2 January 2, 2020, to 17 January 2020), outbreak (18 January 2020 to 21 February 2020), fever (24 February 2020 to 20 March 2020), recovery (21 March 2020 to June 30, 2020) and inoculation (01 July 2020 to 30 April 2021) shaded white, yellow, green, red, cyan, and gray respectively Names and Codes of corresponding Islamic Equity Indexes (IEIs) and Benchmark Equity Indexes (BEIs) is available in Appendix B.