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Oil shocks and the Islamic financial market: Evidence from a causality-in-quantile approach

Ibrahim D. Raheem [a], Sara le Roux [b], Mobeen Ur Rehman [c,*]

[a] School of Business, Southern Alberta Institute of Technology, Calgary, Canada
[b] Oxford Brookes Business School Oxford Brookes University, Headington Campus, Oxford, United Kingdom
[c] Keele Business School, Keele University, New Castle Under-Lyme, Staffordshire, United Kingdom

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ABSTRACT

This study examines the nonlinear relationship between Islamic stock indices and oil shocks. Nonlinearity is viewed from the prism of nonparametric causality-in-quantile, and oil price is decomposed into demand, supply, and risk. The objective of this study is to examine the causality between sectoral Islamic stocks and oil shocks. Using a dataset for ten sectoral Islamic stock indices, we show that causality between the variables of interest is heterogenous across (i) measures of shocks (i.e., demand, supply, or risk), (ii) types of the sector (i.e., the ten sectors), (iii) state of the market (bear, normal, bull) and (iv) model specifications (mean vs. variance equation). We find that for the US, sectoral returns, demand and risk shocks affect Industrial, Information Technology, and ESG sectors across all quantiles, while supply shocks cause changes across normal market conditions. The US healthcare sector remains insensitive and the communications sector is affected only across extreme quantiles. Each oil shock exhibits a significant causal effect on Asian Pacific and Emerging Islamic markets consistently across all quantiles. Developed and European Islamic markets remain sensitive to risk-related shocks. Policy implications of these results are discussed.

1. Introduction

The importance of oil and its pricing dynamics are well documented in the literature, with some studies classifying oil as a feasible financial asset (i.e., financialisation of the oil market). The linkage between oil price (perhaps its return) and other financial markets is often common in the literature, with emphasis heavily laid on the stock markets (see Rehman et al., 2023; Smyth and Narayan, 2018; for detailed literature survey). Recent incidents and activities in the global financial markets have necessitated revisiting the dynamics of the oil price-financial market nexus. The existing literature on the subject matter has three major flaws, as discussed below.

First, the use of oil prices (returns) is flawed, thus leading to falsified results and inherent wrong policy implications. Factors such as oil financialisation, rising geopolitical tensions, and financial crises, among others, have immensely contributed to the rising level of uncertainty in the oil markets (Raheem, 2022; Mensi et al., 2023). There have also been remarkable changes in oil demand and supply dynamics owing to the global economy and political activities (Shahzad et al., 2022). For instance, the British Petroleum Economic Outlook estimated that the global energy demand fell by about 4.3%.[1] This has fuelled the steady decline in the oil price to about US

* Corresponding author.
E-mail address: m.ur-rehman@keele.ac.uk (M.U. Rehman).

[1] Available at https://www.bp.com/en/global/corporate/energy-economics/energy-outlook.html.

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$20 in April 2020. In an attempt to boost the price, the Organization of Petroleum Exporting Countries (OPEC) and Russia agreed to about two-third cut production. Amid these shenanigans, there is an increasing accumulation of precautionary global oil inventories (Kang et al., 2023). All these facts are in addition to the popular notion in the literature that had argued for the decomposition of oil prices. For instance, Kilian (2009) decomposed oil prices in demand and supply. Ready (2018) focuses on the demand, supply, and risk oil price decompositions. Baumeister and Hamilton (2019) document four types of shocks (Oil supply, Economic Activity, Oil Consumption Demand, and Oil Inventory Demand). CBOE Crude Oil ETF Volatility Index (OVX) is another common type of shock.

Second, the international diversification benefits that were hitherto inherent to the conventional stock market have been reducing in recent times, owing to the greater correlation between the stock and oil markets. Another reason is adduced to the increasing level of uncertainty, financial turbulence, and geopolitical tensions in the 21st century. More so is the intuition that the oil market has been unstable since the 2008 global financial crisis. With all these intricacies in place, it is only rational for investors to diversify their portfolios to account for assets that could mitigate these risks.

Islamic finance has proven to be a worthy candidate to provide the much-needed diversification benefits that have previously eluded the global financial system. Islamic finance is based on Shariah-compliant principles, laws, and regulations that prohibits usury (interest), speculation, investment in certain activities such as alcohol, gambling and conventional financial services. Islamic stock indices are designed to adhere to these principles and have a mechanism that follows a very strict screening process that weeds out non-Islamic products (e.g., alcohol and pork, among others). They differ from conventional indices by excluding companies involved in non-compliant sectors and by maintaining a certain level of 'halal' business activities. The popularity, acceptability, and usage of Islamic finance instruments have been on a growing streak over the past two decades (Saeed et al., 2023). Among the attributable factors to this stance is the belief of the Shariah-compliant financial institutions based on the risking sharing belief principle between stakeholders (i.e., borrower and lender). Thus, the influence of risk aversion enables Islamic finance to be less susceptible to shocks and uncertainties, providing portfolio diversification benefits to investors (Lin and Su, 2020; Al-Yahyaee et al., 2020).

Third, until recently, studies assume a linear relationship in the oil-stock markets nexus. Thus, ignoring the fact that most financial series exhibit nonlinearity due to underlining dispersed properties (Chang et al., 2020). There are many forms of nonlinearity: asymmetry, data disaggregation (i.e., sectoral or firm-level data), heterogeneity, and dual causation. The intuition behind asymmetry is that there is no one-for-one relationship between the series in the model. For instance, the reaction of oil price to the financial sector would be different from the manufacturing sector (Chang et al., 2020). Also, the stock market's response to a positive oil shock or news will differ from that of a negative oil price shock or news (Salisu et al., 2019). This is just as the long-run relationship in the model might be different from the short-run. Also, studies have shown that the effects of the return and volatility models are different (Palwishah et al., 2024; Salisu et al., 2019). Islamic stock indices are distinct in how they respond to oil shocks compared to conventional indices. The exclusion of financial sectors (e.g., conventional banks) and other sectors makes Islamic indices less exposed to certain economic risks but potentially more sensitive to oil price movements. Countries that dominate Islamic finance, are traditionally highly dependent on oil, influencing the financial markets' behavior.

This present study seeks to address the shortcomings stated above in the following approach. Oil price will be decomposed into demand, supply, and risk shocks - taking a cue from Ready (2018). The choice of this approach over other competing forms of decompositions is based on (i) work with high-frequency data (Umar et al., 2021); (ii) accounting for the forward-looking nature of traded financial asset prices, thus making it easier to determine whether concerns about future supply influence demand shocks (Riza et al., 2020); and (iii) ability to distinguish between oil-specific demand shocks that are driven by concerns about future oil supply and concerns driven by changes in aggregate demand for oil (Raheem, 2022).

Rather than focusing on conventional stocks, we dwell on Islamic finance owing to the following reasons: (i) Islamic finance is recording an impressive growth rate, thus leading to increasing its proportion in the global financial sphere, (ii) the shariah-compliant market mitigates the risk of crises, thus providing a safe haven and diversification benefits. Regarding the role of nonlinearity, we focus on sectoral Islamic finance and reply on a nonparametric causality in quantile. Unlike the classical linear regression that only estimates the model along the central tendency, our proposed model estimates models along the quantile distributions. The main advantages of this methodology include: (i) it captures endogeneity caused by nonlinearity between dependent and independent variables, (ii) it estimates both the causality in mean and variance causality spillover, (iii) it is not robust to misspecification errors (Balcilar et al., 2017).

The objective is this study is to examine the causality between sectoral Islamic stocks and oil shocks, which is achieved in phases. In the first phase, we decompose oil price into shocks-demand, supply, and risk. The second stage examines the causality between the sectoral stocks and variants of oil shocks. Essentially, we seek answers to the following research questions: (i) what are the trends of the decomposed oil prices? (ii) Are Islamic finance stocks sensitive to the state of the market conditions? (iii) to what extent is the importance of sectoral data analyses?

We are unaware of any study that has simultaneously addressed the three weaknesses (oil shock, rather than price, is a better proxy; nonlinearity and ignoring the important role of Islamic finance) listed above. This is the first attempt to link oil shock with sectoral Islamic finance based on nonlinear causality-in-quantile. This is the broad contribution of this study to the literature. The following are the study's specific objectives: (i) we join the list of a few studies examining the dynamics of sectoral Islamic finance (e.g., Chang et al., 2020). (ii) we use the recently developed nonparametric causality-in-quantiles test of Balcilar et al. (2017), which is a hybrid framework of Nishiyama et al. (2011) and Jeong et al. (2012).[2] (iii) decomposing oil price into different types of shocks has become an

[2] Other related methods include cross-correlation function, and Granger causality test. These tests are not able to account for nonlinearity and misspecification error.

important act in the finance literature. Thus, we test the importance of this decomposition on the oil price.

The rest of the study is structured as follows: Section 2 reviews the relevant literature. The methodology and Data are discussed in Section 3. Section 4 dwells on preliminary analyses and the empirical results, while Section 5 concludes the study and provides some policy implications.

2. Literature review

This section reviews recent literature related to two strands of research that we focus on in the current study: oil financialisation and Islamic finance. Among the first to study the nexus between the oil process and the stock markets were Chen et al. (1986); however, their paper did not find conclusive evidence supporting a causal relationship. In comparison, studies that followed were able to demonstrate that oil futures prices acted as a good proxy for the energy market as a whole and could be linked to movements in the stock marks (See Huang et al. (1996) and Sadorsky (1999). More recently, studies such as Broadstock et al. (2014) have analysed the impact that oil price shocks have on the stock markets using the capital asset pricing model (CAPM), while a time-varying approach was used by Zhang (2017), who demonstrated that there exists a nexus between oil prices and the global financial markets, especially since the 2008 financial crisis.

According to Zhang (2018), the term energy financialisation captures the increased way in which energy-oriented products have become mainstream in financial markets and how financial markets are now responding to changes in energy prices. Many papers have studied the uncertainty that the change in global energy patterns has caused to the systematic risk indices in the energy market (See Jee et al. (2018), Reboredo (2015)). The four main avenues through which energy financialisation impacts stock prices are volatility (Ma et al. (2019b), Zavadska et al. (2018)); uncertainty Agbeyegbe (2015), Liu et al. (2017)); complexity (Zhang et al. (2019)) and infectivity (Ji et al. (2019a) and Mahadeo et al. (2019). See Ji et al. (2019b) for a comprehensive review of this literature.

Hussain et al. (2016) provide an overview of Islamic finance and suggest that though it is limited to a few countries, there has been a steady growth in its prevalence, mainly due to the resilience provided by its governing principles: equity, which is the basis for prohibiting excessive contract ambiguity, thereby mitigating information asymmetry; participation in 'real' or productive activities; and ownership, which mandates the ownership of assets before transacting, thereby negating the probability of short-selling.

Benaicha (2020) defines how the risk-reward principle is applied to Islamic finance and banking products. The study explores various components such as consideration of market, ownership and capital loss risks, contractual costs, and effort that adds value and suggests that Islamic Finance research still needs a more sophisticated framework of reward-risk to be structured, such that it is foregrounded in the normative principles but is more adaptive to reality.

Ahmed (2010) investigates the 2010 financial crisis from the perspective of Islamic finance. He finds that the close link between financial flows and productivity in Islamic finance is responsible for safeguarding it from the shocks that traditional stock markets face due to excessive leverage and speculative financial activities.

Mohd Hussin et al. (2012) examine the impact of oil price shocks on the Islamic financial market in Malaysia. Using an estimation of the Vector Auto Regression (VAR) method and monthly data from January 2007 to December 2011, they find that Islamic stocks are positively co-integrated with oil prices based on Crude Oil Price, Industrial Production Index, and Consumer Production Index, but inversely integrated with Aggregate Money Supply, Islamic Interbank Rate and the Exchange Rate of Malaysian Ringgit-United States Dollar.

Ibrahim and Sufian (2014) also consider data for Malaysia but use a structural vector autoregressive model to examine the relationship between Islamic finance and variables such as real output, prices, interest rates, and stock prices. The paper's findings indicate that Islamic finance responds positively to innovations in real output, significantly negatively to increases in interest rate, and significantly – but with a lag – to price changes. The paper concludes that Islamic banks in Malaysia may not be shielded from the monetary conditions prevalent in the country.

Majdoub et al. (2018) use the bivariate diagonal BEKK econometric method developed by Engle and Kroner (1995) to study oil prices, and market index returns for daily data from April 1, 2011 to April 1, 2015. Their study focuses on a sample of five economies: Saudi Arabia, Kuwait, Qatar, UAE, and Jordan, and finds that Islamic financial principles mitigate volatility transmission and volatility persistence.

Godil et al. (2020) investigate the impact of oil prices, gold prices, uncertainty, and risk on Islamic vs. conventional stocks. They employ the Quantile Autoregressive Distributed Lags Error Correction Model and monthly returns data from the Dow Jones Islamic Market and the Dow Jones Conventional Market Indexes for the period January 1997 to July 2019. Their results show that Islamic stocks behave differently from conventional stocks, particularly when considering the long-term oil price effect under bullish market conditions. However, uncertainty has a more pronounced effect on Islamic stocks under bearish market conditions. This indicates that investing in Islamic stocks may be a way to diversify risks under specific market conditions.

Bouri et al. (2023) explore how oil price volatility and geopolitical risks impact different stock market sectors in the Gulf Cooperation Council (GCC) region under varying market conditions, i.e., bearish, normal, and bullish markets. The study applies a quantile-based regressions on the log-returns and conditional volatility (computed based on GARCH modelling) of stock indices to examine the effect of both crude oil implied volatility and geopolitical risk on the returns and volatility of GCC stock indices at the sectoral level. The study also attempts to differentiate across various stock return conditions and volatility states, reflecting bear/bull markets and low/high regimes. The paper finds that the influence of oil volatility and geopolitical risk differs significantly, with oil implied volatility having a stronger effect, particularly on stock returns. This is especially evident in the Consumer Discretionary and Consumer Staples sectors, which appear largely unaffected by geopolitical risk, offering potential hedging opportunities. Moreover, the impact of global risk factors shows variability between returns and volatility. The effect is also dependent on market conditions, showing a stronger and more significant impact during bull markets and periods of high volatility. This is particularly true for energy-intensive sectors like Energy, Materials, and Industrials, where oil volatility negatively influences returns at lower quantiles but positively at higher quantiles. Finally, during the pandemic, the response of returns and volatility was generally more pronounced, except in the Consumer Discretionary, Consumer Staples, and Telecommunications sectors, which has implications for dynamic hedging strategies during crises.

Al-Fayoumi et al. (2023) examine the connectedness between various oil price shocks and GCC stock market indices. They use quantile-based connectedness measures and find evidence of heterogeneity in the impacts of oil shocks across the various quantiles of stock sector returns and volatility. Interestingly, they find that demand shocks act as net transmitters of spillovers unlike supply shocks, and this is true across all quantiles.

More recently, Bouri et al. (2023) focus on the impact of geopolitical risk, economic policy uncertainty and crude oil volatility on the returns and variance of commodity, Islamic stock, and green bond markets across quantile distributions and various time horizons. The study employs Granger causality tests in quantiles and distributions together with wavelet-based correlation and causality approaches and conclude that asset returns co-move with risk factors in the short term but are found to decouple in the longer term. Risk factors exert short-lived causal impacts in the short term, but the duration of significant causal periods rises with time and the effect intensifies during crisis periods.

3. Method and data

3.1. Method

The analytical approach of this study is carried out in two phases. In the first phase, we construct oil shock by decomposing oil price into three variants of shocks-demand, supply, and risk-following the procedure of Ready (2018). The choice of this model is based on: (i) work with high-frequency data; (ii) accounting for the forward-looking nature of traded financial asset prices; and (iii) ability to distinguish between oil-specific demand shocks that are driven by concerns about future oil supply and concerns driven by changes in aggregate demand for oil.

Ready (2018) decomposed oil price into demand, supply, and risk. The orthogonal shocks are presented in the form below. The orthogonal demand shocks d_t, supply shocks s_t, and risk shocks v_t are defined for primary analysis as:

$$X_t \equiv \left[\Delta p_t \ R_t^{Prod} \ \xi_{VIX,t}\ \right], Z_t \equiv [s_t \ d_t \ v_t\ ], A \equiv [1\ 1\ 1\ 0\ a_{22}\ a_{23}\ 0\ 0\ a_{23}\ ] \tag{1}$$

The detected shocks from the observable factors are mapped by the matrix A, such that:

$$X_t = AZ_t \tag{2}$$

To ensure orthogonality, a_{22}, a_{23}, a_{23} and $\sigma_s, \sigma_d, \sigma_v$ satisfy:

$$A^{-1}\Sigma_X\left(A^{-1}\right)^T = \left[\sigma_s^2\ 0\ 0\ 0\ \sigma_d^2\ 0\ 0\ 0\ \sigma_v^2\ \right], \tag{3}$$

where σ_s, σ_d and σ_v are the identified shocks' volatilities, while Σ_X is the covariance matrix of the observable X_t. The standard orthogonalization is based on the Structural VAR approach. The summation of the shock is constrained to equal the total changes in oil price.

The oil shocks are extracted following Ready (2018) using world integrated oil and gas producer index, the CBOE volatility index and the nearest maturity NYMEX crude-light sweet oil. These disintegrated oil shocks are later used in examining the causality running from each shock i.e. supply-, demand- and risk-shocks towards Islamic sectoral returns. The oil shocks are extracted using structural VAR methodology so they are not at level rather generated from SVAR process.

The second phase of the analytical construct replies on the use of Balcilar et al. (2017) non-parametric causality-in-quantile. This model is renowned for accounting for endogeneity issues and being robust to misspecification errors.

Balcilar et al. (2017) proposed a nonlinear quantile-based causality model based on the works of Nishiyama et al. (2011) and Jeong et al. (2012). Since the model is bivariate, sectoral Islamic stock return is depicted by y_t, while the various indices of oil shocks are represented by x_t. The null hypothesis of the model is that at the Qth quantile, x_t does not cause y_t. Mathematically, Jeong et al. (2012) show that x_t does not cause y_t in the Qth quantile with respect to the lag of vector of $\{y_{t-1}, \dots, y_{t-p}, \quad x_{t-1}, \dots, x_{t-p}\}$ if:

$$Q_\theta\left(y_{t-1}, \dots, y_{t-p}, \quad x_{t-1}, \dots, x_{t-p}\right) = Q_\theta\left(y_t \middle| y_{t-1}, \dots, y_{t-p}\right) \tag{4}$$

Where, x_t causes y_t in the Qth quantile with respect to $\{y_{t-1}, \dots, y_{t-p}, \quad x_{t-1}, \dots, x_{t-p}\}$ if:

$$Q_\theta\left(y_t \middle| y_{t-1}, \dots, y_{t-p}, \quad x_{t-1}, \dots, x_{t-p}\right) \neq Q_\theta\left(y_t \middle| y_{t-1}, \dots, y_{t-p}\right). \tag{5}$$

Note: $Q_\theta(y_t|.)$ is the Qth quantile of y_t condition on t and $1 > \theta > 0$.

Let $Y_{t-1} \equiv \left(y_{t-1}, \dots, y_{t-p}\right), X_{t-1} \equiv \left(x_{t-1}, \dots, x_{t-p}\right), Z_t \equiv (X_t, Y_t)$ and $F_{yi|y_{t-1}}\left(y_t \middle| Y_{t-1}\right)$ represent the conditional distribution functions of y_t given Z_{t-1} and Y_{t-1}, in that order. It is assumed that the conditional distribution $F_{y_t|Z_{t-1}}\left(y_t \middle| Y_{t-1}\right)$ is continuous in y_t for almost Z_{t-1}. If $Q_\theta(Z_{t-1}) \equiv Q_\theta\left(y_t|Z_{t-1}\right)$ and $Q_\theta(Y_{t-1}) \equiv Q_\theta\left(y_t|Y_{t-1}\right)$, then $F_{y_t|z_{t-1}}\{Q_\theta(Z_{t-1})|Z_{t-1}\} = \theta$, with a possibility of unity. Based on equations

(1) and (2) above, the null and alternate hypothesis can be expressed as:

$$H_0 : P\left\{F_{y_t|z_{t-1}}\{Q_\theta(Y_{t-1})|Z_{t-1}\} = \theta\right\} = 1 \tag{6a}$$

$$H_1 : P\left\{F_{y_t|z_{t-1}}\{Q_\theta(Y_{t-1})|Z_{t-1}\} = \theta\right\} < 1 \tag{6b}$$

Jeong et al. (2012) used the distance measure J defined as $J = \varepsilon_t E(\varepsilon_t|Z_{t-1})f_Z(Z_{t-1})$, where, ε_t is the residual, while $f_Z(Z_{t-1})$ is the marginal density of Z_{t-1}. Note that ε_t is observed based on eq (6a), which is only true if $E[1\{y_t \leq Q_\theta(y_{t-1})|Z_{t-1}\}] = \theta$. The distance measured can also be specified as

$$J = E\left[\left\{F_{y_t|Z_{t-1}}\{Q_\theta(y_{t-1}|Z_{t-1})\} - \theta\right\}^2 f_Z(Z_{t-1})\right] \tag{7}$$

It should be noted that $J \geq 0$ in Eq. (a) on the condition that H_0 in Eq. (7) is true. The feasibility kernel-based sample analog of J is expressed as:

$$\widehat{J}_T = \frac{1}{T(T-1)h^{2p}} \sum_{t=p+1}^{T} \sum_{t=p+1, s\neq t}^{T} K\left(\frac{Z_{t-1}Z_{s-1}}{h}\right)\widehat{\varepsilon}_t\widehat{\varepsilon}_s, \tag{8}$$

where, K(.) is the kernel function with bandwidth h and the sample size is represented by T, while p is the lag operator and $\widehat{\varepsilon}_t$ is the estimate of the unknown residual, which is computed as follows:

$$\widehat{\varepsilon}_t = 1\{y_t \leq \widehat{Q}_\theta(\theta|Y_{t-1})\} - \theta, \tag{9}$$

where, $\widehat{Q}_\theta(Y_{t-1})$ is the estimate of the Qth conditional quantile of y_t given Y_{t-1}. $\widehat{Q}_\theta(Y_{t-1})$ can be estimated with the aid of nonparametric kernel method defined as:

$$\widehat{Q}_\theta(Y_{t-1}) = \widehat{F}^{-1}_{y_t|y_{t-1}}(\theta|Y_{t-1}), \tag{10}$$

where $\widehat{F}_{y_t|y_{t-1}}(y_t|Y_{t-1})$ represents the Nadarya-Watson kernel estimator given by:

$$\widehat{F}_{y_t|y_{t-1}}(|Y_{t-1}) = \frac{\sum_{s=p+1, s\neq t}^{T} L\left(\frac{Y_{t-1}-Y_{s-1}}{h}\right)1(y_s \leq y_t)}{\sum_{s=p+1, s\neq t}^{T} L\left(\frac{Y_{t-1}-Y_{s-1}}{h}\right)}, \tag{11}$$

where, L(.) is the kernel function with h bandwidth.

The Jeong et al. (2012) framework can be extended to account for higher order quantile causality and can be specified below:

$$H_0 : P\left\{F^k_{y_{t|Z_{t-1}}}\{Q_\theta(Y_{t-1})|Z_{t-1}\} = \theta\right\} = 1 \text{ for } k = 1, 2, 3, \ldots, k \tag{12a}$$

$$H_1 : P\left\{F^k_{y_t}|z_{t-1}\{Q_\theta(Y_{t-1})|Z_{t-1}\} = \theta\right\} < 1 \text{ for } k = 1, 2, 3, \ldots, k \tag{12b}$$

We integrate the entire framework by defining that x_t Granger causes y_t in quantile θ up to the kth moment using equantion (12) to set up the test statistic given in equation (11) for each k. The Causality-in-variance test is then calculated by replacing y_t in equation (9) with y_t^2. We start testing for the nonparametric Granger Causality in the first moment (*i.e.* $k = 1$). Failure to reject the null for $k = 1$ does not automatically lead to no-causality in the second moment, hence the need to construct the test for when $k = 2$.

3.2. Data

This study's two variables of interest are oil shock and sectoral Islamic finance. The computation of oil shock is based on three variables: (i) the world integrated oil and gas producer index; (ii) the CBOE volatility index; and (iii) the nearest maturity NYMEX crude-light sweet oil futures contract. These data are sourced from the Thomson Reuters DataStream. The sectoral Islamic finance data is sourced from the S&P Global 1200 index classified under the GICS distinct sectors classification system. The ten sectors considered are Industrial (SIND), Utilities(SUTI), Information Technology (SITE), Consumer Discretion (SCSE), Communication services (SCDI), Consumer stables (SCST), Health (SHCA), Financials (SFIN), Energy (SENE) and Basic material (ESG). The timeframe is October 15, 2013–December 27, 2021. The choice of this timeframe is based on data availability.

4. Empirical results

The descriptive statistics are presented in Table 1. Most Islamic stocks have positive mean values, except for energy stocks. The variables' trend is fairly stable, judging by the standard deviation statistics. The result of the Granger Causality test is presented in

Table 2, which shows no evidence of causality between the variables in the model. This result is not unsurprising considering the fact the test has been described to be weak, as it is not robust to misspecification error. Furthermore, we use the BDS test on the residuals of the AR(1) to confirm another source of nonlinearity. The results of the BDS test are presented in Table 3. Summarising the table, there is evidence to reject the null hypothesis at 1% level of statistical significance. The trend analyses of the oil shocks are presented in Fig. 1.

Table 4 presents results for quantile regression of demand shock on Islamic stock markets. To measure the significance of coefficients, we take values of 1.65 and 1.96 as a threshold corresponding to 95% and 99% levels of significance. Applying quantile regression helps examine the effect of oil-related demand shocks across normal and extreme returns distribution. We present results for returns and variance in separate panels in Table 4. Results for returns (Panel A) appear heterogeneous as only a few Islamic equity markets exhibit sensitivity to international oil demand shocks. Industrial, Information Technology, and ESG sectors highlight significant results across almost each quantile, suggesting that returns of these stock markets are consistently explained by the oil demand shocks. Interestingly, all three sectors are not related to each other, and more specifically, the Information Technology and ESG sectors are not highly dependent on oil supply shocks. However, a disruption in the oil supply shocks results in the high returns of ESG and Information Technology shocks. This is because ESG investors are more concerned with environmental and social aspects, and any shocks in international oil demand could induce these investors more toward sustainable investments. Likewise, the Information Technology sector may also result in higher returns, as we witnessed in the recent COVID-19 period when Information Technology was among the few sectors which were quadruplicated in profits. Panel B presents different results than the returns as consumer Services, Financial, and Energy sectors join the Industries, Information Technology, and ESG sectors with significant results across most quantiles. These results highlight that variance in oil demand shocks can affect the variance of returns even if the results appear insignificant for returns. Another notable finding is that the magnitude of this relationship appears strong during normal market conditions rather than extreme quantile returns distribution.

The result of the supply shock is presented in Table 5, which is similar to the demand-based shocks discussed above. Among all Islamic sectors, only the Industrial, Information Technology, and ESG sectors are affected by oil supply shocks. Supply shocks affect returns of these Islamic indices more during median quantiles rather than extreme quantiles. These results highlight that during bearish and bullish returns in Islamic markets, supply shocks do not cause high variations in returns of these indices, suggesting less downside risk during extreme market conditions. However, other Islamic indices highlight no significant effect from supply-related oil shocks. For the variance equation, results appear quite different (Panel B). Most of the Islamic markets are sensitive to supply-related shocks across the majority of the quantiles. Besides Industries, Information Technology, and ESG sectors, which were also significant during causality in returns, we see significant results for Consumer Services, Consumer Discretionary, Financial, and Energy sectors. Results for all these sectors appear significant during median quantiles and highlight a more significant causal relationship between changes in oil supply shocks and variance in returns of the Islamic markets. The healthcare sector does not exhibit any causal relationship with supply shocks across higher moments in either of the quantiles. However, the communication services sector highlights the presence of cause and effect relationships across higher quantiles. These findings are indicative of the fact that changes in international oil markets and the preceding shocks do not affect the variance of health sector returns.

Table 6 presents the result of the causal effect of risk-related oil shocks on Islamic indices. Panel A presents quantile causality results for returns and highlights significant results for the Industrial, Information Technology, and ESG sectors. These three sectors highlight significant results across all quantiles suggesting consistent sensitivity of these stock market returns to international risk-related oil shocks. For all other Islamic markets, results appear insignificant. These results imply that though risk-related shocks may appear quite significant in international oil prices, they do not induce any causality in the returns of Islamic stocks. Panel B presents results for variance. The significance of results appears high for the majority of the sectors. Besides the Industrial, Information Technology, and ESG sectors that appear significant for causality of returns, results for Financial, Energy, and Consumer Staples also appear significant across most quantiles. The Consumer Discretionary sector exhibits significant causality from risk-related shocks only across higher quantiles suggesting spillover of variance towards this sector only occurs across bullish market conditions. Consumer Services and Healthcare are the only sectors that are not related to risk-related shocks across either of the quantiles.

Table 1
Descriptive statistics.

Islamic Finance Stocks										
	SIND	SUTI	SITE	SCSE	SCDI	SCST	SHCA	SFIN	SENE	SESG
Mean	0.038	0.009	0.083	0.028	0.038	0.027	0.038	0.081	−0.018	0.046
Std Dev.	1.013	0.900	1.237	1.109	1.028	0.780	0.879	1.416	1.735	0.943
Min	−4.658	−2.177	−5.662	−7.561	−5.361	−3.971	−2.207	−3.225	−3.565	−4.426
Max	5.673	3.786	5.451	3.929	3.997	6.203	1.482	2.918	4.341	1.308
Oil Shocks										
					Demand	Supply	Risk			
Mean					−0.004	−0.006	−0.003			
Std Dev.					0.028	0.0157	0.079			
Min					−0.283	−0.192	−0.301			
Max					0.239	0.162	0.785			

Source: Authors' computation. NOTE: Std is standard deviation; Min is minimum, and Max is the maximum value.

Table 2
Granger Causality test.

Islamic index	F-Statistics (Demand)	F-Statistics (Supply)	F-Statistics (Risk)
SIND	1.026	1.236	1.201
SUTI	0.265	0.226	0.234
SITE	0.348	0.322	0.354
SCSE	1.021	1.163	0.932
SCDI	1.135	0.998	1.062
SCST	0.523	0.553	0.513
SHCA	0.456	0.444	0.398
SFIN	0.213	0.265	0.229
SENE	0.169	0.176	0.261
SESG	0.517	0.422	0.483

Null hypothesis: Oil shock does not Granger cause Islamic finance.
Source: Authors' computation

Table 3
BDS test.

	z-statistic of residuals of the AR (1) model of T &L stock returns	P-Value	z-statistic of residuals of the VAR (1) model of T &L stock returns	P-Value
2	25.267	0.000	25.161	0.000
3	27.036	0.000	26.862	0.000
4	29.003	0.000	28.962	0.000
5	30.116	0.000	30.001	0.000
6	32.064	0.000	31.984	0.000

Note: m stands for the number of (embedded) dimension which embed the time series into m-dimensional vectors, by taking each m successive points in the series. Value in cell represents BDS z-statistic corresponding to the null of residuals.

Table 7 presents results for causality in quantiles running from structural oil shocks toward aggregate regional Islamic indices. We use regional Islamic stock markets of the world, emerging, Europe, and the Asia Pacific as samples. Panel A presents results for returns, whereas Panel B highlights statistics for variance. Results in Panel A highlight that among all these markets, Emerging and Asia Pacific Islamic markets exhibit significant causal relationships from each oil-related shock consistently across all the quantiles. These results suggest that emerging and developing countries are more sensitive to international oil market shocks. Both developed, and European Islamic markets only highlight the causal effect of the risk-related shocks, which infers that demand and supply shocks do not affect the returns of Islamic equity markets. However, the aggregate world Islamic market exhibits a causal relationship with demand shocks across higher quantiles, highlighting that during bullish market conditions, the returns of World Islamic equity are affected by the demand-driven oil shocks. Results for causality in quantile for variance, i.e., variance appear opposite to that of returns causality. No sampled market exhibits any causal behavior from with of the shocks. Such insignificant results of cause and effect relationship are consistent across all quantiles suggesting that changes in oil shocks do not cause variance in the returns of Islamic equity markets. The only exception is the Asia-Pacific Islamic market which highlights sensitivity to demand-related oil shocks across the majority of the quantiles. These findings highlight that the Islamic equity market in the Asian-Pacific region is affected by demand-driven shocks, which might be attributed to the fact that this region is a net importer of oil, and its economy is affected by the fluctuations in the international oil market.

Our results highlight that only a few Islamic equity sectors are affected by each disintegrated oil shock. The information technology and ESG equity sectors are the most sensitive to shocks in demand. This might be attributed to the fact that the ESG sector is composed of social and environmentally friendly companies whereas, the period of analysis encompasses the COVID-19 period that affected the Information Technology sector. However, it is notable that unlike demand and risk shocks, supply shocks affect these sectors during median quantiles thereby suggesting no tail risk for investors in the Islamic sectors. These results are in accordance with Maghyereh et al. (2022) that it is the nature of Islamic stocks that makes them indifferent to external risk and shocks. However, we noticed that few Islamic stocks, despite their profit and loss nature, remain sensitive to structured oil shocks and therefore, carry implications for investors in these sectors.

5. Conclusion

This paper examines the effect of structural oil shocks on the US Islamic sectors. Our period of analysis ranges from October 15, 2013 to December 27, 2021. We measure this effect by applying the causality from oil supply-, demand- and risk-based oil shocks toward Islamic US sectoral returns. We witness significant causality in the Industrial, Information Technology, and ESG sectors by all three shocks; however, this significance varies across quantiles. Demand and risk shocks affect Industrial, Information Technology, and ESG sectors across all quantiles, whereas supply shocks cause changes across normal market conditions. We also examine results of causality across variances. Most of the sectors are affected by demand shocks across all quantiles, whereas results for supply shocks differ across quantiles. The healthcare sector remains insensitive, whereas the communications sector is affected only across extreme

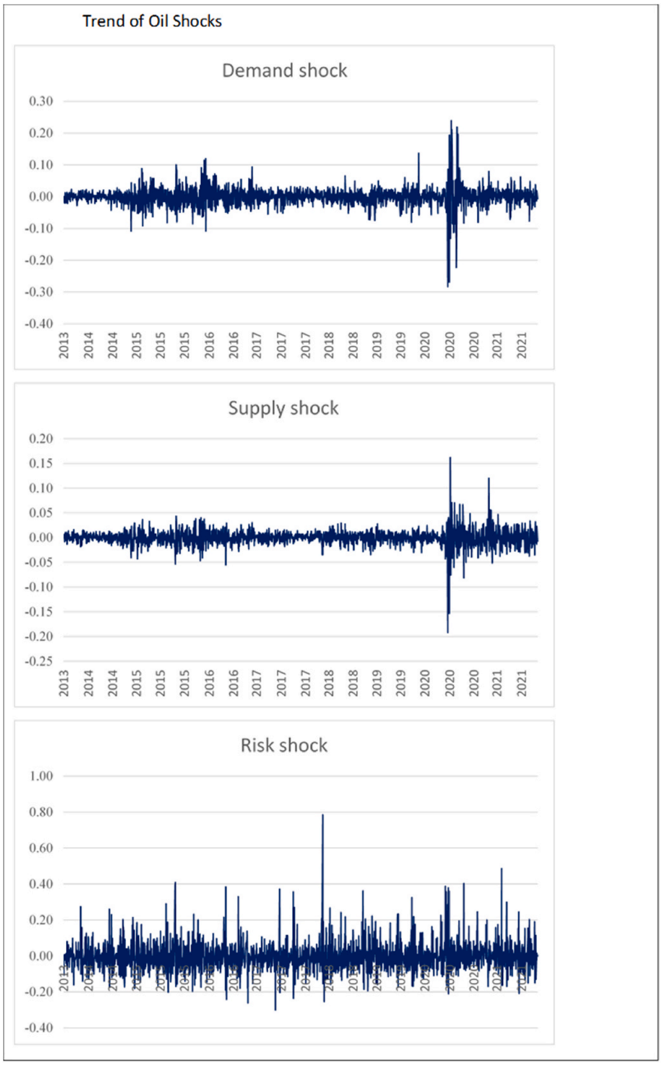

Fig. 1. Trend of oil shocks.

quantiles. Besides Consumer Services and Healthcare sectors, other sectors are consistently affected across all quantiles. We also examine the presence of structural oil shocks on regional-based Islamic equity markets. These include emerging, European and Asian Pacific Islamic equity markets. Each oil shocks exhibit a significant causal effect on Asian Pacific and Emerging Islamic markets consistently across all quantiles. On the contrary, developed and European Islamic markets remain sensitive to risk-related shocks. Causality from oil shocks across the variance equation quantiles yields no effect on these aggregate Islamic markets except the Asian-Pacific market, which is affected by the oil demand shocks.

Our work carries implications for investments in the US Islamic sectoral markets and global Islamic markets. Islamic markets are known to provide superior returns during crisis periods because of their unique investment philosophy. The minimal downside risk of these Islamic markets during crisis periods also makes them an attractive investment. Nevertheless, even these investments are not risk-free and therefore call for careful portfolio selection and periodic rebalancing over time. International oil prices have been known to influence any asset class, making it interesting to study its impact on Islamic stock markets. Our work takes the lead in examining the preceding oil shocks that cause price changes in the international oil market and their effects on Islamic stock markets. Based on the work of Ready (2018), our results highlight that the Industrial, Information Technology, and ESG are affected by the oil shocks however, this effect is felt consistently across all quantiles for demand and risk shocks, whereas not reported across extreme quantiles for supply shocks. Therefore, since most sectors remain favorable for investment, Industrial, Information Technology, and ESG sectors are admissible even during crisis periods in case of supply shocks. Results from the variance equation suggest that the sensitivity of Islamic sectoral returns increases due to oil shocks. Therefore a volatile oil market can affect Islamic sectors through oil-related shocks. Our study also provides insights for investments in regional aggregate Islamic stocks. Interestingly, Asian Pacific and Emerging Islamic markets remain more responsive to oil shocks which call for careful investment in these markets. On the contrary, developed and

Table 4
Causality in quantiles- demand shocks.

	SIND	SUTI	SITE	SCSE	SCDI	SCST	SHCA	SFIN	SENE	SESG
Panel A: Mean Equation										
0.1	1.4773	0.5815	**3.1869**	0.0505	0.3551	0.3551	0.3321	0.5643	0.4374	1.5475
0.2	**2.3423**	1.5715	**4.3498**	0.0607	0.3678	0.3678	1.0322	0.8829	0.5519	1.8867
0.3	**2.7272**	1.0922	**4.7805**	0.5811	0.2367	0.2367	0.7204	0.8276	0.4349	2.4015
0.4	**2.9029**	0.4940	**5.7011**	0.0392	0.1020	0.1020	0.5377	0.7682	0.2413	2.9394
0.5	**3.1623**	0.3068	**5.0460**	0.0429	0.0804	0.0804	0.4902	0.5437	0.2575	2.2607
0.6	**2.9726**	0.1594	**4.5110**	0.0822	0.2518	0.2518	0.3789	0.5746	0.0958	25957
0.7	**3.0265**	0.1030	**4.0898**	0.1653	0.2337	0.2337	0.6622	0.7146	0.3335	2.4067
0.8	**2.2623**	0.1580	**3.2370**	0.2617	0.3465	0.3465	0.5128	0.6821	0.3398	1.8968
0.9	1.3377	0.4684	**2.5005**	0.2209	0.5416	0.5416	0.5287	0.6755	0.2625	1.1439
Panel B: Variance Equation										
0.1	**2.9362**	0.1295	**5.1572**	0.2018	0.1953	**2.2578**	0.1824	1.7652	**4.6192**	1.7771
0.2	**3.6109**	0.1559	**6.5435**	0.2896	0.4650	**2.8415**	0.4839	**2.1317**	**6.2322**	**2.7726**
0.3	**3.6664**	0.4763	**7.5405**	0.3327	1.3583	**2.8371**	0.9593	**2.3107**	**7.6507**	**3.3608**
0.4	**4.2414**	0.895	**7.7186**	0.9914	1.1460	**2.7589**	1.0012	**2.5973**	**7.7581**	**4.1480**
0.5	**4.0173**	1.1657	**7.7851**	1.5130	1.2956	**2.4294**	1.4866	**3.0441**	**7.5498**	**4.0043**
0.6	**3.8284**	1.6033	**7.5439**	1.4324	1.1987	**2.3803**	1.2854	**2.5731**	**7.1664**	**3.7787**
0.7	**3.9313**	1.8246	**6.9971**	1.2159	1.5570	**2.3004**	0.9752	1.9047	**6.4466**	**3.0868**
0.8	**3.3504**	1.3546	**5.5002**	1.1436	1.9832	**1.8907**	0.7917	1.7841	**5.5617**	**2.9587**
0.9	**2.5029**	0.7610	**3.6761**	0.8026	1.6989	**1.3935**	0.7502	1.2151	**3.6763**	1.7329

Authors' computation.
Statistics reported in the table are t-statistics. Values of 1.65 and 1.96 as a threshold corresponding to 95% and 99% levels of significance, respectively. The bold values depict statistics that are significant.

Table 5
Causality in quantiles- supply shocks.

	SIND	SUTI	SITE	SCSE	SCDI	SCST	SHCA	SFIN	SENE	SESG
Panel A: Mean Equation										
0.1	**2.1042**	0.8058	**2.5797**	0.0751	0.5132	0.7125	0.7125	1.0704	0.7269	1.1355
0.2	**3.0014**	1.6902	**3.7301**	0.0877	0.4397	1.4063	1.4063	1.1977	0.9836	1.6615
0.3	**3.2654**	1.2852	**4.3037**	0.0589	0.2101	1.8974	1.8974	0.8978	0.6865	**2.1697**
0.4	**2.8647**	0.7289	**4.3699**	0.0141	0.1279	1.2593	1.2593	0.8487	0.2714	**2.2174**
0.5	**3.1063**	0.3705	**5.0034**	0.0328	0.0148	0.9298	0.9298	0.8627	0.0649	**2.1789**
0.6	**3.1467**	0.2415	**4.5679**	0.1126	0.0841	0.5887	0.5887	0.6333	0.0366	**2.5824**
0.7	**2.8285**	0.0811	**4.1639**	0.1978	0.1128	0.5131	0.5131	0.7737	0.4044	**2.2968**
0.8	**2.0682**	0.3023	**3.6192**	0.2069	0.2389	0.4157	0.4157	1.0215	0.4241	**2.1413**
0.9	1.9553	0.7150	**2.9899**	0.2058	0.6885	0.2582	0.2582	0.8675	0.5042	1.8341
Panel B: Variance Equation										
0.1	**2.4087**	0.1190	**4.6218**	0.4653	0.7382	1.7595	0.2983	1.2260	**4.2474**	**2.5790**
0.2	**3.4580**	0.2481	**6.3942**	0.10050	0.7035	**2.9304**	0.3717	1.8655	**5.5822**	**2.9425**
0.3	**4.2206**	0.6684	**7.3280**	1.3548	1.6875	**2.8441**	0.7092	**2.7518**	**6.8061**	**3.0627**
0.4	**4.5837**	1.3460	**7.7447**	1.9338	1.9140	**3.0900**	0.8433	**3.1101**	**7.9324**	**3.0098**
0.5	**4.4377**	1.6420	**7.6801**	**2.1291**	**2.3100**	**2.7888**	1.3424	**3.5273**	**7.3698**	**3.1354**
0.6	**4.1774**	**2.4168**	**7.3925**	**2.0382**	**2.4755**	**2.4727**	1.4731	**3.5761**	**7.6474**	**2.9824**
0.7	**3.7781**	**3.1049**	**7.2799**	1.9136	**3.5856**	**3.0121**	1.6230	**4.3113**	**7.1962**	**2.9055**
0.8	**3.9387**	**2.2645**	**5.8663**	**1.9867**	**3.9388**	**2.5093**	1.2623	**3.4817**	**6.2555**	**2.6585**
0.9	**2.4657**	1.2804	**3.7224**	1.2057	**3.0864**	1.3077	1.3861	**2.0878**	**4.5176**	**1.8392**

Authors' computation.
Statistics reported in the table are t-statistics. Values of 1.65 and 1.96 as a threshold corresponding to 95% and 99% levels of significance, respectively. The bold values depict statistics that are significant.

European Islamic markets appear responsive only to risk shocks which appear feasible for investments even under international oil demand and supply pressures. Our study highlights that investments in Islamic equity markets need careful selection because of their sensitivity to international oil returns through preceding supply-, demand-, and risk-shocks. This sensitivity varies across different returns distribution and international markets besides the US sectoral returns.

CRediT authorship contribution statement

Ibrahim D. Raheem: Writing – original draft, Methodology, Conceptualization. **Sara le Roux:** Writing – original draft, Investigation, Formal analysis. **Mobeen Ur Rehman:** Writing – review & editing, Methodology, Investigation, Formal analysis, Conceptualization.

Table 6
Causality in quantiles- risk shocks.

	SIND	SUTI	SITE	SCSE	SCDI	SCST	SHCA	SFIN	SENE	SESG
Panel A: Mean Equation										
0.1	**2.1882**	0.3031	**3.2004**	0.0446	0.6060	0.6060	0.9620	1.1857	0.5634	**2.1700**
0.2	**2.3232**	0.6294	**3.7979**	0.0552	0.4199	0.4199	1.3383	1.9060	0.6228	**2.7065**
0.3	**3.0498**	0.5627	**4.6083**	0.1007	0.1539	0.1539	**2.0668**	1.1449	0.3306	**3.0700**
0.4	**3.0163**	0.5858	**5.3217**	0.0143	0.0842	0.0842	1.1452	0.8668	0.0861	**2.6227**
0.5	**3.2241**	0.7196	**5.0550**	0.1014	0.0253	0.0253	1.3172	0.7058	0.0989	**2.3194**
0.6	**2.7439**	0.8180	**4.8888**	0.0457	0.1091	0.1091	0.8884	0.8098	0.0293	**2.9502**
0.7	**2.4092**	0.3606	**4.7283**	0.0733	0.0557	0.0557	0.5019	0.8210	0.3385	**2.6294**
0.8	**2.1079**	0.2603	**4.0018**	0.1117	0.1736	0.1736	0.3007	0.7258	0.3465	**2.0523**
0.9	**1.3204**	0.1830	**2.6433**	0.1620	0.4385	0.4385	0.3077	0.5561	0.5154	1.3784
Panel B: Variance Equation										
0.1	**3.2335**	0.1134	**5.2490**	0.1728	0.12286	**2.1794**	0.1693	1.6769	**4.8288**	1.9527
0.2	**4.2932**	0.2794	**6.9229**	0.6469	0.6688	**2.9745**	0.3218	**2.5306**	**6.2715**	**2.9166**
0.3	**4.8515**	0.2673	**8.1680**	0.9068	1.2437	**2.9147**	0.6899	**2.7555**	**7.5191**	**3.1874**
0.4	**5.0660**	0.2970	**8.5176**	1.0943	1.1160	**3.2748**	0.5073	**3.1385**	**7.5084**	**3.4970**
0.5	**4.8182**	0.5650	**8.5674**	1.1088	1.5741	**3.0799**	0.7358	**3.0426**	**8.6539**	**4.1153**
0.6	**4.4734**	0.7662	**8.0829**	1.1329	**2.3597**	**2.6335**	1.0019	**3.2141**	**8.6947**	**4.7078**
0.7	**4.0486**	0.8027	**7.6251**	0.9708	**2.8247**	**2.7918**	1.2201	**3.2054**	**8.0758**	**3.7395**
0.8	**3.1458**	0.5942	**5.6318**	1.0954	**2.4319**	**2.3238**	1.5537	**2.2036**	**6.5361**	**3.0643**
0.9	**2.4429**	0.2375	**4.2063**	0.8200	1.6967	1.7736	1.4829	**2.0570**	**4.4570**	**2.6433**

Authors' computation.
Statistics reported in the table are t-statistics. Values of 1.65 and 1.96 as a threshold corresponding to 95% and 99% levels of significance, respectively. The bold values depict statistics that are significant.

Table 7
Shocks with aggregate data.

—	World			Emerging			Europe			Asia-Pacific		
	Demand	Supply	Risk	Demand	Supply	Risk	Demand	Supply	Risk	Demand	Supply	Risk
Panel A: Mean Equation												
0.1	1.6785	1.4724	1.6881	**3.0781**	**2.4945**	**2.9738**	0.2474	0.1823	**2.9082**	**2.5794**	**2.6813**	**2.9021**
0.2	1.4868	2.2167	**1.9782**	**3.5634**	**3.3739**	**4.3750**	0.1899	0.1953	**4.1578**	**3.5276**	**3.5938**	**4.1578**
0.3	1.6395	1.9194	**2.0201**	**4.4879**	**3.7894**	**4.7458**	0.0972	0.1312	**4.7470**	**4.1806**	**4.4076**	**4.7470**
0.4	1.7549	1.7802	**2.0462**	**4.7082**	**4.1937**	**5.5181**	0.0458	0.0736	**4.4209**	**437694**	**4.7084**	**4.4209**
0.5	**1.9781**	**2.0693**	**2.3987**	**4.5608**	**4.3694**	**4.9504**	0.0144	0.0306	**4.7110**	**437025**	**4.7358**	**4.7110**
0.6	**2.0917**	1.9687	**2.5326**	**4.4261**	**4.5031**	**4.6280**	0.0512	0.0665	**4.5816**	**4.4515**	**4.6466**	**4.5816**
0.7	**2.4394**	1.9167	**2.3605**	**4.2689**	**4.1545**	**4.4655**	0.1472	0.0911	**5.2809**	**4.3664**	**4.2323**	**5.2809**
0.8	**2.4219**	1.8281	**1.9986**	**3.7409**	**3.3548**	**3.9063**	0.2641	0.1366	**3.9283**	**4.1420**	**3.5241**	**3.9283**
0.9	1.5817	1.1589	1.7592	**2.4460**	**2.6338**	**2.4281**	0.2810	0.1808	**2.4985**	**2.7161**	**2.3075**	**2.4985**
Panel B: Variance Equation												
0.1	0.4539	0.6336	0.3677	0.5153	0.2281	0.2687	0.0114	0.0074	0.3207	0.7764	0.8511	0.3207
0.2	0.6036	0.4057	0.9500	0.5988	0.3794	0.6538	0.0568	0.0507	0.7272	1.3235	0.7354	0.7272
0.3	0.7578	0.5820	0.9507	1.4917	0.8514	1.2147	0.0987	0.0898	0.6481	4.3951	0.6029	0.6481
0.4	0.8728	0.6905	0.7997	0.9098	1.5157	0.9296	0.1539	0.1472	0.6369	1.9486	0.7750	0.6369
0.5	1.8242	1.3870	1.2479	1.1103	1.4270	0.9285	0.1508	0.1362	0.7205	**2.2460**	0.9287	0.7205
0.6	**1.9750**	1.0418	1.2093	1.2674	1.0853	0.7716	0.2291	0.1848	1.1748	**3.5446**	1.6730	1.1748
0.7	**2.5958**	1.4194	1.7596	1.5665	0.6779	1.0658	0.2916	0.2155	0.9921	**4.1961**	1.1514	0.9921
0.8	**2.8955**	1.5786	**1.9678**	1.4485	0.4701	1.2243	0.3970	0.3449	1.2131	**2.8921**	0.9448	1.2131
0.9	1.9022	1.0542	1.9318	1.5480	0.5099	1.5316	0.2644	0.2246	1.0767	1.6292	0.8816	1.0767

Authors' computation.
Statistics reported in the table are t-statistics. Values of 1.65 and 1.96 as a threshold corresponding to 95% and 99% levels of significance, respectively. The bold values depict statistics that are significant.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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