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Modelling Economic Policy Issues

Oil shocks greasing the wheels of Islamic stocks: An explorative forecasting analysis

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ABSTRACT

This paper examines the relationship between Islamic finance and oil shocks by decomposing oil price into demand, supply, and risk shocks. This paper's distinguishing feature lies in assessing the forecasting prowess of —in-and-out-of-sample—oil shocks on Islamic finance. Using pooled data from the Dow Jones regional Islamic finance indices across regions (Emerging economies, Europe, Asia-Pacific, and the world), our results reveal that the three variants of shocks are significant determinants of Islamic finance returns. We also show that the shocks can forecast stock returns, though this forecasting ability is weak for the European market. Accounting for the influence of some macroeconomic fundamentals improves the forecasting prowess of the model and allows for successful robustness checks. The policy implication of the result is that investors and related shareholders in the Islamic financial markets should necessarily consider the divergent activities in the oil market while making portfolio design decisions. We also believe that future studies could consider replicating this paper's analytical construct and hypothesis on a country-level and probably at the sectoral level.

1. Introduction

The popularity, acceptability, and usage of Islamic finance instruments have assumed an accelerating pace in the past two decades.[1] Two major factors play key roles in this expansion: first is the strong confidence in the risk-sharing model between stakeholders—borrower and lender—that constitutes the underlying principles of Islamic financial institutions. Thus, the influence of risk aversion enables Islamic finance to be less susceptible to shocks and uncertainties, hence providing portfolio diversification benefits to investors (Lin and Su, 2020; Maghyereh et al., 2022). The 21st century has witnessed an increasing level of uncertainties, such as the 2007/08 financial crises, the 2010–2012 European debt crisis, the 2014 oil market instability, 2016 Brexit, global political instability, and geopolitical tensions, among others. These uncertainties have reignited investors' interest in risk spillover among financial markets. It is, therefore, purposeful to assume that rational investors who are risk-averse would realign their portfolio to account for assets that have a low correlation with incidences of uncertainty; and this is an edge that the Islamic financial instruments have in the market. The second factor lies in the role of low information asymmetry in the Islamic financial market relative to the conventional financial systems (Tanin et al., 2022). This confers enhanced price predictability in the market and provides relatively higher returns

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[1] The asset size of the market is estimated to be about $3 trillion as at 2021 (IFSB, 2022)

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on investments. Put together, these two factors also lend credence to the theoretical literature on investor conversation and gradual information diffusion hypotheses (e.g., see Narayan et al., 2019; Tuna et al., 2021; Hadri, 2021).

It must be highlighted, too, that the escalating interest in this subject area over the past two decades is predicated on the observed tendency of oil market activities' spillover to the sharia markets. It is therefore not surprising that the concept of Islamic finance was originally coined in the Arab World—the Middle East in particular—which, by no coincidence, also happens to remain a significant force to reckon with in the global oil market. For instance, the oil price glut between 2010 and 2014 was accompanied by massive growth in the market's asset size (see Imam and Kpodar, 2014; Cham, 2018). Similarly, Ernst and Young (2016) and Bitar et al. (2017) show that oil market expansion has led to an increase in Islamic banks' assets in the Gulf Corporation Countries (GCC). Hence, a number of studies examined oil price sensitivity to Islamic finance (e.g. Narayan et al. 2019, among others), the risk transmission of shocks from the oil market to the Islamic market, the asymmetric causality between oil shocks and sectoral stocks (conventional and Islamic finance) (Tuna et al., 2021; Hadri 2021 and Maghyereha et al. 2022;) and the asymmetric dynamic linkages between oil and Islamic stock prices (Adekoya et al., 2022). One result that seems to conjoint these studies seems to be the evidence of how the origins of oil price shocks impact the risk level of banks in oil-exporting countries.

Moreover, while these earlier studies seem to agree on oil price shocks and permeating impacts, they seem to fail on account of the role of distortions or shocks in oil prices. The seminal paper by Kilian and Park (2009) shows that the inability to decompose oil price into demand and supply shocks tends to produce statistically significant biased results and may not be stable over time. Kilian (2009) further argues that oil shocks have heterogeneous impacts on equity markets, thus necessitating the decomposition of oil shocks. The question then arises as to an appropriate measure and origin of the types of oil shocks that would allow salvage of the shortcomings of the earlier theoretical and empirical conceptualization. More so, extant studies have also shown that financial series are sensitive to the types of shocks (e.g., Gu et al., 2021; Assaf et al., 2021; Raheem, 2022).

From the foregoing, some studies have attempted to decompose oil prices into positive and negative shocks, thus accounting for the role of asymmetry (Raheem, 2017; Salisu et al., 2019; Tuna et al., 2021).[2] Similarly, Baumeister and Hamilton (2019) document four types of shocks (Oil supply, Economic Activity, Oil Consumption Demand, and Oil Inventory Demand). Ready et al. (2018) expanded the Kilian (2009) study by creating an additional shock, the risk shock. This risk shock is justified based on experiences from the recent global rising tides of uncertainty and geopolitical tension, which appear to be another source of shock that could have an important stake in both energy and financial markets (Ur Rehman et al., 2023).

Against this background, the objective of this paper is to examine the predictive prowess of oil shocks on Islamic finance markets. Our exploratory attempt in this regard is based on the expansive database of the Dow Jones Islamic indices (World, Emerging, Europe, Asia, and Pacific). Using these indices, we are able to interrogate some analytical issues that relate to: (i) the trends of oil shocks, (ii) the types of oil shocks that could predict Islamic finance, and (iii) the sensitivity of results to varying types of shocks.

The distinguishing feature of our paper, therefore, lies in the attempt to examine out-of-sample forecasts of Islamic finance based on the earlier construct of Westerlund and Narayan (2015).[3] The advantage of this technique is its ability to intrinsically account for some salient features (persistence, endogeneity, and conditional heteroscedasticity). The inability to account for these features when present could alter the reliability and correctness of the results (Salisu et al., 2019). Among others, analyses in this paper reveal that demand and risk shocks have some predictive features on the Islamic finance model. And the forecasting power extends to supply shock when some macroeconomic fundamentals are accounted for.

The rest of the paper is structured as follows. Data, methodology, and preliminary results are presented in Section 2. Empirical results are discussed in Section 3, while Section 4 concludes the study and provides some policy Implications.

2. Methodology and data

2.1. Methodology

The analytical framework for this paper is partitioned into two mutually reinforcing stages. In the first stage, we decompose oil prices into the three variants of shocks—demand, supply, and risk—following Ready's (2018) approach. In the second stage, we specify a predictive model, where the shocks are separately used as predictors of Islamic finance stock returns.

2.1.1. Oil shock computation

As previously mentioned, the additional risk shock created by Ready et al. (2018) implies that the shock index is then comprised of three types: demand, supply, and risk. The index is calculated using three variables: a measure of uncertainty and adjustment in the expected returns, proxied by VIX, a measure to capture fluctuations in oil prices, and an index for oil producer firms. The advantage of Ready's based shocks over other competing types of shocks rests on the following: (i) work with high-frequency data (Umar et al., 2021); (ii) account for the forward-looking nature of traded financial assets prices, thus making it easier to determine whether concerns

[2] Kilian (2009) and Kilian and Parker (2009) were the first to decompose oil shocks into demand and supply. CBOE Crude Oil ETF Volatility Index (OVX) is another common type of shock. OVX is calculated as the expected 30-day volatility of crude oil as priced by the United States Oil Fund.

[3] For instance, studies have shown that results for in-sample analysis could not be replicated for out-of-sample analysis (Salisu et al., 2019). Whereas investors and other financial market stakeholders tend to rely on out-of-sample estimates in making decisions relating to portfolio constructions. This is just as studies have shown that forecast accuracy is determined by the out-of-sample forecast (Isha and Raheem, 2019; Raheem, 2022).

about future supply influence demand shocks (Riza et al., 2020); and (iii) inability 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).[4]

Ready (2018) defined demand shock as the share of returns on the global stock index of oil-producing companies that is orthogonal to the innovation of VIX—the need to account for the changes in the discount rate that affects the stock returns of oil-producing companies dictates the inclusion of the innovations of VIX in the model. Supply shock is the residual of the changes in oil supply that is orthogonal to demand and risk shocks.

Hence, the orthogonal demand shocks d_t, supply shocks s_t, and risk shocks v_t are defined for primary analysis as:

$$X_t \equiv \begin{bmatrix} \Delta p_t \\ R_t^{Prod} \\ \xi_{VIX,\ t} \end{bmatrix},\ Z_t \equiv \begin{bmatrix} s_t \\ d_t \\ v_t \end{bmatrix},\ A \equiv \begin{bmatrix} 1 & 1 & 1 \\ 0 & a_{22} & a_{23} \\ 0 & 0 & a_{23} \end{bmatrix} \tag{1}$$

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:

$$A^{-1}\Sigma_X\left(A^{-1}\right)^T = \begin{bmatrix} \sigma_s^2 & 0 & 0 \\ 0 & \sigma_d^2 & 0 \\ 0 & 0 & \sigma_v^2 \end{bmatrix}, \tag{3}$$

Where: $\sigma_s,\ \sigma_d$ 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 to the total changes in the price of oil.

2.1.2. The forecasting model

Our predictive model on the oil price shocks-stock nexus is motivated by the arbitrary pricing theory (APT). The APT explains that systematic, unavoidable, external shocks such as oil price shocks can influence companies' stock returns. However, while the APT provides us with the basis to assume oil shock as a possible source of systematic stock risk, we follow the Westerlund and Narayan (2012, 2015) procedure to formulate our bivariate predictive model, as shown below.

$$r_t = \alpha + \beta\ s_{t-1} + \varepsilon_t \tag{4}$$

where r_t is the return on Dow Jones Islamic indices; s represents the three types of oil shock—demand, supply, and risk. The bivariate predictive model in Eq. (4) indicates that the predictability of Islamic stock returns is mainly limited to oil price shocks. This raises concerns about the potential correlation between the predictor series and error terms, the likelihood of endogeneity bias, and the possible impact of persistence in the estimate. Thus, while the common practice would have been to ignore the issues of endogeneity and inefficiency altogether and estimate the predictive model with OLS, our preliminary findings of conditional heteroscedasticity, autocorrelation, and persistence effects make the OLS approach suboptimal for some of the biases that may arise. For these reasons, we are strongly inclined towards Westerlund and Narayan (2012, 2015) proposed feasible quasi-generalized least squares (FQGLS) as the most appropriate method to address the potential biases. To begin, the Westerlund and Narayan (2015) procedure requires that we re-specify our bivariate predictive model in Eq. (4) to account for endogeneity and persistence as follows:

$$r_t = \alpha + \beta_1 s_{t-1} + \beta_2(s_t - \gamma s_{t-1}) + \varepsilon_t \tag{5}$$

Where $\beta_1 s_{t-1}$ is the adjusted parameter meant to correct for any persistence effect in the predictor series including any inherent unit root problem in the predictor series (see Lewellen, 2004). The endogeneity bias likely to be caused by the correlation between the predictor series and the error term is expected to be corrected by the inclusion of an additional term in the adjusted predictive model, for instance $\beta_2(s_t - \gamma s_{t-1})$, and captures the persistence effect and the resulting endogeneity incorporated in the parameter. In order to further account for the omitted variable bias and potential conditional heteroscedasticity, we pre-weight the adjusted predictive model in Eq. (5) using the standard deviation of the residuals from its ARCH-based variant. Testing for persistence requires estimating Eq. (6) by OLS. That is:

$$s_t = \alpha + \beta\ s_{t-1} + \mu_t,\ \text{where}\ \mu_t \sim\ N\left(0, \sigma_v^2\right) \tag{6}$$

Examples of studies that have used a similar approach include Salisu et al. (2019), Ur Rehman et al. (2022) and (2023).

[4] Some of the studies that relied on Ready shock index include Anand and Paul (2021), Clements et al. (2019), Gomez-Gozanlez et al. (2021), Liu et al. (2021), Das and Kannadhasan (2020)

2.1.3. Forecast evaluation

The predictive model is based on both the in- and out-of-sample forecasts. The out-of-sample forecast horizons are $H = $ 1-, 3-, 6-, and 12-months forecast ahead. The benchmark model (i.e. Model 1) is the restricted model and is based on AR(1). Model 2 is the unrestricted model in that it uses the variants of shocks as the predictor.[5]

We use three measures of forecast evaluations: Campbell and Thompson (2008), hereafter (C.T.) test; and the Theil-U statistics and the Clark and West (2007) hereafter (C.W.) test. Theil-U statistics is computed as the ratio of forecasting error of the unrestricted model to that of the restricted model. Theil-U statistics, being less than unity, imply that the unrestricted model has higher predictive power than the restricted model.

The CT test is considered to be out-of-sample R^2 (OOS_ R) statistics, which is computed as OOS_R = 1- Theil's U-statistics $\{(\widehat{RMSE}_2 / \widehat{RMSE}_1)\}$, where $\widehat{RMSE}_2$ *and* $\widehat{RMSE}_1$ are the Root Mean Square Error for models 2 and 1, respectively. A positive C.T. value suggests that model 2 outperforms model 1 and vice versa. The shortcoming of the C.T. is its inability to show the level of statistical significance.[6] However, the C.W. provides the test to examine the statistical significance of the C.T. test. That is, whether the difference between the forecast errors of the two models is statistically different from zero, with a value above 2.5 indicating statistical significance at the 5 % level. The entire analyses were conducted using Eviews 10.

2.2. Data and preliminary analysis

To recap, this paper examines the predictive power of oil shocks on Islamic finance. Islamic finance is proxied using the Dow Jones Islamic indices database across regions—World, Emerging, Europe, and Asia and Pacific—for the period 1st March 1999 – 31st January 2023. The variables used to compute oil shocks are: (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. Data on these variables are sourced from the Thomson Reuters DataStream.

The data on the oil shock is presented in Fig. 1. Table 1 presents the descriptive statistics of the variables. Statistics of Islamic stock returns are presented in Panel A. All the regions, except for the Asia-Pacific, show positive returns, with the emerging region taking the lead. Europe represents the most volatile market, based on the standard deviation statistics. All the financial series are stationary at levels (i.e., absence of unit root). Panel B shows statistics of the oil shocks. Demand shock has a negative mean value, with risk shock having the highest mean. Panel C shows the statistics for autocorrelation and heteroscedasticity, depicted by Q-statistics (and Q^2-statistics) and ARCH-LM test, respectively. Fig. 2.

3. Empirical results

The starting point of the empirical analyses is to examine the effect of oil shocks on Islamic stock returns. The results are presented in Table 2. The Table shows that shocks can predict Islamic stock returns. Two points seem to stand out from our results. First, demand and supply shocks have positive effects, with the former having higher magnitudes. Demand shock is considered an improvement in the economy whose positive effects spills over to the stock markets (e.g., see Ready, 2018; Das and Kannadhasan, 2020). Second, the risk element of the shock has a statistically significant negative influence. This conforms with Riza et al. (2020), who justify this negative influence by arguing that risk-averse investors tend to delay investment decisions during periods of high market uncertainty. Lin and Su (2020) also found a negative relationship between oil shocks and Islamic finance, with the effect more pronounced on the oil-importing countries vis-a-vis the exporting countries. Talking about the size of the coefficient, demand shock seems to lead the chart, which is closely followed by supply and risk, respectively. These results imply that the type of oil shocks (i.e., demand, supply, or risk) have heterogeneous effects on Islamic stock. This stance has also been validated by Raheem (2022), who concluded that the different oil shocks affect financial assets and instruments differently.

The results of the in-and out-of-sample forecasting, via the Theil-U statistics, are presented in Table 3. Results in the Table show that the Theil-U statistics are less than unity, implying that the shocks have adequate and correct information to forecast Islamic finance. This stance holds for the four regions under consideration. A closer look at the Table shows the Asia-Pacific region has the highest forecasting power, followed by the emerging region, while the Euro region has the least forecasting prowess. These results are pretty understandable and expected, owing to the fact that the popularity of Islamic finance is more pronounced in the Asia-Pacific. More so, some of the countries with a high penchant for Islamic finance are classified as emerging markets and, coincidentally, geographically located in the Asia-Pacific region.

Moreover, the results indicate that the model's performance is weak for the European region. This might not be unconnected with the fact that the region has only recently begun adopting and using Islamic financial instruments. Thus, the European market might not be mature enough to shield it against shocks in the oil market. Another factor could be the relatively smaller market size of the region.

A section of the literature proffers similar outcomes. For instance, our results align with the findings of Basher et al. (2018) for

[5] Inline with the extant literature, the common practise is to estimate the benchmark model via historical averages or AR(1) (see Ur Rehman et al., 2023 for more details). While model 2 is the expanded model or unrestricted model. The aim of the comparison (i.e Model 1 vs Model 2) is to determine the predictive prowess of each model. In the context of this study, we are interested in knowing which of the models (i.e AR(1) or the variant measures of oil shocks) better predicts Islamic finance.

[6] Due to the inter-linkage between Theil's U-statistics and CT test and for ease to understand the results tabulation, we refrain from presenting the CT test results. In situations where the U-statistics is <1, mathematically, it is expected that the CT test would be positive and vice-versa.

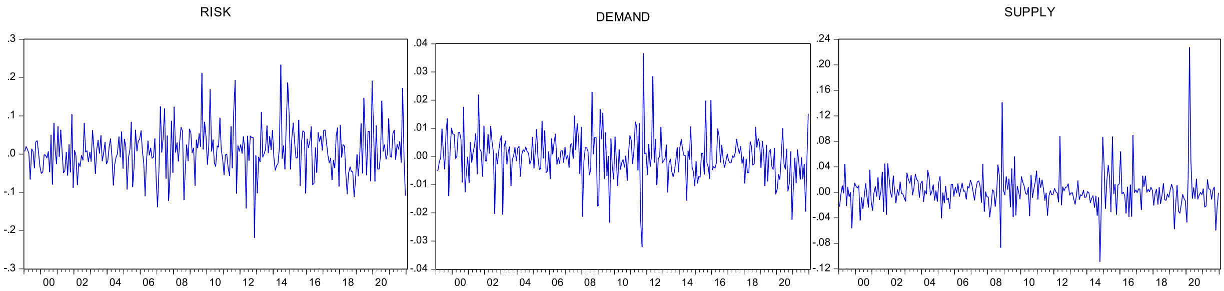

Fig. 1. Trend of the shocks.

Table 1
Preliminary analysis.

Sectors	Mean	Std Dev	Unit Root (ADF)		Persistence	Endogeneity
Stock returns			Level	1st Diff		
Panel A: Descriptive Statistics					N/A	N/A
World	0.0103	0.1523	−11.6522***	–	N/A	N/A
Emerging	0.0167	0.1678	−11.2567***	–	N/A	N/A
Euro	0.0150	0.1885	−11.0845***	–	N/A	N/A
Asia-Pacific	−0.0064	0.1551	−8.2837***	–	N/A	N/A
Panel B: Oil Shocks						
Supply	0.0026	0.0314	−12.1134***	–	0.0027*** (0.0001)	−0.0008 (0.0007)
Demand	−0.0002	0.0099	−11.0957***	–	0.0078*** (0.0015)	−0.0004 (0.0003)
Risk	0.0184	0.0708	−10.1797***	–	0.0403*** (0.0003)	−0.0036 (0.0022)
Panel C: Autocorrelation and Heteroscedasticity						
Variable	Q-Stat		Q^2-Stat		ARCH-LM	
	$K = 10$	$K = 20$	$K = 10$	$K = 20$	$K = 10$	$K = 20$
Supply	70.1543***	96.6565***	1145.3***	2356.3***	6.1468***	7.5659***
Demand	98.269***	120.08***	2356.6***	4356.5***	8.1691***	6.2015***
Risk	95.1993***	140.64***	786.559***	982.01***	1.698	1.0010

Source: Authors' computation.
Note: "***", "**", "*" implies level 1 s statistical significance at 1 %, 5 %, and 10 % respectively. The unit root test is performed using Augmented Dickey–Fuller (ADF) approach. For autocorrelation and heteroscedasticity tests, the reported values are the Ljung-Box test Q-statistics for the former and the ARCH-LM test F-statistics in the case of the latter. The chosen lag lengths are 10 and 20, respectively. The null hypothesis for the autocorrelation test is that there is no serial correlation, while the null for the ARCH-LM (F distributed) test is that there is no conditional heteroscedasticity.

Kuwait and Tanin et al. (2022) for Egypt, UAE, and Indonesia. In the contest, in terms of forecasting power, among the three types of oil shock, the demand shock clearly takes the lead. This is followed by risk and supply shocks. The Theil-U statistics of the demand(supply) shock is, on average, around 0.95(0.99). Notably, the forecasting accuracy is enhanced at the lower forecasting horizon, with the Theil-U statistics slightly increasing as the horizon increases. This holds regardless of the type of shock being considered.

We next present the results of the pairwise measure of prediction performance evaluation in Table 4. The need to conduct the C.W. test becomes vital to showcasing the reliability of the results presented in Table 2. In essence, we rely on the C.W. test to measure the level of statistical significance, with a value above 2.5 indicating statistical significance at 5 % level. A dive into the Table shows that the significance of the C.W. test is more pronounced in the Emerging, and Asia-Pacific regions, implying stronger predictive prowess of the shocks. The results obtained for the emerging markets are unsurprising—the highest predictive value (as previously reported in Table 1). In the same breath of analysis, the significance of the demand and risk shocks are high (mostly at 1 %). In contrast, the supply shock is only relatively significant for the Emerging and Asia-Pacific regions. Summing up Tables 3 and 4, it is safe to assume that oil shocks mainly affect the Emerging and the Asia-Pacific regions.

3.1. Robustness checks

Explicably, some earlier studies have examined the dynamics of Islamic finance as it relates to other macroeconomic fundamentals such as interest rate (Shamsuddin, 2014), financial news (Narayan and Bannigidadmath, 2017), safe haven and diversification properties (Shahzad et al., 2019). Similarly, various researchers have also scrutinized the comparative properties between Islamic finance and conventional financial systems (e.g., see Narayan and Phan, 2017 for an extensive literature survey). These studies and others have shown that including some macroeconomic fundamentals helps improve the forecasting performance of financial models (e.g., see Raheem, 2022; Ur Rehman et al., 2023). Moreover, our choice—interest rate, inflation, and global stock index—from an endless array of macroeconomic fundamentals to consider derives from their impressive performance in previous studies (see Salisu et al., 2019; Ur Rehman et al., 2022).

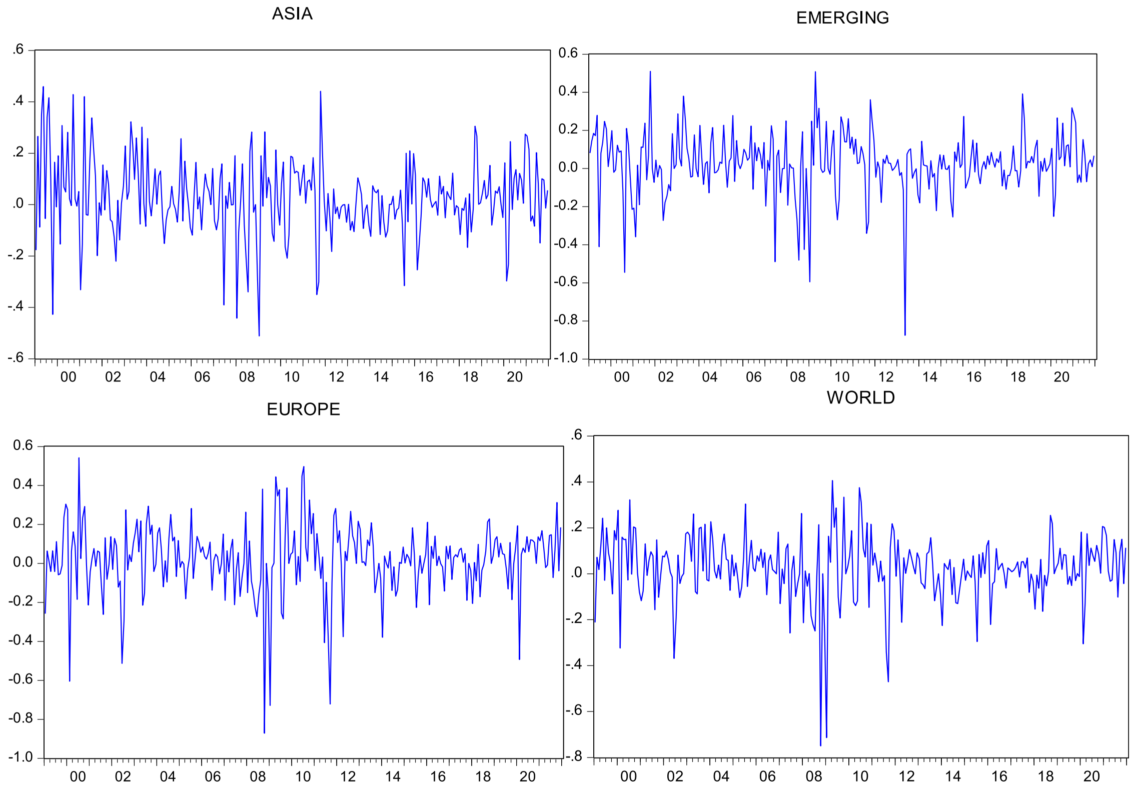

Fig. 2. Trend of Islamic shocks.

Table 2
Predictive model.

	Supply	Demand	Risk
World	1.2468** (0.5314)	4.5517*** (1.336)	−0.7035*** (0.2025)
Emerging	1.3197*** (0.5606)	2.7685*** (0.4106)	−0.891*** (0.2201)
Euro	1.5292** (0.6546)	3.5030** (1.7582)	−0.5808 (0.2607)
Asia-Pacific	1.4031** (0.541)	1.9431*** (0.124)	−1.0939*** (0.203)

Source: Authors' computation.
Note: *, **, *** imply level of statistical significance at 1, 5, and 10 %, respectively. Values in parenthesis are the standard error.

The result of the Theil-U statistics of the expanded model is presented in Table 5. Statistics in the Table show improved performance. For instance, the lower Theil-U statistics in Table 5, relative to those in Table 3, suggest that the model has better/higher forecasting information content. The C.W. test, presented in Table 6, also reveals the enhanced performance of the expanded model. For instance, the multiple predictor model shows that all the regions and shocks combination have significant effects, as against the low statistical significance for the European region reported in Table 4.

Four robustness checks were conducted. The first relates to the use of an alternative measure of shock. Studies have concluded that financial series are sensitive to the measure/types of shocks (e.g. Gu et al., 2021; Assaf et al., 2021). We verify this by using the OVX. The results in Table 7 show that OVX is a weak predictor of Islamic finance. While the Theil-U statistics are less than one, the C.W. statistics are insignificant. The second check uses historical averages as the benchmark model (i.e., model 1 as against the AR(1) used previously). The third check uses Mean Square Error (as against Root Mean Square Error used in the main model). The results of these checks almost mirror the results presented earlier.[7] The last check relied on the use of the rolling window approach. The advantage of this test is that it provides a more robust evaluation of the forecasting model's performance by testing it on different subsets of the data over time and ensuring that the results are not overly reliant on any specific period. The results of this robustness check are provided in Table 8.[8] A snapshot of the results shows that oil shocks have adequate information to forecast Islamic finance literature.

[7] These results are not presented here for sake of space but will be made available upon request.

[8] We thank an anonymous reviewer for this wonderful suggestion.

Table 3
Single predictor: Theil U- statistics.

	Supply					Demand					Risk				
		Out-of-Sample					Out-of-Sample					Out-of-Sample			
Regions	In-Sam	$H = 1$	$H = 3$	$H = 6$	$H = 12$	In-Sam	$H = 1$	$H = 3$	$H = 6$	$H = 12$	In-Sam	$H = 1$	$H = 3$	$H = 6$	$H = 12$
World	0.9816	0.9813	0.9809	0.9814	0.9806	0.9551	0.9555	0.9551	0.9572	0.9564	0.9634	0.9639	0.9630	0.9638	0.9632
Emerging	0.9886	0.9884	0.9867	0.9870	0.9864	0.9345	0.9348	0.9353	0.9380	0.9367	0.9621	0.9625	0.9652	0.9665	0.9647
Euro	0.9903	0.9903	0.9905	0.9910	0.9903	0.9920	0.9920	0.9922	0.9934	0.9928	0.9872	0.9873	0.9873	0.9881	0.9876
Asia-Pacific	0.9829	0.9825	0.9817	0.9817	0.9811	0.8537	0.8549	0.8531	0.8560	0.8554	0.9190	0.9200	0.9182	0.9192	0.9186

Source: Authors' computation.

Table 4
Single predictor: C.W. statistics.

	Supply					Demand					Risk				
		Out-of-sample					Out-of-sample					Out-of-sample			
Regions	In-Sam	$H = 1$	$H = 3$	$H = 6$	$H = 12$	In-Sam	$H = 1$	$H = 3$	$H = 6$	$H = 12$	In-Sam	$H = 1$	$H = 3$	$H = 6$	$H = 12$
World	1.589	1.604	1.624	1.614	1.66	2.452 [b]	2.443 [b]	2.475 [a]	2.435 [b]	2.495 [b]	2.927[a]	2.911 [a]	2.974 [a]	2.961 [a]	3.034 [a]
Emerging	1.807[c]	2.085 [b]	2.040 [b]	2.024[b]	1.821 [c]	3.481 [a]	3.475 [a]	3.684 [a]	3.628 [a]	3.710 [a]	3.270 [a]	3.258 [a]	3.388 [a]	3.342 [a]	3.466 [a]
Euro	1.245	1.276	1.244	1.221	1.248	1.0125	1.011	1.008	0.953	1.004	1.611	1.609	1.624	1.591	1.652
Asia-Pacific	2.496 [c]	2.665 [a]	2.595 [b]	2.602 [b]	2.525 [b]	4.506 [a]	4.493	4.559 [a]	4.535 [a]	4.588 [a]	4.366[a]	4.345 [a]	4.427 [a]	4.419 [a]	4.484 [a]

Source: Authors' computation. Note: [a,b], and [c] indicate the level of statistical significance at 1 %, 5 %, and 10 %, respectively.

Table 5
Multiple predictors: Theil U- statistics.

	Supply					Demand					Risk				
		Out-of-sample					Out-of-sample					Out-of-sample			
Regions	In-Sam	$H = 1$	$H = 3$	$H = 6$	$H = 12$	In-Sam	$H = 1$	$H = 3$	$H = 6$	$H = 12$	In-Sam	$H = 1$	$H = 3$	$H = 6$	$H = 12$
World	0.8947	0.8942	0.8932	0.8966	0.8967	0.8996	0.8999	0.8997	0.9031	0.9043	0.9141	0.9143	0.9136	0.9154	0.9169
Emerging	0.9358	0.9357	0.9513	0.9512	0.9543	0.8858	0.8864	0.8956	0.8977	0.8995	0.9220	0.9225	0.9323	0.9332	0.9343
Euro	0.9340	0.9340	0.9347	0.9360	0.9397	0.9354	0.9355	0.9363	0.9379	0.9424	09,333	0.9334	0.9340	0.9351	0.9398
Asia-Pacific	0.9535	0.9527	0.9509	0.9536	0.9509	0.8237	0.8239	0.8228	0.8298	0.8272	0.8967	0.8966	0.8948	0.8989	0.8964

Source: Authors' computation.

Table 6
Multiple predictors: C.W. statistics.

	Supply					Demand					Risk				
		Out-of-sample					Out-of-sample					Out-of-sample			
Regions	In-Sam	$H=1$	$H=3$	$H=6$	$H=12$	In-Sam	$H=1$	$H=3$	$H=6$	$H=12$	In-Sam	$H=1$	$H=3$	$H=6$	$H=12$
World	2.704[a]	2.740 [a]	2.738 [a]	2.707 [a]	2.715 [a]	3.399 [a]	3.396 [a]	3.432 [a]	3.391 [a]	3.415 [a]	3.659 [a]	3.656 [a]	3.707 [a]	3.681 [a]	3.702 [a]
Emerging	2.862[b]	2.619 [b]	2.664 [b]	2.677 [b]	2.864 [b]	4.068 [a]	4.059[a]	4.215 [a]	4.182 [a]	4.185[a]	3.643[a]	3.633 [a]	3.688 [a]	3.670 [a]	3.679 [a]
Euro	3.146 [a]	3.080 [a]	3.148 [a]	3.128 [a]	3.146 [a]	3.402[a]	3.401 [a]	3.405 [a]	3.371 [a]	3.294 [a]	3.704 [a]	3.702 [a]	3.715 [a]	3.695 [a]	3.609 [a]
Asia-Pacific	4.771[a]	4.774 [a]	4.858 [a]	4.816 [a]	4.920 [a]	3.488 [a]	3.809 [a]	3.567 [a]	3.600 [a]	3.543 [a]	4.412 [a]	4.419 [a]	4.522 [a]	4.483 [a]	4.626 [a]

Source: Authors' computation.
Note: [a], [b] and [c] indicate the level of statistical significance at 1 %, 5 %, and 10 %, respectively.

Table 7
Robustness check: OVX.

	Theil-U statistics					C.W. statistics				
		Out-of-sample					Out-of-sample			
Regions	In-Sam	$H = 1$	$H = 3$	$H = 6$	$H = 12$	In-Sam	$H = 1$	$H = 3$	$H = 6$	$H = 12$
World	0.9431	0.9445	0.9466	0.9573	0.9569	1.6301	1.6175	1.6032	1.5414	1.5413
Emerging	0.9792	0.9801	0.9824	0.9877	0.9875	1.3829	1.2215	1.3041	1.1944	1.3614
Euro	0.9567	0.9563	0.9567	0.9634	0.9636	1.5871	1.5966	1.6023	1.5447	1.5564
Asia-Pacific	0.9900	0.9917	0.9936	0.9983	0.9970	1.1036	1.0213	0.9369	0.7173	0.8058

Source: Authors' computation.

Table 8
Robustness check (Rolling Window).

	Theil-U statistics					C.W. statistics				
		Out-of-sample					Out-of-sample			
Regions	In-Sam	$H = 1$	$H = 3$	$H = 6$	$H = 12$	In-Sam	$H = 1$	$H = 3$	$H = 6$	$H = 12$
World	0.8982	0.8992	0.9015	0.9117	0.9113	3.0205[a]	2.9971[a]	2.9706 [a]	2.8561[b]	2.8559 [b]
Emerging	0.9319	0.9334	0.9341	0.9354	0.9362	2.9408 [a]	2.9584 [a]	2.9690 [a]	2.8622 [b]	2.8839 [b]
Euro	0.9124	0.9130	0.9203	0.9201	0.9254	2.5624 [b]	2.2634 [c]	2.4164 [c]	2.2132 [c]	2.5226 [b]
Asia-Pacific	0.9429	0.9447	0.9471	0.9499	0.9501	4.1385 [a]	3.8299 [a]	4.0755 [a]	3.1203 [a]	3.5052 [a]

4. Conclusion

This paper recognises the growing influence and popularity of Islamic finance in the global financial system. Unlike the extant literature that hitherto ignored the role of oil shocks on the market, we examine the forecasting prowess of oil shocks on four regional Islamic financial markets (World, Emerging, Euro, Asian-Pacific). The study's objective is to proffer analytical justification to issues raised about the out-of-sample predictive ability of oil shocks in the Islamic financial market. Following Ready (2018), oil shock is constructed by decomposing oil price into demand, supply, and risk shocks.

Our hypothesis is tested using the Dow Jones regional Islamic finance indices (world, emerging, Europe, and Asia-Pacific). In the first stage, the analytical construct adopted is to decompose oil prices into the three variants of shocks—demand, supply, and risk—following Ready's (2018) approach. In the second stage, we specify a predictive model, where the shocks are separately used as predictors of Islamic finance stocks. Our results indicate that the shocks are essential determinants of Islamic finance returns. Next, we show that the shocks can predict stock returns, though the predictive ability is weak for the European market. Accounting for the influence of some macroeconomic fundamentals improves the model's forecasting power. The results also remain valid when subjected to robustness checks. Thus, it is concluded that oil shocks are good predictors of Islamic finance. The attendant policy implication of the result is that investors and related shareholders in the Islamic financial markets should necessarily consider the divergent activities in the oil market while making portfolio design decisions. We also believe future studies could consider replicating this paper's analytical construct and hypothesis at the country and probably at the sectoral levels. In addition, future studies could consider adopting another methodology, such as the one proposed by Ibragimov and Muller (2010), to broaden the understanding of the oil price shock - Islamic finance nexus.

CRediT authorship contribution statement

Ibrahim D. Raheem: Conceptualization, Formal analysis, Resources, Writing – review & editing, Methodology. **Oluyele Akinkugbe:** Data curation, Investigation, Supervision, Writing – review & editing. **Xuan Vinh Vo:** Data curation, Resources, Software, Writing – original draft.

Declaration of competing interest

No conflict of interest exists.

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