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How strong are the causal relationships between Islamic stock markets and conventional financial systems? Evidence from linear and nonlinear tests

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Abstract

Past studies suggest that the Islamic finance system is only weakly linked or even decoupled from conventional markets. If this statement is true, then this system may provide a cushion against potential losses resulting from probable future financial crises. In this article, we make use of heteroscedasticity-robust linear Granger causality and nonlinear Granger causality tests to examine the links between the Islamic and global conventional stock markets, and between the Islamic stock market and several global economic and financial shocks. Our findings reveal evidence of significant linear and nonlinear causality between the Islamic and conventional stock markets but more strongly from the Islamic stock market to the other markets. They also show potent causality between the Islamic stock market and financial and risk factors. This evidence leads to the rejection of the hypothesis of decoupling of the Islamic market from their conventional counterparts, thereby reduces the portfolio benefits from diversification with Sharia-based markets. A striking result shows a connection between the Islamic stock market and interest rates and interest-bearing securities, which is inconsistent with the Sharia rules. The results also suggest that modeling Islamic stock markets should be done within a nonlinear VAR system and not through a regression equation.

Keywords: Islamic finance, robust causality tests, financial and economic shocks.

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1. Introduction

One of the new innovations in the world's financial system is the creation of Islamic banks, and stock and bond markets which operate differently from their conventional counterparts. Assets in the Islamic industry have grown 500% in the last five years, reaching $1.3 trillion in 2011. However, this phenomenal growth is still hindered by some structural factors. There is a lack of a secondary market, which prevents this sector from opertating in important regions of the world. The market also requires much more short-dated products in order to enable Islamic banks to effectively manage their liquidity.

Islamic banks are asset-based and asset-driven because they are prohibited from dealing with interest. Islamic equity investments have Sharia-based screens that restrict investment in certain industries and favor growth and small cap stocks. By contrast, conventional banks are interest-based and debt-driven, and conventional stock markets prefer value and mid cap stocks, and do not have investment screens. It will thus be valuable to find out whether the Islamic stock market under consideration is integrated with conventional stock markets. It is also useful to figure out if this market is linked to several diverse global shocks which are pertinent to different asset classes and systems. These issues are of great interest to conventional and Islamic investors. Indeed, investors and managers of a Sharia-compliant Islamic equity fund often pick stocks from the Sharia compliant indices or focus on investing ethically in businesses which comply with the Sharia principles.

Given the recent financial crisis and the presence of nonlinearity among financial markets, we empirically employ both linear and nonlinear causality tests to investigate the interactions between the Islamic stock market and conventional finance systems. The Dow Jones Islamic Market Index (DJIM), which is a Sharia-based equity index, is used to represent the Islamic stock markets.[1] This index includes shares of companies whether located in Muslim or non-Muslim countries as long as they are Sharia-compliant (i.e., they have to pass a set of rules-based screens). Although it is a subset of the Dow Jones Global Index, the DJIM index provides approximately 95% market coverage of 44 countries. It also has an independent Sharia Supervisory Board and its screens have been adopted by the Auditing & Accounting Organization of Islamic Financial Institutions ("AAOIFI")-Standard 21.[2]

The use of nonlinear causality tests is entirely justified by the fact that economic and financial time series tend to interact each other in a nonlinear fashion. This recognition has been enforced by the repeated occurrences of severe economic and financial crises and events including rare black swans like the 2007/2008 global financial crisis.[3] The potential nonlinear-

[1]Most of the published articles on Islamic finance use either DJIM or the FTSE Global Islamic Index, but the former is more comprehensive and more widely used than the latter. Our article also considers the DJIM index as a proxy for the global Islamic stock market because of its global coverage and use, and thus is part of a broader literature that focuses on the performance and behavior of restricted portfolios.

[2]There are companies in the Muslim countries that do not pass those rules, and thus cannot be included in the DJIM index. More details regarding the DJIM index are presented in Section 4.1. Note also that the research is abundant on Islamic banks but is at its infancy when it comes to the Islamic stock market.

[3]In addition to changes in the business cycle, these crises could have been facilitated

ity in the dynamics of the variables of interest can manifest itself in the presence of, among others, regime switching, asymmetry, leverage effects, structural breaks, and heterogeneity of investors including speculators, particularly hedge funds, and long term investors. The mere existence of these stylized facts ultimately requires heteroscedasticity-robust (HR) procedures and nonlinear tests to examine their relationships. For example, if the error terms from a vector autoregressive (VAR) model are heteroscedastic, the conclusions of causality tests might not be robust under the assumption of constant variance (Hafner and Herwartz, 2009).

Therefore, we make use of several tests to examine causal relationships between the Islamic and conventional stock markets, and between the Islamic stock market and financial and economic factors. The tests include the heteroscedasticity consistent covariance matrix estimator (HCCME) proposed by Mackinnon and White (1985), the fixed design wild bootstrap procedure of Hafner and Herwatz (2009), and the nonparametric nonlinear Granger causality test of Hiemstra and Jones (1994).

Overall, the motivation for this research is twofold. First, the magnitude of asset price variations at speculative markets typically exhibits high degree of market interrelations, implying that the errors of the causality in mean regressions may exhibit multivariate conditional heteroscedasticity. Second, the traditional Granger causality test is unable to explore the nonlinear re-

by the continuous flows of complex financial innovations, announcements, regulations, globalization, etc.

lationship between the variables of interest. This is due to the time-varying conditional mean and variance of asset returns (Baek and Brock, 1992; Hiemstra and Jones, 1994).

We use a comprehensive dataset that includes not only the stock market indices but also the international crude oil markets, the federal fund rate, the implied volatility in stock and bond markets, the economic policy uncertainty index, and the EMU 10-year government bond index. We find evidence of significant interactions between the variables and show that the Islamic stock market is not decoupled from external shocks of different types, regions, and sources. This evidence has strong bearing on the relevance of Sharia principles to investments in Islamic and conventional markets. Moreover, the Islamic stock market is also exposed to global shocks affecting the world financial system as well as to contagion risks during times of economic and financial crises.

The rest of this article is organized as follows. Section 2 provides a short review of the related literature. Section 3 introduces the empirical methods. Section 4 reports and discusses the empirical results. Section 5 concludes the article.

2. Literature review

This review categorizes the literature on Islamic finance into four strands: the characteristics of Islamic finance, the relative performance of this financial system in comparison to that of other socially responsible and faith-based investments, possible links between Islamic banks and equity markets and their conventional counterparts, and the potential performance between the two business systems during the global crisis and the shrinking gap between them.

The early literature deals with the unique characteristics of the Islamic financial system, particularly the prohibitions against the payment and receipt of interest. It also deals with the Islamic industry screens that restrict investment in economic activities related to sharia-forbidden activities. The Islamic industry concentrates its investments on these industries: technology, telecommunications, steel, engineering, transportation, health care, utilities, construction and real estate (Abd Rahman, 2010). Bashir (1983) draws a contrast between the Islamic financial and conventional systems by highlighting that Islamic finance is asset-based and asset-driven, while the conventional system is interest-based and debt-driven. Robertson (1990), Usmani (2002), and Iqbal and Mirakhor (2007) discuss the Riba or the premium that must be paid along with the principal by the borrower to the lender.

The more recent strand of the literature investigates the links between Islamic and conventional financial markets in terms of relative return and volatility. It also focuses on the relative performance between these markets during the recent global financial crisis. These markets are represented either by indices from different regions where some are a subset of the Dow Jones indices or the FTSE indices, among others.[4]

A wide range of empirical methodologies have been adopted by previous studies to achieve the stated goals. Using bivariate and the trivariate models, Hakim and Rashidian (2002) examine the dynamic correlation and the short- and long-run (cointegeration) relationships between the Dow Jones Islamic market index (DJIM), the U.S. three-month Treasury bill rate and the U.S. Wilshire 5000 Index. The authors find no statistically significant bivariate links between the DJIM and any of the two U.S. variables. More recently, Dania and Malhotra (2013) find evidence of a positive and significant return spillover from conventional market indices in North America, European Union, Far East, and Pacific markets to their corresponding Islamic index returns. They also find similar evidence for asymmetric volatility spillover. Krasicka and Nowak (2012) compare Malaysian Islamic and conventional security prices and their responses to macroeconomic factors. Their results suggest that Islamic and conventional bond and equity prices are driven by common factors and that the gap between Islamic and conventional financial practices is diminishing. On the other hand, Sukmana and Kholid (2012) examine the risk performance of the Jakarat Islamic stock index (JAKISL) and its conventional counterpart Jakarta Composite Index (JCI) in Indonesia using GARCH models. Their result shows that investing in the Islamic stock index is less risky than that of the conventional counterpart.

[4]The series on the indices related to individual Muslim countries are not comprehensive and short in length.

Hassan et al. (2005) compare the investment performance of an Islamic ethical portfolio with that of a conventional benchmark portfolio. The results indicate that the application of Islamic ethical screens do not necessarily have an adverse impact on investment performance. Hoepner et al. (2011) analyze both the financial performance and investment style of 265 Islamic equity mutual funds from twenty countries. The authors find that Islamic funds' investment style is somewhat tilted towards growth stocks and that the funds from predominantly Muslim economies show a clear preference for small caps. Girard and Kabir (2012) compare the differences in return performance between Islamic and non-Islamic indices and find that Islamic indices are growth and small-cap oriented, while conventional indices are relatively more value and mid-cap focused. Forte and Miglietta (2007) determine whether Islamic mutual funds as faith-based investments (i.e., FTSE Islamic indices) can be included into the category of socially responsible mutual funds, or they would be more fittingly grouped in a separate investment family. The results show that Islamic investments exhibit peculiar portfolios' differences in terms of econometric profile, compared to conventional and SRI indices.

As indicated earlier, the literature also explores the potential importance of Islamic finance, particularly during the recent global financial crisis. Chapra (2008) indicates that excessive lending, high leverage on the part of the conventional financial system, and the lack of an adequate market discipline have created the background for the global crisis. This author contends that the Islamic finance principles can help to introduce better discipline into the markets and preclude new crises from happening. Dridi and Hassan (2010) examine and compare the performance of Islamic banks and conventional banks during the recent global financial crisis in terms of the crisis impact on their profitability, credit and asset growth and external ratings. Those authors find that the two business models are impacted differently by the crisis.

Dewi and Ferdian (2010) also argue that Islamic finance can be a solution to the financial crisis because it prohibits the practice of Riba. Ahmed (2009) claims that the global financial crisis has revealed the misunderstanding and mismanagement of risks at institutional, organizational and product levels. This author also suggests that if institutions, organizations and products had followed the principles of Islamic finance they would have prevented the current global crisis from happening.[5] Arouri et al. (2013) pursue a different approach. While comparing the impacts of the financial crisis on Islamic and conventional stock markets in three global areas and finding less negative effects on the former than the latter, these authors examine diversified portfolios in which the Islamic stock markets supplement the conventional markets. They demonstrate that augmented portfolios lead to less systemic risks and generate more significant diversification benefits.

As can be seen from this review, there is no consensus in the literature on

[5] There is also a growing literature on Islamic Banks (see for example, Cihak and Hesse, 2010; Rahman, 2010; Hesse et al., 2008). Sole (2007) also presents a good review of how Islamic banks have become increasingly more integrated in the conventional banking system.

the directional relationship between Islamic stock market and conventional markets, and needless to say whether the spillover between the markets is linear or nonlinear. Our contribution in this study is to use nonlinear techniques and robustness tests to explore the potential of nonlinear relationships and asymmetric spillovers among those markets, as linear models may be unable to capture these dynamics. We also go beyond the previous research by questioning how the Islamic stock market is linked to some other global equity markets of the conventional finance system (EMU 10-year government bond markets, international crude oil market) as well as some global risk factors (i.e., FFR, VIX, US economic policy uncertainty).

3. Methodology

The traditional approach for testing Granger causality compares the prediction errors obtained by a model that relates Y to past and current values of both X and Y. This approach is naturally attractive because the test is simply asked to determine whether the coefficients of the regression model, associated with past and current values of X, are significant. However, it is now common that the traditional Granger framework is exposed to two main drawbacks. First, the prediction errors from the linear Granger causality tests are ultimately sensitive to the causality in the mean. Higher order structure, such as the conditional heteroscedasticity, is often ignored.

Second, parametric tests require several modeling assumptions, where the linearity of the regression structure is the most important. The nonlinearity of macroeconomic and financial series is becoming increasingly recognized by economists. Nonlinear models are thus more appropriate for modeling dependencies among economic variables. In this article, we address the first drawback by making use of MacKinnon and White (1985)'s heteroscedasticity-consistent covariance estimator (HCCE) for the Granger causality test. We also employ Hafner and Herwatz (2009)'s wild bootstrap method to take account of possible conditional heteroscedasticity of unknown form. For the second drawback, we use the nonparametric nonlinear Granger causality test of Hiemstra and Jones (1994).

3.1. Linear Granger causality tests

Granger (1969) defines causality between two variables, X and Y, in terms of predictability. Accordingly, a process X does not cause series Y if the capability to predict series Y is unaffected by the omission of X's history (Granger, 1980).

The bivariate Granger (1969) framework investigates the linear Granger causality between two processes X and Y, and involves estimating a p- order linear vector autoregressive model, $VAR(p)$, as follows:

$$\begin{aligned}\begin{bmatrix} y_t \\ x_t \end{bmatrix} &= \begin{bmatrix} \nu_1 \\ \nu_2 \end{bmatrix} + \begin{bmatrix} A_{11,1} & A_{12,1} \\ A_{21,1} & A_{22,1} \end{bmatrix} \begin{bmatrix} y_{t-1} \\ x_{t-1} \end{bmatrix} + ... \\ &+ \begin{bmatrix} A_{11,p} & A_{12,p} \\ A_{21,p} & A_{22,p} \end{bmatrix} \begin{bmatrix} y_{t-p} \\ x_{t-p} \end{bmatrix} + \begin{bmatrix} u_{1t} \\ u_{2t} \end{bmatrix} \end{aligned} \quad (1)$$

where $u_t = (u_{1t}, u_{2t})'$ is a vector of white noise processes with a nonsingular covariance matrix Σ_u. The necessary and sufficient condition for x_t being not Granger–causal for y_t (i.e., y_t is not Granger–caused by x_t) is that $A_{12,i} = 0$ for $i = 1, 2, ..., p$.

However, in the presence of heteroscedastic error terms generated by the VAR model, the conclusions to be made when testing non-causality in this framework might not be robust with respect to a priori assumed underlying volatility dynamics (Hafner and Herwartz, 2009). To overcome this limit, two methods are given. The first is based on heteroskedasticity-robust variance-covariance matrices (MacKinnon and White, 1985). The second uses a wild bootstrap procedure, following Hafner and Herwatz (2009), to take into account any possible conditional heteroscedasticity of unknown form.

3.2. Heteroscedasticity-robust analysis

3.2.1. Heteroscedasticity-consistent covariance matrix estimator

To the extent that the linear causality framework with *i.i.d* disturbances may not be relevant in the presence of volatility clustering and spillover across assets and markets (Cheung and Ng, 1996), many procedures for heteroscedasticity consistent covariance matrix estimator (HCCME) have been suggested in literature in order to gauge the causal links between variables (e.g., MacKinnon and White, 1985; Newey and Wesr, 1987; Andrews, 1991). Here, we employ a popular HCCME estimator developed by MacKinnon and White (1985), known in the literature as the HC3 estimator, to robustify the classical linear Granger causality test. This HCCME is given by,

$$HC3 : \hat{\Omega} = dig(\hat{u}_i^2/(1-h_i)^2) \tag{2}$$

where $\hat{u}_i$ are the estimated residuals from a $VAR(p)$ model and h_i is the i^{th} diagonal hat matrix. The HC3 estimator appears to have better performance in small samples. Long and Ervin (2000) carry out a more extensive study of small sample behavior and show that the HC3 estimator provides the best performance in small samples as it gives less weight to influential observations.

3.2.2. Wild bootstrap procedure

A second way to improve the performance of the classical Granger causality test in the presence of heteroscedasticity is to use a fixed design wild bootstrap procedure as in Hafner and Herwartz (2009). The wild bootstrap has been shown to yield reliable finite sample inference even when applied to data that are homoscedastic (Gonçalves and Kilian, 2004).

Specifically, Hafner and Herwartz (2009) introduce a wild bootstrap method to test parameter restrictions in VAR models, that is robust under conditional heteroscedasticity of unknown form. The wild bootstrap procedure is set up as follows.

1. Estimate the $VAR(p)$ model in Eq. (1) and obtain the Wald statistic for non-causality as described by Hafner and Herwatz (2009).

2. Estimate the restricted $VAR(p)$ model and obtain the estimated parameter values and the restricted residuals $\hat{u}_t$.

3. Form a boostrap sample of t observations $u_t^* = \hat{u}_t \eta_t$, where η_t are a sequence of random variables with zero mean and unit variance being also independent of the variables occurring in Eq. (1). The pseudo-disturbances η_t are generated using the Rademacher distribution

$$\eta_t = \begin{cases} -1 & \text{with probability } \pi = 0.5 \\ +1 & \text{with probability } 1 - \pi \end{cases}$$

4. Estimate Eq. (1) for each artificial series and compute the Wald statistic in order to obtain the empirical distribution under the null hypothesis.

5. Repeat previous steps 1000 times to form a bootstrapping distribution. The p-value (p_b) of the test can be obtained as the proportion of the number of times the Wald test is smaller than the bootstrapped-Wald test.

6. Reject the null if p_b is smaller than the chosen significance level.

3.3. The nonlinear Granger causality test of Hiemestra-Jones (1994)

Hiemstra and Jones (1994) extend the work of Baek and Brock (1992) and propose a nonparametric statistical method for detecting nonlinear causal relationships based on the correlation integral.

By defining the m-length lead vector of Y_t by Y_t^m, and the Ly-length and

Le-length lag vectors of Y_t and X_t, respectively, by Y_{t-Ly}^{Ly} and X_{t-Le}^{Le}. For given values of m, Ly and $Le \geq 1$ and for $\epsilon > 0$, the definition of nonlinear Granger noncausality is then given by

$$Pr(\|Y_t^m - Y_s^m\| < \epsilon | \|Y_{t-Ly}^{Ly} - Y_{s-Ly}^{Ly}\| < \epsilon, \|E_{t-Le}^{Le} - E_{s-Le}^{Le}\| < \epsilon)$$
$$= Pr(\|Y_t^m - Y_s^m\| < \epsilon | \|Y_{t-Ly}^{Ly} - Y_{s-Ly}^{Ly}\| < \epsilon), \quad (3)$$

where $Pr\{.\}$ is probability and $\|\|$ is the maximum norm. If Eq. (3) holds, then $\{X_t\}$ does not strictly Granger cause $\{Y_t\}$. Eq. (3) states that the conditional probability that two arbitrary m-length lead vectors of $\{Y_t\}$ are within distance ϵ, given that the corresponding lagged L_y-length lag vectors of $\{Y_t\}$ are ϵ-close, is the same when the L_e-length lag vectors of X_t is ϵ-close.

Hiemstra and Jones (1994) show that under the Granger noncausality null hypothesis formulated by Eq. (3), the following statistic follows an asymptotic normal distribution as

$$\sqrt{n}(\frac{C1(m+Ly, Le, \epsilon, n)}{C2(m+Ly, \epsilon, n)} - \frac{C3(m+Ly, \epsilon, n)}{C4(Ly, \epsilon, n)}) \sim AN(0, \sigma^2(m, Ly, Le, \epsilon)), \quad (4)$$

where $n = T + 1 - m - \max(Ly, le)$, $C1(m+Ly, Le, \epsilon, n)$, $C2(m+Ly, \epsilon, n)$, $C3(m+Ly, \epsilon, n)$, and $C4(Ly, \epsilon, n)$ are correlation-integral estimators of the point probabilities corresponding to the left-hand side and right-hand side of Eq. (3). It has been shown that this test has a very good power against a variety of nonlinear Granger causal and noncausal relations (Hiemstra and Jones, 1994; Ma and Kanas, 2000). The asymptotic variance $\sigma^2(m, Ly, Le, \epsilon)$ is estimated using the theory of U-statistic for weakly dependent processes (Denker and Keller, 1983).[6] The test statistic in Eq. (4) is applied to the estimated residual series from the bivariate VAR model. The null hypothesis is that X_t does not nonlinearly strictly Granger cause Y_t, and Eq. (4) holds for all m, Ly, $Le \geq 1$ and $\epsilon > 0$. By removing a linear predictive power from a linear VAR model, any remaining incremental predictive power of one residual series for another can be considered as nonlinear predictive power (Baek and Brock, 1992).

4. Data and empirical results

4.1. Data and preliminary analysis

We use daily data over the period from January 4, 1999 to October 8, 2010. We aim to capture a causality relationship between the Dow Jones Islamic Market (DJIM) index, on the one hand, and the S&P stock market indices for the United States, Europe and Asia respectively (SPUS, SPEU and SPAS50), the international crude oil markets (Brent and West Texas Intermediate price index benchmarks), the Merrill Lynch Option Volatility Estimate (MOVE) index, the Chicago Board options exchange (CBOE) volatility Index (VIX), the US Federal Funds Rate (FFR), the US Economic

[6]For a complete and detailed derivation of the variance, see the appendix in Hiemstra and Jones (1994).

Policy Uncertainty index (US EPUI), and the EMU benchmark 10-year government bond index (EMU), on the other hand.[7] Many Islamic governments and private investors shuffle their money between equity markets and government securities in Europe and the United States, but these interest-bearing investments are not Sharia-compliant and are prohibited. Since our article uses causality tests and not economic models, the transmission mechanisms between the variables are directional relationships that have to do with information flow-processing across markets. The presence of risk measures also captures the spillover of fear and uncertainty across markets.

As indicated, the DJIM index measures the global universe of investable equities that have been screened for Sharia compliance. The companies in this index are screened based on two sets of screens. The first screens remove any companies with involvement in alcohol, pork-related products, conventional financial services, entertainment, tobacco, and weapons and defense. A second set of screens utilizes financial ratios to remove companies based on debt and interest income levels. The regional allocation of stocks in DJIM is classified as follows: 60.14% for the United states; 24.33% for Europe and South Africa; and 15.5% for Asia/Pacific.

The equity VIX is an index that measures expectations of volatility of the S&P500 index over the next 30-day period. It is calculated based on the

[7] Other Islamic stock market indices include FTSE, S&P 500 and MSCI. These indices define their financial ratio restriction in terms of total assets, in contrast to DJIM which defines this restriction in terms of market capitalization.

options underwritten on the S&P 500 equity index and quoted in percentage points. VIX is referred to as the "fear index" in equity market. An increase of VIX is usually associated with a decrease in the S&P 500 index.

The one-month MOVE index is a yield curve weighted index of the normalized implied volatility on one-month Treasury options, with a 40% weight on the 10-year Treasury and a 20% weight on each of the 2-, 5- and 30-year Treasury bond maturities. The MOVE trades between two extremes: 80 indicating extreme complacency which presages a market problem as a result of satisfaction and contentment of the current situation, and 120 which signals extreme fear. Moves to the extremes in MOVE are quite rare for this credit index. Recently, MOVE's movements signal led a new regime of interest rates characterized by heightened uncertainty as market participants bid up the price for options to hedge their current risk exposure. Unlike its equity counterpart the CBOE's VIX, MOVE can spike as the underlying Treasurys move in either direction. However, the jumps in the MOVE Index are fairly agnostic or doubtful and can be a result of yields moving in any direction.

By contrast, the Islamic finance principles do not allow hedging against market and credit risks, and it is thus important to discern how the DJIM index responds to these risks. If there is sensitivity to risks, then it makes sense not to invest in stocks with high beta in the DJIM index because investors in Islamic stocks do not use hedging instruments.

The daily news-based Economic Policy Uncertainty Index is based on daily news from newspaper archives from Access World News NewsBank

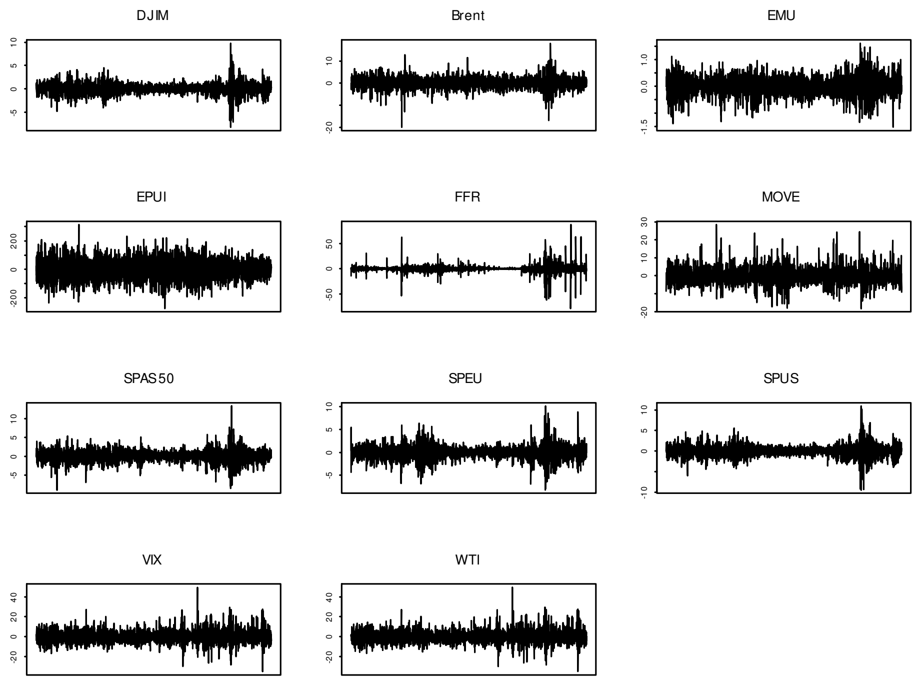

Figure 1: Time-variations of log return series

service. The database of this service holds the archives of thousands of newspapers and other news sources from across the globe. The Saint Louis Fed's Financial Stress index (FSI) is the first (principal) factor responsible for the comovement of a group of 18 variables which include seven interest rates, six yield spreads and five other indicators related to the stock, bond, options and exchange traded fund markets. Financial stress is the primary factor influencing this comovement of this group. Finally, Brent and WTI oil prices represent the cost of raw materials and the financialization of commodity markets.

Daily returns are calculated from daily price data by taking the natural logarithm of the ratio of two successive prices. Table 1 presents some summary statistics of sample data. The daily return averages over the sample period are positive and equal approximatively to 0.005% for DJIM, SPAS50, WTI, Brent, US EPUI and EMU. However, the averages for the rest of the series are negative and range from -0.005% (SPEU) to -0.11% (FFR). On other hand, the standard deviations show that the US Economic Policy Uncertaintly index displays by far the highest volatility, reflecting the impact of news and high instability of the US economy in recent years. Figure 1 shows the time-variations of the daily return series.

Table 1: Summary of basic statistics for returns

	Mean	Min.	Max.	Std. Dev.	ADF	PP
DJIM	5.572×10^{-05}	-0.0818	0.0977	0.0113	0.00	0.00
SPUS	-3.482×10^{-05}	-0.0947	0.1096	0.0134	0.00	0.00
SPEU	-5.007×10^{-05}	-0.0815	0.1013	0.0144	0.00	0.00
SPAS50	0.047×10^{-02}	-0.0892	0.1330	0.0149	0.00	0.00
MOVE	-2.596×10^{-05}	-0.1823	0.2841	0.0401	0.00	0.00
FFR	-0.0011	-0.7885	0.8755	0.0711	0.00	0.00
VIX	-0.002×10^{-02}	-0.3506	0.4960	0.0596	0.00	0.00
WTI	0.005×10^{-01}	-0.1709	0.1641	0.0258	0.00	0.00
Brent	0.058×10^{-02}	-0.1989	0.1813	0.0005	0.00	0.00
US EPUI	0.0005	-2.7560	3.1350	0.6631	0.00	0.00
EMU	5.344×10^{-05}	-0.0152	0.0161	0.0033	0.00	0.00

Notes: This table presents the main statistics of our sample data. Values in columns 7 and 8 are the p-values of the ADF and PP unit root tests applied to return series.

We also test for the existence of unit roots in the return series for the considered variables using the Augmented Dickey-Fuller (ADF) and the Phillips-

Perron (PP) tests.[8] The results indicate that the null hypothesis of a unit root is rejected at the 1% level for all the series. The stationarity property of the first log difference series is thus suitable for further statistical analysis with linear and nonlinear Granger causality tests.

4.2. Results from the linear Granger causality analysis

In order to examine causal relationships between the Dow Jones Islamic Market index and the rest of variables under investigation, we initially carry out the classical linear Granger causality between the returns of the series. The results are reported in Table 2. These causality results support the presence of bidirectional relationships between DJIM and each of the stock market indices under investigation (SPUS, SPEU, and SPAS50), the volatility and fear in the U.S. Treasury bond market (MOVE index) and the US federal funds rate, at the conventional statistical levels. This result that is based on the linear causality clearly shows feedback relations between the Islamic market and the three conventional markets and with other financial variables, negating the isolation or divorce hypothesis for the Islamic market.

Our findings show that there is no linear causality in any direction be-

[8]Note that our results indicate that VIX is not stationary in levels, but it is in first difference. This phenomenon is somewhat similar to the nonstationary interest rates (e.g., Rose, 1988; Rapach and Weber, 2004) and seems to depend on which sample we are dealing with. We also perform the ADF and PP unit root tests for all the variables in natural logarithm. The obtained results, which can be made availabe upon request, show that the null hypothesis of a unit root cannot be rejected at the conventional levels.

Table 2: Results from linear Granger causality test

Causal relationships	p-value	Causal relationships	p-value
H_0: DJIM$\nrightarrow$SPUS	0.0350^b	H_0: SPUS$\nrightarrow$DJIM	0.0005^a
H_0: DJIM$\nrightarrow$SPEU	0.0000^a	H_0: SPEU$\nrightarrow$DJIM	0.0000^a
H_0: DJIM$\nrightarrow$SPAS50	0.0000^a	H_0: SPAS50$\nrightarrow$DJIM	0.0297^a
H_0: DJIM$\nrightarrow$MOVE	0.0021^a	H_0: MOVE$\nrightarrow$DJIM	0.0649^c
H_0: DJIM$\nrightarrow$FFR	0.0115^b	H_0: FFR$\nrightarrow$DJIM	0.0001^a
H_0: DJIM$\nrightarrow$VIX	0.6111	H_0: VIX$\nrightarrow$DJIM	0.6593
H_0: DJIM$\nrightarrow$WTI	0.0156^b	H_0: WTI$\nrightarrow$DJIM	0.1916
H_0: DJIM$\nrightarrow$Brent	0.0000^a	H_0: Brent$\nrightarrow$DJIM	0.8378
H_0: DJIM$\nrightarrow$US EPUI	0.0349^b	H_0: US EPUI$\nrightarrow$DJIM	0.3837
H_0: DJIM$\nrightarrow$EMU	0.0050^a	H_0: EMU$\nrightarrow$DJIM	0.6746

Notes: This table reports the p-values of the Granger causality tests. ^{a} , ^{b} and ^{c} indicate the rejection of the null hypothesis of absence of causality at the 1%, 5% and 10% levels, respectively.

tween the DJIM index and VIX which is a mesure of the level of fear and volatility in the U.S. equity market. Based on the linear causality, this result shows that the Islamic stock market is not affected and does contribute to volatility of the U.S. S&P 500 index. This causality however exists when MOVE replaces VIX, giving more connection with volatility in the Treasury bond market than in the U.S. equity market. This is probably the case because many of the Islamic governments invest in Treasury securities, but these interest-bearing investments are not Sharia-compliant. Still, this result is striking because the financial ratio restrictions do not allow investment in interest-bearing securities. There seems to be inconsistencies in the Sharia-investment screening criteria and the practice of Islamic investments. There is however a difference among Islamic investment institutions particularly in terms of the tolerance level. There are also changes in the Sharia rules

(Binmahfouz, 2012). Nevertheless, it is an indication that the DJIM market is immersed in the global financial markets.

Furthermore, the linear causality results indicate the existence of unidirectional relationships from the DJIM index to oil prices (Brent, WTI), the U.S. Economic Policy Uncertainly index and the EMU benchmark 10-year government bond index, but not in the reverse direction. It is also worth mentioning that the DJIM index does not include equities from the stock markets of the Islamic oil-producing countries in the Middle East and North Africa, and that the news-based U.S. Economic Policy Uncertainty index picks up news from Islamic and other stock markets. These results however underscore the extent and prowess of integration of the Islamic market with markets of different asset classes and in different regions, and with other economic and financial variables, even though the nonlinearity whether in the form of asymmetry, regime switching and structural breaks is ignored.

4.3. Results from the heteroscedasticity-robust causality analysis

Tables 3 and 4 report the results from the Granger causality tests allowing for the HCCME and the wild bootstrap estimators. The pairwise Granger causality test results are similar for these two methods and demonstrate bidirectional causality between the DJIM index and the S&P's Europe stock market index. Moreover, in this analysis the DJIM index has a predictive content for the SPAS50 index, the MOVE index, the Brent oil price, the U.S. Economic Policy Uncertainly Index and the EMU benchmark 10-year government bond index, but not vice versa.

No causality however exists between the DJIM and each of the SPUS, FFR, VIX and WTI, which most of them have different results under the linear causality case. Overall, the heteroscedasticity-robust causality test provides more dynamic causal relationships between the DJIM index and other variables, compared with the results from the classical Granger causality test. This further proves the connection between the Islamic stock and conventional stock markets and with economic and financial shocks.

Table 3: Results from Granger causality tests with the heteroscedasticity-robust variance-covariance matrix

Causal relationships	p-value	Causal relationships	p-value
H_0: DJIM$\nrightarrow$SPUS	0.6116	H_0: SPUS$\nrightarrow$DJIM	0.4379
H_0: DJIM$\nrightarrow$SPEU	0.0000^a	H_0: SPEU$\nrightarrow$DJIM	0.0290^b
H_0: DJIM$\nrightarrow$SPAS50	0.0000^a	H_0: SPAS50$\nrightarrow$DJIM	0.6074
H_0: DJIM$\nrightarrow$ MOVE	0.0072^a	H_0: MOVE$\nrightarrow$ DJIM	0.2525
H_0: DJIM$\nrightarrow$ FFR	0.5196	H_0: FFR$\nrightarrow$ DJIM	0.8955
H_0: DJIM$\nrightarrow$ VIX	0.8554	H_0: VIX$\nrightarrow$ DJIM	0.7759
H_0: DJIM$\nrightarrow$ WTI	0.1819	H_0: WTI$\nrightarrow$ DJIM	0.2979
H_0: DJIM$\nrightarrow$ Brent	0.0000^a	H_0: Brent$\nrightarrow$ DJIM	0.9089
H_0: DJIM$\nrightarrow$US EPUI	0.0272^b	H_0: US EPUI$\nrightarrow$ DJIM	0.2597
H_0: DJIM$\nrightarrow$EMU	0.0194^b	H_0: EMU$\nrightarrow$ DJIM	0.7563

Notes: This table reports the p-values of a robust heteroscedasticity variance-covariance matrix for the Granger causality test. ^{a} , ^{b} and ^{c} indicate the rejection of the null hypothesis of absence of causality at the 1%, 5% and 10% levels, respectively.

4.4. Nonlinear causality analysis results

Table 5 presents the empirical results from the Hiemstra-Jones nonlinear Granger causality test, based on the residuals of a VAR model. Similarly to Hiemstra and Jones (1994), we set the value for the head length as $m =$

Table 4: Results of Granger causality tests with the wild-bootstrap procedure

Causal relationships	p-value	Causal relationships	p-value
H_0: DJIM$\nrightarrow$SPUS	0.573	H_0: SPUS$\nrightarrow$DJIM	0.256
H_0: DJIM$\nrightarrow$SPEU	0.0000^a	H_0: SPEU$\nrightarrow$DJIM	0.011^b
H_0: DJIM$\nrightarrow$SPAS50	0.0000^a	H_0: SPAS50$\nrightarrow$DJIM	0.539
H_0: DJIM$\nrightarrow$ MOVE	0.01^b	H_0: MOVE$\nrightarrow$ DJIM	0.147
H_0: DJIM$\nrightarrow$ FFR	0.679	H_0: FFR$\nrightarrow$ DJIM	0.516
H_0: DJIM$\nrightarrow$ VIX	0.851	H_0: VIX$\nrightarrow$ DJIM	0.795
H_0: DJIM$\nrightarrow$ WTI	0.141	H_0: WTI$\nrightarrow$ DJIM	0.316
H_0: DJIM$\nrightarrow$ Brent	0.0000^a	H_0: Brent$\nrightarrow$ DJIM	0.887
H_0: DJIM$\nrightarrow$US EPUI	0.011^b	H_0: US EPUI$\nrightarrow$ DJIM	0.285
H_0: DJIM$\nrightarrow$EMU	0.017^b	H_0: EMU$\nrightarrow$ DJIM	0.776

Notes: This table reports the p-values of a wild-bootstrap procedure for the Granger test. ^{a} , ^{b} and ^{c} indicate the rejection of the null hypothesis of absence of causality at the 1%, 5% and 10% levels, respectively.

1, the common lag lengths as 1 to 8 and a common scale parameter to be $e = 1.5$. As can be seen, the results show rich interactions between the variables of interest under the nonlinear causality test. In particular, we find evidence of a significant unidirectional nonlinear Granger causality running from each of the SPAS50 index, the VIX index, the WTI oil price and the EMU benchmark 10-year government bond index to the DJIM index, again negating the divorce hypothesis under this nonlinear case. This finding implies that the Islamic equity index is affected by changes in the U.S. and Asian stock markets, U.S. interbank money market, oil market, fear and volatility in the U.S. equity market, news regarding the U.S. economic and political system, and performance and risk across euro-zone fixed income bond markets.

This is an impressive litany of markets and factors that affect the Islamic market. This evidence casts doubt on the effectiveness of the Sharia principles in making the Islamic stock market different from the conventional stock markets because it is not isolated from external shocks of different types, regions, and sources.

The above-presented result assumes the possible existence of structural breaks, asymmetry and regime switching in the markets and the relevant economic and financial variables. Given the multiplicity of crises and events that prevail during the sample period, these nonlinearity results are more credible than those for the linearity case. But both results underscore the integration of the Islamic market with global equity markets and its sensitivity to different sources of shocks.

Table 5: Hiemstra-Jones nonlinear causality test

H_0: DJIM $\nrightarrow$ SPUS			H_0: SPUS $\nrightarrow$ DJIM			H_0: DJIM $\nrightarrow$ SPEU			H_0: SPEU $\nrightarrow$ DJIM			H_0: DJIM $\nrightarrow$ SPAS50			H_0: SPAS50 $\nrightarrow$ DJIM		
Lags	CS	TVAL	Lags	CS	TVAL	Lags	CS	TVAL	Lags	CS	TVAL	Lags	CS	TVAL	Lags	CS	TVAL
1	-0.4680	-25.5922	1	-0.4748	-25.9633	1	-0.5052	-27.6341	1	-0.4601	-25.1676	1	-0.5639	-30.8359	1	-0.4927	-26.9444
2	-0.3512	-19.2069	2	-0.3613	-19.7615	2	-0.4027	-22.0294	2	-0.3791	-20.7384	2	-0.5497	-30.0598	2	-0.3806	-20.8116
3	-0.2299	-12.5758	3	-0.2870	-15.6972	3	-0.3207	-17.5439	3	-0.2974	-16.2722	3	-0.5757	-31.4821	3	-0.1943	-10.6289
4	-0.1753	-9.5882	4	-0.2172	-11.8777	4	-0.2276	-12.4540	4	-0.1781	-9.7469	4	-0.7493	-40.9775	4	0.0129	0.7092
5	-0.1423	-7.7844	5	-0.1684	-9.2108	5	-0.1231	-6.73456	5	-0.0331	-1.8159	5	-1.0167	-55.5948	5	0.4405	24.0872^{a}
6	-0.1109	-6.0675	6	-0.1122	-6.1391	6	-0.1188	-6.50037	6	-0.0407	-2.2272	6	-0.5420	-29.6391	6	1.2340	67.4769^{a}
7	-0.0866	-4.7395	7	-0.1068	-5.8427	7	-0.0701	-3.83770	7	-0.0065	-0.3565	7	-0.0221	-1.2106	7	0.7997	43.7292^{a}
8	-0.0548	-2.9996	8	-0.0898	-4.9137	8	-0.0328	-1.79624	8	-0.0056	-0.3105	8	-0.0321	-1.7601	8	0.4723	25.8260^{a}

H_0: DJIM $\nrightarrow$ MOVE			H_0: MOVE $\nrightarrow$ DJIM			H_0: DJIM $\nrightarrow$ FFR			H_0: FFR $\nrightarrow$ DJIM			H_0: DJIM $\nrightarrow$ VIX			H_0: VIX $\nrightarrow$ DJIM		
Lags	CS	TVAL	Lags	CS	TVAL	Lags	CS	TVAL	Lags	CS	TVAL	Lags	CS	TVAL	Lags	CS	TVAL
1	-0.5424	-29.6738	1	-0.5839	-31.9493	1	-0.1736	-9.4920	1	-0.5278	-28.8464	1	-0.5996	-32.7784	1	-0.5149	-28.1509
2	-0.6524	-35.6953	2	-0.7211	-39.4534	2	-0.0863	-4.7178	2	-0.5538	-30.2697	2	-0.6140	-33.5670	2	-0.4407	-24.0914
3	0.7368	40.3136^{a}	3	-3.6464	-199.4927	3	0.0272	1.4866	3	-0.6068	-33.1653	3	-0.6515	-35.6154	3	-0.1276	-6.9787
4	5.2179	285.4675^{a}	4	-5.4231	-296.6920	4	0.2591	14.1621^{a}	4	-0.6889	-37.6525	4	-0.4055	-22.1694	4	0.14722	8.0475^{a}
5	1.7979	98.3645^{a}	5	-0.5539	-30.3039	5	0.3124	17.0769^{a}	5	-0.9220	-50.3911	5	-0.3916	-21.4108	5	0.2361	12.9089^{a}
6	0.6025	32.9637^{a}	6	0.28298	15.4815^{a}	6	0.5824	31.8303^{a}	6	-1.5966	-87.2632	6	0.0228	1.2495	6	0.3556	19.4396^{a}
7	0.1535	8.4006^{a}	7	-0.0505	-2.7678	7	7.5071	410.294^{a}	7	-17.5711	-960.3229	7	0.0041	0.2245	7	0.1947	10.6430^{a}
8	-0.0349	-1.9099	8	0.11105	6.0756^{a}	8	-0.6410	-35.0330	8	1.6775	91.6848^{a}	8	-0.0499	-2.7277	8	0.1389	7.5930^{a}

H_0: DJIM $\nrightarrow$ WTI			H_0: WTI $\nrightarrow$ DJIM			H_0: DJIM $\nrightarrow$ Brent			H_0: Brent $\nrightarrow$ DJIM			H_0: DJIM $\nrightarrow$ US EPUI			H_0: US EPUI $\nrightarrow$ DJIM		
Lags	CS	TVAL	Lags	CS	TVAL	Lags	CS	TVAL	Lags	CS	TVAL	Lags	CS	TVAL	Lags	CS	TVAL
1	-0.7302	-39.9623	1	-0.5292	-28.9619	1	-0.7245	-39.6496	1	-0.5487	-30.0301	1	-0.9215	-50.3825	1	-0.6505	-35.5665
2	-1.0280	-56.2603	2	-0.2616	-14.3184	2	-1.0680	-58.4515	2	-0.8519	-46.6222	2	3.1363	171.4698^{a}	2	0.94875	51.8701^{a}
3	-0.8813	-48.2342	3	0.5119	28.0160^{a}	3	1.3080	71.5828^{a}	3	-0.1111	-6.0835	3	-0.4118	-22.5168	3	-0.2926	-16.0008
4	-0.1426	-7.8058	4	0.5596	30.6258^{a}	4	0.0442	2.4196^{b}	4	-1.8650	-102.0691	4	-21.5799	-1179.8115	4	-18.6175	-1017.852
5	-0.1216	-6.6600	5	0.2779	15.2095^{a}	5	-0.2062	-11.2889	5	1.7747	97.1240^{a}	5	0.5617	30.7119^{a}	5	0.0829	4.5357^{a}
6	-0.0930	-5.0913	6	0.1240	6.7902^{a}	6	-0.4214	-23.0633	6	0.6380	34.9204^{a}	6	0.2051	11.2185^{a}	6	-0.0382	-2.0919
7	-0.0624	-3.4202	7	0.0353	1.9351^{b}	7	-0.3661	-20.0362	7	0.4154	22.7364^{a}	7	0.0733	4.0100^{b}	7	-0.0527	-2.8838
8	-0.0998	-5.4660	8	0.0543	2.9749^{b}	8	-0.2992	-16.3762	8	0.1914	10.4773^{a}	8	-0.1135	-6.2086	8	-0.0862	-4.7145

H_0: DJIM $\nrightarrow$ EMU			H_0: EMU $\nrightarrow$ DJIM		
Lags	CS	TVAL	Lags	CS	TVAL
1	-0.7987	-43.718	1	-0.5329	-29.1738
2	-1.1227	-61.455	2	-0.4998	-27.3575
3	-1.3998	-76.624	3	1.0542	57.7037^{a}
4	-0.4574	-25.040	4	0.5915	32.3809^{a}
5	-0.0955	-5.2322	5	0.8300	45.4332^{a}
6	-0.0419	-2.2943	6	0.4076	22.3151^{a}
7	-0.1338	-7.3287	7	0.2351	12.8701^{a}
8	-0.2059	-11.274	8	0.0847	4.6411^{a}

Notes: CS and TVAL are respectively the difference between the two conditional probabilities, and the standardized test statistic. "lags" denotes the number of lags in the residual series used in the test. ^{a} and ^{b} indicate the rejection of the null hypothesis of absence of causality at the 1% and 5% levels, respectively.

To sum up, the Hiemstra-Jones nonparametric test detects bidirectional causality relationships between the DJIM index and each of the MOVE index, the U.S. federal funds rate, the Brent oil price and the U.S. Economic Policy Uncertainty index. However, the unidirectional causality is found from all remaining variables to the DJIM index, except the SPEU and SPUS. These additional findings reinforce the nonlinear causality of previous tests, but do not support the nonlinear causality from the SPEU to the DJIM, which is detected by the two heteroscedasticity-robust causality tests.

5. Conclusion

It is common that economic and financial systems are characterized by time series that are not linearly related. This article investigates the linear and nonlinear links between Islamic and global conventional equity markets, and between the Islamic market and several global (economic and financial) shocks. For this purpose, we make use of both linear heteroscedasticity-robust (HR) and nonlinear causality testing procedures to examine those relationships. Specifically, we perform causality tests using the heteroscedasticity-consistent covariance matrix estimator proposed by Mackinnon and White (1985), the fixed design wild bootstrap of Hafner and Herwatz (2009), and the nonparametric nonlinear Granger causality test of Hiemstra and Jones (1994). Altogether, these tests allow one to account for some of the most important characteristics of financial and economic time series in testing for their causality.

Our results based on nonlinear causality analysis display rich interactions between variables and show that the Islamic equity market is not isolated from external shocks of different types, regions, and sources. In particular, the results show that there is a causal link coming from the Islamic market to both the European and the Asian stock markets and Brent oil market. This result is somewhat surprising because it excludes an Islamic causal link to the United States market which is the major market among the 44 world markets included in the DJIM index. This proves that the selection of stocks based on the strict Sharia principles may make some difference in the causal relationships and links for the DJIM index. The causal link with Europe and Asia shows that there is stronger Islamic relationship with regions in which Islamic Finance is more developed. The reversal link is not as strong. This shows the restrictive domain of Islamic investments because of the Sharia restrictions. Moreover, conventional markets use several kinds of hedging strategies against risks which may have helped them somewhat to shield themselves from cross market spillovers from the unhedged Islamic market. Consequently, the Islamic market may outperform the conventional counterparts during bull markets but underperform in bear markets because of lack of hedging.

Our findings thus suggest the rejection of the decoupling hypothesis of Islamic equity finance from conventional equity finance, still implying that the Islamic finance system may not provide either a good cushion against financial shocks affecting the conventional markets or large diversification benefits for portfolio managers. Overall, the Islamic finance system is also exposed to global shocks common to the world financial system as well as to contagion risks in the case of economic and financial crises. Therefore, the Islamic stock market may not be a strong therapy that heals from global financial crises.

Accurate modeling of the Islamic market dynamics should account for some interactions with, among others, changes in conventional equity markets, the U.S. bond market implied volatility, the economic policy uncertainty, oil price movements, and the US policy interest rate despite the financial ratio restrictions on investing on interest-based securities. For instance, a nonlinear VAR model incorporating the global economic and financial factors as endogenous variables will straightforwardly provide better estimates than a univariate model.

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