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Article

Modeling the interaction across international conventional and Islamic stock indices

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FINANCIAL ECONOMICS | RESEARCH ARTICLE

Modeling the interaction across international conventional and Islamic stock indices

Abdul Hakim¹*, Awan Setya Dewanta¹, Sahabudin Sidiq¹ and Riska Dwi Astuti¹

Abstract: Islamic financial instruments have been experiencing rapid growth in the last 50 years. Despite the unique motivation in formulating them, namely based on Syariah law, their movement might link to those of the conventional ones. This paper is devoted to investigating such interactions. It does so by applying two multivariate time series models to estimate various instruments, both Islamic and conventional ones. The models are the VAR (Vector Autoregression) and the VARMA-GARCH (Vector Autoregressive Moving Average-Generalized Autoregressive Heteroskedasticity). From the VAR model it finds evidence of bidirectional influences across both instruments. It also finds a conventional stock index that dominates the other series, namely the DJI (Dow Jones Index). From the VARMA-GARCH model, it finds influences from the conventional to Islamic index and vice versa, both in conditional mean and conditional variances. This paper suggests that the behavior of Islamic instruments are inseparable from the conventional ones. Future research might consider conditional correlations across these variables.

Subjects: International financial assets simulation; international financial markets

Keywords: Islamic instruments; Syariah law; conventional instruments; interaction Subjects: numbers: F37; G15

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PUBLIC INTEREST STATEMENT

Islamic stock indices have some unique characteristics in terms of the companies included in the index, as well as the issues of Muslim loyalties who buy the stocks. These have raised questions of whether the stock indices have some correlation, comovement, or causality relationship with the conventional stock indices. This paper is meant to answer some parts of the questions. To be precise, this paper models the causality relationship across such indices. The results will be beneficial in some ways, such as the possibility of constructing a portfolio by combining both types of indices or predicting the behavior of Islamic stock indices based on the conventional ones, or vice versa. It finds evidence of bidirectional influences across both instruments. It also finds a conventional stock index that dominates the other series, namely the DJI (Dow Jones Index). This paper suggests that the behavior of Islamic instruments are inseparable from the conventional ones.





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1. Introduction

Capital markets provide venues both for investment and speculation activities. The presence of Islamic instruments has provided more opportunities to do both. It also opens a new possibility in constructing an efficient portfolio that distributes the risk to minimize the individual risk. Investing in capital market would need to understand the behavior of instruments in such markets. This paper focuses on analyzing the interaction across Islamic and conventional instruments. Understanding such interaction would help to construct a portfolio that provides profit the most. Various articles have suggested such benefits (Kim & Sohn, 2016; Rahim & Masih, 2016).

The flow of information around the world provides the investors with various options of portfolio diversification to minimize risks based on real-time basis data tracking. Previous studies have provided a suggestion of strategies such as considering the interdependency and correlations among the stock markets (Rahim & Masih, 2016), combining Islamic stocks with the conventional ones (Kim & Sohn, 2016), and so on. Understanding the interaction of conventional and Islamic stocks provides a deeper analysis of why the investors should consider Islamic stocks on their portfolio and subsequently make it a more beneficial strategy to construct a portfolio that generates more benefits and minimizes the risks by combining and predicting the interbehaviour of both types of indices.

Despite the rapid growth of the Islamic economy, reaching 7% each year (Nurgalieva et al., 2018, p. 7), the portion of Islamic economy to conventional one is still shallow, namely 2.64%. Here is the calculation: the world GDP in 2020 is USD 91.98 trillion (World Population Review, 2020). In 2019, the world's Islamic economy size was USD 2.2 trillion (Arabian Business, 2019). If the Islamic world economy grew by 7%, it could be expected that the statistic becomes USD 2.354. This means that in 2020, the Islamic economy is 2.6% of the world economy. This fact generates questions: despite their small number in economic magnitude, does the Islamic stock index influences the conventional ones. We would like to know as well whether the Islamic stock index is independent of the conventional counterpart.

There are a lot of papers that have investigated the nature of the relationship across both stock indices. Most of them include only stock indices, but some others consider economic variables such as Nazlioglu et al. (2015) and Mensi et al. (2017). Most papers use a multivariate model, while a small amount of them use a univariate model. Those who use the univariate model are Nazlioglu et al. (2015), Rejeb (2017), and Albaity and Ahmad (2011). As predicted, multivariate models provide more straightforward steps in finding interdependencies across variables. However, univariate models are more flexible in including the independent variables, so they have a better chance to construct a theoretical model.

Various articles have estimated multivariate models to analyze both instruments, with or without the second-moment regressions. Those who do not consider the second-moment regressions are Ajmi et al. (2014), who use Granger causality test, and Djedovic and Ergun (2018), who use VAR and impulse response.

The articles that consider the second-moment regressions are Habibi and Pakizeh (2017) who use VaR based on GED-GARCH (Generalized error distribution—GARCH); Mensi et al. (2017) who use DECO-FIAPARCH (Dynamic Equicorrelation-Fractionally Integrated Asymmetric ARCH) by Engle and Kelly (2012); Umar and Suleman (2017) who use MVR-GARCH (Multi Variance-GARCH); and Toraman et al. (2016) who uses multivariate GARCH. Some papers also accommodate dynamic conditional correlations such as Hashmi (2018) and Majdoub and Mansour (2014), who use DCC-GARCH (Dynamic Conditional Correlation-GARCH). Some articles find evidence of the asymmetric impact of a negative shock compared to positive counterparts such as Kareem (2017) and Albaity and Ahmad (2011).

This paper model the interactions across international stock indices, both Islamic and conventional ones. It uses a simple VAR model with the help of three techniques to interpret the results, namely the impulse response function, the forecast error variance decomposition, and the Granger causality test. It hopes that the results will reveal the true nature of the interactions across those instruments.

2. Methods

This paper uses time-series data of stock indices that represent both international conventional and Islamic stock indices. The variables are DJI (Dow Jones Industrial Average), DJII (Dow Jones Islamic Index), IMANX (Iman Fund Class K), NASD (Nasdaq Composite), and SP (S&P500). DJII and IMANX are selected to represent the international stock indices, and they are available in a reasonably long series. DJI, SP, and NASD are chosen to represent the global conventional stock indices. However, the model is more about simulation since there are no sound theories that link the index. For such purpose, this paper select a VAR (Vector Autoregressive) model of Sims (1980) to estimate the empirical model. It is worth noted that VARs are not the ideal model for forecasting since it was not based on fully explicit economic theory (Sims, 1989). To better interpret the result, it considers Granger causality tests. The detail of the variables is in Table 1.

This paper also considers estimating a VARMA-GARCH model of Ling and McAleer (2003). This model accommodates the volatilities as well as the volatility spillovers across the indices.

Table 1. Detail of variables in the model					
No	Variable Name	Stock Name	Notes		
1	ILD	Dow Jones Industrial Average (^DJI). DJI—DJI Real-Time Price (in USD)	DJI has three missing observations, namely observations on 10 July 2001; 12 July 2001; and 17 September 2001. They are estimated using an average of observations pre and post the corresponding observations.		
2	IILD	Dow Jones Islamic Market U.S. I (^IMUS). DJI—DJI Real-Time Price (in USD)	-		
3	IMANX	Iman Fund Class K (IMANX). Nasdaq—Nasdaq Delayed Price (in USD)	The Iman Fund (symbol: IMANX) invests in Shariah-compliant companies. Since its inception on 30 June 2000, IMANX has provided Muslim investors with financial alternatives based on Islamic law		
4	NASD	NASDAQ Composite (^IXIC) Nasdaq GIDS—Nasdaq GIDS Real-Time Price (in USD).	-		
5	SP	S&P 500 (^GSPC). SNP—SNP Real-Time Price (in USD)	-		

Source: www.yahoofinance.com

VAR is a generalization of autoregressive models popularised by Sims (1980). A VAR is a system regression model, namely. Let $Y_t = (y_{1t}, y_{2t}, \dots, y_{nt})'$ denote an $(n \times 1)$ vector of time series variables. The basic *p*-lag vector autoregressive (VAR(*p*)) model is written as

$$Y_{t} = c + \prod_{1} Y_{t-1} + \prod_{2} Y_{t-2} + \ldots + \prod_{p} Y_{t-p} + \varepsilon_{t}, \quad t = 1, \ldots, T$$
(1)

where \prod_i are $n \times n$ coefficient matrices and ε_t is an $n \times 1$ unobservable zero-mean white noise vector process (serially uncorrelated or independent) with a time-invariant covariance matrix. In this paper, $Y_t = (y_{1t}, y_{2t}, \dots, y_{nt})' = (DJI_t, DJII_t, IMANX_t, NASD_t, SP_t)'$.

VAR modeling has some advantages. First, it does not need to specify which variables are endogenous or exogenous—all are endogenous. Second, it allows the value of a variable to depend on more than just its lags or combinations of white noise terms, so more general than ARMA modeling. Third, if there are no contemporaneous terms on the RHS of the equations, we can use OLS on each equation. Fourth, the forecasts that can be made from this model are often better than the traditional structural models.

VARMA-GARCAH model of Ling and McAleer (2003) is a type of VAR model that accommodates the presence of volatility as well as volatility spillovers across variables in the model. A VARMA-GARCH model can be represented as follows:

$$Y_{t} = E(Y_{t}|F_{t-1}) + \varepsilon_{t}$$
(2)

$$\Phi(L)(Y_{t} - \mu) = \Psi(L)\varepsilon_{t}$$

$$\varepsilon_{t} = D_{t}\eta_{t}$$
(3)
where-

$$Y_{t} = (y_{1t}, \dots, y_{mt})', \varepsilon_{t} = (\varepsilon_{1t}, \dots, \varepsilon_{mt})', H_{t} = (h_{1t}, \dots, h_{mt})', W = (\omega_{1}, \dots, \omega_{m})', D_{t} = diag(h_{it}^{2}), -$$

 $\eta_t = (\eta_{1t}, \dots, \eta_{mt}), \epsilon_t = (\epsilon_{1t}^2, \dots, \epsilon_{mt}^2)', A_l, C_l \text{ and } B_l \text{are } mxm \text{ matrices with typical elements } \alpha_i, \gamma_i \text{ and } \beta_i,$ respectively, for $i, j = 1, \dots, m, I(\eta_t) = diag(I(\eta_{it}))$ is an mxm matrix, $\Phi(L) = I_m - \Phi_1 L - \dots - \Phi_p L^p$ and $\Psi(L) = I_m - \Psi_1 L - \dots - \Psi_q L^q$ are polynomials in L, the lag operator, F_t is the past information available to time t, I_m is the mxm identity matrix, and $I(\eta_{it})$ is an indicator function, given as:

$$I(\eta_{i,t}) = \begin{cases} 1, \varepsilon_{i,t} \le 0\\ 0, \varepsilon_{i,t} > 0 \end{cases}$$
(4)

In this model, $Y_t = (y_{1t}, \dots, y_{mt})' = (DJI_t, DJII_tI, IMANX_t, NAS_t, SP_t)'$.

Since the data are time series in nature, it is imperative that the paper test for the nature of stationarity of the variables. This paper will do so by conducting an ADF test for all the variables. However, since the variables are in terms of returns, they will likely be stationary in level. If that is the case, the paper will not need to construct a VECM (vector error correction model) to estimate the coefficients of the variables.

3. Results and discussion

The data of all variables, which are daily data with 5 days in a week, are presented in Figure 1—the data spans from 5/11/2001 to 4/03/2020, which accounts for 7,754 observations. We can see from the graph





Figure 1. The variables to be analyzed.





THURSDAY AND AND

1500 1000

200

-15

-10 -

-2-



Figure 2. Series of variables in returns.



Table 2. Unit root test, series in-level, ADF					
Variable	t- statistics	5% t-critical	Prob		
DJI	-2.542	-3.411	0.308		
DJII	-2.820	-3.411	0.190		
IMANX	-3.000	-3.411	0.132		
NASD	-2.274	-3.411	0.447		
SP	-2.527	-3.411	0.315		

Table 3. Statistics of series in returns					
	ILD	DJII	IMANX	NASD	SP
Mean	0.014	0.019	0.006	0.026	0.015
Median	0.048	0.065	0.090	0.088	0.060
Maximum	10.764	11.740	11.542	11.159	10.957
Minimum	-13.842	-12.888	-13.455	-13.149	-12.765
Std. Dev.	1.186	1.221	1.345	1.420	1.234
Skewness	-0.423	-0.306	-1.081	-0.305	-0.456
Kurtosis	17.846	14.853	15.682	9.989	15.553
Jarque-Bera	43,789.4	27,897.5	32,774.6	9746.6	31,369.6
Probability	0.000	0.000	0.000	0.000	0.000
Observations	4753	4753	4753	4753	4753

Table 4. Unit root test, series in-returns, ADF					
Variable	t- statistics	5% t-critical	Prob		
DJI	-77.897	-3.411	0.0001		
DJII	-76.774	-3.411	0.0001		
IMANX	-74.414	-3.411	0.0001		
NASD	-74.946	-3.411	0.0001		
SP	-77.818	-3.411	0.0001		

that the data have positive trends, which is a sign that the series is nonstationary. Indeed, the Augmented Dickey–Fuller test results suggest that the series are nonstationary (see Table 1 and 2).

This paper uses a series in terms of return to overcome a spurious estimation. For a series of Y_t , the return (R_t) is calculated using the following formula:

$$R_t = \ln(Y_t/Y_{t-1}) \tag{5}$$

where Y_t and Y_{t-1} are Y at time t and Y at time t-1, respectively. The resulted series of returns can be seen in Figure 2. The statistics of the return series are in Table 3. Figure 2 shows that the variables have constant means, which is a good sign of stationarity. We will use an Augmented

Table 5. Serial correlation LM test for two lag length model					
Lags	LM-Stat	Prob			
1	51.085	0.002			
2	62.268	0.000			
3	51.896	0.001			

Table 6. VAR lag order selection criteria						
Lag	LogL	LR	FPE	AIC	SC	HQ
0	-14,262.140	NA	0.000321	6.1440	6.1508	6.1464
1	-14,201.910	618.1034	0.000284	6.0241	6.0650*	6.0384
2	-14,174.740	120.1738	0.000280	6.0092	6.0842	6.0356*
3	-14,148.590	54.1572	0.000280	6.0083	6.1173	6.0466
4	-14,125.090	52.0748	0.000280	6.0078	6.1509	6.0581
5	-14,096.480	46.7423	0.000280	6.0085	6.1856	6.0707
6	-14,058.550	56.8412	0.000280	6.0069	6.2181	6.0812
7	-14,036.050	75.2838	0.000278*	6.0015*	6.2467	6.0877
8	-14,262.140	44.6257*	0.000278	6.0025	6.2819	6.1007

*indicates lag order selected by the criterion, LR: sequentially modified LR test statistic (each test at 5% level), FPE: Final prediction error, AIC: Akaike information criterion, SC: Schwarz information criterion, and HQ: Hannan-Quinn information criterion.

Dickey–Fuller (ADF) test to confirm the stationary of the variables. The results are in Table 4. We can see that all variables are stationary in-level.

After testing the stationarity of the variables, this paper proceeds by estimating the VAR model. We let the data determine the lag length using various criteria such as AIC, SIC, and HQ. We start by estimating a VAR model using a maximum lag of 2. The result of the estimation is not presented in this paper to save space; the interested readers can get them from the author. To find whether the lag length is sufficient, the paper tests for the serial correlation. The result is in Table 5. Using a three lag of residuals, we can see that there is evidence of serial correlation, suggesting that the lag-length is not sufficient. The paper uses various criteria to find the appropriate lag length, as in Table 6.

Table 6 shows that the HQ criterion suggests two lag-length, which we have seen to be not sufficient. SC criterion suggests even less lag length, namely one. AIC, as well as FPE, suggest seven lag-length, which this paper will use. The result of VAR estimation using lag of 7 is in Table 7. We have adjusted the table from the initial EViews output, wherein this table, each cell contains three numbers, from top to bottom one, namely the coefficient, *t*-statistic, and probability, respectively.

Testing the autocorrelation of this model, we can see that only in lag four and eight that we cannot reject the null. It seems that overall, the model suffers from autocorrelation (see Table 8). To overcome this problem, we will estimate a VARMA-GARCH model, assuming the autocorrelation is caused by the absence of volatility modeling in the system. This paper also tests for the system stationarity of the VAR model to avoid having spurious estimates (see Table 9). From Table 9 we can see that each modulus is less than 1, suggesting that the system is stationary, and the VAR satisfies the stability condition.

Table 7. VAR estimation, maximum of seven lags					
	ILD	DJII	IMANX	NASD	SP
DJI(-1)	0.071	0.023	-0.042	0.047	0.047
	0.972	0.308	0.506	0.532	0.611
	0.331	0.758	0.613	0.595	0.541
DJI(-2)	0.235	0.231	0.229	0.202	0.236
	3.198	3.060	2.738	2.293	3.086
	0.001	0.002	0.006	0.022	0.002
DJI(-3)	0.155	0.143	0.099	0.052	0.139
	2.116	1.903	1.188	0.588	1.814
	0.034	0.057	0.235	0.557	0.070
DJI(-4)	0.178	0.195	0.267	0.278	0.176
	2.422	2.581	3.191	3.159	2.302
	0.016	0.010	0.001	0.002	0.021
DJI(-5)	-0.041	0.026	0.037	-0.068	0.007
	0.564	0.343	0.441	0.776	0.095
	0.573	0.732	0.660	0.438	0.924
DJI(-6)	-0.192	-0.155	-0.101	-0.175	-0.174
	2.620	2.046	1.208	1.985	2.279
	0.009	0.041	0.227	0.047	0.023
DJI(-7)	0.071	0.108	0.066	0.147	0.098
	0.967	1.436	0.790	1.668	1.278
	0.334	0.151	0.429	0.095	0.201
DJII(-1)	-0.080	-0.428	-0.085	-0.136	-0.083
	1.169	6.110	1.093	1.668	1.169
	0.242	0.000	0.274	0.095	0.243
DJII(-2)	-0.206	-0.361	-0.315	-0.240	-0.245
	2.866	4.880	3.839	2.786	3.273
	0.004	0.000	0.000	0.005	0.001
DJII(-3)	-0.001	-0.019	0.006	0.034	0.033
	0.007	0.257	0.071	0.389	0.431
	0.994	0.797	0.943	0.698	0.667
DJII(-4)	-0.126	-0.126	-0.090	-0.091	-0.113
	1.740	1.694	1.089	1.046	1.494
	0.082	0.090	0.276	0.296	0.135
DJII(-5)	0.037	-0.009	0.016	0.034	0.033
	0.506	-0.117	0.193	0.392	0.439
	0.613	0.907	0.847	0.695	0.660
DJII(-6)	-0.008	-0.059	-0.017	-0.079	-0.007
	0.117	0.802	0.209	0.916	0.093
	0.907	0.423	0.835	0.360	0.926
DJII(-7)	0.056	-0.014	0.016	-0.034	0.045
	0.822	0.199	0.200	0.420	0.629
	0.411	0.842	0.841	0.674	0.529

(Continued)

Table 7. (Continued)					
	DJI	DJII	IMANX	NASD	SP
IMANX(-1)	0.046	0.109	0.034	0.055	0.056
	1.221	2.837	0.802	1.228	1.439
	0.222	0.005	0.423	0.219	0.150
IMANX(-2)	0.031	0.041	0.038	0.037	0.030
	0.834	1.050	0.882	0.823	0.763
	0.405	0.294	0.378	0.410	0.445
IMANX(-3)	0.104	0.080	0.058	0.070	0.089
	2.757	2.066	1.348	1.552	2.276
	0.006	0.039	0.178	0.121	0.023
IMANX(-4)	0.018	0.026	0.016	0.015	0.025
	0.479	0.681	0.365	0.334	0.633
	0.632	0.496	0.715	0.738	0.527
IMANX(-5)	-0.009	-0.022	-0.029	-0.031	-0.009
	0.231	0.564	0.666	0.691	0.239
	0.817	0.573	0.506	0.490	0.811
IMANX(-6)	0.063	0.049	0.032	0.051	0.067
	1.664	1.258	0.748	1.134	1.690
	0.096	0.209	0.455	0.257	0.091
IMANX(-7)	0.025	0.030	0.022	0.021	0.038
	0.662	0.762	0.501	0.464	0.962
	0.508	0.446	0.616	0.643	0.336
NASD(-1)	0.191	0.259	0.198	0.231	0.195
	4.675	6.189	4.261	4.719	4.597
	0.000	0.000	0.000	0.000	0.000
NASD(-2)	0.077	0.106	0.080	0.033	0.082
	1.888	2.511	1.719	0.670	1.926
	0.059	0.012	0.086	0.503	0.054
NASD(-3)	-0.034	-0.026	-0.052	-0.054	-0.046
	0.821	0.605	1.103	1.093	1.075
	0.412	0.545	0.270	0.274	0.282
NASD(-4)	0.033	0.008	0.018	0.000	0.007
	0.795	0.184	0.375	0.010	0.166
	0.427	0.854	0.708	0.992	0.868
NASD(-5)	-0.024	0.014	0.022	-0.010	-0.001
	0.594	0.322	0.476	-0.197	-0.034
	0.553	0.748	0.634	0.844	0.973
NASD(-6)	-0.010	-0.005	-0.015	-0.026	-0.021
	0.236	0.125	0.329	0.538	0.502
	0.813	0.901	0.742	0.591	0.616
NASD(-7)	-0.014	0.002	0.001	0.004	-0.013
	0.339	0.058	0.028	0.080	0.302
	0.734	0.954	0.978	0.937	0.763
SP(-1)	-0.362	-0.107	-0.236	-0.352	-0.355
	3.653	-1.046	-2.084	-2.957	3.435
	0.000	0.296	0.037	0.003	0.001

(Continued)

	ILD	DJII	IMANX	NASD	SP
SP(-2)	-0.142	-0.042	-0.067	-0.043	-0.119
	1.411	0.406	0.585	0.362	1.144
	0.158	0.685	0.559	0.718	0.253
SP(-3)	-0.183	-0.142	-0.070	-0.066	-0.175
	1.823	1.374	0.615	0.551	1.676
	0.068	0.169	0.538	0.581	0.094
SP(-4)	-0.128	-0.129	-0.227	-0.211	-0.122
	1.281	1.253	1.986	1.756	1.170
	0.200	0.210	0.047	0.079	0.242
SP(-5)	0.005	-0.035	-0.074	0.043	-0.059
	0.052	0.342	0.645	0.360	0.564
	0.958	0.733	0.519	0.719	0.573
SP(-6)	0.097	0.122	0.067	0.180	0.090
	0.970	1.179	0.587	1.494	0.859
	0.332	0.238	0.557	0.135	0.390
SP(-7)	-0.097	-0.097	-0.090	-0.091	-0.135
	0.972	0.947	0.795	0.764	1.306
	0.331	0.344	0.427	0.445	0.192
С	0.017	0.024	0.008	0.029	0.018
	1.014	1.363	0.423	1.436	1.033
	0.311	0.173	0.673	0.151	0.302
R-squared	0.037144	0.038702	0.026183	0.031135	0.035301
Adj. R-squared	0.029989	0.031558	0.018947	0.023935	0.028133
F-statistic	5.191344	5.417833	3.618268	4.324526	4.924388

Note 1) Entries in each cell are, from top to bottom, the coefficient, t-statistic, and probability, respectively. 2) Entries in bold are significant at a 5% significance level.

Table 8. Serial correlation LM test, maximum of eight lags					
Lags	LM-Stat	Prob			
1	47.79157	0.0039			
2	42.96383	0.0141			
3	41.95935	0.0182			
4	33.38283	0.1218			
5	99.19875	0.0000			
6	60.41242	0.0001			
7	51.87958	0.0012			
8	34.14394	0.1049			

The estimation result of VAR in Table 7 shows that DJI is influenced by all other variables; DJII is influenced by all variables except SP; IMANX is influenced by all variables, but it is not influenced by its own lag; NASD is influenced by all variables except IMANX, and SP is influenced by all variables. We can also say that DJI affects the other variables in three lags. DJII, IMANX, NASD, and SP affect the other variables only in lag 1. Therefore, we conclude that DJI is the dominant variable.

Table 9. System stationarity test		
Root	Modulus	
-0.111953 + 0.710143i	0.719	
-0.111953-0.710143i	0.719	
-0.623375 + 0.324957i	0.703	
-0.623375-0.324957i	0.703	
0.539291 + 0.436548i	0.694	
0.539291-0.436548i	0.694	
-0.670750 + 0.020719i	0.671	
-0.670750-0.020719i	0.671	
0.616644 + 0.263510i	0.671	
0.616644-0.263510i	0.671	
0.564491 + 0.321634i	0.650	
0.564491-0.321634i	0.650	
-0.423257-0.478411i	0.639	
-0.423257 + 0.478411i	0.639	
0.123706-0.620618i	0.633	
0.123706 + 0.620618i	0.633	
0.095055-0.613508i	0.621	
0.095055 + 0.613508i	0.621	
-0.028951 + 0.610192i	0.611	
-0.028951-0.610192i	0.611	
0.481854 + 0.342790i	0.591	
0.481854-0.342790i	0.591	
-0.349328-0.471661i	0.587	
-0.349328 + 0.471661i	0.587	
-0.456155-0.300634i	0.546	
-0.456155 + 0.300634i	0.546	
-0.286130 + 0.452094i	0.535	
-0.286130-0.452094i	0.535	
0.394579 + 0.330012i	0.514	
0.394579-0.330012i	0.514	
0.476386	0.476	
-0.417865-0.116567i	0.434	
-0.417865 + 0.116567i	0.434	
0.090501 + 0.395810i	0.406	
0.090501-0.395810i	0.406	

In addition to looking at the significance level in testing the significant influence of the independent variables on a particular dependent variable, we will confirm it using a Granger causality test.

4. Granger causality test

Causality in econometrics refers to the ability to predict. Econometricians refer to Granger causality in the sense that X is said to be a Granger cause of Y if current Y can be predicted with greater accuracy by using past values of X (see Thomas, 1997, p. 461). Granger causality is different from the causality measure given by an individual t-test in a way that the Granger causality test accommodates the influence of lags in the model. Table 10 presents the test result. The table

Table 10. Granger causality test (lags: 7)				
Null Hypothesis:	Obs	F-Statistic	Prob.	
DJII does not Granger Cause DJI	4746	3.671	0.0006	
DJI does not Granger Caus	e DJII	3.764	0.0004	
IMANX does not Granger Cause DJI	4746	2.265	0.0266	
DJI does not Granger Caus	e IMANX	4.106	0.0002	
NASD does not Granger Cause DJI	4746	2.545	0.0129	
DJI does not Granger Caus	e NASD	8.356	4.E-10	
SP does not Granger Cause DJI	4746	3.389	0.0013	
DJI does not Granger Caus	e SP	3.361	0.0014	
IMANX does not Granger Cause DJII	4746	3.058	0.0033	
DJII does not Granger Cause IMANX		2.316	0.0234	
NASD does not Granger Cause DJII	4746	7.650	3.E-09	
DJII does not Granger Cau	se NASD	6.495	1.E-07	
SP does not Granger Cause DJII	4746	1.790	0.0848	
DJII does not Granger Cau	se SP	2.601	0.0112	
NASD does not Granger Cause IMANX	4746	0.479	0.8506	
IMANX does not Granger C	ause NASD	2.060	0.0444	
SP does not Granger Cause IMANX	4746	3.250	0.0019	
IMANX does not Granger C	ause SP	2.360	0.0209	
SP does not Granger Cause NASD	4746	9.099	3.E-11	
NASD does not Granger Ca	use SP	4.294	0.0001	

shows evidence of Granger causality from all variables to the others, except that SP does not Granger cause DJII, and that NASD does not Granger cause IMANX.

The interaction between conventional to Islamic stock indices is supported by Abbes and Trichilli (2015), although it tends to change over time. The support also comes from Ajmi et al. (2014), who refute the longstanding decoupling hypothesis about Islamic financial markets. However, a different view is given by Rizvi et al. (2015). They found that although the authors show that most of the economic downturns since 1996 can be attributed to excessive linkages from the US to the Asia Pacific, the real sector grounded Islamic markets exhibit a reduced exposure to crises. This indicates a weak interaction between conventional instruments and Sharia-based instruments. But the upside is that the Islamic stock market can be a buffer for economic crises, as well as a vehicle for spreading the risk.

5. VARMA-GARCH estimation

As previously mentioned, this paper estimates a VARMA-GARCH model of Ling and McAleer (2003). This paper estimates three models, namely VARMA-GARCH with a lag of 1, 2, and 3, using EViews 9.0 software package. However, when estimating the model with a lag of 3, the software was not able to provide a result. This might be because the estimated coefficient was to many. This is known as the curse of dimensionality.

Table 11. Finding the most appropriate lag length in VARMA-GARCH models					
Dependent Variables and Criterion	VARMA-GARCH Lag 1	VARMA-GARCH Lag 2	Chosen lag		
DJI					
AIC	3.165698	2.967667	LAG2		
SC	3.190196	3.012588	LAG2		
HQC	3.174306	2.983452	LAG2		
DJII					
AIC	3.285556	3.103271	LAG2		
SC	3.310054	3.148192	LAG2		
HQC	3.294164	3.119056	LAG2		
IMANX					
AIC	3.041714	3.042669	LAG1		
SC	3.066212	3.08759	LAG1		
HQC	3.050323	3.058454	LAG1		
NASDAQ					
AIC	3.774396	3.638483	LAG2		
SC	3.798894	3.683404	LAG2		
HQC	3.783004	3.654268	LAG2		
SP					
AIC	3.385645	3.26393	LAG2		
SC	3.410143	3.308851	LAG2		
HQC	3.394253	3.279715	LAG2		

Note: AIC = Akaike Information Criterion; SC = Schwartz Criterion; and HQC = Hannan-Quinn Criterion

Table 12. Summary of mean and volatility spillovers in a VARMA-GARCH lag 2 model			
Mean Spillovers	Volatility Spillovers		
SP to DJI	IMANX to DJI		
NASDAQ to DJI	NADSDAQ to DJI		
DJI to DJII	IMANX to DJII		
NASDAQ to DJII			
DJII to IMANX	None to IMANX		
IMANX to NASDAQ	IMANX to NASDAQ		
DJII to SP	IMANX to SP		
IMANX to SP			
NASDAQ to SP			

To choose which model is more appropriate, we use the Akaike Information Criterion, Schwartz Criterion, and Hannan–Quinn Criterion. The results are in Table 11. Based on the AIC, SC, and HQC, it seems that VARMA-GARCH with lag 2 is more appropriate than VARMA-GARCH with lag 1, except for IMANX, in which VARMA-GARCH with lag 1 is the more appropriate one, even though the difference between the criteria is very small. Therefore, we will use lag 2 as the basis for analysis, and in addition, we will compare the result of both lag for the IMANX estimation.

The estimation output of the VARMA-GARCH with a lag of 2 is available in the Appendix. The estimation output of the VARMA-GARCH with a lag of 1 is available upon request to the authors.

The results of VARMA-GARCH lag two estimations are available in the Appendix (Tables A1-A10). The summary of the mean and volatility spillovers from the VARMA-GARCH lag two estimations is in Table 12.

Table 12 shows that, in terms of conditional mean, NASDAQ influences all variables except IMANX. Therefore, we can say that NASDAQ dominates the influences. We also find the influence of conventional indices to Islamic indices, namely from DJI to DJII and NASDAQ to DJII. We also find the influence of Islamic indices to conventional indices, namely from IMANX to both NASDAQ S&P500, and from DJII to S&P500. In addition, we find the influence across Islamic indices, namely from DJII to IMANX. We can conclude as well that the results of Granger that SP does not Granger cause DJII, and that NASD does not Granger cause IMANX, are supported by the result of VARMA-GARCH.

Table 12 also shows that, in terms of conditional variances, IMANX influences all variables. Therefore, we can say that IMANX dominates the influences. We do not also find any influence from conventional indices to Islamic indices. We see the influence of Islamic indices to conventional indices, namely from IMANX to all other variables. In addition, we find the influence across Islamic indices, namely from IMANX to DJII.

The evidence of volatility spillovers across conventional and Islamic indices is supported by Muharam et al. (2020), but only for cases in developed countries. Meanwhile, Majdoub and Mansour (2014) do not provide strong evidence of US market spillovers into the Islamic emerging equity markets. In addition, there is evidence of weak correlation across the Indonesian market and the developed markets for both conventional and Islamic stock prices, suggesting the possibility of portfolio diversification. Another paper by Ben Nasr et al. (2014) suggests the possibility of Islamic instruments as a venue to diversify risk. In addition, Saiti et al. (2014) found that Islamic countries can be better diversification venues compared to Far East countries. However, Majdoub et al. (2016) suggest a high connection between the developed markets for both conventional and Islamic indices. This can demotivate investors to use Islamic instruments as a potential venue to diversify financial risk.

6. Conclusion

This paper estimates a VAR model to analyze the mean interactions across international conventional and Islamic stock indices. It uses the Granger causality test to help confirm the result. This paper also estimates a VARMA-GARCH model of Ling and McAleer (2003) to accommodate the presence of volatility and volatility spillovers across the indices,

The VAR estimation results suggest evidence of the influence across the indices, except for two cases, namely from the SP to DJII and from IMANX to NASDAQ. The estimation results of the Granger causality test also suggest similar results, namely that there is evidence of the influence of each index to the other index, except for two cases, namely from the DJI to SP to and from NASDAQ to IMANX.

The results of the VARMA-GARCH provide more limited evidence about the effect of one index to another. However, it can be said that there are influences of conventional indices to Islamic indices, namely from DJI to DJII and NASDAQ to DJII. We also find the influence of Islamic indices to conventional indices, namely from IMANX to both NASDAQ and SP, and from DJII to SP. In addition, we find the influence across Islamic indices, namely from DJII to IMANX. We can conclude as well that the results of Granger that the SP does not Granger cause DJII, and that NASD does not Granger cause IMANX, is supported by the result of VARMA-GARCH.

From the estimation result, this paper suggests that to construct an efficient portfolio, namely a portfolio which offers the highest expected return for a given level of risk or a portfolio with the lowest level of risk for a given expected return, one should consider including Islamic indices into it. However, one should not treat the Islamic indices with the same manner, because the behavior of an Islamic index might be different from the other, especially in its relation to the conventional ones.

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Table A1. Mean estimation, dependent variable: DJI					
Variable	Coefficient	Std. Error	z-Statistic	Prob.	
С	0.033	0.028	1.163	0.245	
DJI(-1)	0.125	0.288	0.435	0.664	
DJI(-2)	0.134	0.112	1.197	0.231	
DJII(-1)	-0.067	0.092	-0.730	0.465	
DJII(-2)	-0.143	0.089	-1.607	0.108	
IMANX(-1)	0.084	0.050	1.666	0.096	
IMANX(-2)	0.034	0.052	0.652	0.514	
SP(-1)	-0.317	0.124	-2.548	0.011	
SP(-2)	-0.096	0.166	-0.577	0.564	
NASD(-1)	0.103	0.051	1.998	0.046	
NASD(-2)	0.038	0.061	0.626	0.532	
MA(1)	0.006	0.275	0.022	0.983	

Appendix. The Result of a VARMA-GARCH model with lag of 2

Entries in bold are significant at 5% confidence level

Table A2. Variance estimation, dependent variable: DJI				
Variable	Coefficient	Std. Error	z-Statistic	Prob.
С	0.786	0.297	2.649	0.008
RESID(-1)^2	0.101	0.050	2.014	0.044
RESID(-2)^2	0.074	0.072	1.035	0.301
GARCH(-1)	0.450	0.204	2.203	0.028
GARCH(-2)	0.013	0.003	4.026	0.000
DJII_RES2(-1)	-0.007	0.053	-0.139	0.889
DJII_RES2(-2)	0.010	0.055	0.181	0.856
DJII_H(-1)	0.006	0.197	0.030	0.976
DJII_H(-2)	0.006	0.175	0.034	0.973
SP_RES2(-1)	0.013	0.041	0.306	0.760
SP_RES2(-2)	0.033	0.095	0.354	0.723
SP_H(-1)	0.009	0.503	0.018	0.986
SP_H(-2)	0.009	0.395	0.024	0.981
IMANX_RES2(-1)	-0.010	0.001	-8.132	0.000
IMANX_RES2(-2)	-0.002	0.009	-0.246	0.806
IMANX_H(-1)	-0.005	0.045	-0.108	0.914
IMANX_H(-2)	-0.004	0.051	-0.084	0.933
NASD_RES2(-1)	-0.035	0.016	-2.173	0.030
NASD_RES2(-2)	-0.020	0.034	-0.595	0.552
NASD_H(-1)	-0.004	0.299	-0.012	0.991
NASD_H(-2)	-0.003	0.265	-0.010	0.992

Table A3. Mean estimation, dependent variable: DJII					
Variable	Coefficient	Std. Error	z-Statistic	Prob.	
С	0.055	0.032	1.707	0.088	
DJI(-1)	0.083	0.104	0.804	0.421	
DJI(-2)	0.153	0.117	1.317	0.188	
DJII(-1)	-0.422	0.232	-1.824	0.068	
DJII(-2)	-0.320	0.120	-2.673	0.008	
IMANX(-1)	0.092	0.052	1.788	0.074	
IMANX(-2)	0.042	0.058	0.733	0.464	
SP(-1)	-0.107	0.136	-0.791	0.429	
SP(-2)	-0.011	0.149	-0.074	0.941	
NASD(-1)	0.230	0.058	3.991	0.000	
NASD(-2)	0.079	0.077	1.029	0.303	
MA(1)	0.006	0.219	0.025	0.980	

Table A4. Variance estimation, dependent variable: DJII				
Variable	Coefficient	Std. Error	z-Statistic	Prob.
С	0.949	0.554	1.715	0.086
RESID(-1)^2	0.101	0.050	2.012	0.044
RESID(-2)^2	0.043	0.088	0.494	0.621
GARCH(-1)	0.446	0.413	1.079	0.280
GARCH(-2)	0.008	0.152	0.050	0.960
DJI_RES2(-1)	0.001	0.036	0.019	0.985
DJI_RES2(-2)	0.019	0.121	0.156	0.876
DJI_H(-1)	0.009	0.693	0.013	0.989
DJI_H(-2)	0.009	0.587	0.016	0.988
SP_RES2(-1)	0.003	0.055	0.055	0.956
SP_RES2(-2)	0.019	0.120	0.158	0.875
SP_H(-1)	0.009	0.741	0.013	0.990
SP_H(-2)	0.009	0.637	0.014	0.989
IMANX_RES2(-1)	-0.013	0.001	-18.210	0.000
IMANX_RES2(-2)	0.001	0.015	0.087	0.931
IMANX_H(-1)	-0.008	0.070	-0.112	0.911
IMANX_H(-2)	-0.007	0.068	-0.102	0.919
NASD_RES2(-1)	-0.028	0.030	-0.941	0.347
NASD_RES2(-2)	-0.006	0.050	-0.115	0.908
NASD_H(-1)	-0.006	0.414	-0.014	0.989
NASD_H(-2)	-0.005	0.368	-0.012	0.990

Table A5. Mean Estimation, dependent variable: IMANX				
Variable	Coefficient	Std. Error	z-Statistic	Prob.
С	0.017	0.018	0.957	0.339
DJI(-1)	0.003	0.077	0.042	0.966
DJI(-2)	0.103	0.080	1.295	0.195
DJII(-1)	-0.041	0.072	-0.575	0.566
DJII(-2)	-0.196	0.074	-2.645	0.008
IMANX(-1)	0.038	0.255	0.148	0.883
IMANX(-2)	0.084	0.049	1.721	0.085
SP(-1)	-0.149	0.106	-1.406	0.160
SP(-2)	-0.044	0.119	-0.369	0.712
NASD(-1)	0.083	0.044	1.869	0.062
NASD(-2)	0.010	0.047	0.215	0.830
MA(1)	0.006	0.253	0.025	0.980

Table A6. Variance estimation, dependent variable: IMANX				
Variable	Coefficient	Std. Error	z-Statistic	Prob.
С	0.201	0.145	1.387	0.165
RESID(-1)^2	-0.004	0.008	-0.528	0.598
RESID(-2)^2	0.025	0.020	1.261	0.207
GARCH(-1)	0.453	1.032	0.439	0.661
GARCH(-2)	0.019	0.749	0.026	0.979
DJII_RES2(-1)	0.001	0.040	0.019	0.985
DJII_RES2(-2)	0.005	0.048	0.096	0.923
DJII_H(-1)	0.043	0.255	0.170	0.865
DJII_H(-2)	0.052	0.200	0.261	0.794
SP_RES2(-1)	0.058	0.045	1.278	0.201
SP_RES2(-2)	0.044	0.086	0.515	0.607
SP_H(-1)	0.062	0.878	0.070	0.944
SP_H(-2)	0.064	0.727	0.089	0.929
DJI_RES2(-1)	0.013	0.037	0.345	0.730
DJI_RES2(-2)	0.041	0.071	0.585	0.559
DJI_H(-1)	0.055	0.357	0.156	0.876
DJI_H(-2)	0.057	0.217	0.262	0.793
NASD_RES2(-1)	-0.017	0.016	-1.054	0.292
NASD_RES2(-2)	-0.020	0.038	-0.524	0.600
NASD_H(-1)	-0.001	0.346	-0.004	0.997
NASD_H(-2)	0.006	0.308	0.018	0.985

Table A7. Mean estimation, dependent variable: NASDAQ				
Variable	Coefficient	Std. Error	z-Statistic	Prob.
С	0.043	0.048	0.906	0.365
DJI(-1)	0.076	0.150	0.503	0.615
DJI(-2)	0.138	0.168	0.823	0.411
DJII(-1)	-0.130	0.137	-0.951	0.342
DJII(-2)	-0.218	0.140	-1.552	0.121
IMANX(-1)	0.084	0.043	1.956	0.050
IMANX(-2)	0.034	0.067	0.503	0.615
SP(-1)	-0.352	0.201	-1.752	0.080
SP(-2)	-0.011	0.252	-0.044	0.965
NASD(-1)	0.214	0.387	0.554	0.580
NASD(-2)	0.015	0.117	0.132	0.895
MA(1)	0.004	0.372	0.010	0.992

Table A8. Variance estimation, dependent variable: NASDAQ				
Variable	Coefficient	Std. Error	z-Statistic	Prob.
С	1.742	1.681	1.036	0.300
RESID(-1)^2	0.092	0.067	1.377	0.168
RESID(-2)^2	0.024	0.111	0.218	0.827
GARCH(-1)	0.470	0.740	0.635	0.526
GARCH(-2)	0.030	0.284	0.107	0.915
DJII_RES2(-1)	-0.007	0.125	-0.056	0.955
DJII_RES2(-2)	0.007	0.100	0.074	0.941
DJII_H(-1)	-0.002	0.287	-0.007	0.994
DJII_H(-2)	-0.002	0.266	-0.007	0.995
SP_RES2(-1)	-0.003	0.135	-0.025	0.980
SP_RES2(-2)	0.017	0.193	0.088	0.930
SP_H(-1)	0.000	1.267	0.000	1.000
SP_H(-2)	0.000	1.075	0.000	1.000
IMANX_RES2(-1)	-0.024	0.008	-3.018	0.003
IMANX_RES2(-2)	-0.008	0.020	-0.412	0.681
IMANX_H(-1)	-0.007	0.108	-0.063	0.950
IMANX_H(-2)	-0.006	0.110	-0.056	0.955
DJI_RES2(-1)	-0.003	0.101	-0.031	0.976
DJI_RES2(-2)	0.019	0.169	0.114	0.909
DJI_H(-1)	0.000	1.194	0.000	1.000
DJI_H(-2)	0.000	1.020	0.000	1.000

Table A9. Mean estimation, dependent variable: SP					
Variable	Coefficient	Std. Error	z-Statistic	Prob.	
С	0.067	0.042	1.587	0.113	
DJI(-1)	0.081	0.119	0.679	0.497	
DJI(-2)	0.158	0.134	1.181	0.238	
DJII(-1)	-0.098	0.112	-0.872	0.383	
DJII(-2)	-0.216	0.111	-1.952	0.051	
IMANX(-1)	0.100	0.050	1.983	0.047	
IMANX(-2)	0.030	0.052	0.571	0.568	
SP(-1)	-0.344	0.354	-0.970	0.332	
SP(-2)	-0.080	0.207	-0.386	0.699	
NASD(-1)	0.150	0.069	2.176	0.030	
NASD(-2)	0.063	0.086	0.729	0.466	
MA(1)	0.006	0.313	0.019	0.985	

Table A10. Variance estimation, dependent variable: SP				
Variable	Coefficient	Std. Error	z-Statistic	Prob.
С	1.241	0.651	1.907	0.057
RESID(-1)^2	0.116	0.062	1.856	0.063
RESID(-2)^2	0.055	0.088	0.620	0.535
GARCH(-1)	0.464	0.270	1.715	0.086
GARCH(-2)	0.025	0.000	183.352	0.000
DJII_RES2(-1)	-0.010	0.071	-0.143	0.887
DJII_RES2(-2)	0.007	0.060	0.113	0.910
DJII_H(-1)	0.005	0.200	0.023	0.982
DJII_H(-2)	0.004	0.192	0.023	0.981
DJI_RES2(-1)	-0.004	0.058	-0.070	0.945
DJI_RES2(-2)	0.017	0.106	0.160	0.873
DJI_H(-1)	0.008	0.593	0.014	0.989
DJI_H(-2)	0.008	0.472	0.016	0.987
IMANX_RES2(-1)	-0.017	0.001	-12.240	0.000
IMANX_RES2(-2)	-0.007	0.006	-1.243	0.214
IMANX_H(-1)	-0.004	0.070	-0.057	0.955
IMANX_H(-2)	-0.003	0.073	-0.046	0.963
NASD_RES2(-1)	-0.040	0.027	-1.482	0.138
NASD_RES2(-2)	-0.017	0.046	-0.372	0.710
NASD_H(-1)	-0.004	0.416	-0.010	0.992
NASD_H(-2)	-0.003	0.393	-0.008	0.994



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