Oil price and the global conventional and islamic stock markets: Is the relationship symmetric or asymmetric ? evidence from nonlinear ARDL

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Abstract

The objective of this study is to investigate the relationship between the global oil and stock markets using the Islamic and conventional global stock indexes. We test the short- and long-run asymmetric impact of oil prices on both the conventional and Islamic stock prices in the global markets. The nonlinear ARDL approach developed by Shin et al.(2014) is utilized to examine the asymmetric relationship between the variables. The results tend to indicate that the impact of oil prices on stock prices is asymmetric during the short-run for both the Islamic and conventional stock markets. However, the long-run asymmetric relationship exists for the impact of the Oil price on Islamic stocks only and not on conventional stocks.The results carry important policy implications for the investors and policymakers.

Key words: global oil and stock markets, ARDL, NARDL, causality.

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Introduction

Global oil prices have become one of the most important determinants of international stock market volatility. Therefore, given the oil intensity of emerging economies, investors should be susceptible to the impact that changes in oil prices have on future equity returns (Shafaai and Masih, 2013). As an important production input for an economy, variations in its price could bring uncertainty to the overall economic growth and development.

Previous studies also document that as oil price is one of the major indicators for an economy, fluctuations in its volatility can have substantial impacts on the stock markets (Noor and Dutta, 2017). An empirical work by Ciner (2013), for example, claims that oil prices tend to impact the stock returns in two ways. First oil price shocks can cause changes in expected cash flows by their effect on the overall economy. Second, oil price shocks can affect the discount rate used to value equities by changing inflationary expectations. In addition, Bouri (2015) argues that oil price shocks can transmit into equity markets leading to immediate instabilities in financial markets and distant disruptions of economic activities.

There are also numerous literature investigating the oil-stock link but very few studies examine the association between oil and global equity markets, with Islamic equity stock indexes. Notable contributions include Henriques and Sadorsky (2008), McSweeney and Worthington (2008), Soytas and Oran (2011), Sadorsky (2012a,b), Kumar et al. (2012), Broadstock et al. (2012), Managi and Okimoto (2013), Wen et al. (2014), Reboredo (2015), Bondia et al. (2016), Dutta (2017) and Reboredo et al. (2017), among others. As such, it is no surprise that little attention has been paid to the asymmetric link between oil price and Islamic or conventional stock prices.

These studies demonstrate that, while rising oil prices may contribute to economic growth by providing the financial resources needed for investment, they may also undermine economic growth as they may worsen economic conditions contributing to economic growth (Moshiri and Banijashem, 2012). This suggests that positive oil shocks may have negative effects on economic activity through the stock market. In other words, oil price shocks may have asymmetric effects on the economy. Accordingly, assuming a linear relationship between oil price shocks and stock market prices may not be appropriate. Against this background, the objective of this paper is to examine the effects of oil price shocks on the global Islamic and conventional economy by allowing for asymmetries in the relationship between oil price shocks and stock market prices for both Islamic and conventional market comparatively. Precisely, the paper examines short-run and long-run effects of oil price shocks on global Islamic and conventional stock prices stemming from asymmetric oil price shocks.

We contribute to the existing literature in that to the best of our knowledge, this is the initial work to assess the asymmetric nature using NARDL model. We justify this study by looking at the impact of the global oil price and Islamic stock index as a key variable. We thus investigate a market's expectation of future uncertainty and changes in these expectations rather than the realized price movements. Second, as majority of oil and gas are produced in the Muslim- dominated countries, the impact of oil price on Islamic stocks is innovating. We examined the changes in the relationship in both short- and long-run.

The rest of the paper is organized as follows. Section 2 will describe the data, methodology and result, which include the ARDL and NARDL. Section 3 outline the conclusion.

Theoretical Underpinnings: Oil Prices and Stock Prices

Huge literature abounds the links between oil price shocks and several economic variables. A theoretical motivation for the link between crude oil and stock market prices can be found from asset pricing theory. Traditional asset pricing theory suggests that asset prices are determined based on expected cash-flows. Thus, an increase in oil price should induce higher costs for companies, which use oil as an input in production. Higher costs, in turn, decrease expected cash-flows, which should lead to a decrease in stock prices.

Jones and Kaul (1996) were among the first to investigate how stock markets react to oil price shocks. Using a standard cash-flow dividend valuation model they provided evidence on the negative relationship between crude oil price changes and aggregate stock market returns. Few other studies have confirmed this negative relationship. For example, Park and Ratti (2008) used a multivariate VAR analysis to investigate the impacts of oil price shocks on real stock returns over the period from January 1986 to December 2005. Based on a sample of real stock returns from the US and 13 European countries, they showed that oil price shocks have a statistically significant impact on real stock market returns. Furthermore, oil price shocks had a negative effect on the stock market returns for the US and 12 European countries.

These results gave further support for the asymmetric impacts of oil price shocks. Miller and Ratti (2009) used a vector autoregressive model (including cointegration) to study the long-run relationship between the crude oil prices and international stock markets over the period from January 1971 to March 2008 and found a negative long-run relationship between the world price of crude oil and stock market returns for six OECD countries.

Empirical literature has also provided evidence on a positive relationship between crude oil and stock market returns. The positive impacts are usually reported for oil-exporting economies. For example, Arouri and Rault (2012) studied the links between oil prices and stock markets in countries belonging to the Gulf Cooperation Council (GCC)4 using bootstrap panel cointegration and SUR methods. Their cointegration analysis suggested that there is a long-run relationship between oil prices and stock markets. Moreover, the results of SUR analysis indicated a positive impact of higher oil prices on stock market returns, except in Saudi Arabia, which is theoretically justifiable, because GCC countries are major oil exporters in global oil markets, and hence, benefit from high oil prices.

Our study takes a different perspective of the equities-Oil nexus from the one in previous studies. In this light, we contribute to the literature by examining the asymmetric upside/downside impact between these Islamic stock, conventional stock and oil markets, using the novel Non-Linear Autoregressive Distributed Lag (NARDL) technique. This is crucial, not only for investing purposes and managing portfolios effectively, but also for promoting economic and financial stability in the oil-equity markets.

Methodology: Symmetric vs Asymmetric Analysis

Data

The data in this paper are in daily frequency from 21st April 2008 to 21st April 2018. For crude oil price data, Brent crude oil spot prices are collected from the Thomson-Reuters data energy data base. As for the global stocks price, we make use of the daily average stock price of SP BMI Global Shariah Index (USD), S&P 500 Index, Dow Jones Industrial Average Index and Dow Jones Islamic Market World Index all from Thomson Reuters Eikon. The key motivation of this study is to show how much the relationship between oil shocks and the stock market can be understood in a systemic way, therefore, we have focused on using the global stock markets and Islamic stock Index. The choice of a daily data is influenced by the short effect of changes in oil price on the global stock market.

Methodology

Empirical framework

In existing studies, the relationship between oil shocks and Stock prices (Islamic or conventional) are normally examined by means of the standard time series econometrics: (i) employing cointegration tests to verify the presence of a long run relation between interest rates, (ii) applying such long-run estimators as the OLS, dynamic OLS or fully-modified OLS estimators to estimate a long run equation, if it exists, and (iii) using variants of vector autoregressions (VAR) to discern short-run dynamic interactions among the variables (iv) Variance decomposition and (v) Impulse response. The approach, however, assumes symmetric relations among the variables, which may be too restrictive. Since Oil price movement can behave asymmetrically as posited by the asset pricing theory, allowing for asymmetry would thus be more appropriate.

We employed The Auto-Regressive Distributive Lag (ARDL) method (also known as the bounds testing approach) proposed by Pesaran-Shin-Smith (2001) that we have employed is free from the above limitations of the unit root and cointegration tests. The ARDL bounds testing approach does not require the restriction imposed by cointegration technique that the variables are I(1) or I(0).

The ARDL technique involves two stages. At the first stage, the existence of a long-run relationship among the variables is investigated. This is done by constructing an unrestricted error correction model (UECM) with each variable in turn as a dependent variable and then testing whether or not the 'lagged levels of the variables' in each of the error correction equations are statistically significant (i.e., whether the null of 'no long run relationship' is accepted or rejected).

Basically, the ARDL method is the Wald test (F-statistic version of the bounds testing approach) for the lagged level variables in the right-hand side of UECM. That is, we test the null hypothesis of non-cointegrating relation (Ho: $\delta_1= \delta_2= \delta_3=\ldots= \delta_8=0$) by performing a joint significance test on the lagged level variables. The asymptotic distribution of the F- statistic is non-standard under the null hypothesis of no cointegrating relation between the examined variables, irrespective whether the explanatory variables are purely I(0) or I(1).

We specify our ARDL Model as follows

$y_t = \alpha_0 + \alpha_1 x_t + e_t$

Eq. 1

In the empirical implementation, we frame long run Eq. (1) in an ARDL setting as in Shin et al. (2014). That is,

$$\Delta y_t = \beta_0 + \beta_1 y_{t-1} + \beta_2 x_{t-1} + \sum_{i=1}^{p} \varphi_i \Delta y_{t-i} + \ + \sum_{i=0}^{q} (\theta_i x_{t-1}) + u_t$$

Eq. 2

where all variables are as defined above and p and q are lag orders.

Then we employed the novel nonlinear ARDL (NARDL) approach recently developed by Shin et al. (2014) as an asymmetric extension to the well-known ARDL model of Pesaran and Shin (1999) and Persaran et al. (2001). Apart from its simplicity, the approach offers flexibility in that it jointly models long-run relation, short-run dynamics and asymmetries and, in doing so, does not require the variables' integration order to be the same (Apergis and Cooray, 2015). More importantly, in our context, the nonlinear ARDL enables evaluation of both the long-run and short run relationship between variables.

To begin, we start with the following long-run equation:

$$y_t = \alpha_0 + \alpha_1 x_t^+ + \alpha_2 x_t^- + e_t$$

Eq. 3

where $\boldsymbol{y}$ is Stock Price rate, $\boldsymbol{x}$ is Oil Price, and $(\alpha_0, \alpha_1, \alpha_2)$ is a vector of long run parameters to be estimated. x_t^+ and x_t^- are partial sums of positive and negative changes in $\boldsymbol{x}$:

$$x_t^+ = \sum_{i=1}^{t} \Delta x_t^+ = \sum_{i=1}^{t} \max(\Delta x_i, 0)$$

Eq. 4

and

$$x_t^- = \sum_{i=1}^{t} \Delta x_t^- = \sum_{i=1}^{t} min(\Delta x_i, 0)$$

Eq. 5

Based on the above formulation, the long run relation between the stock market fluctuations and Oil price shocks is α1 and α2 for respectively the increase and decrease in the latter. We have no a priori expectation whether α1 < α2 or α1 > α2.
In the empirical implementation, we frame long run Eq. (3) in an ARDL setting as in Shin et al. (2014). That is,

$$\Delta y_t = \beta_0 + \beta_1 y_{t-1} + \beta_2 x_{t-1}^{+} + \beta_3 x_{t-1}^{-} + \sum_{i=1}^{p} \varphi_i \Delta y_{t-i} + \ + \sum_{i=0}^{q} (\theta_i^{+} \Delta x_{t-i}^{+} + \theta_i^{-} \Delta x_{t-i}^{-}) + u_t$$

Eq. 6

where all variables are as defined above and *p* and *q* are lag orders. The long run parameters in (3) are derivable from (6), i.e. $-\beta_2/\beta_1 = \alpha_1$ and $-\beta_3/\beta_1 = \alpha_2$. In addition, in (6), $\sum_{i=0}^{q} \theta_i^{+}$ and $\sum_{i=0}^{q} \theta_i^{-}$ capture the short-run effects of respectively positive and negative changes in the oil prices.

We follow the following four steps, as in Katrakidilis and Trachanas (2012) and Fousekis et al. (2016). First, we estimate Eq. (6) using the OLS. To arrive at the final specification of (6), we apply the general-to-specific approach to sequentially trimming the insignificant lags from the model. In the second step, we perform the ARDL cointegration test for the presence of a long run relation between the two interest rates. This involves the Wald F test of the null hypothesis β ββ 12 3== =0 (Pesaran et al., 2001) or the t-test of the null hypothesis that β =01 (Banerjee et al., 1998).

Third, verifying the presence of a long-run relation, we test for both the long-run and short-run asymmetries. For the long run asymmetry, the null hypothesis is ββ β β −/ =− /21 3 1 (i.e. α α 12 . Meanwhile, the corresponding null hypothesis for the short-run asymmetry is given as $\sum_{i=0}^{q} \theta_i^{+} = \sum_{i=0}^{q} \theta_i^{-}$

Finally, we also graph the asymmetric cumulative dynamic multiplier effects of a one percentage point change in x+ and x− to demonstrate visually the asymmetric Oil – Stock price (Islamic and Conventional) relation. Namely,

$$m_h^{+} = \sum_{j=0}^{h} \frac{\partial y_{t+j}}{\partial x_t^{+}}, \quad m_h^{-} = \sum_{j=0}^{h} \frac{\partial y_{t+j}}{\partial x_t^{-}}, \quad h = 0, 1, 2, \ldots$$

Note that as $h \rightarrow \infty, m_h^{+} \rightarrow \alpha_1$ *and* $m_h^{-} \rightarrow \alpha_2$

Results

Descriptive statistics of our series are reported in Table1.

Descriptive Statistics					
	BRT	***SPI***	***SPC***	***DJI***	***DJC***
Mean	80.61	102.97	1653.31	1484.09	2486.38
Standard Error	0.56	0.49	10.32	8.55	11.08
Median	77.22	101.56	1583.93	1473.81	2423.31
Standard Deviation	28.25	24.19	515.37	427.37	556.14
Kurtosis	-1.42	-0.52	-1.01	-0.44	-0.44
Skewness	0.04	0.05	0.25	0.42	0.06

Table 1 presents the descriptive statistics and the results of statistical tests of the daily brent crude oil price and stock prices. The stock prices comprised of both Islamic and Conventional indices for S&P 500 and Dow Jones indices. From the result the DJC exhibit the highest standard deviation and mean. The man signifies the average price of the stock while the standard deviation present the degree of volatility. Surprisingly, SPI is the least volatile.

Unit Root Test

We begin our empirical testing by determining the stationarity of our series. This is important in order to proceed with the testing of cointegration later, ideally, our variables should be I(1), in that in their original level form, they are non-stationary and in their first differenced form, they are stationary. We then conducted both the Augmented Dickey-Fuller (ADF) test and the Philips Perrone (PP) test on each variable (in both level and differenced form). The table below summarizes the results.

ADF Result in log form

	VARIABLE	ADF	VALUE	T-STAT.	C.V.	RESULT
LOG FORM	LBRT	ADF(1)=AIC	6011.10	- 1.625	- 3.489	Non-Stationary
		ADF(1)=SBC	5999.40	- 1.625	- 3.489	Non-Stationary
	LSPI	ADF(3)=AIC	87.43	- 1.249	- 3.592	Non-Stationary
		ADF(1)=SBC	84.29	- 1.598	- 3.510	Non-Stationary
	LSPC	ADF(2)=AIC	2989.80	- 3.083	- 3.487	Non-Stationary
		ADF(2)=SBC	2977.20	- 3.083	- 3.487	Non-Stationary
	LDJI	ADF(3)=AIC	3099.80	- 3.322	- 3.510	Non-Stationary
		ADF(2)=SBC	3087.10	- 3.301	- 3.487	Non-Stationary
	LDJC	ADF(3)=AIC	7851.00	- 4.057	- 3.510	Stationary
		ADF(2)=SBC	7835.80	- 3.994	- 3.487	Stationary

ADF Result after 1st Difference

	VARIABLE	ADF	VALUE	T-STAT.	C.V.	RESULT
1st Difference	DBRT	ADF(1)=AIC	6011.90	- 34.417	- 2.872	Stationary
		ADF(1)=SBC	6008.90	- 34.417	- 2.872	Stationary
	DSPI	ADF(2)=AIC	86.87	- 2.996	- 2.826	Stationary
		ADF(1)=SBC	82.87	- 2.996	- 2.826	Stationary
	DSPC	ADF(1)=AIC	2982.90	- 27.331	- 2.872	Stationary
		ADF(1)=SBC	2975.30	- 27.331	- 2.872	Stationary
	DDJI	ADF(2)=AIC	3092.20	- 20.241	- 2.880	Stationary
		ADF(1)=SBC	3084.50	- 27.409	- 2.872	Stationary
	DDJC	ADF(4)=AIC	7841.00	- 23.325	- 2.832	Stationary
		ADF(1)=SBC	7831.70	- 36.280	- 2.872	Stationary

From the table above, we rely primarily on the AIC and SBC criteria to determine the stationarity of our series. In determining which test statistic to compare with the 95% critical value for the ADF statistic, we selected the ADF regression order based on the highest computed value for AIC and SBC. In some instances, AIC and SBC give different orders and in that case, we have taken different orders and compared both (for example, this applies to the variable LSPI). This is not an issue as in all cases, the implications are consistent. The conclusion that can be made from the above results is that all the variables we are using for this analysis are I(1) except for LDJC.

To further confirm the ADF result, we conducted the Philips Perrone test for Unit root. The results are presented as follows

PP Test

PP Result in log form

	VARIABLE	T-STAT.	C.V.	RESULT
LOG FORM	LBRT	- 2.041	- 3.453	Non-Stationary
	LSPI	- 0.859	- 3.539	Non-Stationary
	LSPC	- 3.115	- 3.453	Non-Stationary
	LDJI	- 3.311	- 3.453	Non-Stationary
	LDJC	- 4.060	- 3.453	Stationary

PP Result after 1st Difference

	VARIABLE	T-STAT.	C.V.	RESULT
1ST Difference	LBRT	- 50.051	- 2.855	Stationary
	LSPI	- 4.479	- 2.945	Stationary
	LSPC	- 37.906	- 2.855	Stationary
	LDJI	- 38.207	- 2.855	Stationary
	LDJC	- 45.004	- 2.855	Stationary

The Philips Perrone result confirms our finding in the ADF test[3]. All variables are I(1) series except for LDJC that turned out stationary in level form and remain so after first difference.

After checking for the unit root, can we then employ either the Johansen and Juselius (1990), and the Engle Granger cointegration test if the series of each variable is integrated of the same order. But, since we found that the variables used in our study are not all integrated of the same order (i.e a mixture of I(1) and I(0), we ought to proceed directly to employ the ARDL approach to test for cointegration that is appropriate for both I(1) and I(0) series.

For test and robustness purposes, we proceeded first with the Engel-Granger and Johansen method for testing for cointegration, even though both test requires the variables to be integrated of the same order. And in our case, the predictive power of the models tested would be affected.

[3] The null hypothesis for the ADF and PP test is that the variable is non-stationary. In all cases (except for LDJC) of the variable in level form, the test statistic is lower than the critical value and hence we cannot reject the null. Conversely, in all cases of the variable in differenced form, the test statistic is higher than the critical value and thus we can reject the null and conclude that the variable is stationary (in its differenced form).

DETERMINATION OF ORDER OF THE VAR MODEL

Before proceeding with test of cointegration, we need to first determine the order of the vector auto regression (VAR), that is, the number of lags to be used. However, our VAR order selection result returned contradictory. As per the table below, AIC recommends order of 3 whereas SBC favours zero lag. This is based on highest computed values for AIC and SBC, after stipulating an arbitrary relatively high VAR order of 6.

VAR lag order

Lag Order	LL	AIC	SBC	LR test	Adjusted LR test
3	640.075	560.075	508.241	------	------
2	603.963	548.963	513.327	CHSQ(25)= 72.2236[.000]	29.4244[.247]
1	571.601	541.601	522.163	CHSQ(50)= 136.9479[.000]	55.7936[.266]
0	545.62	540.62	537.38	CHSQ(75)= 188.9095[.000]	76.9631[.416]
AIC=Akaike Information Criterion				*SBC=Schwarz Bayesian Criterion*	

Our result under VAR lag order found a conflicting in the optima order of variables between AIC and SBC. That is all the variables are not integrated at the same order. This has necessitated the use of ARDL approach to test for cointegration, as Johansen cointegration methodology suggested that variables to be integrated at the order. Otherwise the predictive power of the models tested would be affected.

TESTING COINTEGRATION

Ideally, we can only proceed to test for cointegration using Engel-Granger or Johansen approach once we have established that the variables are I(1) and determined the optimal VAR order. In our case, our variables are a mixture of I(1) and I(0) series and there is a conflict in the selection of VAR order. AIC criteria opt for 3 and SBC opts for 0.

However, to fulfil the test exercise and ensure robustness of our empirical examination, we proceeded with both Engel-Granger and Johansen test for cointegration. We do this bearing in mind the predictive power of our models tested would be compromised.

Engel-Granger Test for Cointegration.

As presented below, Engel-Granger test shows the absence of any cointegration among our variables. This is not surprising at all, since we know that the predictive power of our model has been compromised from beginning since we had a mixture of I(1) and I(0) variables.

E&G						
Test	**Statistic**	**95% Critical Value**	**LL**	**AIC**	**SBC**	**HQC**
DF	-2.7787	-5.0236	62.9281	61.9281	61.3391	61.7719
ADF(1)	-3.0454	-5.0236	63.7203	61.7203	60.5422	61.4078
ADF(2)	-2.6206	-5.0236	63.7618	60.7618	58.9948	60.293
ADF(3)	-3.1627	-5.0236	65.2407	61.2407	58.8846	60.6156
ADF(4)	-2.654	-5.0236	65.274	60.274	57.3288	59.4926
ADF(5)	-2.6958	-5.0236	65.7717	59.7717	56.2375	58.8341
ADF(6)	-3.2096	-5.0236	67.3871	60.3871	56.2639	59.2932

The null hypothesis for the Engel-Granger test is that the variables have no long run theoretical relationship (i.e no cointegration) is non-stationary. In our case, the test statistic is lower than the critical value and hence we cannot reject the null. So, it can be noted that no cointegration among our variables according to the Engel-Granger test for cointegration.

Johansen Test for Cointegration

The result of the Johansen test, presented in the table below, indicates the presence of three cointegration vectors. This is somewhat contradictory to the Engel-Granger result presented previously. However, the Johansen test is ascertained using two stochastic metrix; the Maximal Eigenvalue and Trace of the stochastic Metrix. In both cases of Maximal Eigenvalue and Trace, the test statistic for null of r = 2 is greater than the 95% critical value whereas for other null hypotheses, statistic is less than the critical values. Hence the alternative of r = 3 is upheld, and 3 cointegrating vectors are confirmed.

Cointegration LR Test Based on Maximal Eigenvalue of the Stochastic M

Null	Alternative	Statistic	95% Critical Value	90% Critical Value
r = 0	r = 1	70.0801	37.86	35.04
r<= 1	r = 2	39.5983	31.79	29.13
r<= 2	r = 3	27.6831	25.42	23.1
r<= 3	r = 4	17.3937	19.22	17.18
r<= 4	r = 5	5.3802	12.39	10.55

Cointegration LR Test Based on Trace of the Stochastic Matrix

Null	Alternative	Statistic	95% Critical Value	90% Critical Value
r = 0	r = 1	160.1355	87.17	82.88
r<= 1	r = 2	90.0553	63	59.16
r<= 2	r = 3	50.457	42.34	39.34
r<= 3	r = 4	22.7739	25.77	23.08
r<= 4	r = 5	5.3802	12.39	10.55

From the above, we found contradictory cointegration outcome between both the Engel-Granger and Johansen test due to a fundamental limitation of both estimates with regards to the order of integration among variables. Both cointegration tests require the variables to be I(1) but the order of integration of a variables turned out to be a mixture of I(1) and I(0). Moreover, the Johansen cointegrating tests have small sample bias and simultaneity bias among the regressors.

As such, these cointegration results are unreliable. Hence we employ the Auto-Regressive Distributive Lag (ARDL) method (also known as the bounds testing approach) proposed by Pesaran-Shin-Smith (2001).

ARDL Bounds Testing for Cointegration.

Unlike the previous tests where we face limitations of the unit root and cointegration tests, the ARDL bounds testing approach does not require the restriction imposed by cointegration technique that the variables are I(1) or I(0). The ARDL cointegration test are presented below;

ARDL AIC

ARDL Cointegration Test (AIC)	F-Statistic	95% Lower Bound	95% Upper Bound	Remarks
F(LBRT I LSPI, LSPC, LDJI, LDJC)	9.6707	3.4787	4.8669	Cointegrate
F(LSPI I LBRT, LSPC, LDJI, LDJC)	4.911	3.4787	4.8669	Cointegrate
F(LSPC I LSPI, LBRT, LDJI, LDJC)	5.7565	3.4706	4.8535	Cointegrate
F(LDJI I LSPI, LBRT, LSPC, LDJC)	3.7217	3.4706	4.8535	inconclusive
F(LDJC I LDJI, LSPI, LBRT, LSPC)	3.8807	3.4706	4.8535	inconclusive

ARDL SBC

ARDL Cointegration Test (SBC)	F-Statistic	95% Lower Bound	95% Upper Bound	Remarks
F(LBRT I LSPI, LSPC, LDJI, LDJC)	6.2585	3.4706	4.8535	Cointegrate
F(LSPI I LBRT, LSPC, LDJI, LDJC)	5.1437	3.4706	4.8535	Cointegrate
F(LSPC I LSPI, LBRT, LDJI, LDJC)	5.7565	3.4706	4.8535	Cointegrate
F(LDJI I LSPI, LBRT, LSPC, LDJC)	3.7217	3.4706	4.8535	inconclusive
F(LDJC I LDJI, LSPI, LBRT, LSPC)	3.8807	3.4706	4.8535	inconclusive

The results reveal that the calculated F-statistics exceeded the upper critical value in three out of Five equations tested at standard acceptable significance levels. We conclude that the variables are cointegrated and there is long-run theoretical relationship among the variables. This confirm with our empirical result below. However, we could not reliably determine if there is long-run relationship or cointegration among DJI and DJC. As it shows an inconclusive result.

Testing Causality (Endogeneity and Exogeneity): Error Correction Model (ECM)

The ECM confirms the long-run relationship indicated in the first step of the ARDL modelling. This is to determine the leading (exogenous) and lagging (endogenous) variables. The results of our ECM are shown in table below, where all the variables are at one point made as the dependent variable respectively. Our result under AIC and SBC shows DJC as an exogenous variable, which mean the P-value of DJC is greater than 5% critical value. The p-values of all the endogenous variables are less than 5%, necessitating the rejection of the null of hypothesis. This result may be counter intuitive, especially for Oil price (BRT) which mean BRT does not influence the global stock price in the long-run. The only explanation to this could be the fact that Oil price is influence by demand-supply effect and reflect quickly in the stock price due to available reliable forecast of the oil price and reserve outlook. The following table shows the result of ECM.

ecm1(-1)-AIC	Coefficient	Standard Error	T-Ratio [Prob.]	C.V.	Result
BRT	-1.3313	0.20333	-6.5476[.000]	5%	Endogenous
SPI	-.61842	0.16696	-3.7040[.001]	5%	Endogenous
SPC	-2.2435	0.66376	-3.3799[.007]	5%	Endogenous
DJI	-0.76892	0.24984	-3.0776[.012]	5%	Endogenous
DJC	-0.14797	0.14637	-1.0109[.336]	5%	Exogenous

ecm1(-1)-SBC	Coefficient	Standard Error	T-Ratio [Prob.]	C.V.	Result
BRT	-2.0066	0.41487	-4.8366[.001]	5%	Endogenous
SPI	-.41946	0.15184	-2.7625[.020]	5%	Endogenous
SPC	-2.2435	0.66377	-3.3799[.007]	5%	Endogenous
DJI	-0.76892	0.24984	-3.0776[.012]	5%	Endogenous
DJC	-0.14797	0.14637	-1.0109[.336]	5%	Exogenous

However, the above ECM result fails to determine the degree of exo-endo of the variable, as well as the symmetric or asymmetric nature of the result. Therefore, we would employ VDC, Impulse Response and NARDL for better justification of the above.

Variance Decompositions (VDCs)

We used the VDC generalised approach in determining the degree of relativity of the variables, the horizon is in number of days. From ECM, we know the endogeneity and exogeneity of a variable during the sample period. As for the policymakers, the more important is to recognise the relative degree of endogeneity and exogeneity of the variables for some forecasted horizon so that they could focused on the right variable(s). This useful information can be derived from the output of VDC. VDC decomposes the variance of the forecast error of each variable into proportions attributable to shocks from each variable in the system including its own. The relative endogeneity and exogeneity of a variable can then be determined by the proportion of variance that is explained by its own past. The variable that is explained mostly by its own past variations and depends relatively less on other variables is deemed to be the most exogenous (most leading) amongst the variables.

GENERALIZED DECOMPOSITIONS APPROACH

Horizon	Variable	BRT	SPI	SPC	DJI	DJC
	BRT	53.70%	11.36%	11.18%	12.13%	11.63%
5	SPI	9.49%	25.59%	20.56%	19.01%	25.35%
	SPC	8.92%	21.00%	24.38%	23.63%	22.06%
	DJI	8.86%	20.92%	23.90%	24.29%	22.03%
	DJC	9.59%	24.92%	20.81%	19.68%	25.00%
	Exogeneity	53.70%	25.59%	24.38%	24.29%	25.00%
	Ranking	1	2	4	5	3

Horizon	Variable	BRT	SPI	SPC	DJI	DJC
	BRT	31.41%	16.42%	17.45%	17.89%	16.83%
10	SPI	9.26%	25.59%	20.84%	19.14%	25.16%
	SPC	8.85%	21.51%	24.04%	23.41%	22.18%
	DJI	9.11%	20.91%	23.78%	24.38%	21.82%
	DJC	9.21%	25.03%	21.09%	19.79%	24.88%
	Exogeneity	31.41%	25.59%	24.04%	24.38%	24.88%
	Ranking	1	2	5	4	3

Horizon	Variable	BRT	SPI	SPC	DJI	DJC
	BRT	32.27%	16.14%	17.31%	17.76%	16.52%
15	SPI	9.37%	25.53%	20.85%	19.13%	25.12%
	SPC	8.74%	21.39%	24.14%	23.61%	22.12%
	DJI	8.83%	20.80%	23.98%	24.64%	21.76%
	DJC	9.20%	24.99%	21.13%	19.83%	24.85%
	Exogeneity	32.27%	25.53%	24.14%	24.64%	24.85%
	Ranking	1	2	5	4	3

Horizon	Variable	BRT	SPI	SPC	DJI	DJC
	BRT	30.79%	16.53%	17.67%	18.10%	16.91%
20	SPI	9.48%	25.47%	20.86%	19.14%	25.05%
	SPC	9.03%	21.36%	24.03%	23.52%	22.06%
	DJI	9.15%	20.74%	23.87%	24.56%	21.67%
	DJC	9.33%	24.92%	21.14%	19.83%	24.78%
	Exogeneity	30.79%	25.47%	24.03%	24.56%	24.78%
	Ranking	1	2	5	4	3

Horizon	Variable	BRT	SPI	SPC	DJI	DJC
	BRT	30.87%	16.44%	17.71%	18.15%	16.83%
25	SPI	9.53%	25.44%	20.86%	19.14%	25.03%
	SPC	9.03%	21.30%	24.06%	23.58%	22.03%
	DJI	9.13%	20.69%	23.92%	24.62%	21.64%
	DJC	9.37%	24.90%	21.14%	19.84%	24.76%
	Exogeneity	30.87%	25.44%	24.06%	24.62%	24.76%
	Ranking	1	2	5	4	3

Horizon	Variable	BRT	SPI	SPC	DJI	DJC
	BRT	30.68%	16.53%	17.72%	18.16%	16.91%
30	SPI	9.53%	25.45%	20.86%	19.14%	25.03%
	SPC	9.07%	21.31%	24.03%	23.56%	22.03%
	DJI	9.18%	20.68%	23.89%	24.61%	21.63%
	DJC	9.37%	24.90%	21.14%	19.84%	24.75%
	Exogeneity	30.68%	25.45%	24.03%	24.61%	24.75%
	Ranking	1	2	5	4	3

The results show BRT as a leading variable. This may be through as most developed and emerging economy depend greatly on Oil, hence the influence is felt in all sector.

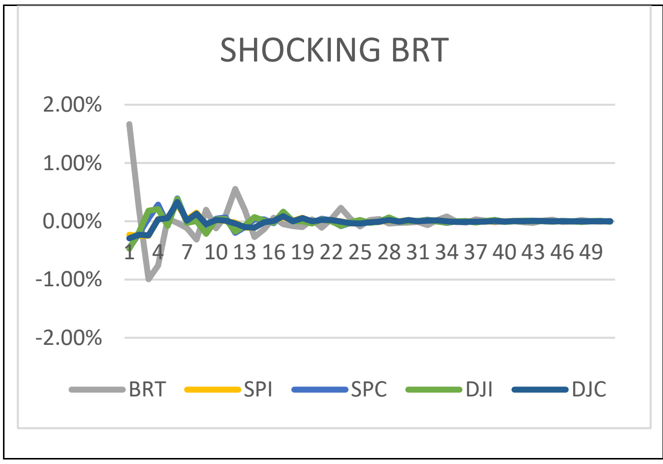
Granger Causality Chain

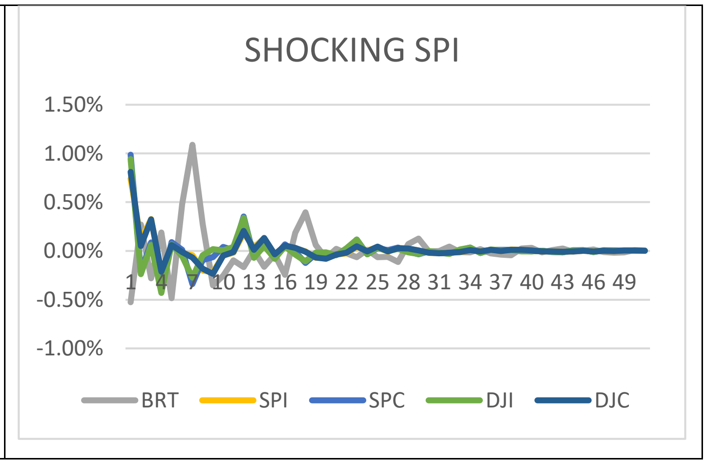
BRT	→	SPI	→	DJC	→	DJI	→	SPC
→ **The order of Exogeneity** →								

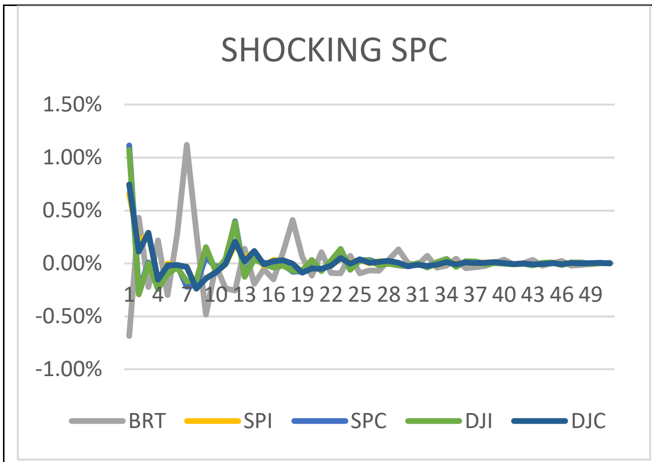
The BRT is the most exogenous and SPC the weakest. For policy maker, it means they could focus on the control of oil price in determining the direction of the global stock price and company and economy performance in specific. See table below for references.

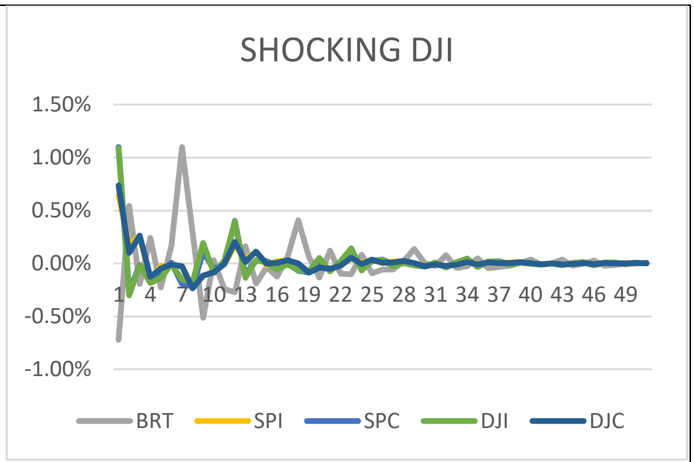
Impulse Response Functions (IRFs)

We also applied the generalised impulse response functions to look at the impact of shock of one variable on the other variables and their degree of response. The IRFs produces the result as VDC generalised in graphical format. All the variables are shocked to produce five different results. The result shows a return to equilibrium after the shock of variables within 50 days horizon. See the below table for references.






SHOCKING SPC
1.50%
1.00%
0.50%
0.00%
-0.50%
-1.00%
1 4 7 10 13 16 19 22 25 28 31 34 37 40 43 46 49
BRT
SPI
SPC
DJI
DJC


SHOCKING DJI
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1.00%
0.50%
0.00%
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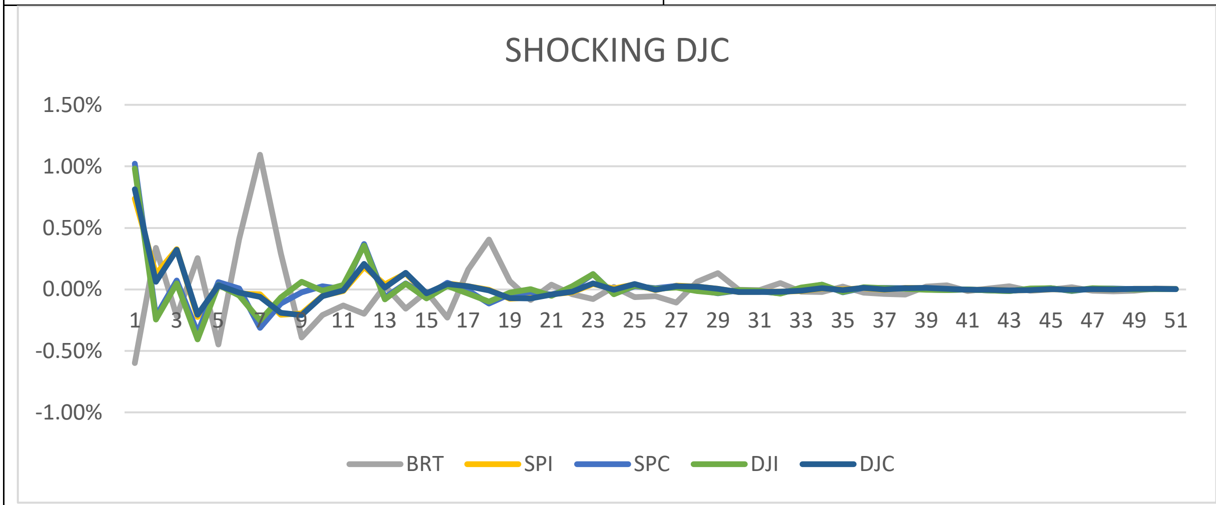
-1.00%
1 4 7 10 13 16 19 22 25 28 31 34 37 40 43 46 49
BRT
SPI
SPC
DJI
DJC


SHOCKING DJC
1.50%
1.00%
0.50%
0.00%
-0.50%
-1.00%
1 3 5 7 9 11 13 15 17 19 21 23 25 27 29 31 33 35 37 39 41 43 45 47 49 51
BRT
SPI
SPC
DJI
DJC

NARDL: Asymmetric Relationship Tests

The empirical estimates of asymmetric specifications are summarized in the table that follows. After confirmation of cointegration among the variables, we proceed with the findings of both the long-run and short-run asymmetric impact of oil prices on the stock prices for both Islamic and conventional markets.

Long-run Asymmetry

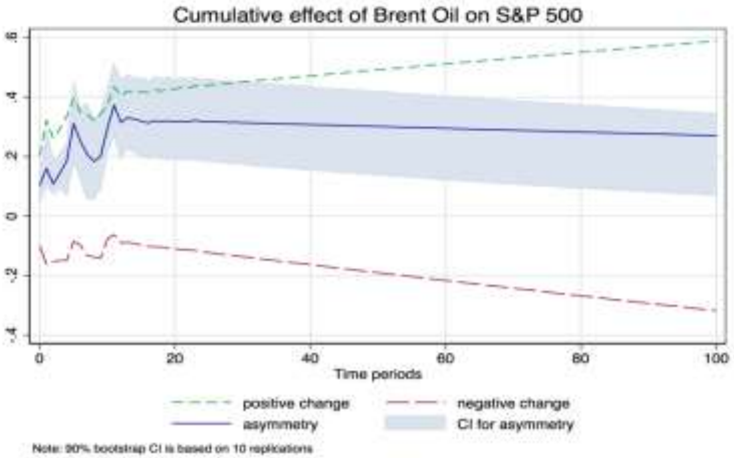
Our NARDL result shows that there is no statistically significant asymmetry in the impact of Oil prices on the conventional stock prices in the long-run. However, in the case of Islamic stock market using both indexes for robustness, the NARDL result shows a statistically significant asymmetry in the impact of Oil prices on Islamic stocks at 10% significance level. However, the positive and negative impact of the long run asymmetry is not statistically significant even at 10% level.

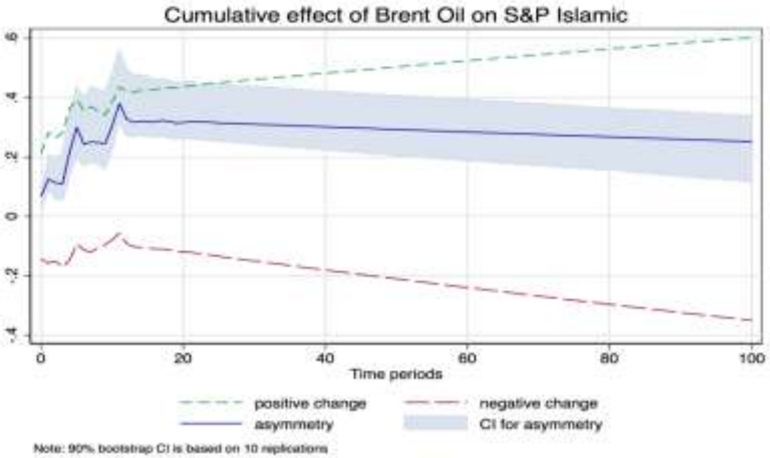
Short-run Asymmetry

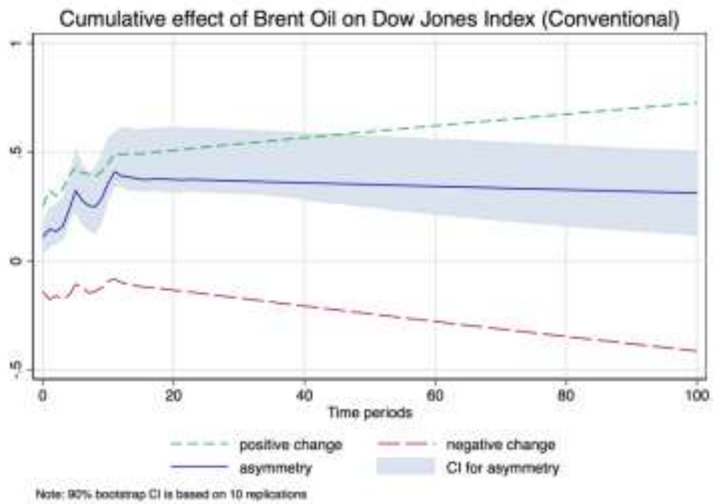
Using daily data frequency does provide an advantage in estimating the short run asymmetry. The NARDL result shows that there is statistically significant asymmetry in the impact of Oil prices on both the conventional and Islamic stock prices in the short-run. From this result, it seems that positive and negative previous day oil shocks have significant positive impact on prices of both stock markets.

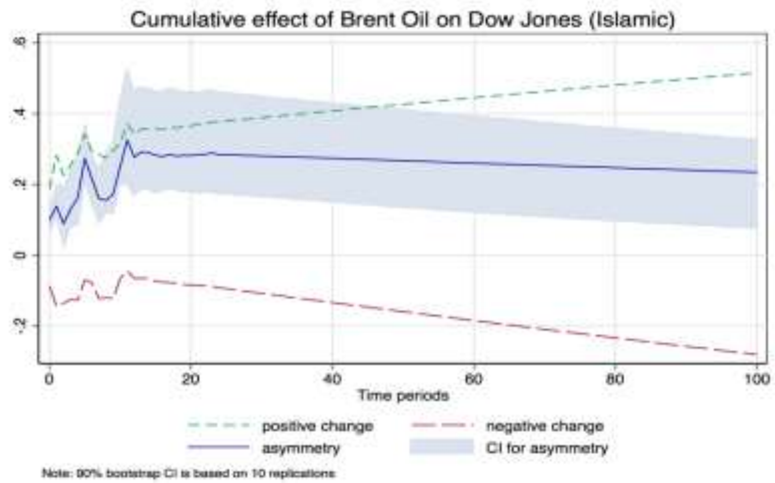
Asymmetry statistics: Impact of Oil Prices (Brent Crude) on Islamic and Conventional Stocks												
	Asymmetric Impact on Conventional Stocks?						**Asymmetric Impact on Islamic Stocks?**					
	S&P 500			***Down Jones***			***S&P 500***			***Down Jones***		
	Coefficient	***F-Stat***	***P>F***	***Coefficient***	***F-Stat***	***P>F***	***Coefficient***	***F-Stat***	***P>F***	***Coefficient***	***F-Stat***	***P>F***
Longrun Asymmetry		1.377	0.241		2.201	0.138		**3.448**	**0.063**		**3**	**0.083**
Longrun Effect *[+]*	2.261	0.714	0.398	1.836	0.7119	0.399	1.402	0.8457	0.358	1.465	1.085	0.298
Longrun Effect *[-]*	-2.399	0.7387	0.39	-1.96	0.7565	0.385	-1.495	0.9093	0.34	-1.571	1.15	0.284
Shortrun Asymmetry		**23.57**	**0.000**		**12.99**	**0.000**		**10.93**	**0.001**		**17.1**	**0.000**
Remarks	*No significant longrun asymmetry, nor longrun positive and negative effect. Only shows the presence of shortrun asymmetry.*						*Significant longrun asymmetry at 10% Significant Level. However, neither longrun positive nor negative effect shows same statistical significance. Shows the presence of asymmetry in shortrun.*					

Lastly, we present graphically these findings by tracing the asymmetric cumulative dynamic multipliers for the stock indexes. The graphs represent temporal evolution of the respective Islamic or Conventional stock prices in response to a unit increase and decrease in the corresponding global oil price over 100-Day horizon. The differences in the upward and downward movements together with 90% confidence interval are also presented.









As clearly demonstrated by the graphs, the impacts of Oil price increase on Islamic stocks are relatively larger than the impacts of the conventional stocks over the entire horizon. Meanwhile, asymmetry is apparent in both cases (Islamic and conventional) in the short run.

CONCLUSION AND POLICY IMPLICATIONS

In this paper, we examined the presence of long-run theoretical relationship between Crude Oil price, global Islamic and conventional S&P and Dow Jones stocks performance. We examine the short- and long-run asymmetric impact of oil prices on both the conventional and Islamic stock prices in the global markets. The NARDL bounds testing approach developed by Shin et al. (2014) is utilized to determine the asymmetric relationship among the variables.

The results indicate that the impact of oil prices on stock prices is asymmetric during the short-run for both Islamic and conventional stock markets. However, the long-run asymmetric relationship only exists for the impact of the Oil price on Islamic Stocks and not on conventional stocks. These findings are important mainly because understanding the price volatility behaviour can play a vital role during the valuation of derivatives and for hedging purposes. This may also help in better forecasting of stock market trends, especially for the oil producing emerging stock markets.

Moreover, significant reactions of stock markets to the changes in oil prices also make these markets more vulnerable to bad news/events that further contribute towards volatile and uncertain economic environment. Finally, the nonlinear ARDL analysis of oil and stock price volatilities provides a better understanding of possible investment risks.

The policy implication is that the policy maker should respond faster to any changes in oil price. They should pre-plan for any potential changes in oil price and their effect simulated on the stock prices.

LIMITATIONS

The theoretical foundation and framework of this study also leave something to be desired. Underlying theory is crucial or otherwise studies such as this may be accused as purely exercises of number crunching or statistical data mining. Developing theory in such an area would be challenging as Islamic finance is at its nascent stages of development. Nonetheless, effort should be directed towards this end.

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APPENDIX

Assymetric Impact of Oil Prices (Brent Crude) on Conventional Stocks (Dow Jones)

Source	SS	df	MS		
				Number of obs =	2,505
				F(41, 2463) =	17.01
Model	0.063884539	41	0.001558159	Prob > F =	0.000
Residual	0.225621147	2,463	0.000091604	R-squared =	0.2207
				Adj R-squared =	0.2077
Total	0.289505687	2,504	0.000115617	Root MSE =	0.00957

_dy	Coef.	Std. Err.	t	P>/t/	[95% Confidence Interval]	
L1._y	-0.0017484	0.0021292	-0.82	0.412	-0.0059235	0.0024268
L1._x1p	0.0039539	0.0009535	4.15	0	0.0020842	0.0058237
L1._x1n	0.0041949	0.0010221	4.1	0	0.0021906	0.0061992
_dy						
L1.	0.0697724	0.0202257	3.45	0.001	0.0301112	0.1094335
L2.	-0.0793343	0.0202353	-3.92	0	-0.1190143	-0.0396543
L3.	0.0107402	0.0202778	0.53	0.596	-0.0290232	0.0505036
L4.	-0.039386	0.0202677	-1.94	0.052	-0.0791295	0.0003575
L5.	-0.0379993	0.0203105	-1.87	0.061	-0.0778268	0.0018281
L6.	0.0052529	0.0203183	0.26	0.796	-0.0345898	0.0450956
L7.	-0.0131881	0.0203258	-0.65	0.517	-0.0530456	0.0266693
L8.	0.0150456	0.0202388	0.74	0.457	-0.0246413	0.0547325
L9.	-0.0037118	0.020174	-0.18	0.854	-0.0432714	0.0358479
L10.	0.0012978	0.0201507	0.06	0.949	-0.0382163	0.040812
L11.	-0.0229316	0.0200679	-1.14	0.253	-0.0622832	0.0164201
L12.	0.0344949	0.0199016	1.73	0.083	-0.0045306	0.0735204
_dx1p						
--.	0.2518331	0.0163005	15.45	0	0.219869	0.2837973
L1.	0.0498613	0.0168661	2.96	0.003	0.016788	0.0829346
L2.	-0.0137963	0.0168901	-0.82	0.414	-0.0469166	0.019324
L3.	0.0335831	0.0168649	1.99	0.047	0.0005122	0.066654
L4.	0.0649307	0.016826	3.86	0.000	0.0319361	0.0979253
L5.	0.0434141	0.0168715	2.57	0.01	0.0103303	0.0764978
L6.	-0.0271303	0.0168874	-1.61	0.108	-0.0602453	0.0059846
L7.	0.0022217	0.0169052	0.13	0.895	-0.0309282	0.0353715
L8.	-0.015816	0.0168818	-0.94	0.349	-0.04892	0.017288
L9.	0.0213842	0.0168942	1.27	0.206	-0.0117441	0.0545124
L10.	0.0350061	0.0169107	2.07	0.039	0.0018455	0.0681668
L11.	0.043074	0.0168945	2.55	0.011	0.0099451	0.076203
L12.	-0.0136234	0.0169683	-0.8	0.422	-0.0468971	0.0196503
_dx1n						
--.	0.1410978	0.0157179	8.98	0	0.1102761	0.1719196
L1.	0.0221232	0.0161128	1.37	0.17	-0.0094728	0.0537193
L2.	-0.0115604	0.0161266	-0.72	0.474	-0.0431836	0.0200627
L3.	0.0101433	0.0161023	0.63	0.529	-0.0214322	0.0417187
L4.	-0.0151146	0.0160888	-0.94	0.348	-0.0466636	0.0164343
L5.	-0.047431	0.0160893	-2.95	0.003	-0.078981	-0.015881
L6.	0.0178702	0.016131	1.11	0.268	-0.0137616	0.049502
L7.	0.0139555	0.016113	0.87	0.387	-0.0176409	0.045552
L8.	-0.0106615	0.0160781	-0.66	0.507	-0.0421895	0.0208666
L9.	-0.025124	0.0161059	-1.56	0.119	-0.0567066	0.0064585
L10.	-0.0337274	0.0161259	-2.09	0.037	-0.0653491	-0.0021057
L11.	-0.0072354	0.016119	-0.45	0.654	-0.0388436	0.0243728
L12.	0.0071719	0.016185	0.44	0.658	-0.0245657	0.0389095
_cons	0.0121939	0.0175963	0.69	0.488	-0.0223134	0.0467012

Cointegration statistics:

t_BDM	=	-0.8212
F_PSS	=	5.7682

Asymmetry statistics:

	Long-run effect [+]			Long-run effect [-]		
Exog. var.	*coef.*	*F-stat*	*P>F*	*coef.*	*F-stat*	*P>F*
LBRT	2.261	0.714	0.398	-2.399	0.7387	0.39

	Long-run asymmetry		Short-run asymmetry	
	F-stat	*P>F*	*F-stat*	*P>F*
LBRT	1.377	0.241	23.57	0

Note: Long-run effect [-] refers to a permanent change in exog. var. by -1

Assymetric Impact of Oil Prices (Brent Crude) on Conventional Stocks (Dow Jones)						
Source	**SS**	**df**	**MS**	**Number of obs**	=	2,505
				F(41, 2463)	=	17.01
Model	0.063884539	41	0.001558159	**Prob > F**	=	0.000
Residual	0.225621147	2,463	0.000091604	**R-squared**	=	0.2207
				Adj R-squared	=	0.2077
Total	0.289505687	2,504	0.000115617	**Root MSE**	=	0.00957

_dy	**Coef.**	**Std. Err.**	**t**	**P>/t/**	**[95% Confidence**	**Interval]**
L1._y	-0.0017484	0.0021292	-0.82	0.412	-0.0059235	0.0024268
L1._x1p	0.0039539	0.0009535	4.15	0	0.0020842	0.0058237
L1._x1n	0.0041949	0.0010221	4.1	0	0.0021906	0.0061992
_dy						
L1.	0.0697724	0.0202257	3.45	0.001	0.0301112	0.1094335
L2.	-0.0793343	0.0202353	-3.92	0	-0.1190143	-0.0396543
L3.	0.0107402	0.0202778	0.53	0.596	-0.0290232	0.0505036
L4.	-0.039386	0.0202677	-1.94	0.052	-0.0791295	0.0003575
L5.	-0.0379993	0.0203105	-1.87	0.061	-0.0778268	0.0018281
L6.	0.0052529	0.0203183	0.26	0.796	-0.0345898	0.0450956
L7.	-0.0131881	0.0203258	-0.65	0.517	-0.0530456	0.0266693
L8.	0.0150456	0.0202388	0.74	0.457	-0.0246413	0.0547325
L9.	-0.0037118	0.020174	-0.18	0.854	-0.0432714	0.0358479
L10.	0.0012978	0.0201507	0.06	0.949	-0.0382163	0.040812
L11.	-0.0229316	0.0200679	-1.14	0.253	-0.0622832	0.0164201
L12.	0.0344949	0.0199016	1.73	0.083	-0.0045306	0.0735204
_dx1p						
--.	0.2518331	0.0163005	15.45	0	0.219869	0.2837973
L1.	0.0498613	0.0168661	2.96	0.003	0.016788	0.0829346
L2.	-0.0137963	0.0168901	-0.82	0.414	-0.0469166	0.019324
L3.	0.0335831	0.0168649	1.99	0.047	0.0005122	0.066654
L4.	0.0649307	0.016826	3.86	0.000	0.0319361	0.0979253
L5.	0.0434141	0.0168715	2.57	0.01	0.0103303	0.0764978
L6.	-0.0271303	0.0168874	-1.61	0.108	-0.0602453	0.0059846
L7.	0.0022217	0.0169052	0.13	0.895	-0.0309282	0.0353715
L8.	-0.015816	0.0168818	-0.94	0.349	-0.04892	0.017288
L9.	0.0213842	0.0168942	1.27	0.206	-0.0117441	0.0545124
L10.	0.0350061	0.0169107	2.07	0.039	0.0018455	0.0681668
L11.	0.043074	0.0168945	2.55	0.011	0.0099451	0.076203
L12.	-0.0136234	0.0169683	-0.8	0.422	-0.0468971	0.0196503
_dx1n						
--.	0.1410978	0.0157179	8.98	0	0.1102761	0.1719196
L1.	0.0221232	0.0161128	1.37	0.17	-0.0094728	0.0537193
L2.	-0.0115604	0.0161266	-0.72	0.474	-0.0431836	0.0200627
L3.	0.0101433	0.0161023	0.63	0.529	-0.0214322	0.0417187
L4.	-0.0151146	0.0160888	-0.94	0.348	-0.0466636	0.0164343
L5.	-0.047431	0.0160893	-2.95	0.003	-0.078981	-0.015881
L6.	0.0178702	0.016131	1.11	0.268	-0.0137616	0.049502
L7.	0.0139555	0.016113	0.87	0.387	-0.0176409	0.045552
L8.	-0.0106615	0.0160781	-0.66	0.507	-0.0421895	0.0208666
L9.	-0.025124	0.0161059	-1.56	0.119	-0.0567066	0.0064585
L10.	-0.0337274	0.0161259	-2.09	0.037	-0.0653491	-0.0021057
L11.	-0.0072354	0.016119	-0.45	0.654	-0.0388436	0.0243728
L12.	0.0071719	0.016185	0.44	0.658	-0.0245657	0.0389095
_cons	0.0121939	0.0175963	0.69	0.488	-0.0223134	0.0467012

Cointegration statistics:

t_BDM	=	-0.8212
F_PSS	=	5.7682

Asymmetry statistics:

	Long-run effect [+]			Long-run effect [-]		
Exog. var.	*coef.*	*F-stat*	*P>F*	*coef.*	*F-stat*	*P>F*
LBRT	2.261	0.714	0.398	-2.399	0.7387	0.39

	Long-run asymmetry		Short-run asymmetry	
	F-stat	*P>F*	*F-stat*	*P>F*
LBRT	1.377	0.241	23.57	0

Note: Long-run effect [-] refers to a permanent change in exog. var. by -1

Assymetric Impact of Oil Prices (Brent Crude) on Conventional Stocks (S&P)						
Source	**SS**	**df**	**MS**		**Number of obs =**	2,222
					F(41, 2463) =	10.11
Model	0.061225463	41	0.001493304		**Prob > F =**	0.000
Residual	0.321877255	2,180	0.00014765		**R-squared =**	0.1598
					Adj R-squared =	0.144
Total	0.383102719	2,221	0.000172491		**Root MSE =**	0.01215
_dy	**Coef.**	**Std. Err.**	**t**	**P>/t/**	**[95% Confidence Interval]**	
L1._y	-0.0018752	0.0022183	-0.85	0.398	-0.0062254	0.0024751
L1._x1p	0.003442	0.001241	2.77	0.006	0.0010083	0.0058756
L1._x1n	0.0036754	0.0013248	2.77	0.006	0.0010773	0.0062734
_dy						
L1.	-0.1512804	0.0214974	-7.04	0	-0.1934379	-0.109123
L2.	-0.0822901	0.0216633	-3.8	0	-0.124773	-0.0398071
L3.	0.0226853	0.0216207	1.05	0.294	-0.019714	0.0650847
L4.	-0.0310927	0.02162	-1.44	0.151	-0.0734907	0.0113053
L5.	-0.0608108	0.021622	-2.81	0.005	-0.1032127	-0.0184088
L6.	0.0100823	0.0215886	0.47	0.641	-0.0322541	0.0524187
L7.	-0.0385184	0.0215761	-1.79	0.074	-0.0808304	0.0037935
L8.	0.0461438	0.0214764	2.15	0.032	0.0040276	0.0882601
L9.	-0.0150974	0.0214014	-0.71	0.481	-0.0570667	0.0268719
L10.	0.0350192	0.0213962	1.64	0.102	-0.0069399	0.0769784
L11.	-0.0315615	0.0213323	-1.48	0.139	-0.0733954	0.0102723
L12.	0.0440362	0.020862	2.11	0.035	0.0031248	0.0849477
_dx1p						
--.	0.2031822	0.0221546	9.17	0	0.1597359	0.2466286
L1.	0.1468876	0.022341	6.57	0	0.1030756	0.1906996
L2.	-0.0293767	0.022605	-1.3	0.194	-0.0737062	0.0149529
L3.	0.0254007	0.0224898	1.13	0.259	-0.0187029	0.0695043
L4.	0.0423068	0.0222086	1.9	0.057	-0.0012455	0.0858591
L5.	0.0845147	0.0221907	3.81	0	0.0409975	0.1280319
L6.	-0.035711	0.0222932	-1.6	0.109	-0.0794291	0.0080071
L7.	-0.0082285	0.0223232	-0.37	0.712	-0.0520054	0.0355484
L8.	-0.0305153	0.0222625	-1.37	0.171	-0.0741732	0.0131426
L9.	0.0151124	0.0222346	0.68	0.497	-0.0284908	0.0587155
L10.	0.0299867	0.0222618	1.35	0.178	-0.0136699	0.0736432
L11.	0.0636143	0.0221699	2.87	0.004	0.020138	0.1070907
L12.	-0.0243213	0.0223774	-1.09	0.277	-0.0682047	0.019562
_dx1n						
--.	0.0997396	0.0212004	4.7	0	0.0581644	0.1413148
L1.	0.0743721	0.0215118	3.46	0.001	0.0321862	0.116558
L2.	0.0051279	0.021645	0.24	0.813	-0.0373191	0.0475748
L3.	-0.0063482	0.0217389	-0.29	0.77	-0.0489792	0.0362829
L4.	-0.002491	0.0219075	-0.11	0.909	-0.0454528	0.0404709
L5.	-0.0596163	0.0219845	-2.71	0.007	-0.102729	-0.0165036
L6.	0.0009158	0.0220654	0.04	0.967	-0.0423557	0.0441872
L7.	0.0318731	0.0219527	1.45	0.147	-0.0111774	0.0749235
L8.	0.0065433	0.0218507	0.3	0.765	-0.0363071	0.0493937
L9.	0.0004898	0.0219149	0.02	0.982	-0.0424864	0.0434661
L10.	-0.0734716	0.0219124	-3.35	0.001	-0.1164429	-0.0305003
L11.	-0.0250994	0.0218945	-1.15	0.252	-0.0680356	0.0178369
L12.	0.0147051	0.0218492	0.67	0.501	-0.0281422	0.0575525
_cons	0.0121939	0.0175963	0.69	0.488	-0.0223134	0.0467012

Cointegration statistics:

t_BDM	=	-0.8453
F_PSS	=	2.7589

Asymmetry statistics:

	Long-run effect [+]			Long-run effect [-]		
Exog. var.	***coef.***	***F-stat***	***P>F***	***coef.***	***F-stat***	***P>F***
LBRT	1.836	0.7119	0.399	-1.96	0.7565	0.385

	Long-run asymmetry		Short-run asymmetry	
	F-stat	*P>F*	*F-stat*	*P>F*
LBRT	2.201	0.138	12.99	0

Note: Long-run effect [-] refers to a permanent change in exog. var. by -1

Assymetric Impact of Oil Prices (Brent Crude) on Islamic Stocks (Dow Jones)

Source	SS	df	MS			
				Number of obs	=	2,222
				F(41, 2180)	=	9.61
Model	0.04938163	41	0.00120443	Prob > F	=	0.000
Residual	0.27309782	2,180	0.000125274	R-squared	=	0.1531
				Adj R-squared	=	0.1372
Total	0.32247945	2,221	0.000145196	Root MSE	=	0.01119

_dy	Coef.	Std. Err.	t	P>/t/	[95% Confidence Interval]	
L1._y	-0.0022236	0.0025005	-0.89	0.374	-0.0071271	0.00268
L1._x1p	0.0031171	0.0011709	2.66	0.008	0.000821	0.0054132
L1._x1n	0.0033238	0.0012677	2.62	0.009	0.0008377	0.0058098
_dy						
L1.	-0.1474721	0.0215277	-6.85	0	-0.1896891	-0.1052552
L2.	-0.0740519	0.0216799	-3.42	0.001	-0.1165673	-0.0315364
L3.	0.0455468	0.0215838	2.11	0.035	0.0032198	0.0878738
L4.	-0.0240203	0.0215929	-1.11	0.266	-0.0663652	0.0183246
L5.	-0.0650722	0.0215924	-3.01	0.003	-0.1074159	-0.0227284
L6.	0.007338	0.0215355	0.34	0.733	-0.0348943	0.0495703
L7.	-0.0349406	0.0214978	-1.63	0.104	-0.077099	0.0072179
L8.	0.0491455	0.021397	2.3	0.022	0.0071849	0.0911061
L9.	-0.0070078	0.0213386	-0.33	0.743	-0.0488539	0.0348384
L10.	0.0353984	0.021326	1.66	0.097	-0.0064229	0.0772197
L11.	-0.0070721	0.021243	-0.33	0.739	-0.0487307	0.0345865
L12.	0.0529274	0.0208273	2.54	0.011	0.0120841	0.0937708
_dx1p						
--.	0.1864273	0.0204111	9.13	0	0.1464001	0.2264545
L1.	0.1210074	0.0205741	5.88	0	0.0806606	0.1613543
L2.	-0.0317257	0.0207873	-1.53	0.127	-0.0724906	0.0090393
L3.	0.01683	0.0206775	0.81	0.416	-0.0237196	0.0573795
L4.	0.032609	0.0204145	1.6	0.110	-0.0074249	0.072643
L5.	0.0749933	0.0203896	3.68	0	0.0350081	0.1149784
L6.	-0.0398201	0.0204814	-1.94	0.052	-0.0799852	0.000345
L7.	-0.0138579	0.0205104	-0.68	0.499	-0.0540798	0.026364
L8.	-0.0217333	0.0204518	-1.06	0.288	-0.0618404	0.0183738
L9.	0.0161252	0.0204184	0.79	0.43	-0.0239164	0.0561669
L10.	0.0216942	0.0204419	1.06	0.289	-0.0183934	0.0617819
L11.	0.0503826	0.0203529	2.48	0.013	0.0104695	0.0902957
L12.	-0.0288162	0.0205303	-1.4	0.161	-0.0690773	0.0114448
_dx1n						
--.	0.0868881	0.0195075	4.45	0	0.0486329	0.1251434
L1.	0.0672117	0.019778	3.4	0.001	0.028426	0.1059973
L2.	0.003573	0.0199129	0.18	0.858	-0.0354772	0.0426233
L3.	-0.0154932	0.0199969	-0.77	0.439	-0.0547082	0.0237219
L4.	-0.0026289	0.0201529	-0.13	0.896	-0.0421498	0.036892
L5.	-0.0539051	0.0202245	-2.67	0.008	-0.0935664	-0.0142438
L6.	-0.0010234	0.0202977	-0.05	0.96	-0.0408281	0.0387814
L7.	0.0416926	0.0201917	2.06	0.039	0.0020956	0.0812897
L8.	0.0003121	0.0201131	0.02	0.988	-0.0391308	0.039755
L9.	-0.0009102	0.0201737	-0.05	0.964	-0.0404718	0.0386515
L10.	-0.0679623	0.0201722	-3.37	0.001	-0.1075211	-0.0284035
L11.	-0.0310035	0.0201526	-1.54	0.124	-0.0705238	0.0085168
L12.	0.006793	0.0201183	0.34	0.736	-0.03266	0.0462461
_cons	0.0199358	0.0252055	0.79	0.429	-0.0294935	0.0693652

Cointegration statistics:

t_BDM	=	-0.8893
F_PSS	=	2.7373

Asymmetry statistics:

	Long-run effect [+]			Long-run effect [-]		
Exog. var.	*coef.*	*F-stat*	*P>F*	*coef.*	*F-stat*	*P>F*
LBRT	1.402	0.8457	0.358	-1.495	0.9093	0.34

	Long-run asymmetry		Short-run asymmetry	
	F-stat	*P>F*	*F-stat*	*P>F*
LBRT	3.448	0.063	10.93	0.001

Note: Long-run effect [-] refers to a permanent change in exog. var. by -1

Assymetric Impact of Oil Prices (Brent Crude) on Islamic Stocks (S&P)

Source	SS	df	MS			
Model	0.04697949	41	0.001145841	Number of obs	=	2,278
Residual	0.16816615	2,236	0.000075208	F(41, 2236)	=	15.24
Total	0.21514564	2,277	0.000094486	Prob > F	=	0.000
				R-squared	=	0.2184
				Adj R-squared	=	0.204
				Root MSE	=	0.00867

_dy	Coef.	Std. Err.	t	P>/t/	[95% Confidence	Interval]
L1._y	-0.0021528	0.0021332	-1.01	0.313	-0.006336	0.0020303
L1._x1p	0.0031549	0.0009052	3.49	0.001	0.0013797	0.00493
L1._x1n	0.0033822	0.0009746	3.47	0.001	0.0014709	0.0052935
_dy						
L1.	0.0835383	0.0211766	3.94	0	0.0420105	0.1250662
L2.	-0.0518435	0.021259	-2.44	0.015	-0.0935329	-0.0101541
L3.	-0.0007986	0.021412	-0.04	0.97	-0.042788	0.0411908
L4.	-0.0158184	0.0213436	-0.74	0.459	-0.0576737	0.0260368
L5.	-0.0581488	0.0214338	-2.71	0.007	-0.1001811	-0.0161165
L6.	0.0249882	0.0217568	1.15	0.251	-0.0176773	0.0676538
L7.	0.0095291	0.0218448	0.44	0.663	-0.0333092	0.0523673
L8.	-0.0298575	0.0219304	-1.36	0.174	-0.0728637	0.0131486
L9.	-0.007713	0.0216668	-0.36	0.722	-0.0502022	0.0347763
L10.	0.0249337	0.0213391	1.17	0.243	-0.0169128	0.0667802
L11.	0.010072	0.021467	0.47	0.639	-0.0320253	0.0521694
L12.	0.0194101	0.0212562	0.91	0.361	-0.0222738	0.061094
_dx1p						
--.	0.2123505	0.0158191	13.42	0	0.1813288	0.2433723
L1.	0.0502793	0.0161206	3.12	0.002	0.0186663	0.0818922
L2.	-0.0170684	0.0161941	-1.05	0.292	-0.0488254	0.0146886
L3.	0.0211781	0.0161919	1.31	0.191	-0.0105747	0.0529309
L4.	0.0808597	0.0161388	5.01	0.000	0.0492111	0.1125083
L5.	0.0338698	0.0162498	2.08	0.037	0.0020035	0.0657361
L6.	-0.0384508	0.0163102	-2.36	0.018	-0.0704356	-0.0064659
L7.	0.0110986	0.0163317	0.68	0.497	-0.0209284	0.0431255
L8.	-0.0114194	0.0163779	-0.7	0.486	-0.0435369	0.0206981
L9.	-0.0061852	0.0163569	-0.38	0.705	-0.0382615	0.025891
L10.	0.0362704	0.0163971	2.21	0.027	0.0041153	0.0684256
L11.	0.0379775	0.0163751	2.32	0.02	0.0058656	0.0700895
L12.	-0.0224653	0.0164146	-1.37	0.171	-0.0546547	0.0097242
_dx1n						
--.	0.1435039	0.0150598	9.53	0	0.1139713	0.1730365
L1.	-0.0007568	0.0154621	-0.05	0.961	-0.0310784	0.0295648
L2.	-0.0046649	0.0154682	-0.3	0.763	-0.0349984	0.0256686
L3.	0.0200814	0.015447	1.3	0.194	-0.0102106	0.0503734
L4.	-0.0286398	0.0154221	-1.86	0.063	-0.058883	0.0016034
L5.	-0.0442992	0.0154649	-2.86	0.004	-0.0746263	-0.0139721
L6.	0.0176126	0.015525	1.13	0.257	-0.0128324	0.0480576
L7.	-0.0029567	0.0154415	-0.19	0.848	-0.0332379	0.0273246
L8.	-0.0108504	0.0154557	-0.7	0.483	-0.0411593	0.0194586
L9.	-0.0136299	0.0154647	-0.88	0.378	-0.0439566	0.0166967
L10.	-0.0258991	0.0154315	-1.68	0.093	-0.0561607	0.0043626
L11.	-0.022888	0.0153934	-1.49	0.137	-0.0530748	0.0072988
L12.	0.0288854	0.0154462	1.87	0.062	-0.001405	0.0591758
_cons	0.0090648	0.010821	0.84	0.402	-0.0121555	0.0302851

Cointegration statistics:

t_BDM	=	-1.0092
F_PSS	=	4.0746

Asymmetry statistics:

	Long-run effect [+]			Long-run effect [-]		
Exog. var.	*coef.*	*F-stat*	*P>F*	*coef.*	*F-stat*	*P>F*
LBRT	1.465	1.085	0.298	-1.571	1.15	0.284

	Long-run asymmetry		Short-run asymmetry	
	F-stat	*P>F*	*F-stat*	*P>F*
LBRT	3	0.083	17.1	0

Note: Long-run effect [-] refers to a permanent change in exog. var. by -1

Constraints													
	_dy	**L1.**	**L2.**	**L3.**	**L4.**	**L5.**	**L6.**	**L7.**	**L8.**	**L9.**	**L10.**	**L11.**	**L12.**
constraint 1			L2._dy	L3._dy			L6._dy	L7._dy	L8._dy	L9._dy	L10._dy	L11._dy	
constraint 2	**_dx1p**		L2._dx1p		L4._dx1p		L6._dx1p	L7._dx1p	L8._dx1p	L9._dx1p			L12._dx1p
constraint 3	**_dx1n**	L1._dx1n	L2._dx1n	L3._dx1n	L4._dx1n		L6._dx1n	L7._dx1n	L8._dx1n	L9._dx1n		L11._dx1n	L12._dx1n

Constraints													
	_dy	**L1.**	**L2.**	**L3.**	**L4.**	**L5.**	**L6.**	**L7.**	**L8.**	**L9.**	**L10.**	**L11.**	**L12.**
constraint 1				L3._dy	L4._dy		L6._dy			L9._dy	L10._dy	L11._dy	
constraint 2			L2._dx1p	L3._dx1p			L6._dx1p	L7._dx1p	L8._dx1p	L9._dx1p	L10._dx1p		L12._dx1p
constraint 3			L2._dx1n	L3._dx1n	L4._dx1n		L6._dx1n	L7._dx1n	L8._dx1n	L9._dx1n		L11._dx1n	L12._dx1n

Constraints													
	_dy	**L1.**	**L2.**	**L3.**	**L4.**	**L5.**	**L6.**	**L7.**	**L8.**	**L9.**	**L10.**	**L11.**	**L12.**
constraint 1					L4._dy		L6._dy	L7._dy		L9._dy		L11._dy	
constraint 2			L2._dx1p	L3._dx1p	L4._dx1p			L7._dx1p	L8._dx1p	L9._dx1p	L10._dx1p		L12._dx1p
constraint 3			L2._dx1n	L3._dx1n	L4._dx1n		L6._dx1n		L8._dx1n	L9._dx1n		L11._dx1n	L12._dx1n

Constraints													
	_dy	**L1.**	**L2.**	**L3.**	**L4.**	**L5.**	**L6.**	**L7.**	**L8.**	**L9.**	**L10.**	**L11.**	**L12.**
constraint 1				L3._dy	L4._dy		L6._dy	L7._dy	L8._dy	L9._dy	L10._dy	L11._dy	L12._dy
constraint 2			L2._dx1p	L3._dx1p				L7._dx1p	L8._dx1p	L9._dx1p			L12._dx1p
constraint 3		L1._dx1n	L2._dx1n	L3._dx1n			L6._dx1n	L7._dx1n	L8._dx1n	L9._dx1n		L11._dx1n	

Constraints													
	_dy	**L1.**	**L2.**	**L3.**	**L4.**	**L5.**	**L6.**	**L7.**	**L8.**	**L9.**	**L10.**	**L11.**	**L12.**
Constraint 1	**_dy**	L1._dy	L2._dy	L3._dy	L4._dy	L5._dy	L6._dy	L7._dy	L8._dy	L9._dy	L10._dy	L11._dy	L12._dy
Constraint 2	**_dx1p**	L1._dx1p	L2._dx1p	L3._dx1p	L4._dx1p	L5._dx1p	L6._dx1p	L7._dx1p	L8._dx1p	L9._dx1p	L10._dx1p	L11._dx1p	L12._dx1p
Constraint 3	**_dx1n**	L1._dx1n	L2._dx1n	L3._dx1n	L4._dx1n	L5._dx1n	L6._dx1n	L7._dx1n	L8._dx1n	L9._dx1n	L10._dx1n	L11._dx1n	L12._dx1n