International Journal of Business and Management Invention (IJBMI)
ISSN (Online): 2319 – 8028, ISSN (Print): 2319 – 801X
www.ijbmi.org || Volume 7 Issue 5 Ver. III || May. 2018 || PP—28-36

The Uncertainty Risk of Oil and Ramadan Season on Stock Return and Volatility: Empirical Findings from Saudi Arabia

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ABSTRACT :*This study focuses on the influence of the Oil pricesand Ramadan season on the Saudi stock market return. Stock returns data of the Tadawul All-Shares Index (TASI) and several sector indices from October 1998 to February 2018 are used to examine the impact of the Oil prices and Ramadan seasonon the return and volatility of the stock indices. The FIAPARCH-BBM found to be the best fitting model for Saudi stock index return; the result shows a negative and significant relationship between oil price and stock market return in Saudi Arabia. Nevertheless, Ramadan effect in stock market volatility is not statistically significant. Investors can use the findings of the study for making proper investment decisions and achieving superior risk adjusted returns and to gain better portfolio diversification benefits.*

KEYWORDS: *Oil Prices, Ramadan Season, Stock Market, Return and Volatility, Saudi Arabia.*

Date of Submission: 28-04-2018 Date of acceptance: 14-05-2018

I. INTRODUCTION

The aim of this study is to analyse the determinants and factors that affects the performance of the Saudi stock market (SSM), which in away affects the compliance with the Saudi Vision 2030. Factors such as Ramadan (the month where Muslims fast from the dawn to sunset) time-frame and the fluctuation of oil price.

It's important for investors and practitioners to understand the relationship between trade size and price impact, to minimize the effect of block trades on their investment performance.

The SSM is an order driven market, where ninety percent of trades are generated by private investors rather than institutional investors (Alzahrani, 2013). Its restricted for foreigner investors to gain full ownership of the shares purchased. However, portfolio selection is entirely left to market participants and any moral obligation depends on the ethical attitude of investors (Alessandra et al., 2014).

The SSM has several characteristics that linked with the Saudi economy, as its heavily relied on oil revenue. Its characterized as market capitalization and trading volume with a limited foreign investment, as GCC national and other Arab residents account for a small proportion, whereas the non-Arab resident proportion is close to zero (Alessandra et al., 2014).

The SSM uses two different trading mechanisms a call auction (maintenance and trading states) and a continues auction (trading state) (Alzahrani, 2013). The SSM has encountered an important structural reforms since the establishment of the Capital Market Authority (CMA).

The CMA has a goal of promoting stability and liquidity by introducing regulations and standards that enhances institutional investment and reduce information asymmetry in the market. In relation with the Saudi vision 2030, CMA has started a program to assure the implementation of its (2015 – 2019) strategic plan that will cope-up with the new vision. As CMA's plays a great role to develop the capital market to be one of the important contributors to the investment power in the (Saudi Vision 2030).

Accordingly, the main function of SSM and CMA is to regulate, and brings stability to Saudi Market, as Saudi Arabia considered the religious hop for Muslims over the world. Millions of Muslims fly to Saudi Arabia annually visiting the two holy mosques in Mecca and Madinah. Its known that in some occasions such visits reach its ultimate where muslins gathered, especially during Ramadan (it’s a compulsory fasting month for Muslims, it’s once a year for a month) and Hajj (it’s a religious journey to the Holy city of Mecca, It's a must for every able-bodied and financially capable Muslim to perform at least once in each Muslim lifetime) seasons.

It's quite known that Muslims during these two events acts in more positive valence, piety, prayers, charity and hope from Allah to forgive their past sins. Muslims gathering events has its positive economic figures on Saudi Arabia. It considered the main non-oil industry contributor to the GDP with a total annual economic impact estimated to be around $30 billion, representing around 7 percent of the total Saudi economy (Mahajan, 2012).

Therefore, Ramadan effect on seasonality in capital market has been given the most attention in studies, most studies confirming the presence of the anomaly in selected Islamic markets around the world (Al-Ississ, 2010; AlKhazali, 2014; Ramezaniet al., 2013; Seyyedet al., 2005). Saudi Arabia, besides its religious position as the country who in hold and custody of the most two importance cities for Muslims in the world (Meccah and Madinah), It's a country that been blessed from Allah to have the world's second largest proven petroleum reserves and the largest exporter of petroleum (Brady, 2011).

Saudi Arabia also the fifth-largest proven natural gas reserves (Coskunet al,2009). It has the third highest total estimated value of natural resources, valued at US$34.4 trillion in 2016 (Craig, 2016). The crude oil price movements can do a great role in the world economy. Oil shocks also have several important effects to international stock markets. Effects in terms of portfolio risk management and asset allocations. Therefore, this research effort will investigates the impact of the Ramadan and oil fluctuations prices on the return and volatility of the Saudi stock market, which known as the Tadawul All-Share Index, or TASI.

II. LITERATURE REVIEW

A number of worldwide studies that address stock markets behavior and trends asserted that stock returns are predictable and influenced by investor sentiment and behavior (Seyyed, Abraham, & Al-Hajji, 2005) they suggests that investor judgment rely on their mood, whereby investor pessimism (optimism) tends to be a result of bad good) mood (Wright and Bower, 1992).

Other researchers who in favor of the Efficient Market Hypothesis (EMH) suggested that stock prices follow a random walk and are unpredictable (Fama, 1970). Cross (1973); Drogalasetal,(2007); French, (1980); Tinicet al, (1984) have found that stock prices are calendar anomalies, such as the January effect and the holiday effect, the day of the week effect.

On other hand other studies have focuses on the impact of religious events on stock market returns (Al-Khazali, 2014; Abbes &Abdelhédi-Zouch, 2015; Hussain, 1998; Ramezani, Pouraghajan, &Mardani, 2013; Seyyedet al., 2005). They concluded that moods and emotions linked with religious occasions are believed to be able to influence investor decision making process and the associate stock market behavior.

Other researchers have studied the impact of Hajj and Ramadan seasons on the stock market's performance. Wasiuzzaman's (2017) finds an influence of religious sentiments on the stock return and volatility. Abbes and Abdelhédi-Zouch (2015) uses the ARMA-GARCH methodology used by Wasiuzzaman (2017), however they extends the analysis to the Saudi stock exchange indices, also providing a more in-depth analysis of the anomaly and the possible reason(s) for the existence of the anomaly.

Various arguments can be made with regards to the influence of the Hajj pilgrimage on the returns of the Tadawul stock exchange. Millions of Hajj pilgrimage gathered in Mecca and Medina. They usually arrive 1 to 3 weeks earlier and may stay behind after the completion of the acts of Hajj to visit other significant places. While staying in Saudi Arabia, pilgrims enhances the economic activity by spending money on food, transport, lodgings and souvenirs to be brought back home. Accordingly, it's been argued such economic activites will influence the stock returns positively, as this brings positive mood resulting in the tendency of investors to thus investment in the Saudi stock market (Abbes &Abdelhédi-Zouch, 2015, pp. 139).

However, other argued that because Muslims at Hajj are trying to purified themselves from their sins and misdeeds, they will act in piety and devotion to Allah. Such an act will refrain Muslims from participating in speculative trading activities in the stock market as it is considered a form of gambling (Husain, 1990). Hajj timing will increase social activities as they feel unity among Muslims in Hajj and worldwide community. Hence, it is expected that the volatility of the TASI index would be higher during the Hajj period. Contrary, other researchers asserted that reduction in the participation of stock market during Hajj period, makes it illiquid. Which causes high volatility especially for riskier securities (Brunnermeier& Pedersen, 2009).

They also argue that reduced liquidity disables speculators from taking positions to smooth price fluctuations (Garleanu& Pedersen, 2011). Which will bring positive impact on the volatility of the TASI index (Wasiuzzaman, 2017). As for Ramadan season, Seyyedet al. (2005) asserted that there will a change in the daily routine and increased in consumer spending and socio religious activities after sundown. Which will cause an increase in stock returns during the Ramadan month.

Similar to Hajj season, Seyyedet al. (2005) argued that stock market volatility is expected to be lower during the month of Ramadan. As Muslims abstain from vice activities and acts on piety and charity, and hence reducing involvement in speculative trading activities as it is considered a form of gambling and due to prohibition of Riba (or interest). However, Al-Hajiehet al. (2011) argue that because of the social mood which will gives rise to trends in financial markets, resulting in herding behavior.

They also expected a higher levels of stock volatility during Ramadan, as a results of positive emotions of happiness and optimism and increasing social activities, which will lead to higher volatility. Alternatively, Al-Hajiehet al. (2011) argue that social mood gives rise to trends in financial markets resulting in an increased synchronization of opinions thus resulting in herding behavior. They also argue that higher levels of stock volatility can be expected during the Ramadan month because its associated with positive mood.

Therefore, it will be accompanied by positive emotions such as optimism and happiness. Increased social interaction during this month influences the decision making process and results in increased synchronization of opinions, hence leading to higher volatility (Al-Hajiehetal, 2011).

On the other hand, a number of studies has launched to examine the linkages between oil price shocks and stock market returns. Kaul and Jones (1996), Kilian and Park (2009), Kling (1985) finds negative relationship between oil shock and stock returns. While, El-Sharif et al., (2005), Narayan and Narayan (2010) indicated a positive linkages between oil and stock markets return. Another studies suggested an insignificant relationships (Apergis and Miller, 2009; Henriques and Sadorsky, 2008).

Elyasianiet al. (2011) have studied thirteen U.S industries in terms of oil return and oil return volatility on excess stock returns and return volatility. They found a strong evidence that the fluctuations of oil prices form a systematic asset price risk at the industry level. In specific, he found nine firms shows statistically significant relationships between oil futures return distribution and industry excess return. In more details study, Caporaleet al. (2014), have conducted a Weekly data between January 1997 to February 2014, for Ten sectoral indices in china (Healthcare, Telecommunications, Basic Materials, Consumer Services, Consumer Goods, Financials, Industrials, Oil and Gas, Utilities, and Technology) and WTI oil prices.

They indicated that the Oil price volatility affects stock returns positively during the period of demand side shocks for Consumer Services, Financials, and Oil and Gas sectors. The remaining two sectors reported a negative response to oil price uncertainty during periods with supply side shocks instead. However, the impact of oil price uncertainty appears to be insignificant with the period of precautionary demand shocks.

Khalfaouiet al. (2015) studied a daily observations from June 2003 to February 2012 for crude oil market (WTI) and stock markets of the G-7 countries. He found strong evidence of significant volatility between oil and stock markets and time varying correlations for various market pairs, with an evidence of oil market was leading.

Recently, Zhang (2017) have examine the relationship between oil shocks and stock market returns for the Dow Jones industrial average "(DJI), FTSE 100, DAX, Nikkei 225, Singapore Straits Times Index (STI), and the Shanghai Stock Exchange (SSE) Composite Index", by using the risk index of Diebold and Yilmaz (2009). He founds a limited impact of oil shocks to the world financial system.

III. METHODOLOGY

Financial research presents considerable evidence that returns are non-normally distributed and characterized by leptokurtosis, skewness and volatility clustering. A common way to capture the above stylized facts would be to model the conditional variance as a GARCH process. The GARCH (p, q) model captures the tendency in financial data for volatility clustering and also incorporates heteroscedasticity into the estimation procedure (see Engle (1982), Bollerslev (1986), and Engle and Ng (1993)).

Determining the most appropriate GARCH specification for KSA's stock market returns was undertaken by testing the index return against a range of ten GARCH specifications and selecting the most appropriate one. The alternative models are subsequently evaluated by an evaluation of model parameters based on log likelihood ratio test (LLRT) and the AIC test. The LLRT allows the selection of the best GARCH specification, taking into account the principle of parsimony.

The range of GARCH specifications covers basic GARCH, GJR-GARCH, APARCH, IGARCH, FIGARCH BBM, FIGARCH Chung, FIEGARCH, FIAPRCH BBM, FIAPRCH Chung, and HYGARCH.

GARCH -Models

The equation below presents GARCH(p, q):

$$\sigma_t^2 = \alpha_0 + \alpha_1\epsilon_{t-1}^2 + \cdots + \alpha_q\epsilon_{t-q}^2 + \beta_1\sigma_{t-1}^2 + \cdots + \beta_p\sigma_{t-p}^2 = \alpha_0 + \sum_{i=1}^{q}\alpha_i\epsilon_{t-i}^2 + \sum_{i=1}^{p}\beta_i\sigma_{t-i}^2$$

Equation.1

where, Nelson (1991) proposes the exponential GARCH or EGARCH model. e is:

$$\mathbf{log(\sigma_t^2) = \omega + \sum_{j=1}^{p}\beta_j log(\sigma_{t-j}^2) + \left(\sum_i^q \alpha_i \left|\frac{\varepsilon_{t-i}}{\sqrt{\sigma_{t-i}^2}}\right| + \gamma_i\frac{\varepsilon_{t-i}}{\sqrt{\sigma_{t-i}^2}}\right)} \quad \textbf{Equation.2}$$

Glosten, Jagannathan, and Runkle (1993) introduce GJR models. Its generalized version is given by:

$$\sigma_t^2 = \omega + \sum_{i=1}^{q}\left(\alpha_i\varepsilon_{t-i}^2 + \gamma_i S_{t-i}^{-}\varepsilon_{t-i}^2\right) + \sum_{j=1}^{p}\beta_j\sigma_{t-j}^2,$$

Equation.3

Furthermore, Ding, Granger, and Engle (1993) introduce APARCH (p,q) model, it can be expressed as:

$$\sigma_t^{\delta} = \omega + \sum_{i=1}^{q} \alpha_i \left(|\varepsilon_{t-i}| - \gamma_i \varepsilon_{t-i}\right)^{\delta} + \sum_{j=1}^{p} \beta_j \sigma_{t-j}^{\delta},$$ **Equation.4**

where $\delta>0$ and $-1 < \gamma_i < 1$ (i= 1,...,q).
The GARCH(p,q) model can be expressed as an ARMA process. Using the lag operator L, we can rearrange Equation (6) as:

$$[1-\alpha(L)-\beta(L)]\varepsilon_t^2 = \omega + [1-\beta(L)]\left(\varepsilon_t^2 - \sigma_t^2\right)$$ **Equation.5**

When the $[1-\alpha(L)-\beta(L)]$ polynomial contains a unit root, i.e. the sum of all the α_i and the β_j is one, we have the IGARCH(p,q) model of Engle and Bollerslev (1986).
Furthermore, Baillie, Bollerslev, and Mikkelsen (1996) (BBM) introduced the Fractionally Integrated GARCH (FIGARCH) model:

$$\sigma_t^2 = \omega[1-\beta(L)]^{-1} + \{1-[1-\beta(L)]^{-1}\phi(L)(1-L)^d\}\varepsilon_t^2$$ **Equation.6**

Chung (1996) proposed a slightly different process:

$$\phi(L)(1-L)^d(\varepsilon_t^2 - \sigma^2) = [1-\beta(L)](\varepsilon_t^2 - \sigma_t^2)$$ **Equation.7**

Bollerslev and Mikkelsen (1996) proposed FIEGARCH (p, d, q):

$$log(\sigma_t^2) = \omega + \phi(L)^{-1}(1-L)^{-d}[1+\alpha(L)]g(z_{t-1})$$ **Equation.8**

Tse (1998) proposed the fractionally integrated APARCH (FIAPARCH) model, as:

$$\sigma_t^{\delta} = \alpha_0 - [1-\beta(L)]^{-1} + [1-\phi(L)[1-\beta(L)]^{-1}(1-L)^d](|\varepsilon_i| - \gamma_i\varepsilon_i)^{\delta}$$ **Equation.9**

Davidson (2004) proposed a hyperbolic GARCH (HYGARCH) model,

$$y_t = \varepsilon_t\sqrt{h_t}$$ **Equation.10**

$$h_t = \frac{\gamma}{\beta(1)} + \left\{1 - \frac{\delta_H(B)}{\beta(B)}\left[1 - \phi + \phi(1-B)^d\right]\right\} y_t^2$$ **Equation.11**

(see Davidson, 2004 for more details).

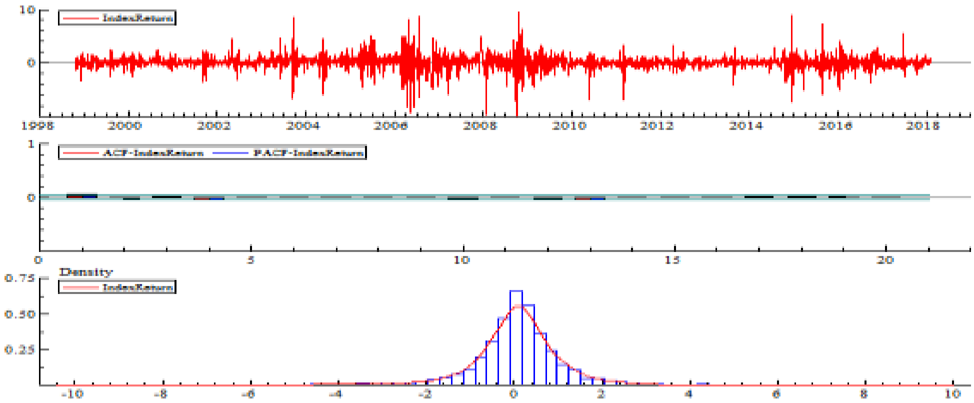
Data preliminary

The dataset used in this research consists of the daily closing prices of the Saudi Stock markets. The data comprises of a total of 3424 trading days. Daily returns were computed as the log-difference of the daily closing prices. Fig. 1, 2 illustrates the price index, and the daily returns. It can be observed that series display volatility clustering effects as periods of high volatility are followed by periods of low volatility. Furthermore, there is also evidence of synchronized behavior, with the great majority of peaks and troughs visibly occurring at the same time. This may suggest that the series are somehow correlated or that there is some kind of association among them.

Figure 1. Daily Price Index

Source: Authors Own.

Figure 2. Daily Percentage Returns, ACF, and Distribution



Source: Authors Own.

Descriptive statistics for the daily returns are summarized in Table 1. It shows that series display a positive but close to zero sample mean, which is very small when compared to the variable's standard deviation.The return distribution is non-normally distributed with fat tails, as indicated by the Jarque–Bera test, skewness and kurtosis statistics. Series is skewed toward the left, moreover, Series exhibit high levels of kurtosis indicating that these distributions have thicker tails than the normal distribution. The rejection of the Jarque–Bera test further confirms that daily returns are non-normally distributed.

The null hypothesis of a white-noise process is also assessed using the Ljung–Box test statistics (Q(10)) for the returns. According to estimated values of Q(10), the null hypothesis of no serial correlation is rejected for all market returns. Figure 3, ACF test shows that the returns are serial dependent. This can be removed by fitting an AR(p) (Autoregressive) model. Finally, the ARCH-LM test reveals the presence of conditional heteroscedasticity in the return series.

Table 1. Descriptive Statistics of Daily Returns

	Saudi Arabia
Obs	3424
Starting date	19/10/1998
Ending Date	01/02/2018
MIN	-9.813
MAX	9.4698
Mean	0.0450
std.dev	1.2831
Skewness	-0.6425**
Excess Kurtosis	11.561**
Jarque-Bera	19304**
ARCH 1-10 test	67.290**
ADF Statistics	-32.562**
Q(10)	1470.49**

Source: Authors Own.

An AR model was fitted to remove any serial correlation in the series. The following specifications were estimated:AR(1) for Saudi Arabia.

Dummy Variables:

The dummy variable used to represent; Oil returns, data divided into two dummy variables, first variable represented positive oil returns (OilPositiveD.) take value of 1 if the oil return is positive in that specific day and 0 otherwise, second variables represented negative oil returns (OilNegativeD.) take value of 1 if the oil return is negative in that specific day and 0 otherwise. Monday dummy variable is used to minimize the impact of day-of -the-week effects. Eventhe first trading day in Saudi Arabia is Sunday, but the first trading day of oil is Monday, therefore if the oil return has impact in Saudi markets,it's important to eliminate the Monday effects that might maximums or minimize the oil return impact.The Monday dummy variable (Monday) take value of 1 if the of day-of -the-week is Monday and 0 otherwise.LastlyRamadan dummy variable is also used (Ramadan) take value of 1 if the stock return occurs during the month of Ramadan and 0 otherwise.

IV. EMPIRICAL RESULTS

We evaluated the different models by (i) an assessment of the parameters associated with each model set and (ii) an evaluation of each model set's forecasting performance.

Tables 2, present the parameter values and associated significance tests for the APARCH, FIAPARCH-Chung, FIEGARCH, FIGARCH- Chung, FIGARCH-BBM, GARCH, GJR- GARCH, HYGARCH, and IGARCH specified model sets.

For models, the constants in the mean parameter are positive and statistically significant. The exceptions were for APARCH, where the constants are not statistically significant. The constants in the variance equations parameter are positive and statistically significant (except for FIEGARCH, which is are negative). The exceptions were for HYGARCH, where the constants are not statistically significant.

The d-FIGARCH coefficient for all models is statistically significant at the 99% confidence level in all countries, indicating the existence of long memory.

The ARCH coefficient (alpha) in APARCH, FIEGARCH, GARCH, GJR- GARCH, and IGARCH models is statistically significant at the 99% level of confidence. This implies the existence of the ARCH process in the residuals term. The returns exhibit time-varying volatility clustering that indicates periods of volatility are followed by periods of relative calm. However this is not the case for other models. For example, in FIAPARCH-BBM models show that the alpha coefficient is not statistically significant.

The GARCH coefficient (beta) is larger than the ARCH term (alpha) in all model sets. This is a further indication that the conditional variance will exhibit long persistence in volatility. Furthermore, the sum of alpha and beta1 is less than unity for all models, which indicates stationary models.

The FIEGARCH coefficients (Theta1, and Theta2) are statistically significant at the 99% level of confidence in the magnitude effect and sign effect.

The APRCH coefficients (Gemma1, and Delta) are different than zero and 2 for APARCH, FIAPARCH-BBM, and FIAPARCH- Chung models and statistically significant at the 99% level of confidence. Furthermore, Gemma1 > 0, implies that negative shocks give rise to higher volatility than positive shocks, as well as, delta of returns indicates that there is a predictable structure in the volatility pattern.

The HYGARCH coefficients (Log Alpha) are more than zero but not statistically significant. This implies that the process is stationary in the HYGARCH model and therefore, component observed are restricted by covariance stationarity.

The Monday dummy's variable coefficient in mean equation (Monday) is negative and statistically significant at the 90% level of confidence in all model sets.

Whereas, the positive oil dummy's variable coefficient (OilPositiveD.) in mean equation is negative and statistically significant at the 99% level of confidence in all model sets. Furthermore, the negative oil dummy's variable coefficient (OilNegativeD.) in mean equation is positive and statistically significant at the 99% level of confidence in all model sets.

The Ramadan dummy's variable coefficient in variance equation (Ramadan) is positive but not statistically significant in all model sets.

Table 3. GARCH-Models

Model	APARCH		FIAPARCH-BBM		FIAPARCH-Chung		FIEGARCH		FIGARCH-Chung		FIGARCH-BBM		GARCH		GJR		HYGARCH		IGARCH	
	Coeff.	t-prob	Coeff.	t-prob	Coeff.	t-prob	Coeff.	t-prob	Coeff.	t-prob	Coeff.	t-prob	Coeff.	t-prob	Coeff.	t-prob	Coeff.	t-prob	Coeff.	t-prob
Cst(M)	0.034	0.094	0.041	0.036	0.043	0.029	0.034	0.102	0.046	0.019	0.045	0.023	0.042	0.031	0.039	0.050	0.043	0.030	0.044	0.025
Monday (M)	-0.046	0.062	-0.046	0.061	-0.046	0.060	-0.043	0.071	-0.045	0.070	-0.045	0.067	-0.047	0.055	-0.047	0.054	-0.045	0.066	-0.047	0.056
OilNegativeD. (M)	0.104	0.000	0.106	0.000	0.107	0.000	0.105	0.000	0.107	0.000	0.106	0.000	0.105	0.000	0.105	0.000	0.106	0.000	0.105	0.000
OilPositiveD. (M)	-0.059	0.009	-0.066	0.003	-0.066	0.003	-0.060	0.006	-0.065	0.004	-0.065	0.004	-0.062	0.006	-0.064	0.005	-0.065	0.004	-0.062	0.006
AR(1)	0.072	0.000	0.080	0.000	0.081	0.000	0.077	0.000	0.067	0.000	0.066	0.001	0.061	0.001	0.072	0.000	0.066	0.000	0.061	0.001
Cst(V)	0.048	0.000	0.050	0.013	2.087	0.001	-1.824	0.000	1.906	0.001	0.044	0.007	0.041	0.000	0.043	0.000	0.033	0.068	0.041	0.000
Ramadan (V)	0.022	0.279	0.082	0.142	0.052	0.579	-0.074	0.677	0.087	0.334	0.094	0.091	0.044	0.101	0.040	0.132	0.098	0.103	0.043	0.089
ARCH(Alpha1)	0.269	0.000	0.169	0.164	0.134	0.326	-0.394	0.003	0.141	0.248	0.162	0.146	0.275	0.000	0.220	0.000	0.148	0.227	0.247	0.000
GARCH(Beta1)	0.768	0.000	0.380	0.007	0.303	0.038	0.798	0.000	0.318	0.016	0.378	0.004	0.749	0.000	0.745	0.000	0.351	0.013	0.752	0.000
GJR(Gamma1)															0.112	0.015				
APARCH(Delta)	1.423	0.000	1.959	0.000	2.011	0.000														
APARCH(Gamma1)	0.131	0.003	0.130	0.004	0.128	0.004														
d-Figarch			0.520	0.000	0.474	0.000	0.349	0.000	0.470	0.000	0.518	0.000					0.500	0.000		
EGARCH(Theta1)							-0.076	0.001												
EGARCH(Theta2)							0.506	0.000												
Asymmetry	-0.100	0.000	-0.090	0.000	-0.086	0.000	-0.084	0.004	-0.091	0.000	-0.094	0.000	-0.096	0.000	-0.094	0.000	-0.086	0.000	-0.096	0.000
Log Alpha																	0.090	0.111		

Source: Authors Own.

We turn now to the issue of identifying the most efficient model(s) from the groups that have been tested. The diagnostic tests of the standardized residuals (Table 4) represent the results for bothARCH(10) and Q2(10) statistics indicate that heteroscedasticity has been fully accounted for by the models. Log likelihood and Akaike tests indicate that the FIAPARCH-BBM model produces the best performance.

Table 4. The Diagnostic Tests of The Standardized Residuals

Model		**Log Likelihood**	**Akaike**	**Q(10)**	**ARCH 1-10**
GARCH	Coefficient	-4386.4	2.5686	11.4225	1.1374
	t-prob			[0.1788888]	[0.3295]
GJR	Coefficient	-4382.6	2.5669	11.5499	1.1543
	t-prob			[0.1724458]	[0.3173]
APARCH	Coefficient	-4378.9	2.5653	12.7058	1.2642
	t-prob			[0.1223798]	[0.2449]
IGARCH	Coefficient	-4387.2	2.5685	11.1446	1.1069
	t-prob			[0.1936396]	[0.3526]
FIGARCH-BBM	Coefficient	-4368.9	2.5590	9.8260	0.9913
	t-prob			[0.2774500]	[0.4484]
FIGARCH-Chung	Coefficient	-4371.7	2.5605	9.6593	0.9766
	t-prob			[0.2897612]	[0.4615]
FIEGARCH	Coefficient	-4369.4	2.5604	8.7937	0.8770
	t-prob			[0.3600007]	[0.5542]
FIAPARCH-BBM	Coefficient	-4363.8	2.5571	10.7015	1.0844
	t-prob			[0.2191919]	[0.3701]
FIAPARCH-Chung	Coefficient	-4366.4	2.5586	10.3802	1.0537
	t-prob			[0.2393477]	[0.3950]
HYGARCH	Coefficient	-4367.6	2.5587	9.7957	0.9880
	t-prob			[0.2796613]	[0.4514]

Source: Authors Own.

V. DISCUSSION:

Oil represents one of the major production inputs for the global economy and hence variations in crude oil price are likely to bring uncertainty to the overall economic development and growth. Fowowe (2013) contends that high oil prices lead to a slower pace of economic activities and this may affect consumers and producers alike by dampening consumption and investment which adversely impacts the stock markets. Furthermore, Hong et al. (2002), in a study for the United States from 1970 to 2000, also identify a negative correlation between oil prices and stock market returns.

This study, find a negative relationship between oil price and stock market return in Saudi Arabia. Gogineni (2008) found that the direction and magnitude of the market's reaction to oil price changes depend on the magnitude of change in the oil price. He found that oil price changes caused by supply shocks have a negative impact on stock returns, while oil price changes caused by shifts in aggregate demand have a positive impact on the same day market returns. Basher and Sadorsky (2006) analyzed the impact of oil price risk on emerging stock markets. In their study, they pointed out that oil prices affect stock prices by having an impact on the cost structure of non-oil-producing companies. In a similar approach, Chung-Rou and Shih-Yi (2014) studied the impact of oil price shocks on the stock prices of large emerging economies such as China, India, and Russia. They found that shocks in oil prices affect the stock returns in three of those emerging economies. Yanfeng and Xiaoying (2017) analyze the relationship between oil price shocks and China's stock market. They state that the responses of stock return to oil shocks are different and are crucially related to the causes of the oil price changes, while the responses of stock volatility to oil shocks are almost insignificant.

However,Probalet.al., (2017) examines 23 emerging countries: Brazil, Chile, China, Colombia, Czech Republic, Egypt, Greece, Hungary, India, Indonesia, Korea, Malaysia, Mexico, Peru, Philippines, Poland, Qatar, Russia, South Africa, Taiwan, Thailand, Turkey and United Arab Emirates. Their findings show that emerging market equity returns are highly sensitive to oil volatility shocks. Moreover, they found that variations in conventional oil price series affect the equity returns positively.

On the other hands, studies on behavior and trends in stock markets worldwide have put forward the idea that stock returns are predictable and influenced by investor sentiment and behavior (Al-Hajieh et.al., 2011). Wright and Bower(1992) suggest that investor judgment tends to stem from their mood, whereby investor optimism (pessimism) tends to be a result of good (bad) mood. This is contrary to claims by proponents of the Efficient Market Hypothesis (EMH) that stock prices follow a random walk and are unpredictable (Fama, 1970). Often examined are calendar anomalies such as the day of the week effect, the January effect and the holiday effect. Moods and emotions associated with religious events are believed to be able to influence investor decision-making process and hence their stock market behavior, for example; Al-Hajieh et. al., (2011) pointed out that the holy month of Ramadan is usually a time of celebration and renewal in Muslim countries. They examine 8 Muslim countries (Bahrain, Egypt, Jordan, Kuwait, Qatar, Saudi Arabia, Turkey, and United Arab Emirates), the result indicates strong evidence of significant and positive calendar effects in respect to the whole period of Ramadan in most countries and it is argued that this can be attributed to the generally positive investor mood, or sentiment. Although Ramadan is a time of celebration for Muslims it also can be a time of uncertainty and this appears to result in the impact of the festival not being uniformly positive throughout Ramadan.

In this research, Ramadan dummy variables equations in order to examine whether or not Ramadan effects will disappears when oil data allocated in mean equations. The result in general indicated that Ramadan effect is not statistically significant in all models. Whereas, Studies on the Ramadan effect argue that stock market volatility is expected to be lower during the month due to the fact that Muslims abstain from vice activities and devote their time to acts of piety and charity, thus reducing involvement in speculative trading activities as it is considered a form of gambling (Seyyed et al.,2005). Additionally, margin based or interest-based trading is also expected to decline due to the prohibition of Riba (or interest) in Islam. However, reduced participation in the stock market during the Ramadan period makes it illiquid. When liquidity is low, volatility is high and this is especially true for the case of riskier securities (Brunnermeier& Pedersen, 2009). Reduced liquidity disables speculators from taking positions to smooth price fluctuations(Garleanu& Pedersen, 2011). Therefore, this argument indicates a positive impact of the Ramadan on the volatility of the Saudi stock market (Wasiuzzaman, 2017). Alternatively, Al-Hajieh et al. (2011)argue that social mood gives rise to trends in financial markets resulting in an increased synchronization of opinions thus resulting in herding behavior. They argue that higher levels of stock volatility can be expected during the Ramadan month because the month is being associated with positive mood and therefore is accompanied by positive emotions such as optimism and happiness. Increased social interaction during this month influences the decision making process and results in increased synchronization of opinions, hence leading to higher volatility.

VI. CONCLUSION:

Saudi Arabia has announced the opening of its Stock Exchange for qualified foreign investors starting June 15, 2015. This decision marks a major milestone that deserves special recognition. Therefore, this study examines the influence of the oil price and Ramadan on the Saudi stock market.

Stock returns data of the Tadawul All-Shares Index (TASI) from October 1998 to February 2018 are used to determine the most appropriate GARCH specification for KSA’s stock market returns, by testing the index return against a range of ten GARCH specifications and selecting the most appropriate one(GARCH, EGARCH, GJR-GARCH, APARCH, IGARCH, FIGARCH BBM, FIGARCH Chung, FIEGARCH, FIAPRCH BBM, FIAPRCH Chung, and HYGARCH). The FIAPARCH-BBM is the best fitting model for Saudi stock index return; the result shows a negative and significant relationship between oil price and stock market return in Saudi Arabia. Nevertheless, Ramadan effect in stock market volatility is not statistically significant.

The findings of our empirical investigation carry important suggestions for investors and policymakers. Investors, for instance, could use the results of this study for taking proper investment decisions and achieving superior risk adjusted returns. Besides, the results can also be advantageous for gaining better portfolio diversification benefits. In addition, the results could be useful for the risk management purposes as well. Overall, financial market participants should be aware of the linkages between oil price uncertainty and stock market returns while using oil to hedge and diversify equities (Maghyereh and Awartani, 2015).

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Dr. Hashem A. AlNemer "The Uncertainty Risk of Oil and Ramadan Season on Stock Return and Volatility: Empirical Findings from Saudi Arabia "International Journal of Business and Management Invention (IJBMI) , vol. 07, no. 05, 2018, pp. 28-36