European Online Journal of Natural and Social Sciences 2019; www.european-science.com
Vol.8, No 2 (s) Special Issue on Current Approaches to Economic and Social Development
ISSN 1805-3602

Do Outliers Matter in Return and Volatility Linkages? A Case of Sectoral Stock of PSX and Brent Oil

Muhammad Irfan Malik[1]*, Abdul Rashid[2]
[1]Punjab Economic Research Institute, Lahore; [2]International Islamic University, Islamabad
*Email: Irfanmalik@outlook.com

Abstract

This paper focuses at the return and volatility link between Brent Oil and stock sectors of Pakistan Stock Exchange by taking into account the outliers. The newly proposed Laurent et al. (2016) methodology has been applied for the detection and correction of outliers. Bivariate VAR(1)-AGARCH(1,1) model has been estimated using data sampled from 01-01-2001 till 31-12-2015. Optimal weights and hedge ratios for oil-stock portfolio holdings have also been analyzed. It has been observed that the model estimates are alive to the presence of outliers. Unidirectional short-run price spillovers are found significant from oil market to the stock sectors. Whereas, no volatility spillover between Brent oil and sectors of Pakistan Stock Exchange have been found neither in the short-run and nor in the long-run. The outcomes of this study will help investors, portfolio and hedge fund managers in making sane decisions about portfolio diversification, risk management, and international assets allocation.

Keywords: Pakistan Stock Exchange, Brent, Outliers, VAR-AGARCH, Spillover, Portfolio, Hedging

Introduction

International oil prices fluctuation leads to changes in cash flows and corporate gains which resultantly influence the stock market. It has gained significant attention of finance practitioners and researchers. The effect of rise and fall in oil prices and its subsequent effect on stock price can be demonstrated by equity theory valuation. Oil price shock has been treated as supply shock and influence the macroeconomic dynamics of oil importing economies (Sadorsky, 1999; Park and Ratti, 2008; Apergis and Miller, 2009). Shocks in oil price also affect stock market performance through economic activities which are closely linked with the discount rate and corporate cash flow.

Equity pricing model deals with the stock price wherein it equates present value of future profits of a company with stock prices. Beneath the presumption of frictionless and efficient markets, oil price shocks are anticipated to be exhibited in price of stocks quickly. In this perspective, oil price increases cause reduction in expected profits. According to Huanget al. (1996), stock prices have negative association with shocks in oil price. The brunt of oil price shock on stock prices can also be expounded through interest rate channel. Therefore, it is also recommended that decision makers may increase the interest rate to control inflation due to oil price increase. It is of great significance to understand the channels through which interest rate affects stock prices. First, rise in interest rate increases the discount rate for the stock price and leads to decline in expected profits. second, it make the bonds market more attractive for the investors (Huang et al., 1996).

In response to oil price increases, policymakers in order to control the inflationary pressures in the economy raise the interest rate which affect the stock prices because of subsequent increase in discount rate. It makes the investment in bonds market more attractive and thus lowers the demand of stock. Thus stock prices decrease due to increase in discount rate and decline in demand (Huang et al., 1996). Oil and stock relationship has been explored many researchers at sectoral as well as at aggregate level using different rigorous econometric methods (Malik and Ewing, 2009; Jouini, 2013; Bouri et al., 2016; Ewing and Malik, 2016; Cheong, 2009; Hamma et al., 2014; Hamilton, 1983; ; Sattary et al., 2014; Arouri et al., 2011, 2012).

It is well documented in the existing theoretical and empirical literature that financial markets are prone to some particular episodes (i.e. outliers) that have deforming impacts on the model estimates (Bali and Guirguis, 2007; Charles and Darné, 2005; Balke and Fomby, 1994;). Many researchers have theoretically and empirically investigated the outliers effect and found that they have detrimental effects on the parameter estimates of the model, regularity conditions, volatility forecasts, detection of variance breaks and tests of heteroscedasticity etc. (Charles and Darné, 2005, 2014; Carnero et al., 2001; Carnero et al., 2016; Verhoeven and McAleer, 2000; Charles, 2004, 2008; Franses et al., 1998; van Dijk et al., 1999). Whereas, the empirical literature on the return and volatility and their transmission among different financial markets considering the outliers is very limited. Therefore, this study closes the existing gap in the empirical literature by examining the impact of outliers on the estimates of return and volatility, and their spillover between the oil and sectoral indices of Pakistan Stock Exchange. To the best of researchers' knowledge, the phenomenon of return and volatility and their linkages between Brent oil and sectors of PSX has hardly been investigated before by taking outliers into considerations. This study has great significance because Pakistan is energy thirsty country and more than 17% of import bill consist of petroleum products during year 2014-2015[1]. The share of oil as primary energy source was 35% of total energy supply during year 2014-2015[2] in Pakistan. Sectoral level consumption of oil revealed that 40.6% oil was used as input in power generation and more than 50% oil was consumed by transport sector of Pakistan.

For the detection and correction of outliers, we employ the recently proposed methodology of Laurent et al. (2016). To gage the effect of outliers on the estimates of return and volatility and their transmission, we used VAR-AGARCH model suggested by McAleer et al. (2009) . The model is capable of providing efficient estimates of parameters and avoid the complications of other alternatives such as BEKK-GARCH and VEC-GARCH models. It has been found that the presence of outliers has no impact on the estimates of both return and volatility. Furthermore, our finding reveals significant return spillover from Brent oil to sectors of Pakistan Stock Exchange. On the other hand, no association have been discovered in the volatilities in short-run and long-run. Portfolio weights suggest that to minimize the investment risk investor may invest at least 64% of investment in sectors of PSX.

Different sections of the paper are as under a short introduction of Pakistan Stock Exchange has been presented in section II, review of literature is given in section III. Econometric methodology has been discussed in section IV. Data and preliminary analysis have been reported in section V. The empirical findings have been discussed in section VI and finally in section VII conclusions and policy recommendations are given.

Pakistan Stock Exchange (PSX)

Pakistan Stock Exchange Limited (PSX) was established in 1949 as Karachi Stock Exchange (KSE). After the integration of Karachi Stock Exchange (KSE), Lahore Stock Exchange (LSE) and Islamabad Stock Exchange (ISE) in 2016, PSX emerged. FTSE categorized PSX as a secondary emerging market while MSCI in June 2017, upgraded PSX from frontier market to emerging market. KSE-100 index is the bench mark index of PSXI introduced in 1991. KSE-100 index based on 100 listed companies at PSX, which accumulate almost 80% of the free float market capitalization.

[1] "Economic Survey of Pakistan 2015-16, Government of Pakistan."
[2] Pakistan Energy Year Book 2015.

These hundred firms are opted on the basis of sector depiction and their market capitalization. On June 30, 2017, 560 companies were listed with market capitalization of 9.5 Trillion. During the year 2016-2017, total trade volume of share was 88.6 trillion. During year 2016-2017, market bench mark index increased by 23% which was the 3rd best in the world after Borsa Istanbul and Hong Kong. Pakistan Stock Exchange offer highest rate of return on investment (22%) among other class of assets. The listed firms are classified into 35 different sectors with respect to their business however, DataStream international distributed listed firms among eight sectors namely: industry, healthcare, telecom, basic material, financial, oil and gas, utility, consumer goods sectors.

Literature review

The seminal work of Hamilton (1983) has provided the link of oil price shock with the real side of the economy in response to the oil price shock of 1973 and afterwards, both theoretical and empirical literature evolves around the supply side economic dynamics. However, the linkage between oil prices and stock prices have been explored lately by many researchers and policy makers such as Jones and Kaul (1996) and Huang et al. (1996). Most of these studies used vector autoregressive (VAR) model. Huang et al. (1996) argued that oil price changes had a significant impact on the returns of oil sector companies, but found a negligible impact of oil prices on the overall market index. Jones and Kaul (1996) concluded that stock markets in Canada and USA respond through expected cash flow channel entirely. According to Sadorsky (1999), stock market returns are significantly affected by both oil price and its volatility. Later, Sadorsky (2001) argued positive association between oil and stock returns. However, these studies mainly relied on VAR model and focused on investigating the price spillovers whereas volatility spillovers have been ignored.

Some recent studies have paid attention to the volatility linkages between oil prices and stock prices by utilizing BEKK model specification of Engle and Kroner (1995) and found these spillovers significant (Tansuchat et al., 2009; Malik and Hammoudeh, 2007; Ågren, 2006; Ewing and Thompson, 2007). According to Ågren (2006), there is significant spillover from oil to stock markets of Norway, Japan, the US and the UK whereas for Sweden, it is insignificant. Malik and Hammoudeh (2007), while working on Gulf markets, found that oil price volatility spillovers significantly affect the stock markets whereas there is bi-directional volatility spillover in Saudi Arabia. Chang et al. (2009) used the multivariate GARCH model to explore the volatility linkages between future crude oil returns and the stock market returns of world oil companies. These findings suggest no volatility spillover. Similarly, Chang et al. (2011) analyzed the interdependence between oil and stock price volatility for selected oil companies and found no volatility spillover in either direction. The literature provides limited insight into the volatility spillovers at sectoral level which is important to explore because different sectors of stock market behave differently to the oil price shock. Further, the literature usually ignores the emerging stock markets.

Malik and Ewing (2009) discovered significant volatility spillover between oil and stock prices of five sectors of United States whereas they used BEKK model. Hamma et al. (2014), using the same model, explored the unidirectional volatility for selected sectors of stock market of Tunisia. Using daily data Sattary et al. (2014) explored the volatility transmission between oil price and sectors of Turkish stock market (transport, non-metal mineral and electricity sectors) under BEKK framework, they found significant relationship between oil price volatility and volatility of stock prices except non-metal mineral. Gencer and Demiralay (2014) explored the volatility spillovers for various sectors of stock market of Turkey and found volatility spillover from oil market to stock for all sectors.

Using VAR-GARCH model for investigating the volatility linkages between oil and stock, Arouri, Jouini, et al. (2011) endorsed the bidirectional transmission of volatility in USA and unidirectional transmission in Europe. Using same model, Arouri et al. (2012) examined the transmission of volatility at sectoral level for European market. Their findings suggest significant transmission. For Saudi stock market at sectoral level, Jouini (2013) estimated VAR-GARCH model wherein he revealed that there exists return and volatility spillover between oil and stock prices. Recently, Bouri et al. (2016) investigated the connection between first as well as second moments of oil prices and sectors of Jordanian stock market and found non-uniformity of oil price effects on different sectors.

It is well established that specific events affect the financial markets however these events affect the distribution of data and create outliers which influence the whole estimation. Therefore, these outliers must be treated rigorously. Many authors (Ané et al., 2008; Verhoeven and McAleer, 2000; Carnero et al., 2016; Charles, 2004; Charles and Darné, 2005, 2014; Laurent et al., 2016; Franses and Ghijsels, 1999; van Dijk et al., 1999) have studied the effect of outliers theoretically as well as empirically on the volatility estimates, test of conditional heteroscedasticity, asymmetry, regularity conditions of the models, out of sample forecast and on portfolio optimization. This study contributed to existing empirical literature by estimating the effect of outliers on the estimates of return and volatility, and their the directon of causationss between oil and the PSX at sectroal level. We applied a recently proposed methodology by Laurent et al. (2016) for the detection and correction of outliers. To quantity the spillovers between these two markets, we estiamted the VAR-AGARCH model because of its capability to treat both returns and volaitlity efficiently.

It is crucial to comprehend the dynamics of oil price shock for the economy. However, financial markets are more closely linked with the oil price fluctuations. Better understanding of the impact require caution to develop the model theoretically, the level of analysis, treatment of the outliers and the most appropaoraite econoemtric mdoel. In the existing literature, we hardly find a study in which the phenomena of return and volatilty and its spillvoer have been intestigated by taking into accout the outleirs in multivariate framework bewteen oil prices and sectors of equity market in case of Pakistan.

Econometric Methodology

Empirical methodology of the paper in detial in this section. Our empirical methodology consist of two parts. In subsection IV.1 the outlier detection and correction procedure is discussed in detail. The model that was used for estimation of returns and volatility, and their spillover is given in subsection IV.2.

Detection and Correction of Outliers

Number of researchers have shown that the financial data may be affected by contaminated observations (Charles and Darné, 2005; Balke and Fomby, 1994). Such observations are called outliers and have unexpected impact on microeconomic and financial models. Several methods were proposed for detection and correction of outliers in nonlinear models (Franses and Van Dijk, 2000; Hotta and Tsay, 2012; Charles and Darné, 2005; Zhang and King, 2005; Doornik and Ooms, 2005; Sakata and White, 1998; Laurent et al., 2016). This study have used the robust method for detection and correction of outliers that was recently suggested by Laurent et al. (2016). This method is based on the standardization of returns that are scaled through the estimation of their expectation and volatility in a robust way. The proposed test is similar to the non-parametric test that was suggested by and Lee and Mykland (2008) and Andersenet al.(2007). for daily data.

Let the stock returns series $r_t$which is described as $r_t = 100 * [\log(P_t) - \log(P_{t-1})]$, where P_t is closing price at time t and $P_{t-1}$is closing price observed at time $t-1$. The ARMA(p, q)-GARCH(1,1) model is:

$$\Phi(L)(r_t - \mu) = \theta(L)\varepsilon_t \tag{1}$$

$r_t = \mu_t + \varepsilon_t$ (2)
$\varepsilon_t = \sigma_t z_t$ and $z_t \sim N(0,1)$ (3)
$\sigma_t^2 = w + \alpha_1 \varepsilon_{t-1}^2 + \beta_1 \sigma_{t-1}^2$ (4)

where L is the lag operator, $\Phi(L) = 1 - \sum_{i=1}^{p} \Phi_i L^i$ and $\theta(L) = 1 - \sum_{i-1}^{q} \theta_i L^i$ are polynomials of orders p and q, respectively, which represent coefficients of the autoregressive (AR) and moving average (MA) terms (with root outside the unit circle) such that $\mu_t = \mu + \sum_{i=1}^{\infty} \zeta_i \varepsilon_{t-i}$ is the conditional mean of r_t, ζ_i are the coefficients of $\zeta(L) = \Phi^{-1}(L)\theta(L) = 1 + \sum_{i=1}^{\infty} \zeta_i L^i$ and σ_t^2 is the conditional variance of r_t. The terms w, α_1 and β_1 respresent the constant, contribution of own lagged squared past shock and contribution of own past volatility in the current conditional variance of r_t. Consider the return series with an independent additive outlier component $a_t I_t$, with outlier size a_t

$r_t^* = r_t + a_t I_t$ (5)

where r_t^* is the observed series of return and I_t is binary variable taking values 1 in case of outliers at time t and 0 otherwise, and a_t is the size of outlier (negative or positive). It is assumed that a_t and I_t are independent from each other. The model for r_t^* has the property that an outlier $a_t I_t$ does not affect σ_{t+1}^2 and it allows for non-Gaussian fat tailed conditional distribution of r_t^*.

Let us denote $\tilde{\mu}_t$ and $\tilde{\sigma}_t$ as estimates of μ_t and σ_t that are robust to the presence of potential additive outliers $a_t I_t$, estimated using r_t^* not r_t.

$\tilde{J}_t = \frac{r_t^* - \tilde{\mu}_t}{\tilde{\sigma}_t}$ (6)

$\tilde{J}_t$ is the standardized return on day t. If $a_t I_t = 0$ on day t, then $\tilde{J}_t$ follows standard normal distribution asymptotically.

To test the null hypothesis, we have

$H_0: a_t I_t = 0$ for $t = 1, \ldots, T$

Against $H_1: a_t I_t \neq 0$

They proposed to compute $|\tilde{J}_t|$ and reject the null if $|\tilde{J}_t| > g_{T,\lambda}$, where $g_{T,\lambda}$ is the critical value of the test. In case of null hypothesis is rejected, the outlier detection rule is as follows

$\tilde{I}_t = I(|\tilde{J}_t| > g_{T,\lambda})$ (7)

where $I(.)$ is the indicator function, with $\tilde{I}_t = 1$ when an observation is detected as an outlier at time t and 0 otherwise, and critical value $g_{T,\lambda}$ defined as

$g_{T,\lambda} = -\log(-\log(1-\lambda)\, b_T + c_T$ (8)

with $b_T = 1/\sqrt{2\log T}$ and $c_T = (2\log T)^{1/2} - [\log\pi + \log(\log T)/[2(2\log T)^2]$, here T represent the length of time series. Therefore, following equation (8), all the returns for which $|\tilde{J}_t| > k$ are considered as affected by additive outliers. Following the Laurent et al. (2016), $\lambda = 0.5$ was set. Given $\tilde{I}_t$, detected outliers can be corrected form r_t^* using the flowing equation

$\tilde{r}_t = r_t^* - (r_t^* - \tilde{\mu}_t)\, \tilde{I}_t$ (9)

Laurent et al. (2016) have proposed to use robust estimation of $\tilde{\mu}_t$ and $\tilde{\sigma}_t$ based on the BIP[3]-ARMA as suggested by et al. (2009) (MPY hereafter) and the BIP-GARCH(1,1) proposed by Muler and Yohai (2008) (MY hereafter) respectively. The specification of conditional mean and conditional variance are as follows.

$\tilde{\mu}_t = \mu + \sum_{i=1}^{\infty} \tilde{\zeta}_i\, \tilde{\sigma}_{t-i} \omega_{k_\delta}^{MPY}(\tilde{J}_{t-i})$ (10)
$\tilde{\sigma}_t^2 = \omega + \alpha_1 \tilde{\sigma}_{t-1}^2 c_\delta \omega_{k_\delta}^{MPY}(\tilde{J}_{t-1})^2 + \beta_1 \tilde{\sigma}_{t-1}^2$ (11)

3 BIP stand for Bounded Innovation Propagation.

where the function $\omega_{k_\delta}^{MPY}(\tilde{J}_{t-i})$ is the weight function and c_δ a factor ensuring the conditional expectation of the weighted squared unexpected shocks to be the conditional variance of r_t in the absence of jumps.

Econometric Model

The GARCH model of Engle (1982) and Bollerslev (1986), and its different versions have been widely recognized by the researchers. These models have the ability to apprehend the fat tails, volatility clustering, persistence of shocks and other facts of financial time series. These models are generally used to evaluate the forecasting performance (Mohammadi and Su, 2010; Agnolucci, 2009; Kang et al., 2009; Sadorsky, 2006; Cheong, 2009). Many researchers also used these models to estimate value-at-risk (Aloui and Mabrouk, 2010; ; Arouri et al., 2010; Cabedo and Moya, 2003; Sadeghi and Shavvalpour, 2006).

Keeping in view the objective of modelling the returns and volatility spillovers along with examining conditional correlation between different series, multivariate models are more suitable as univariate models do not serve the purpose. VARMA-AGARCH model developed by McAleer et al. (2009), VARMA-GARCH model of Ling and McAleer (2003) and BEKK–MGARCH model developed by Engle and Kroner (1995) are among the candidates to meet the objective of estimating the spillovers and conditional correlation. However, the drawback of BEKK model is the number of parameters, the number of variables increases the parameters increases exponentially which leads to the convergence problem. Further to it, the interpretation of its estimates is also complicated. Therefore, multivariate VAR(k)–GARCH(p,q) model is a better alternative because it also includes CCC-GARCH model of Bollerslev (1990).

There are at least three advantages to use VAR–GARCH model. First, it is less expensive to estimate the parameters through this model keeping in view the fact that it gives more expressive and interpretable estimates of parameters. Second, it allows analysis of volatility spillovers, conditional cross effects and conditional volatility in multivariate framework. Third, the estimated mean and variance equations are more efficient with no complexity of computation. The equation for conditional mean in VAR(1)-GARCH(1,1) model is given below:

$$Y_t = \mu + \Phi Y_{t-1} + \varepsilon_t \tag{12}$$

$$\varepsilon_t = D_t \eta_t \tag{13}$$

The conditional volatility equation is

$$H_t = W + A\vec{\varepsilon}_{t-1} + BH_{t-l} \tag{14}$$

In equation (12), $Y_t = \left(Y_{O,t}, Y_{S,t}\right)'$ and $\varepsilon_t = \left(\varepsilon_{O,t}, \varepsilon_{S,t}\right)'$is a vector of returns and error terms respectively. Where subscript 1 denote oil and 2 denote PSX $\mu = (c_1, c_2)'$is 2×1vector of constant of mean equation and Φ is 2×2 matrix. The elements on diagonal of Φ capture the own past lag effect and off diagonal components quantify the spillover effect. In equation (13), $D_t = \operatorname{diag}\left(\sqrt{h_{O,t}}, \sqrt{h_{S,t}}\right)$ and $\eta_t = \left(\eta_{O,t}, \eta_{S,t}\right)'$ is a sequence of IID random vectors with $E(\eta_t) = 0$, and $Var(\eta_t) = I_t$. In equation (14), $H_t = \left(h_{O,t}, h_{S,t}\right)'$, $\vec{\varepsilon_t} = \left(\epsilon_{O,t}^2, \epsilon_{S,t}^2\right)'$, W vector of constants and A and *B* are (2×2) matrices. The diagonal elements of these matrices capture own lagged shocks and volatility effect respectively and off diagonal elements measures shocks and volatility spillovers respectively.

The VAR-GARCH model assumed that the negative and positive shocks have homogeneous effect on the volatility which may be restrictive. However, this issue has been addressed by McAleer et al. (2009) who VAR–AGARCH model wherein conditional variance is defined as follows:

$$H_t = W + A\vec{\varepsilon}_{t-1} + DI_{t-1}\vec{\varepsilon}_{t-1} + BH_{t-l} \tag{15}$$

D is (2×2) diagonal matrix, and $I_t = \mathrm{diag}(I_{1t}, I_{2t})$ represents indicator function and is given as

$$I_t = \begin{cases} 0, & \varepsilon_{O,t} > 0 \\ 1, & \varepsilon_{S,t} \leq 0 \end{cases} \tag{16}$$

This model embedded GJR model of Glosten et al., (1993). If $D = 0$, It reduces to VAR-GARCH model. When A and $B$are diagonal matrices then it transforms as CCC model developed by Bollerslev (1990). McAleer et al. (2009) have explained statistical as well as structural properties of VARMA-AGARCH model. For stationary and ergodicity of the model, necessary and sufficient conditions are discussed. Equation 15 implies that conditional variance of a market is dependent on lag of shock and lag of volatility of its own market and that of the other market.

The conditional co-variance between oil and stock can be defined as

$$h_{O,S,t} = \rho_{O,S}\sqrt{h_{O,t}}\sqrt{h_{S,t}} \tag{17}$$

$\rho_{O,S}$is constant conditional correlation (CCC).

Log Likelihood function which needs to be maximized wherein the model assumes that data follows normal distribution.

$$l(\theta) = -T\ln(2\pi) - 1/2\sum_{i=1}^{T}(\ln(|H_t| + \varepsilon_t' H_t^{-1}\varepsilon_t) \tag{18}$$

where T represents total number of observations. BFGH method is used to maximize.

Data and Preliminary Analysis

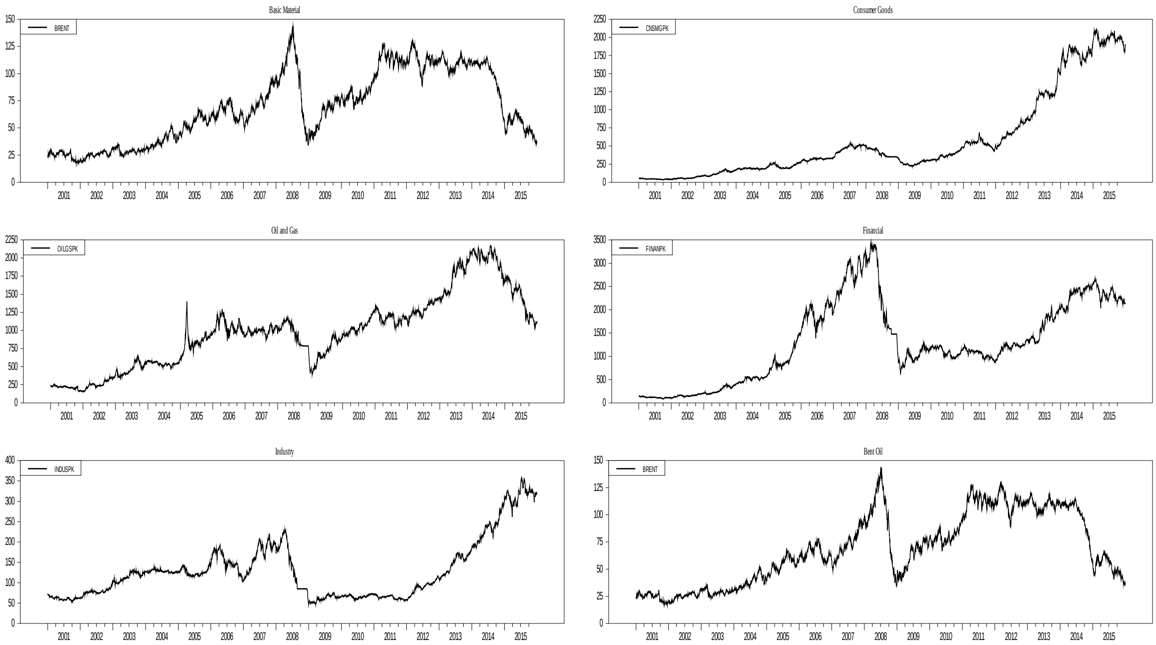
A daily data sampled from 01-01-2001 to 31-12-2015 is used for analysis. All the data has been extracted from DataStream, a data base of Thompson Reuters. World oil prices have proxied by Brent oil price keeping in view that it is leading benchmark of oil price globally. As such, two third of the crude oil, traded globally, is priced based on bent oil. Five major sectors of Pakistan stock exchange (Oil and Gas sector, Industry sector, Basic Material sector, Consumer Goods sector, and Financial sector) have been selected for analysis. DataStream classified listed firms into these sectors according to their business activities. For example, oil and gas sector consist of all upstream, middle stream and downstream oil related firms listed at Pakistan Stock Exchange. Following Jouini (2013) and Khan, (2010), stock prices have been taken in local currency units to avoid any source of distortion in currency whereas data for oil prices is expressed in US dollar. Time series graph of price of Brent oil and sectoral stock indices for the selected time period was charted in in Figure 1. It has been observed from the figure that price of sectoral indices of PSX have different relationship with the oil price.

Table 1: Descriptive Analysis of Unadjusted and Adjusted Returns (%)

Sector	Return	Average	SD	Skewness	Kurtosis	JB-statistics
Basic Material	Unadjusted	0.060	1.59	0.09*	6.64*	7186.13*
	Adjusted	0.072	1.49	-0.04	2.44*	971.94*
Oil and Gas	Unadjusted	0.039	1.74	-0.50*	8.30*	11401.67*
	Adjusted	0.054	1.62	0.02	2.51*	1027.20*
Industry	Unadjusted	0.039	1.54	-0.71*	6.81*	7879.59*
	Adjusted	0.056	1.42	-0.26*	2.82*	1339.66*
Consumer Goods	Unadjusted	0.091	1.31	0.13*	4.13*	2797.12*
	Adjusted	0.087	1.25	0.04	2.15*	756.28*
Financial	Unadjusted	0.069	1.68	-0.16*	2.62*	1133.06*
	Adjusted	0.091	1.64	-0.03	2.43*	960.17*
Brent Oil	Unadjusted	0.013	2.08	-0.12	5.45*	4844.1*
	Adjusted	0.032	2.08	0.09	1.88*	581.0*

*Note: * shows significance at 5% level.*

Figure 1: Time series graph of sectoral stock indices and Bent oil



The daily returns are estimated by taking log difference of two consecutive working days prices using the following formula. $r_t = 100 * \{\log[P_t] - \log[P_{t-1}]\}$, while P_t and P_{t-1}denotes the day end prices at time $t$and $t-1$ respectively. Descriptive statistics of unadjusted and adjusted Brent oil returns and sectoral stock returns are summarized in Table 1, whereas time series properties and unconditional correlation between (UCC) the return series of Brent oil and sectoral indices has been reported in Table 2.

The average percentage return of Brent oil and sectoral indices are positive for both unadjusted and adjusted returns (Table 1). When returns are cleaned for outliers, the average percentage returns increased marginally apart from Consumer Goods sector. Among sectors, maximum increase is observed in financial sector followed by industry sector. The average percentage return of financial sector increased to 0.091 from 0.069. This might be due to presence of large negative outliers in these sectors. The average return value of consumer goods sector reduced to 0.87 from 0.091 give an indication of positive outliers. The standard deviation (SD), which is the crude gage of volatility or associated risk also reduced when returns are adjusted for outliers. The reduction in standard deviation shows that the risk associated with returns is overvalued due to presence of outliers. The presence of outlier have serious effect on the third moment (skewness) of these return series, except Brent oil returns. In the presence of outliers, sectoral returns are skewed either negative or positive. When returns are cleaned for outliers, the coefficient of skewness reduced, and become statistically insignificant apart for Industry sector. These outcomes are in accordance with the outcomes of Charles and Darné (2005) and Carnero et al.(2001) and Charles and Darné (2005). These authors pointed out that the significance of skewness may be due to the outliers in the data. The normality test (JB test) straightaway rejected the normality of unadjusted. The adjusted returns are also non-normal, but they are nearer to normality compared to unadjusted returns, as the values of JB test significantly dropped when correction of outliers were made. Q-statistics is found significant for sectoral stock returns pronounced existence of significant auto correlation. The rejection of null of no autocorrelation provides evidence against the market efficiency. In an efficient market, current returns have no information about the future returns (Chan et al., 1997). All the sector returns (unadjusted and adjusted) are leptokurtic i.e. fat tail and therefore returns are examined for possible existence of conditional heteroscedasticity (ARCH effect).

Table 2: Unconditional Correlation and Time Series Properties of Unadjusted and Adjusted Returns

Sector	Return	Q-Stat	LM-ARCH Test	ADF Test	UC Between Oil and Sectoral Stocks
Basic Material	Unad-	42.82*	101.08*	-25.69*	0.022
	Adjusted	44.35*	135.90*	-25.94*	0.023
Oil and Gas	Unad-	55.88*	44.81*	-22.78*	0.068*
	Adjusted	33.24*	224.67*	-23.52*	0.060*
Industry	Unad-	79.73*	131.63*	-25.05*	0.049*
	Adjusted	58.40*	182.27*	-26.49*	0.029
Consumer Goods	Unad-	68.97*	83.53*	-23.91*	0.010
	Adjusted	69.21*	86.55*	-23.90*	0.017
Financial	Unad-	129.12*	118.04*	-24.35*	0.033*
	Adjusted	129.86*	154.29*	-24.66*	0.036*
Brent Oil	Unad-	10.5	39.4*	-25.8*	
	Adjusted	5.40	53.4*	-25.7*	
*Note: * shows significance at 5% level.*					

LM-ARCH Test strongly rejects the null of homoscedasticity. When returns are corrected for potential outliers the conclusion of LM-ARCH test remains the same. Further, augmented Dicky Fuller test is applied to test the returns series for unit root. Test confirms that unadjusted as well as adjusted series are stationary at level. For data with such characteristics, GARCH family models are more suitable for the return and volatility analysis. Knowing the interlinkages between different markets is important for a portfolio manager as well as for international investors as well. As a first step, association between oil and sectoral stock returns is estimated, which helps investors to apt hedging strategies and construct an efficient investment portfolio get to benefit from diversification. The results reveal that UC between oil and sectoral returns is very low and insignificant between most of the oil-stock pairs. The UC between the returns of Brent oil and sectoral indices is not sensitive to the outlier presence. The estimated values of UC coefficient almost identical to those of unadjusted returns except industry sector. The value of correlation coefficient between oil and gas sector and Brent oil is 0.068 (0.060) for unadjusted (adjusted) returns. The correlation of Brent oil is significant with industry (unadjusted) sector and financial sector. The correlation of oil with these stock ranges between 0.033 to 0.049.

Results and Discussion

Five bivariate VAR (1)-AGARCH (1,1) model have been estimated to look at the return and volatility and their transmission between Brent oil and sectoral returns of Pakistan Stock Exchange. The results of maximum likelihood estimates are presented from Table 3 to Table 7. Finally, adequacy of the model checked through residuals diagnostics. Formal residual tests are applied on standardized residuals for each pair separately. The average optimal portfolio weights and hedge ratios for oil-stock portfolio are presented in Table 8. The estimated values of Log Likelihood (LLH) function of outliers adjusted model are greater than those of unadjusted return model. This shows the superiority of model of adjusted return.

Table 3: VAR (1)-AGARCH (1,1) model estimates for Brent Oil and Basic Material sector

	Unadjusted Returns		Adjusted Returns	
	Oil	Basic Material	Oil	Basic Material
Panel A: Mean Equation				
$C_{1,0}$	-0.001(0.961)		0.002(0.937)	
$\Phi_{1,1}$	-0.006(0.779)		-0.01(0.543)	
$\Phi_{1,2}$	0.024(0.206)		0.018(0.432)	
$C_{2,0}$		0.069(0.000)*		0.086(0.000)*
$\Phi_{2,2}$		0.079(0.000)*		0.076(0.000)*
$\Phi_{2,1}$		0.020(0.003)*		0.019(0.016)*
Panel B: Variance Equation				
$\alpha_{1,0}$	0.000(0.994)		-0.002(0.622)	
$\alpha_{1,1}$	0.019(0.011)*		0.016(0.003)*	
$\alpha_{1,2}$	-0.009(0.341)		0.006(0.460)	
$\beta_{1,1}$	0.954(0.000)*		0.955(0.000)*	
$\beta_{1,2}$	0.840(0.598)		0.716(0.258)	
d_1	0.039(0.001)*		0.042(0.000)*	
$\alpha_{2,0}$		0.098(0.000)*		0.075 (0.000)*
$\alpha_{2,2}$		0.131(0.000)*		0.129(0.000)*
$\alpha_{2,1}$		0.001(0.973)		-0.002(0.871)
$\beta_{2,2}$		0.761(0.000)*		0.798(0.000)*
$\beta_{2,1}$		1.632(0.629)		0.222(0.734)
d_2		0.080(0.010)*		0.075(0.002)*
CCC	0.015(0.57)		0.022(0.199)	
Panel C: Residuals Diagnostic				
Q-Stat	3.293(0.655)	4.976(0.419)	0.980(0.964)	4.909(0.427)
ARCH Test	1.502(0.186)	0.305(0.91)	0.878(0.495)	0.503(0.774)
LLH	-15012		-14595	

*Note: 1 represent Brent Oil and 2 represent Basic Material sector. P-values are reported in in parenthesis. * shows significance at 5% level. Q-Stat and ARCH Test refers the test for autocorrelation and test for conditional heteroscedasticity of lag order 5.*

Conditional Mean

Estimates of conditional mean for unadjusted and adjusted returns of oil-stock pair are given in Panel A of Table 3 to Table 7. The coefficient $\Phi_{1,1}$ and $\Phi_{2,2}$ captures the effect of own past return of oil and stock respectively. Similarly, $\Phi_{2,1}$ ($\Phi_{1,2}$) captures the return transmission from oil (stock) to stock (oil). The return of Brent oil is statistically insignificant in all pairs of oil-stock for unadjusted as well as adjusted returns. The findings suggest that current oil price have no ability to foresee the future price in the short run. The outcomes are coherent with the outcomes of Hamma et al. (2014) but not in lined with Jouini (2013). Whereas, coefficient $\Phi_{2,2}$ is significant for all sectoral stock unadjusted and adjusted returns. The coefficient ($\Phi_{2,2}$) value varies from 0.058 (oil and gas sector) to 0.143 (financial sector) respectively for unadjusted returns. On the other hand, for adjusted returns the coefficient value varies from 0.045 for oil and gas sector to 0.149 for the financial sector. This shows that the estimated values of own lag coefficient are insensitive to the outliers' presence in the data. The constant (intercept) in the conditional mean of sectoral stock are marginally underestimated by the model due the presence of outliers.

Table 4: VAR (1)-AGARCH (1,1) model estimates for Brent Oil and Oil & Gas sector

	Unadjusted Returns		Adjusted Returns	
	Oil	Oil and Gas	Oil	Oil and Gas
Panel A: Mean Equation				
$C_{1,0}$	0.001(0.967)		0.005(0.823)	
$\Phi_{1,1}$	-0.004(0.816)		-0.01(0.632)	
$\Phi_{1,2}$	-0.018(0.402)		-0.027(0.034)*	
$C_{2,0}$		0.045(0.031)		0.053(0.010)*
$\Phi_{2,2}$		0.058(0.006)*		0.045(0.020)*
$\Phi_{2,1}$		0.053(0.000)*		0.042(0.000)*
Panel B: Variance Equation				
$\alpha_{1,0}$	-0.001(0.916)		0.000(0.990)*	
$\alpha_{1,1}$	0.020(0.028)		0.015(0.003)	
$\alpha_{1,2}$	-0.011(0.289)		-0.003(0.756)	
$\beta_{1,1}$	0.951(0.000)*		0.957(0.000)*	
$\beta_{1,2}$	0.332(0.085)		0.255(0.056)	
d_1	0.037(0.001)*		0.041(0.000)*	
$\alpha_{2,0}$		0.076(0.002)*		0.055(0.000)*
$\alpha_{2,2}$		0.120(0.000)*		0.131(0.000)*
$\alpha_{2,1}$		0.03(0.068)		0.0000(0.972)
$\beta_{2,2}$		0.767(0.000)*		0.804(0.000)*
$\beta_{2,1}$		0.906(0.109)		0.304(0.375)
d_2		0.062(0.043)*		0.065(0.002)*
CCC	0.051(0.002)*		0.048(0.003)*	
Panel C: Residuals Diagnostic				
Q-Stat	3.637(0.603)	10.808(0.055)	1.14(0.951)	8.874(0.114)
ARCH Test	2.06(0.067)	1.246(0.285)	0.979(0.429)	1.427(0.211)
LLH	-15272		-14781	
*Note: 1 represent Brent Oil and 2 represent Oil and Gas sector. P-values are reported in in parenthesis. * shows significance at 5% level. Q-Stat and ARCH Test refers the test for autocorrelation and test for conditional heteroscedasticity of lag order 5.*				

Table 5: VAR (1)-AGARCH (1,1) model estimates for Brent Oil and Industry sector

	Unadjusted Returns		Adjusted Returns	
	Oil	Industry	Oil	Industry
Panel A: Mean Equation				
$C_{1,0}$	-0.004(0.893)		0.005(0.861)	
$\Phi_{1,1}$	-0.005(0.771)		-0.011(0.559)	
$\Phi_{1,2}$	-0.005(0.849)		-0.025(0.199)	
$C_{2,0}$		0.06(0.000)*		0.060(0.000)*

$\Phi_{2.2}$		0.079(0.000)*		0.074(0.000)*
$\Phi_{2.1}$		0.010(0.146)		0.009(0.231)
Panel B: Variance Equation				
$\alpha_{1.0}$	-0.015(0.029)*		-0.003(0.469)	
$\alpha_{1.1}$	0.014(0.158)		0.015(0.005)*	
$\alpha_{1,2}$	-0.011(0.305)		-0.012(0.164)	
$\beta_{1.1}$	0.952(0.000)*		0.961(0.000)*	
$\beta_{1.2}$	0.714(0.069)		0.320(0.139)	
d_1	0.04(0.000)*		0.041(0.000)*	
$\alpha_{2.0}$		0.217(0.004)*		0.082(0.000)*
$\alpha_{2.2}$		0.119(0.000)*		0.124(0.000)*
$\alpha_{2.1}$		-0.022(0.336)		-0.014(0.246)
$\beta_{2.2}$		0.691(0.000)*		0.81(0.000)*
$\beta_{2.1}$		0.772(0.309)		-0.133(0.652)
d_2		0.108(0.016)		0.069(0.010)*
CCC	0.038(0.021)*		0.031(0.018)*	
Panel C: Residuals Diagnostic				
Q-Stat	3.54(0.617)	8.563(0.128)	0.997(0.963)	7.586(0.181)
ARCH Test	2.781(0.016)	0.315(0.904)	0.972(0.433)	2.508(0.028)
LLH	-14992		-14388	

*Note: 1 represent Brent Oil and 2 represent Industry sector. P-values are reported in in parenthesis. * shows significance at 5% level. Q-Stat and ARCH Test refers the test for autocorrelation and test for conditional heteroscedasticity of lag order 5.*

Table 6: VAR (1)-AGARCH (1,1) model estimates for Brent Oil and Consumer Goods sector

	Unadjusted Returns		Adjusted Returns	
	Oil	Consumer Goods	Oil	Consumer Goods
Panel A: Mean Equation				
$C_{1.0}$	-0.001(0.967)		0.001(0.960)	
$\Phi_{1.1}$	-0.007(0.710)		-0.012(0.496)	
$\Phi_{1.2}$	0.014(0.569)		0.020(0.470)	
$C_{2.0}$		0.055(0.069)		0.055(0.006)
$\Phi_{2.2}$		0.121(0.000)*		0.125(0.000)*
$\Phi_{2.1}$		0.004(0.632)		0.006(0.247)
Panel B: Variance Equation				
$\alpha_{1.0}$	0.004(0.541)		0.000(0.955)	
$\alpha_{1.1}$	0.018(0.018)*		0.016(0.002)*	
$\alpha_{1,2}$	-0.023(0.108)		-0.004(0.756)	
$\beta_{1.1}$	0.959(0.000)*		0.958(0.000)*	
$\beta_{1.2}$	0.543(0.612)		0.474(0.338)	
d_1	0.041(0.000)*		0.043(0.000)*	
$\alpha_{2.0}$		0.007(0.807)		0.008(0.517)
$\alpha_{2.2}$		0.092(0.008)*		0.090(0.000)*
$\alpha_{2.1}$		-0.007(0.342)		-0.005(0.357)

$\beta_{2.2}$		0.904(0.000)*		0.912(0.000)*
$\beta_{2.1}$		0.003(0.996)		-0.119(0.622)
d_2		0.020(0.178)		0.008(0.575)
CCC	0.011(0.525)		0.020(0.237)	
Panel C: Residuals Diagnostic				
Q-Stat	3.54(0.617)	8.563(0.128)	1.007(0.962)	2.745(0.739)
ARCH Test	2.781(0.016)	0.315(0.904)	0.882(0.492)	1.873(0.096)
LLH	-14389		-14044	
*Note: 1 represent Brent Oil and 2 represent Consumer Goods sector. P-values are reported in in parenthesis. * shows significance at 5% level. Q-Stat and ARCH Test refers the test for autocorrelation and test for conditional heteroscedasticity of lag order 5.*				

Table 7: VAR (1)-AGARCH (1,1) model estimates for Brent Oil and Financial sector

	Unadjusted Returns		Adjusted Returns	
	Oil	Finanical	Oil	Finanical
Panel A: Mean Equation				
$C_{1.0}$	-0.009(0.769)		0.002(0.949)	
$\Phi_{1.1}$	-0.007(0.716)		-0.012(0.494)	
$\Phi_{1.2}$	0.014(0.581)		0.001(0.957)	
$C_{2.0}$		0.067(0.005)*		0.080(0.000)*
$\Phi_{2.2}$		0.143(0.000)*		0.149(0.000)*
$\Phi_{2.1}$		0.039(0.000)*		0.031(0.011)*
Panel B: Variance Equation				
$\alpha_{1.0}$	-0.005(0.391)		-0.001(0.882)	
$\alpha_{1.1}$	0.011(0.078)		0.016(0.002)*	
$\alpha_{1,2}$	-0.028(0.011)*		-0.011(0.236)	
$\beta_{1.1}$	0.961(0.000)*		0.96(0.000)*	
$\beta_{1.2}$	0.718(0.288)		0.278(0.224)	
d_1	0.039(0.000)*		0.04(0.000)*	
$\alpha_{2.0}$		0.106(0.000)*		0.067(0.000)*
$\alpha_{2.2}$		0.084(0.000)*		0.104(0.000)*
$\alpha_{2.1}$		0.016(0.375)		0.015(0.288)
$\beta_{2.2}$		0.748(0.000)*		0.806(0.000)*
$\beta_{2.1}$		2.298(0.344)		0.359(0.541)
d_2		0.132(0.000)*		0.116(0.000)*
CCC	0.022(0.208)		0.030(0.069)	
Panel C: Residuals Diagnostic				
Q-Stat	3.056(0.691)	10.243(0.069)	1.055(0.958)	11.729(0.083)
ARCH Test	1.204(0.304)	0.732(0.599)	1.07(0.375)	0.754(0.583)
LLH	-15278		-14902	
*Note: 1 represent Brent Oil and 2 represent Financial sector. P-values are reported in in parenthesis. * shows significance at 5% level. Q-Stat and ARCH Test refers the test for autocorrelation and test for conditional heteroscedasticity of lag order 5.*				

Turning to return spillovers, the findings suggest no return spillovers from stock to oil. These findings are in line with Jouini (2013) who did not find spillovers from stock to oil in case of Saudi Arabia. However, return spillovers is statistically significant from the Brent oil to the sectoral stocks. When returns are cleaned for outliers, the values of the spillover coefficient ($\Phi_{2,1}$) marginally reduce as compared to those with outlier contaminated returns. These findings are in consistence with Bouri (2015) who found a positive return spillover from oil market to stock market in Lebanon. Conclusions of same type were made by Nath Sahu et al. (2014) for India, Mohanty et al. (2011) for GCC and Narayan and Narayan (2010) for Vietnam.. Our findings contradict with the findings of Driespronget al. (2008), who found significant but negative return spillover from oil market to stock market in case of the United States.

Conditional Variance

In Panel B of Table 3 to Table 7, estimates of conditional volatility both for unadjusted and adjusted returns of Brent oil and stock indices are reported along conditional constant correlation. In the conditional variance of Brent oil, the estimated values of $\alpha_{1,1}$, $\beta_{1,1}$ and $d_1$coefficients are significant for all oil-stock pairs. Estimated values of these coefficients are approximately identical in all pairs. When returns are adjusted for outliers, value of these estimates for Brent oil returns remain the same. This suggests that the presence of outliers does not have any significant effect on the estimates of Brent oil volatility. The result also reveals that the ARCH effect is relatively small (approximately 0.02), whereas, GARCH effect is very large (0.9575). This reveals that future volatility of Brent oil is likely to revolve around its current volatility and shocks will take a long time to vanish. A relatively small ARCH coefficient implies that the volatility of Brent oil does not change very rapidly (Arouri et al. 2011). In response to negative news in the Brent oil market, volatility increases by 4% more than the positive shock of same intensity.

Contrary to Brent oil, in the second moment (volatility) of stock returns the ARCH, GARCH and leverage coefficients varies. The ARCH (GARCH) estimates are 0.131(0.761), 0.120(0.767), 0.191(0.691), 0.092(0.904), and 0.084(0.748) for Basic Material, Oil and Gas, Industry, Consumer Goods, and Financial sectors respectively. These estimates show how the own lagged shock and own past volatility contributes to the volatility of these sectors. Most of the sectoral volatility is jumpy as the coefficient of ARCH is greater than 10% (Alexander, 2008). The Consumer Goods volatility revolves around its past volatility and jumps take time to disappear in the long run. When returns are adjusted for outliers, the coefficient value of sectoral volatility slightly changes for all sectors excluding the Industry sector. The estimates of Industry sector show dramatic variation in comparison to other sectors when returns are cleaned for outliers. Careful comparison of volatility result suggests that the constant is over estimated and the GARCH effect is underestimated by the model due to the outliers. Furthermore, the ARCH effect is overestimated in two out of five sectors and the leverage effect is overvalued in four sectors. Looking at the estimate of volatility for unadjusted returns, there is no spillover of volatility between Brent oil and sectoral stock of PSX. The results regarding volatility spillovers are not sensitive to the presence of outliers. When returns are cleaned for outliers, the results almost remain the same. The CCC between Brent oil and stock is very low and significant for Oil and Gas, and Industry sectors only. Low correlation between Brent oil and sectoral stock provides an opportunity to construct optimal portfolio without lowering the expected returns.

Portfolio weights and hedge ratios

Lastly, in Panel C of Table 3 to Table 7, the result of the diagnostic tests based on the standardized residuals to check the adequacy of the models have been presented. Specifically, the empirical statistics of the Engle (1982) LM-ARCH test for conditional heteroscedasticity and Ljung and

Box (1978) Q-test for autocorrelation are calculated. It has been found that the standardized residuals are no more heteroscedastic and auto-correlated. These results pronounced that the model estimates are reliable since estimated model fulfill the assumptions of standard regression.

The core objective of investors is to curtail risk of his investment without lowering its expected returns. we have VAR (1) AGARCH model (1, 1) to calculate weights of oil and stock and hedge ratios that minizines associated investment risk without lower the expected investment gain.Kroner and Ng (1998) proposed the following formula to find the optimal portfolio weights in oil-stock portfolio.

$$w_{s,t} = \frac{h_{o,t} - h_{so,t}}{h_{o,t} - 2h_{o,s,t} + h_{s,t}} \tag{19}$$

$$w_{s,t} = \begin{cases} 0, & \text{if } w_{s,t} < 0 \\ w_t^s & \text{if } 0 < w_{s,t} < 1 \\ 1, & \text{if } w_{s,t} > 1 \end{cases}$$

The stock weight in stock-oil portfolio is equal to $w_{s,t}$ whereas, the weight of oil in the portfolio is obtained by $1 - w_{s,t}$. Here $h_{o,t}$and $h_{s,t}$ represent the volatilities of oil market returns and respect stock sector returns respectively. The covariance between the returns of oil and a sector is denoted by $h_{o,s,t}$ at time t.

For computing the hedge ratio for the portfolios which may minimize the risk, we follow Kroner and Sultan (1993). It is critical to specify how much a long (buy) in stock sector in 1$ portfolio ben be short (sell) of $\beta_{s,t}$$ in oil market. The hedge ratio has been calculated by employing the following.

$$\beta_{s,t} = \frac{h_{so,t}}{h_{o,t}} \tag{20}$$

The results of optimal weights and hedge ratios are reported in Table 8. The results exhibit that in order to curtail risk, without abating the projected return, investors have to invest more in equities than oil. The value of optimal weights varies between 0.64 (Financial and Oil and Gas sectors) to 0.71 (Consumer Goods). The correction of outliers has no effect on the estimate of optimal weights. The average values of hedge coefficient are very low. $1 long in the stock can be hedged by few cents in short in oil. The hedge values range from 0.04 to 0.07 for unadjusted and adjusted returns.

Table 8: Optimal Weights and Hedge Ratios

	Unadjusted Returns		Adjusted Returns	
	Weights	Hedge Ratio	Weight	Hedge Ratio
Basic Material Sector/Oil	0.66	0.02	0.67	0.03
Oil and Gas Sector /Oil	0.64	0.07	0.65	0.07
Industry Sector /Oil	0.66	0.06	0.68	0.05
Consumer Goods Sector /Oil	0.71	0.02	0.71	0.04
Financial Sector /Oil	0.64	0.03	0.63	0.04

Conclusions

Current study has reviewed the returns and volatility linkages between Brent oil market and Pakistan Stock Exchange at sectoral level, by taking into account outliers in the data. Daily data has been utilized for the time span from January 01, 2001 to December 31, 2015. Laurent et al. (2016) method has been used for the detection and correction of outliers. VAR (1)-AGARCH(1,1) model has been used to estimate the extent to which outliers effect the return and volatility transmission between oil returns and sectors of equity market of Pakistan.

Our result has revealed that presence of outliers has does not make any significant impact on the estimates conditional mean and conditional volatility of Brent oil. These estimates almost remain unchanged when outliers ae corrected. However, the sectoral stock return estimates have been found sensitive to the outliers in the data. Spillovers results show significant return spillovers from Brent oil market to the sectoral stock of PSX. Whereas, no volatility spillover in the short-run as well as long-run has been found. The optimal portfolio weights and hedge ratio have also been calculated. It is observed that average values of optimal portfolio weights and hedge ratio have been found insensitive to the presence of outliers. These statistics suggests that investor may invest more in stocks than oil to maximize his investment returns. Similarly, they can hedge their investment risk by taking long position in stock and short in oil.

Apprehension of the nature of volatility in stock and oil prices is not merely imperative for decision making regarding portfolio diversification and hedging but it is also important in broader perspective i.e. oil industry, finance markets and the economy as a whole. It is imperative for stake holders to know the process of volatility transmission so that they can take right decisions. For the future perspective of research on this topic it may be exciting to outspread current research to permit an investigation of the volatility spillover between stock markets and other man energies items like natural gas and coal.

References

Agnolucci, P. (2009). Volatility in crude oil futures: a comparison of the predictive ability of GARCH and implied volatility models. *Energy Economics, 31*(2), 316-321.

Ågren, M. (2006). Does oil price uncertainty transmit to stock markets? : Working Paper, Department of Economics, Uppsala University.

Alexander, C. (2008). *Market Risk Analysis: Pricing, Hedging and Trading Financial Instruments*: John Wiley & Sons.

Aloui, C., & Mabrouk, S. (2010). Value-at-risk estimations of energy commodities via long-memory, asymmetry and fat-tailed GARCH models. *Energy Policy, 38*(5), 2326-2339.

Andersen, T. G., Bollerslev, T., & Dobrev, D. (2007). No-arbitrage semi-martingale restrictions for continuous-time volatility models subject to leverage effects, jumps and iid noise: Theory and testable distributional implications. *Journal of Econometrics, 138*(1), 125-180.

Ané, T., Ureche-Rangau, L., Gambet, J.-B., & Bouverot, J. (2008). Robust outlier detection for Asia–Pacific stock index returns. *Journal of International Financial Markets, Institutions and Money, 18*(4), 326-343.

Apergis, N., & Miller, S. M. (2009). Do structural oil-market shocks affect stock prices? *Energy Economics, 31*(4), 569-575.

Arouri, M. E. H., Dinh, T. H., & Nguyen, D. K. (2010). Time-varying predictability in crude-oil markets: the case of GCC countries. *Energy Policy, 38*(8), 4371-4380.

Arouri, M. E. H., Jouini, J., & Nguyen, D. K. (2011). Volatility spillovers between oil prices and stock sector returns: implications for portfolio management. *Journal of International Money and Finance, 30*(7), 1387-1405.

Arouri, M. E. H., Jouini, J., & Nguyen, D. K. (2012). On the impacts of oil price fluctuations on European equity markets: Volatility spillover and hedging effectiveness. *Energy Economics, 34*(2), 611-617. doi: 10.1016/j.eneco.2011.08.009

Arouri, M. E. H., Lahiani, A., & Nguyen, D. K. (2011). Return and volatility transmission between world oil prices and stock markets of the GCC countries. *Economic Modelling, 28*(4), 1815-1825. doi: 10.1016/j.econmod.2011.03.012

Bali, R., & Guirguis, H. (2007). Extreme observations and non-normality in ARCH and GARCH. *International Review of Economics & Finance, 16*(3), 332-346.

Balke, N. S., & Fomby, T. B. (1994). Large shocks, small shocks, and economic fluctuations: outliers in macroeconomic time series. *Journal of Applied Econometrics, 9*(2), 181-200.

Bollerslev, T. (1986). Generalized autoregressive conditional heteroskedasticity. *Journal of Econometrics, 31*(3), 307-327.

Bollerslev, T. (1990). Modelling the coherence in short-run nominal exchange rates: a multivariate generalized ARCH model. *The Review of Economics and Statistics, 72*(3), 498-505.

Bouri, E. (2015). Return and volatility linkages between oil prices and the Lebanese stock market in crisis periods. *Energy, 89*, 365-371. doi: 10.1016/j.energy.2015.05.121

Bouri, E., Awartani, B., & Maghyereh, A. (2016). Crude oil prices and sectoral stock returns in Jordan around the Arab uprisings of 2010. *Energy Economics, 56*, 205-214.

Cabedo, J. D., & Moya, I. (2003). Estimating oil price 'Value at Risk'using the historical simulation approach. *Energy Economics, 25*(3), 239-253.

Carnero, M. Á., Peña, D., & Ruiz, E. (2001). Outliers and conditional autoregressive heteroscedasticity in time series: Universidad Carlos III de Madrid. Departamento de Estadística.

Carnero, M. Á., Pérez, A., & Ruiz, E. (2016). Identification of asymmetric conditional heteroscedasticity in the presence of outliers. *SERIEs, 7*(1), 179-201.

Chan, K. C., Gup, B. E., & Pan, M. S. (1997). International stock market efficiency and integration: A study of eighteen nations. *Journal of Business Finance & Accounting, 24*(6), 803-813.

Chang, C.-L., McAleer, M., & Tansuchat, R. (2011). Crude oil hedging strategies using dynamic multivariate GARCH. *Energy Economics, 33*(5), 912-923.

Chang, M. C., Jiang, S., & Lu, K. (2009). Lead-lag relationship between different crude oil markets: evidence from Dubai and Brent. *Middle Eastern Finance and Economics, 5*, 1450-2889.

Charles, A. (2004). Outliers and portfolio optimization. *Banque et Marché*(72), 44–51.

Charles, A. (2008). Forecasting volatility with outliers in GARCH models. *Journal of Forecasting, 27*(7), 551-565.

Charles, A., & Darné, O. (2005). Outliers and GARCH models in financial data. *Economics Letters, 86*(3), 347-352.

Charles, A., & Darné, O. (2014). Volatility persistence in crude oil markets. *Energy Policy, 65*, 729-742.

Cheong, C. W. (2009). Modeling and forecasting crude oil markets using ARCH-type models. *Energy Policy, 37*(6), 2346-2355.

Doornik, J. A., & Ooms, M. (2005). Outlier Detection in GARCH Models.

Driesprong, G., Jacobsen, B., & Maat, B. (2008). Striking oil: Another puzzle? *Journal of Financial Economics, 89*(2), 307-327.

Engle, R. F. (1982). Autoregressive Conditional Heteroscedasticity with Estimates of the Variance of United Kingdom Inflation. *Econometrica, 50*(4), 987-1007.

Engle, R. F., & Kroner, K. F. (1995). Multivariate simultaneous generalized ARCH. *Econometric Theory, 11*(01), 122-150.

Ewing, B. T., & Malik, F. (2016). Volatility spillovers between oil prices and the stock market under structural breaks. *Global Finance Journal, 29*, 12-23. doi: 10.1016/j.gfj.2015.04.008

Ewing, B. T., & Thompson, M. A. (2007). Dynamic cyclical comovements of oil prices with industrial production, consumer prices, unemployment, and stock prices. *Energy Policy*, *35*(11), 5535-5540.

Franses, P., & Van Dijk, D. (2000). Outlier detection in GARCH models. *Econometric Institute Report EI-9926/RV, Erasmus University Rotterdam*.

Franses, P. H., & Ghijsels, H. (1999). Additive Outliers, GARCH and Forecasting Volatility. *International Journal of Forecasting, 15*(1), 1-9.

Franses, P. H., van Dijk, D., & Lucas, A. (1998). Short patches of outliers, ARCH and volatility modeling: Tinbergen Institute.

Gencer, H. G., & Demiralay, S. (2014). Shock and Volatility Spillovers between Oil Prices and Turkish Sector Returns. *International Journal of Economics and Finance, 6*(2), 174.

Glosten, L. R., Jagannathan, R., & Runkle, D. E. (1993). On the relation between the expected value and the volatility of the nominal excess return on stocks. *The Journal of Finance, 48*(5), 1779-1801.

Hamilton, J. D. (1983). Oil and the macroeconomy since World War II. *The Journal of Political Economy*, 228-248.

Hamma, W., Jarboui, A., & Ghorbel, A. (2014). Effect of Oil Price Volatility on Tunisian Stock Market at Sector-level and Effectiveness of Hedging Strategy. *Procedia Economics and Finance, 13*, 109-127.

Hotta, L. K., & Tsay, R. S. (2012). *Outliers in GARCH processes*: CRC Press.

Huang, R. D., Masulis, R. W., & Stoll, H. R. (1996). Energy shocks and financial markets. *Journal of Futures Markets*, *16*(1), 1-27.

Jones, C. M., & Kaul, G. (1996). Oil and the stock markets. *The Journal of Finance, 51*(2), 463-491.

Jouini, J. (2013). Return and volatility interaction between oil prices and stock markets in Saudi Arabia. *Journal of Policy Modeling*, *35*(6), 1124-1144.

Kang, S. H., Kang, S.-M., & Yoon, S.-M. (2009). Forecasting volatility of crude oil markets. *Energy Economics*, *31*(1), 119-125.

Kroner, K. F., & Ng, V. K. (1998). Modeling Asymmetric Comovements of Asset Returns. *Review of Financial Studies, 11*(4), 817-844.

Kroner, K. F., & Sultan, J. (1993). Time-varying distributions and dynamic hedging with foreign currency futures. *Journal of Financial and Quantitative Analysis, 28*(04), 535-551.

Laurent, S., Lecourt, C., & Palm, F. C. (2016). Testing for jumps in conditionally Gaussian ARMA-GARCH models, a robust approach. *Computational Statistics & Data Analysis*, *100*(C), 383-400.

Lee, S. S., & Mykland, P. A. (2008). Jumps in financial markets: A new nonparametric test and jump dynamics. *Review of Financial Studies, 21*(6), 2535-2563.

Ling, S., & McAleer, M. (2003). Asymptotic theory for a vector ARMA-GARCH model. *Econometric Theory*, *19*(2), 280-310.

Ljung, G. M., & Box, G. E. (1978). On a measure of lack of fit in time series models. *Biometrika, 65*(2), 297-303.

Malik, F., & Ewing, B. T. (2009). Volatility transmission between oil prices and equity sector returns. *International Review of Financial Analysis, 18*(3), 95-100. doi: 10.1016/j.irfa.2009.03.003

Malik, F., & Hammoudeh, S. (2007). Shock and volatility transmission in the oil, US and Gulf equity markets. *International Review of Economics & Finance, 16*(3), 357-368. doi: 10.1016/j.iref.2005.05.005

McAleer, M., Hoti, S., & Chan, F. (2009). Structure and asymptotic theory for multivariate asymmetric conditional volatility. *Econometric Reviews, 28*(5), 422-440.

Mohammadi, H., & Su, L. (2010). International evidence on crude oil price dynamics: Applications of ARIMA-GARCH models. *Energy Economics, 32*(5), 1001-1008.

Mohanty, S. K., Nandha, M., Turkistani, A. Q., & Alaitani, M. Y. (2011). Oil price movements and stock market returns: Evidence from Gulf Cooperation Council (GCC) countries. *Global Finance Journal, 22*(1), 42-55.

Muler, N., Peña, D., & Yohai, V. J. (2009). Robust estimation for ARMA models. *The Annals of Statistics, 37*(2), 816-840.

Muler, N., & Yohai, V. J. (2008). Robust estimates for GARCH models. *Journal of Statistical Planning and Inference, 138*(10), 2918-2940.

Narayan, P. K., & Narayan, S. (2010). Modelling the impact of oil prices on Vietnam's stock prices. *Applied Energy, 87*(1), 356-361.

Nath Sahu, T., Bandopadhyay, K., & Mondal, D. (2014). An empirical study on the dynamic relationship between oil prices and Indian stock market. *Managerial Finance, 40*(2), 200-215.

Park, J., & Ratti, R. A. (2008). Oil price shocks and stock markets in the US and 13 European countries. *Energy Economics, 30*(5), 2587-2608.

Sadeghi, M., & Shavvalpour, S. (2006). Energy risk management and value at risk modeling. *Energy Policy, 34*(18), 3367-3373.

Sadorsky, P. (1999). Oil price shocks and stock market activity. *Energy Economics, 21*(5), 449-469.

Sadorsky, P. (2001). Risk factors in stock returns of Canadian oil and gas companies. *Energy Economics, 23*(1), 17-28.

Sadorsky, P. (2006). Modeling and forecasting petroleum futures volatility. *Energy Economics, 28*(4), 467-488.

Sakata, S., & White, H. (1998). High breakdown point conditional dispersion estimation with application to S&P 500 daily returns volatility. *Econometrica, 66*(3), 529-567.

Sattary, A., Sinan Temurlenk, M., Bilgic, A., & Kemal Celik, A. (2014). Volatility Spillovers between World Oil Market and Sectors of BIST. *Asian Social Science, 10*(8). doi: 10.5539/ass.v10n8p156

Tansuchat, R., McAleer, M., & Chang, C. (2009). *Volatility spillovers between crude oil futures returns and oil company stock returns.* Paper presented at the 18th World IMACS/MODSIM congress.

van Dijk, D., Franses, P. H., & Lucas, A. (1999). Testing for ARCH in the presence of additive outliers. *Journal of Applied Econometrics, 14*(5), 539-562.

Verhoeven, P., & McAleer, M. (2000). Modeling Outliers and Extreme Observations for ARMA-GARCH Processes (pp. 1-67): Working Paper, University of Western Australia

Zhang, X., & King, M. L. (2005). Influence diagnostics in generalized autoregressive conditional heteroscedasticity processes. *Journal of Business & Economic Statistics, 23*(1), 118-129.