ENERGY PRICES AND EMERGING MARKET INVESTOR SENTIMENTS

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Abstract: Energy prices are known to have significant impact on equity returns, however its impact on investor sentiments is a new concept. This paper investigates the relationship between investor sentiments and energy price in an emerging market. Current literature deals with the impact of investor sentiments on energy prices however we have tried to investigate the reverse of it. This is because uncertainty in energy prices has major influence on investor confidence which affects their investment decisions in energy sector. Generalized autoregressive conditional heteroscedasticity (GARCH) with its exponential form (E-GARCH) is used to investigate the impact of energy prices on investor sentiments. A sharp increase in investor sentiment index is observed in the first and third quarter of 2006 and 2009 respectively that might be attributed to an increase in economic growth. Results of the study show that energy prices have noticeable effect on investor sentiments in Pakistani equity market. This finding highlights the fact that even in an emerging market like Pakistan with least market efficiency, investors are sensitive to the global energy prices.

Keywords: Investor sentiments, Energy prices, GARCH/EGARCH models.

JEL Classification: G02, P18, P28, P48

Introduction

Energy sector has an important contribution in the development of any country. This development can be either of an economic or financial nature as many¹ studies highlighted the role of energy sector having an impact on both of them. The reason behind this ever increasing role of energy prices is significant industrial development with an increasing level of population. These energy prices have significant impact on its users (i.e. in household, industrial and at various government levels) resulting in an increase in incremental unit cost (Lescaroux and Mignon, 2008). Because of this ever increasing role of energy prices and its impact on its users, any future uncertainty can result in shaken confidence of investors about the performance of any company (Ferderer, 1996;

¹ See Borovkova (2011)

Bernanke, 1983; Pindyck, 1991). Therefore, these energy prices have the ability to formulate or shape the investor sentiments² as some researchers like.

Market sentiment is a set of broad existing feelings of investment community to expected changes in stock pricing in an equity market. This approach is a combination of different technical and fundamental factors including equity pricing history, past economic statistics, temporary seasonal factors, and local or global events. For the purpose of identification and segregation of investors on such behavioral basis, three categories of investors are identified in financial markets. First type consists of rational investors making decisions on the basis of their knowledge. Second category is of emotional investors as they take their decisions based on emotions and selfperceptions (Kuzmina 2010). Last category comprises of noise traders as they make decisions randomly without any perceptions, emotions or basic knowledge. In emerging markets, these noise traders have much influence on financial markets and on the economy³. Emotional aspect of investor's decision making process is well explained in current literature⁴. According to Wang (2009), security prices are well determined by human sentiments rather than any economic variables. According to Baker and Wurgler (2006); Kumar and Lee (2006), investor sentiments are sensitive to shifts in stock prices as investors are pessimistic about future prices of equity. In current literature, only few researchers⁵ found negative relationship between energy prices and investors sentiments. Therefore, this study aims to highlight the effect of energy prices on investor's behavior as this is the first time that relationship between these two variables is investigated, specifically in an emerging Asian market.

Different investors or firms are sensitive to fluctuations in energy prices. Firms depending on energy input extensively in their production processes are more prone to such energy price fluctuations (Industries using oil based products will be much affected by the increase in energy prices). Therefore, strategies for making investments in equipment and machinery with energy efficiency, adoption of novel business procedures, alternative energy sources, or hedging through available financial instruments becomes even more important. Increase in energy prices also leads to investment decline in energy sector. Such investments are also influenced by factors like management strategies and practices of the firm, information availability, investor energy literacy, etc.

Remainder of the paper is structured as follows. Section 2 reviews existing literature. Section 3 presents paper methodology. Section 4 describes data, analysis and discussion. In the end, section 5 concludes our study with future implications.

Review of past literature

In current literature discussion on relationship between energy prices and investor sentiment is limited. According to Zheng (2014), increase in energy prices has negative impact on investor sentiments. Abeysinghe (2001) found negative impact of increase in energy prices on investor sentiments. Baker and Wurgler (2006); Kumar and Lee (2006) worked on investor sentiments and reported its forecasting ability of cross section and aggregate stock returns. According to their

² Abeysinghe (2001) reported negative impact of energy prices on investor's decision making and financing patterns

³ We assume that stock markets are an important and efficient indicator of an economy.

⁴ See Ahmed et al. (2016); Rehman and Shahzad (2016); Rehman (2013); Rehman (2013b)

⁵ See Zheng (2014); Feuerriegel and Neumann (2013)

findings, investor sentiments have the ability to respond to shifts in stock prices. Zheng (2014) applied cross-sectional analysis by controlling effects of liquidity and open interest and found negative relationship between investor sentiments and commodity future returns (i.e. agricultural, energy, metal and livestock). Further analysis revealed the presence of pronounced negative relationship between investor sentiment and commodity futures returns when high conditional volatilities were observed.

Investor sentiments are also sensitive to importing or exporting status of countries. This is because economic growth of energy exporting countries increases due to escalating energy prices whereas the situation is opposite for energy importing countries (Yong et al. 2011; Abeysinghe, 2001). According to Feuerriegel and Neumann (2013), negative news sentiment act as a strong driver of oil and gold market compared to positive sentiment. Differences in oil news response across bullish and bearish market regimes are also observed. According to Feuerriegel et al. (2014), nature of oil news causes price reactions. Borovkova and Mahakena (2015) also found a link between news tone and commodities in gasoline market. Oil price model was used by Lechthaler and Leinert (2012) to check effect of news sentiment on monthly crude oil returns. Simon et al. (2015) found positive influence of news sentiment on noise residual of decomposed crude oil prices. According to Morgan Stanley Capital International (MSCI), energy sector declined to 30% of its value from June 23rd to December 15th, 2015. There is also a negative impact on investment in energy sector due to increasing energy prices. This decrease in investment might be due to the perception that increasing energy prices leads to increase in cost of production (Lardic and Mignon, 2008). In short term, decrease in energy prices result in multibillion-dollar tax cut for oil-importing countries leading to increased consumer spending. This can benefit transport and other related industries with substantial energy costs. In long term, better investment opportunities exist (Capital Group Inc, 2015). Turbulence in financial markets increases fear among different investors for example, SP500 Index went down 5% just before the announcement that US Federal Reserve would be "patient" before increasing interest rates. Borovkova (2011) concluded that forward curve is affected by either a strong or a weak investor sentiment. According to Lucey (2014), there are psychological price barriers in crude oil markets. According to Coleman (2012) and Kaufmann (2011), speculation is an important driver of oil prices (also see Fan and Xu 2011; Cifarelli and Paladino 2010). Deenay et al. (2014) found that sentiment exists in energy market due to speculation and asymmetric information between relevant market participants and oil producers. Short term hedging positions are required by oil producers due to unexpected changes in oil prices. However, oil consumers are less exposed to such unexpected changes. Baker and Wurgler (2006) examined stock markets by using an orthogonalization procedure (also see Lemmon and Portniaguina 2006; Chung et al. 2012). They identified and removed factors from sentiments that could be related with economic cycle⁶. According to Fredriek et al. (2014), uncertainty can be an important variable affecting investment decisions due to a firm inability to easily undo a current investment in case of reversal of energy prices⁷. Investors will react only to energy price changes identified as permanent whereas least probable in responding to any transitory effects (Elder and Serletis, 2010). Investors can use financial instruments e.g. energy derivative to manage risks associated to energy prices (Kaminski, 2004; Clewlow & Strickland, 2000). Ratti et al. (2011) studied relationship between investment decisions and energy prices by using bootstrap GMM. They used data from firms from 15 European economies across 25 sectors. They highlighted

⁶ Also see Baker and Stein (2004); Lemmon and Portniaguina (2006); Baker and Wurgler (2006).

⁷ See Bernanke (1983); Dixit & Pindyck (1994).

negative sensitivity of investments (manufacturing sector showing more sensitivity to the underlying effects) due to energy prices. According to Ratti et al. (2011), FDI leads to higher energy consumption however the impact is stronger for countries other than the developed ones. In high income countries there is bidirectional causation flow, with high energy consumption leading to higher FDI but this is not the case in developing countries. Investors making investment decisions are also influenced by external market forces (international market uncertainty, unsustainable equity markets, strongly regulated capital markets etc.)

Modelling conditional volatility of energy process and investor sentiments

To find the relationship between investor sentiments and energy prices, energy price time series indexes from Arshad et al. (2015) and investor sentiment index from Rehman (2013) is adopted. These two indices were originally estimated for Pakistani market and are relevant for our study. The proxies used for energy price index consist of weighted average of HOBC, high speed diesel oil, gasoline, highlight diesel oil and furnace oil. Expression for energy price index is presented below.

$$EPI_t = \frac{\sum_{i=1}^5 w_i x_i}{\sum_{i=1}^5 w_i} \ 100 \ \cdots \ (1)$$

Investor sentiment index consists of dividend premium, discount on closed end mutual fund, initial public issues per year, share turnover in KSE, first day return on an initial public offering and number of equity shares from total long term debt and equity issuance. Expression for energy price index and investor sentiment index is given in equation (2) and (3) respectively. *Investor Sentiment Index (ISI)* = 0.1873DP + 0.4672KSET - 0.3960CEMFD + 0.5109NOIPO + 0.3956FDRIPO + 0.4151EQSHARE⁸ -- (2)

Energy Price Index (EPI) = $0.044HOBC + 0.10GO + 0.41HSDO + 0.006LDO + 0.44FO^9 - (3)$

After taking log of equation (2) and (3), relationship between these two series is analyzed using GARCH (p,q) and ERAGCH (p,q) models presented by Bollerslev (1986) and Nelson (1991) respectively. With these models, conditional mean and variance equation are calculated. Unit root test is applied to check level of stationarity for both series and results revealed the presence of unit root at level.

⁸ DP stands for dividend premium, KSET indicates KSE equity turnover, CEMFD denotes discount on closed end mutual fund, NOIPO represents Initial public issues per year, FDRIPO represents First day IPO return and EQSHARE represent stock share in total long term debt and equity issuance.

⁹ LDO = Light Diesel Oil, HOBC= High Octane Blending Component, GO= Gasoline, HSDO = High Speed Diesel Oil, FO = Furnace Oil.



Figure 1: Return on Energy Prices and Investor Sentiments

Mean equation representing both models is presented below. $SI_t = \psi + \theta EP_t + \varepsilon_t --- (4)$

We include another alternative mean equation by introducing GARCH in our mean (GARCH-M) equation. The resultant equation is presented below.

 $SI_t = \psi + \theta EP_t + \xi \sigma_t^2 + \varepsilon_t \dots (5)$

Expression for the GARCH and GARCH-M variance equation is

$$\sigma_t^2 = \omega + \alpha_1 \varepsilon_{t-p}^2 + \alpha_2 \sigma_{t-q}^2 - (6)$$

Variance equation for E-GARCH and EGARCH-M model is mentioned below.

$$\log(\sigma_t^2) = \omega + \left(\left| \frac{\varepsilon_{t-p}}{\sigma_{t-q}} \right| - \sqrt{\frac{2}{n}} \right) + \gamma \frac{\varepsilon_{t-1}}{\sigma_{t-1}} + \beta \log(\sigma_{t-q}^2) - (7)$$

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Figure 2: The quantile-quantile plot

EGARCH models measures oscillatory behavior in conditional variance as β as a coefficient can either have negative or positive values. Value of β allows for evaluation of shocks persistence. According to Nelson (1991), value of β less than 1 ensures ergodicity and stationarity of EGARCH (p,q). This model allows to test for nature of shocks (measured by the parameter γ) if they have symmetric or asymmetric effect on volatility. Positive value of γ implies that positive shocks results in more volatile behavior than negative shocks.





Figure 3: Conditional Standard Deviations

Parameter α gives the magnitude of conditional shocks and its impact on conditional variance (ω represent constant term). Robust values of standard errors proposed by Bollerslev and Wooldridge (1992) are used to get robust inference. We use maximum likelihood process for our model estimation following the assumption of normal distribution of errors. Lag length for p and q is selected using Schwartz Bayesian Criteria (Schwartz, 1978).

Results

Data

Monthly data for investor sentiments¹⁰ and energy prices¹¹ are plotted in Figure 1. For energy prices, sharp decline is visible in 2008-09 due to global financial crises. Similar decline is also present for sentiment index, however magnitude is comparatively small. A sharp increase in investor sentiment index is also present in 2006 and 2009. Reasons for such sharp increase might be attributed to increasing economic growth and reemergence of financial market especially after the global financial crisis.

¹⁰ Data on investor sentiments is collected from Securities and Exchange Commission of Pakistan (SECP), Bloomberg and Karachi Stock Exchange (KSE).

¹¹ Data on energy prices is collected from World Development Indicators, Economic Survey of Pakistan and Pakistan Energy Year Book.

	Sentiment Index	Energy price index
Mean	4.9834	4.6001
Std. dev.	1.4381	0.5249
Skew.	0.3595	0.1472
Kurt.	1.3959	1.7544
J-B	16.995	9.0010
	(0.0002)	(0.0110)
Unconditional correlation		
Sentiment Index	1	-
Energy Price Index	0.7623	-
Auto-correlation values		
(lag-length, k)	Q-stat. (prob. values)	Q-stat. (prob. value)
1	125.83	129.41
	(0.0000)	(0.0000)
15	1127.4	1391.3
	(0.0000)	(0.0000)
36	1589.0	2075.6
	(0.0000)	(0.0000)

Investor sentiments and energy prices exhibit volatility and volatility clustering, however the magnitude of investor sentiment is higher especially after the global financial crisis. Descriptive statistics for both indices are presented in Table 1. Mean and variance of investor sentiment index is comparatively greater than energy price index (Figure 3.1). Higher volatility clustering for investor sentiment is also consistent with higher recorded values of standard deviations. However, the quantile-quantile distribution for both series shown in Figure 2 suggests sharing of similar distribution at smaller level. Ljung-Box Q statistics tests null hypothesis with lag length of 1, 15 and 36. For both series, null hypothesis of no autocorrelation is rejected suggesting evidence of autocorrelation.

Unit root test statistics

In this section, stationarity property of both series is checked before application of GARCH models. Initially, OLS was applied before the application of GARCH technique to check the ARCH effect of residuals. The presence of ACRH effect implies presence of spurious regression and application of models correcting ARCH effect is justified. Table 2

ADF test statistics

Results			
Sentiment Index Energy price index			
With trend	Without trend	With trend	Without trend
-2.8264[0]	-1.9547[0]	-4.6764[0]	-0.2500[0]
-8.8832*[1]	-8.9018*[1]	-4.7183*[1]	-4.7108*[1]

ADF test statistic tests for null hypothesis of unit root both with and without time trend tests is applied. Optimal lag length was selected following a maximum of 8 lags. This lag length was obtained using Schwartz Information Criteria (SIC). Unit root test statistics are highlighted in Table 2. Both series are not stationary at level but stationary at first difference.

Table 3

Diagnostic tests (Ordinary Least Squares-OLS)

Tests	Ordinary Least Squares
Autoregressive CH, LM(1)	716.086
	(0.0000)
Autoregressive CH, LM(6)	132.53
	(0.0000)
Autoregressive CH, LM(12)	68.165
	(0.0000)
Autoregressive CH, LM(36)	26.454
	(0.0000)

Bivariate OLS is applied on mean equation to check the suitability of regression as a proper tool of analysis. The ARCH effect is tested after the application of regression. It is clear that all values are significant at 99 percent confidence interval. It means that null hypothesis (i.e. no ARCH effect) is rejected for all lag values. Therefore application of OLS is not suitable due to presence of ARCH effect and therefore GARCH/EGARCH models are used.

GARCH Application

Schwartz Information Criteria (SIC) highlighted values of p=1, q=1. Values in Table 4 shows the results of GARCH (1,1) and GARCH-M (1,1) models suggesting that 10 percent change in oil prices changes financial market investor sentiments by almost 19 percent. Similarly, results of GARCH-M (1,1) model suggests that 10 percent change in oil prices induces change of almost 15 percent in investor sentiments. However, variance in GARCH-M (1,1) model is not significant indicating no role of investor sentiment volatility on its own value.

Table 4

Generalized ARCH (1,1) estimation

Mean equation -3,7084* -2,0441* (0.1137) (0.1578) θ 1.8267* 1.4206* (0.0269) (0.0378) ξ - 0.3978 (0.0269) (0.0378) ξ - 0.013 $Variance equation$ 0 0.0013 0.0003 (0.0013) (0.0005) (0.0013) (0.0005) α 0.8278^* 1.0840^* (0.3018) (0.2626) (0.2890^*) α 0.3523^* 0.2890^* (0.0983) (0.0743) (0.000) Q -statistics (1) 74.494 49.089 (0.000) (0.000) (0.000) Q -statistics (15) 163.00 115.75 (0.000) (0.000) (0.000) Q -statistics (36) 170.96 134.60 (0.000) (0.000) (0.000) Q -statistics (36) (0.0167) (0.1083) $Autoregressive CH, LM (15)$ <t< th=""><th></th><th>Generalized ARCH (1,1)</th><th>Generalized ARCH-M (1,1)</th></t<>		Generalized ARCH (1,1)	Generalized ARCH-M (1,1)
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Q-statistics (15) 163.00 115.75 (0.000) (0.000) Q-statistics (36) 170.96 134.60 (0.000) (0.000) Autoregressive CH, LM (1) 5.8854 2.6147 (0.0167) (0.1083) Autoregressive CH, LM (15) 1.4415 1.1769 (0.1428) (0.3019) Autoregressive CH, LM (36) 1.0924 0.6958 (0.3748) (0.8773)		(0.000)	(0.000)
(0.000) (0.000) Q-statistics (36) 170.96 134.60 (0.000) (0.000) Autoregressive CH, LM (1) 5.8854 2.6147 (0.0167) (0.1083) Autoregressive CH, LM (15) 1.4415 1.1769 (0.1428) (0.3019) Autoregressive CH, LM (36) 1.0924 0.6958 (0.3748) (0.8773)	Q-statistics (15)	163.00	115.75
Q-statistics (36) 170.96 134.60 (0.000) (0.000) Autoregressive CH, LM (1) 5.8854 2.6147 (0.0167) (0.1083) Autoregressive CH, LM (15) 1.4415 1.1769 (0.1428) (0.3019) Autoregressive CH, LM (36) 1.0924 0.6958 (0.3748) (0.8773)		(0.000)	(0.000)
(0.000) (0.000) Autoregressive CH, LM (1) 5.8854 2.6147 (0.0167) (0.1083) Autoregressive CH, LM (15) 1.4415 1.1769 (0.1428) (0.3019) Autoregressive CH, LM (36) 1.0924 0.6958 (0.3748) (0.8773)	Q-statistics (36)	170.96	134.60
Autoregressive CH, LM (1) 5.8854 2.6147 (0.0167) (0.1083) Autoregressive CH, LM (15) 1.4415 1.1769 (0.1428) (0.3019) Autoregressive CH, LM (36) 1.0924 0.6958 (0.3748) (0.8773)		(0.000)	(0.000)
(0.0167) (0.1083) Autoregressive CH, LM (15) 1.4415 1.1769 (0.1428) (0.3019) Autoregressive CH, LM (36) 1.0924 0.6958 (0.3748) (0.8773)	Autoregressive CH, LM (1)	5.8854	2.6147
Autoregressive CH, LM (15) 1.4415 1.1769 (0.1428) (0.3019) Autoregressive CH, LM (36) 1.0924 0.6958 (0.3748) (0.8773)		(0.0167)	(0.1083)
(0.1428) (0.3019) Autoregressive CH, LM (36) 1.0924 0.6958 (0.3748) (0.8773)	Autoregressive CH, LM (15)	1.4415	1.1769
Autoregressive CH, LM (36) 1.0924 0.6958 (0.3748) (0.8773)		(0.1428)	(0.3019)
(0.3748) (0.8773)	Autoregressive CH, LM (36)	1.0924	0.6958
		(0.3748)	(0.8773)

Moving towards the variance equation, we can see that values for both the ARCH and generalized ARCH are statistically significant. We also applied residual based diagnostic tests i.e. Engle ARCH test and Ljung Box test statistic to check autocorrelation. These tests are also reported in Table 4. Q statistics reports autocorrelation in both models however there is no ARCH effect in GARCH (1,1) and GARCH-M (1,1) models.

EGARCH Application

Results of EGARCH (1,1) and EGARCH-M (1,1) models are presented in second and third columns of Table 5. Values in both models highlight increasing values for investor sentiments due to energy prices. An increase of 10 percent change in oil prices induces a change of almost 18 percent in investor sentiments according to EGARCH (1,1) model and 15 percent according to EGARCH-M (1,1) model. According to the variance equation, γ shows asymmetric value and is statistically significant for EGARCH-M (1,1) model and insignificant for EGARCH (1,1) model.

Table 5

E-GARCH(1,1) model

	EGARCH (1,1)	EGARCH-M (1,1)
Mean		
Ψ	-3.6791*	-2.3721*
	(0.0863)	(0.1557)
θ	1.8197*	1.4973
	(0.0210)	(0.0373)
ξ	-	0.3856
		(0.0118)
Variance		
ω	-1.3946*	-1.3942*
	(0.3078)	(0.1681)
α	1.5189*	1.5647*
	(0.4614)	(0.2473)
γ	-0.1552	-0.2973**
	(0.2382)	(0.1752)
β	0.9458*	0.9308*
	(0.0506)	(0.0289)
Diagnostics		
Q-statistics (1)	67.530	42.207

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	(0.000)	(0.000)
Q-statistics (15)	168.98	117.41
	(0.000)	(0.000)
Q-statistics (36)	171.28	130.04
	(0.000)	(0.000)
Autoregressive CH, LM(1)	0.2014	0.1209
	(0.6543)	(0.7286)
Autoregressive CH, LM(15)	0.8639	1.6119
	(0.6055)	(0.0836)
Autoregressive CH, LM(36)	1.3163	0.9211
	(0.1718)	(0.5979)

These values show that shocks to investor sentiments have asymmetric effects according to exponential GARCH (1,1) model. The negative sign with coefficient value implies that negative shocks induce more volatility in investor sentiments than positive shocks. Term measuring volatility persistence is β and statistically significant for both models. Higher coefficient value shows that shocks to investor sentiments have noticeable effect. Last panel of Table 5 presents diagnostic checks. Q statistics at lag positions of 1, 15 and 36 has not rejected null hypothesis of no autocorrelation for EGARCH (1,1) and EGARCH-M (1,1) model. ARCH effect for both models have no ARCH effect suggesting that the model is well behaved.

Conclusion and Discussion

We examine the presence of existing relationship between investor sentiments and energy prices for Pakistan over the span of 11 years monthly data from 2001-2011. The application of GARCH and exponential GARCH is used to check the impact of energy prices on investor sentiments. Results of the study show that energy prices have noticeable effect on investor sentiments in Pakistani financial market. A 10 percent change in energy prices induces an increase of 20 percent in investor sentiments. This indicates the effect that energy prices have on the minds of investment community. Even in an emerging market like Pakistan, investors are quite sensitive about global energy prices and its spillover in local market. It also shows that energy price sensitivity is a global phenomenon and can have effects on any economy regardless of its economic and financial development status.

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