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Price Discovery in Crude Oil Markets: Intraday Volatility Interactions between Crude Oil Futures and Energy Exchange Traded Funds

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ABSTRACT

In this paper, we investigate the integration of financial derivatives with crude oil prices. The novelty of our paper is its focus on the impact of energy related exchange related funds (exchange traded funds [ETFs]) on crude oil prices. In the previous studies this relationship was studied only between equity markets and crude oil markets however, ETFs are now a crucial tool for information dispersion. First, we examine price discovery of crude oil prices by utilizing causality tests. We conclude that price discovery does not flow consistently from the futures to spot markets or vice versa. The causality is mostly bi-directional from futures market to spot markets for crude oil. Coherently, futures market drives energy-based ETFs market however cross market information increases the explanation power of volatility. Secondly, we tested whether there is any interaction between price volatility, the crude oil prices and energy-based ETF markets by employing EGARCH models using 5-min data. We used three different volatility measures which are square return, Garman and Klass (1980), Rogers and Satchell (1991) and Rogers et al. (1994).

Keywords: Oil Prices, Time Series, Volatility, Exchange Traded Funds, EGARCH, Granger Causality, News Impact Curves

JEL Classifications: C58, G13, Q02

1. INTRODUCTION

Exchange traded funds (ETFs) exist in United States since 1993 and in Europe since 1999. They typically track an index and so are an alternative to an index mutual fund for investors who are risk averse. ETFs are created by institutional investors. Since they can be bought or sold at any time of the day ETFs have advantage over open ended mutual funds¹. They can be shorted in the same way that share in any stock are shorted. This ensures that the shares in the ETF trade at a price very close to the fund's net asset valued. In the past three years 90% of the net fund

flows in the US have been in to passive funds². According to the forecasts, growing investment market will overtake the active fund industry in the US by 2024³. ETFs have achieved a greater penetration in the US compared to Europe. 185 of mutual fund

1 An open-end fund is a type of mutual fund that does not have restrictions on the amount of shares the fund can issue. The majority of mutual funds are open-end, providing investors with a useful and convenient investing vehicle (www.investopedia.com).

2 Source: ETFGI LLP, an equity research firm which provides proprietary research on the global exchange traded fund and exchange traded products industry. The firm publishes industry data and statistics and identifies trends within the industry on a global, regional and country basis. It offers specialist reports, bespoke data analysis and governance services on all aspects of this industry. The firm provides monthly report on global and regional industry trends. It offers monthly newsletter outlining the global asset movements within the industry.

3 The shift towards cheap index-trading funds which account for nearly a third of assets under management in the US has already become a big challenge for active asset manager. The trend towards passive funds will mean less money invested in the active managers.

assets are invested in ETFs⁴ in the US while it is below 4% in Europe.

Hedging demand in energy sector increases due to the high volatility in energy prices. Moreover, energy commodity's inflation-hedged nature and its low correlation with stocks and bonds makes it a strong investment alternative for fund managers. ETFs that track energy commodities or energy related companies enabled investors to invest in or hedge in energy sector as well as providing diversified portfolio strategies. ETFs are highly liquid and enables investors to expose quickly to the underlying index. Not necessarily you have to buy a "basket" of securities to replicate and track the index when you invest in ETFs. Also non-synchronous trading⁵ problems associated with stock index price data are not a problem in case you make your investment via ETFs.

Energy companies use derivatives very intensely and create a significant volume and flow in the markets. Many energy products are traded in both the OTC market and on exchanges.

1.1. Crude Oil Derivatives

A number of oil futures option contracts are traded on The New York Mercantile Exchange (NYMEX) and the International Petroleum Exchange (IPE). Crude oil contracts, which are underlined by one of the most important commodities in the world, are settled sometimes in cash and sometimes they require settlement by physical delivery. For example, the Brent crude oil futures traded on NYMEX requires physical delivery. In both cases the amount of oil underlying one contract is 1000 barrels. NYMEX also trades popular contracts on two refined products Heating oil and gasoline. In both cases one contract is for the delivery of 42,000 gallons. In the last decade exchange-traded contracts became also popular in the markets.

Energy producers are exposed to risks which have mainly two components such as; price risk and volume risk. When there is a fluctuation in crude oil production prices adapt themselves to the new market equilibrium however, there is a not perfect relationship between the two.

1.1.2. Modeling energy prices

A realistic model for an energy and other commodity prices should incorporate both mean reversion and volatility. One possible model is:

$$\partial \ln S = [\theta(t) - \alpha \ln S] \partial_t + \sigma \partial_z \quad (1)$$

where S is the energy price, and α and σ are constant parameters and can be estimated from historical data. The parameters α and

σ are different for different sources of energy. For crude oil, the reversion rate parameter α in equation [1] is about 0.5 and the volatility parameter σ is about 20%. The $\theta(t)$ term captures seasonality and trends (Hull, 2005).

Define:

Y : Profit for a month

P : Average energy prices for the month

T : Relevant temperature variable (HDD or CDD) for month.

An energy producer can use historical data to obtain a best-fit linear regression relationship of the form

$$Y = \alpha + \beta P + \gamma T + \epsilon \quad (2)$$

Where ϵ is the error term. The energy producer can then hedge risks for the month by taking a position $\beta P - \beta$ in energy forwards or futures and a position of $-\gamma$ in weather forwards or futures (Hull, 2005).

1.2. Other Commodity Investment Vehicles

Commodity exposure can be achieved through other means than direct investment in commodities or commodity derivatives. One of the recent popular investment tools for commodities is ETFs.

ETFs may be suitable for investors who can buy only equity shares or seek simplicity of trading them. ETFs may invest in commodities or futures of commodities (often specializing in a particular sector) seeking to track the performance of the commodities. There are also index-linked ETFs.

Managers of portfolios invest in either passively or actively in the financial markets. Passive managers assume that markets are efficient and focus on beta drivers of return. Beta, a measure of sensitivity relative to a particular market index is a measure of systemic risk. Beta driven portfolios are positioned to efficiently take on market risk.

Holding highly diversified portfolios without spending too much efforts or other resources like using investment bank reports or individual asset valuation is the main essence of Passive Management. Obviously it is beneficial and more efficient to follow passive strategies if markets are perfect and prices reflect all available information to all investor universe without any discrimination. Portfolios of real estate investment trusts (REITs) and commodity ETFs may provide beta exposure to a category of alternative investments.

2. LITERATURE REVIEW

Tang and Xu (2016) examine nine leveraged ETFs tied to oil. Five are based on oil stocks and the other four use commodity futures to track the price of oil itself. Their main findings are; stock based ETFs are much more correlated with the stock market than with oil prices, whereas the reverse is true for crude oil ETFs.

Ivanov (2011) found that the introduction of ETFs to the markets has shifted price discovery for gold and silver to the ETF market

4 The survey known as ETFGI's treasure map, shows that about 256\$ bn of ETF assets are also held by Wells Fargo, Morgan Stanley, Goldman Sachs, UBS, JP Morgan, BMO and Citigroup, which control massive positions due to their dual roles as market makers and investment advisers. ETFG's report identifies ETF holdings of at least 1\$ bn at four hedge funds: Passport Capital, Citadel, Two Sigma and Parallax Volatility Advisers. Citadel is a well-known-ETF market maker. (FTfm, September, 2017).

5 Different stocks have different trading frequencies. Although even for a single stock the trading frequency varies from hour to hour and from day to day, we often analyze a return series in a fixed time interval such as daily.

however the oil market does not verge to this development yet and has price discovery still occurs dominantly in the futures market for crude oil commodities. Chang and Ke (2014) examined the relationship between flows and return for 5 ETFs in the US energy sector in which they concluded that energy returns and subsequent energy ETF flows have a negative relationship.

Bernstein (2009) claims that high fluctuations in the underlying assets and futures markets of commodities happen due to the demand for ETFs. Garbade and Silber (1993) found that the futures commodity market drives the cash commodities market in price discovery. According to their findings 75% of the information for wheat, corn and orange juice is determined by the futures market.

Choi et al. (2015) applied a Granger-causality test for the OPEC crude oil spot market and the crack spread⁶ futures market by splitting their dataset in to three sub-sample periods the pre-crisis, crisis, and post-crisis periods. Due to their findings, a change in the lead-lag relationship between the oil spot and crack spread futures markets is observed over the sub-sample periods. In particular, a unidirectional relationship from the crude oil spot market to crack spread futures was detected for the pre-crisis and crisis periods. One interesting point is that this relationship between the two markets was reversed in the post-crisis period. This is also a good example why the essence of all the recent commodity prices and commodity derivative prices should be applied in different subsets for a huge dataset. In the last decade financial markets experienced various crisis and many different investment or hedging vehicles were introduced to the markets. Especially for major commodities which is both physically and financially traded so heavily in the market the direction and the level of interaction may change frequently based on mentioned developments. Also since we have experienced a recent oil price crisis in the last 4 years it is quite crucial to explore specific information for this period. At that point rather than introducing a new econometrical model or quantitative approach, updating the existing literature empowered by new dataset supported by new assets and their datasets will propose interesting results.

However, Quan (1992) states that the spot market for crude oil always leads the futures market and the crude oil futures market does not play an important role in price discovery. Schwarz and Szakmary (1994) start their study by criticizing Quant and concludes that light sweet crude oil futures dominate in price discovery relative to its deliverable spot instruments.

Consequently, cross-market volatility transmission become an important topic introducing a significant result between the crude oil price and the US stock market to the existing literature. The content of the literature works are quite rich which focus on the volatility interaction between the crude oil and equity markets in the Gulf Cooperation Council (GCC countries). Arouri et al., 2011

point out that if there is a risk for oil prices, international portfolio management highly depends on the level of return and volatility spillovers between world oil prices and GCC stock markets. Malik and Hammoudeh (2007) used daily data between 14 February 1994 and 25 December 2001 and concluded that there is a significant interaction between second moments of the US equity and global oil markets. The study focused on the transmission of volatility and shocks among the markets of oil, US equity and each of the three oil-rich Gulf countries. Awartani and Maghyereh (2013) exploit a new spillover directional measure proposed by Diebold and Yilmaz (2009; 2012) to analyze the dynamic spillover of return and volatility between oil and equities and find that the information flow from oil returns and volatilities to the GCC stock exchanges is important, while the flow in the opposite direction is marginal. Jouini and Harrathi (2014) revisited the empirical issue related to the shock and volatility transmissions among Gulf stock and oil markets based on the asymmetric BEKK-GARCH process developed by Kroner and Ng (1998).

In our study we will merge these two literature scopes and investigate the interaction and price discovery direction of crude oil and energy based ETFs.

3. METHODOLOGY

Since commodity forward prices are based upon expected spot prices and expected spot prices are dependent upon expected supply and demand forces, forward prices for commodities need to be constant from period to period. In this context future contracts are essentially forward contracts that are arranged by an organized exchange. Since they usually require a margin deposit and this position is marked to market daily. ETFs appeared as a more flexible investment tools for asset managers.

However, there is one important topic which is how closely can the ETFs track their underlying assets. Briefly, Tracking Error (TE) is the variance between the return on the underlying asset and the return of the EFT (Frino and Gallagher, 2001). Another important measure is the price deviation (PD) of the ETF which is the variance between the log price of the underlying asset and the log price of the ETF.

ETFs are designed to have a price which is based on a proportion of the underlying asset like index mutual funds. Since spot, ETF and future prices have unit roots and pricing deviations are stationary we will go for a cointegration test following Engle-Granger cointegration methodology as discussed in Enders (2004).

In this context, first we will employ Johansen Cointegration Test and the results are presented in Tables 1 and 2. Secondly, based on causality model results we will include additional information from bid-ask spread and trading volume and tests whether adding it will improve the quality of price volatility predictability.

Bid-ask spreads corresponds to the difference between prices at which one can buy (ask) and sell (bids). The bid-ask spread represents part of the profit of a market maker who posts bid-ask prices at which they are willing to buy and sell. Bid-ask prices

⁶ Crack spread refers to the overall pricing difference between a barrel of crude oil and the petroleum products refined from it. The "crack" being referred to is an industry term for breaking apart crude oil into the component products, including gases like propane, heating fuel, gasoline, light distillates like jet fuel, intermediate distillates like diesel fuel and heavy distillates like grease.

differentiate from location to location, market to market and generally increase based on the contract size.

As a matter of fact, a liquid market is often defined as a market in which one can make transactions in significant volumes without affecting the prices or widening the bid-ask spreads. In this context the bid-ask spreads range differentiation between WTI and IYE exhibited in Figure 1 is quite coherent with the market principles. Bid-ask spread range is quite tighter compared to ETF spread range which is a much more liquid market than ETF market.

We propose three specifications of EGARCH (1,1) models, as Narayan et al. (2016) did, which use different levels of trading information in estimating volatility of crude oil and ETF markets.

These three models are as follows:

$$\text{Model 1: } \begin{cases} V_t^{WTI} = \beta_0^{WTI} + \beta_1^{WTI} V_{t-1}^{WTI} + \varepsilon_t \\ V_t^{IYE} = \beta_0^{IYE} + \beta_1^{IYE} V_{t-1}^{IYE} + \varepsilon_t \end{cases} \quad (3)$$

$$\varepsilon \rightarrow N(0, \sigma^2)$$

$$\ln(0, \sigma^2) = \omega + \gamma \frac{\varepsilon_{t-1}}{\sigma_{t-1}} + \alpha \left| \frac{\varepsilon_{t-1}}{\sigma_{t-1}} \right| + \beta \ln(\sigma_{t-1}^2)$$

$$\text{Model 2: } \begin{cases} V_t^{WTI} = \beta_0^{WTI} + \beta_1^{WTI} V_{t-1}^{WTI} + \beta_2^{WTI} BAS_{t-1}^{WTI} + \\ \beta_3^{WTI} ASKSIZE_{t-1}^{WTI} + \varepsilon_t \\ V_t^{IYE} = \beta_0^{IYE} + \beta_1^{IYE} V_{t-1}^{IYE} + \beta_2^{IYE} BAS_{t-1}^{IYE} + \\ \beta_3^{IYE} ASKSIZE_{t-1}^{IYE} + \varepsilon_t \end{cases}$$

$$\varepsilon \rightarrow N(0, \sigma^2)$$

$$\ln(0, \sigma^2) = \omega + \gamma \frac{\varepsilon_{t-1}}{\sigma_{t-1}} + \alpha \left| \frac{\varepsilon_{t-1}}{\sigma_{t-1}} \right| + \beta \ln(\sigma_{t-1}^2) \quad (4)$$

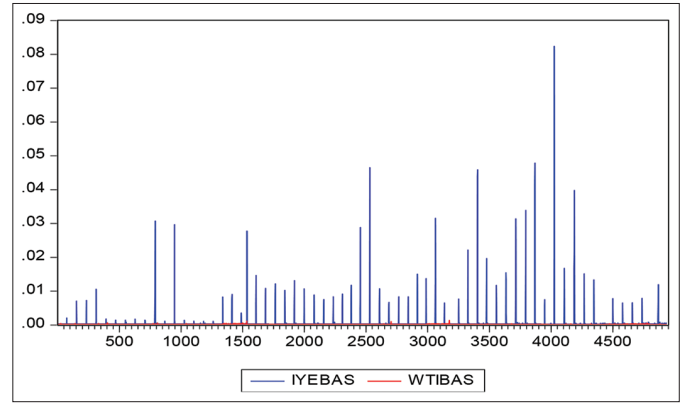
$$\text{Model 3: } \begin{cases} V_t^{WTI} = \beta_0^{WTI} + \beta_1^{WTI} V_{t-1}^{WTI} + \beta_2^{WTI} BAS_{t-1}^{WTI} + \\ \beta_3^{WTI} ASKSIZE_{t-1}^{WTI} + \beta_4^{IYE} V_{t-1}^{IYE} + \beta_5^{IYE} BAS_{t-1}^{IYE} + \\ \beta_6^{IYE} ASKSIZE_{t-1}^{IYE} + \varepsilon_t \\ V_t^{IYE} = \beta_0^{IYE} + \beta_1^{IYE} V_{t-1}^{IYE} + \beta_2^{IYE} BAS_{t-1}^{IYE} + \\ \beta_3^{IYE} ASKSIZE_{t-1}^{IYE} + \beta_4^{IYE} V_{t-1}^{WTI} + \beta_5^{WTI} BAS_{t-1}^{WTI} + \\ \beta_6^{WTI} ASKSIZE_{t-1}^{WTI} + \varepsilon_t \end{cases}$$

$$\varepsilon \rightarrow N(0, \sigma^2)$$

$$\ln(0, \sigma^2) = \omega + \gamma \frac{\varepsilon_{t-1}}{\sigma_{t-1}} + \alpha \left| \frac{\varepsilon_{t-1}}{\sigma_{t-1}} \right| + \beta \ln(\sigma_{t-1}^2) \quad (5)$$

where BAS_{IYE} , $ASKSIZE_{IYE}$, $BIDSIZE_{IYE}$ and V_{IYE} are the bid-ask spread, trading volume, and the price volatility of the ETF market, respectively, while BAS_{WTI} , $ASKSIZE_{WTI}$ and V_{WTI} are the corresponding variables for the crude oil market ε_t is the residual from mean equation, and σ_t^2 is the conditional variance generated from the model.

Figure 1: WTI and IYE bid-ask spread graph



4. ECONOMETRIC DATA AND DESCRIPTION

Our dataset contains daily Brent crude oil spot prices (BRT), Brent crude oil futures prices (LCOc1), WTI crude oil spot prices (WTC), WTI crude oil futures prices (CLc1) and ETF funds such as Power Shares DB Commodity Index Tracking Fund (DBC), Barclays Bank iPath Commodity ETF (BCM), First Trust Global Tactical Commodity Strategy (FTGC.O), iShares US Energy ETF (IYE⁷), Vanguard Energy Index Fund (VDE) and Energy Select Sector SPDR Fund (XLE) over the period from September 15, 2008 to October 2, 2017 (Table 3). All the data is provided from Thompson Reuters Eikon. In the first part, for causality tests we will analyze the data in two sub-periods. First, we will use whole data period from September 15, 2008 to October 2, 2017 which we will emphasize as “Global Financial Crisis Period” in our models. We will also analyze the oil prices in a second sub-sample namely “oil price crisis” which includes the data between November 1, 2014 and October 2, 2017.

In the second part we will employ a 5-min interval intraday time series data for daily Brent crude oil spot prices (BRT), Brent crude oil futures prices (LCOc1) which are used as a proxies for crude oil markets and ETF funds such as Power Shares DB Commodity Index Tracking Fund (DBC), Barclays Bank iPath Commodity ETF (BCM), First Trust Global Tactical Commodity Strategy (FTGC.O), iShares US Energy ETF (IYE), and Energy Select Sector SPDR Fund (XLE) which are used as proxies for the energy derivatives market.

The data was collected for the period from August 23, 2017 to November 23, 2017. For both the data samples, the intraday tick data is used to form a 5-min interval time series, consisting of bid-ask spread (BAS), high price, low price, open price, close price and total number of shares traded in the 5-min interval.

In this context our paper employs the EGARCH models to remedy the presence of heteroskedasticity of variables as noted in Table 4.

The bid-ask spread (BAS) is calculated as $BAS = \frac{ASK - BID}{(ASK + BID) / 2}$

7 The First stock-based regular energy ETF (ticker: IYE, tracking the DJUSEN Energy Stocks Index) was introduced to the market in June 2000, and the first futures-based energy ETF (ticker: USO, tracking the USCRWTIC Crude Oil Index) was launched in April of 2006. These two earliest energy ETFs both have over US\$1 billion in AUM, representing the two largest and most popular energy ETFs.

Table 1: Granger causality tests for brent spot prices, brent futures and selected ETFs

Null hypothesis	Global financial crisis period		Oil crisis period	
	F-statistic	Prob.	F-statistic	Prob.
LNBRD does not Granger Cause LNBCM	1.52	0.05	1.04	0.41
LNBCM does not Granger Cause LNBRD	1.15	0.28	0.83	0.70
LNLCOC1 does not Granger Cause LNBRD	4.58	0.00	2.42	0.00
LNBRD does not Granger Cause LNLCOC1	0.91	0.59	1.32	0.14
LNDBC does not Granger Cause LNBRD	1.32	0.13	0.48	0.98
LNBRD does not Granger Cause LNDBC	5.63	0.00	2.01	0.00
LNIYE does not Granger Cause LNBRD	1.02	0.43	0.51	0.98
LNBRD does not Granger Cause LNIYE	4.46	0.00	1.79	0.01
LVNDE does not Granger Cause LNBRD	1.06	0.39	0.52	0.97
LNBRD does not Granger Cause LVNDE	4.59	0.00	1.81	0.01
LNFTGCO does not Granger Cause LNBRD	0.80	0.74	0.58	0.95
LNBRD does not Granger Cause LNFTGCO	1.26	0.18	1.66	0.03
LNXLLE does not Granger Cause LNBRD	1.04	0.40	0.52	0.97
LNBRD does not Granger Cause LNXLLE	4.38	0.00	1.84	0.01
Observations	2312		728	
Lags	24		24	

Table 2: Granger causality tests for WTI spot prices, WTI futures and selected ETFs

Null hypothesis	Global financial crisis period		Oil crisis period	
	F-statistic	Prob.	F-statistic	Prob.
LNWTC does not granger cause LNBCM	1.12	0.31	1.55	0.05
LNBCM does not granger cause LNWTC	1.07	0.38	0.66	0.89
LNWTC does not granger cause LNCLC1	0.75	0.80	1.83	0.01
LNCLC1 does not granger cause LNWTC	0.62	0.92	1.62	0.03
LNWTC does not granger cause LNDBC	0.84	0.69	1.74	0.02
LNDBC does not granger cause LNWTC	1.35	0.12	1.85	0.01
LNWTC does not granger cause LNIYE	0.67	0.88	1.53	0.05
LNIYE does not granger cause LNWTC	2.10	0.00	1.91	0.01
LNWTC does not granger cause LVNDE	0.69	0.86	1.65	0.03
LVNDE does not granger cause LNWTC	2.49	0.00	2.16	0.00
LNWTC does not granger cause LNFTGCO	2.15	0.00	1.47	0.07
LNFTGCO does not granger cause LNWTC	0.94	0.55	1.97	0.00
LNXLLE does not granger cause LNWTC	2.31	0.00	2.20	0.00
LNWTC does not granger cause LNXLLE	0.67	0.89	1.70	0.02
Observations	2312		728	
Lags	24		24	

while the trading volume (ASKSIZE) is measured as the natural log of trading volume in each 5-min interval. In our study, the intraday volatility (V) is calculated using three approaches, as below

$$V_t^{SQ} = \ln \left(\frac{CP_t}{CP_{t-1}} \right)^2 \quad (6)$$

$$V_t^{GK} = \frac{0.5 [\ln(HP_t) - \ln(LP_t)]^2 - [2 \ln(2) - 1] [\ln(CP_t) - \ln(OP_t)]^2}{2} \quad (7)$$

$$V_t^R = \frac{[\ln(HP_t) - \ln(OP_t)][\ln(HP_t) - \ln(CP_t)] + [\ln(LP_t) - \ln(OP_t)][\ln(LP_t) - \ln(CP_t)]}{2} \quad (8)$$

where VO_t^{SQ} , VO_t^{GK} , and VO_t^{RS} are the square return, volatility proposed by Garman and Klass (1980) which derives an estimator that has a minimum-variance among the class of unbiased estimators which are quadratic in $HP(t)$, $CP(t)$ and $LP(t)$, and volatility proposed by Rogers and Satchell (1991) and Rogers

et al. (1994), respectively. HP , LP , CP , and OP represent the high price, low price, closing price, and opening price, respectively.

5. APPLICATIONS AND FINDINGS

With TE and PD we capture the fact that ETFs track both return and price level of the underlying for all three sub-periods. Table 5 provides the results for tracking errors and pricing deviations of the commodities ETFs. The calculations are based on the global financial crisis period.

The tracking errors of funds are economically small and statistically not different from zero as suggested by the high P-values (close to one for DBCM, FTGCO and DBC). However, the pricing deviations are statistically different from zero with P-values close to zero. The pricing deviation of DBC is approximately 20 cents showing on average the price of the ETF is lower than the price of spot crude prices. The pricing deviation is a 10 cents negative for VDE suggesting that it is trading on average above the spot price of oil.

It is not an unexpected result that there is an insignificant tracking error but a significant pricing deviation since ETFs are designed to have a price which is based on a proportion of the underlying asset. In this context pricing deviation can be a measure of the success of the ETF manager. Investors in the futures based or stock based ETFs should be aware that the underlying stock index may not well represent the energy commodity.

Coherently, we applied Granger Causality tests to crude oil spot prices, futures and selected energy ETFs to figure out

the direction of the price discovery in crude oil commodity markets. We tested separately both for Brent and WTI⁸ prices and concluded that for Brent spot prices still drive futures prices and ETFs as exhibited in Table 1, however, the

8 Backmeier and Griffin (2006) examine daily prices for five different crude oils-WTI, Brent, Alaska, North Slope, Dubai Fateh and Indonesian Arun and conclude that the world oil markets are tightly linked to each other. Hammoudeh et al. 2008 also found cointegration in four oil benchmark prices-WTI, Brent, Dubai and Maya.

Table 3: Model dataset descriptions

#	Variable	Description	Frequency
1	RBRT	Returns of Brent crude oil spot prices	Daily
2	RLCOc1	Returns of Brent crude oil futures prices	Daily
3	RWTC	Returns of WTI crude oil spot prices	Daily
4	RCLc1	Returns of WTI crude oil futures prices	Daily
5	RDBC	Returns of PowerShares DB Commodity Index Tracking Fund	Daily
6	RBCM	Returns of Barclays Bank iPath Commodity ETF	Daily
7	RFTGC.O	Returns of First Trust Global Tactical Commodity Strategy	Daily
8	RIYE	Returns of iShares US Energy ETF	Daily
9	RVDE	Returns of Vanguard Energy Index Fund	Daily
10	RXLE	Returns of Energy Select Sector SPDR Fund	Daily
11	TEDBC	Tracking Error for PowerShares DB Commodity Index Tracking Fund	Daily
12	TEBCM	Tracking Error for Barclays Bank iPath Commodity ETF	Daily
13	TEFTGC.O	Tracking Error for First Trust Global Tactical Commodity Strategy	Daily
14	TEIYE	Tracking Error for iShares US Energy ETF	Daily
15	TEVDE	Tracking Error for Vanguard Energy Index Fund	Daily
16	TEXLE	Tracking Error for Energy Select Sector SPDR Fund	Daily
17	PDDBC	Pricing Differences for PowerShares DB Commodity Index Tracking Fund	Daily
18	PDBCM	Pricing Differences for Barclays Bank iPath Commodity ETF	Daily
19	PDFTGC.O	Pricing Differences for First Trust Global Tactical Commodity Strategy	Daily
20	PDIYE	Pricing Differences for iShares US Energy ETF	Daily
21	PDVDE	Pricing Differences for Vanguard Energy Index Fund	Daily
22	PDXLE	Pricing Differences for Energy Select Sector SPDR Fund	Daily

Table 4: Descriptive statistics-1

Brent oil	Mean	SD	JB	ADF	ARCH (1)	ARCH (12)	LB (1)	LB (12)
BAS _{Brent}	0.000229	0.000129	0.00	0.00	0.00	0.00	0.00	0.00
ASKSIZE _{Brent*}	9.452084	2.207209	0.00	0.00	0.00	0.00	0.00	0.00
BIDSIZE _{Brent*}	9.441165	2.200334	0.00	0.00	0.00	0.00	0.00	0.00
VSQ _{Brent}	0.000023	0.001689	0.00	0.00	0.00	0.00	0.00	0.00
VRS _{Brent}	0.000001	0.000001	0.00	0.00	0.02	0.26	0.00	0.00
VSGK _{Brent}	0.000001	0.000001	0.00	0.00	0.00	0.00	0.00	0.00
WTI	Mean	SD	JB	ADF	ARCH (1)	ARCH (12)	LB (1)	LB (12)
BAS _{WTI}	0.000204	0.00005	0.00	0.00	0.99	1.00	0.442	1.00
ASKSIZE _{WTI}	11.65384	1.97314	0.00	0.00	0.00	0.00	0.00	0.00
BIDSIZE _{WTI}	11.65932	1.97573	0.00	0.00	0.00	0.00	0.00	0.00
VSQ _{WTI}	0.00002	0.00161	0.00	0.00	0.00	0.00	0.721	0.037
VRS _{WTI}	0.00000	0.00000	0.00	0.00	0.00	0.00	0.00	0.00
VSGK _{WTI}	0.00000	0.00000	0.00	0.00	0.00	0.00	0.00	0.00
iShares	Mean	SD	JB	ADF	ARCH (1)	ARCH (12)	LB (1)	LB (12)
BAS _{IYE}	0.000576	0.002642	0.00	0.00	0.00	0.00	0.00	0.00
ASKSIZE _{IYE}	15.51631	1.119692	0.00	0.00	0.00	0.00	0.00	0.00
BIDSIZE _{IYE}	15.58425	1.106352	0.00	0.00	0.00	0.00	0.00	0.00
VSQ _{IYE}	0.000030	0.001450	0.00	0.00	0.00	0.00	0.00	0.00
VRS _{IYE}	0.000000	0.000001	0.00	0.00	0.83	0.00	0.00	0.00
VSGK _{IYE}	0.000000	0.000001	0.00	0.00	0.76	0.00	0.00	0.00

This table reports the correlations between bid-ask spread, trading volume, the price volatility of the ETF market/crude oil market and each of three measures of price volatility including square return, Garman and Klass (1980) volatility, and the volatility proposed by Rogers and Satchell (1991) and Rogers et al. (1994). BAS_{IYE}, ASKSIZE_{IYE}, BIDSIZE_{IYE} and V_{IYE} are the bid-ask spread, trading volume, and the price volatility of the ETF market, respectively, while BAS_{BRENT}, BAS_{WTI}, ASKSIZE_{BRENT}, ASKSIZE_{WTI}, BIDSIZE_{BRENT}, BIDSIZE_{WTI}, V_{BRENT} and V_{WTI} are the corresponding variables for the crude oil market. In the fourth column of each panel, the table reports the P-value from the Jarque-Bera (JB) test, for which the null hypothesis is a joint hypothesis of the skewness and the excess kurtosis being zero. The P-values of the ADF test, which examines the null hypothesis of a unit root, are in the fifth column. The last four columns contain the P-values for the test of autoregressive conditional heteroskedasticity (ARCH) and the Ljung-Box (LB) test for the autocorrelation at lag 1 and lag 12. In addition Bid and Ask sizes are calculated as natural logarithm of trading volumes

direction of causality is bi-directional for WTI⁹ as exhibited in Table 2.

Overall results represented in Tables 6 and 7 confirming that negative relationship between bid-ask spread and price volatility and a positive relationship between trading volumes and price volatility. It is also interesting that trading volumes of WTI has positive relationship with ETF price volatility which is also consistent with our Granger Causality test results in Table 2. In the oil prices period we found out that there is a

two-way direction causality between WTI¹⁰ Futures and IYE ETF¹¹ prices.

Initially we display the impulse response functions using the oil price changes of WTI (Figure 2). Crude oil spot price returns (WTC) has a positive and persistent impact of the linear specification of oil future price returns with PowerShares DB Commodity Index Tracking Fund (DBC) returns which has a

9 The study results of Elder et al. (2014) strongly support the leading role of WTI incorporating new information in to oil prices. Our causality test results in Table 7 also supports this. Global Financial Crisis period and Oil Crisis Period results differ from each other which makes us to make the comment that WTI can catch the current dynamics of the cross-markets.

10 Elder et al. (2014) found that WTI maintains a dominant role in price discovery relative to Brent with an estimated information share in excess of 80%.

11 Blackrock's iShares ETF arm registered record inflows of 140\$ bn, beating the 130\$ bn gathered in 2015. The ETF is composed of Exxon Mobil, Chevron Corp, Schlumberger, Conoco Phillips and others 24,0%, 15,3%, 5,9% and 4,2% as of 27.11.2017 respectively.

Table 5: Descriptive statistics-2

	PDBCM	PDFTGCO	PDDBC	PDXLE	PDVDE	PDIYE
Mean	0.206	0.164	0.518	0.041	-0.109	0.275
Median	0.247	0.000	0.537	0.097	-0.050	0.338
Maximum	0.462	0.589	0.650	0.279	0.110	0.518
Minimum	0.000	0.000	0.000	-0.303	-0.441	-0.052
Std. dev.	0.178	0.204	0.128	0.144	0.137	0.149
Skewness	-0.065	0.584	-2.580	-0.463	-0.548	-0.429
Kurtosis	1.335	1.625	10.744	1.818	1.859	1.761
t-test (mean=0)	0.000	0.000	0.000	0.000	0.000	0.000
Observations	2,336	2,336	2,336	2,336	2,336	2,336
	TEBCM	TEFTGCO	TEDBC	TEXLE	TEVDE	TEIYE
Mean	0.000	0.000	0.000	0.000	0.000	0.000
Median	0.000	0.000	0.000	0.000	0.000	0.000
Maximum	0.180	0.180	0.145	0.166	0.124	0.132
Minimum	-0.167	-0.167	-0.142	-0.188	-0.186	-0.221
Std. dev.	0.020	0.021	0.018	0.022	0.022	0.022
Skewness	0.129	0.167	0.143	-0.471	-0.574	-0.797
Kurtosis	10.686	9.660	9.766	11.903	10.931	13.481
t-test (mean=0)	0.972	0.821	0.997	0.504	0.525	0.518
Observations	2,336	2,336	2,336	2,336	2,336	2,336

Table 6: Correlations and probability-Panel A

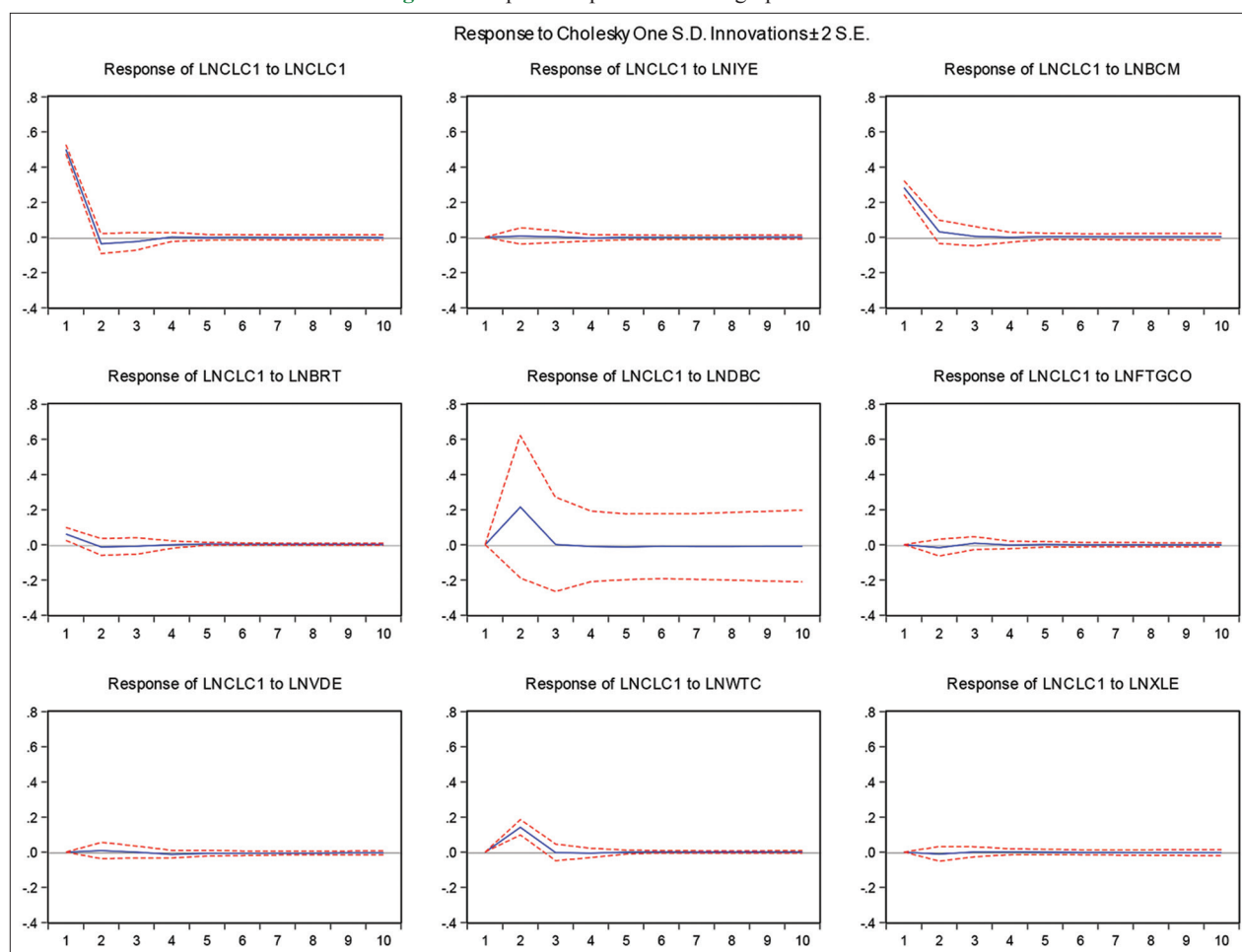
Panel A	Square return		Garman and Klass volatility		Roger and Satchel volatility	
	Brent	iShares	Brent	iShares	Brent	iShares
BAS _{Brent}	-0.015	-0.009	-0.014	-0.021	-0.015	-0.017
	0.30	0.54	0.32	0.14	0.30	0.24
BAS _{IYE}	-0.008	0.000	-0.053	-0.007	-0.056	-0.015
	0.59	0.99	0.00	0.61	0.00	0.30
ASKSIZE _{Brent*}	0.015	0.008	0.356	0.099	0.354	0.083
	0.28	0.56	0.00	0.00	0.00	0.00
BIDSIZ _{Brent*}	0.000	-0.001	0.367	0.103	0.364	0.086
	0.99	0.97	0.00	0.00	0.00	0.00
ASKSIZE _{IYE*}	0.015	-0.003	0.179	0.012	0.179	-0.005
	0.29	0.83	0.00	0.41	0.00	0.70
BIDSIZ _{IYE*}	0.000	-0.001	0.193	0.012	0.194	0.012
	0.99	0.97	0.00	0.41	0.00	0.40
V _{Brent}	1.000	0.418	1.000	0.158	1.000	0.131
	0.00	0.00	0.00	0.00	0.00	0.00
V _{IYE}	0.418	1.000	0.158	1.000	0.131	1.000
	0.00	0.00	0.00	0.00	0.00	0.00

This table reports the correlations between bid-ask spread, trading volume, the price volatility of the ETF market/crude oil market and each of three measures of price volatility including square return, Garman and Klass (1980) volatility, and the volatility proposed by Rogers and Satchell (1991) and Rogers et al. (1994). BASIYE, ASKSIZEIYE, BIDSIZIYE and VIYE are the bid-ask spread, trading volume, and the price volatility of the ETF market, respectively, while BASBRENT, BASWTI, ASKIZEBRENT, ASKSIZEBRENT, BIDSIZBRENT, BIDSIZWTI, VBRENT and VWTI are the corresponding variables for the crude oil market. Panel A reports the results when the crude oil market is proxied by the Brent Futures while the results when using the WTI are in Panel B. In addition Bid and Ask sizes are calculated as natural logarithm of trading volumes

Table 7: Correlations and probability-panel B

Panel B	Square return		Garman and Klass volatility		Roger and Satchel volatility	
	WTI	iShares	WTI	iShares	WTI	iShares
BAS_{WTI}^*	0.015	0.015	0.046	-0.006	0.043	-0.003
	0.30	0.28	0.00	0.66	0.00	0.82
BAS_{IYE}^*	-0.010	-0.001	-0.049	-0.009	-0.052	-0.016
	0.49	0.95	0.00	0.52	0.00	0.26
$ASKSIZE_{WTI}^*$	0.010	0.011	0.486	0.162	0.481	0.140
	0.49	0.42	0.00	0.00	0.00	0.00
$BIDSIZE_{WTI}^*$	0.000	0.009	0.487	0.159	0.483	0.137
	0.99	0.52	0.00	0.00	0.00	0.00
$ASKSIZE_{IYE}^*$	0.014	-0.002	0.166	-0.002	0.166	-0.004
	0.32	0.90	0.00	0.88	0.00	0.77
$BIDSIZE_{IYE}^*$	-0.002	-0.003	0.176	0.013	0.177	0.013
	0.90	0.85	0.00	0.35	0.00	0.35
V_{WTI}	1.000	0.456	1.000	0.177	1.000	0.151
	0.00	0.00	0.00	0.00	0.00	0.00
V_{IYE}	0.456	1.000	0.177	1.000	0.151	1.000
	0.00	0.00	0.00	0.00	0.00	0.00

This table reports the correlations between bid-ask spread, trading volume, the price volatility of the ETF market/crude oil market and each of three measures of price volatility including square return, Garman and Klass (1980) volatility, and the volatility proposed by Rogers and Satchell (1991) and Rogers et al. (1994). BAS_{IYE}^* , $ASKSIZE_{IYE}^*$, $BIDSIZE_{IYE}^*$ and V_{IYE} are the bid-ask spread, trading volume, and the price volatility of the ETF market, respectively, while BAS_{BRENT}^* , BAS_{WTI}^* , $ASKSIZE_{BRENT}^*$, $ASKSIZE_{WTI}^*$, $BIDSIZE_{BRENT}^*$, $BIDSIZE_{WTI}^*$, V_{BRENT} and V_{WTI} are the corresponding variables for the crude oil market. Panel A reports the results when the crude oil market is proxied by the Brent Futures while the results when using the WTI are in Panel B. In addition Bid and Ask sizes are calculated as natural logarithm of trading volumes

Figure 2: Impulse response function graphs for WTI

temporary positive impact on WTI. Responses of WTI to other ETF impulses are quite weak which guides us to the conclusion that price discovery is still in crude oil futures market and energy

ETFs in our dataset do not drive the oil prices. Volatility in both crude oil and ETF market react irregularly to their bid-ask spread, trade volumes and three different volatility measures namely;

square return, German and Klass, Roger and Satchel¹². Also not all the correlation coefficients between variables are all statistically significant across all volatility measures.

Price volatility of Brent futures is negatively correlated with ETF bid-ask spread and correlation coefficients statistically significant for GK and RS volatility measures. When we test the same relationship replacing Brent futures with WTI we find out that the price volatility for GK and RS volatility measures are statistically significant for both WTI's own bid-ask spread and ETF bid-ask spread. Furthermore, price volatility is positively correlated with its own bid-ask spread while it is negatively ETF bid-ask spread. This result is consistent with Ivanov (2011) since oil markets have price discovery. All the volatility for WTI and IYE are exhibited in Figure 3. Above row represents square returns, GK and RS volatilities for WTI respectively while in the row below square returns, GK and RS volatilities for IYE.

12 In this context our results differ from our reference paper Narayan et al. (2016). In their paper they concluded that volatility, bid-ask spread and trading volumes are positively correlated both with their own markets and cross markets.

In 1973, Clark suggested with the mixture of distributions hypothesis a positive relationship between trading volume and price volatility. The price volatility with GK and RS measures are statistically significant and positively correlated with their own trading volumes for both WTI and Brent. However, correlation coefficients of ETF price volatility is not statistically significant for its own trading volume while it is positively correlated and statistically significant for Brent and WTI trading volumes. The correlation coefficients vary and in the range of 0,086 and 0,367 in the case of Brent while the range is 0,137 and 0,487 when using WTI.

The most obvious difference of energy commodities is that they cannot be treated as purely financial assets. The underlying assets of energy commodity derivatives re inputs to production process (especially crude oil), and/or consumption goods and this explains why many models developed to analyze financial markets may break down in the case of energy related assets are studied.

In Table 8, Model 1 (eq. 3) estimates the price volatility of the crude oil or ETF market based on its own lagged volatility, while Model

Figure 3: Five minute volatilities using SQ, GK and RS for WTI and IYE

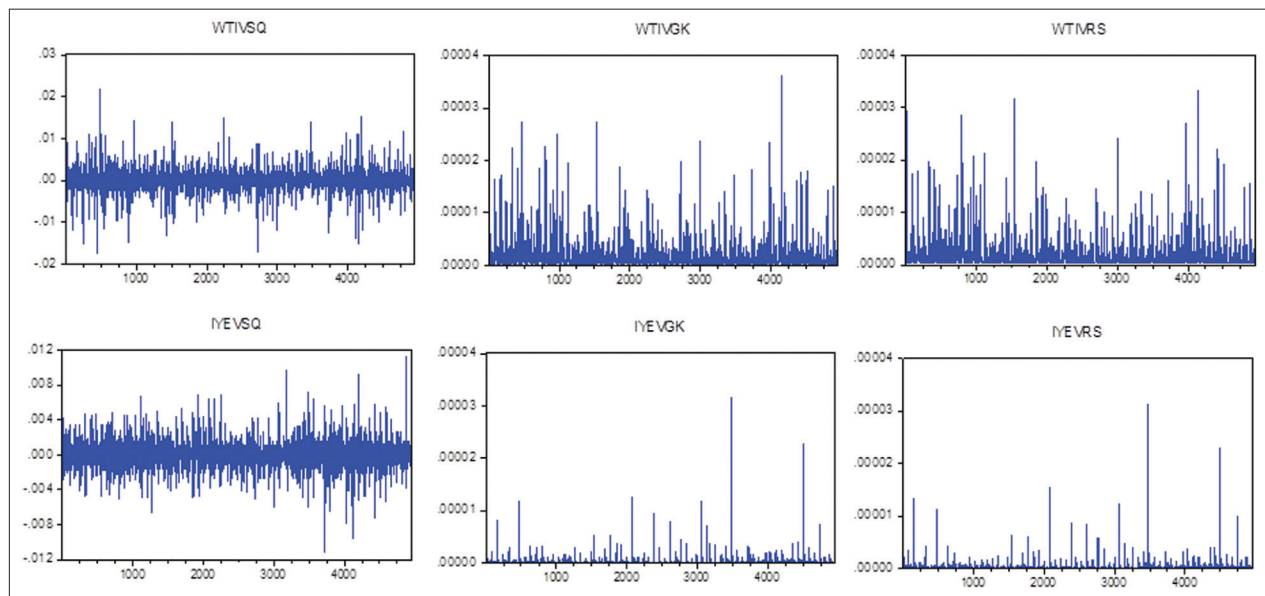


Table 8: Information criterion

	Square return			Garman and Klass volatility			Roger and Satchel volatility		
	Model 1	Model 2	Model 3	Model 1	Model 2	Model 3	Model 1	Model 2	Model 3
WTI									
AIC	-9.4400	-9.412486	-9.411901	-23.41342	-23.29399	-23.430	-23.40362	-23.43506	-23.4237
SIC	-9.432205	-9.403282	-9.39875	-23.40553	-23.28347	-23.416	-23.396	-23.42454	-23.40923
ADJ R-squared	-0.001%	-0.093%	-0.02%	6.53%	13.61%	12.72%	9.68%	11.61%	13.83%
IYE									
AIC	-10.31901	-10.35566	-10.3815	-25.38437	-25.46981	-25.39615	-25.51535	-25.29518	-25.27442
SIC	-10.31627	10.34646	-10.36706	-25.37648	-25.4593	-25.38169	-25.507	-25.28466	-25.260
ADJ R-squared	0.000%	-2.70%	-2.32%	2.42%	11.67%	12.82%	-5.11%	9.59%	10.41%

This table reports the Akaike information criterion, Schwarz Information criterion, and the adjusted R-square of three EGARCH (1,1) models predicting volatility in the crude oil and equity markets. The predictive regression models are presented as Eqs. (1)-(3) in the main text. Three price volatility measures are used, namely, square return, Garman and Klass (1980) volatility, and the volatility proposed by Rogers and Satchell (1991) and Rogers et al. (1994)

2 (eq. 4) is based on its own past trading information including volatility, bid-ask spread and trading volume. On the other hand, Model 3 (eq. 5) estimates price volatility using lagged volatility, lagged bid-ask spread, and the lagged trading volume of crude oil futures market and also from the ETF market.

News impact (NI) curves of all volatility types and EGARCH (1,1) for crude oil are exhibited in Figure 4. All the WTI

volatility models have asymmetric NICs however they distinguish among themselves. In square return models, negative shocks have more impact on future volatility than positive shocks of the same magnitude. For GK and RS models the outcome is just the opposite, positive shocks have more impact on future volatility than negative shocks of the same magnitude.

Figure 4: News impact curves for WTI volatility models

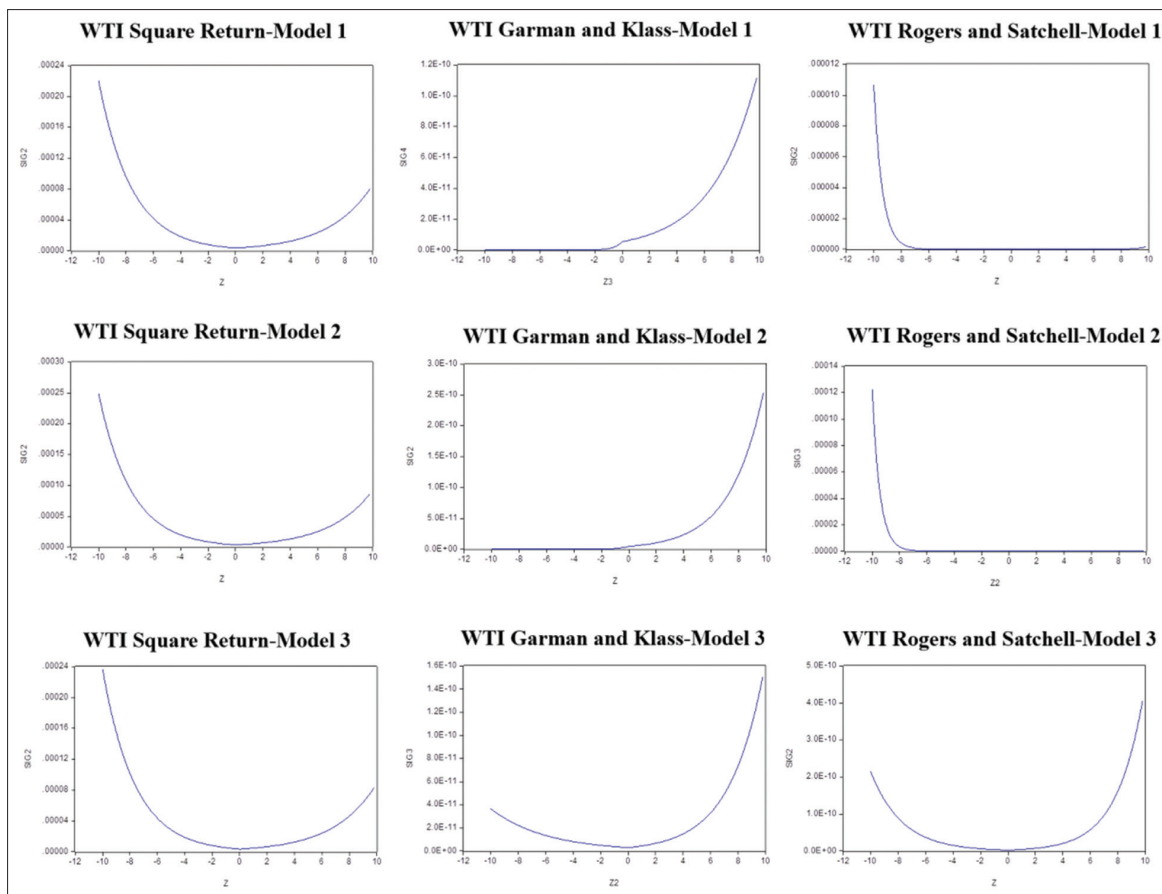
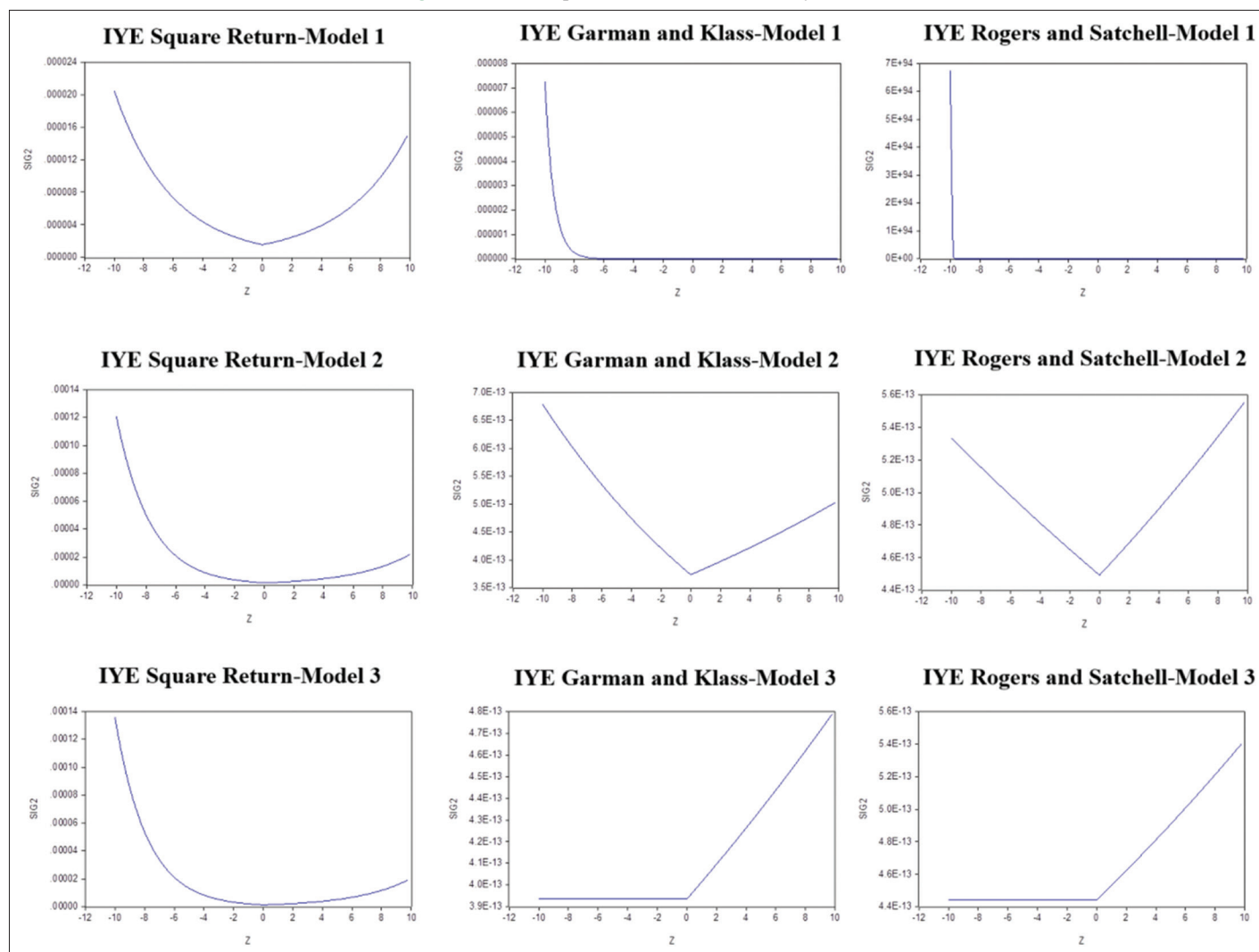


Table 9: Lagged effects

	Square return		Garman and Klass volatility		Roger and Satchel volatility	
	WTI	IYE	WTI	IYE	WTI	IYE
C	-0.0009	0.0027	0.0000	0.0000	0.0000	0.0000
	-0.018	0.000	0.000	0.000	0.000	0.000
$BAS_{WTI, t-1}$	-0.1518	1.6441	0.0024	0.0000	0.0029	0.0001
	0.735	0.000	0.000	0.930	0.000	0.404
$BAS_{IYE, t-1}$	0.0102	0.0198	0.0000	0.0000	0.0000	0.0000
	0.235	0.000	0.001	0.000	0.000	0.000
$ASKSIZE_{WTI, t-1}$	0.0001	0.0000	0.0000	0.0000	0.0000	0.0000
	0.678	0.285	0.000	0.000	0.000	0.000
$ASKSIZE_{IYE, t-1}$	0.0000	-0.0002	0.0000	0.0000	0.0000	0.0000
	0.333	0.000	0.000	0.000	0.000	0.000
$V_{WTI, t-1}$	-0.0009	0.0455	0.1291	0.0135	0.2241	0.0129
	0.018	0.000	0.000	0.011	0.000	0.017
$V_{IYE, t-1}$	0.0052	-0.0576	0.2247	0.1261	0.1707	0.0859
	0.735	0.002	0.000	0.000	0.000	0.000

BAS_{IYE} , $ASKSIZE_{IYE}$ and V_{IYE} are the bid-ask spread, trading volume, and the price volatility of the ETF market, respectively, while BAS_{WTI} , $ASKSIZE_{WTI}$, V_{WTI} are the corresponding variables for the crude oil market. Three price volatility measures are used, namely, square return, Garman and Klass (1980) volatility, and the volatility proposed by Rogers and Satchell (1991) and Rogers et al. (1994). The specification of the model underlying the results is presented by Eq. (3) in the main text. The P-value of the coefficient for each variable is under the coefficient numbers

Figure 5: News impact curves for IYE volatility models

News impact (NI) curves¹³ of all volatility types and EGARCH (1,1) ETF are exhibited in Figure 5. Most the IYE volatility models have asymmetric NICs however they distinguish among themselves. In square return models, negative shocks have more impact on future volatility than positive shocks of the same magnitude. GK and RS volatility NICs show irregularities for models 1-2 and 3. For Model 1 both GK and RS curves show that negative shocks have more impact on future volatility than positive shocks of the same magnitude. For Model 2 the results are much closer to a symmetric response structure for the shocks. Finally, for Model 3 both GK and RS curves show that positive shocks have more impact on future volatility than negative shocks of the same magnitude.

Model 2 outperformed Model 1 in predicting price volatility especially with GK and RS measures as Model 2 utilizes extra information, such as bid–ask spread and trading volume. Similarly,

Model 3 is expected to be and is superior to Model 1 and Model 2 because of the additional information contained in the cross-market.

6. CONCLUSION

This paper contributes to the existing literature focusing on the impact of energy related ETFs on crude oil prices. First we examine the price discovery and causality relationship between spot, futures and ETF prices. In the previous studies we overviewed so far we concluded that this relationship is studied only between equity markets and crude oil markets however, ETFs are now an important source of information dissemination. We find that price discovery does not flow consistently from the futures to spot markets or vice versa. The causality is mostly bi-directional from futures market to spot markets for crude oil.

Secondly, we addressed the relative importance of information on trading volume and bid–ask spread using intraday data in predicting cross-market volatility in the crude oil and ETF markets. We tested price volatility interaction between the crude oil and energy based ETF markets by employing EGARCH models using 5-min data

¹³ The news impact curve plots the next period volatility (σ_t^2) that would arise from various positive and negative values of u_{t-1} , given an estimated model. The curves are drawn by using the estimated conditional variance equation for the model under consideration, with its given coefficient estimates, and with the lagged conditional variance set to the unconditional variance (Table 9).

and three different volatility measures which are square return, volatility proposed by Garman and Klass (1980), and volatility proposed by Rogers and Satchell (1991) and Rogers et al. (1994).

Finally, we concluded that futures market drives energy based ETFs market however cross market information increases the explanation power of volatility.

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