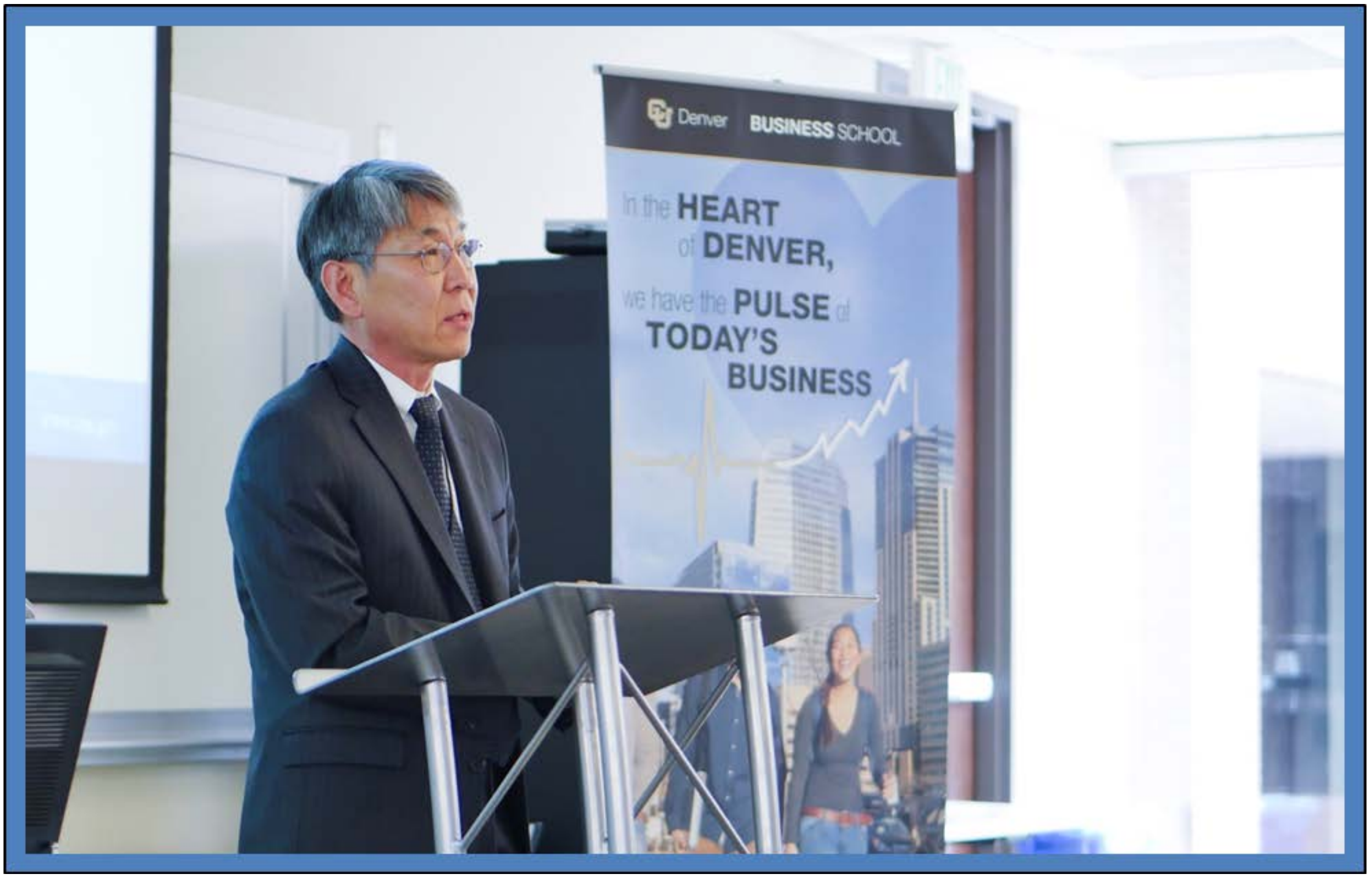
Revisiting Price Volatility Behavior in the Crude Oil Market

Thomas K. Lee, Ph.D.
Senior Economist, Office of Energy Markets and Financial Analysis, Energy Information Administration (EIA), U.S. Department of Energy; and Editorial Advisory Board Member, *Global Commodities Applied Research Digest*

John Zyren, Ph.D.
Senior Industry Economist/Econometrician, Office of Energy Markets and Financial Analysis, EIA, U.S. Department of Energy



Dr. Thomas K. Lee, Ph.D., of the U.S. Energy Information Administration, presenting at the JPMCC's 2nd International Commodities Symposium, which was held at the University of Colorado Denver Business School in August 2018. Dr. Lee, who is also an Editorial Advisory Board member of the *GCARD*, lectured on "Oil Market Dynamics and the Short-Term Outlook."

Introduction

This paper studies the price volatility behavior of the oil markets, updating our previous research on issues related to this topic in Lee and Zyren (2007). But before covering our new study, we will briefly review why oil prices can be so volatile along with the history of highly volatile episodes in the oil markets that have occurred since the mid-1980s.

Generally speaking, changes in price can be large in the oil market since the underlying demand and supply curves are so price-inelastic that shocks to supply or demand will be immediately reflected in the price. Regarding research on this subject, there is no consensus on whether supply shocks or demand shocks are more prone to causing changes in prices. The different magnitude in price response caused by these shocks varies over time, and an increased price caused by unexpected supply restrictions or geopolitical reasons has tended to be transitional.

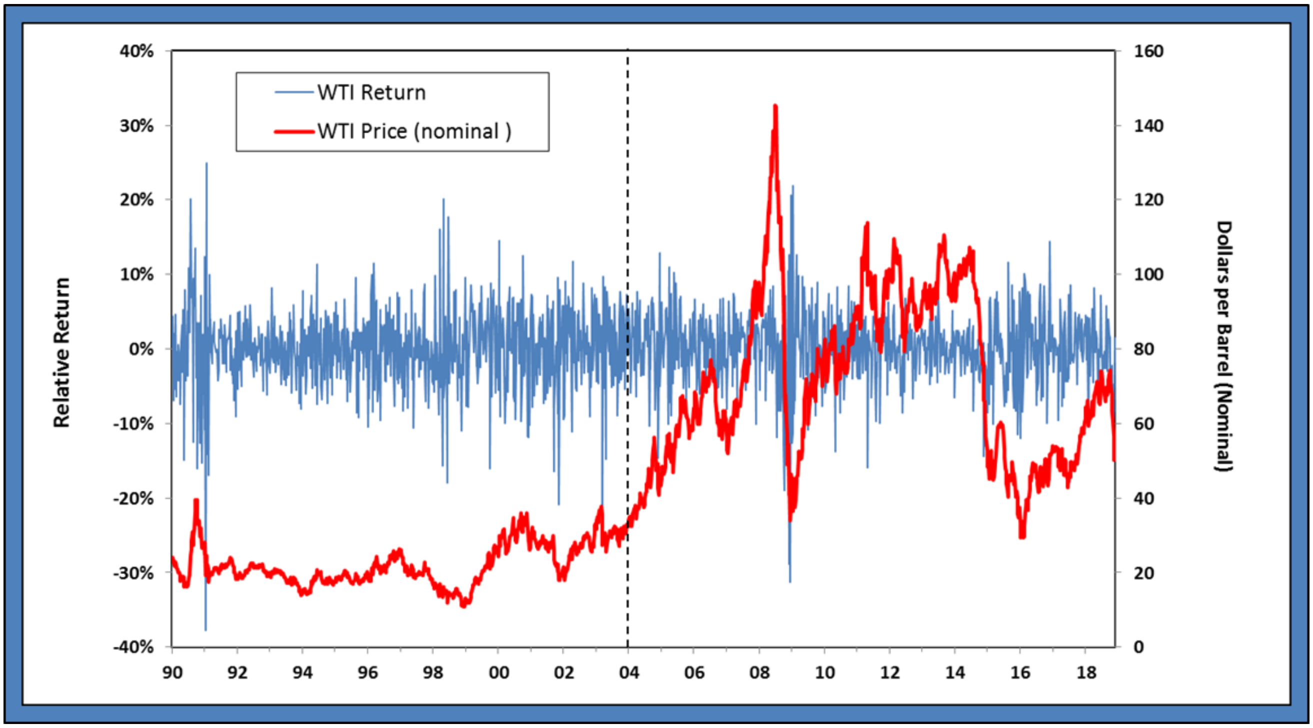
According to a number of academic studies, speculative financial activity in the oil markets, and commodity markets in general, can have some influence on oil prices, but at least historically, there have not been *sustained* price changes caused by such activity. Kilian and Lee (2014) explained and empirically demonstrated, for example, that the 2003-08 oil price surge was mainly influenced by increases in demand, driven largely by the unexpected economic growth of emerging market countries. Prices can also be affected by unexpected fundamental information or announcements. However, such price responses have been very short lived and have not had much long-term impact on volatility.

Figure 1 on the next page shows the percent returns and spot price movement for nominal West Texas Intermediate (WTI) crude oil prices from January 1990 to November 2018. The weekly percent returns show that the volatility of returns varies over time and, as we expect, the price returns exhibit volatility clustering. This implies volatility shocks today could influence the volatility many periods into the future. The nominal prices have historically shown substantial variations, ranging from a low monthly average of $11 in December 1998 to $134 in July 2008. On July 14, 2008, the WTI price registered a level of $145.16, the highest price in history. The price movements in the 1990s were relatively smooth although we had some spikes and downturns with the uncertainty surrounding Gulf War I (1990-1991), the Asian Financial Crisis (1997), and afterwards with the Dot-com Crash (2000-2002). In comparison, oil price movements have widely varied by a larger degree since 2004. There are two noticeable price swings in the oil market after 2004. One occurred during the Global Financial Crisis in 2008 when the oil price peaked at $145 in July 2008 before plummeting to $30 by the end of December 2008, and the other event is the oil price collapse, which took place from the second part of 2014 to early 2016. In the latter episode, the price went as high as $108 in June 2014, followed by a decline to $26 in February 2016.

We can compare the price declines during these two events with the decline in oil prices that occurred in 1985-1986 when members of the Organization of the Petroleum Exporting Countries (OPEC) reversed earlier production cuts. There are different reasons for the various price collapses. The 1985-1986 price collapse was mainly supply-driven whereas the drop in 2008 was mostly due to demand-side factors.

In contrast, the 2014-2016 price collapse appeared to be due to a mix of these two factors. On the supply side, a failure to come to agreement amongst OPEC and non-OPEC producers to control oil production occurred in November 2014, and which was described in Jesse (2017). On the demand side, slowing growth in emerging markets, noticeably in China, also took its toll later on oil prices.

Figure 1
Weekly WTI Price and Return



These types of rapid fluctuations have become of great concern to individual consumers, firms, policymakers and society in general. For each stakeholder, there are different concerns regarding price volatility. For example, from an oil producer's point of view, volatility, whether persistent or transitory, could discourage fixed capital investment due to uncertainty regarding the price path. From a trader's point of view, accurate predictions of price volatility are crucial for arbitrage opportunities since this variable is a key determinant for derivatives valuation. With respect to these concerns, Lee and Zyren (2007) analyzed the volatility interactions between crude oil and petroleum products as well as the magnitude of price volatility in these related markets. The specific interest of this study was to analyze price reactions in both crude oil and the petroleum product markets when OPEC's crude oil pricing behavior changed. This study also hypothesized that the gasoline and heating oil markets would have higher price volatility since these markets have their own set of market factors that would lead to this effect. The study concluded that 1) volatility is higher when OPEC intervenes in the oil market; 2) the price volatility of petroleum products is higher than crude oil; and 3) price volatility for near-month futures contracts is higher than more distant futures contracts.

In our current paper, we are revisiting the fundamental question as to whether the oil price volatility structure is stable over time. This analysis will give us a chance to reevaluate how the composition of the underlying supply, demand, and other exogenous shocks impacts the oil price differently. Both shocks to price and price volatility could be much different today than in earlier periods. Because the effects of shocks change over time and, given technological progress and changing market dynamics, there may be different price impacts resulting from supply or demand shocks as compared to the past.

Understanding the structure of volatility should help us with uncertainty management. One may want to know whether volatility is persistent or transitory and to know its magnitude. If volatility is high and persistent, it may lead firms to rely more heavily on hedging operations and other types of risk management and to place more emphasis on the evaluation of investments in the context of uncertainty. Thus, it is imperative to understand the behavior of crude oil price volatility, its magnitude and duration, as well as its economic implications.

This study on crude oil price volatility is organized as follows. The following section describes the data and empirical methodologies used to estimate volatilities conditioned on types of past information, i.e., "conditional volatilities." The next section summarizes the estimation results and analyzes conditional volatilities in different periods, including a discussion of the analysis' implications. Concluding remarks are in the final section.

Data and Methodology

In order to have a comprehensive understanding of WTI crude oil volatility behavior, we obtained the end-of-week closing prices for the spot and futures markets, including 1-month, 3-month, and 6-month futures contracts, for WTI crude oil.[1] The spot price series were obtained from Reuters while the New York Mercantile Exchange (NYMEX) prices were obtained from Bloomberg. The sample period studied is from January 1990 to November 2018.[2] Table 1 on the next page displays descriptive statistics for both weekly nominal WTI prices and returns for the full period (January 1990 to November 2018), Period 1 (January 1990 to December 2003), and Period 2 (January 2004 through November 2018).

Table 1
Descriptive Statistics for Weekly Nominal WTI Prices and Returns January 1990 through November 2018

Panel a: Nominal Price

	n	WTI Spot	Futures Contract by Month CL1	CL3	CL6
Full Period	*1509*				
Mean		$47.48	$47.49	$47.73	$47.73
Median		37.14	37.14	36.75	37.30
Std. Dev		29.79	29.80	30.06	30.25
Max		145.29	145.29	146.12	146.68
Min		10.83	10.79	11.57	12.33
Period 1	*730*				
Mean		$22.20	$22.17	$21.80	$21.28
Median		20.83	20.86	20.57	20.37
Std. Dev		5.61	5.55	4.99	4.28
Max		39.60	39.69	36.75	33.00
Min		10.83	10.79	11.57	12.33
Period 2	*779*				
Mean		$71.17	$71.22	$72.04	$72.52
Median		68.10	68.35	68.69	69.36
Std. Dev		23.00	22.97	22.48	22.02
Max		145.29	145.29	146.12	146.68
Min		29.42	29.42	31.21	29.90

Panel b: Return (percent)

Return	*n*	WTI Spot	Futures Contract by Month CL1	CL3	CL6
Full Period	*1508*				
Mean		0.0525	0.0525	0.0577	0.0622
Median		0.2548	0.3137	0.3011	0.2589
Std. Dev		5.21	4.99	4.25	3.67
Max		24.99	24.12	21.13	18.60
Min		-37.73	-34.90	-29.56	-21.76
Period 1	*729*				
Mean		0.0480	0.0485	0.0544	0.0559
Median		0.2345	0.2164	0.2541	0.1809
Std. Dev		5.47	5.08	4.10	3.26
Max		24.99	20.05	14.13	12.78
Min		-37.73	-34.90	-29.56	-21.76
Period 2	*779*				
Mean		0.0566	0.0563	0.0609	0.0681
Median		0.2616	0.3809	0.3550	0.3050
Std. Dev		4.96	4.91	4.38	4.02
Max		21.95	24.12	21.13	18.60
Min		-31.22	-31.22	-24.33	-21.05

Table 1 shows that the variation of the nominal price for Period 2 is much higher than for Period 1. The price variation measured by standard deviation in Period 2, which includes the Global Financial Crisis and its aftermath, is four times higher than that of Period 1, with a standard deviation of $5.61 and $23.00 in Period 1 and Period 2, respectively. The price range in each corresponding period, Period 1 and Period 2, is \$28.77 and \$115.87, respectively. Several noteworthy episodes during Period 2 contributed to such a large variation in price (as touched upon in the Introduction), namely: 1) the demand shock resulting from the Global Financial Crisis in 2008; 2) the supply shock arising from OPEC's decision not to steady the oil markets in late 2014; and 3) the demand shocks due to slowing growth in emerging economies in late 2015. In the 2008 episode, within a 6-month period, from the beginning of July to the end of December, WTI spot price declined 77% before rebounding. The declining price journey in the second episode stretched for a year and a half with the price decreasing by 72% from July 2014 to February 2016. These events manifestly led to a large variation in price as compared with Period 1.

We will now turn to formalizing our study of crude oil price volatility with the use of sophisticated statistical models. Since the seminal works of Engle (1982) and Bollerslev (1986), autoregressive conditional heteroskedasticity (ARCH) and generalized autoregressive conditional heteroskedasticity (GARCH) models have found extraordinarily wide use. GARCH models have been very successful at modeling time-varying volatility in financial time series, and they seem to be as good as that of more complex models.[3] In the petroleum markets, Lee *et al.* (1995), Sadorsky (1999), Pindyck (2004), Lee and Zyren (2007), and Salisu and Fasanya (2013) used GARCH models to estimate oil price volatility. The GARCH (p, q) model used in this study is formulated as follows:

$$R_t = \mu + \varepsilon_t \tag{1}$$

$$\sigma_t^2 = \omega + \sum_{i=1}^{p} \alpha_i \varepsilon_{t-i}^2 + \sum_{j=1}^{q} \beta_j \sigma_{t-j}^2 \tag{2}$$

The mean equation, Equation (1), expresses oil price returns as a random walk process with ε_t as the error term. The variance equation, Equation (2), uses the error term, ε_t, of the mean equation to help explain total model variance. In the variance equation, the conditional variance at time *t*, σ_t^2, is specified as a function of three terms: the mean, ω; ARCH terms representing the effect of news in the previous period(s) on current volatility, ε_{t-1}^2; and GARCH terms representing the effect that previous periods' forecast variance(s) have on current volatility, σ_{t-1}^2. The GARCH (1, 1) model is utilized to estimate the conditional volatility for our data series in all three periods.[4] The methodology is based on the assumption that the conditional volatility of the return in oil prices is affected symmetrically by both positive and negative innovations. This means we treat any impact equally, whether it is positive or negative to the price.[5]

Similar to financial data series, energy market volatilities in a period of relative tranquility are often followed by periods of higher volatility. For that reason, an assumption of constant variance over time for the return of oil prices is not appropriate. Thus, to help understand certain aspects of oil price volatility, we utilized the GARCH model for estimating the conditional variance of returns, which allows the conditional variance to be time-variant. However, one must note the usual reservations regarding this model. Our univariate approach does not take into consideration the comovements of returns. To have a better understanding of relevant comovements, one can use the multivariate GARCH (MGARCH) models, which enable the estimation of the relative magnitude of volatilities, systematic information (GARCH effect) and unsystematic information (ARCH effect) in any given time period. While the volatility interaction in MGARCH is an important issue, it is out of scope for this study and we will focus on conditional volatility comparisons only.

Estimation, Results and Implications

Our estimated results can illuminate characteristics of oil price volatility in the spot and futures markets and in different market conditions (Period 1 vs. Period 2). If the sum of ARCH (α) and GARCH (β) coefficients is less than one ($\alpha + \beta < 1$) then the time series exhibit a mean-reversion process. When the sum of these coefficients is equal to one ($\alpha + \beta = 1$) then it is said that the time series follows a random walk. The estimation results in Table 2 on the next page reveal that the sum of ARCH and GARCH coefficients is less than one ($\alpha + \beta < 1$) for both spot and futures contracts in both periods, confirming that oil price volatilities revert back to their historical value after a certain time period. This mean reversion in volatility also means that there is a normal level of volatility to which volatility will eventually return.

Given that oil price volatilities are mean-reverting, we examine their half-lives over our sample periods. The half-life of volatility measures the average time period for the volatility to return back to its mean value in a long-run horizon. It is a measure of volatility persistence. A volatility study of energy markets by Pindyck (2004) concluded that changes in volatility are short-lived with a half-life of 5 to 10 weeks and that volatility has a small positive time trend, which implies little impact on firms' investment activities or on the economy. The half-life volatility in a GARCH specification is calculated by:

$$\text{Half life}_{GARCH} = \frac{\log(0.5)}{\log\left(\sum_{i=1}^{p}\alpha_i + \sum_{j=1}^{q}\beta_j\right)} \tag{3}$$

Our calculations for this specification are also shown in Table 2 on the next page. The conditional variance estimated using a GARCH specification was found to exhibit larger GARCH (moving average) effects than ARCH (autoregressive) effects in all markets and periods. This means that previous period information about observed volatility (ARCH effect) has had much less of an impact on conditional volatility than the previous period's forecast of volatility (GARCH effect). Conceptually, the former measure maps into the effect of news or events during the previous period on conditional volatility while the latter measure maps into the effect of systematic information on conditional volatility.

The speed of mean reversion as calculated by the half-life method reveals that the half-life for Period 1 is about 12 weeks while for Period 2, the half-life is about 18 weeks, as shown in Table 2 below. This indicates that there is more of a persistent volatility condition in the second period as compared to the first period. We believe this persistence is mainly due to two events: the 2008 Global Financial Crisis and the 2014-2016 oil price collapse.

Table 2
Crude Oil – Volatility Estimation Results

Panel a: Period 1 (January 1990 through December 2003)

	Spot	Futures Contracts		
	Cushing	1	3	6
n	729	729	729	729
Constant	0.000194	0.000160	0.000074	0.000039
	(3.01)	(3.02)	(3.06)	(3.51)
ARCH(1)	0.160482	0.129159	0.104048	0.085116
	(5.09)	(4.64)	(5.26)	(5.48)
GARCH(1)	0.781624	0.815481	0.856804	0.881403
	(17.09)	(19.47)	(29.11)	(40.87)
Sum	0.942	0.945	0.961	0.967
Half-life	11.6	12.2	17.4	20.4

Panel b: Period 2 (January 2004 through November 2018)

	Spot	Futures Contracts		
	Cushing	1	3	6
n	779	779	779	779
Constant	0.000088	0.000085	0.000067	0.000055
	(2.64)	(2.74)	(2.79)	(2.92)
ARCH(1)	0.090090	0.090815	0.080472	0.085293
	(4.98)	(5.15)	(4.43)	(4.50)
GARCH(1)	0.871739	0.871106	0.884084	0.881516
	(31.11)	(31.91)	(32.98)	(33.99)
Sum	0.962	0.962	0.965	0.967
Half-life	17.8	17.9	19.2	20.5

Note: Z-statistics are in parentheses.

We will now examine implied volatility in the crude oil futures market. Implied volatility provides a measure of market participants' expectations of uncertainty regarding future price movements. This measure is also known as a proxy for investor sentiment. Although crude oil and stock markets often move independently because of different factors affecting each market, the price volatility of these markets can often be positively correlated. There are four noticeable market uncertainty spikes in oil implied volatility (OVX), which took place in 2008, 2011, 2014-16, and in 2018. Reviewing Figure 2 below, we see that the stock market implied volatility (VIX) spiked with similar magnitudes as the OVX during the Global Financial Crisis in 2008 and the Libyan crisis of 2011. But the OVX's pattern during the oil price collapse in 2014-2016 is very different from what the equity markets experienced: the OVX's spikes are much higher than those of the VIX. The higher implied volatility in the oil market as compared with equity volatility was also witnessed in November 2018 when the market became concerned with the slowing growth in demand and oversupply issues.

Figure 2
Weekly VIX and OVX Indices (in Percent)

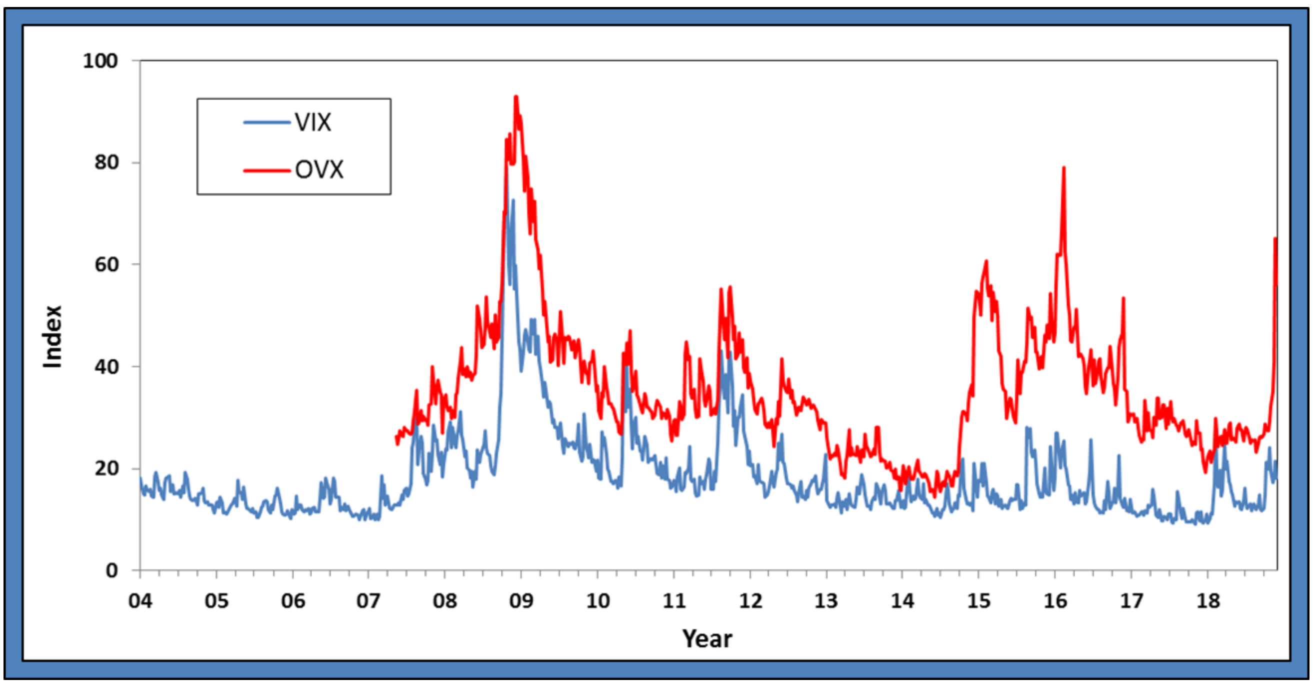


Figure 3
Weekly WTI Historical and Conditional Volatility Comparison

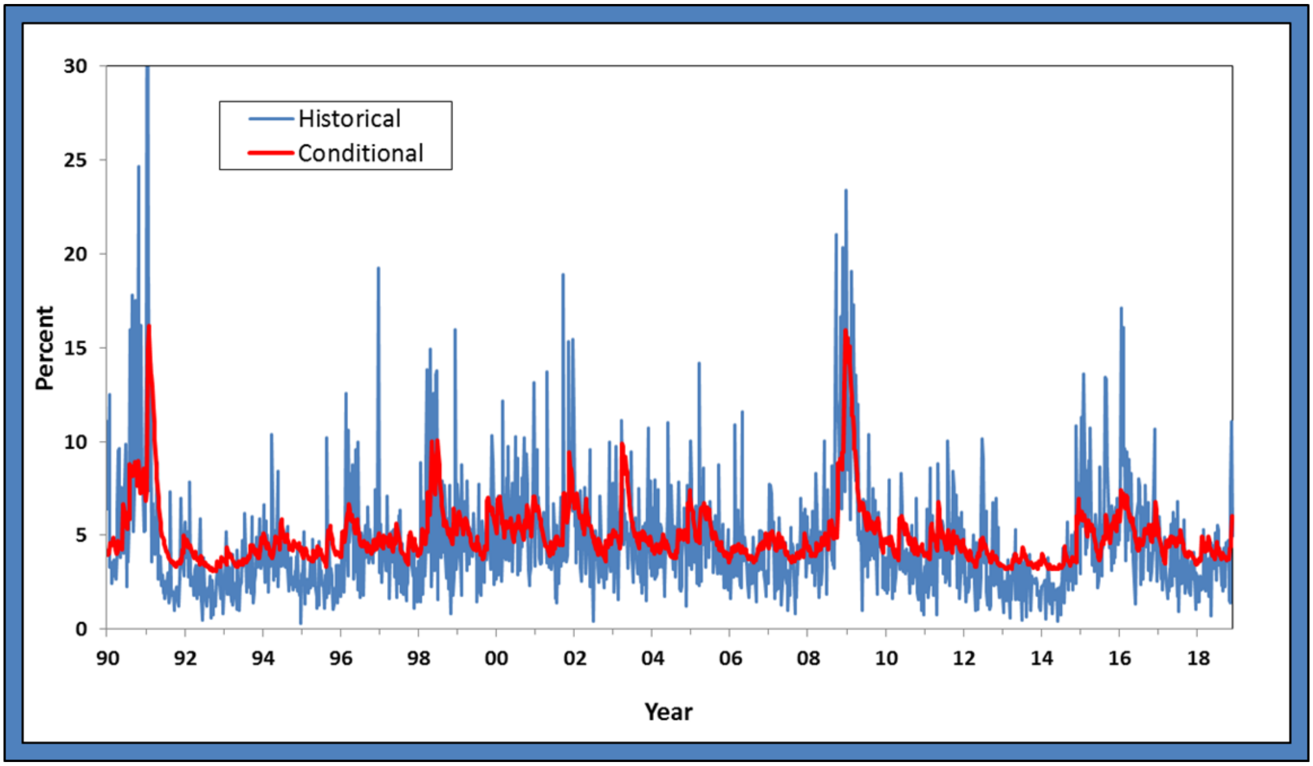


Figure 3 above provides a comparison between the historical and conditional volatilities of weekly crude oil returns for the entire sample from January 1990 to November 2018. The estimated conditional volatility captures major events in the sample period; thus, it appears that the model is reasonable and acceptable. However, the conditional volatility fails to capture a number of the weekly spikes, especially for the 2014-2016 period. During this period, the pattern and size of the OVX is about the same as the historical volatility, but the estimated conditional volatility did not exhibit the magnitude of this uncertainty. The ARCH effect in the conditional volatility is also diminishing in the second period relative to the first one. This may be due to the fact that with the advent of 24-hour electronic trading and technology improvements (e.g., algorithmic trading), the volatility reaction to surprise shocks has become quick and diminishing (Ederington *et al.* (2019)). We may need to refine the specification or use other models to deal with this issue.

Conclusion

The goal of this paper has been to provide an updated analysis of crude oil volatility, incorporating more recent data than our original work in Lee and Zyren (2007). In our current paper, we compared the behavior of oil price volatility during two different time horizons: 1990 to 2003 and 2004 to 2018. We empirically examined the conditional volatilities and volatility persistence in the oil markets during very eventful times. Our results suggest two important findings: 1) the component of oil price volatility due to current information has diminished more quickly than previously while 2) the systematic information component of oil price volatility has persisted longer than previously.

Another way of framing our results is that while the price reactions due to current news or events have not been as important as in the 1990s or early 2000s, we also documented an increasing pattern of volatility persistence in the more recent data. The persistence of price volatility in the oil market may negatively impact business investment decisions and/or economic activity as a whole. To build confidence in our results, though, we recommend that researchers use different specifications and models than our GARCH specification in studying these issues.

Although this study documents that the recent level of volatility is higher than that of earlier in the decade,[6] we have not addressed what has caused this phenomenon. It is an important issue to have a better understanding of the drivers of volatility behavior in the oil market. There may be several or many different reasons for the change in price volatility conditions. The candidate hypotheses include fundamental changes in market conditions such as the shale revolution, technology advancement, and geopolitics, but a definitive answer awaits future research.

Endnotes

1 Lee and Zyren (2007) used daily data for WTI, conventional and reformulated (RFG) gasoline, and heating oil in both New York Harbor (NYH) and U.S. Gulf Coast (USG).

2 The data period in Lee and Zyren (2007) was from January 1990 to May 2005.

3 Hansen and Lunde (2005) argue that the best volatility models do not provide a significantly better forecast than the GARCH model. See Poon and Granger (2003) for a comprehensive review of alternative methods for estimating and forecasting volatility.

4 The Lee and Zyren (2007) study included a shift variable, capturing a structural break. Specifically, the shift variable indicated how OPEC's decision to create a new price regime in April 1999 impacted the mean of the conditional volatility. However, our main aim in the current study is to see whether volatility behavior has changed in the 2000s with the Global Financial Crisis and the oil supply glut period.

5 This assumption is not appropriate when petroleum products prices are evaluated. Lee and Zyren (2007) applied the threshold-GARCH (TARCH) process to estimate the conditional variance for gasoline and heating oil prices, given asymmetric responses of petroleum product prices. They found that the heating oil market and the one-month futures contract in gasoline seem to exhibit "leverage effects," i.e., an asymmetric tendency for volatility. Ederington *et al.* (2019) provide a survey of the literature on volatility and asymmetric responses of product prices.

6 McNally (2018) also discussed concerns with heightened oil price volatility.

The views expressed in this paper reflect the opinions of the authors only. It is not meant to represent the position of the U.S. Department of Energy or the Energy Information Administration, nor the official position of any staff members. The authors are solely responsible for all errors and omissions.

References

Bollerslev, T., 1986, "Generalized Autoregressive Conditional Heteroskedasticity," *Journal of Econometrics*, Vol. 31, No. 3, April, pp. 307-327.

Ederington, L., Fernando, C., Lee, T., Linn, S. and S. Hoelscher, 2019, "Behavior and Determinants of Petroleum Product Prices," *Journal of Commodity Markets*, Forthcoming.

Engle, R., 1982, "Autoregressive Conditional Heteroscedasticity with Estimates of the Variance of United Kingdom Inflation," *Econometrica*, Vol. 50, No. 4, July, pp. 987-1007.

Hansen, P. and A. Lunde, 2005, "A Forecast Comparison of Volatility Models: Does Anything Beat a GARCH (1, 1) Model?," *Journal of Applied Econometrics*, Vol. 20, No. 7, December, pp. 873-889.

Jesse, J.-H., 2017, "The History of a Supply-Driven Bear Market: Oil Price Surprises from 2014 through 2015," *Global Commodities Applied Research Digest*, Editorial Advisory Board Commentaries, Vol. 2, No. 2, Winter, pp. 98-110.

Kilian, L. and T. Lee, 2014, "Quantifying the Speculative Component in the Real Price of Oil: The Role of Global Oil Inventories," *Journal of International Money and Finance*, Vol. 42, Issue C, April, pp. 71-87.

Lee, K., Ni, S. and R. Ratti, 1995, "Oil Shocks and the Macroeconomy: The Role of Price Variability," *Energy Journal*, Vol. 16, No. 4, October, pp. 39-56.

Lee, T. and J. Zyren, 2007, "Volatility Relationship Between Crude Oil and Petroleum Products," *Atlantic Economic Journal*, Vol. 35, No. 1, March, pp. 97-112.

McNally, R., 2018, "What are the Factors that are Impacting Global Oil Prices?," *Global Commodities Applied Research Digest*, Industry Commentaries, Vol. 3, No. 2, Winter, pp. 92-102.

Pindyck, R., 2004, "Volatility in Natural Gas and Oil Markets," *Journal of Energy and Development*, Vol. 30, No. 1, Autumn, pp. 1-19.

Poon, S.H. and C. Granger, 2003, "Forecasting Volatility in Finance Markets: A Review," *Journal of Economic Literature*, Vol. 41, No. 2, June, pp. 478-539.

Sadorsky, P., 1999, "Oil Price Shocks and Stock Market Activity," *Energy Economics*, Vol. 21, No. 5, October, pp. 449-469.

Salisu, A., and I. Fasanya, 2013, "Modelling Oil Price Volatility with Structural Breaks," *Energy Policy*, Vol. 52, Issue C, January, pp. 554-562.

Author Biographies

THOMAS K. LEE, Ph.D.
Senior Economist, Office of Energy Markets and Financial Analysis, Energy Information Administration (EIA), U.S. Department of Energy

Dr. Thomas K. Lee has been with the Office of Energy Markets and Financial Analysis at the U.S. Energy Information Administration (EIA) since 2010. As a senior economist, he is mainly responsible for the research and analysis of issues related to financial market and physical oil market linkages, focusing on factors that influence oil prices and volatilities and the relationship between financial market activities and oil prices. Most of his recent research has focused on the sources of fluctuations in the price of oil and petroleum products. He is also responsible for variables and modeling issues beyond the physical fundamentals of oil prices in the National Energy Modeling Systems (NEMS) to support the EIA's core publications, *Short-Term and Annual Energy Outlook* (*STEO*). Prior to this role, he served as Industry Economist for the Office of Integrated Analysis and Forecast at EIA from 2001 to 2010.

Dr. Lee also had been associated with Marymount University as a finance faculty member from 1999 to 2010. He has published scholarly articles in a number of journals including *Journal of International Money and Finance, Journal of Applied Econometrics*, *Journal of Energy Markets*, *Energy Economics*, *Energy Journal*, *International Advances in Economic Research*, *Atlantic Economic Journal*, *Journal of Derivative Markets*, and *International Finance Review*, among others. He received an M.A. in Finance and a Ph.D. in Economics from the Catholic University of America.

John Zyren, Ph.D.
Senior Industry Economist/Econometrician, Office of Energy Markets and Financial Analysis, EIA, U.S. Department of Energy

Dr. John Zyren has been employed at the EIA from 1993 and with the Office of Energy Markets and Financial Analysis since 2013. As a senior industry economist/econometrician he has been responsible for the analysis and forecasting of crude oil and petroleum product markets. His current research interests include improving the analysis/forecasting methodology for EIA's *Drilling Productivity Report* (a monthly publication which uses estimates of drilling productivity and estimated changes in production from existing oil and natural gas wells to provide estimated changes in oil and natural gas production for seven key regions.)

He has published scholarly articles in a number of journals including *Atlantic Economic Journal*, *Journal of Energy Markets*, *International Advances in Economic Research*, *Energy Policy*, and *International Journal of Forecasting*, among others. He received his degree in Economics from the North Carolina State University. In his early professional career, he worked at the U.S. Department of Agriculture and the National Food Processors Association.