VOLATILITY INTERACTIONS BETWEEN EQUITY AND CRUDE OIL MARKETS: EVIDENCE FROM INTRADAY ETF DATA

by

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Abstract

This study replicates and extends the study done by Phan, Sharma and Narayan (2015) using intraday data from two widely available exchange traded funds (SPY and USO), before and after the recent regime change, which was represented by the drop in crude oil prices of 2014. Phan, Sharma and Narayan (2015) use data from futures contracts to demonstrate that lagged trading information like bid-ask spread, number of shares traded and price volatility, from the same market and cross-market, when incorporated in a single volatility prediction setup, can significantly improve future volatility prediction for equity and crude oil markets. The main findings of our study confirms the conclusion reached by the reference paper and also demonstrate that these results hold before and after the drop in crude oil prices, which occurred in 2014.

Keywords: intraday volatility; volatility interactions; trading information; crude oil market; equity markets; oil price drop

Dedication

To my parents, who have supported me at every step of my life.

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Introduction

In this paper, we studied the volatility interactions between equity and crude oil markets.This paper confirms the conclusion reached by Phan, Sharma and Narayan (2015) and extend their study using a different set of securities and a different time period. We use data from exchange traded funds (ETFs) instead of using future contracts, as used by Phan et.al (2015), considering that ETFs are easily available to the individual investor, are simple to understand and extenstively traded.

Phan, Sharma and Narayan (2015) use data from three different futures contracts, namely E-mini S&P 500 index futures, E-mini Nasdaq 100 index futures and Light Sweet Crude Oil (WTI) Futures. E-mini S&P 500 index futures contract and the E-mini 100 Nasdaq index futures contract are used as proxies for the equity market and the WTI futures contract is used as a proxy for crude oil market. Combining the studies done by Hussain (2011), Copeland (1976), Nelson (1991), Ewing & Malik (2009) and many others, they propose three specifications of the EGARCH(1,1) model, to demonstrate that using intraday lagged trading information for the futures contracts, like the bid-ask spread, number of shares traded and price volatility, from the same market and cross-market, when incorporated in a single volatility prediction setup, can significantly improve future volatility prediction for equity and crude oil markets.

Over the years, there have been a lot of studies on the relationship between equity and crude oil markets and how shocks in crude oil prices can have a negative effect on a number of economic factors. A study done by Hamilton (1983) document few of these negative effects due to shocks in crude oil prices on the aggregate measures of output and employment. Mork (1989) document that there are asymmetric effects of shocks in crude oil prices on world economic growth. Studies done by Aloui and Rania Jammazi (2009), demonstrate that these changes in the economic factors lead by shocks in crude oil prices, change the stock price behaviour for a number of listed firms. Studies done by Aloui et al. (2008) demonstrate that the change in stock price behaviour triggers a change in the volatility of the overall equity markets. In such a situation, a number of commonly employed conditional mean and conditional variance models generate unjustifible results. This change in structural form of variance generating process is known as a *regime change*.

Considering the fact that the drop in crude oil prices in 2014, did change a lot of the above mentioned economic factors, we decide to extend the study done by Phan et.al (2015) with the purpose of evaluating if their conclusion holds true before and after a major drop in crude oil prices.

To study if any there was any diversion from the conclusion reached by the authors of the reference paper, we propose two more conditional mean models and use them along with those proposed by the reference paper for our analysis. Acknowledging the study done by Liu & Hung(2010) in which they compare various conditional variance models, we decide to add GJR-GARCH conditional variance specification to our analysis. In all, we use five conditional mean models with two different conditional variance specifications to conduct this study. Following Phan, Sharma and Narayan (2015), we use a *two-step* estimation method to conduct this study. Using the *two-step* method, we first fit the data to the mean equations using linear regression and then calculate the residuals from the estimated model. These residuals are then subjected and modelled by the conditional variance specifications.

The results of this paper not only verifies the conlcusion made by Phan, Sharma, & Narayan (2015), but also confirms that the prediction of intraday price volatility is improved by combining lagged trading information of the same market and that of the cross market, both before and after the drop in crude oil prices of 2014.

Data and Methodology

This study employs a 5-minute interval intraday time series data from two exchange traded funds (ETFs) namely, SPDR S&P 500 ETF TRUST (NYSE ARCA ticker: SPY) and UNITED STATES OIL FUND LP (NYSE ARCA ticker: USO). SPY is used as a proxy for the equity market, while USO is used as a proxy for crude oil market. SPY closely tracks the S&P 500 index and consists of securities forming the S&P 500 index, weighted according to market capitalization. USO tracks the daily price movements of West Texas Intermediate light (WTI), sweet crude oil and is the largest WTI tracking ETF by market capitalization and volume traded.

To conduct the study, data has been sourced from the Trade and Quotes (TAQ) database provided by the Wharton Research Data Service (WRDS). Intraday tick data was downloaded for a total of 200 calendar days, starting 12th March, 2014 through 28th September 2014. This dataset was split into two data samples of 100 calendar days each, using 20th June, 2014 as the split date. This gave us two data samples, one referring to the period before the crude oil prices dropped and the other referring to the period after the crude oil prices dropped. The crude oil prices peaked on 20th June 2014, which is why it was used to split the data into two different samples.

For both the data samples, the intraday tick data is used to form a 5-minute 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-minute interval. This time series is for the core trading hours of 09:30:00 AM through 04:00:00 PM Eastern Time which amounts to 79 data points per trading day. To calculate the 5-Minute interval BAS, we follow the method demonstrated by McInish & Wood (1992). We apply the following formula to each tick entry in the quotes table and split the records into 79 baskets of 5-minutes each. Then an average is taken for each 5-minute interval bucket.

$$BAS = \frac{(Ask - Bid)}{(Ask + Bid)/2}$$

We follow the following definitions to calculate the rest of the variables of the 5-minute interval intraday time series:

Variable	Method
High Price	The highest trade price in the 5 minute interval
Low Price	The lowest trade price in the 5 minute interval
Open Price	The first tick entry for the trade price in the 5 minute interval
Close Price	The last tick entry for the trade price in the 5 minute interval
Volume	The sum of all the trade sizes in the 5 minute interval

Following this, the data is filtered for any negative values of the BAS. This study calculates trading volume TV , as natural log of the total number of shares traded in the 5-minute interval. We employ three measures to calculate volatility, following the methods described by Phan, Sharma, & Narayan (2015) as below:

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

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

$$V_t^{RS} = [\ln(HP_t) - \ln(OP_t)][\ln(HP_t) - \ln(CP_t)] + [\ln(LP_t) - \ln(OP_t)][\ln(LP_t) - \ln(CP_t)]$$

where V_t^{SQ} is square returns, V_t^{GK} is volatility originally proposed by Garman & Klass (1980) , and V_t^{RS} is volatility originally proposed by Rogers and Satchell (1991). HP is the highest price at which the security traded in the 5-minute interval, LP is the lowest price at which the security traded in the 5-minute interval, OP is the first price at which the security traded in the 5-minute interval and CP is the last price at which the security traded in the 5-minute interval. Appendix A, shows plots for BAS, trading volume, square returns, Garman and Klass volatility and Rogers and Satchell volatility, for SPY and USO, both before and after the fall in crude oil prices.

This study follows Phan, Sharma, & Narayan (2015) in selecting descriptive statistics for a better comparison with the original study. Table 1 and Table 2 shows selected descriptive statistics for the 5-minute interval intraday data, before and after the drop in crude oil prices, respectively. All the five variables for the two markets in both data samples were subjected to Jarque-Bera test for normality at 1% level of significance, Augmented Dickey-Fuller test for unit root at 1% level of significance, Ljung-Box Q-test for residual autocorrelation and Engle test for residual heteroscedasticity at Lags 1 and 12, and at 1% level of significance.

Table 1: Descriptive statistics for 5-minute interval intraday data sample before drop in crude oil prices

	Mean	S.D.	JB	ADF	ARCH(1)	ARCH(12)	LB(1)	LB(12)
Panel A: Equity								
BAS	0.00233190	0.00333187	**R**	**R**	**R**	**R**	**R**	**R**
			(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
TV	13.64505411	0.74316863	**R**	CNR	**R**	**R**	**R**	**R**
			(0.00)	0.06	(0.00)	(0.00)	(0.00)	(0.00)
V^{SQ}	0.00000045	0.00000178	**R**	**R**	CNR	CNR	**R**	**R**
			(0.00)	(0.00)	0.98	1.00	(0.00)	(0.00)
V^{GK}	0.00000179	0.00000965	**R**	**R**	**R**	**R**	**R**	**R**
			(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
V^{RS}	0.00000283	0.00001731	**R**	**R**	**R**	**R**	**R**	**R**
			(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Panel B: Crude Oil								
BAS	0.00058802	0.00154433	**R**	**R**	CNR	CNR	**R**	**CNR**
			(0.00)	(0.00)	0.97	1.00	(0.00)	0.01
TV	9.54889560	1.19471394	**R**	**R**	**R**	**R**	**R**	**R**
			(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
V^{SQ}	0.00000090	0.00000613	**R**	**R**	CNR	CNR	CNR	CNR
			(0.00)	(0.00)	0.98	1.00	0.88	1.00
V^{GK}	0.00000040	0.00000228	**R**	**R**	CNR	CNR	CNR	CNR
			(0.00)	(0.00)	0.98	1.00	0.21	0.88
V^{RS}	0.00000045	0.00000407	**R**	**R**	CNR	CNR	CNR	CNR
			(0.00)	(0.00)	0.98	1.00	0.69	1.00

R – Null hypothesis of the test rejected at given level of significance
CNR – Could not reject the null hypothesis of the test at given level of significance

Where JB, ADF, ARCH (1), ARCH (12), LB (1) and LB (12) stands for Jarque-Bera test, Augmented Dickey-Fuller test for unit root, Ljung-Box Q-test for residual autocorrelation at Lag 1, Ljung-Box Q-test for residual autocorrelation at Lag 12, Engle test for residual heteroscedasticity at Lags 1 and Engle test for residual heteroscedasticity at Lag 12 respectively. BAS, TV, V^{SQ}, V^{GK} and V^{RS} for Bid Ask Spread, Trading Volume, Square returns, Garman and Klass volatility and Rogers and Satchell volatility respectively.

It is visible in both the tables that trading volume data for SPY fails to reject the null hypothesis of Augmented Dickey-Fuller test for unit root in both the data samples, though the results of the Augmented Dickey-Fuller tests are statistically insignificant. Table 1 and Table 2 also shows that the data fails to reject various other tests, although all statistically insignificantly.

Table 2: Descriptive statistics for 5-minute interval intraday data sample after drop in crude oil prices

	Mean	S.D.	JB	ADF	ARCH(1)	ARCH(12)	LB(1)	LB(12)
Panel A: SPY								
BAS	0.00009083	0.00086007	**R**	**R**	CNR	CNR	CNR	**R**
			(0.00)	(0.00)	0.99	0.75	0.78	(0.00)
TV	13.50902697	0.75180462	**R**	CNR	**R**	**R**	**R**	**R**
			(0.00)	0.08	(0.00)	(0.00)	(0.00)	(0.00)
V^{SQ}	0.00000037	0.00000192	**R**	**R**	CNR	CNR	CNR	CNR
			(0.00)	(0.00)	0.96	1.00	0.36	0.12
V^{GK}	0.00000210	0.00001129	**R**	**R**	**R**	**R**	**R**	**R**
			(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
V^{RS}	0.00000355	0.00002088	**R**	**R**	**R**	**R**	**R**	**R**
			(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Panel B: USO								
BAS	0.00045284	0.00131195	**R**	**R**	**R**	**R**	**R**	**R**
			(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
TV	10.03520832	1.12272972	**R**	**R**	**R**	**R**	**R**	**R**
			(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
V^{SQ}	0.00000118	0.00000750	**R**	**R**	CNR	CNR	CNR	CNR
			(0.00)	(0.00)	0.92	1.00	1.00	1.00
V^{GK}	0.00000058	0.00000134	**R**	**R**	CNR	CNR	**R**	**R**
			(0.00)	(0.00)	0.99	1.00	(0.00)	(0.00)
V^{RS}	0.00000061	0.00000205	**R**	**R**	CNR	CNR	**R**	**R**
			(0.00)	(0.00)	0.98	1.00	(0.00)	(0.00)

R – Null hypothesis of the test rejected at given level of significance
CNR – Could not reject the null hypothesis of the test at given level of significance

Table 3 and Table 4 report the correlation coefficients between the bid-ask spread, trading volume and the volatility of equity and crude oil market with the three different measures used to calculate volatility, as described above. Table 3 shows the correlation coefficients before the drop in crude oil prices and Table 4 shows the correlation coefficients after the drop in crude oil prices.

This study employs three conditional mean models with an EGARCH (1,1) conditional variance specification, proposed by Phan, Sharma, & Narayan (2015), to remove heteroscedasticity and model conditional variance. In addition to that, we also propose two more conditional mean models with EGARCH (1,1) specification to remove heteroscedasticity and model conditional variance. Also, following contributions made by Liu and Hung (2010) demonstrating GJR-GARCH model as a slightly better specification than EGARCH, to model conditional variance, we separately employ the GJR-GARCH (1,1) specification along with the previously mentioned conditional mean equations to remove heteroscedasticity and model conditional variance. This gives us a wider set of results to form a conclusion.

Table 3: Correlation coefficient values for data sample before the drop in crude oil prices

	Square Return		Garman and Klass Volatility		Roger and Satchel Volatility	
	Equity	Crude Oil	Equity	Crude Oil	Equity	Crude Oil
BAS_E	0.055	-0.024	0.047	0.001	0.036	-0.004
	(0.00)	0.07	(0.00)	0.96	(0.01)	0.74
BAS_O	0.049	0.106	0.002	0.004	0.002	0.002
	(0.00)	(0.00)	0.88	0.75	0.90	0.88
TV_E	0.083	-0.062	0.220	0.050	0.197	0.034
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.01)
TV_O	-0.093	-0.060	0.011	0.152	0.004	0.104
	(0.00)	(0.00)	0.43	(0.00)	0.78	(0.00)
V_E	1.000	0.295	1.000	-0.005	1.000	-0.005
	(0.00)	(0.00)	(0.00)	0.73	(0.00)	0.72
V_O	0.295	1.000	-0.005	1.000	-0.005	1.000
	(0.00)	(0.00)	0.73	(0.00)	0.72	(0.00)

Where V_E is volatility of equity markets and V_O is volatility of crude oil markets

Table 4: Correlation coefficient values for data sample after the drop in crude oil prices

	Square Return		Garman and Klass Volatility		Roger and Satchel Volatility	
	Equity	Crude Oil	Equity	Crude Oil	Equity	Crude Oil
BAS_E	-0.001	-0.001	-0.003	-0.006	-0.003	-0.004
	0.95	0.96	0.84	0.65	0.85	0.75
BAS_O	0.217	0.100	-0.010	-0.008	-0.009	-0.007
	0.00	0.00	0.49	0.54	0.51	0.63
TV_E	0.102	-0.016	0.211	0.078	0.194	0.052
	0.00	0.25	0.00	0.00	0.00	0.00
TV_O	-0.039	0.031	0.019	0.322	0.015	0.215
	0.00	0.02	0.17	0.00	0.29	0.00
V_E	1.000	0.187	1.000	-0.007	1.000	-0.007
	0.00	0.00	0.00	0.62	0.00	0.62
V_O	0.187	1.000	-0.007	1.000	-0.007	1.000
	0.00	0.00	0.62	0.00	0.62	0.00

Where V_E is volatility of equity markets and V_O is volatility of crude oil markets

Table 5: Conditional mean and variance models

Conditional Mean Equations	
Model 1	$V_t^E = \beta_0^E + \beta_1^E V_{t-1}^E + \varepsilon_t$ $V_t^O = \beta_0^O + \beta_1^O V_{t-1}^O + \varepsilon_t$
Model 2	$V_t^E = \beta_0^E + \beta_1^E BAS_{t-1}^E + \beta_2^E TV_{t-1}^E + \beta_3^E V_{t-1}^E + \varepsilon_t$ $V_t^O = \beta_0^O + \beta_1^O BAS_{t-1}^O + \beta_2^O TV_{t-1}^O + \beta_3^O V_{t-1}^O + \varepsilon_t$
Model 3	$V_t^E = \beta_0^E + \beta_1^E BAS_{t-1}^E + \beta_2^E TV_{t-1}^E + \beta_3^E V_{t-1}^E + \beta_4^O BAS_{t-1}^O + \beta_5^O TV_{t-1}^O + \beta_6^O V_{t-1}^O + \varepsilon_t$ $V_t^O = \beta_0^O + \beta_1^O BAS_{t-1}^O + \beta_2^O TV_{t-1}^O + \beta_3^O V_{t-1}^O + \beta_4^E BAS_{t-1}^E + \beta_5^E TV_{t-1}^E + \beta_6^E V_{t-1}^E + \varepsilon_t$
Model 4	$V_t^E = \beta_0^E + \beta_1^E V_{t-1}^E + \beta_2^O BAS_{t-1}^O + \beta_3^O TV_{t-1}^O + \beta_4^O V_{t-1}^O + \varepsilon_t$ $V_t^O = \beta_0^O + \beta_1^O V_{t-1}^O + \beta_2^E BAS_{t-1}^E + \beta_3^E TV_{t-1}^E + \beta_4^E V_{t-1}^E + \varepsilon_t$
Model 5	$V_t^E = \beta_0^E + \beta_1^E VO_{t-1}^E + \beta_4^O VO_{t-1}^O + \varepsilon_t$ $V_t^O = \beta_0^O + \beta_1^O VO_{t-1}^O + \beta_4^E VO_{t-1}^E + \varepsilon_t$

$$\varepsilon_t \to N(0, \sigma_t^2)$$

EGARCH(1,1) specification to model conditional variance

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

GJR-GARCH(1,1) specification to model conditional variance

$$\sigma_t^2 = \mathrm{K} + \gamma \sigma_{t-1}^2 + \alpha \varepsilon_{t-1}^2 + \xi I[\varepsilon_{t-1} < 0] \varepsilon_{t-1}^2$$

The indicator function $I[\varepsilon_{t-1} < 0]$ equals 1 if $\varepsilon_{t-1} < 0$, and 0 otherwise

Table 5 shows the conditional mean model equations and conditional variance specifications, where V_t^E and V_t^O are price volatility of equity markets and crude oil markets, respectively, BAS_t^E and

BAS_t^O are the bid-ask spreads of equity and oil markets respectively, TV_t^E and TV_t^O are trading volumes of equity and crude oil markets respectively. ε_t is the residual from the mean equation, and σ_t^2 is the conditional variance generated from the models.

Model 1 predicts price volatility based on its own lagged volatility. Model 2 predicts price volatility based on its own lagged BAS, trading volume and volatility. Model 3 predicts price volatility based on its own lagged trading information as well as lagged cross-market trading information. Here trading information refers to BAS, trading volume and volatility. Model 1, Model 2 and Model 3 are the models proposed by Phan, Sharma, & Narayan (2015). To test their conclusion, we propose Model 4 which predicts price volatility based on its own lagged volatility, cross-market lagged BAS, trading volume and volatility. We also propose Model 5 predicts the price volatility based on its own lagged volatility and cross-market lagged volatility.

The study done Phan, Sharma, & Narayan (2015) concludes that out of their three proposed models, Model 3, which contains lagged trading information from both the markets best, predicts price volatility. To evaluate their conclusion, we test the volatility predicting capability of the three models proposed by Phan, Sharma and Narayan (2015) along with two additional proposed models using two different conditional variance specifications, i.e. EGARCH (1,1) as proposed by Phan, Sharma, & Narayan (2015) and GJR-GARCH (1,1) conditional variance specification.

We perform linear regressions on the data according to the conditional mean models described in Table 5, and then address the volatility clustering and leverage effects in the residuals generated, using conditional variance models. To find the best model, we calculate the Akaike information criteria (AIC) and the Bayesian information criteria (BIC) statistics for all the 5 models and compare them to empirically find the best model to predict volatility. We then observe if these results differ before and after the drop in crude oil prices, which happened in 2014.

Empirical Results

We begin by discussing the results of descriptive statistics reported in Table 1 and Table 2. Then we discuss the correlations coefficients between bid-ask spread, trading volume, volatility of equity and crude oil market, with the three measures of volatility as reported in Table 3 and 4. Finally, we discuss if cross-market trading information helps in improving price volatility prediction, and then we compare these results before and after the drop in crude oil prices.

Table 1 and Table 2 show that, intraday data for several variables fails to reject null hypothesis for some descriptive statistics tests, though all these rejections were statistically insignificant. The most noticeable rejection is that of the Augmented Dickey-Fuller Test (ADF) for unit root by the trading volume data of SPY, both before and after the drop in crude oil price. This means that the data for trading volume of SPY may not be stationary. The other noticeable result is for the measures of volatility, where all the three measures of volatility for USO fail to reject the null hypothesis of Engle test for residual heteroscedasticity, both before and after the drop in crude oil prices. The rejections are however statistically insignificant.

Table 3 and Table 4 report the correlation coefficients between various components of trading information and volatility measures, before and after the drop in crude oil price, respectively. We observe a change in the correlation of BAS of the equity and crude oil markets with the measures of volatility of equity and crude oil markets. The correlations, which were mostly positive, changed to mostly negative; however, the magnitude of correlations is small and statistically insignificant for the given data. The correlation of trading volume of equity and crude oil markets with volatility measures of equity and crude oil markets, did not change their sign before and after the drop in crude oil prices. There was also no change in the sign of the cross market correlations of volatility measures between equity and crude oil markets. However, it was interesting to notice a negative correlation between equity and crude oil market for both Garman and Klass volatility and Rogers and Satchell volatility.

Table 6, Table 8, Table 10 and Table 12 report the AIC and BIC statistics and adjusted R squared values from the five conditional mean and variance models described in Table 5. These results will help us evaluate, which model out of the given five models, works the best in predicting volatility. Table 6 and Table 8 report the AIC and BIC statistics and adjusted R squared values for the models using EGARCH (1,1) conditional variance specification and the GJR-GARCH (1,1) conditional variance specification before the drop in crude oil prices, respectively. Table 9 and Table 11 report the AIC and BIC statistics and adjusted R squared values for the models using EGARCH (1,1) conditional variance specification and GJR-GARCH (1,1) conditional variance specification after the drop in crude oil prices, respectively.

We will first discuss the results for the data sample, before the drop in crude oil prices. Table 7 summarizes the results from Table 6 by selecting the models with the minimum AIC and BIC statistics. It is visible that Model 2 performs the best among all the models, when the selected measure of volatility is Rogers and Satchell volatility, for equity markets. However, when compared with Model 3, there is a very small difference in the AIC and BIC values between the two models. In crude oil markets, we observe that when square returns are used as a volatility measure, Model 4 performs considerably better than Model 3 in predicting volatility. However, for the rest of the 10 cases, Model 3 was observed to be the better model among the five models tested.

To confirm our results from the EGARCH (1,1) specification, we evaluate the results from models using the GJR-GARCH (1,1) specification, reported in Table 8. Table 9 gives a summary of Table 8 by selecting models with the minimum values for AIC and BIC statistics. Table 9 shows that, Model 3, which uses lagged information from both the markets, helps to improve volatility predictability for all the cases. Combining the results from both the conditional variance specifications, we conclude that, for the in sample data before the drop in crude oil prices, Model 3 performs better in 22 out of 24 cases, and therefore we find Model 3 as the best model to predict price volatility.

Table 11 summarizes the results from Table 10 by selecting the models with the minimum AIC and BIC values for the data sample after the drop in crude oil prices. It will be worthwhile to mention that for crude oil market, when Rogers and Satchell volatility is used as volatility measure, model 2 outperformed all the other models. However, when compared with Model 3, the difference in the values of AIC and BIC is very small. For rest of the 11 cases, Model 3 was observed as the best model to predict volatility.

To confirm the results reported using the EGARCH (1,1) specification, we look at Table 13, which summarizes the results by selecting the minimum AIC and BIC values for models using GJR-GARCH (1,1) specification to model conditional variance. Here again, Model 3 results as the best choice for predicting future volatility for all the cases. Therefore, we conclude that, for the in sample data after the drop in oil prices, Model 3 performs better in 23 out of 24 cases, as the best model to predict future volatility, and therefore we find Model 3 as the best model to predict price volatility.

Overall from the above discussion, we conclude that Model 3 which uses lagged trading information from both itself and the cross market, helps to improve volatility predictability.

Table 6: Information criterion statistics and adjusted R squared values to compare volatility predicting capability of conditional mean models using EGARCH(1,1) conditional variance specification, before the drop in crude oil prices.

	Square Returns					
		Model 1	**Model 2**	**Model 3**	**Model 4**	**Model 5**
Equity	AIC	-133751.657	-137154.669	**-137220.198**	-133459.871	-133734.716
	BIC	-133725.135	-137128.147	**-137193.677**	-133433.350	-133708.194
	Adjusted R^2	0.26%	5.59%	**6.46%**	2.79%	0.25%
Crude Oil	AIC	-121295.704	-120189.407	-121471.287	**-121881.254**	-118490.489*
	BIC	-121269.183	-120162.885	-121444.766	**-121854.733**	-118483.859*
	Adjusted R^2	-0.02%	1.83%	3.20%**	**2.28%**	-0.01%
	Garman and Klass volatility					
		Model 1	**Model 2**	**Model 3**	**Model 4**	**Model 5**
Equity	AIC	-113823.805*	-121636.547	**-121651.411**	-121188.126	-113824.026*
	BIC	-113817.175*	-121610.026	**-121624.889**	-121161.605	-113817.396*
	Adjusted R^2	7.06%	7.74%	**7.80%**	7.01%	7.05%
Crude Oil	AIC	-130037.419	-134287.711	**-134383.790**	-129636.402	-130034.713
	BIC	-130010.898	-134261.190	**-134357.268**	-129609.881	-130008.191
	Adjusted R^2	0.01%	0.32%**	**0.26%**	-0.01%	-0.01%
	Rogers and Satchell volatility					
		Model 1	**Model 2**	**Model 3**	**Model 4**	**Model 5**
Equity	AIC	-107250.570*	-115190.902	**-115181.498*** **	-114578.889	-107250.693*
	BIC	-107243.940*	-115164.381	**-115154.977*** **	-114552.368	-107244.063*
	Adjusted R^2	6.57%	7.13%	**7.18%**	6.53%	6.56%
Crude Oil	AIC	-123077.781*	-127928.119	**-127980.551**	-52972.338	-123077.857*
	BIC	-123071.151*	-127901.597	**-127954.029**	-52945.817	-123071.226*
	Adjusted R^2	-0.02%	0.10%**	**0.05%**	-0.06%	-0.03%

Note: The AIC and BIC values highlighted in green are for the models which performed the best in predicting future volatility among the 5 models described in Table 5, for the selected market and according the measure of volatility selected. The models for which the AIC and BIC values are marked with the *****, were subjected to an EGARCH (0,0) specification instead of the EGARCH (1,1) specification. The Adjusted R^2 values marked with ****** represent the best linearly fitted model, however, in this study the AIC and BIC values have a greater significance in selecting the best model due to the nature of the models employed. The values marked with *** represent the AIC and BIC values for the model which has been selected over the best model for the given market and volatility measure, which in this case is model 2. It can be seen that there is a very slight difference in the AIC and BIC values between model 2 and model 3, which has been ignored after comparing it with the results from the GJR-GARCH conditional variance specification.

Table 7: Summary for results reported in Table 6. The model values shown below are the best model to predict volatility for the selected measure of volatility.

	Measure of volatility	Result according to AIC	Result according to BIC
Equity	Square return	Model 3	Model 3
	Garman and Klass volatility	Model 3	Model 3
	Roger and Satchell volatility	Model 3	Model 3
	Measure of volatility	**Result according to AIC**	**Result according to BIC**
Crude Oil	Square return	Model 4	Model 4
	Garman and Klass volatility	Model 3	Model 3
	Roger and Satchell volatility	Model 3	Model 3

Table 8: Information criterion statistics and adjusted R squared values to compare volatility predicting capability of conditional mean models using GJR-GARCH(1,1) conditional variance specification, before the drop in crude oil prices.

	Square Returns					
		Model 1	**Model 2**	**Model 3**	**Model 4**	**Model 5**
Equity	AIC	-76058.337	-76058.342	**-76058.343**	-76058.340	-76058.337
	BIC	-76051.707	-76051.712	**-76051.713**	-76051.709	-76051.707
	Adjusted R^2	0.26%	5.59%	**6.46%**	2.79%	0.25%
Crude Oil	AIC	-76057.374	-76057.394	**-76057.409**	-76057.399	-76057.374
	BIC	-76050.744	-76050.763	**-76050.778**	-76050.768	-76050.744
	Adjusted R^2	-0.02%	1.83%	**3.20%**	2.28%	-0.01%
	Garman and Klass volatility					
		Model 1	**Model 2**	**Model 3**	**Model 4**	**Model 5**
Equity	AIC	-76056.005	-76056.024	**-76056.027**	-76056.005	-76056.005
	BIC	-76049.375	-76049.394	**-76049.396**	-76049.375	-76049.375
	Adjusted R^2	7.06%	7.74%	**7.80%**	7.01%	7.05%
Crude Oil	AIC	-76058.281	-76058.281	**-76058.281**	-76058.281	-76058.281
	BIC	-76051.650	-76051.651	**-76051.651**	-76051.650	-76051.650
	Adjusted R^2	0.01%	0.32%**	**0.26%**	-0.01%	-0.01%
	Rogers and Satchell volatility					
		Model 1	**Model 2**	**Model 3**	**Model 4**	**Model 5**
Equity	AIC	-76050.594	-76050.644	**-76050.652**	-76050.595	-76050.594
	BIC	-76043.964	-76044.013	**-76044.022**	-76043.964	-76043.964
	Adjusted R^2	6.57%	7.13%	**7.18%**	6.53%	6.56%
Crude Oil	AIC	-76057.962	-76057.963	**-76057.963**	-76057.962	-76057.962
	BIC	-76051.332	-76051.333	**-76051.333**	-76051.332	-76051.332
	Adjusted R^2	-0.02%	0.10%**	**0.05%**	-0.06%	-0.03%

Note: The AIC and BIC values highlighted in green are for the models which performed the best in predicting future volatility among the 5 models described in Table 5, for the selected market and according the measure of volatility selected. The Adjusted R^2 values marked with ** represent the best linearly fitted model, however, in this study the AIC and BIC values have a greater significance in selecting the best model due to the nature of the models employed.

Table 9: Summary of results reported in Table 8. The model values shown below are the best model to predict volatility for the selected measure of volatility.

	Measure of volatility	Result according to AIC	Result according to BIC
Equity	Square return	Model 3	Model 3
	Garman and Klass volatility	Model 3	Model 3
	Roger and Satchell volatility	Model 3	Model 3
	Measure of volatility	**Result according to AIC**	**Result according to BIC**
Crude Oil	Square return	Model 3	Model 3
	Garman and Klass volatility	Model 3	Model 3
	Roger and Satchell volatility	Model 3	Model 3

Table 10: Information criterion statistics and adjusted R squared values to compare volatility predicting capability of conditional mean models using EGARCH(1,1) conditional variance specification, after the drop in crude oil prices.

		Model 1	Model 2	Model 3	Model 4	Model 5
	Square Returns					
Equity	AIC	-122840.815	-126083.117	**-126900.204**	-124745.026	-122831.057
	BIC	-122814.583	-126056.886	**-126873.972**	-124718.794	-122804.826
	Adjusted R^2	-0.003%	3.310%	**3.905%**	1.693%	-0.022%
Crude Oil	AIC	-110221.497	-111808.985	**-113989.036**	-113186.493	-110186.350
	BIC	-110195.266	-111782.753	**-113962.804**	-113160.261	-110160.118
	Adjusted R^2	-0.019%	1.895%	**2.901%**	1.913%	-0.035%
	Garman and Klass volatility					
Equity	AIC	-104099.060*	-112349.003	**-112384.312**	-111637.148	-111655.029
	BIC	-104092.502	-112322.771	**-112358.080**	-111610.916	-111628.797
	Adjusted R^2	4.600%	5.239%**	**5.217%**	4.572%	4.585%
Crude Oil	AIC	-127577.330	-126839.991	**-127845.034**	-127347.372	-127578.804
	BIC	-127551.098	-126813.759	**-127818.803**	-127321.140	-127552.572
	Adjusted R^2	1.194%	2.130%	**2.161%**	1.469%	1.177%
	Rogers and Satchell volatility					
Equity	AIC	-105444.205	-106102.699	**-106148.827**	-105423.949	-105444.061
	BIC	-105417.973	-106076.467	**-106122.596**	-105397.717	-105417.829
	Adjusted R^2	4.226%	4.767%**	**4.742%**	4.191%	4.211%
Crude Oil	AIC	-126148.456	-126180.235	**-126167.004*****	-126133.938	-126143.184
	BIC	-126122.224	-126154.003	**-126140.772*****	-126107.707	-126116.952
	Adjusted R^2	0.170%	0.761%**	**0.735%****	0.275%	0.153%

Note: Conditional mean models for which AIC and BIC values are marked with the *, were subjected to an EGARCH (0,0) conditional variance specification instead of the EGARCH (1,1) conditional variance specification. The values marked with *** represent the AIC and BIC values for the model which has been selected over the best model for the given market and volatility measure, which in this case is model 2. It can be seen that there is a very slight difference in the AIC and BIC values between model 2 and model 3, which has been ignored after comparing it with the results from the GJR-GARCH conditional variance specification. The Adjusted R^2 values marked with ** represent the best linearly fitted model, however, in this study the AIC and BIC values have a greater significance in selecting the best model due to the nature of the models employed.

Table 11: Summary of results reported in Table 10. The model values shown below are the best model to predict volatility for the selected measure of volatility.

	Measure of volatility	Result according to AIC	Result according to BIC
Equity	Square return	Model 3	Model 3
	Garman and Klass volatility	Model 3	Model 3
	Roger and Satchell volatility	Model 3	Model 3
	Measure of volatility	**Result according to AIC**	**Result according to BIC**
Crude Oil	Square return	Model 3	Model 3
	Garman and Klass volatility	Model 3	Model 3
	Roger and Satchell volatility	Model 3	Model 3

Table 12: Information criterion statistics and adjusted R squared values to compare volatility predicting capability of conditional mean models using GJR-GARCH (1,1) conditional variance specification, after the drop in crude oil prices.

	Square Returns volatility					
		Model 1	**Model 2**	**Model 3**	**Model 4**	**Model 5**
Equity	AIC	-70745.785	-70741.788	**-70745.789**	-70745.787	-70745.785
	BIC	-70739.227	-70722.114	**-70739.231**	-70739.229	-70739.227
	Adjusted R^2	-0.003%	3.310%	**3.905%**	1.693%	-0.022%
Crude Oil	AIC	-70744.415	-70744.444	**-70744.459**	-70744.444	-70744.415
	BIC	-70737.857	-70737.886	**-70737.901**	-70737.886	-70737.857
	Adjusted R^2	-0.019%	1.895%	**2.901%**	1.913%	-0.035%
	Garman and Klass volatility					
		Model 1	**Model 2**	**Model 3**	**Model 4**	**Model 5**
Equity	AIC	-70742.715	-70742.738	**-70742.739**	-70742.716	-70742.715
	BIC	-70736.157	-70736.180	**-70736.181**	-70736.158	-70736.157
	Adjusted R^2	4.600%	5.239%**	**5.217%**	4.572%	4.585%
Crude Oil	AIC	-70745.835	-70745.835	**-70745.835**	-70745.835	-70745.835
	BIC	-70739.277	-70739.277	**-70739.277**	-70739.277	-70739.277
	Adjusted R^2	1.194%	2.130%	**2.161%**	1.469%	1.177%
	Rogers and Satchell volatility					
		Model 1	**Model 2**	**Model 3**	**Model 4**	**Model 5**
Equity	AIC	-70735.016	-70735.082	**-70735.085**	-70735.018	-70735.016
	BIC	-70728.458	-70728.524	**-70728.527**	-70728.460	-70728.458
	Adjusted R^2	4.226%	4.767%**	**4.742%**	4.191%	4.211%
Crude Oil	AIC	-70745.772	-70745.773	**-70745.773**	-70745.772	-70745.772
	BIC	-70739.214	-70739.215	**-70739.215**	-70739.214	-70739.214
	Adjusted R^2	0.170%	0.761%**	**0.735%**	0.275%	0.153%

Note: The AIC and BIC values highlighted in green are for the models which performed the best in predicting future volatility among the 5 models described in Table 5, for the selected market and according the measure of volatility selected. The Adjusted R^2 values marked with ****** represent the best linearly fitted model, however, in this study the AIC and BIC values have a greater significance in selecting the best model due to the nature of the models employed.

Table 13: Summary of results reported in Table 12. The model values shown below are the best model to predict volatility for the selected measure of volatility.

	Measure of volatility	**Result according to AIC**	**Result according to BIC**
Equity	Square return	Model 3	Model 3
	Garman and Klass volatility	Model 3	Model 3
	Roger and Satchell volatility	Model 3	Model 3
	Measure of volatility	**Result according to AIC**	**Result according to BIC**
Crude Oil	Square return	Model 3	Model 3
	Garman and Klass volatility	Model 3	Model 3
	Roger and Satchell volatility	Model 3	Model 3

Robustness of results

This study uses two types of conditional variance models to address conditional heteroscedasticity. These conditional variance models are innovation processes and model the current conditional variance as a function of past conditional variances and past innovations in one form or another depending on the type of conditional variance model applied. In a financial time-series study, two methods are commonly employed to model conditional variance. The first and the most widely used method, is a *two-step* estimation method. Using a *two-step* method, the data is first subjected to the conditional mean model and residuals are calculated. In the second step, these residuals are subjected to the conditional variance equation to address conditional heteroscedasticity. On the other hand, in a *one-step* estimation method, the coefficients of the mean equation and the coefficients of the conditional variance model are estimated simultaneously. Theoretically, the *one-step* method is a superior method to estimate and model conditional variances. However, as the number of estimated variables increase in a model, it becomes impractical to use the one-step method to get a robust result.

The results presented in this study have been estimated using a two-step method following the methodology represented in the reference paper. However, we did perform this study using a one-step method to evaluate the difference. We found that, the *one-step* method, did not lead us to a clear conclusion. Out of the three volatility measures used in this study, we only got a robust result when square returns were used as a volatility measure, both before and after the drop in crude oil prices. The same conditional model variations when subjected to the other two measures of volatility, did not lead to a robust result, either before, or after the drop in crude oil prices. Therefore, using the *one-step* method, we could not confirm the superiority of any model to predict future volatility, using lagged trading information. These results are available on request, but are not included in this study.

Conclusion

This study investigated the presence of volatility interactions between equity and crude oil markets. In order to do that, we investigated if lagged trading information, like bid-ask spread, trading volume and lagged volatility helped to improve volatility prediction. We extended the study done by Phan, Sharma and Narayan (2015) and used 5-minute interval intraday data for two widely traded ETFs as a proxy for equity and crude oil markets. We proposed two new conditional mean models to test the interactions between equity and crude oil markets. The study finds that, not only did, lagged trading information, like, bid-ask spread, trading volume and volatility from the same market helped to improve volatility predicitibility, but further improvement in volatility prediction can be achieved, by incorporating lagged trading information from the cross market. We also found this conclusion true both before and after a regime change, triggered by the fall in crude oil prices in 2014. This conclusion confirms and extends the results found by Phan, Sharma and Narayan (2015) which used futures contracts as a proxy for equity and crude oil markets to come to this conclusion.

Appendix

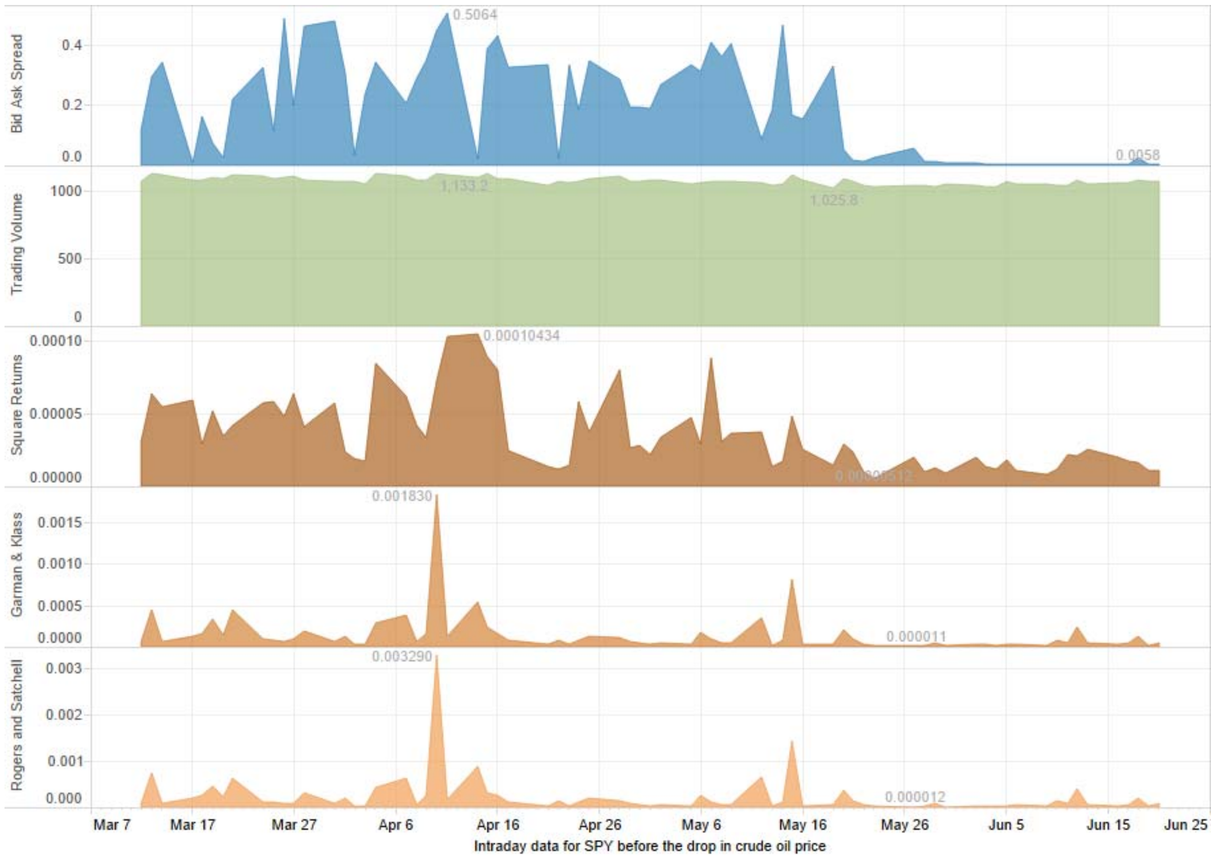

Figure 1: Intraday data for SPY before the drop in crude oil prices. From top-to-bottom, Bid-Ask Spread, Trading volume, Square Returns, Garman & Klass Volatility, Rogers & Satchell Volatility

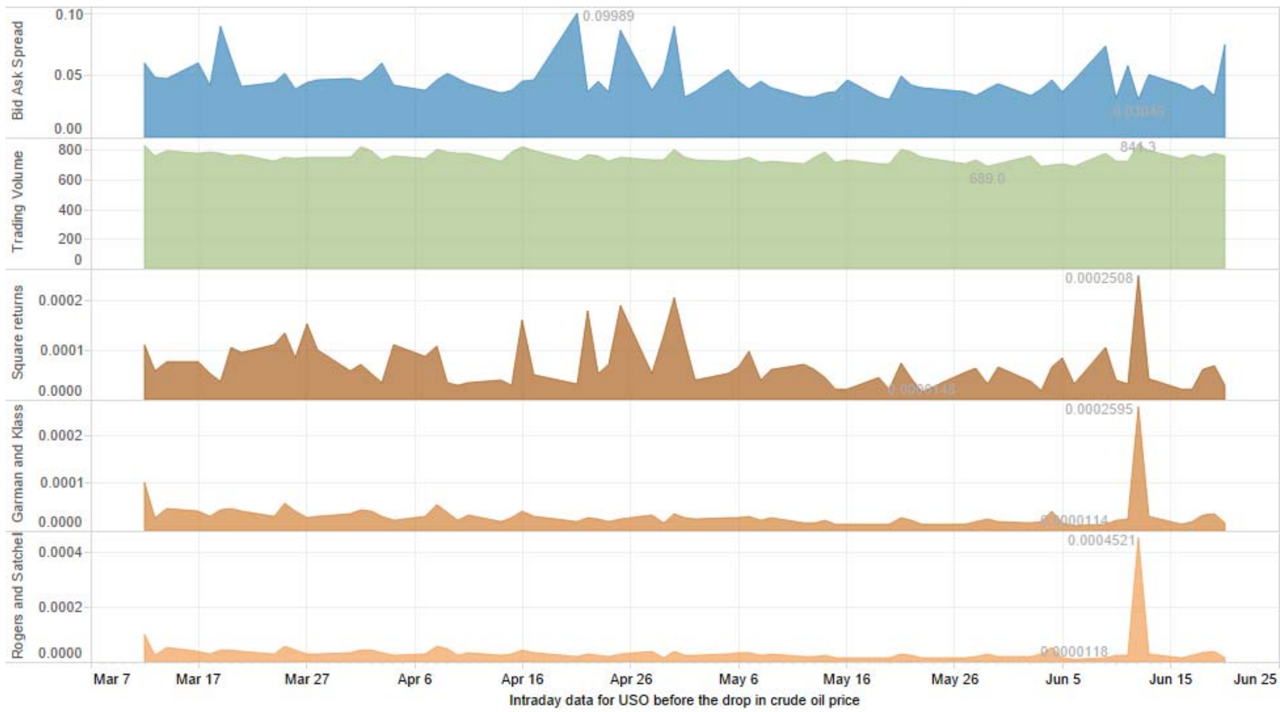

Figure 2: Intraday data for USO before the drop in crude oil prices. From top-to-bottom, Bid-Ask Spread, Trading volume, Square Returns, Garman & Klass Volatility, Rogers & Satchell Volatility

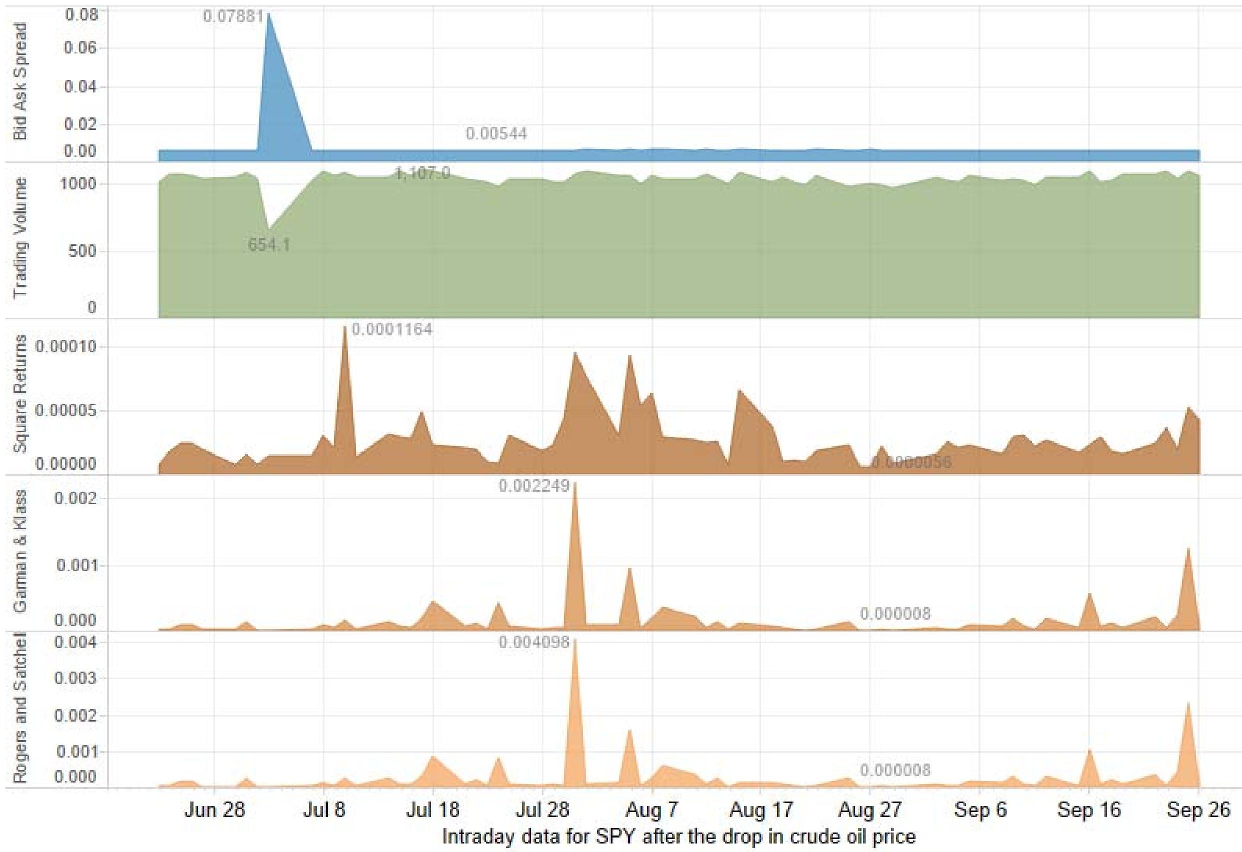

Figure 3: Intraday data for SPY before the after in crude oil prices. From top-to-bottom, Bid-Ask Spread, Trading volume, Square Returns, Garman & Klass Volatility, Rogers & Satchell Volatility

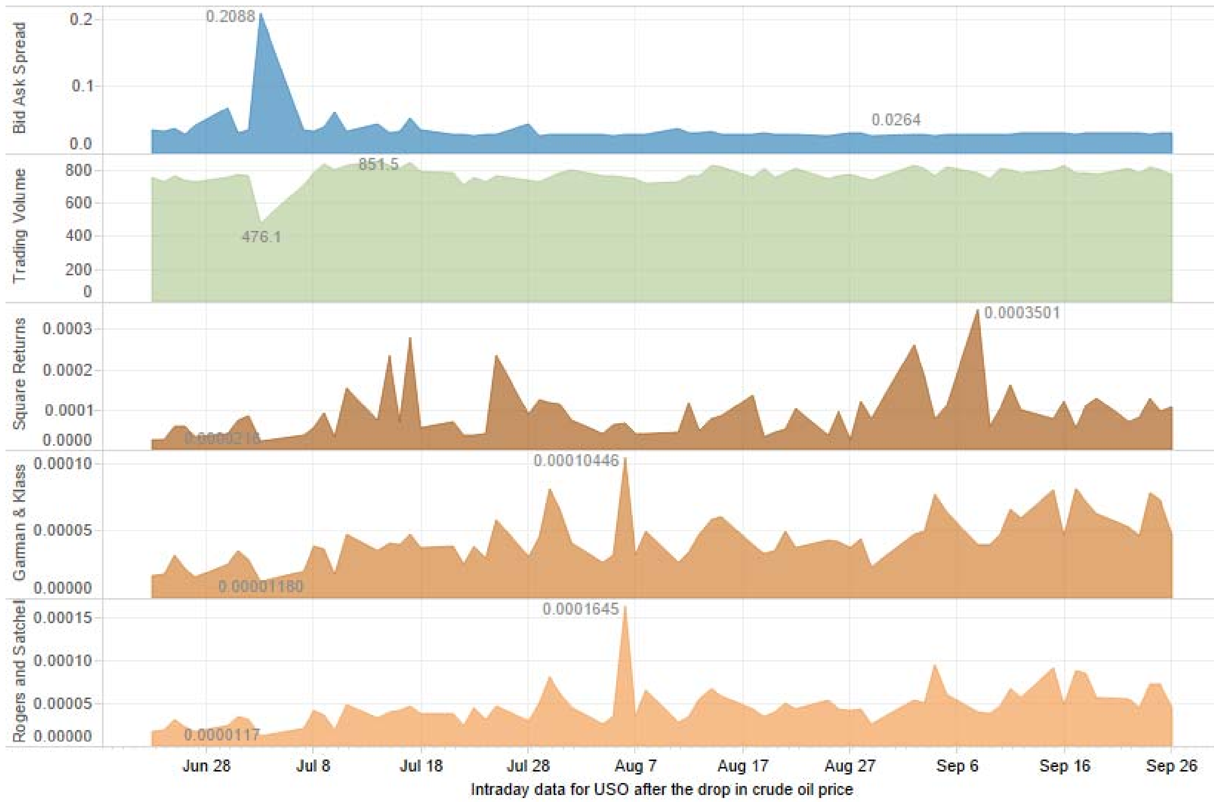

Figure 4: Intraday data for USO after the drop in crude oil prices. From top-to-bottom, Bid-Ask Spread, Trading volume, Square Returns, Garman & Klass Volatility, Rogers & Satchell Volatility

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