APPLIED FINANCE LETTERS

SPECIAL ISSUE, 2022

THE IMPACT OF OIL PRICE UNCERTAINTY ON THE US STOCK RETURNS

YIUMAN TSE[1*]

1. University of Missouri - St Louis, USA

* Corresponding Author: Yiuman Tse, Endowed Chair and Professor of Finance, University of Missouri—St. Louis, 1 University Blvd. 202 Anheuser-Busch Hall, St. Louis, MO 63121-4400, USA. ✉: tseyi@umsl.edu

Abstract

Oil price uncertainty has a negative and significant impact on stock returns during the period of 2003-2020, but not the earlier period of 1984-2002. The impact of stock price uncertainty on oil returns for both periods is not significant. Oil price uncertainty is important in examining stock price movement, particularly during years of financial crises. The cross-market causalities in returns and volatilities are not significant in both directions.

JEL classification: G14, G15

Keywords: Oil price uncertainty, futures markets, return causality, volatility spillovers

1. Introduction

Many papers have studied the relationship between oil and stock prices over the past four decades. The results, nevertheless, are not conclusive. Kling (1985) and Jones and Kaul (1986) report that oil price shocks negatively affect the stock market because higher oil prices increase the cost of production for firms. In contrast, Chen et al. (1986) and Huang et al. (1996) find no significant relationship between oil and stock returns. Hamilton (2009) and Kollias et al. (2013) document that the relationship is positive because rising oil prices suggest a thriving economy and high business confidence.

Kilian (2009) and Kilian and Park (2009) point out that previous empirical studies on the relationship between oil and stock returns restrict the oil price to be exogenous with respect to the US economy. However, the oil price since 1970s has responded to economic forces that drive stock prices. Oil and stock returns, therefore, should be considered endogenous in a dynamic model. Killian (2009) and Kilian and Park (2009) also show that how the stock price responds to oil price shocks depends on where the shocks come from.[1]

Instead of examining the relationship between oil and stock returns, several recent papers have provided theories and empirical results to show the negative effects of oil price uncertainty on economic activities. Elder and Serletis (2010) show that uncertainty about oil prices depresses investment, consumption, and total productivity in the US. Rahman and Serletis (2012) find similar results in the Canadian economy. According to Gao et al. (2022), firms accumulate inventories and postpone investments in order to mitigate the negative consequences of oil shocks, resulting in lower

[1] Killian (2009) states that the sharp oil price increase did not cause a recession because it was driven by sustained strong demand for oil fueled by a booming world economy, not by supply shocks or unanticipated increases in the precautionary demand for oil. See, e.g., Bauseister and Kilian, 2016, and Kilian et al., 2020, for recent evidence.

economic growth and negative stock returns. Christofferson and Pan (2018) show that oil price volatility is significantly related to various measures of funding constraints of financial intermediaries.

Elder and Serletis (2010) and Rahman and Serletis (2012) use a vector autoregressive (VAR) model that is modified to accommodate GARCH-in-mean shocks. As a measure of oil price uncertainty, the authors use the conditional standard deviation of the forecast error for the change in the oil returns. They only examine the oil price uncertainty on the economy, assuming that the oil price is exogenous. In this paper, I follow their models but consider oil and stock returns endogenous, examining both the impact of the oil price uncertainty on stock returns and that of the stock price uncertainty on oil returns.

I use daily returns of the crude oil futures and S&P 500 futures for the period of January 1984 through December 2020. I separate all the results into two subperiods: 1984-2002 and 2003-2020. For the earlier subperiod, the impact of the oil price uncertainty on stock returns is insignificant, but the impact is negative and significant for the more recent subperiod. The second subperiod overlaps the financialization of commodities and the 2008 global financial crisis. The impact of the stock price uncertainty on oil returns is negative, but not significant in both subperiods.

I also examine the return causality in a VAR model (without oil and stock price uncertainties) and find no cross-market causality in both subperiods. To investigate the volatility spillovers or connectedness between the oil and stock returns, I use the variance decomposition of the intraday range-based volatility proposed by Booth et al. (1997) and Diebold and Yilmaz (2009, 2012). The volatility connectedness between these two markets is small for both subperiods, with a total volatility connectedness index of less than 10%. Overall, the oil price uncertainty negatively affects the stock returns for recent years, but not the reverse. There is no cross-market return and volatility causality in both directions for both subperiods.

2. Data and Methodology

I obtain futures prices, open (P_t^{open}), high (P_t^{high}), low (P_t^{low}), and close (P_t^{close}), from Commodity Systems Inc. for NYMEX West Texas Intermediate (WTI) crude oil futures (ticker symbol, CL), the world's most liquid oil contract, and S&P 500 index futures (SP). Both futures contracts are traded on CME Group. I use the most liquid contracts (usually the nearby contracts) from January 3, 1984 through December 30, 2020, sample of 9283 days. 1984 is the first full year after crude futures started trading in March 1983. I separate this 37-year period into two subperiods: 1984-2002 (4761 days) and 2003-2020 (4522 days).[2]

The daily returns, ΔCL_t and ΔSP_t, are calculated as the log price changes in P_t^{close}. The bivariate VAR-GARCH-m model is as follows:

$$\Delta CL_t = a_1 + \sum_{j=1}^{q} b_{1j}\Delta CL_{t-j} + \sum_{j=1}^{q} c_{1j}\Delta SP_{t-j} + k_{11}\sigma_{1,t-1} + k_{12}\sigma_{2,t-1} + \varepsilon_{1t} \tag{1}$$

$$\Delta SP_t = a_2 + \sum_{j=1}^{q} b_{2j}\Delta CL_{t-j} + \sum_{j=1}^{q} c_{2j}\Delta SP_{t-j} + k_{21}\sigma_{1,t-1} + k_{22}\sigma_{2,t-1} + \varepsilon_{2t} \tag{2}$$

$$\varepsilon_{it}|\Omega_t \sim N(0, \sigma_{it}^2) \tag{3}$$

$$\sigma_{it}^2 = \omega_i + \alpha\varepsilon_{i,t-1}^2 + \beta\sigma_{i,t-1}^2, \; i = 1 \; or \; 2 \tag{4}$$

[2] I discard the week of April 20, 2020 because oil prices plummeted to negative for the first time as stockpiles overwhelmed storage facilities.

The parameters of interest are k_{12} in Eq. (1) and k_{21} in Eq. (2). k_{12} captures the stock price uncertainty (measured by $\sigma_{1,t-1}$) on oil return and k_{21} captures the oil price uncertainty ($\sigma_{2,t-1}$) on stock returns. Elder and Serletis (2010) assume $k_{12} = 0$.[3] A negative coefficient indicates negative impact of cross-market uncertainty.

k_{11} in Eq. (1) and k_{22} in Eq. (2) describe the own-market risk premium of the oil and stock markets, respectively. A positive coefficient of k_{11} (k_{22}) shows that the oil (stock) return is positively related to its volatility. I include $q = 10$ lags of returns in the VAR of Eqs. (1) and (2). The results are virtually the same using 5 lags. Eqs (1)-(4) are jointly estimated using maximum likelihood with heteroscedasticity adjusted standard errors.

The usual return causality is examined in a VAR with the two null hypotheses of all cross-markets coefficients being zero and the sum of cross-market coefficients being zero. The GARCH-*m* model uses the conditional standard deviation of shocks as uncertainty or volatility. In the following VAR (denoted by GK-VAR) and the forecast error variance decomposition, intraday volatility is measured by the Glass-Klass volatility estimator, σ_i^{GK} :

$$\sigma_{CL,t}^{GK} = f_1 + \sum_{j=1}^{q} g_{1j}\sigma_{CL,t-j}^{GK} + \sum_{j=1}^{q} h_{1j}\sigma_{SP,t}^{GK} + \epsilon_{1t} \tag{5}$$

$$\sigma_{SP,t}^{GK} = f_2 + \sum_{j=1}^{q} g_{2j}\sigma_{CL,t-j}^{GK} + \sum_{j=1}^{q} h_{2j}\sigma_{SP,t}^{GK} + \epsilon_{2t} \tag{6}$$

σ_i^{GK} is the square root of

$$(\sigma_i^{GK})^2 = 0.5\left(\log(P_{i,t}^{high}) - \log(P_{i,t}^{low})\right)^2 - 0.386\left(\log(P_{i,t}^{close}) - \log(P_{i,t}^{open})\right)^2 \tag{7}$$

as in the volatility spillovers across international index futures by Booth et al. (1997).[4]

I use the variance decomposition of the GK-VAR (5) and (6) in a 20-day forecast interval to examine volatility connectedness named by Diebold and Yilmaz (2009, 2012). Booth et al. (1997) and Diebold (2009) use Cholesky factorization to identify orthogonal innovations. In their examination of volatility spillovers across US stock, bond, foreign exchange, and commodities markets, Diebold and Yilmaz (2012) use the generalized VAR of Koop et al. (1996) and Pesaran and Shin (1998) that eliminates the dependence of results of ordering.

In addition to calculate the contributions from and to each market's volatility, Diebold and Yilmaz (2009, 2012) summarize the volatility connectedness across all the markets in a single index, the total spillover index. Higher the value of the index, higher the volatility spillovers across all the markets.

3. Empirical Results

I present all the results in three panels of each table, the first subperiod (1984-2002), the second subperiod (2003-2020), and the whole period (1984-2020). Table 1 reports the summarized statistics of

[3] They consider oil price uncertainty exogenous in a structural VAR and use $\sigma_{1,t}$, instead of $\sigma_{1,t-1}$, in the VAR.

[4] As Garman and Klass (1980, p.74) point out, Eq. (7) is more "practical" than the longer GK estimator that includes the cross-product terms. The results using the longer GK estimator as in Diebold et al. (2017) are qualitatively the same.

daily futures returns. CL offered moderately higher returns than SP during the first subperiod, but much lower return during the second subperiod, resulting in a lower return for the whole period (0.0036% vs 0.027%). CL is about twice as volatile as SP in both subperiods, measured by the standard deviation of returns (2.33% vs 1.23% for the whole period).

Table 1: Summary Statistics of Daily Returns

Panel A: January 1984 – December 2002								
	N	Mean	Median	Std	t-stat	Min	Max	Corr.
ΔCL	4761	0.0339	0.055	2.212	1.06	-38.41	13.57	N/A
ΔSP	4761	0.0209	0.043	1.243	1.16	-33.7	17.75	-0.048
Panel B: January 2003 – December 2020								
	N	Mean	Median	Std	t-stat	Min	Max	Corr.
ΔCL	4522	-0.0283	0.069	2.444	-0.78	-28.22	22.05	N/A
ΔSP	4522	0.0335	0.074	1.209	1.86	-10.95	13.2	0.288
Panel C: January 1984 – December 2020								
	N	Mean	Median	Std	t-stat	Min	Max	Corr.
ΔCL	9283	0.0036	0.058	2.328	0.15	-38.41	22.05	N/A
ΔSP	9283	0.027	0.059	1.227	2.21	-33.7	17.75	0.121

Note: The daily returns, ΔCL_t and ΔSP_t, are calculated as the log changes in closing prices.

The correlation between the oil and stock returns is close to zero, -0.048, during the first subperiod, but it increases to 0.288 during the second subperiod. Figure 1 plots the normalized futures prices (starting at 100). It shows that the higher correlation in the later subperiod is the result of the comovement during the financialization of commodities from 2004 to 2012 (Tang and Xiong, 2012, Cheng and Xiong, 2014). The price collapses during the 2008 global financial crisis and the Covid-19 pandemic in the first half of 2020 for both markets are also noticeable in the figure.

Table 1: Bivariate GARCH-m Models

$$\Delta CL_t = a_1 + \sum_{j=1}^{10} b_{1j}\Delta CL_{t-j} + \sum_{j=1}^{10} c_{1j}\Delta SP_{t-j} + k_{11}\sigma_{1,t-1} + k_{12}\sigma_{2,t-1} + \varepsilon_{1t}$$

$$\Delta SP_t = a_2 + \sum_{j=1}^{10} b_{2j}\Delta CL_{t-j} + \sum_{j=1}^{10} c_{2j}\Delta SP_{t-j} + k_{21}\sigma_{1,t-1} + k_{22}\sigma_{2,t-1} + \varepsilon_{2t}$$

$$\varepsilon_{it}|\Omega_t \sim N(0,\sigma_{it}^2), \qquad \sigma_{it}^2 = \omega_i + \alpha\varepsilon_{i,t-1}^2 + \beta\sigma_{i,t-1}^2, \ \ i = 1 \ or \ 2$$

	ΔCL		ΔSP	
	Coef.	**t-stat**	**Coef.**	**t-stat**
Panel A: January 1984 – December 2002				
k_{i1}	0.051	2.585	0.019	1.374
k_{i2}	-0.057	-1.909	0.063	4.397
ω_i	0.023	2.905	0.034	2.164
α_i	0.087	6.338	0.125	2.287
β_i	0.908	65.284	0.858	15.286
Panel B: January 2003 – December 2020				
k_{i1}	0.07	1.884	-0.031	-5.65
k_{i2}	-0.043	-0.517	0.125	6.317
ω_i	0.078	2.773	0.028	5.848
α_i	0.087	5.185	0.15	9.988
β_i	0.899	47.57	0.829	57.141
Panel C: January 1984 – December 2020				
k_{i1}	0.056	5.642	0.003	1.163
k_{i2}	-0.045	-1.757	0.083	11.694
ω_i	0.035	5.349	0.029	3.557
α_i	0.087	9.858	0.133	4.587
β_i	0.908	102.23	0.851	35.923

Note: t-statistics are calculated with heteroscedasticity adjusted standard errors.

Table 2 presents the results of the GARCH-*m* model. For the first subperiod, although both own-market risk premia are significant, 0.051 (t = 2.59) and 0.063 (t = 4.40), the cross-market impact of uncertainties are not significant at the 5% level. For the second subperiod, while the impact of stock price uncertainty on oil returns is not significant, the impact of oil price uncertainty on stock returns is negative and significant, -0.031 (t = -5.65). The cross-market impact of uncertainty is not significant for both markets using the whole period. In sum, the GARCH-m model shows significant own-market risk premium, but it only shows significant oil price uncertainty on stock returns during the second subperiod. This subperiod contains the period of financialization of commodities and the 2008 global finance crisis.

I examine the usual return causality in the VAR and present the results in Table 3. The cross-market return causality is not significant in both subperiods and the whole period. Table 4 further shows that volatility spillovers between the two markets are weak for all periods, although the second period has greater spillovers. The total spillover indexes of Diebold and Yilmaz (2009, 2012) are 1.7%, 8.2%, and 4.7% for the first, second, and the whole periods, respectively, indicating that over 90% of a market's volatility is contributed by its own volatility. For example, for the whole period, 94% of oil volatility is contributed by the oil market itself and 96% of stock volatility by itself. These results are consistent with Diebold and Yilmaz (2012) who find that cross-market volatility spillovers across US stocks, bonds, foreign exchange, and commodities markets are quite limited. In short, both the cross-market causality in returns and volatilities are not significant in both directions for all periods.

Table 3: Return Causality

	ΔCL (i = 1) value	statistic	p-value	ΔSP (i = 2) value	statistic	p-value
Panel A: January 1984 – December 2002						
$b_{ij} = 0, \forall j$=1 to 10, $\chi^2(10)$	N/A	20.04	0.0289	N/A	5.8	0.8315
$c_{ij} = 0, \forall j$=1 to 10, $\chi^2(10)$	N/A	7.21	0.7053	N/A	6.37	0.7837
$\sum\{j$=1 to 10$\}\ b_{ij} = 0$, t-stat.	-0.144	-1.87	0.061	-0.019	-0.77	0.4425
$\sum\{j$=1 to 10$\}\ c_{ij} = 0$, t-stat.	0.026	0.26	0.7964	-0.219	-1.27	0.2044
Panel B: January 2003 – December 2020						
$b_{ij} = 0, \forall j$=1 to 10, $\chi^2(10)$	N/A	12.12	0.2771	N/A	14.18	0.1651
$c_{ij} = 0, \forall j$=1 to 10, $\chi^2(10)$	N/A	11.31	0.334	N/A	12.34	0.2623
$\sum\{j$=1 to 10$\}\ b_{ij} = 0$, t-stat.	-0.031	-0.28	0.7776	0.03	0.73	0.4674
$\sum\{j$=1 to 10$\}\ c_{ij} = 0$, t-stat.	0.31	1.42	0.1559	-0.166	-1.16	0.2443
Panel C: January 1984 – December 2020						
$b_{ij} = 0, \forall j$=1 to 10, $\chi^2(10)$	N/A	9.55	0.4811	N/A	13.94	0.1756
$c_{ij} = 0, \forall j$=1 to 10, $\chi^2(10)$	N/A	7.13	0.7129	N/A	13.63	0.1905
$\sum\{j$=1 to 10$\}\ b_{ij} = 0$, t-stat.	-0.033	-0.47	0.6383	0.016	0.54	0.596
$\sum\{j$=1 to 10$\}\ c_{ij} = 0$, t-stat.	0.162	1.33	0.1831	-0.207	-1.75	0.0799

Note: The usual return causality is examined in a VAR (without oil and stock price uncertainties) with the two null hypotheses of all cross-markets coefficients (c_{1j} for ΔSP and b_{2j} for ΔCL) being zero and the sum of cross-market coefficients being zero. Statistics are calculated with heteroscedasticity adjusted standard errors.

Table 4: Volatility connectedness in return volatilities

	Oil	Stock
Panel A: January 1984 – December 2002		
Oil	97.97	2.03
Stock	1.40	98.60
Contribution including own	99.40	100.60
Total spillover index	1.70	
Panel B: January 2003 – December 2020		
Oil	90.12	9.88
Stock	6.50	93.50
Contribution including own	96.60	103.40
Total spillover index	8.20	
Panel B: January 1984 – December 2020		
Oil	94.45	5.55
Stock	3.92	96.08
Contribution including own	98.40	101.60
Total spillover index	4.70	

Note: The total spillover index (%) proposed by Diebold and Yilmaz (2009, 2012) estimates the overall cross-market volatility spillovers.

4. Conclusions

Previous studies have shown that oil price uncertainty has a negative impact on economy activities. Using daily crude oil and US stock index futures for the period of 1984 through 2020, I examine the impact of a market's price uncertainty on the other. I find oil price uncertainty decreased stock returns during the subperiod of 2003-2020, but not the earlier subperiod. The impact of stock price uncertainty on oil returns (albeit, negative) is not significant. Neither are cross-market causalities in returns and volatilities are significant in both directions. These results suggest that oil price uncertainty should be included in examining stock price movement, particularly during crisis periods.

References

Baumeister, C., Kilian, L., 2016. Lower oil prices and the US economy: Is this time different? Brookings Papers on Economic Activity, 287-336.

Booth, G.G., Chowdhury, M., Martikainen, T., Tse, Y., 1997. Intraday volatility in international stock index futures markets: meteor showers or heat waves? *Management Science* 43, 1564-1576.

Chen, N.-F., Roll, R., Ross, S.A., 1986. Economic forces and the stock market. *Journal of Business* 59, 383-403.

Cheng, I.-H., Xiong, W., 2014. Financialization of Commodity Markets. *Annual Review of Financial Economics* 6, 419-441.

Christoffersen, P., Pan, X., 2018. Oil volatility risk and expected stock returns. *Journal of Banking and Finance* 95, 5–26.

Diebold, F.X, Yilmaz, K., 2009. Measuring financial asset returns and volatility spillovers, with application to global equity markets. *Economic Journal* 119, 158-171.

Diebold, F.X, Yilmaz, K., 2012. Better to give than to receive: Predictive directional measurement of volatility spillovers. *International Journal of Forecasting* 28, 57-66.

Diebold, F.X., Liu, L, Yilmaz, K., 2017. Commodity connectedness. NBER Working Paper 23685.

Elder, J., Serletis, A., 2010. Oil price uncertainty. *Journal of Money, Credit and Banking* 42, 1137-1159.

Gao, L., Hitzemann, S., Shaliastovich, I., Xu, L., 2022. Oil volatility risk. Journal of Financial Economics, forthcoming.

Garman, M., Glass, M., 1980. On the estimation of security price volatilities from historical data. *Journal of Business* 53, 67-78.

Hamilton, J.D., 2009. Causes and consequences of the oil shock of 2007-08. NBER Working Paper, 15002.

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

Jones, C.M., Kaul, G., 1996. Oil and stock markets. *Journal of Finance* 51, 463-491

Kilian, L., 2009. Not all oil price shocks are alike: Disentangling demand and supply shocks in the crude oil market. *American Economic Review* 3, 1053-1069.

Kilian, P., Park, C., 2009. The impact of oil price shocks on the US stock market. *International Economic Review* 50, 1267-1287.

Kilian, L., Plante, M.D., Zhou, X. 2020. How falling oil prices in early 2020 weakened the US economy. Working Paper, Federal Reserve Bank of Dallas.

Kling, J.L., 1985. Oil price shocks and the stock market behavior. Journal of Portfolio Management 12, 34-39.

Kollias, C., Kyrtsou, C., Papadamou, S. 2013. The effects of terrorism on the oil price stock index relationship. Energy Economics 40, 743-752.

Koop, G., Pesaran, M.H., and Potter, S.M., 1996. Impulse response analysis in non-linear multivariate models. *Journal of Econometrics* 74, 119-147.

Pesaran, M.H., Shin, Y., 1998. Generalized impulse response analysis in linear multivariate models. *Economics Letters* 58, 17-29.

Rahman, S., Serletis, A., 2012. Oil price uncertainty and the Canadian economy: Evidence from a VARMA, GARCH-in-mean, asymmetric BEKK model. *Energy Economics* 34, 603-310.

Tang, K., Xiong, W., 2012. Index investment and financialization of commodities. *Financial Analysts Journal* 68, 54-74.