Temporal and spectral volatility spillover between oil and oil and gas firms

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Overview

Over the recent years, the applied research on the spillover dynamics has grown significantly. However, these studies mainly utilize information pertaining in the time-domain, thereby neglecting information embedded in the frequency domain. Whereas, understanding the time-frequency volatility spillover has important implications for asset allocation, investment and risk management, and policymaking. Therefore, in distinction with previous contributions on spillover dynamics, we estimate wavelet-based volatility spillover to evaluate temporal and spectral connectedness structure. More specifically, we implement maximal overlap discrete wavelet transform (MODWT) as introduced by Percival and Walden (2000) to decompose the underlying return series into short-, medium-, and long-run signal. Furthermore, we evaluate the volatility spillover dynamics by utilizing Diebold and Yilmaz (2014, 2015) (DY) frameworks.

Methods

Wavelet transform is an effective tool to evaluate the dynamic behavior of the underlying time series as it enables us to simultaneously undertake information embedded in the time and frequency domain of the underlying series. We utilize a modified version of discrete wavelet transform (DWT) called maximal overlap discrete wavelet transform (MODWT) to decompose the underlying time series. The MODWT decompose the underlying time $X_t, t = 0, \ldots, N-1$, into a set of subsequent wavelets based on two types of filters called the wavelet and the scaling filter. Denoting the wavelet filter and the scaling filter by h_l and g_l where $l = 0, \ldots, L-1$, respectively, we can then obtain the jth level wavelet and scaling coefficients, $W_{j,t}$ and $V_{j,t}$, as follows:

$$W_{j,t} = \sum_{l=0}^{L-1} \widetilde{h_l}\, X_{t-1} \qquad \text{and} \qquad V_{j,t} = \sum_{l=0}^{L-1} \widetilde{g_l}\, X_{t-1}.$$

and

$$\widetilde{h_{j,l}} = \frac{h_{j,l}}{2^{j/2}} \qquad \text{and} \qquad \widetilde{g_{j,l}} = \frac{g_{j,l}}{2^{j/2}}, \qquad j = 0, \ldots, J,$$

where J is the total number of levels. We select the Daubechies least asymmetric (LA) wavelet and scaling filter as it is based on the localized differences of the adjacent average weights and provide appealing regularity characteristics (Daubechies, 1992). We determine the optimal decomposition level for MODWT, which is estimated by $J \leq \log_2(\frac{T}{L-1} + 1)$, where L is the length of the filer and T is the length of the underlying time series.

To evaluate the volatility spillover dynamics between the underlying series, we utilized Diebold and Yilmaz (2014, 2015)(DY) frameworks. The primary advantage of applying DY frameworks compared to the more common approach of using impulse response functions with Cholesky factor decomposition is the elimination of order dependence in the obtained results. The total volatility spillover index (TVI) can be constructed as:

$$S^g(H) = \frac{\sum_{\substack{i,j=1 \\ i \neq j}}^{N} \tilde{\theta}^g_{ij}(H)}{\sum_{i,j=1}^{N} \tilde{\theta}^g_{ij}(H)} \cdot 100 = \frac{\sum_{\substack{i,j=1 \\ i \neq j}}^{N} \tilde{\theta}^g_{ij}(H)}{N} \cdot 100.$$

We chose nearby futures prices for crude oil as it reflects the expectation of investors regarding future spot prices. To evaluate firm-level spillover, we select the 25 largest oil and gas firms in the world. Based on the screening criteria, our final dataset comprises of 12 of the 25 largest firms. We collected data from the DataStream database, and all the series are expressed in USD. The starting period is 18th June 2001, which is dictated due to data availability. Table 1 provides the descriptive statistics and preliminary tests on the log returns of the series.

Table 1. Descriptive statistics

	Mean	SD	SR	Max	Min	Skew	Kurt	JB STAT	Q Stat	ARCH
Crude oil	3.55%	0.37	0.04	0.16	-0.17	-0.08	7.29	3378.18	32.47	697.70
BP	-1.78%	0.28	-0.14	0.15	-0.17	-0.43	13.60	20759.57	57.46	1011.83
Chevron	4.96%	0.25	0.12	0.19	-0.13	0.01	14.66	24934.79	80.15	1411.36
PetroChina	6.95%	0.35	0.14	0.14	-0.15	-0.04	8.54	5625.36	47.16	1088.62
ENI	1.23%	0.29	-0.03	0.14	-0.13	-0.27	8.43	5454.74	37.56	1104.85
Exxon Mobil	3.07%	0.24	0.04	0.16	-0.15	-0.04	14.90	25962.99	120.55	1437.03
Lukoil	9.99%	0.42	0.19	0.23	-0.40	-0.90	22.48	70158.43	83.86	1110.03
PetroBras	4.13%	0.51	0.04	0.26	-0.26	-0.10	8.95	6492.01	30.82	893.00
SHELL	-0.22%	0.27	-0.08	0.16	-0.12	-0.12	11.40	12938.55	49.73	1430.98
SINOPEC	9.14%	0.48	0.15	0.19	-0.17	0.06	7.30	3393.42	25.97	565.35
Equinor	6.21%	0.35	0.12	0.13	-0.16	-0.43	7.82	4405.15	41.12	1121.33
Total	2.39%	0.28	0.01	0.14	-0.13	-0.17	8.69	5954.28	35.84	1259.76
Valero	12.04%	0.39	0.26	0.17	-0.22	-0.55	9.44	7831.21	22.91	705.65

Results

Based on the conditional volatility estimates from the marginal distribution model, we estimate the volatility spillover between crude oil and the oil and gas companies. Specifically, the conditional volatility for each undecomposed and decomposed returns series are estimated by employing an ARMA(1,0)-EGARCH(1,1) specification. In the next step, the estimated volatilities are employed in the DY frameworks to estimate spillover between the underlying assets. Table 2 presents the bidirectional volatility spillovers based on full sample estimation. These estimates are based on the vector autoregression of order 1 (VAR(1)) and the generalized forecast error variance decomposition of 200-days-ahead. Application of DY frameworks yield a $N \times N$ matrix of directional volatility spillover. The diagonal elements represent self-caused volatility, while the off-diagonal elements represent variations caused in different markets. The row “To others” and “From others” represents the volatility spillover to and from other markets, respectively. The positive and negative values of “Net spillover” indicate whether an underlying asset is net transmitter or receiver.

Table 2. Volatility spillovers between crude oil and the oil and gas companies

	1	2	3	4	5	6	7	8	9	10	11	12	13
1	14.1	4.6	11.2	4.2	4.9	7.3	13.9	7.9	7.9	0.5	10.0	7.3	6.3
2	1.4	14.5	10.9	4.3	8.5	9.2	9.2	4.6	9.4	0.7	7.3	11.6	8.5
3	1.7	6.3	17.8	4.1	6.1	11.0	11.4	5.7	8.2	0.8	9.3	8.6	8.9
4	0.9	2.5	10.5	27.6	3.7	7.3	13.2	4.8	4.4	5.7	6.8	5.7	7.0
5	1.3	6.1	9.0	4.5	14.0	7.6	11.7	6.6	9.2	0.5	8.1	12.6	9.0
6	1.2	6.7	16.4	3.5	5.3	17.3	10.7	4.3	9.3	0.6	7.5	8.1	9.2
7	2.7	3.5	9.5	5.8	3.9	6.6	29.1	5.9	4.6	1.3	11.3	6.6	9.3
8	1.0	4.8	10.8	8.2	5.7	7.1	13.7	23.2	6.1	0.8	7.5	7.0	4.1
9	1.5	6.7	12.1	5.3	7.3	9.7	12.0	6.6	12.5	0.7	7.9	10.1	7.7
10	0.5	0.6	6.7	12.5	4.0	6.3	11.8	4.2	3.0	31.9	5.8	4.5	8.4
11	2.0	4.9	11.2	7.1	5.3	7.7	14.3	6.6	6.7	1.5	15.1	8.5	9.1
12	1.3	7.2	10.1	4.4	9.6	8.6	10.9	5.9	9.9	0.7	8.4	14.3	8.6
13	0.9	4.8	11.3	3.4	5.2	8.7	12.7	4.1	6.1	0.7	9.4	7.6	25.2
To others	16.4	58.7	129.7	67.5	69.4	96.9	145.4	67.2	84.7	14.4	99.2	98.1	96.1
From others	85.9	85.6	82.2	72.4	86.0	82.7	70.9	76.8	87.5	68.1	84.9	85.7	74.8
Net spillovers	-69.5	-26.9	47.4	-5.0	-16.7	14.1	74.5	-9.5	-2.8	-53.7	14.3	12.4	21.3
TVI													80.3

Notes. This table reports the variance decomposition of the estimated vector autoregressive model for the conditional volatilities (estimated by utilizing an ARMA(1,0)-EGARCH(1,1) specification) of the series. The estimates are based on the VAR order of 1 (determined by Schwartz Bayesian information criterion) and the 200-days-ahead forecasts. 1. Crude oil, 2. BP, 3. Chevron, 4. CNPC, 5. ENI, 6. EXXON, 7. LUKOIL, 8. PETROBRAS, 9. SHELL, 10. SINOPEC, 11. STATOIL, 12. TOTAL, and 13. Valero.

Conclusions

In this paper, we contribute to the spillover literature by evaluating time-frequency spillover between crude oil and the oil and gas firms using MODWT and spillover index. Our findings indicate that crude oil is net receiver of volatility from the large oil and gas corporations in our sample. However, the temporal spillover analysis indicates that the direction of spillover in time-varying and necessitates further investigation by employing the decomposed series.

References

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