Does Multi-scale Decomposition Improve Forecasting Horizons in Crude Oil Market?

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Overview

Importance

Predicting the crude oil prices, arguably the most important commodity in the world today, is of considerable interests to economists, policymakers, and investors, as the business cycle of the crude oil prices, is heterogeneous among the commodity classes.

One of the problems faced by policy maker in economics and finance is how to forecast the oil price, as the crude oil is one of the most important economic factors and its price has a vital effect on different countries' economies.

Background

- There are few studies on employing the wavelet approach for forecasting time series.
- One recent study is done by Zhang et.al. (2017), in which it has been shown how to decompose a univariate time series into "a set of constitutive series" and perform proper forecasting based on the framework suggested by Hyndmann et al. (2011)

Purpose

- In this paper, we introduce a new class of the optimal multi-scale forecasting dynamics in the crude oil return that characterize into a set of constitutive series with an explicitly defined hierarchical structure.
- We intend to adopt the wavelet-based MRA (Zhang et.al. 2017) to enhanced predictability in forecast horizons via monthly information.
- We concentrate on the optimal level of the wavelet decomposition via entropy and wavelet coherence.

Contribution

- This approach provides a useful mean to explore the complex dynamics of oil price. The wavelet forecasting method is a relatively new tool for the analysis of time series aftermath of the global financial and geopolitical crisis in crude oil market but it has extensive applications in areas of economics and finance in recent years (Gençay et al. 2011; Bekiros et al. 2013; Zhang et.al. 2017).
- The application of wavelet decomposition provided an enhanced predictability in many forecast horizons for the monthly returns.
- These results may have important implications for market predictability of the crude oil markets.

Methodology

- Our estimation approach is based on the wavelet-based multi resolution analysis (MRA), which could be combined with ordinary least squares (OLS) regression model to reconcile the decomposed series.
- We decomposed the original time series, we obtain wavelet multiple details and smooths. This multi-scale daily and monthly series are employed to forecast 1 to 14-step ahead values.

Methodology Cont.

- To the purpose of forecasting, we consider the most commonly used measure autoregressive moving average (ARMA) model. We use rolling window estimation and it makes sense to apply the automatic algorithm of auto ARIMA (Khandakar and Hyndman, 2008).
- The optimal AR and MA orders are selected based on the Akaike's information criterion (AIC).

Methodology Cont.

- Following that, based on the algorithm presented by Zang et al. (2017) and Hyndman et al. (2011), by defining the "summing" matrix, which presents the linear relationship in the hierarchy structure, and regressing the first-round predictions on the summing matrix, we compute the base level forecasts.
- Finally, we obtain the optimal predictions at all hierarchy levels based on the "summing" matrix and base level forecasts. As mentioned before, we are interested in comparing the accuracy of our forecasts based on different decomposition levels.

Data

- Our dataset includes monthly WTI prices of Crude Oil obtained from QUANDL data base . The monthly series is from February 29, 1980, to April 31, 2017. We use log returns to compute the original series.

Table 1. Descriptive Statistics

Series	No. Observations	Mean	Std.	Skew	Kurtosis	JB
ODA/POILWTI_USD	447	0.073	8.171	-0.394	3.231	209***

Notes: JB shows the result of the Jarque-Bera's normality test. *** denotes significance at 1%.

Results

Table 2. Forecast Improvement (rMSE) for Monthly Crude Oil Data (ODA/POILWTI_USD)

Forecasting Model	Forecast Horizon							
	1	2	3	4	5	6	7	8
auto ARMA-MRA (8)	0.878	0.977	0.981	0.973	0.984	0.971	0.983	0.985
auto ARMA-MRA (2)	0.936	0.990	0.993	0.985	0.993	0.986	0.995	0.993
auto ARMA-MRA (7)	0.923	0.990	1.001	1.000	1.001	1.001	0.993	0.998
auto ARMA-MRA (2)	0.973	1.000	1.002	1.001	1.001	0.999	0.993	1.000
auto ARMA-MRA (6)	0.942	1.036	1.044	1.009	1.004	0.998	0.990	1.016
auto ARMA-MRA (2)	0.982	1.030	1.034	1.007	1.006	1.001	0.990	1.006
auto ARMA-MRA (5)	0.974	1.020	1.058	1.038	1.032	1.007	1.007	1.012
auto ARMA-MRA (2)	0.998	1.019	1.050	1.033	1.023	1.001	1.003	1.008
auto ARMA-MRA (4)	1.003	1.046	1.080	1.072	1.127	1.166	1.197	1.224
auto ARMA-MRA (2)	1.015	1.040	1.067	1.060	1.105	1.129	1.158	1.177
auto ARMA-MRA (3)	1.028	1.065	1.108	1.133	1.160	1.231	1.267	1.304
auto ARMA-MRA (2)	1.025	1.057	1.094	1.116	1.139	1.195	1.227	1.257

Note: This Table reports the improvements in rMSE criteria

Results Cont.

Table 2 Cont. Forecast Improvement (rMSE) for Monthly Crude Oil Data (ODA/POILWTI_USD)

Forecasting Model	Forecast Horizon						
	9	10	11	12	13	14	Average
auto ARMA-MRA (8)	1.003	1.000	1.001	0.996	0.990	0.992	0.979
auto ARMA-MRA (2)	1.007	1.002	1.004	1.001	0.993	0.995	0.991
auto ARMA-MRA (7)	0.999	1.002	1.004	1.007	1.000	1.003	0.994
auto ARMA-MRA (2)	1.003	1.003	1.004	1.004	0.999	1.001	0.999
auto ARMA-MRA (6)	1.014	1.021	1.018	1.002	1.006	1.014	1.008
auto ARMA-MRA (2)	1.007	1.008	1.009	0.996	0.998	1.000	1.005
auto ARMA-MRA (5)	1.020	1.013	1.012	0.992	1.005	1.027	1.015
auto ARMA-MRA (2)	1.010	1.005	1.007	0.995	1.008	1.019	1.013
auto ARMA-MRA (4)	1.232	1.281	1.291	1.278	1.290	1.310	1.193
auto ARMA-MRA (2)	1.184	1.215	1.228	1.228	1.237	1.257	1.157
auto ARMA-MRA (3)	1.341	1.382	1.406	1.441	1.466	1.502	1.290
auto ARMA-MRA (2)	1.285	1.318	1.334	1.363	1.381	1.409	1.244

Note: This Table reports the improvements in rMSE criteria

Results Cont.

Table 3. Forecast Improvement (MAE) for Monthly Crude Oil Data (ODA/POILWTI_USD)

Forecasting Model	Forecast Horizon							
	1	2	3	4	5	6	7	8
auto ARMA-MRA (8)	0.943	0.985	0.989	0.983	0.997	0.988	0.996	0.999
auto ARMA-MRA (2)	0.943	0.985	0.989	0.983	0.997	0.988	0.996	0.999
auto ARMA-MRA (7)	0.916	0.979	0.989	0.998	1.001	1.004	0.991	1.005
auto ARMA-MRA (2)	0.959	0.994	1.000	1.006	1.006	1.004	0.994	1.005
auto ARMA-MRA (6)	0.944	1.008	1.018	0.998	0.996	0.995	0.979	1.017
auto ARMA-MRA (2)	0.980	1.003	1.016	1.007	1.005	1.002	0.984	1.006
auto ARMA-MRA (5)	0.964	1.000	1.032	1.034	1.014	0.994	1.001	1.006
auto ARMA-MRA (2)	0.988	1.006	1.035	1.030	1.011	0.997	0.998	1.006
auto ARMA-MRA (4)	0.976	0.979	0.978	0.991	1.004	1.002	1.012	1.024
auto ARMA-MRA (2)	0.994	0.990	0.991	1.000	1.018	1.010	1.015	1.031
auto ARMA-MRA (3)	1.006	1.020	1.018	1.043	1.041	1.056	1.060	1.056
auto ARMA-MRA (2)	1.006	1.019	1.018	1.038	1.035	1.049	1.054	1.050

Note: This Table reports the improvements in MAE criteria.

Results Cont.

Table 3 Cont. Forecast Improvement (MAE) for Monthly Crude Oil Data (ODA/POILWTI_USD)

Forecasting Model	Forecast Horizon						
	9	10	11	12	13	14	Average
auto ARMA-MRA (8)	1.015	1.005	1.012	1.000	0.994	0.992	0.992
auto ARMA-MRA (2)	1.015	1.005	1.012	1.000	0.994	0.992	0.992
auto ARMA-MRA (7)	1.007	1.000	1.003	1.002	0.997	1.002	0.992
auto ARMA-MRA (2)	1.007	1.002	1.005	1.001	0.998	1.002	0.999
auto ARMA-MRA (6)	1.013	1.028	1.027	1.003	1.003	1.013	1.003
auto ARMA-MRA (2)	1.006	1.010	1.018	0.997	0.999	0.998	1.002
auto ARMA-MRA (5)	1.017	1.012	1.023	0.987	0.996	1.015	1.007
auto ARMA-MRA (2)	1.008	1.004	1.011	0.991	1.004	1.003	1.007
auto ARMA-MRA (4)	1.022	1.024	1.015	0.986	0.967	0.963	0.995
auto ARMA-MRA (2)	1.025	1.028	1.019	1.005	0.998	0.999	1.009
auto ARMA-MRA (3)	1.048	1.051	1.052	1.045	1.047	1.066	1.044
auto ARMA-MRA (2)	1.043	1.046	1.045	1.039	1.040	1.057	1.039

Note: This Table reports the improvements in MAE criteria.

Results Cont.

Table 4. Paired t-statistics (rMSE) for Monthly Crude Oil Data (ODA/POILWTI_USD)

Forecasting Model	Forecast Horizon							
	1	2	3	4	5	6	7	8
auto ARMA-MRA (8)	-2.884	-1.352	-1.547	-2.496	-1.731	-3.037	-1.848	-1.510
auto ARMA-MRA (2)	-2.234	-1.022	-1.056	-2.100	-1.048	-2.429	-1.057	-1.151
auto ARMA-MRA (7)	-2.487	-0.649	0.067	-0.014	0.078	0.155	-0.932	-0.258
auto ARMA-MRA (2)	-1.286	0.045	0.261	0.170	0.171	-0.222	-1.531	-0.069
auto ARMA-MRA (6)	-1.773	1.604	1.736	0.560	0.261	-0.163	-0.926	1.720
auto ARMA-MRA (2)	-0.703	1.801	1.894	0.727	0.619	0.055	-1.303	1.063
auto ARMA-MRA (5)	-1.048	0.970	1.686	2.211	1.868	0.498	0.654	0.765
auto ARMA-MRA (2)	-0.113	1.218	1.953	2.677	1.767	0.139	0.401	0.672
auto ARMA-MRA (4)	0.135	0.964	1.016	0.944	1.283	1.070	1.121	1.089
auto ARMA-MRA (2)	0.780	1.104	1.153	1.017	1.382	1.119	1.186	1.143
auto ARMA-MRA (3)	1.229	1.149	1.132	1.275	1.176	1.106	1.109	1.079
auto ARMA-MRA (2)	1.262	1.177	1.152	1.281	1.178	1.110	1.114	1.084

Note: This Table reports the Paired t-statistics of the difference in mean between the squared errors.

Results Cont.

Table 4 Cont. Paired t-statistics (rMSE) for Monthly Crude Oil Data (ODA/POILWTI_USD)

Forecasting Model	Forecast Horizon					
	9	10	11	12	13	14
auto ARMA-MRA (8)	0.417	0.038	0.157	-0.604	-1.470	-1.503
auto ARMA-MRA (2)	1.518	0.404	0.987	0.158	-1.600	-1.278
auto ARMA-MRA (7)	-0.139	0.258	0.712	1.209	0.094	0.553
auto ARMA-MRA (2)	0.822	0.970	1.479	1.358	-0.445	0.382
auto ARMA-MRA (6)	1.465	2.379	1.863	0.265	0.667	0.920
auto ARMA-MRA (2)	1.085	1.295	1.435	-0.599	-0.422	-0.031
auto ARMA-MRA (5)	1.601	1.376	1.305	-0.783	0.390	0.909
auto ARMA-MRA (2)	1.063	0.686	1.122	-0.879	0.987	0.832
auto ARMA-MRA (4)	0.996	1.059	0.986	0.915	0.877	0.875
auto ARMA-MRA (2)	1.048	1.091	1.035	0.987	0.949	0.960
auto ARMA-MRA (3)	1.043	1.029	1.025	1.026	1.017	1.022
auto ARMA-MRA (2)	1.046	1.032	1.025	1.027	1.018	1.023

Note: This Table reports the Paired t-statistics of the difference in mean between the squared errors.

Results Cont.

Table 5. t-statistics (MAE) for Monthly Crude Oil Data (ODA/POILWTI_USD)

Forecasting Model	Forecast Horizon							
	1	2	3	4	5	6	7	8
auto ARMA-MRA (8)	-2.305	-1.508	-1.682	-1.971	-0.611	-1.922	-0.694	-0.323
auto ARMA-MRA (2)	-1.926	-1.170	-1.157	-2.063	-0.432	-1.551	-0.618	-0.104
auto ARMA-MRA (7)	-2.577	-1.293	-0.714	-0.153	0.089	0.370	-0.879	0.543
auto ARMA-MRA (2)	-1.766	-0.607	0.031	0.770	0.855	0.568	-0.914	0.902
auto ARMA-MRA (6)	-1.833	0.426	0.957	-0.121	-0.264	-0.321	-1.605	1.474
auto ARMA-MRA (2)	-0.861	0.222	1.294	0.635	0.471	0.155	-1.777	0.800
auto ARMA-MRA (5)	-1.390	0.003	1.616	2.044	0.940	-0.507	0.057	0.432
auto ARMA-MRA (2)	-0.549	0.468	2.398	2.453	0.971	-0.289	-0.235	0.551
auto ARMA-MRA (4)	-1.162	-1.073	-0.966	-0.390	0.138	0.076	0.360	0.700
auto ARMA-MRA (2)	-0.376	-0.639	-0.499	0.017	0.827	0.439	0.605	1.181
auto ARMA-MRA (3)	0.478	1.305	0.976	1.983	1.632	1.963	1.858	1.576
auto ARMA-MRA (2)	0.481	1.455	1.121	2.076	1.640	2.044	1.980	1.648

Note: This Table reports the Paired t-statistics of the difference in mean between the absolute errors.

Results Cont.

Table 5 Cont. t-statistics (MAE) for Monthly Crude Oil Data (ODA/POILWTI_USD)

Forecasting Model	Forecast Horizon					
	9	10	11	12	13	14
auto ARMA-MRA (8)	1.494	0.625	1.470	-0.763	-1.812	-1.901
auto ARMA-MRA (2)	2.507	0.787	1.995	0.008	-0.915	-1.425
auto ARMA-MRA (7)	0.817	-0.001	0.426	0.290	-0.491	0.329
auto ARMA-MRA (2)	1.437	0.405	1.289	0.368	-0.739	0.518
auto ARMA-MRA (6)	1.273	2.565	2.721	0.327	0.307	1.157
auto ARMA-MRA (2)	0.948	1.444	2.659	-0.557	-0.178	-0.289
auto ARMA-MRA (5)	1.160	1.000	1.795	-0.966	-0.259	0.878
auto ARMA-MRA (2)	0.787	0.410	1.359	-1.110	0.422	0.282
auto ARMA-MRA (4)	0.569	0.580	0.337	-0.315	-0.707	-0.738
auto ARMA-MRA (2)	0.852	0.891	0.594	0.134	-0.060	-0.032
auto ARMA-MRA (3)	1.234	1.179	1.171	0.929	0.928	1.202
auto ARMA-MRA (2)	1.288	1.258	1.180	0.953	0.941	1.242

Note: This Table reports the Paired t-statistics of the difference in mean between the absolute errors.

Results Cont.

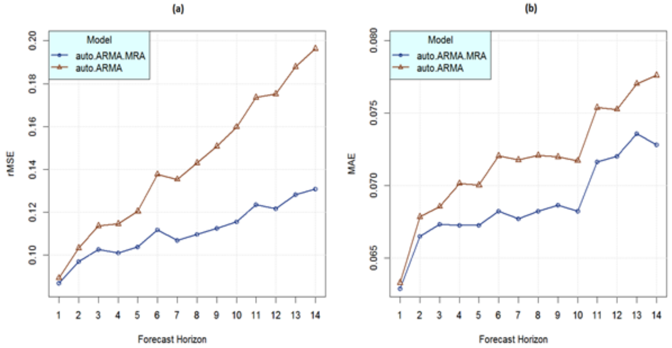

Figure: rMSE (a) and MAE (b) for monthly crude oil returns from auto ARMA-MRA model with 4 levels of decomposition with the forecast errors from simple auto ARMA model as the benchmark

Results Cont.

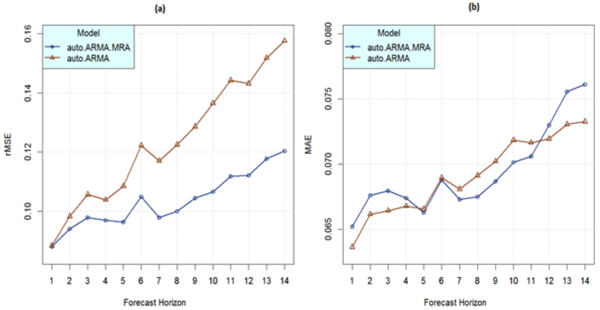

Figure: rMSE (a) and MAE (b) for monthly crude oil returns from auto ARMA-MRA model with 3 levels of decomposition with the forecast errors from simple auto ARMA model as the benchmark

Results Cont.

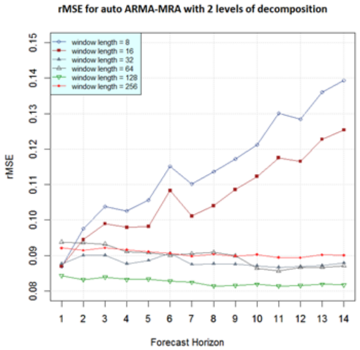

Figure: rMSE for monthly crude oil returns

Conclusion Remarks

- In this work, we explored the wavelet-based MRA to forecast monthly crude oil prices.
- Our results suggest that the auto ARMA-MRA model is more accurate than the simple auto ARMA model, in terms of forecasting monthly crude oil prices.
- Our forecast accuracy would decrease (leading to higher forecast errors) by increasing the level of the decomposition, which could be due to the requirement of increasing the estimation window length.

Conclusion Remarks Cont.

- As the market participants may have diverse trading objectives (Aguiar-Conraria and Soares, 2013; Bekiros et al. 2016), our results provide interesting investment insights for long-term investors who focus on long-run oscillations (i.e., months).
- These results may have important implications for market predictability of the crude oil markets.

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