CHAPTER 2
DEVELOPMENT OF FINANCE, ACCOUNTING AND AUDITING

LINKAGES BETWEEN CRUDE OIL FUTURES AND SELECTED SECTORAL INDICES: EVIDENCE FROM CAUSALITY APPROACH

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Abstract. *The aim of this study is to empirically show the dynamic causal relationship between crude oil future prices and sectoral indices of India using daily data from November 30th, 2011 to November 18th, 2021 and its subsets. First, we apply ADF, P-P and KPSS unit root tests and then Johansen tests for estimating the cointegration. We use Granger Causality to find linkages and further VAR and VECM as per cointegration. VAR results are supported by Impulse Response whereas Wald tests ascertain the shortterm relationship for insignificant coefficients. The study found that crude oil futures and sectoral indices are integrated of order one in subset 2 whereas subset 1 and full data period doesn't show cointegration. The overall result for the full data period shows the metal sector and crude oil futures have bidirectional causality with significant impact on the metal sector. The Metal Index also has symmetric results on different time horizons. Subdata 2 shows long term relations between crude oil futures and all the sectors except FMCG and Health. Subdata 1 shows the lag of crude oil futures influences the metal sector only in the short term. The study is conducted for a period of ten years and based in India, which is an oil importing country. The availability of commodity derivatives data is also limited in India, hence the study cannot be generalized for all the countries. No study has been done considering crude oil futures and sectoral indices of India, hence providing the gap for the study.*

Keywords: *Crude Oil Futures, Sector Index, Granger Causality, Vector Autoregression, VECM.*
***JEL Classification**: C39, C58, F41, G11*
Formulas: 10; fig.: 3; tabl.: 9; bibl.: 41

Introduction. Crude oil is extensively used in production and is the most traded commodity in the world. India's consumption of crude oil and its products grew four and half percent in Financial Year 2020 and retained third spot in consumer oil in the world in 2019 (IBEF report, November 2021*). Further, oil usage in India is projected to register a two times to eleven million barrel growth in next twenty three years whereas diesel demand is expected to double to one hundred sixty three metric ton by 2029-2030.

The dependence on imported crude has increased from 82.9 percent (Financial Year 2018) to 83.7 percent (Financial Year 2019) and crude production has stagnated around thirty five metric ton in the past decade. This will have a negative impact on the fiscal deficit which in turn influences the economy and touches every sector of the country (Economic Times, 2020[1]).

Since, WTI crude is considered as the world benchmark for crude oil futures, therefore, a number of studies are there showing the market efficiency of WTI crude with its spot price (Bekiros & Diks, 2008). Further, there is an existence of information flow and a long-term relationship exists between Indian and US crude oil futures (Sharma, 2017). Moreover, the volume of crude oil granger causes the prices or absolute returns in India (Biswas, S. and Rajib, 2011) and there is a lack of cointegration relationship between crude oil futures and the stock market in India (Bakshi et al. ,2021). Crude oil shocks have a significant negative impact on economic development in India (Sreenu, 2018) and a fall in crude oil price gives positive signs to FMCG sector[2] (Business Standard, 2020) whereas rise in crude oil would have a negative impact on Auto sector[3](Business Standard, 2021). In the Indian metal sector industrial metal shows weak correlation with crude oil whereas precious metals do not show any trend (Kaushik, 2018). Later, the financialization of commodity futures also serves as the mechanism of price discovery and risk management; the presence of financialization is also found in Indian commodity futures (Shamsher, 2021). Crude oil futures are the derivative instruments which not only help the market participants to manage risk but are also considered as a part of investment portfolios by financial market participants. Some of the studies like (Lu *et al*., 2021; see also LI *et al*.,2021) evidenced that in the Chinese derivative market, crude oil futures are good hedging tools.

Crude oil in itself is very vital from an economic point of view and a small variation can affect the whole economy which in turn impacts the stock market and hence every sector will get affected. Any change in crude oil prices can be reflected in its futures market as both the markets are efficient (Bekiros & Diks, 2008). Therefore, to see the direction of impact between crude oil futures and sectoral indices, VAR-VECM-Granger Causality is applied, also the movement of crude oil futures on sectoral indices can be seen in different time frames i.e long run and short run which can be confirmed initially using cointegration and further wald test is applied (Sharma, 2017).

This paper mainly contributes to the research related to Crude oil futures' impact on sectoral indices and as far as we have studied, there is only one study considering crude oil spot prices and Indian sectoral indices (Tiwari *et al*., 2018) and till now no study exists considering the futures prices. In addition to this, the study period is also divided into two sub-period which give us the evidence of long and short term relationships in comparison to full data and all three sets of data are further tested for relationships of different time frames which will provide the robust results. These results are important for trading strategies and can be used by active market players.

Literature Review. Crude oil is considered as a leading factor in today's oil intensive economy, that is why there are many studies that have focused on showing the evidence of oil impact on the economy (Berument *et al*., 2010) as well as on the stock market (Alamgir *et al*.,2021). We can see the negative impact of oil price change on the stock market in (Apergis & Miller, 2009; see also Al-hajj *et al*., 2018) whereas (Arouri & Rault, 2012) explained that the oil price change has a significant positive relationship with the stock market. However, some researchers also found no significant influence (Apergis *et al*., 2009; see also Aloui *et al*., 2012) found no significant repercussions for oil importing countries like India. All this is due to different scenarios of different countries i.e. countries importing oil have different impacts than the countries with oil export.

There are many studies explaining the lead & lag relationship of spot and future prices of crude oil like in (Bekiros & Diks, 2008) shows the bidirectional causal linkage of WTI crude oil and (Wang & Wu, 2013) also found that the long term relationship exists between futures and spot prices of WTI Crude Oil but in regime only and the price differentials are greater than the threshold value. Looking at the relationship of futures prices of crude oil and stock index futures, we found that in (Lu *et al*., 2021) stock index futures of US shows causality with WTI Crude oil futures having weak significance as compared to china. Also, the short term fluctuations of WTI futures have less influence on Chinese index futures than US. The researchers also found that that the returns and volatility returns of stock index futures lead the stock market index (Liu & Dong, 2011) and in general stock index futures lead the stock index (Antoniou & Garrett, 1993).

Sector specific study is important for investment purposes and further helps in diversification. There are few studies that focus on oil's impact on industry level. Also, there is a correlation between changing oil prices and the industrial sector (Degiannakis *et al*., 2013). The impact of oil price volatility varies from sector to sector (Arouri & Nguyen, 2010; see also Fang & Egan, 2018; Faff & Brailsford, 1999). The impact of oil is negative where oil is an input and positive where oil is an output (Ramos & Veiga, 2011). All these studies consider the spot price of oil and not the future price, therefore, this study considers the future prices of oil and sectoral indices of India.

There are numerous studies between oil prices and the stock market showing the causality approach. Sometimes, it is unidirectional causality and sometimes bidirectional and also there is evidence of no causality (Table-1). Different models are used in the previous literature according to the data and the relationship can be found between oil prices and stock market, oil prices and sectoral indices and oil futures and stock index futures (Table 1).

Methods. The sample used in the study is daily Crude Oil Futures (close prices) and Sectoral Indices (daily) of India. The period of study is based on the availability of data from November 30th, 2011 to November 18th, 2021; 2467 observations. Further, the data has been divided into two sub-data (approx. equally) to get the more reliable results:

- Sub-data 1 from November 30th, 2011 to December 30th, 2016; 1262 observations,
- Sub-data 2 from January 2nd, 2017 to November 18th, 2021; 1205 observations.

The selection of the sector is based on the sectoral indices provided by NSE India but the data is collected from S&P Global whereas the future prices of crude oil are retrieved from MCX India. All the sectoral indices data are not available from 2011 but S&P Global provides data with the use of a backtesting approach. The unmatched data of crude oil futures and sectoral indices has been eliminated from the time series for analysis.

Table 1. Studies Analyzing the relationship between prices of oil and stock market/sectoral indices and oil futures and stock index/stock index futures

Authors	Countries	Data	Methodology	Empirical Findings
Tiwari et al., (2018)	India	BSE Sectoral Indices, BSE Sensex and Brent Crude oil prices	Quantile Regression, VAR Granger Causality & Frequency Domain Granger Causality	Banks, energy and capital goods are interdependent with oil , other sectors' impacts are mixed. Carbon resistant to oil shocks.
Ciner, (2001)	USA	NYMEX Crude oil Futures, S&P 500 Stock Index	VAR Model, Nonlinear Granger Causality	Causality test suggests a nonlinear causal relationship between oil and stock index.
Lu et al. (2021)	USA & China	Futures prices of WTI crude oil, S&P 500 Index and CSI 300 Index	Granger Causality, VAR, MIC, DCC-GARCH	US and Chinese stock futures granger-cause of WTI futures, VAR shows weak significance for US but strong for china.
Yadav et al. (2021)	India	Crude oil price, BSE Sensex	VAR, Granger Causality	Causal relationships exist between oil and sensex.
Shabbir et al. (2020)	Pakistan	Gold Price, Crude oil Price and stock market	ARDL Model	Prices of Oil and Gold have a significant impact on the stock market.
Arouri & Nguyen, (2010)	Europe	Stock Index and Sectoral Indices	VAR - GARCH Model	Significant transmission between oil and stock market with spillover from oil prices to stock market
Lee et al. (2012)	G7	Oil prices and Stock Index	Unrestricted VAR	There is no impact of fluctuations in oil prices on G7 stock indexes, however it influences some sectors of some countries.
Mensi et al. (2022)	Europe	Gold Price, Crude oil Price and Equity Sectoral Indices	VAR Model	Gold is a weak recipient of the spillover effect from all sectors and crude oil is weakly connected to few sectors.
Aydogan & İstemi, (2014)	Turkey	Brent crude oil price, ISE 100	VAR Model	Global liquidity has a more significant impact on the Turkish stock market than the oil price variations
Bouri et al. (2017)	India	Volatility Index of Gold, Crude oil and Nifty	ARDL Model, Causality Test	Causality from volatility of Gold price and Oil price to volatility in the Indian stock market.
Huang et al. (1996)	USA	Crude oil futures, Interest rate, S&P 500, Oil equities.	VAR Model	Crude oil future returns are not related to the stock market except oil companies and the volatility relationship for both is not clear.
Sharma, (2017)	India & USA	Crude oil futures of India and USA.	VECM and Wald test	Bidirectional information flows in the long term but in the short term it flows only from US crude oil to India. The US market is more efficient.

Source: developed by authors

Also, there are three future prices on a given date but we have selected that close price which is closer to the expiry date. All the data in this paper is used in logarithmic form as it reduces the problem of heteroscedasticity by compressing the scale of variables (Gujarati, D.N., 1995).

Literature shows the evidence of a relationship between prices of crude oil and stock market index but the relationship is found to be complex. The models used in the literature are very useful for finding the causal relationship, therefore, we have used VAR (Sims, C. A., 1980) or VECM as per the cointegration relationship and Granger Causality approach (Granger, C. W. J., 1969) in our study.

The relationship between crude oil futures and sectoral indices of India can be written as:

$$CF_t = \alpha + \beta_1 A_t + \beta_2 B_t + \beta_3 C_t + \beta_4 F_t + \beta_5 H_t + \beta_6 I_t + \beta_7 M_t + \beta_8 O_t + \beta_9 R_t + \varepsilon_t \quad (1)$$

Here, ε_t = white noise. Logarithmic form of the above equation is as follows:

$$LCF_t = a_0 + a_1 + \beta_1 LA_t + \beta_2 LB_t + \beta_3 LC_t + \beta_4 LF_t + \beta_5 LH_t + \beta_6 LI_t + \beta_7 LM_t + \beta_8 LO_t + \beta_9 LR_t + \varepsilon_t \quad (2)$$

Here, t = trend variable, LCF = Log of Crude oil Futures, LA = Log of Auto, LB = Log of Bank, LC = Log of Consumer Durables, LF = Log of FMCG, LH = Log of Healthcare, LI = Log of IT, LM = Log of Metal, LO = Log of Oil and Gas, LR = Log of Realty.

Modern society is an energy intensive society and the major player of the energy sector is Crude Oil, hence, every sector has direct or indirect impact on crude oil price or vice-versa. After solving the above equation every β represents how impactful the relationship it holds with crude oil futures. The sign of β also shows whether it leads to an increase or decrease in the prices of crude oil futures. Some of the variables in our equation suffer from the problem of multicollinearity which we test by coefficient diagnostics considering all dependent and independent variables. Since we are also considering two sub-data in our study, therefore, we eliminated different independent variables in different data sets based on Variance Inflation Factors (only variables with VIF value less than 10 are included). Following independent variables are considered for further study in all the data sets:

Sub-Data 1 variables	*Sub-Data 2 variables*	*Full-Data*
Bank Index	Auto Index	Auto Index
FMCG Index	Bank Index	Bank Index
Metal Index	FMCG Index	Health Index
Oil and Gas Index	Health Index	Metal Index
Realty Index	Metal Index	Realty Index
	Oil and Gas Index	
	Realty Index	

Since we have already eliminated some of the variables, therefore, new equations can be written as follows:

For sub-data 1 (2011-2016):

$$CF_t = \alpha + \beta_1 B_t + \beta_2 F_t + \beta_3 M_t + \beta_4 O_t + \beta_5 R_t + \varepsilon_t \quad (3)$$

Here, ε_t = white noise. Logarithmic form of the above equation is as follows:

$$LCF_t = a_0 + a_1 + \beta_1 LB_t + \beta_2 LF_t + \beta_3 LCM + \beta_4 LO_t + \beta_5 LR_t + \varepsilon_t \quad (4)$$

Here, t = trend variable, LCF = Log of Crude oil Futures, LB = Log of Bank, LF = Log of FMCG, LM = Log of Metal, LO = Log of Oil and Gas, LR = Log of Realty.

For sub-data 2 (2017-2021):

$$CF_t = \alpha + \beta_1 A_t + \beta_2 B_t + \beta_4 F_t + \beta_5 H_t + \beta_7 M_t + \beta_8 O_t + \beta_9 R_t + \varepsilon_t \quad (5)$$

Here, ε_t = white noise. Logarithmic form of the above equation is as follows:

$$LCF_t = a_0 + a_1 + \beta_1 LA_t + \beta_2 LB_t + \beta_4 LF_t + \beta_5 LH_t + \beta_7 LM_t + \beta_8 LO_t + \beta_9 LR_t + \varepsilon_t \quad (6)$$

Here, t = trend variable, LCF = Log of Crude oil Futures, LA = Log of Auto, LB = Log of Bank, LF = Log of FMCG, LH = Log of Healthcare, LM = Log of Metal, LO = Log of Oil and Gas, LR = Log of Realty.

For Full-Data (2011-2021):

$$CF_t = \alpha + \beta_1 A_t + \beta_2 B_t + \beta_3 H_t + \beta_4 M_t + \beta_5 R_t + \varepsilon_t \quad (7)$$

Here, ε_t = white noise. Logarithmic form of the above equation is as follows:

$$LCF_t = a_0 + a_1 + \beta_1 LA_t + \beta_2 LB_t + \beta_3 LH_t + \beta_4 LM_t + \beta_5 LR_t + \varepsilon_t \quad (8)$$

Here, t = trend variable, LCF = Log of Crude oil Futures, LA = Log of Auto, LB = Log of Bank, LH = Log of Healthcare, LM = Log of Metal, LR = Log of Realty.

We can further study the relationship of dependent and independent variables by looking at their time series properties and testing the order of integration. We would be using the Granger Causality approach to check the line of causality among the variables. This paper would estimate the impact of crude oil futures on different sectoral indices of India using the Johansen cointegration approach on the basis of stationarity results and testing the long-term relationship between them. Our approach to this paper includes the following steps:

1) We need to check for stationarity of the series mentioned in (4) (6) (8). We are using ADF (Augmented Dickey Fuller, 1979; 1981), PP (Philips-Perron, 1988) and KPSS (Kwiatkowski-Phillips-Schmidt-Shin, 1992) unit root tests. In any variable case, if the results of any two unit root tests contradict each other then the third one will break the tie (as used by Pandey, V., & Vipul., 2017).

2) If all the variables are either I (0) or I (1) but show no cointegration, we can run them in VAR (Vector Auto Regressive).

3) If variables are I (1) and show cointegration then they have a long-term relationship and VAR is not appropriate, hence, we use VECM (Vector Error Correction Model).

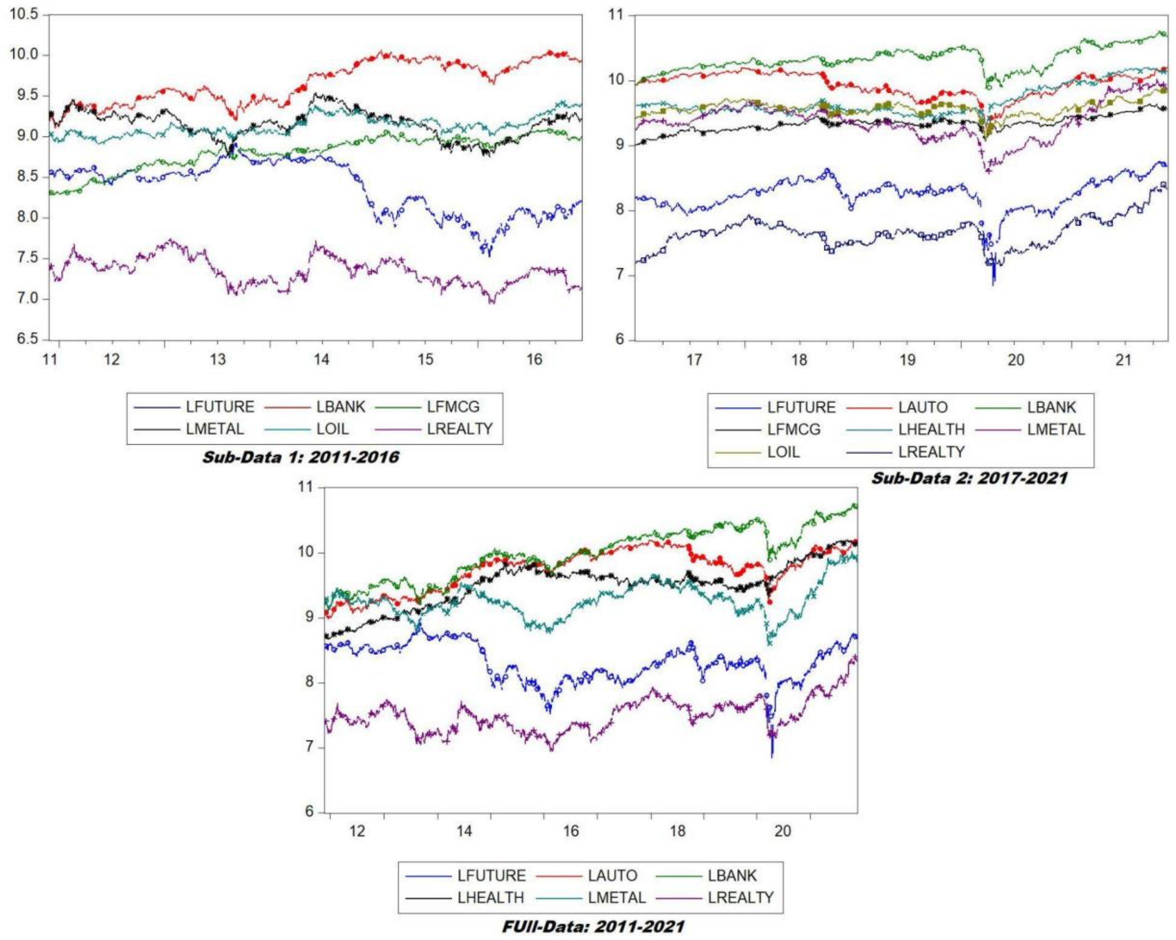

Figure 1. Graphical form of data sets for India

Source: Author's Calculation

Fig. 1 shows all the series in logarithmic form. The movement of variables overtime shows a trend in LFUTURES stand for Log of Crude oil Futures; LAUTO stands for Log of Auto Index; LBANK stand for Log of Bank Index; LFMCG stands for Log of FMCG Index; LHEALTH stands for Log of Health Sector Index; LMETAL stands for Log of Metal Index; LOIL stands for Log of Oil and Gas Index; LREALTY stands for Log of Realty sector Index.

To get a better understanding of the relationship between the futures prices of crude oil and sectoral indices of India, a descriptive analysis of data is first carried out. Table 2 presents the descriptive results of Log of Crude oil futures and Log of sectoral indices of India. It shows the results in three categories: For Sub-data1, Sub-data2 and Full-Data.

Table 2. Summary of Descriptive Statistics for all the data sets used in study

				Sub-Data 1							
	Mean	**Median**	**Max**	**Min**	**Std. Dev.**	**Skewness**	**Kurtosis**	**J-B**	**Prob.**	**Obs**	**C with LCF**
LFUTURE	8.368	8.495	8.923	7.519	0.321021	-0.473212	1.991649	100.57	0	1262	1
LBANK	9.671	9.722	10.065	9.102	0.252913	-0.151456	1.622109	104.66	0	1262	-0.7046
LFMCG	8.808	8.847	9.108	8.284	0.206126	-0.956475	3.037487	192.5	0	1262	-0.5415
LMETAL	9.159	9.192	9.545	8.753	0.169074	-0.2843	2.518067	29.21	0	1262	0.4694
LOIL	9.132	9.11	9.428	8.907	0.117148	0.581686	2.547816	81.92	0	1262	-0.2538
LREALTY	7.345	7.344	7.745	6.94	0.167002	0.148657	2.313515	29.43	0	1262	0.3504
				Sub-Data 2							
	Mean	**Median**	**Max**	**Min**	**Std. Dev.**	**Skewness**	**Kurtosis**	**J-B**	**Prob.**	**Obs**	**C with LCF**
LFUTURE	8.245	8.266	8.757	6.842	0.249184	-1.17633	6.774938	992.556	0	1204	1
LAUTO	9.936	9.989	10.207	9.236	0.186792	-0.970589	3.665849	211.2783	0	1204	0.576
LBANK	10.328	10.308	10.763	9.87	0.180284	0.076789	2.452801	16.20448	0.000303	1204	0.7024
LFMCG	9.332	9.336	9.636	9.004	0.115706	0.006789	3.496257	12.36384	0.002066	1204	0.5754
LHEALTH	9.68	9.578	10.199	9.306	0.226938	1.033895	2.709737	218.727	0	1204	0.3436
LMETAL	9.376	9.369	10.017	8.594	0.286907	-0.101762	3.02994	2.122974	0.345941	1204	0.7577
LOIL	9.569	9.581	9.872	9.098	0.111206	-0.409745	4.664474	172.6756	0	1204	0.7325
LREALTY	7.656	7.653	8.395	7.145	0.236964	0.491529	3.749168	76.63731	0	1204	0.6689
				Full-Data							
	Mean	**Median**	**Max**	**Min**	**Std. Dev.**	**Skewness**	**Kurtosis**	**J-B**	**Prob.**	**Obs**	**C with LCF**
LFUTURE	8.308	8.312	8.923	6.842	0.294627	-0.513064	3.417106	126.0654	0	2466	1
LAUTO	9.741	9.821	10.207	8.977	0.314397	-0.64096	2.224311	230.675	0	2466	-0.3539
LBANK	9.992	10.001	10.763	9.102	0.395331	-0.240336	2.01032	124.3801	0	2466	-0.2923
LMETAL	9.265	9.251	10.017	8.594	0.258026	0.403189	3.37188	81.02238	0	2466	0.4314
LHEALTH	9.499	9.56	10.199	8.661	0.346693	-0.444216	2.86001	83.11542	0	2466	-0.423
LREALTY	7.497	7.48	8.395	6.94	0.256558	0.610237	3.513411	180.136	0	2466	0.2557

Note: LCF = Log of Crude oil Futures, LA = Log of Auto, LB = Log of Bank, LF = Log of FMCG, LH = Log of Healthcare, LM = Log of Metal, LO = Log of Oil and Gas, LR = Log of Realty, C with LCF = Correlation with Log of Crude Futures.
Source: Author's Calculation

Descriptive Statistics of daily futures prices and all selected sectors shows that the average mean value of all the variables are increased in the period 2017-2021 as compared to the previous period and an overall increase can be seen in full data as compared to sub data 1. The reason could be covid crisis because of which the values of skewness and kurtosis also show high values in the period covering 2019-2020, hence the distribution is not skewed and leptokurtic except one variable in sub data 1 and three variables in sub data 2 and three variables in full data. Crude oil futures show a slightly high negative correlation with sectoral indices in sub data 1 but it changed to slightly high positive correlation with different sectors but full data shows a weak negative correlation. A positive correlation signifies that an increase in crude oil futures prices results in positive growth in the sectoral index and negative correlation means increase in crude oil futures prices results in a decline of that sector Index.

Results. To see the relationship between the futures prices of crude oil and sectoral indices, first we should examine the stochastic properties of the series chosen for the study and analyze their order of integration on the basis of their stationarity.

Stationarity (Unit Root) Tests. Tabulated reports in Table 3 shows the results for stationarity of the series and we have applied three tests i.e. ADF (Augmented

Dicky Fuller), P-P (Phllips-Perron) and KPSS (Kwiatkowski–Phillips–Schmidt–Shin) to determine the stationarity of crude oil futures and sectoral indices of India. The results are determined by considering the linear trend (MacKinnon, 1991) and indicate that all the series are stationary at first difference series i.e. I (1) for all the variables allowing us to model VAR or VECM based on their cointegration relationship.

Table 3. Stationarity (Unit Root) Tests results of Augmented Dickey Fuller (ADF), Phillips-Perron (P-P), Kwiatkowski-Phillips-Schmidt-Shin (KPSS).

Sub-Data 1	ADF		P-P		KPSS	
Variables	I(0)	I(1)	I(0)	I(1)	I(0)	I(1)
LFUTURE	-1.603(0.7916)	-35.454(0.000)***	-1.673(0.7628)	-35.451(0.000)***	0.582	0.1198***
LBANK	-2.319 (0.4225)	-32.251(0.000)***	-2.248(0.4615)	-32.202(0.000)***	0.272	0.0481***
LFMCG	-2.367(0.3967)	-33.845(0.000)***	-2.445(0.3554)	-33.830(0.000)***	0.725	0.0217***
LMETAL	-1.712(0.7455)	-34.495(0.000)***	-1.7943(0.7072)	-34.494(0.000)***	0.223	0.0816***
LOIL	-2.463(0.3466)	-34.260(0.000)***	-2.501(0.3272)	-34.271(0.000)***	0.235	0.0536***
LREALTY	-2.803(0.1963)	-32.726(0.000)***	-2.848(0.1802)	-32.707(0.000)***	0.115***	0.0358***
Sub-Data 2						
LFUTURE	-2.376(0.3916)	-39.050(0.000)***	-2.513(0.3213)	-38.560(0.000)***	0.3595	0.0479***
LAUTO	-0.868(0.9576)	-35.031(0.000)***	-0.868(0.9576)	-35.031(0.000)***	0.684	0.1511**
LBANK	-2.126(0.5301)	-33.907(0.000)***	-2.137(0.5237)	-33.907(0.000)***	0.2857	0.0953***
LFMCG	-3.440(0.0466)**	-11.624(0.000)***	-3.088(0.1094)	-36.692(0.000)***	0.4136	0.0750***
LHEALTH	-1.417(0.8556)	-32.778(0.000)***	-1.581(0.7999)	-32.945(0.000)***	0.9816	0.0408***
LMETAL	-0.653(0.9753)	-35.897(0.000)***	-0.741(0.9690)	-35.933(0.000)***	0.6683	0.1843**
LOIL	-2.029(0.5843)	-12.234(0.000)***	-2.017(0.5907)	-35.138(0.000)***	0.4014	0.0787***
LREALTY	-0.978(0.9451)	-32.319(0.000)***	-1.236(0.9017)	-32.419(0.000)***	0.4520	0.1732**
Full-Data						
LFUTURE	-2.201(0.4877)	-53.893(0.000)***	-2.360(0.4003)	-53.645(0.000)***	0.5516	0.0414***
LAUTO	-0.868(0.9576)	-35.031(0.000)***	-0.868(0.9576)	-35.031(0.000)***	0.6843	0.1511*
LBANK	-2.833(0.1852)	-46.952(0.000)***	-3.079(0.1115)	-46.985(0.000)***	0.3445	0.0318***
LHEALTH	-1.752(0.7275)	-46.006(0.000)***	-1.784(0.7120)	-46.199(0.000)***	0.8344	0.1468***
LMETAL	-1.378(0.8673)	-50.009(0.000)***	-1.574(0.8030)	-50.163(0.000)***	0.2163	0.0776***
LREALTY	-1.800(0.7046)	-45.985(0.000)***	-1.895(0.6564)	-46.075(0.000)***	0.3910	0.0496***

Note: *** represents significance at 1% level, ** at 5% and * at 10%. Probability values are shown in ( ). Lag selection is based on SIC.
Source: Author's calculation

All the tests consider the Schwarz Information Criteria with automatic selection as it gives the most consistent results. All the variables are considered as the I(1) stationary in the similar way as by Aydogan & İstemi (2014). Thus we can now proceed to testing the Johansen Cointegration.

Johansen Cointegration. Table 3 presents the Johansen Cointegration tests with crude oil futures prices and sectoral indices of India. The results are presented in trace statistics and Max Eigen values as per (Johansen, S., 1995). The number of variables are different in different samples and the null hypothesis in both trace and eigen statistics is that, there are r cointegrating vectors but alternative is opposite saying more than r, therefore, we have to test sequentially, starting with r=0 and if we find trace or max value smaller than the critical value, then we can not reject the null and if trace or max value is greater than the critical value and p value is less than five percent then we have to reject the null and there is at most one cointegrating vector. For the eigenvalue test the alternative is r+1 and we have to go sequentially again.

Table 4. Johansen Cointegration Tests Results

	Trace Statistics			Max-Eigen Statistics		
Subdata 1	Trace Value	Critical Value	p-Value	Max	Critical Value	p-Value
Ho: r=0	74.33852	83.93712	0.2025	31.11357	36.63019	0.1913
Ho: r=1	43.22495	60.06141	0.5567	17.48284	30.43961	0.7388
Ho: r=2	25.74212	40.17493	0.602	11.71912	24.15921	0.8027
Ho: r=3	14.02299	24.27596	0.5352	8.158732	17.7973	0.6886
Ho: r=4	5.864262	12.3209	0.4527	5.861689	11.2248	0.3657
Ho: r=5	0.002573	4.129906	0.9653	0.002573	4.129906	0.9653
Subdata 2						
Ho: r=0	188.0831	169.5991	**0.0036****	67.6975	53.18784	**0.0009****
Ho: r=1	120.3856	134.678	0.2525	35.52656	47.07897	0.4792
Ho: r=2	84.85901	103.8473	0.4494	34.16691	40.9568	0.2371
Ho: r=3	50.6921	76.97277	0.8338	20.15624	34.80587	0.8035
Ho: r=4	30.53586	54.07904	0.8956	13.67789	28.58808	0.8965
Ho: r=5	16.85797	35.19275	0.8921	9.711471	22.29962	0.8569
Fulldata						
Ho: r=0	111.4965	117.7082	0.1158	42.33713	44.4972	0.0843
Ho: r=1	69.15941	88.8038	0.54	26.75832	38.33101	0.5439
Ho: r=2	42.40109	63.8761	0.7608	20.20121	32.11832	0.6361
Ho: r=3	22.19989	42.91525	0.9058	11.39052	25.82321	0.9074
Ho: r=4	10.80937	25.87211	0.8858	5.722762	19.38704	0.9665
Ho: r=5	5.086606	12.51798	0.584	5.086606	12.51798	0.584

Note: *** represents significance at 1% level, ** at 5% and * at 10%. Lag selection is based on SIC
Source: Author's calculation

In Johansen cointegration tests optimal lag length is determined by VAR model and in this study we have followed SIC criteria because of its consistency and it selected relatively low lag values as compared to AIC (Akaike Information Criterion). Also, SIC is preferred to AIC on the basis of Monte Carlo evidence (Pesaran et al., 1998). (MacKinnon et al., 1999) is being followed for the p values reported in Table 3 and the results are consistent, showing the one cointegrating relationship between variables in sub data-2 at five percent significance level. This result shows that there is a long-term relationship between the variables in sub-data 2 only, meaning that we have to check for short-term relationships in all the data samples now.

Granger Causality. We can find the causal relationship between two variables by using the Granger Causality approach where the previous information must have some impact on the current values or prices. Here the log of crude oil futures and log of sectoral indices are used to construct this approach and significant F values mean a significant causal relationship. Example: if Y causes X and individually both series are I(1) and cointegrated then causal relationship is in atleast one direction. It also determines if X can be explained using current values or past values and if adding lagged values can forecast better or not. Table-5 shows the results for Granger Causality with significant F-values.

Table 5. Granger Causality Test results

Sub-Data 1					
Causality from Oil Futures to Sectors	F-statistics	P-value	Causality from Sectors to Oil Futures	F-statistics	P-value
Crude oil Futures => Bank	0.85962	0.4236	Bank => Crude oil Futures	3.0611	**0.0472****
Crude oil Futures => FMCG	0.14636	0.8639	FMCG => Crude oil Futures	1.05029	0.3501
Crude oil Futures => Metal	4.51775	**0.0111****	Metal => Crude oil Futures	0.39218	6.76E-01
Crude oil Futures => Oil	1.58101	0.2062	Oil => Crude oil Futures	1.41276	2.44E-01
Crude oil Futures => Realty	0.65721	0.5185	Realty => Crude oil Futures	0.18084	0.8346
Sub-Data 2					
Causality from Oil Futures to Sectors	F-statistics	P-value	Causality from Oil Futures to Sectors	F-statistics	P-value
Crude oil Futures => Auto	1.58196	0.206	Auto => Crude oil Futures	3.8771	**0.021****
Crude oil Futures => Bank	2.55434	0.0782	Bank => Crude oil Futures	4.42637	**0.0122****
Crude oil Futures => FMCG	0.60342	0.5471	FMCG => Crude oil Futures	11.614	1.00E-05
Crude oil Futures => Health	2.46674	0.0853	Health => Crude oil Futures	12.1746	6.00E-06
Crude oil Futures => Metal	4.33783	**0.0133****	Metal => Crude oil Futures	7.42125	**0.0006****
Crude oil Futures => Oil	3.70534	**0.0249****	Oil => Crude oil Futures	11.1125	2.00E-05
Crude oil Futures => Realty	1.53841	0.2151	Realty => Crude oil Futures	4.32053	**0.0135****
Full-Data					
Causality from Oil Futures to Sectors	F-statistics	P-value	Causality from Oil Futures to Sectors	F-statistics	P-value
Crude oil Futures => Auto	1.89555	0.1505	Auto => Crude oil Futures	2.32213	0.0983
Crude oil Futures => Bank	0.86839	0.4198	Bank => Crude oil Futures	1.4103	0.2443
Crude oil Futures => Health	1.68739	0.1852	Health => Crude oil Futures	4.66635	**0.0095****
Crude oil Futures => Metal	7.44602	**0.0006****	Metal => Crude oil Futures	1.07686	0.3408
Crude oil Futures => Realty	0.54845	0.5779	Realty => Crude oil Futures	0.68762	0.5029

Note: *** represents significance at 1% level, ** at 5% and * at 10%
Source: Author's calculation

For Sub-Data 1 only two cases show the probability values of F-statistics smaller than 0.05 or five percent. Therefore, only in these two cases we can not accept the null hypothesis i.e. Bank sector Index granger-cause crude oil futures and crude oil futures granger-cause metal index i.e. unidirectional causality only. Rest of the null hypothesis is accepted. Similarly, in Sub-Data 2 Crude oil futures causes oil sector index and auto, bank and oil sectoral indices causes crude oil futures showing unidirectional causality but crude oil futures and metal sector shows a bidirectional causality.

Vector Autoregressive. If we want to capture transmission accurately between different variables, then we can use the VAR Model. In our study we did not find cointegrating relationships in Sub-Data 1 and Full-Data, therefore, we will be using VAR in both of these cases. The lag selection criteria is followed by considering AIC, SIC and HQC but the more reliable value is chosen on the basis of least change in value by a particular criterion. Here in Table 6, and Table 8 we can see that the results are slightly different from Granger Causality and are more accurate.

As per granger causality test banking sector granger causes crude oil futures but no such evidence exists in the VAR model. Instead, the banking sector has more impact of its lagged values but the metal sector results are similar and shows the evidence of the impact on the metal sector is from the lagged value of crude oil futures. Additionally, VAR shows the impact from the lag of the Bank Index. Full-Data results also show that crude oil futures have a significant impact of lagged value of crude oil futures as well as lag of health index which coincides with granger causality results.

Table 6. Vector Autoregressive (Sub-Sample 1)

	D1FUTURE	D1BANK	D1FMCG	D1METAL	D1OIL	D1REALTY
D1FUTURE(-1)	0.000558	-0.024022	-0.005161	**0.062343****	0.034089	-0.007953
	(-0.02829)	(-0.02061)	(-0.01445)	(-0.0227)	(-0.0179)	(-0.02925)
	[0.01974]	[-1.16567]	[-0.35705]	[2.74690]	[1.90420]	[-0.27190]
D1BANK(-1)	-0.04906	**0.182533****	**0.063618****	**0.165448****	**0.13142****	**0.19066****
	(-0.06019)	(-0.04385)	(-0.03075)	(-0.04829)	(-0.03809)	(-0.06224)
	[-0.81510]	[4.16274]	[2.06859]	[3.42604]	[3.45012]	[3.06346]
D1FMCG(-1)	0.000563	-0.019601	**0.068125****	-0.053043	0.005973	0.003391
	(-0.06165)	(-0.04491)	(-0.0315)	(-0.04946)	(-0.03902)	(-0.06375)
	[0.00914]	[-0.43641]	[2.16265]	[-1.07237]	[0.15308]	[0.05320]
D1METAL(-1)	-2.94E-05	-0.038115	-0.042573	-0.060556	-0.05459	-0.061825
	(-0.05077)	(-0.03699)	(-0.02594)	(-0.04073)	(-0.03213)	(-0.0525)
	[-0.00058]	[-1.03052]	[-1.64118]	[-1.48667]	[-1.69909]	[-1.17773]
D1OIL(-1)	0.019594	-0.039019	-0.03168	-0.018863	-0.038802	0.013987
	(-0.06355)	(-0.0463)	(-0.03247)	(-0.05099)	(-0.04022)	(-0.06571)
	[0.30831]	[-0.84275]	[-0.97560]	[-0.36993]	[-0.96475]	[0.21285]
D1REALTY(-1)	0.032539	-0.030982	-0.024705	0.013779	0.015084	0.01328
	(-0.04068)	(-0.02964)	(-0.02079)	(-0.03264)	(-0.02575)	(-0.04207)
	[0.79981]	[-1.04532]	[-1.18841]	[0.42212]	[0.58584]	[0.31568]
C	-0.000239	0.000465	0.00048	-8.40E-05	0.000248	-0.000318
	(-0.00058)	(-0.00042)	(-0.00029)	(-0.00046)	(-0.00036)	(-0.0006)
	[-0.41530]	[1.10813]	[1.62771]	[-0.18155]	[0.67929]	[-0.53393]

Note: *** represents significance at 1% level, ** at 5% and * at 10%. Standard Errors in ( ) and t-statistics in [ ]. Lag selection is based on SIC.
Source: Author's calculation

Table 7. Vector Autoregressive Tests results (Full-Sample)

	D1FUTURE	D1AUTO	D1BANK	D1HEALTH	D1METAL	D1REALTY
D1FUTURE(-1)	**-0.042351****	**0.020728****	-0.009108	0.016025	**0.054269****	-0.015375
	(-0.01961)	(-0.01044)	(-0.01196)	(-0.00848)	(-0.01367)	(-0.01553)
	[-2.15989]	[1.98619]	[-0.76148]	[1.89076]	[3.97008]	[-0.99009]
D1AUTO(-1)	-0.033742	0.009938	0.014422	0.008205	-0.057661	-0.026854
	(-0.05943)	(-0.03163)	(-0.03625)	(-0.02569)	(-0.04143)	(-0.04707)
	[-0.56775]	[0.31420]	[0.39781]	[0.31938]	[-1.39173]	[-0.57056]
D1BANK(-1)	-0.054566	**0.060619****	**0.111207****	-0.013757	**0.079424****	**0.100488****
	(-0.05116)	(-0.02723)	(-0.03121)	(-0.02211)	(-0.03566)	(-0.04052)
	[-1.06661]	[2.22634]	[3.56351]	[-0.62213]	[2.22700]	[2.48025]
D1HEALTH(-1)	**-0.15602****	0.012998	**-0.081013****	**0.072894****	**-0.085212****	-0.017782
	(-0.05611)	(-0.02986)	(-0.03423)	(-0.02425)	(-0.03912)	(-0.04444)
	[-2.78064]	[0.43524]	[-2.36689]	[3.00550]	[-2.17845]	[-0.40018]
D1METAL(-1)	0.01646	**-0.055387****	**-0.068827****	-0.022257	-0.036049	-0.019551
	(-0.04164)	(-0.02216)	(-0.0254)	(-0.018)	(-0.02903)	(-0.03298)
	[0.39530]	[-2.49928]	[-2.70975]	[-1.23666]	[-1.24189]	[-0.59288]
D1REALTY(-1)	0.070565	0.015857	0.01669	0.022432	0.042636	0.053321
	(-0.03632)	(-0.01933)	(-0.02216)	(-0.0157)	(-0.02532)	(-0.02876)
	[1.94287]	[0.82031]	[0.75330]	[1.42883]	[1.68389]	[1.85373]
C	0.000341	0.000431	0.000596	**0.000532****	0.000288	0.000336
	(-0.00052)	(-0.00027)	(-0.00031)	(-0.00022)	(-0.00036)	(-0.00041)
	[0.66190]	[1.57062]	[1.89585]	[2.38799]	[0.80253]	[0.82272]

Note: *** represents significance at 1% level, ** at 5% and * at 10%. Standard Errors in ( ) and t-statistics in [ ]. Lag selection is based on SIC.
Source: Author's calculation

Health index also has a significant impact on its lag and constant term, meaning some other variables are also affecting this sector but we have not considered those factors. Also, the metal index has a significant impact from the lag of crude oil futures and additionally, lag of the bank and health sector shows the significant impact.

Impulse Response Function (IRF). We complement VAR (in sub-data1 and full-data samples) using the Impulse response function by plotting the multiple graphs with monte carlo applying one million simulations.We have considered 10 lags to show the data of ten year meaning that we are assuming each lag as each year. IRF is basically a response to a shock or change in the system caused by some external event. It not only provides dynamic behavior but also traces the transmission of shock within the whole system.

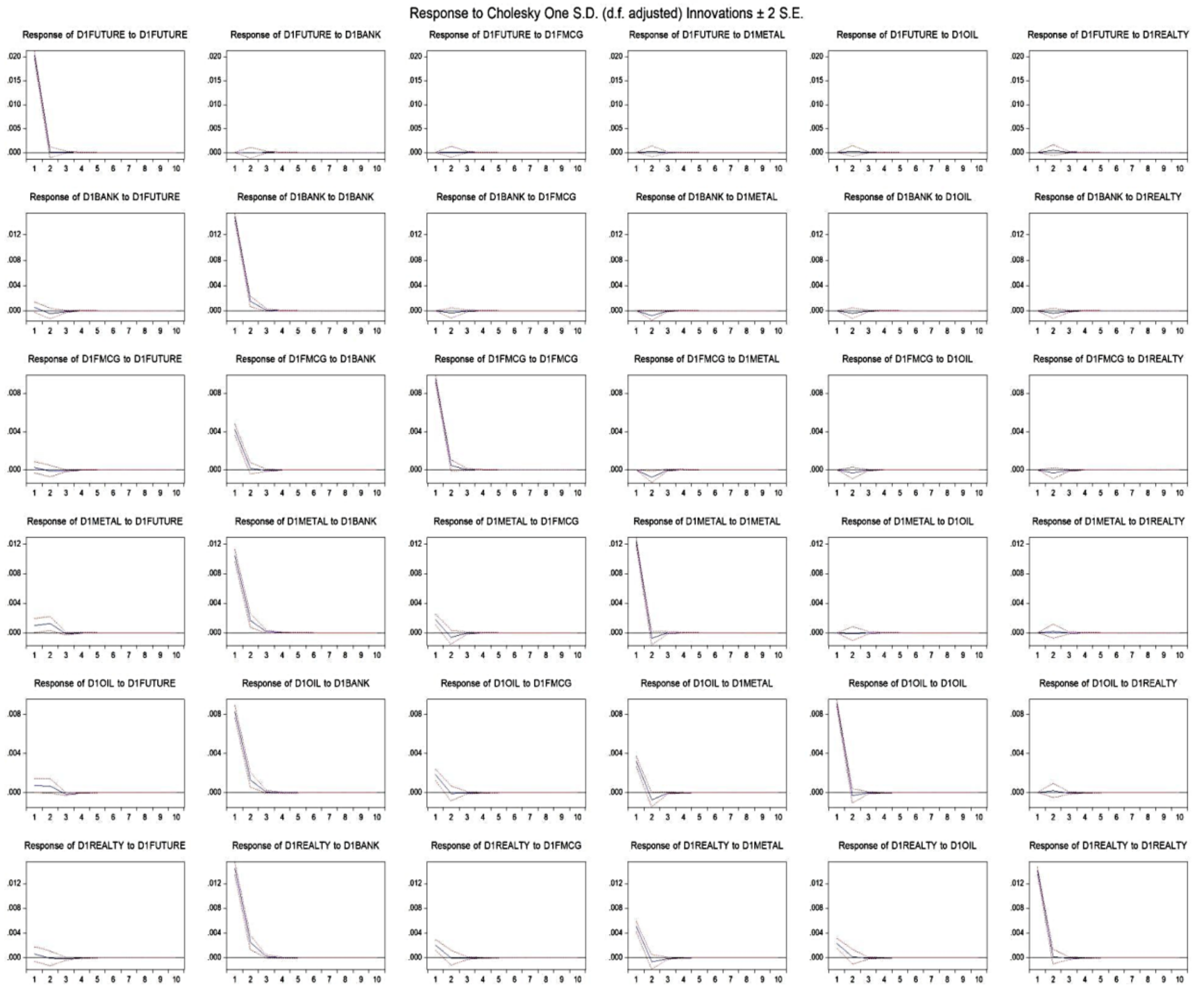

Figure 2. Impulse Response of log of crude oil futures and sectoral indices in sub-sample 1

Source: Author's calculation

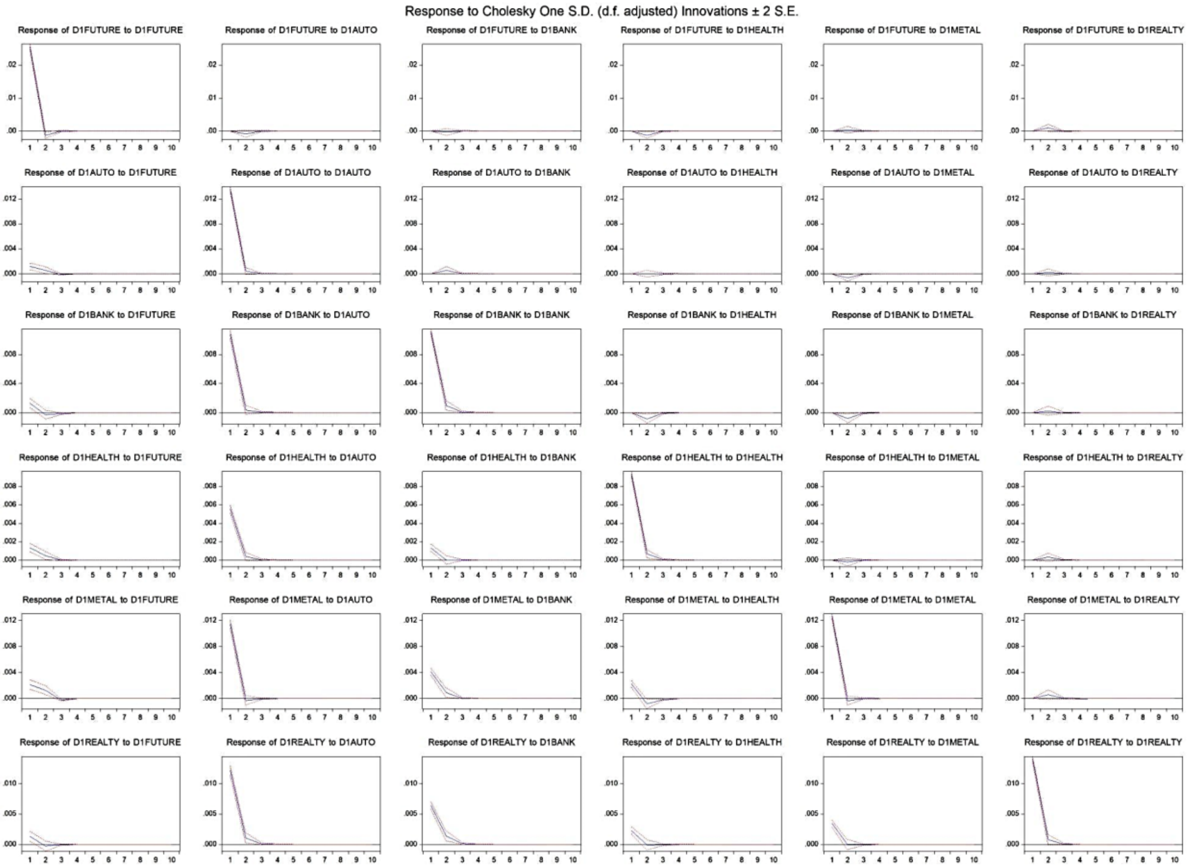

Figure 3. Impulse Response of log of crude oil futures and sectoral indices in full-sample

Source: Author's calculation

For sub-data1, we can see that the crude oil futures and all the sectoral indices react in a positive way to their own past innovation in the first year but only the metal and oil sector becomes negative in the second year and the rest remains positive . In the third year, the response of all the variables dies out to their own past innovation. Additionally, shocks in crude oil futures have no significant impact on any sector and vice-versa.

For a full-data sample, all the sector and crude oil oil futures react in a positive way to their own past innovation in the first year but only metal and crude oil futures become negative in the second year while others remain positive but in the third year all the responses die out. In addition to this, shocks on crude oil futures show a slight significance but shocks on sectoral indices show no significance at all.

Vector Error Correction Model. For long run cointegrating vectors, VECM is used for causal relationship and error correction term is also used to test the stationarity. If error estimates are stationary at level, then the model is correct and we can see the relationship between log of variables.

Table 8. Vector Error Correction Model Tests results (Sub-Sample 2)

Cointegrating Eq:	CointEq1
D1FUTURE(-1)	1
D1AUTO(-1)	0.652131 (-0.13758) [4.74009]
D1BANK(-1)	0.468169 (-0.11449) [4.08901]
D1FMCG(-1)	1.379576 (-0.15576) [8.85717]
D1HEALTH(-1)	-0.166071 (-0.13174) [-1.26065]
D1METAL(-1)	-1.253953 (-0.09533) [-13.1534]
D1OIL(-1)	-0.542237 (-0.12125) [-4.47188]
D1REALTY(-1)	-0.284608 (-0.08963) [-3.17554]
C	-0.000367 (-0.00087) [-0.42091]

Error Correction:	D(D1FUTURE)	D(D1AUTO)	D(D1BANK)	D(D1FMCG)	D(D1HEALTH)	D(D1METAL)	D(D1OIL)	D(D1REALTY)
CointEq1	**-0.726406****	-0.018924	-0.028073	**-0.068092****	0.031002	**0.18948****	**0.062198****	0.054758
	(-0.03625)	(-0.02132)	(-0.02354)	(-0.01541)	(-0.0168)	(-0.02701)	(-0.02119)	(-0.02736)
	[-20.0364]	[-0.88765]	[-1.19237]	[-4.41798]	[1.84554]	[7.01533]	[2.93535]	[2.00143]
D (D1FUTURE (-1))	**-0.067784****	**0.034986****	0.02227	**0.045354****	-0.000838	-0.035537	**0.007669****	-0.043895
	(-0.02647)	(-0.01556)	(-0.01719)	(-0.01125)	(-0.01226)	(-0.01972)	(-0.01547)	(-0.01997)
	[-2.56096]	[2.24775]	[1.29566]	[4.03064]	[-0.06831]	[-1.80220]	[0.49577]	[-2.19755]
D(D1AUTO(-1))	**0.272224****	**-0.529727***	-0.006764	-0.023345	-0.017018	**-0.156227****	-0.059863	-0.0464
	(-0.07144)	(-0.04201)	(-0.04639)	(-0.03037)	(-0.0331)	(-0.05322)	(-0.04175)	(-0.05391)
	[3.81051]	[-12.6093]	[-0.14580]	[-0.76867]	[-0.51412]	[-2.93533]	[-1.43371]	[-0.86064]
D(D1BANK(-1))	**0.191833***	0.052006	**-0.403322****	0.008442	-0.024095	-0.043322	0.040533	-0.011957
	(-0.06292)	(-0.037)	(-0.04086)	(-0.02675)	(-0.02915)	(-0.04688)	(-0.03678)	(-0.04748)
	[3.04874]	[1.40552]	[-9.87044]	[0.31558]	[-0.82647]	[-0.92417]	[1.10217]	[-0.25181]
D(D1FMCG(-1))	**0.261776****	0.050032	0.056325	**-0.428647****	-0.063601	-0.070363	-0.036946	-0.035138
	(-0.08182)	(-0.04812)	(-0.05314)	(-0.03479)	(-0.03791)	(-0.06096)	(-0.04782)	(-0.06175)
	[3.19928]	[1.03982]	[1.06001]	[-12.3228]	[-1.67759]	[-1.15429]	[-0.77257]	[-0.56905]
D(D1HEALTH(-1))	**-0.225524****	0.040535	-0.03941	0.02372	**-0.460781****	-0.039365	0.032053	0.068471
	(-0.07258)	(-0.04268)	(-0.04714)	(-0.03086)	(-0.03363)	(-0.05407)	(-0.04242)	(-0.05478)
	[-3.10713]	[0.94968]	[-0.83610]	[0.76870]	[-13.7012]	[-0.72797]	[0.75558]	[1.25003]
D(D1METAL(-1))	**-0.570012****	-0.034213	-0.049331	**-0.069063****	0.011721	**-0.40039****	0.001921	0.031677
	(-0.05359)	(-0.03152)	(-0.0348)	(-0.02278)	(-0.02483)	(-0.03993)	(-0.03132)	(-0.04044)
	[-10.6358]	[-1.08557]	[-1.41740]	[-3.03122]	[0.47200]	[-10.0280]	[0.06134]	[0.78320]
D(D1OIL(-1))	**-0.131288****	-0.063058	**-0.129266****	-0.037892	-0.023216	0.021532	-0.511384	-0.018771
	(-0.06288)	(-0.03698)	(-0.04083)	(-0.02673)	(-0.02913)	(-0.04684)	(-0.03675)	(-0.04745)
	[-2.08799]	[-1.70542]	[-3.16576]	[-1.41753]	[-0.79686]	[0.45965]	[-13.9155]	[-0.39559]
D(D1REALTY(-1))	-0.061494	-0.024975	0.034879	-0.010881	0.025464	0.060693	0.010752	**-0.459877****
	(-0.0475)	(-0.02793)	(-0.03085)	(-0.02019)	(-0.02201)	(-0.03539)	(-0.02776)	(-0.03585)
	[-1.29464]	[-0.89413]	[1.13075]	[-0.53884]	[1.15701]	[1.71513]	[0.38731]	[-12.8294]

Note: *** represents significance at 1% level, ** at 5% and * at 10%. Standard Errors in ( ) and t-statistics in [ ]. Lag selection is based on SIC.
Source: Author's calculation

Here, Error Correction Term can be written as:

$$ECT_{t-1} = D1\ FUTURES_{t-1} + 0.652D1\ AUTO_{t-1} + 0.468D1\ BANK_{t-1} + 1.379D1\ FMCG_{t-1} - 0.166D1\ HEALTH_{t-1} - 1.253D1\ METAL_{t-1} - 0.542D1\ OIL_{t-1} - 0.284D1\ REALTY_{t-1} - 0.000367C_{t-1} \quad (9)$$

Here, D1 means the first difference series of all the variables considered for the VEC Model. Since we are considering the crude oil futures as the target variable, therefore, the equation can be written as:

$$D1\,FUTURES_t = -0.726ECT_{t-1} - 0.067D1\,FUTURES_{t-1} + 0.272D1\,AUTO_{t-1} + 0.1918D1\,BANK_{t-1} + 0.261D1\,FMCG_{t-1} - 0.225D1\,HEALTH_{t-1} - 0.57D1\,METAL_{t-1} - 0.131D1\,OIL_{t-1} - 0.061D1\,REALTY_{t-1} \quad (10)$$

The significant and negative value of error correction estimates shows a significant long-term equilibrium, i.e., expected long-term convergence. The previous period deviation from long-run equilibrium is corrected at a speed of about seventy-two percent each period, Also the explanatory variables granger causes the crude oil futures. Equation 10 represents the *ceteris paribus* effect of the variables and the error correction term shows the longterm relation whereas the other variables show a short run relationship.

Wald Test. Wald test is used in case of short-term causality examination. It works considering the set of variables that are insignificant and tested for combined effect by equalizing them to zero. This is the null hypothesis for this test and if it is rejected then it means there is a short-run causality whereas the alternative of that can not confirm the short-run causality. Sub-Data 2 already has all the variables significant resulting in the long-term as well as the short-run causality running from sectoral indices to crude oil futures except the realty index. But from crude oil futures to sectors, the lag of futures, fmcg, metal, oil and realty sectors are caused by future prices.

Table 9. Wald Test for Short-run Causality

Sub-data 1			
Test Statistic	Value	df	Probability
Null Hypothesis: C(1) = C(2) = C(3) = C(4) = C(5) = C(6) = 0			
Chi-square	1.064317	6	0.9831
Full-data			
Test Statistic	Value	df	Probability
Null Hypothesis: C(2) = C(3) = C(5) = C(6) = 0			
Chi-square	4.606871	4	0.3301

Source: Author's calculation

Here in Table 9, only Sub-Data 1 and Full-Data are considered for short-term causality and as per the result in Wald statistics, all the variables in both the data sets for different periods did not confirm the short-run causality because the null hypothesis can not be rejected. Hence, for sub-data 1 no sectoral index granger causes crude oil futures prices in the short run model, instead of lag of crude oil futures only granger causes the metal sector in the short run model. In the full data sample only lag of future prices and the health sector causes crude oil futures prices but also future prices causes lag of futures, auto sector and metal sector in the short run.

Conclusion. Being an oil importing nation, the Indian economy and its financial sector are exposed to oil price risk and crude oil futures market being an investment opportunity serves as a hot plate to investors and risk managers. We put crude oil futures and sectoral indices of India to the test of the causal relationship between them. Combined with impulse response function, the wald test, VAR-VECM model and Granger Causality approach, this paper examines the transmission between crude oil futures and sectoral indices. Also, all this is done by dividing full data into two sub samples to get more robust and reliable results.

For sub-data1, bank granger causes oil futures but is not confirmed by VAR; instead, the bank has more impact on its lagged value. Also, crude futures cause the metal sector. For sub-data 2, the granger causality approach shows the metal sector provides a bidirectional causality result supported by VECM. A negative and significant error correction term shows long term relationship and significant values of other variables coefficient also shows a short term relationship for all sectors except the realty sector.

In full sample data, only oil futures granger causes metal and the health sector causes oil futures with the significant values of coefficients. The remaining insignificant values are tested for significance in the wald test for short run relationship but the null hypothesis can not be accepted which results in non confirmation of a short term relationship. IRF results also show very weak significant responses of sectoral indices to the crude oil futures shock and no significance in response of oil to sectoral shocks but only significant responses from their own past innovation. The FMCG and Health sectors are independent of oil futures but the Metal index is most resistant to it. There are few policy implications of the study:

Cointegration between oil futures and the metal, oil, bank and realty sector (different relationship in different data sets) indicates that holders or traders need to be aware of different behavior of the stock prices of sectors towards the prices of futures. Investors and policy makers should also consider the change in the benchmark information to maintain their decisions for different performing sectors. The bidirectional relationship of oil futures and the metal sector may help the investor to utilize the information of one variable to speculate the other market.

The future direction of research may include the findings from other oil importing countries, also, the relationship between oil futures and sectoral indices may lead to predictability in both the markets. Some of the studies can also focus on the market efficiency of any sector with oil futures like efficiency of crude oil futures and the metal sector.

Notes:

**IBEF is a trust established by the Department of Commerce, Ministry of Commerce and Industry, Government of India.*

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