COVID-19 and Energy

Interconnectedness and Nonlinearity in Indian Energy Futures During the COVID-19 Pandemic

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This study examines interconnectedness and nonlinearity between energy futures indices, the exchange rate, and COVID-19 cases in India. Using a dynamic connectedness approach, the study confirms that, on average, 39.71% of the shock to one index spills over to all the other indices, including the exchange rate, whereas, on average, 60.29% of the shock affects itself. Further, the study finds nonlinear causality from crude oil futures to the exchange rate.

I. INTRODUCTION

The objective of this study is to investigate the interconnectedness and nonlinearity between energy futures (EF) indices, the exchange rate (ER), and active COVID-19 cases in India. Our hypothesis is that EF in India cause the ER to fluctuate. The proposed relation between EF and the ER is motivated by theory developed by Krugman (1980) and Golub (1983). Many empirical studies find that ER volatility causes financial market returns (e.g., Chkili & Nguyen, 2014; Kasman et al., 2011; Wong, 2017). Similarly, another strand of the literature specifically uses a nonlinear relation between the ER and commodity prices. For example, Chkir et al. (2020) find a nonlinear and negative relation between crude oil and the ER. Further, Bal and Rath (2015) argue that the oil price has a nonlinear causal relation with the ER. Similarly, Wen et al. (2018) conclude that crude oil prices have a nonlinear Granger-causal relation to the ER. On the contrary, Benhmad (2012) find a nonlinear causal relation from crude oil prices to the real ER.

Studies find a theoretical linkage between crude oil and the balance of payment, hence EF (Golub, 1983; Krugman, 1980). An increase in energy prices leads to a transfer of wealth from oil-importing to oil-exporting countries, hence the impact on the ER. However, the impact will be different in the short and long run, depending on the portfolio and import preferences of oil-importing countries, respectively. Further, oil-exporting countries prefer dollar-denominated assets. Thus, any change in crude oil prices affects the ER due to dollar fluctuations. Some empirical studies find a nonlinear relation between crude oil volatility, the ER. and remittance outflow (Akçay, 2021; Bal & Rath, 2015; Wen et al., 2018). Other studies also investigate crude oil volatility during the COVID-19 pandemic. For instance, Devpura and Narayan (2020) find oil price volatility increases due to the COVID-19 pandemic. Similarly, the findings of Mugaloglu et al. (2021) suggest that the impact of structural shocks related to the global oil price on FTSE-OG returns is negligible during the pandemic.

However, to best of our knowledge, no study has assessed a nonlinear impact of the ER on commodity futures (CF) during the pandemic. The novelties of this study are as follows. First, while the bulk of the literature uses crude oil, the present study examines EF indices in India during the pandemic. India is the third largest energy consumer in the world, consuming around 809.2 million tons of oil equivalents (Annual Report, 2019). Second, although studies show a nonlinear relation between commodity prices and the ER (e.g., Bal & Rath, 2015; Chkir et al., 2020), our study focuses on the relation between EF and the ER during the COVID-19 pandemic. The pandemic has adversely affected CF across the world, including in India (Borgards et al., 2021; Sifat et al., 2021). Thus, it is necessary to unravel volatility spillover from nonlinearity among the ER and EF indices during pandemic. Third, the interconnectedness and nonlinearity among asset classes help investors in optimal portfolio decisions, whereas policymakers are more concerned about market stabilization. Finally, we employ volatility connectedness based on dynamic conditional correlation generalized autoregressive conditional heteroskedasticity (DCC-GARCH), which has certain advantages over connectedness based on vector autoregression (Diebold & Yilmaz, 2009, 2012).

The contribution of this study is threefold. First, an average of 39.71% of a shock to one index spills over to all the other indices, whereas, on average, 60.29% of the shock af-

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Table 1. Average connectedness among commodity futures indices and exchange rate

	CF	EF	COF	NGF	ER	Acases	**FROM**
CF	52.57	22.12	24.97	0.30	0.03	0.01	47.43
EF	4.32	61.62	32.67	1.17	0.15	0.07	38.38
COF	4.32	28.93	66.27	0.10	0.27	0.11	33.73
NGF	1.58	0.95	2.64	56.16	33.04	0.61	43.84
ER	0.21	0.23	0.22	0.75	91.90	8.10	37.34
Acases	0.42	0.26	0.33	0.19	18.37	81.63	18.37
Contribution **TO** others	10.23	83.03	60.64	1.57	19.17	8.72	TCI
NET Directional Connectedness	-37.20	44.65	26.91	-35.77	11.07	-9.65	30.56

The table reports interconnectedness results between indices and exchange rate. We find that, on average, 39.71% of a shock on one index spills over to all other indices, whereas 60.29% of the shock affects itself. That indicates market is interconnected.

fects itself. The result suggests that the major transmitters of shock are EF and crude oil futures (COF), and the least-transmitting variable is the natural gas futures (NGF) index. Second, the findings also suggest that the EF index is the net transmitter of shocks. Further, commodity and NGF indices are net receiver of shocks. Finally, the study finds a nonlinear causal relation from COF to the ER

The remaining sections of this paper are organized as follows. Section II presents the data and methodology. Section III briefly discusses the major findings, and Section IV concludes the study.

II. DATA AND METHODLOGY

The present study uses daily data from March 17, 2020, to June 11, 2021. The closing price of EF indices in India are extracted from the Multi Commodity Exchange of India Limited (www.mcxindia.com). These indices are *CF, EF, COF, and NGF* developed by the Multi Commodity Exchange of India. Further, we consider the *ER* in terms of Indian rupees with respect to the US dollar. Finally, the number of active *COVID-19* cases are extracted from the CIEC database for the analysis.

We employ a dynamic connectedness technique, namely, DCC-GARCH–based volatility connectedness, to evaluate interconnectedness between the EF indices, the ER, and COVID-19 cases in India (Gabauer, 2020). The detailed technique is described by Gabauer (2020) and Bouri et al. (2021). This approach has certain advantages over the vector autoregression–based connectedness measure of Diebold and Yilmaz (2009, 2012). One advantage that suits our empirical setup is that the DCC-GARCH approach does not require the arbitrary selection of the estimation window size. This avoids bias resulting from the window choice.

Lastly, we use a nonlinear Granger causality technique to investigate the existence of nonlinear causality between EF indices and the ER. The technique uses a multilayer perception (MLP) artificial neural network (ANN). Two MLP ANNs are evaluated to analyze the test. The assumption of nonlinear causality is tested between dependent and independent variables. The null hypothesis of the technique is that the independent variable does not cause the dependent variable.

III. MAJOR FINDINGS

In this section, we briefly elaborate the volatility spillover among the CF indices. Table 1 reports the dynamic connectedness results. We find that, on average, 39.71% of a shock to one index spills over to all the other indices, whereas 60.29% of the shock affects itself. This indicates that the market is highly interconnected when it comes to CF in India and the ER. Further, the results suggest that the major transmitters of shock is EF and COF; these transmit 60.64–83.03% and 60.64%, respectively, whereas the variable that transmits the least amount of shock is that for NGF, which transmits only 1.57% of a shock, on average. Thus, EF and COF play key roles in transmitting shocks to the other futures indices. The outcome is obvious, since India is one of the major crude oil–importing countries. For example, India imports a little over 800 million tons of oil equivalents every year (Annual Report, 2019). The findings of interconnectedness are consistent with the outcomes of Gabauer (2020), Behera and Rath (2021), Bouri et al. (2021), and Narayan (2021). We use active COVID-19 cases in India to observe volatility transmission among the variables. We find that the number of active cases are neither a significant transmitter nor net receiver of shocks.

Next, the net total directional connectedness measures the transmitters and receivers of the shocks. The findings suggest that the EF index is a net transmitter of shocks, transmitting 44.65% of shocks, on average. This indicates that a shock to the EF index influences other commodities. Further, the CF and NGF indices are net receivers of shocks, since the net directional value is negative.

Next, we use an alternative econometric model for a robustness test. To do so, we add two new variables, the gold futures index and the number of confirmed COVID-19 cases, to the analysis. We then apply the dynamic connectedness approach developed by Gabauer (2020). The results are reported in Table 2. We find that, on average, 24.53% of a shock to one index spills over to all the other indices, whereas 75.47% of the shock affects itself. This indicates the markets are interconnected. The results are consistent with the outcomes reported in Table 1.

In the last set of results, we test for nonlinear Granger

Table 2. Average connectedness with gold futures index

	CF	CO	NGF	GF	ER	Ccases	**FROM**
CF	55.55	35.02	0.34	0.08	0.08	0.01	44.45
CO	7.92	91.44	0.17	0.01	0.22	0.25	8.56
NGF	2.46	5.40	90.58	0.14	0.22	1.19	9.42
GF	54.08	0.26	0.12	44.64	0.60	0.30	55.36
ER	0.00	0.00	0.00	0.00	86.27	13.72	13.73
Ccases	0.00	0.01	0.00	0.00	15.64	84.36	15.64
Contribution **TO** others	64.46	40.69	0.63	9.17	16.75	15.47	TCI
NET Directional Connectedness	20.01	32.13	-8.79	-46.19	3.02	-0.17	24.53

The table reports robustness results where we take commodity futures and confirmed COVID-19 cases as alternate variables. We find that, on average, 24.53% of a shock on one index spills over to all other indices, whereas 75.47% of the shock affects itself. That results are consonance with the outcomes in Table 1.

Table 3. Nonlinear Granger causality test

SN	Null Hypothesis	F-stat. (p-alue)
1	Energy futures does not nonlinearly cause exchange rate	-0.67 (1.00)
	Exchange rate does not nonlinearly cause energy futures	-0.13 (0.99)
2	Crude oil futures do not nonlinearly cause exchange rate	-1.63*** (0.05)
	Exchange rate does not nonlinearly cause crude oil futures	-1.84 (1.00)
3	Natural gas futures do not nonlinearly cause exchange rate	-0.25 (1.00)
	Exchange rate does not nonlinearly cause natural gas futures	2.059** (0.01)
4	Commodity futures does not nonlinearly cause exchange rate	0.18 (0.99)
	Exchanger rate does not nonlinearly cause commodity futures	0.02 (1.00)

The table reports nonlinear Granger Causality test results. We find that crude oil futures nonlinearly cause exchange rate, whereas exchange rate nonlinearly causes natural gas futures.

causality. Using this test, we find nonlinear relations between the EF indices and the ER (see Table 3). We also find that CF indices have a nonlinear Granger causal relation with the ER. The finding is obvious, since the crude oil price is determined in the international market and India is a major importer. Further, we find that the ER has a nonlinear Granger causal relation to the NGF index. However, it is inconclusive whether all the indices and the ER under observation are nonlinearly related.

IV. CONCLUDING REMARKS

The primary objective of the study is to investigate the interconnectedness and nonlinearity between the EF indices, the ER, and COVID-19 cases. The study uses a dynamic connectedness approach and confirms the presence of volatility spillover among the EF indices and the ER. For example, we find that, on average, 39.71% of a shock to one index spills over to all the other indices, whereas, on average, 60.29% of the shock affects itself. Further, the results suggest that the major transmitters of shocks are the EF and COF indices, whereas the variable that transmits the least is the NGF index. Further, the CF and NGF indices are net receivers of shocks. Then, from the nonlinear Granger causality test, we find a nonlinear relation between COF and the ER.

From the policy perspective, our findings could help investors in selecting an optimal portfolio to earn returns from CF markets.

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