Price Discovery and Volatility Spillover for Indian Energy Futures Market in the Pre- and Post-Crisis Periods

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Abstract

The present paper examined the price discovery and volatility spillovers in pre and post-crisis (global financial crisis and European sovereign debt crisis) periods of spot and futures energy markets in India from January 1, 2007 – December 31, 2018, with the help of closing price series listed on the Multi Commodity Exchange Limited (MCX) for both spot and futures crude oil and natural gas markets. The data were examined using Johansen cointegration test, vector error correction (VEC) model, autoregressive distributed lag (ARDL) model, and Glosten-Jagannathan-Runkle generalized autoregressive conditional heteroscedasticity (GJR-GARCH) model to measure the price discovery and volatility spillovers. For price discovery, most of the sample cases had a long-run equilibrium relationship between their spot and futures prices, and the futures (spot) market led the spot (futures) market in the long-run in most sample periods (post-ESDC period). In case of volatility spillover, most of the results concluded the dominance of the futures market over the spot market except crude oil in the post-ESDC period. All these factors made the futures market more efficient and cost-competitive in terms of price discovery. So, it can be concluded that the market participants may depend on the futures market's price changes for their investment and trading decisions. The results of during and post-crisis periods may be helpful for the current investors for modification of their optimum portfolio. Investors and policy makers may draw meaningful conclusions and become prepared for the next crisis period.

Keywords : ARDL model, crisis period, energy futures market, GJR - GARCH, price discovery, VECM, volatility spillover

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The oil and gas sector plays an influential role in decision-making for all other sectors of any economy. Globally, India is identified as the third-largest giant in energy consumption. Presently, India is Asia's second-largest refiner with 294.4 million tones capacity. The investment in the energy sector in India increased by 12% in the last three years (International Energy Agency, 2019). Due to 100% FDI (foreign direct investment) in private sector refining projects and 49% in public sector projects, the Indian energy sector got the attention of academicians and investors to dig information allied with investment and growth. Due to high demand, India's oil imports credibly increased from 3.19 mbpd (million barrels per day) in 2009 – 2010 to 4.53 mbpd in 2018–2019, and simultaneously, India's gas imports increased at a compound annual growth rate of 10% during 2009 – 2019.

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The Indian commodity derivative market dominates the spot market in terms of overall turnover (Dutt & Sehgal, 2018). Traditionally, derivatives are developed for risk management to prevent losses to farmers from falling crop prices. But now, they are an investment and hedging tool for almost every stock and commodity. The Indian commodity market itself created its niche within the Indian financial market. The commodity market's financialization increased integration between spot and derivative markets, which ultimately escorted the convergence of volatility spillover and risk-adjusted returns between these markets (Dutt & Sehgal, 2018). Although the commodity market is perfectly random and efficiently reflects full market information, some regional, individual, and sectoral information have substantial positive and negative impacts on its spot and derivative markets. During different crisis periods, the world economy has witnessed large volatility changes pertaining to many financial instruments. But mainly in all crisis periods, prices of most of the financial instruments went down. Thus, it can be said that that the crisis periods have a great impact on the volatility of prices and the number of contracts traded in an economy. The need for the present study is to ascertain the price discovery and volatility spillover within the Indian energy market with reference to recent global and European debt crises periods.

Literature Review

The main abstract issue which has been debated in the literature revolves around the need, scope, and techniques to be used to know price discovery and volatility spillover in the commodity markets. The concepts of the commodity market, price discovery, and volatility spillovers began gaining importance during the 1990s, but during the last six to seven years, an unprecedented amount of research work has been done on these topics. While reviewing the existing literature on the energy market, it was observed that most of the past studies checked hypotheses using cointegration tests, regression analysis, univariate and bivariate GARCH (generalized autoregressive conditional heteroskedasticity) models as a means for analyzing the data.

On the other hand, recent articles by Choi and Hammoudeh (2010), Nazlioglu and Soytas (2012), Grosche and Heckelei (2014), Antonakakis and Kizys (2015), Bouri (2015), Baldi et al. (2016), Ewing et al. (2018), Kaushik (2018), Mishra (2019), Danak and Patel (2020), and Kotishwar (2020) used new econometric modeling techniques such as wavelet-based (vector autoregression) VAR-GARCH-BEKK (Baba, Engle, Kraft, and Kroner) model, VECM-MGARCH (modified GARCH) model, structural breaks, (dynamic conditional correlation) DCC-AGARCH model, ARDL (autoregressive distributed lag), etc. to test their hypotheses.

Choi and Hammoudeh (2010) examined the volatility behavior of weekly closing spot prices for WTI, oil, silver, copper, gold, brent oil, and the US S&P 500 index. The results showed different volatility persistence responses during the crisis period. Nazlioglu and Soytas (2012) examined the volatility spillover between oil and agriculture commodities and reported the volatility spillover from oil to agriculture commodities markets after the crisis period, but no spillover was found during the pre-crisis period. Grosche and Heckelei (2014) showed the volatility transmission flow from equity and real estate to other sample commodities (energy and metal) during the financial crisis. Nazlioglu et al. (2015) employed the same procedures as Nazlioglu and Soytas (2012), which showed the results of volatility spillover patterns to be quite similar before and after the crisis period, while comparatively strong and long live effects were observed during the crisis period. Bouri (2015) indicated that the global financial crisis had a strong impact on the dynamic spillover between the oil and stock indices over the crisis period. Antonakakis and Kizys (2015) helped to forecast the returns and volatilities of crude oil, palladium, EUR/CHF, and GBP/USD exchange rates with the information contents of other five commodities and currencies. Gold and CHF/USD played the dominant role in transmitting returns and volatility ; gold and silver showed the dynamic spillover effect in the global financial crisis period. Brayek et al. (2015) observed the independent behavior between the oil prices and exchange rates in the pre-crisis period and showed the dependence after the crisis period. Gozgor (2016) showed the long-run relationship and positive impact of oil prices on the equity indices of Russia, India, and China. Baldi et al. (2016) showed that there was a significant increase in the volatility spillovers after the 2008 financial crisis. The paper concluded that the interconnection between the financial and commodity markets increased day by day after the crises. Junttila et al. (2018) analyzed the interdependency in oil prices, gold futures, and energy stock indices and supported the strong impact of the crisis on all the sample indices. In addition to that, the authors observed that neither crude oil nor gold futures helped to hedge energy sector equity during the crisis period. Sharma (2017) explored the interdependency of crude oil futures markets between the USA and India and concluded that both markets were efficient on a daily basis, while the USA futures market was more efficient than the Indian futures market.

Ewing et al. (2018) showed significant spillover from energy markets to the emerging markets mutual funds, while the impact of oil prices comparatively declined after the crisis period. The study also reported that the reverse spillover from mutual funds to the energy markets was generally stronger for natural gas than oil prices. Gupta et al. (2017) studied the static as well as dynamic hedging effectiveness of Indian commodity futures markets and reported that the precious metal futures had higher hedge effectiveness as compared to the energy and industrial metal futures. Eryiğit (2017) found a long-run relationship between gold and crude oil with gasoline, while no long-run relationship was observed between gasoline and crude oil with gold prices. Roy and Roy (2017) targeted the Indian financial markets to examine the spillover and contagion effect and identified the net volatility transmission from commodity and stock markets to the bond, foreign exchange, and gold markets. The results also found the volatility spillover from stock to commodities markets, which was comparatively higher during the period of the financial crisis. Kaushik (2018) examined the effect of oil price on the metal markets and reported no relationship (weak relationship) from precious metals (industrial metal) to the oil price over the GFC period. Rehman et al. (2018) focused only on the precious metal returns and detected the disintegrated structural shock of oil prices on the metal return dynamics. The study found that the interconnectedness among the precious metals increased significantly during the crisis period, while platinum (gold) showed the maximum (minimum) to total market connectedness. From the oil price perspective, oil-specific demand shock was maximum for gold and minimum for palladium over the crisis period. Chang et al. (2018) revealed significant spillover among the energy and financial markets of the USA and UK. Gupta et al. (2018) explored evidence of short-term inefficiency in both the spot and futures Indian commodity markets and suggested that the future movements were detected to be the important indicators for the commodity market. Fasanya and Akinbowale (2019) examined the degree of interdependency over the Nigerian agriculture commodities' spot and oil prices. The results concluded the significant volatility spillover behavior during and post-global and European crisis periods between the sample variables.

At last, the research gaps are identified on the basis of past research studies that form the base for the present study. In order to fulfill the research gap, the research questions are mentioned as follows :

(1) Is there any cointegration relationship between spot and futures energy markets during the crisis period in India ?

(2) Does any price discovery function exist between spot and futures energy markets during the crisis period in India ?

(3) Is there any volatility spillover effect between the spot and futures energy markets during the crisis period in India ?

Research Methodology

Data and Data Sources

Data were retrieved from the official websites of the MCX for the time period of January 1, 2007 – December 31, 2018. Further, to examine price discovery and volatility spillover between spot and futures closing prices of sample commodities and to have time-varying results, the whole sample data period was divided into four sub-periods as the period of the global financial crisis (GFC) (from January 1, 2007 – November 12, 2008), post-GFC (from November 13, 2008 – April 11, 2011), period of European sovereign debt crisis (ESDC) (from April 12, 2011 – August 31, 2015), and post-ESDC (September 1, 2015 – December 31, 2018). The data is divided using multiple structural break analysis (Parthasarathy, 2019). The entire analysis has been conducted in SPSS 16 and EVIEWS 9.

Research Techniques

Initially, descriptive statistics were calculated and examined with the help of daily spot and futures returns series.

(1) Unit Root Test : The flow of many time series like price series, commodity price index series, stock market series, exchange rates, and macroeconomic series have a random walk property. To ensure stationarity in all the sample commodity price series, the present study uses the Augmented Dickey – Fuller (1979) and Phillips – Perron (1988) tests for the proposed econometric models to be used. The lag length of the sample data series is selected on the basis of the Schwarz information criterion (SIC). The following regression model is explained for the ADF test :

$$\overset{n}{\underset{i=1}{\Delta}} R_t = P_0 + PR_{t-1} + \Sigma\delta_i\, \Delta R_{t-1} + \varepsilon_t \qquad (1)$$

where, R_t = log price series, P_0 = a drift, $P = \alpha$ is less than 1, Δ = first difference function, ε_t = an error term, and $\Delta R_{t-1} = (R_{t-1} - R_{t-2})$, $\Delta R_{t-2} = (R_{t-2} - R_{t-3})$, etc. The null hypothesis is to test that $P = 0$. If $P = 0$, then $\alpha = 1$, that is, we have a unit root, meaning the time series under consideration is non-stationary. But for stationarity, α must be less than one, and hence, P must be negative. To reconfirm the results, the PP test is used as an additional model.

(2) Cointegration Test : To know the price discovery process, the present research uses Johansen's cointegration test (1988) test and VECM. The causal relationship between spot and futures commodity series is analyzed by calculating the following VECM (Johansen, 1988) :

$$\Delta Y_t = \sum_{i=1}^{P-1} r_i \Delta Y_{t-1} + IIY_{t-1} + \varepsilon_t \qquad (2)$$

$$\varepsilon_t / \Omega_{t-1} \sim \text{distr}\,(0, H_t)$$

Here, Y_t is 2×1 vector (S_t , F_t) log futures price and log spot price, ε_t is 2×1 vector of white noise ($\varepsilon_{s,\,t}$, $\varepsilon_{f,\,t}$) with time-varying covariance matrix (H_t) and zero mean, r and II show the coefficient matrix which contains information for both long-run as well as short-run adjustments to ΔY_t.

To evaluate cointegration between spot and futures energy price series, there are two likelihood ratio tests, that is, trace statistics and maximum eigen-value statistics. Trace statistics check the number of cointegration vectors, and maximum eigen-value checks the sufficiency of a single cointegration equation or two equations. If r cointegrating vector is correct, then the test statistics are as follows :

$$\lambda_{trace}(r) = -T\sum_{i=r+1}^{n} ln\,(1-\widehat{\lambda_l}) \tag{3}$$

$$\lambda_{max}(r, r+1) = -Tln\,(1-\widehat{\lambda_{r+l}}) \tag{4}$$

Here, T shows the number of usable observations, $\widehat{\lambda_l}$ and $\widehat{\lambda_{r+l}}$ show eigen value taken from the estimate of II matrix. The null hypotheses for trace statistics and maximum eigen-value statistics are at most r cointegrating vectors, and the number of the cointegrating vectors is r, respectively.

(3) Vector Error Correction (VEC) Model : If two series are cointegrated, then there is an existence of valid error correction representations of data series, which add short-term forms and long-term information (Engle & Granger, 1987). VECM analyzes whether spot and futures price series are moving one after the other or simultaneously. The regression forms of VECM (Johansen, 1988) for the present research are as follows :

$$\Delta S_t = \alpha_S + \sum_{i=1}^{n} \beta_{si}\,\Delta S_{t-i} + \sum_{i=1}^{n} \theta_{si}\,\Delta F_{t-i} + \gamma_S\,Z_{t-i} + \varepsilon_{st} \tag{5}$$

$$\Delta F_t = \alpha_F + \sum_{i=1}^{n} \beta_{Fi}\,\Delta S_{t-i} + \sum_{i=1}^{n} \theta_{Fi}\,\Delta F_{t-i} + \gamma_F\,Z_{t-i} + \varepsilon_{Ft} \tag{6}$$

Δ is the first difference operator, α_S and α_F are intercepts, and ε_{st} and ε_{Ft} are random error terms. β_{Si} ,β_{Fi} , θ_{Si} ,θ_{Fi} , γ_S , and γ_F are parameters. Z_{t-i} is error correction term, which examines how the dependent variable in one model makes adjustments to prior period deviation, that is, taking from long term equilibrium (7) :

$$Z_{t-i} = S_{t-i} - \alpha - \delta F_{t-i} \tag{7}$$

Here, the cointegration factor and the intercept are δ and α. If some of the θ_{Si} coefficients, that is, $i = 1, 2, \ldots n-1$ are not equal to zero, and γ_S for spot price is significant at default levels, then F_t Granger causes S_t; if coefficient (β_{Fi}) is not at zero and γ_F for futures price is significant at default levels, then S_t Granger causes F_t.

(4) Autoregressive Distributed Lag Model (ARDL) : The selection of different models depends upon the order of integration of a time series. First, if the closing price of both the spot and futures markets of a particular commodity is integrated with level zero, that is, $I(0)$, employ the simple VAR*(p)* model. Second, if both the closing prices of spot and futures markets of a particular commodity are integrated differently, and none of the series are integrated at second order, that is, $I(2)$, then ARDL is the favorable model for the selected data series.

ARDL (Pesaran et al., 2001)

ARDL model is more flexible with respect to lag order selection; it allows different lag- orders for each variable (Bekhet & Matar, 2013). The present study employs the ARDL model to test the cointegration between the spot and futures markets for those particular commodity series with different integration orders. This study formulates the ARDL representation for the spot and futures markets as follows :

$$\Delta\, lnS_t = \beta_{01} + \sum_{i=1}^{n1} \beta_{11}\Delta\, lnS_{t-i} + \sum_{i=1}^{n2} \beta_{12}\Delta\, \ln F_{t-i} + \phi_{11}\,\ln S_{t-i} + \phi_{12}\ln F_{t-i} + \epsilon_{t1} \tag{8}$$

$$\Delta \ln F_t = \beta_{02} + \sum_{i=1}^{n1} \beta_{21}\Delta \ln F_{t-i} + \sum_{i=1}^{n2} \beta_{22}\Delta \ln S_{t-i} + \phi_{21} \ln F_{t-i} + \phi_{22} \ln S_{t-i} + \in_{t2} \qquad (9)$$

where, Δ is the difference operator, $\beta_{11}, \ldots , \beta_{22}$ are short-run while $\phi_{11}, \ldots , \phi_{22}$are the long-run coefficients. $n1$, $n2$ and $\in_{t,1}, \in_{t,2}$ are the lag-length and the error term for the system equation, respectively.

(5) Volatility Spillover : The present study uses the bivariate GJR – GARCH (1,1) model to examine the volatility spillover effect. Here, the research question for the volatility spillover process arises : how does one market's news affect the volatility process of another market ? Bivariate GJR – GARCH (1, 1) (Glosten et al., 1993) has been used because it considers the asymmetric impact of volatility on data series. This study ignores the (Bollerslev, 1986) generalized autoregressive conditional heteroscedasticity (GARCH) model because it assumes that positive and negative news have the same impact on the market. Secondly, all coefficients should be positive to ensure that conditional variance is never negative. The present study uses the following models (10 to 12) for examining the volatility spillover :

$$\varepsilon_t = \begin{pmatrix} \varepsilon_{s,t} \\ \varepsilon_{s,t} \end{pmatrix}_{t-1} \sim N(0,\Omega),\ \Omega_t = \{\rho_{ij}\ \sigma_{i,t}\sigma_{j,t}\} \qquad (10)$$

$$\sigma^2_{s,t} = \omega_s + \alpha_s \in^2_{t-1} + \gamma_s \in^2_{t-1} I\,[\in_{t-1}<0] + \beta_s \sigma^2_{2,\,t-1} + \theta_s \varepsilon^2_{f,\,t-1} \qquad (11)$$

$$\sigma^2_{f,t} = \omega_f + \alpha_{sf} \in^2_{t-1} + \gamma_f \in^2_{t-1} I\,[\in_{t-1}<0] + \beta_f \sigma^2_{2,\,t-1} + \theta_f \varepsilon^2_{s,\,t-1} \qquad (12)$$

Here, the unrelated residual $\varepsilon_{s,t}$ and $\varepsilon_{f,t}$ are obtained from the VECM equations (5) and (6). This is a two-step approach ; wherein the first step VECM is applied, and in the second step, with the help of residual of VECM, bivariate GJR – GARCH (1,1) model is analyzed. For calculating volatility spillover, the errors of the error correction term should be added in the conditional variance equation. Later on, Engle's (1982) ARCH test is considered for testing autocorrelation in square residual. For testing the magnitude of serial correlation in sample series, the Ljung – Box (LB) statistics is selected.

Analysis and Results

Descriptive Statistics

In Part A of Table 1, the results show that mean returns are positive in all sample periods except the ESDC period. The empirical results show positive skewness in all sample periods except spot prices of GFC and ESDC periods and futures prices of the post-GFC period, which ultimately show negative skewness. In Part B Table 1, the results show that mean returns are positive in GFC, spot market of ESDC, and post-ESDC periods. The negative mean returns are found in the full sample (2007 – 2018), the futures market of ESDC, and post-GFC periods. The sample distributions are positively skewed in all sample periods except the GFC period.

The volatility in the spot markets is high in both commodities compared to futures markets in all sample time periods. All sample return series show that the kurtosis values are greater than three, which means distributions are leptokurtic or highly peaked. Both tests (skewness and kurtosis) violate the normality assumptions. The JB statistics of both commodities data series are statistically significant at the 1% level. So, the time - series for both two commodities are appropriate to be used for any model.

Table 1. ***Descriptive Statistics***

Particulars	Spot	Futures	Spot	Futures	Spot	Futures	Spot	Futures	Spot	Futures
Time Period	**2007 – 2018**		**GFC Period**		**Post - GFC Period**		**ESDC Period**		**Post - ESDC Period**	
Part A - Crude Oil										
Mean	0.0001	0.0001	0.0001	0.0001	0.0008	0.0008	–0.0003	–0.0002	0.0002	0.0003
Std. Dev.	0.0227	0.0201	0.0230	0.02	0.0268	0.0244	0.0185	0.0163	0.0245	0.0213
Skewness	0.0746	0.0593	–0.3984	0.0307	0.2318	–0.0501	–0.2627	0.1366	0.3349	0.1214
Kurtosis	8.3278	9.6791	6.7984	7.2632	9.8701	12.8374	6.9974	5.6850	4.8508	3.9257
Jarque – Bera	3547.549	5572.58	320.7192	387.0565	1373.031	2802.753	819.5547	367.238	93.3051	22.0599
Probability	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Observations	2997	2997	511	511	695	695	1210	1210	578	578
Correlation	0.2644		0.2041		0.3051		0.167		0.3862	
Part B - Natural Gas										
Mean	–8.77E-05	–9.56E-05	0.0005	0.0006	–0.0008	–0.0008	2.59E-05	–4.99E-05	8.84E-05	0.0001
Std. Dev.	0.0289	0.0273	0.0289	0.0264	0.0333	0.032	0.026	0.0246	0.0287	0.0274
Skewness	0.2085	0.2976	–0.4091	–0.2133	0.7014	0.72	0.089	0.0494	0.0691	0.2862
Kurtosis	6.3863	7.0312	9.6059	9.4994	5.9709	7.0319	5.3818	6.2753	4.6489	4.7011
Jarque – Bera	1453.685	2073.553	943.3914	903.2863	312.5924	530.8184	287.6307	541.345	65.9403	77.5855
Probability	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Observations	2997	2997	511	511	695	695	1210	1210	578	578
Correlation	0.3544		0.3038		0.2186		0.1739		0.9236	

Unit Root Test

Before applying econometric models, the ADF and PP tests are used to ensure stationarity in all sample commodities' price series. In the case of crude oil (Table 2), both spot and futures log price series cannot (can) reject the null hypothesis of unit root, indicating non-stationarity (stationarity) at level (first difference) for all sample periods, and confirm the same order of integration, that is, $I(1)$ for each sample period. In the case of natural gas (Table 2), both (ADF and PP) tests confirm non-stationarity at level and stationarity at the first difference in GFC, ESDC, and post-ESDC periods.

Table 2. ***Results of Unit Root Test***

Particulars	Level	First Diff.	Level	First Diff.	Level	First Diff.	Level	First Diff.	Level	First Diff.
Time Period	**2007 – 2018**		**GFC Period**		**Post - GFC Period**		**ESDC Period**		**Post ESDC Period**	
	***t*-stat.**	***t*-stat.**	***t*-stat.**	***t*-stat.**	***t*-stat.**	***t*-stat.**	***t*-stat.**	***t*-stat.**	***t*-stat.**	***t*-stat.**
PART A - CRUDE OIL										
Augmented Dickey – Fuller Test										
Spot	–2.1349	–60.7068*	–1.0371	–24.8511*	–1.2177	–28.2001*	–0.2651	–39.9034*	–1.8991	–27.128*
Futures	–2.1001	–53.3713*	–0.9127	–23.5675*	–1.0873	–24.9132*	–0.6208	–33.1616*	–1.6150	–23.3478*

					Phillips - Perron Test					
Spot	–2.1817	–60.7068*	–1.0716	–24.7668*	–1.0565	–28.3077*	–0.4297	–39.7294*	–1.7716	–27.1028*
Futures	–2.1187	–53.3593*	–0.9949	–23.6574*	–1.1410	–24.8742*	–0.7357	–33.1832*	–1.6835	–23.3409*
PART B - NATURAL GAS										
					Augmented Dickey - Fuller Test					
Spot	–2.6743***	-	–1.5608	–23.5103*	–3.3365**	-	–2.0141	–35.5474*	–1.9840	–25.1516*
Futures	–2.3226	–54.5026*	–1.3046	–22.0628*	–3.3055**	-	–1.7116	–34.28*	–1.9162	–24.3287*
					Phillips - Perron Test					
Spot	–2.5749***	-	–1.4286	–23.8181*	–3.2253**	-	–1.9684	–35.5896*	–1.9210	–25.1583*
Futures	–2.3104	–54.5404*	–1.2210	–22.1647*	–3.2619**	-	–1.6505	–34.3116*	–1.9339	–24.3282*

Note. *, ** , and *** show significance at 1%, 5%, and 10% levels.

Cointegration Test

Johansen's cointegration test is used to analyze whether spot and futures markets of all commodities address the same information at the same time or not. Besides this, the ARDL model is used for natural gas in the whole sample period (2007 – 2018), where all the underlying pairwise log price series are stationary at different integration orders. Table 3 shows that both trace and max-eigen value statistics reject the null hypothesis, that is, higher than 5% critical values, and accept the alternative hypothesis of at most one cointegrating vector. The results confirm

Table 3. ***Results of Johansen's Cointegration Test***

Time Period	Variables	Lag Lengtha	Trace Statistics	5% Critical Value	Max –Eigen Statistics	5% Critical Value	Cointegrating Equations
2007 – 2018	CRUDES and CRUDEF	2	657.4324*	25.8721	652.7437*	19.3870	1
			4.6886	12.5179	4.6886	12.5179	
GFC Period	CRUDES and CRUDEF	2	79.5845*	15.4947	78.5914*	14.2646	1
			0.9931	3.8414	0.9931	3.8414	
	NATURALS and NATURALF	1	242.3351*	15.4947	239.5097*	14.2646	1
			2.8253	3.8414	2.8253	3.8414	
Post - GFC Period	CRUDES and CRUDEF	2	162.081*	15.4947	161.1539*	14.2646	1
			0.9270	3.8414	0.9270	3.8414	
ESDC Period	CRUDES and CRUDEF	1	629.3731*	15.4947	628.7578*	14.2646	1
			0.6152	3.8414	0.6152	3.8414	
	NATURALS and NATURALF	1	618.336*	15.4947	614.8312*	14.2646	1
			3.5047	3.8414	3.5047	3.8414	
Post - ESDC Period	CRUDES and CRUDEF	1	202.013*	15.4947	199.2662*	14.2646	1
			2.7467	3.8414	2.7467	3.8414	
	NATURALS and NATURALF	1	134.9399*	15.4947	131.3162*	14.2646	1
			3.6237	3.8414	3.6237	3.8414	

Note. [a] indicates lag order is selected as per SIC. * shows rejection of hypothesis at the 1% level of significance.

Table 4. ***Results of ARDL Model for Natural Gas (2007–2018)***

Variable	Spot	Futures
SPOT(1)	0.0806*	-
SPOT	-	**0.8191***
FUTURES (1)	0.5841*	0.1756*
FUTURES (2)	–0.0501*	-
FUTURES	**0.3880***	-

Note. * shows rejection of hypothesis at the 1% level of significance.

the long-term relationship between the spot and futures prices of crude oil and natural gas for all sample periods except natural gas in the whole sample period and the post-GFC period.

Table 4 shows the long-run relationship between spot and futures prices of natural gas during the whole sample period. If these variables are cointegrated, then there must be the existence of price transmission, which helps in price discovery. So, to ascertain the long-term and short-term price discovery, VAR and VEC tests are used.

Auto-Regressive Distributed Lag (ARDL), Vector Auto Regression (VAR), and Vector Error Correction (VEC) Models

Table 5 and Table 6 show that the error correction coefficients in all spot equations are statistically significant with a negative sign. Also, the error correction coefficients of all futures equations are statistically significant at 1% and 5% levels, indicating bidirectional error correction in the long-run for the whole sample (2007 – 2018) period and post-ESDC period.

For all other three sample (GFC, post-GFC, and ESDC) periods, the empirical results show unidirectional error correction in the long-run except for natural gas (post-GFC). For calculation of natural gas (post-GFC), the study uses VAR methodology due to linear stationarity series at the level, and the results only show short-run behavior dynamics. Although the error correction coefficients of all spot equations are more in magnitude as compared to

Table 5. ***Results of VEC Model for Crude Oil***

Variables	Spot	Futures	Spot	Futures	Spot	Futures	Spot	Futures	Spot	Futures
Time Period	**2007–2018**		**GFC Period**		**Post - GFC Period**		**ESDC Period**		**Post - ESDC Period**	
Z_{t-i}	**–0.5568***	**0.2051***	**–0.4431***	**0.0672**	**–0.6554***	**0.1393**	**–0.9237***	**0.0161**	**–0.2045***	**0.5470***
ΔS_{t-1}	–0.0984*	0.0504***	–0.2393	0.0035	–0.1577*	0.0175	–0.0425**	0.0336**	–0.0535	0.0683*
ΔS_{t-2}	–0.0314**	–0.0108	–0.0179*	0.0345	–0.0105	–0.0533	-	-	-	-
ΔF_{t-1}	0.3314*	0.1334*	0.5194*	0.0021	0.3553*	0.1443***	0.0506	0.0464	0.1111**	0.0484
ΔF_{t-2}	0.0517**	–0.0641**	0.2137*	–0.0321	0.0891***	–0.0901	-	-	-	-
C	0.0001	0.0001	4.15E-05	0.0001	0.0005	0.0007	–0.0003	–0.0002	0.0004	0.0003
LB-*Q* (20)	49.059*	22.107*	23.795*	22.204*	47.342*	33.786**	49.056*	19.355	44.069*	60.967*
LB²-*Q* (10)	765.15*	808.31*	9.8038	30.013*	179.71*	211.31*	77.438*	235.27*	242.49*	472.04*
ARCH-LM(10)	27.7128*	25.8562*	0.7197	2.1046*	10.844*	7.6873*	5.025*	10.1645*	6.1907*	14.1811*
Conclusion	**F↔S(F)**		**F→S(F)**		**F→S(F)**		**F→S(F)**		**F↔S(S)**	

Note. *, ** , and *** show significance at 1%, 5%, and 10% levels.

Table 6. ***Results of ARDL, VAR, and VEC Models for Natural Gas***

Variables	**Spot**	**Futures**	**Spot**	**Futures**	**Spot**	**Futures**	**Spot**	**Futures**	**Spot**	**Futures**
Time Period	**2007–2018**		**GFC Period**		**Post - GFC Period**		**ESDC Period**		**Post - ESDC Period**	
Z_{t-i}	**–0.9193***	**–0.8244***	**–0.8580***	**0.1135**	**-**	**-**	**–0.8675***	**–0.017**	**–0.2354****	**0.3537****
ΔS_{t-1}	-	0.8190	–0.0094	–0.0329	–0.7880*	0.1488**	–0.0043	0.0144	–0.2523**	–0.0748
ΔS_{t-2}			-	-	–0.5752*	0.2071**				
ΔS_{t-3}					–0.3924*	0.093				
ΔS_{t-4}					–0.2714*	–0.02993				
ΔS_{t-5}					–0.0428**	–0.0707**				
ΔF_{t-1}	0.3879*		0.1352*	0.1267	0.9752*	–0.052	0.0729***	–0.0035	0.2489***	0.0616
ΔF_{t-2}	0.0501*				0.7113*	–0.1574***				
ΔF_{t-3}					0.5182*	–0.1966**				
ΔF_{t-4}					0.3226*	–0.0189				
ΔF_{t-5}					0.1810*	–0.0539				
C	–0.0178*	0.0374*	0.0003	0.0003	–0.0003	–0.0009	–2.42E-05	–6.91E-06	9.50E-05	8.99E-05
LB - Q (20)	36.107**	36.441**	25.89*	19.108***	42.57*	27.269*	18.756	28.711**	23.036*	16.475
LB^2-Q (10)	205.64*	340.89*	7.7948	21.26I***	4.535	31.931*	54.319*	90.876*	84.268*	7.9455
ARCH-LM(10)	13.6723*	20.5673*	0.374	1.2614*	0.3533	1.8936**	2.299*	3.8786*	1.0405*	0.6428
Conclusion	**F↔S(F)(ARDL)**		**F→S(F)**		**VAR**		**F→S(F)**		**F↔S(S)**	

Note. *, ** , and *** show significance at 1%, 5% , and 10% levels.

all futures equations in absolute terms for all sample periods except post-ESDC (post-GFC) period in both commodities (natural gas), it is concluded that the spot market makes a greater adjustment to achieve equilibrium when the cost of carry relationship is unsettled except in the post-ESDC period. Here, the results conclude that the futures (spot) market lead the spot (futures) market in price discovery for all sample periods (post-ESDC).

Among all of the error correction coefficients of crude oil (natural gas) spot equations, the error correction coefficient for the ESDC period (2007 – 2018) shows the highest statistical significant value as –0.9237 (–0.9193). It means the speed of adjustment from disequilibrium to equilibrium in the spot market is highest among all other crude oil (natural gas) error coefficients. For short-run dynamics, the lagged coefficients of crude oil spot (futures) prices significantly affect the calculation of futures (spot) prices in all sample periods except the GFC period. The lagged coefficients of natural gas futures prices significantly affect the calculation of spot prices in all sample periods except the post-GFC period. The results conclude that there is a short-run bidirectional (unidirectional) causal relationship between crude oil's (natural gas) spot and futures prices in all sample periods except the GFC (post-GFC) period. During the GFC (post-GFC) period, the results show a unidirectional (bidirectional) causal relationship between futures and spot prices.

To check the efficiency of time series modeling, Q-statistics and $Q^{\wedge 2}$- statistics report autocorrelation and presence of ARCH effect in the model's residuals and support to run GJR-GARCH model to identify the volatility spillover between spot and futures markets.

Volatility Spillover

In Table 7, the coefficient values of crude oil spot (θ_s) are positive and significant as compared to their crude oil

Table 7. ***Results of GJR – GARCH Test***

Variables	Crude Oil	Natural Gas	Crude Oil	Natural Gas	Crude Oil	Natural Gas	Crude Oil	Natural Gas	Crude Oil	Natural Gas
Time Period	**2007–2018**		**GFC Period**		**Post - GFC Period**		**ESDC Period**		**Post - ESDC Period**	
ω_s	1.99E-07*	1.73E-05*	5.47E-05*	5.46E-05*	–6.15E-07	34.3333*	0.0002*	1.93E-05*	4.59E-06	3.91E-05*
α_s	0.0451*	0.0756*	0.0878	0.3833*	0.037	4.2071*	0.0288*	0.3871*	–0.0006	0.1155*
γ_s	0.0465*	0.0023	0.4542*	–0.3775*	–0.0052	–9.1443*	–0.0535*	–0.3149*	0.0876*	0.0951*
β_s	0.9075*	0.8916*	0.3737*	0.6849*	0.8301*	–128.577*	–1.0025*	0.5971*	0.9406*	0.8996*
θ_s	**0.0169***	**0.0622***	**0.0804***	**–0.0093*****	**0.0471***	**–3.9716***	**0.0020***	**0.0250***	**0.0167**	**–0.109***
ω_f	3.41E-06*	1.79E-05*	2.00E-05*	0.1791*	4.89E-06*	1.9911**	0.3597*	1.00E-05*	2.20E-06**	0.0012*
α_f	0.0293*	0.0454*	–0.0262	–1.9987*	–0.0202*	0.7801	–4.5949	0.0450*	0.0755*	0.0999
γ_f	0.0679*	0.0075	0.1887*	17.5184	0.0672*	–2.3661**	–4.7061	–0.0206	0.0669**	0.0055
β_f	0.9295*	0.9446*	0.8707*	0.0631	0.9611*	2.1358**	–0.9477*	0.9358*	0.8679*	–0.6017**
θ_f	**–0.0018*****	**–0.022****	**0.0274***	**–6.2701****	**0.0263***	**–1.5353**	**–14.7555**	**0.0465****	**0.0008**	**–0.1145*****
LB-Q_s- (20)	31.993**	19.284	23.023	21.779	18.519	42.069	181.42*	15.985	26.069	10.256
LB-Q_s^2- (10)	4.368	5.9471	3.8724	22.159**	26.356*	8.9922	110.75*	8.011	6.9188	6.3156
ARCH-LM$_s$ (20)	0.341	0.4922	0.4306	1.1438	1.7715	0.3573	5.96035*	0.8357	6.9188	0.7401
LB-Q$_f$- (20)	15.384	15.994	16.873	80.167*	17.275	29.842***	29.868***	27.354	35.195*	16.795
LB-Q$_f$^2- (10)	19.071**	2.7753	5.2773	1.2221	19.124**	39.317*	0.7339	15.273	4.7883	10.228
ARCH-LM$_f$ (20)	1.278	0.674	1.1676	7.1452*	1.1401	2.1571*	0.0404	0.9791	0.4183	0.7426
Conclusion	**F↔S(F)**	**F↔S(F)**	**F↔S(F)**	**F↔S(F)**	**F↔S(F)**	**F→S(F)**	**F→S(F)**	**F↔S(S)**	**F≠S**	**F↔S(F)**

Note. *, ** and *** show significance at 1%, 5%, and 10% levels.

futures (θ_f) coefficient values for all sample periods except the post-ESDC period. The results indicate bidirectional volatility spillover between crude oil spot market and crude oil futures market in the total sample, GFC, and post-GFC periods. But in the case of the ESDC period and post-ESDC period, unidirectional (futures to spot) spillover and no spillover, respectively exist between crude oil spot market and crude oil futures market. Volatility spillover exists from futures market to spot market and is more dominant than the opposite direction in all sample periods except the post-ESDC period. The results confirm the crude oil futures market as a market leader in price discovery prices over the crude oil spot market.

In the case of natural gas, all spillover coefficient values are significant except the futures coefficient of the post-GFC period. The results indicate bidirectional volatility spillover between natural gas spot market and natural gas futures market in all sample periods except the post-GFC period. In the post-GFC period, volatility spillover exists unidirectionally from futures to spot. The dominance of volatility spillover in natural gas is found from the futures (spot) to spot (futures) market in all cases (except ESDC). The results conclude the futures market as a market leader in the price discovery process in both commodities.

For checking efficiency, Q-statistics and $Q^{\hat{}2}$-statistics do not report statistical significance. It means that the mean and variance equation of most commodities are approximately defined. The results show no proof of autocorrelation and serial dependence on squared normalized residuals and squared residuals. The results confirm that the GJR-GARCH model is most appropriate to check the ARCH effect in the sample time series.

Conclusion

Natural gas and crude oil are the most critical commodities in the energy sector. This study analyzes the price discovery and volatility spillover between the two recent financial crises. Out of the two, natural gas data for the post ESDC period shows the highest correlation between spot and futures markets in all different time slabs. This indicates that the natural gas market has more potential than crude oil in the energy sector. If the crisis period is concerned, the highest correlation is found in the post-ESDC period, which clearly shows market efficiency after the European crisis. Both ADF and PP tests show that most sample variables are integrated at order $I(1)$. For price discovery, most of the sample cases have a long-run equilibrium relationship between their spot and futures prices, and the futures (spot) market leads the spot (futures) market in the long-run in most sample (post-ESDC) periods. In the case of volatility spillover, most of the results conclude the dominance of the futures market over the spot market, except for crude oil in the post-ESDC period. The results also conclude that the volatility spillover is higher during both crises periods compared to their post-crises periods.

The results of this study are found to be in line with the results of Grosche and Heckelei (2014), Nazlioglu et al. (2015), Antonakakis and Kizys (2015), Brayek et al. (2015), Roy and Roy (2017), Rehman et al. (2018), and Kaura, et al. (2019). The reasons behind these results are electronic trading platform, high trading volume, risk management efficiency, etc., in the futures market compared to the spot market.

Managerial Implications

All overstated factors make the futures market more efficient and cost-competitive in terms of price discovery. So, it can be concluded that the market participants may depend on the futures market's price changes for their investment and trading decisions. The results during and post-crisis periods may be helpful for the current investors for modification of their optimum portfolios. The market players can consider the findings of this study for price discovery, which will further improve the process of price discovery. Investors and policy makers may draw meaningful conclusions and become prepared for the next crisis period.

Limitations of the Study and Scope for Further Research

Although volatility spillover can be transmitted through many channels like the stock market, bond market, option market, swap market, currency market, etc., but the commodity market is assumed as the only channel of volatility spillover in this study. The present research can be extended by using other financial markets to test the price discovery and spillover effect.

High-frequency data may be used that provide more useful results about the volatility spillovers. Other concepts like pricing and forecasting are not considered in the present research. So, future research can be carried out in these areas.

Authors' Contribution

Dr.Neha Seth thought of the idea and established qualitative and quantitative design to undertake the empirical study. Dr. Arpit Sidhu extracted highly reputed research papers, filtered these based on keywords, and generated concepts and codes relevant to the study design. Dr.Neha Seth verified the analytical methods and supervised the study. The analysis and interpretation were conducted by Dr. Arpit Sidhu.

Conflict of Interest

The authors certify that they have no affiliations with or involvement in any organization or entity with any financial interest or non-financial interest in the subject matter or materials discussed in this manuscript.

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References

Antonakakis, N., & Kizys, R. (2015). Dynamic spillovers between commodity and currency markets. *International Review of Financial Analysis, 41,* 303–319. https://doi.org/10.1016/j.irfa.2015.01.016

Baldi, L., Peri, M., & Vandone, D. (2016). Stock markets' bubbles burst and volatility spillovers in agricultural commodity markets. *Research in International Business and Finance, 38,* 277–285. https://doi.org/10.1016/j.ribaf.2016.04.020

Bekhet, H. A., & Matar, A. (2013). Co-integration and causality analysis between stock market prices and their determinates in Jordan. *Economic Modelling, 35,* 508–514. https://doi.org/10.1016/j.econmod.2013.07.012

Bollerslev, T. (1986). Generalized autoregressive conditional heteroskedasticity. *Journal of Econometrics, 31*(3), 307–327. https://doi.org/10.1016/0304-4076(86)90063-1

Bouri, E. (2015). Oil volatility shocks and the stock markets of oil-importing MENA economies : A tale from the financial crisis. *Energy Economics, 51,* 590–598. https://doi.org/10.1016/j.eneco.2015.09.002

Brayek, A. B., Sebai, S., & Naoui, K. (2015). A study of the interactive relationship between oil price and exchange rate : A copula approach and a DCC-MGARCH model. *The Journal of Economic Asymmetries, 12*(2), 173–189. https://doi.org/10.1016/j.jeca.2015.09.002

Chang, C. - L., McAleer, M., & Wang, Y. (2018). Testing co-volatility spillovers for natural gas spot, futures and ETF spot using dynamic conditional covariances. *Energy, 151,* 984–997. https://doi.org/10.1016/j.energy.2018.01.017

Choi, K., & Hammoudeh, S. (2010). Volatility behavior of oil, industrial commodity and stock markets in a regime-switching environment. *Energy Policy, 38*(8), 4388–4399. https://doi.org/10.1016/j.enpol.2010.03.067

Danak, D., & Patel, N. (2020). A study of efficiency of index futures, lead-lag relationship, and speed of adjustments in India using high-frequency data. *Indian Journal of Finance, 14*(4), 07–23. https://doi.org/10.17010/ijf/2020/v14i4/151705

Dickey, D. A., & Fuller, W. A. (1979). Distribution of the estimators for autoregressive time series with a unit root. *Journal of the American Statistical Association, 74*(366), 427– 431. https://doi.org/10.2307/2286348

Dutt, M., & Sehgal, S. (2018). Domestic and international information linkages between gold spot and futures markets : An empirical study for India. *Metamorphosis : A Journal of Management Research, 17*(1), 1–17. https://doi.org/10.1177%2F0972622518761745

Engle, R. F. (1982). Autoregressive conditional heteroscedasticity with estimates of the variance of United Kingdom inflation. *Econometrica, 50*(4), 987–1007. https://doi.org/10.2307/1912773

Eryiğit, M. (2017). Short-term and long-term relationships between gold prices and precious metal (palladium, silver and platinum) and energy (crude oil and gasoline) prices. *Economic Research - Ekonomska Istraživanja, 30*(1), 499–510. https://doi.org/10.1080/1331677X.2017.1305778

Ewing, B. T., Gormus, A., & Soytas, U. (2018). Risk transmission from oil and natural gas futures to emerging market mutual funds. *Emerging Markets Finance and Trade, 54*(8), 1827–1836. https://doi.org/10.1080/1540496X.2017.1400965

Fasanya, I., & Akinbowale, S. (2019). Modelling the return and volatility spillovers of crude oil and food prices in Nigeria. *Energy, 169,* 186 – 205. https://doi.org/10.1016/j.energy.2018.12.011

Glosten, L. R., Jagannathan, R., & Runkle, D. E. (1993). On the relation between the expected value and the volatility of the nominal excess return on stocks. *The Journal of Finance, 48*(5), 1779–1801. https://doi.org/10.1111/j.1540-6261.1993.tb05128.x

Gozgor, G. (2016). Are shocks to renewable energy consumption permanent or transitory ? An empirical investigation for Brazil, China, and India. *Renewable and Sustainable Energy Reviews, 66,* 913–919. https://doi.org/10.1016/j.rser.2016.08.055

Grosche, S., & Heckelei, T. (2014). *Price dynamics and financialization effects in corn futures markets with heterogeneous traders* (Discussion Paper 172077). https://doi.org/10.22004/ag.econ.172077

Gupta, S., Choudhary, H., & Agarwal, D. R. (2017). Hedging efficiency of Indian commodity futures: An empirical analysis. *Paradigm, 21*(1), 1–20. https://doi.org/10.1177%2F0971890717700529

Gupta, S., Choudhary, H., & Agarwal, D. R. (2018). An empirical analysis of market efficiency and price discovery in Indian commodity market. *Global Business Review, 19*(3), 771–789. https://doi.org/10.1177%2F0972150917713882

International Energy Agency. (2019). *World energy investment 2019.* https://webstore.iea.org/world-energy-investment-2018

Johansen, S. (1988). Statistical analysis and cointegrating vectors. *Journal of Economic Dynamics and Control, 12*(2 – 3), 231 – 254. https://doi.org/10.1016/0165-1889(88)90041-3

Junttila, J., Pesonen, J., & Raatikainen, J. (2018). Commodity market based hedging against stock market risk in times of financial crisis : The case of crude oil and gold. *Journal of International Financial Markets, Institutions and Money, 56,* 255–280. https://doi.org/10.1016/j.intfin.2018.01.002

Kaura, R., Kishor, N., & Rajput, N. (2019). Arbitrage, error correction, and causality: Case of highly traded agricultural commodities in India. *Indian Journal of Finance, 13*(9), 07–21. https://doi.org/10.17010/ijf/2019/v13i9/147095

Kaushik, N. (2018). Do global oil price shocks affect Indian metal market ? *Energy & Environment, 29*(6), 891 – 904. https://doi.org/10.1177%2F0958305X18759790

Kotishwar, A. (2020). Impact of high frequency trading on equity market with reference to NSE India. *Indian Journal of Finance, 14*(1), 58 – 76. https://doi.org/10.17010/ijf/2020/v14i1/149858

Ljung, G. M., & Box, G. E. (1978). On a measure of lack of fit in time series models. *Biometrika, 65*(2), 297 – 303. https://doi.org/10.1093/biomet/65.2.297

Mishra, A. (2019). Foreign exchange, gold, and real estate markets in India : An analysis of return volatility and transmission. *Indian Journal of Finance, 13*(7), 50–64. https://doi.org/10.17010/ijf/2019/v13i7/145535

Nazlioglu, S., & Soytas, U. (2012). Oil price, agricultural commodity prices, and the dollar : A panel cointegration and causality analysis. *Energy Economics, 34*(4), 1098–1104. https://doi.org/10.1016/j.eneco.2011.09.008

Nazlioglu, S., Soytas, U., & Gupta, R. (2015). Oil prices and financial stress : A volatility spillover analysis. *Energy Policy, 82,* 278 – 288. https://doi.org/10.1016/j.enpol.2015.01.003

Parthasarathy, S. (2019). Revisiting the weak form efficiency with structural breaks: Evidence from the Indian stock market. *Indian Journal of Finance, 13*(10), 7 – 21. https://doi.org/10.17010/ijf/2019/v13i10/147744

Pesaran, M. H. Shin, Y., & Smith, R. J. (2001). Bounds testing approaches to the analysis of level relationships. *Journal of Applied Econometrics, 16*(3), 289 – 326. https://doi.org/10.1002/jae.616

Phillips, P. C., & Perron, P. (1988). Testing for a unit root in time series regression. *Biometrika, 75*(2), 335 – 346. https://doi.org/10.1093/biomet/75.2.335

Rehman, M. U., Shahzad, S. J., Uddin, G. S., & Hedström, A. (2018). Precious metal returns and oil shocks : A time varying connectedness approach. *Resources Policy, 58,* 77–89. https://doi.org/10.1016/j.resourpol.2018.03.014

Roy, R. P., & Roy, S. S. (2017). Financial contagion and volatility spillover : An exploration into Indian commodity derivative market. *Economic Modelling, 67,* 368–380. https://doi.org/10.1016/j.econmod.2017.02.019

Sharma, S. (2017). Market efficiency between Indian & US crude oil future market. *Procedia Computer Science, 122,* 1039–1046. https://doi.org/10.1016/j.procs.2017.11.471

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