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RESEARCH ARTICLE

Dynamic Interaction Between Food and Fuel Markets in India: Has India Joined the Global Race?

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Abstract: The study makes an attempt to investigate co-integrating relation between crude and three energy crops, namely sugarcane, soyabean, and wheat, for India for a sampled period Jan 2011–Dec 2020 by taking log-transformed daily closing spot prices. The dynamic relation between crude and energy crops is established using ARDL (ARDL) and non-linear ARDL co-integration techniques. The results revealed co-integration being established only for sugarcane with crop's critical region improving from 5% to 1% when dummy representing break was included in the ARDL model. The asymmetric impact of crude on sugarcane was visible both in short and long run. Further, short-run results were in one direction only, i.e., a rise in crude was impacting prices of two crops, namely sugarcane and wheat, with no visible impact of any of energy crops on crude. The coefficient of error correction term (ECM(−1)) term for sugarcane was −0.005 which was negative and significant showing stability of equilibrium; however, adjustment speed was rather slow at 0.5% per period. The study recommends policy makers to harmonize and synergize energy and agricultural policies as both sugarcane and wheat are food staples in India. The country needs to develop a pre-warning and a crisis response mechanism regarding biofuel policies so as to avoid any food crisis situation as seen in early 2000 in some of the countries where energy crops significantly make way to biofuels.

Keywords: energy crops, ARDL, NARDL, asymmetry, co-integration

1. Introduction

Traditionally, empirical research on commodities focused primarily on prices and returns and revolved around theoretical pricing model of demand–supply dynamics. However, during the last two decades what has been witnessed is a clear shift in approach of the researchers toward this asset class, the primary reason being unexpected recurring price swings which go beyond the economic fundamentals, thereby resulting in financialization of this asset class (Dahl et al., 2020). Moreover, researchers now tend to focus on less-researched areas including commodity price variability and return volatility and have started applying models to commodities, which are commonly applied to stocks and shares. This again would be viewed by many as growing importance of commodities, which is now ready to give tough fight to traditional assets like stocks and bonds.

Among the commodities, a center of attraction has been exploring the linkages between energy crops and crude. The interest began after a seminal work by Pindyck and Rotemberg (1990) when they formulated the excess co-movement hypothesis, explaining how commodity prices like crude, wheat, and cotton were moving in excess of what macros could explain. Further, when researchers started exploring the reasons responsible for this excess co-movement hypothesis, interaction between food and fuel markets was brought to limelight. Researchers initially worked on a theoretical model framework (de Gorter & Just, 2008; Gardner, 2007) with some applying partial and general equilibrium models to study this relation (Banse et al., 2008; Hertel & Beckman, 2011). The recent studies have gone ahead and developed the relation by studying the time series models (Shahani et al., 2022; Zhang et al., 2010).

Among those who have studied crude–crops relation by developing theoretical models include Gardner (2007) who showed that when crude prices were high, there was a substantial price transmission from crude to corn. On the other hand, Lapan and Moschini (2012) showed how energy prices get delinked from biofuel prices when the mandate determined these prices over and above the tax credit. Then researchers like Searchinger et al. (2015) using partial equilibrium models proved that all the emission gains from using biofuels were obtained only at the cost of reduction in food resources primarily used for consumption. Banse et al. (2008) in their study showed that mandatory blending policies of the government were impacting strongly the crop prices.

Apart from theoretical models explaining crude energy crops relation, the field of crude–energy crops nexus has been studied using empirical time series models. Such models have gained importance after the food crisis of 2006 for which blame was placed on biofuels obtained from energy crops. The research also showed that the link between energy crops and crude had actually strengthened during the period of the food crisis and thereby enabling academicians and practitioners to look out for in-depth reasons as to what had changed during this period of food crisis which had created a strong bonding between energy crops and crude (Eissa & Al Refai, 2019).

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A number of interesting explanations have been put forth for this crude oil-energy crops nexus, and these include rise in input costs of cultivation due to increased transportation costs, costs associated with running tube wells and tractors, rise in prices of fertilizers, pesticides, and so on (Fowowe, 2016; Janda & Krištoufek, 2018). Then, research has proved that high crop prices triggered a land use competition among different crops with farmers inclined toward plantation of profitable energy crops (Cheng & Cao, 2019). Also, rise in crude prices has a macro dimension, i.e., it adds to the overall economy's import bill impacting balance of payment and foreign exchange reserves of the economy (Eissa & Al Refai, 2019).

Studies have also found that state interference through government policies has also contributed to increased correlations among the crude and agricultural crops. Government policies aimed at promoting ethanol production like renewable fuel mandate, subsidies to blenders, import tariffs, etc. actually performed the role of a catalyst in energy crops-crude nexus. Government also provided support to the markets of biofuels indirectly through the sustainability criteria (Chakravorty et al., 2017; Janda & Krištoufek, 2018; Merkusheva, 2014; Serletis & Xu, 2019). On the other hand, some researchers do not agree to above arguments and studies like Tadesse et al. (2016) and Nazlioglu et al. (2013) showed that co-movement in crude and grains was mainly driven by the financialization of commodities, their openness, and integration with other global markets of equities and bonds. Then projections about the impact of crude price rise on food prices tend to differ quite significantly among researchers. Whereas Zhang et al. (2013) estimated a price rise of corn owing to its usage as fuel between 5% and 53% in a short time span of 2 years, National Research Council's (2011) report puts this figure between 20 and 40% during 2007–2009. A working paper by National Center for Environmental Economics estimated a nominal 2–3 % increase in long-run corn prices of ethanol produced through corn (Condon et al., 2013).

There is still a pool of researchers who do not believe that such a relation between crude and energy crops does exist or even if such a relation exists, then their view is that such a relation has not gained strength after the food crisis of 2006. As claimed by many researchers, their studies have found either negative or no co-movement between crude and agriculture crops (Du et al., 2011; Gardebroek & Hernandez, 2013; Nazlioglu & Soytas, 2011). These studies primarily support the neutrality hypothesis. For them, the crop price rise was simply as a result of rise in food needs of growing population and not due to crude price rise (Reboredo, 2012; Zhang et al., 2010). A study by Fernandez-Perez et al. (2016) pointed out rise in economic activities being responsible for global rise in demand for grains. Then, Myers et al. (2014) showed that co-movement between crude and crops was primarily a short-run phenomenon, which simply disappeared in the long run. In an interesting study, Wetzstein and Wetzstein (2011) argued that entrepreneurs who ventured into a biofuel capacity invested substantially keeping into consideration a long-time horizon and hence studying the relation between the crops and crude by focusing only on short/limited period of time as approached by some researchers cannot be fully justified.

Going ahead, the study is an attempt to empirically investigate the co-integrating relation between crude and three energy crops for India, namely soyabean, wheat, and sugarcane. The choice of three energy crops has been made considering the share and contribution of these crops to biofuels (primarily ethanol production) in major ethanol producing economies including US and Brazil, which together contribute 84% of global ethanol production (Sarwal et al., 2021). The study would achieve its objective of establishing dynamic linkages among crude and energy crops by developing co-integrating relation. The study would further test whether crude has an asymmetric impact on these energy crops. The period of current study has been taken as 10 years: Jan 2011–Dec 2020 (daily closing prices, 2446 data points), and the co-integration has been tested by employing autoregressive distributed lag methodology (ARDL) developed by Pesaran et al. (2001) and Pesaran and Shin (1999). Further, we have applied both linear and non-linear ARDL models, the non-linear version (NARDL) developed by Shin et al. (2014) being an asymmetric expansion of linear ARDL. The variables considered under the study include crude (INR per barrel), wheat (INR per metric ton), soyabean (INR per metric ton), and sugarcane (INR per Kg).

The study is mainly an outcome of the desire to comprehensively investigate crude–energy crops nexus for India, which has become so important nowadays not only owing to global concerns but also considering recent state promotion of biofuel in the country (Sarwal et al., 2021). The blending targets as laid down by Govt. of India have now been advanced by 5 years. These pertain to achieving a mix of 20% ethanol in petrol and 20% biodiesel in diesel by 2025 and not 2030 as planned earlier (Sarwal et al., 2021; Shahani et al., 2022). Moreover, the blending model also provides a big jump in usage of biofuels from current E-5 to E-20 fuels. This change in blending model would be a big savings in terms of foreign exchange outflows, which has been estimated at 32 billion US $ (Sarwal et al., 2021), which also constitutes a substantial portion of India's import bill for crude, which for the year 2022–23 was 158 billion US $. This though would be a significant development, the flipside here is that India being the largest consumer of sugarcane in the world, diverting even a small portion of sugarcane crop which also is a staple food might have far-reaching implications on local consumption and therefore the paper makes an attempt to discuss this aspect with some realistic projections.

The rest of the paper is structured as follows: Section 2 reviews the existing literature in the area of co-integrating relation between crude and energy crops, Section 3 gives the distribution characteristics of our variables, Section 4 explains the methodology employed, Section 5 provides empirical results, and finally Section 6 ends with conclusion, and limitations of study and policy implications.

2. Literature Review

Empirical studies on crude–energy crops nexus have decisively gained momentum after the world saw a simultaneous surge in their prices during 2000–2010. Dimensions explored through these empirical studies include crude demand and supply linkages, short- and long-run co-integration, causality and spillover studies, asymmetric impact of crude on energy crops, establishing linear and non-linear relation, time-varying analysis, and so on. However, considering the focus of the present study which is on investigating the dynamic time series asymmetric linkages among crude and energy crops by establishing a linear and non-linear co-integrating relation, the literature review mainly highlights these aspects of crude-food crops linkages. Some important papers reviewed along with their key findings are discussed as follows.

Eissa and Al Refai (2019) applied both ARDL and NARDL models to study the dynamic linkages between three energy crops and oil prices and found that while ARDL showed no long-run co-integration, NARDL model showed the opposite, i.e., long-run co-integration was proved along with asymmetric impact of crude on two of the three crops. Another study examining ARDL and NARDL Models was carried out by Hadj cherif et al. (2021)

where they tested asymmetric relation for the Middle East North American (MENA) countries totalling 19 in number and after grouping them as oil exporters, oil importers and also together as a pool. The asymmetric impact of crude on food crops was seen in both short and long run for entire pool of MENA countries, with long-run food prices always rising irrespective of rise or fall in crude. ARDL results showed co-integration for both subgroups. In another study, Karakotsios et al. (2021) found no long-term effects using plain ARDL model; however, after incorporation of a break, the causality was seen moving from crude to food prices and when model was made NARDL, causality became bi-directional. The asymmetry was also proved along with long-run co-integration for this NARDL model.

In a study on Chinese markets, Wang et al. (2015) found using ARDL that when rice was taken as a function of other crops and crude, co-integration was proved but the same was not seen with other variables. Also long-run price elasticities from crude, corn, and wheat to rice were also seen from the results. Another country-specific study by Fasanya et al. (2019) on Nigerian markets employed ARDL and NARDL on crude and six agricultural crops. The co-integration was proved using both ARDL (linear) and ARDL (linear with breaks) models, the only difference being the results of the ARDL with breaks being more robust.

Nigerian markets were also considered by Gokmenoglu et al. (2021) where they could establish the long-run relation between oil and crop prices with uni-directional causality from oil to agricultural prices. On the other hand, different study results for short and long run were noticed by Abdul-Rahim and Zariyawati (2011) where short-run results showed that crude was not impacting any crop while in long run, crude was impacting rice but not soyabean.

Some studies have focused exclusively on explaining crude–energy crop relation during crisis periods; Vatsa and Miljkovic (2022) observed a clear shift in crude–crop relation after the global financial crisis (GFC) of 2008. It was noticed that till 2009, crude led crop prices; however, post-2010, crude lagged crop prices clearly reflecting the impact of GFC in shifting the relation. The correlations however remained positive both before and after GFC, with only crude prices witnessing a change from being lead variable to lagged variable in relation to crops. A study by Chen et al. (2022) found that the relation between crops and crude gained strength during the Covid-19 crisis period with more strength seen between crude and crop soyabean.

Asymmetric impact of crude on energy crops was studied by Zhang and Qu (2015) where they found negative asymmetric impact of crude on both cash crops and food crops with asymmetry of cash crops being higher. Similarly, Bakhat and Würzburg (2013) found that in the short run, positive as well as negative deviations existed among crops and crude; however, long-run adjustment process was highly asymmetric. Further, Zmami and Ben-Salha (2019) concluded that energy crop prices were seen rising with rising crude, while for falling crude no impact was visible on crop prices. Other researchers who could find asymmetric response of crude to crops include Merkusheva (2014) and Nazlioglu (2011). Among the reasons identified for asymmetry were state policies like fuel mandates, import tariffs, and subsidies to blenders among others.

Thus, literature review on co-integration and asymmetry studies on biofuels do provide some interesting takeaways: first, many researchers tend to go for NARDL only when co-integration is not proved using ARDL, second, the quasi-linear ARDL (i.e., ARDL with structural breaks) does not alter the results to a significant extend in most studies but only makes the results more robust, third, NARDL, an asymmetric expansion of ARDL is considered as an independent approach by most research studies, fourth, in almost all studies, the results of linear and NARDL did not match and co-integration was primarily detected only after the relation was shifted to non-linear, fifth, asymmetry due to rise of crude prices on energy crops was seen from results while negligible impact of fall in crude on energy crops was noticed by most studies, and lastly during the crisis periods the relation between crops and crude did gain additional strength, be it GFC or the Covid-19 pandemic.

3. Descriptive Statistics

3.1. Statistical description of returns

Table 1 gives statistical description of daily returns for the 10-year period Jan 2011–Dec 2020 (2446 data points) of all four variables employed in our study viz. crude, wheat, soyabean, and sugarcane. Out of four commodities, crude generated highest average return of 0.358% on daily basis (130% in annualized terms) followed by wheat at 0.075% as daily return (27% on annualized basis), soyabean at 0.059% (21%), and finally sugarcane at 0.014% (5%). The average return comparison clearly reveals that crude is way ahead of all the three energy crops and enjoyed a return, which was approximately five times the nearest competitor, i.e., wheat. Further, among the three energy crops, wheat had the highest while sugarcane had the lowest daily return with none of four variables giving negative daily average returns, which constitutes an important consideration for investors and those hedging through commodity derivatives.

Table 1
Statistical description of returns of crude and three energy crops during the period Jan 1, 2011–Dec 30, 2020

Parameter	Crude	Wheat	Sugarcane	Soyabean
Mean	0.003583	0.000750	0.000141	0.000589
Maximum	8.697759	1.620574	0.179365	0.892088
Minimum	−0.901841	−0.620676	−0.145626	−0.470611
Std. Dev.	0.179232	0.041556	0.014395	0.026998
Skewness	46.64058	26.44504	0.938980	17.04870
Kurtosis	2265.708	1063.421	37.09536	679.5777
Coeff. of variation	50.02	55.408	102.127	45.83
JB statistics	5.23E+08	1.15E+08	118836.9	46771596
Probability (JB)	0.000000	0.000000	0.000000	0.000000
Observations	2446	2446	2446	2446

Note (1): JB statistics $= \frac{n}{6}\{S^2 + \frac{1}{4}(K-3)^2\}$,
Note (2): Coefficient of variation $(CV) = \sigma/\mu$

Crude, being the highest return generator, also had the highest standard deviation of returns, a popular proxy for risk, thereby making this variable a high risk-high return candidate. Among the three energy crops, sugarcane had the lowest standard deviation followed by soyabean while wheat had the highest. Although wheat had the highest standard deviation of the three crops, the standard deviation of wheat was mere 22% of standard deviation of crude.

We apply coefficient of variation (CV) = σ/μ, to balances risk with return and the results reveal that crop soyabean had the lowest CV among all four variables, thereby making this crop the best risk-adjusted return performer followed by crude.

In terms of the shape of the distribution of four variables, all the four distributions were positively skewed and leptokurtic. Their distributions had tails, which were taller and appeared to be a profusion of outliers. Peaks of all four distributions were higher and sharper than that of a normal distribution (Figures 1, 2, 3, and 4). Clearly with these characteristics and shapes, all the four variables/distributions rejected the formal test for normality, i.e., JB test statistic. These variables were therefore modified at their log prices and log returns for subsequent analysis.

Figure 1
Log return crude vs normal

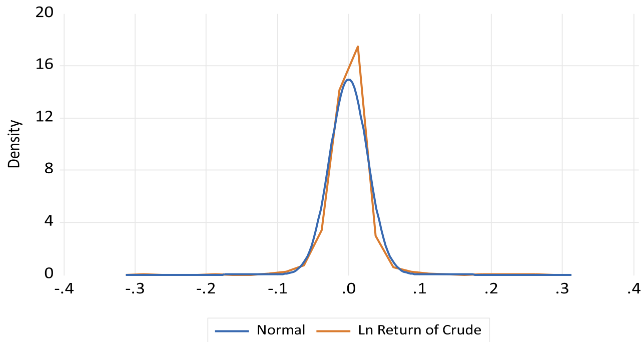


Figure 2
Ln return of sugarcane vs normal

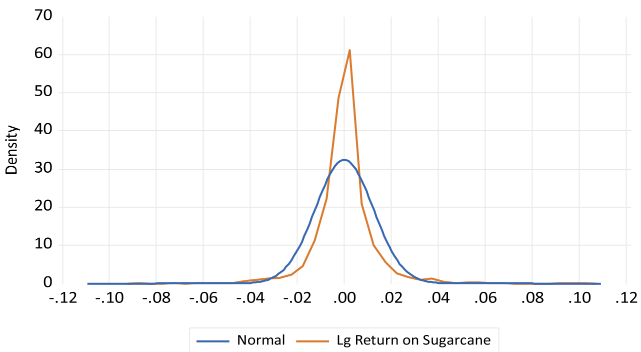


Figure 3
Log return soyabean vs normal

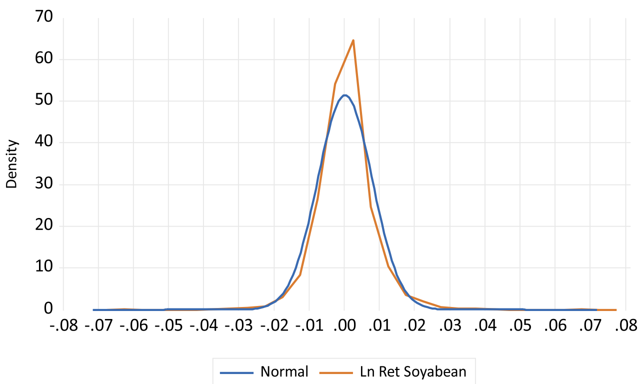
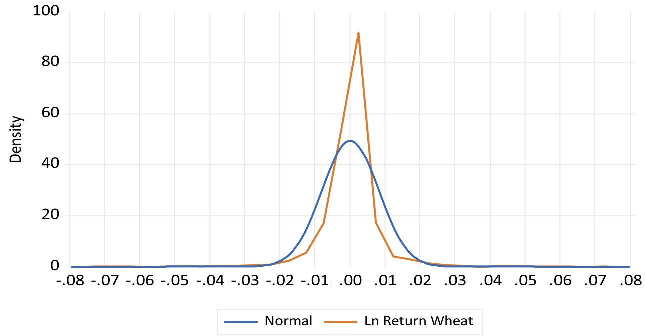


Figure 4
Log return wheat vs normal



3.2. Graphic representation of return of crude and three energy crops

The section provides for the plots of returns of crude and three energy crops (Figures 5, 6, 7 and 8) for the sampled period Jan 2011–Dec 31, 2020.

The plots (Figures 5, 6, 7, and 8), besides displaying the daily return, also display the dates for highest single day rise and single day fall in returns. The following analysis has been made on the basis of these plots: (i) maximum fall in returns for all the four variables could be seen in the first half of year 2020 and matches with the early phase of Covid-19 pandemic. (ii) Highest rise in returns for crude and sugarcane could also be seen during the Covid-19 period, reflecting the vulnerability of these two asset classes during crisis periods while for other two crops, wheat and soyabean highest return was witnessed during the months of November 2016 and 2017, respectively. (iii) There appears to be a clear indication of increase in volatility in sugarcane for the sub-period 2018–2020 showing some kind of external forces inflicting their prices. (iv) During first 6 months of 2020, high volatility was noticed not only for energy crops but also crude, which witnessed extremely high volatility during this period. (iv) During the entire sampled period, return volatility for all the three energy crops was seen to be far lower as compared to crude.

4. Methodology

4.1. Model development

In this section, we would first develop the linear ARDL model (Pesaran et al., 2001; Pesaran & Shin, 1999) followed by NARDL (Shin et al., 2014). The complete ARDL/NARDL model has been covered in five parts: the first part (sub Section 4.1.1.–4.1.2.) discusses the ARDL and NARDL model representative equation, a single equation which includes both short and long-run variables, the second part (Section 4.2) discusses the co-integration relation, while the third and fourth parts (Section 4.3 and 4.4) reveal the long-run and the short-run relation among the variables. This section also provides for error correction toward equilibrium. The fifth and the final part (Section 4.5.) provides for short- and long-run asymmetry among the variables. For all these models, we would consider Y_1 as the dependent while Y_2, Y_3 and Y_4 as independent variables; Y_1 could be any of the three crops while Y_2 and Y_3 would signify the remaining two crops and Y_4 would represent the variable crude.

Figure 5
Ln return (crude)

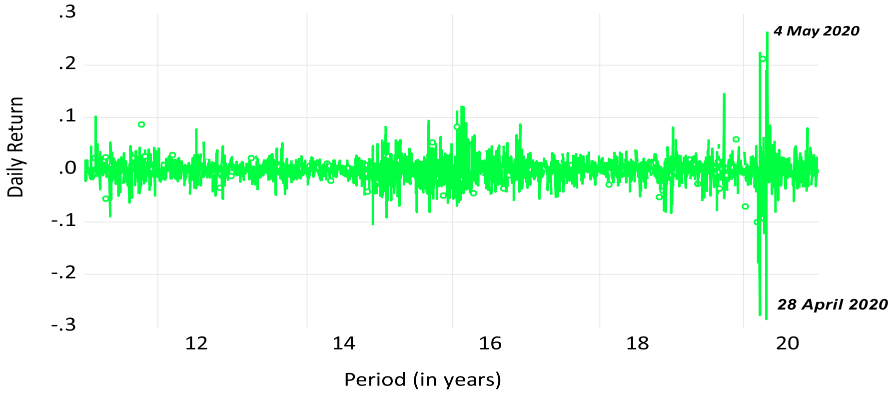


Figure 6
Ln return (wheat)

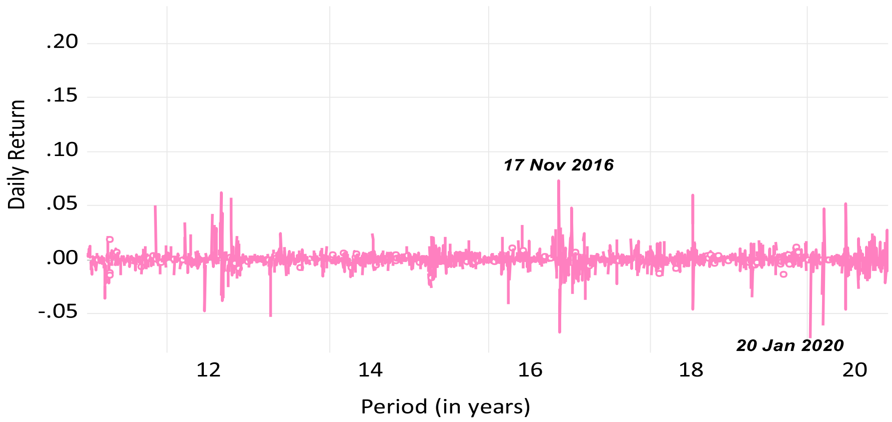


Figure 7
Ln return (sugarcane)

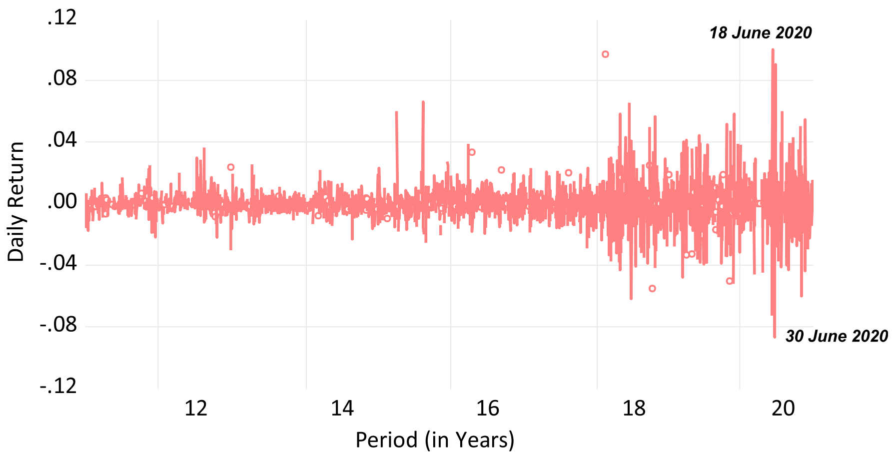
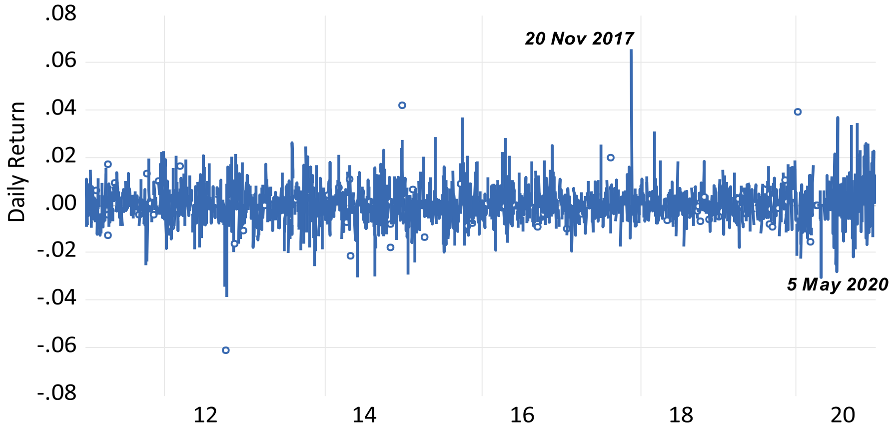


Figure 8
Ln return (soyabean)



4.1.1. ARDL model representation

$$\Delta ln.Y_{1,t} = \delta_1 + \delta_{1,BD}{}^{\#} D_{1,t} + \delta_2\, ln.\, Y_{1,t-1} + \delta_3\, ln.\, Y_{2,t-1} + \delta_4\, ln.\, Y_{3,t-1} + \delta_5\, ln.\, Y_{4,t-1} + \sum\nolimits_{i=1}^{r}\left(\delta_{6,i}\Delta\ \mathrm{ln.Y_{1,t-i}}\right) + \sum\nolimits_{i=0}^{n_1}\left(\delta_{7i,}\ \Delta\ \mathrm{ln.Y_{2,t-i}}\right) + \sum\nolimits_{i=0}^{n_2}\left(\delta_{8,i}\Delta\ \mathrm{ln.Y_{3,t-i}}\right) + \sum\nolimits_{i=0}^{m_1}\left(\delta_{9,i}\Delta\ \mathrm{ln.Y_{4,t-i}}\right) + e_t \ldots. \tag{1}$$

For Equation (1), which is the ARDL model equation, Δ ln. $Y_{1,t}$ is the logarithms change in Y_1 in period "*t*" (Y_1 being the dependent variable and as already stated would be any one of the three energy crops, viz. sugarcane, wheat, or soyabean), "δ_1" is the intercept while "$\delta_1{}^{\#}$" is the coefficient of intercept dummy (D_1) reflecting a single break (with BD as break date) in intercept of the dependent variable (if any). To identify the break, we have applied Perron and Vogelsang's (1992) methodology, which uses innovative outlier method and the test compares the results obtained with asymptotic one-sided "*p*" values. The intercept dummy variable (D_1) takes the following values $D_{1,t} = \begin{cases} 1 \text{ if } t \geq BD \\ 0 \text{ if } t < BD \end{cases}$

i.e., dummy shall be "'0" if "*t*" is before the break date (BD) and shall be "1" if "*t*" is after the break, including break date.

The next term "δ_2" in Equation (1) is the slope coefficient of first lag of dependent variable Y_1, which is of the nature of AR (1) representation. Y_2, Y_3, and Y_4 with slopes δ_3, δ_4, and δ_5, respectively, are the three independent variables and these are included in the regression at first lag only and all together represent long-run relation with the dependent variable. The term $\sum_{i=1}^{r}\left(\delta_{6,i}\Delta\ \mathrm{ln.Y_{1,t-i}}\right)$ is the log change in dependent variable Y_1 with "*r*" being the optimal number of lags as determined by Akaike Information Criteria (AIC). All the coefficients $\delta_{6,i}; i = 1, 2, \ldots r$ are summed up in Equation (1). Similarly, $\sum_{i=0}^{n_1}\left(\delta_{7i,}\Delta\ \mathrm{ln.\ Y_{2,t-i}}\right)$ and $\sum_{i=0}^{n_2}\left(\delta_{8,i}\Delta\ \mathrm{ln.Y_{3,t-i}}\right)$ reflect the logarithm change in the independent variables (two energy crops) Y_2, and Y_3, with "n_1" and "n_2" being the number of lags for these variables again determined by AIC lag determination criteria. The last term $\sum_{i=0}^{m_1}\left(\delta_{9,i}\Delta\ \mathrm{ln.Y_{4,t-i}}\right)$ is a natural log change in variable crude. Again just like the long-run relation, all the terms $\sum_{i=0}^{n_1}\left(\delta_{7i,}\Delta\ \mathrm{ln.Y_{2,t-i}}\right)$, $\sum_{i=0}^{n_2}\left(\delta_{8,i}\Delta\mathrm{ln.Y_{3,t-i}}\right)$ and $\sum_{i=0}^{m_1}\left(\delta_{9,i}\Delta\ \mathrm{ln.Y_{4,t-i}}\right)$ collectively make up the short-run relation with the dependent variable. Finally, the equation has e_t as stochastic error term.

4.1.2. NARDL model representation

NARDL was developed by Shin et al. (2014) to capture the asymmetric effects and here a variable is decomposed into positive and negative values. Non-linear model representation Equation (1(a)) has same variables as in ARDL Equation (1) except the variable crude, Y_4, which has been decomposed as Y_4^{+} and Y_4^{-} both in short as well as long run, i.e.,

$$Y_4{}^{+} = \begin{cases} Y_4 \text{ if } Ret\ Y_4 > 0 \\ 0 \text{ if } Ret\ Y_4 \leq 0 \end{cases} \text{and } Y_4^{-} = \begin{cases} Y_4 \text{ if } Ret\ Y_4 < 0 \\ 0 \text{ if } Ret\ Y_4 \geq 0 \end{cases}$$

$$\Delta ln.Y_{1,t} = \lambda_1 + \lambda_{1,BD}{}^{\#}D_{1,t} + \lambda_2\, ln.\, Y_{1,t-1} + \lambda_3\, ln.\, Y_{2,t-1} + \lambda_4\, ln.\, Y_{3,t-1} + \lambda_{5A}^{+}\, ln.Y_{4,t-1}^{+} + \lambda_{5A}^{-} ln.Y_{4,t-1}^{-} + \sum\nolimits_{i=1}^{r}\left(\lambda_{6,i}\Delta\mathrm{ln.Y_{1,t-i}}\right) + \sum\nolimits_{i=0}^{n_1}\left(\lambda_{7,i}\Delta\mathrm{ln.Y_{2,t-i}}\right) + \sum\nolimits_{i=0}^{n_2}\left(\lambda_{8,i}\Delta\mathrm{ln.Y_{3,t-i}}\right) + \sum\nolimits_{i=0}^{m_{1A}}\left(\lambda_{9A,i}^{+}\Delta\mathrm{ln.Y_{4,t-i}^{+}}\right) + \sum\nolimits_{i=0}^{m_{2A}}\left(\lambda_{9B,i}^{-}\Delta\mathrm{ln.Y_{4,t-i}^{-}}\right) + e_t \ldots. \tag{1a}$$

4.2. Partial "*F*" bounds long-term co-integration test

Under this section we discusses the model decision, i.e., decision with respect to existence of long-run co-integration and tool employed would be partial '*F*' bounds test which establishes the null hypothesis for co-integration as a joint null amongst the long-run parameters: H_o: $= \delta_2 = \delta_3 = \delta_4 = \delta_5 = 0$ (see Equation (1)). "*F*" bounds upper and lower critical values are given by Pesaran et al. (2001) and decision on existence of co-integration follows the following criteria:

- If F_{computed} < Lower bound critical, result: no co-integration.
- If F_{computed} > Upper bound critical, co-integration gets established.

4.3. Long-term relation and long-run elasticity

If the co-integration gets proved, then one (or more) of the independent variables shall be impacting dependent variable. We then establish long-run relation given as Equation (2) below:

$$ln.Y_{1,t} = \beta_1 + \beta_{1,BD}{}^{\#}D_{1t} + \sum_{i=1}^{r_2}(\beta_{2,i}\ln.Y_{1,t-i}) + \sum_{i=0}^{n_3}(\beta_{3i,}\ln.Y_{2,t-i}) + \sum_{i=0}^{n_4}(\beta_{4,i}\ln.Y_{3,t-i}) + \sum_{i=0}^{m_2}(\beta_{5,i}\ln.Y_{4,t-i}) + e_t \quad (2)$$

For Equation (2), we would be considering r_2, n_5, n_6, and m_2 as notations for lags of dependent variable, two energy crops, and crude, respectively, and all these lags would be following lag criteria as given by AIC. The coefficient of these natural log variables shall be interpreted as long-run elasticities and we shall be applying "L" backshift operator and the modified equation is displayed as Equation (2(a)) below:

$$A(L, r_2)ln.Y_{1,t} = \beta_1 + +\beta_{1,BD}{}^{\#}D_{1t} + B(L, n_3)\ln.Y_{2,t} + C(L, n_4)\ln.Y_{3,t} + D(L, m_2)\ln.Y_{4,t} + e_t \quad (2(a))$$

For Equation (2(a)), A represents the dependent variable (energy crop) while B and C would be representing the remaining two crops while D represents crude. The long-run price elasticity under ARDL for each of the three energy crops against crude shall be determined by applying the following formula shown as Equation (3(b)) below:

$$\frac{A(L, r_2)}{D\ (L,\ m_2)} = \frac{1 - \beta_{2,1} - \ \beta_{2,2} - \ \ldots.\ \beta_{2,r_2}}{\beta_{5,0} + \ \beta_{5,1} + \beta_{5,2} + \ \beta_{5,3}\ \ldots\ldots.\beta_{5,m_3}} \quad (3(b))$$

4.4. Short-term relation and error correction toward equilibrium

The **estimated residuals** from regression of first lag of long-run variables are considered for specifying the short-run relation and error correction representation, which takes the shape as Equation (3) below:

$$\Delta\ ln.Y_{1,t} = \alpha_1 + \alpha_{1.BD}\#D_{1t} + \alpha_2 EC_{t-1} + \sum_{i=1}^{r_3}(\alpha_{3,i}\Delta\ln.Y_{\ 1,t-1}) + \sum_{i=0}^{n_5}(\alpha_{4i,}\Delta\ln.Y_{\ 2,t-1}) + \sum_{i=0}^{n_6}(\alpha_{5,i}\Delta\ln.Y_{\ 3,t-1}) + \sum_{i=0}^{m_3}(\alpha_{6,i}\Delta\ln.Y_{\ 4,t-1})u_t \quad (3)$$

The coefficients $\alpha_{4,0}$ and $\alpha_{5,0}$ reveal the price transmission elasticities with respect to two crops Y_2 and Y_3, and coefficient $\alpha_{6,0}$ shows price elasticity with respect to crude. The ECM term (EC_{t-1}) shows how fast the market would adjust to achieve long-run equilibrium following a shock in the system with speed of adjustment given by α_2. The speed of adjustment must decrease as we move toward long-run equilibrium reflecting convergence. The proportion of shock adjusted after "n" periods is given by $1-(1- \ \alpha_2)^n$

Coming to the adjustment mechanism under NARDL, the same has been shown under Equation (3(a)) below:

$$\Delta Y_{1,t} = \beta_1 + \beta_{1.BD}{}^{\#}D_{1t} + \beta_2 EC_{t-1} + \ \sum_{i=1}^{r_3}(\beta_{3,i}\Delta Y_{\ 1,t-1}) + \sum_{i=0}^{n_5}(\beta_{4i,}\Delta Y_{\ 2,t-1}) + \sum_{i=0}^{n_6}(\beta_{5,i}\Delta Y_{\ 3,t-1}) + \sum_{i=0}^{m_{3A}}\left(\beta_{6A,i}^{+}\Delta Y_{\ 4,t-1}\right)\sum_{i=0}^{m_{3B}}\left(\beta_{6B,i}^{-}\Delta Y_{\ 4,t-1}\right) + u_t) \quad (3a)$$

4.5. Test for short- and long-run asymmetry

Under this section, we determine short- and long-run asymmetric response of each of the energy crops to the changes in the price of crude. The long-run asymmetry is tested by applying standard Wald procedure with null hypothesis as $\theta^{+} = \theta^{-}$, $\theta^{+} = \frac{\lambda_{5A}{}^{+}}{\lambda_2}$, and $\theta^{-} = \frac{\lambda_{5B}{}^{-}}{\lambda_2}$ (from Equation (1(a)), while for short-run symmetry null is defined as $\sum_{i=1}^{n}\left(\beta_{6A,i}^{+}\right) = \sum_{i=1}^{n}\left(\beta_{6B,i}^{-}\right)$ (from Equation (3(a)); the results of the same are discussed under the next section Empirical Results.

5. Empirical Results

Tables 2, 3, and 4 summarize the results of our study. Whereas Table 2 gives co-integration test results using ARDL and ARDL with dummy approaches, Tables 3 and 4 give the long- and short-run relation of energy crops with crude. Using NARDL, these tables also give response of decomposed variable, crude on energy crops. We first discuss Table 2 co-integration results using partial "F" bounds test (Pesaran et al., 2001; Pesaran & Shin, 1999). Table 2 displays the results for two models: ARDL and ARDL after incorporation of dummy with single structural break, break follows Perron and Vogelsang's (1992) methodology.

Column (1) under Table 2 gives the model specification and the bounds test specifies different normalization schemes for variables (energy crops) as dependent variable, keeping the rest as forcing variables. Column (2) displays the exact date of structural break for the dependent variable using a dummy variable, the parenthesis showing "p" values for respective break dates. The results revealed all breaks as significant, hence it was strongly felt a need for the further construction of NARDL model. Further, two of four dummy variables, crude and wheat, had their breakpoints during the Covid-19 pandemic period, reflecting the vulnerability of the pandemic on the prices of these commodities.

Column (3) of Table 2 gives "F" test results; for sugarcane, the computed "F" was 4.178907 under ARDL and 5.140523 under ARDL with break. Null hypothesis was rejected for sugarcane under both models at 1% level showing that co-integration exists. For wheat and soyabean, no co-integration was observed from the results.

Table 3 discusses long-run relation results and here column (1) lists all the regressors while column (2) gives three regressands along with slope coefficients and their "p" values. The decomposed independent variable crude takes the following shape:

$$Crude^{+} = \begin{cases} Crude^{+}\ if\ \ Ret\ Crude > 0 \\ 0\ if\ \ Ret\ Crude \leq 0 \end{cases} \text{and}\ Crude^{-} = \begin{cases} Crude^{-}\ if\ \ Ret\ Crude < 0 \\ 0\ if\ \ Ret\ Crude \geq 0 \end{cases}$$

The table reveals that for energy crop, sugarcane, regressor variable crude contemporaneous, and at lag 1 are statistically significant; however, the same is not true for other two crops. We also computed long-run elasticity for sugarcane with respect to crude (see Equation (2(a)) and Table 3 footnotes) and found the same to be elastic with elasticity being + 1.227.

Table 2
Results of the partial bounds test ARDL and ARDL with break models

Model specification (1)	Break date ("*p*" values) (2)	"*F*" bounds (computed value) (3)	Critical table value at 5%* and 1% **: Lower bound I(0) (4)	Upper bound I(1) (5)	Inference (6)
ARDL: F $_{Sugarcane}$/wheat, soyabean, and crude	NA	4.178907*	2.79* 3.65**	3.67* 4.66**	Co-integration is established at 5% level
ARDL (with dummy): F $_{Sugarcane}$/wheat, soyabean, and crude	21 JAN 2011 (0.0264)	5.140523**	2.79* 3.65**	3.67* 4.66**	Co-integration is established at 1% level
ARDL: F $_{Wheat}$/sugarcane, soyabean, and crude	NA	1.441628	2.79* 3.65**	3.67* 4.66**	Co-integration is not established
ARDL (with dummy): F $_{Wheat}$/sugarcane, soyabean, and crude	24 APRIL 2020 (0.0343)	1.681698	2.79* 3.65**	3.67* 4.66**	Co-integration is not established
ARDL: F $_{Soyabean}$/sugarcane, wheat, and crude	NA	0.844736	2.79* 3.65**	3.67* 4.66**	Co-integration is not established
ARDL (with dummy): F $_{Soyabean}$/sugarcane, wheat, and crude	24 Jan 2011 (0.0276)	1.062441	2.79* 3.65**	3.67* 4.66**	Co-integration is not established

*Note (1): *significant at 5% and ** significant at 1% levels (value for "n" = 1000 and above; nearest to number of observations)*
Note (2): Null hypothesis H_o: $\delta_2 = \delta_3 = \delta_4 = \delta_5 = 0$ (Equation (1))
Note (3): Table result: Co-integration is established only for sugarcane and the relation becomes stronger after inclusion of break dummy variable

Table 3
Long-run relation

(1) Regressors	(2) Regressand: (wheat) Coeff.	(wheat) "*p*" val	(sugarcane) Coeff.	(sugarcane) "*p*" val	(soyabean) Coeff.	(soyabean) "*p*" val
Crude$_t$	9.66E-05	0.115	0.013	0.03	0.023	0.343
Crude(−1)	–	–	0.012	0.06	0.002	0.154
Crude(−2)	–	–	–	–	–	–
Wheat$_t$			0.006	0.019	0.025	0.186
Wheat(−1)	0.832	0.000	0.051	0.033	−0.001	0.953
Wheat(−2)	0.071	0.000	−0.111	0.723	−0.028	0.139
Soyabean$_t$	0.027	0.194	0.001	0.452	–	–
Soyabean(−1)	0.002	0.937	–	–	0.643	0.000
Soyabean(−2)	−0.034	0.113	–	–	0.033	0.000
Sugarcane$_t$	0.002	0.118	–	–	0.001	0.938
Sugarcane(−1)	–	–	0.264	0.040	–	–
Sugarcane(−2)	–	–	0.067	0.032	–	–
Crude$^+$	0.002	0.314	0.168	0.037	0.044	0.046
Crude$^-$	0.002	0.119	0.005	0.041	0.007	0.123
Long-run asymmetry $\theta^+ = \theta^- = 0$ (*F* Wald test)	Null accepted		Null rejected		Null accepted	

Note (1): $\theta^+ = \left(\frac{\lambda_{5A}{}^+}{\lambda_2}\right)$ and $\theta^- = \left(\frac{\lambda_{5A}{}^-}{\lambda_2}\right)$; $\lambda_{5A}{}^+$ and $\lambda_{5A}{}^-$ are coefficients from eq (1a),
Note (2): Long-run elasticity of sugarcane with respect to crude $\frac{A(L, r_2)}{D\,(L,\, m_2)} = \frac{1-0.264-0.067}{0.413+0.132} = +1.227$

Further, the study employed Wald test to test for long-run symmetry with null hypothesis: H_o: $\theta^+ = \theta^- = 0$ (Equation 1(a)). The null of long-run symmetry was rejected for sugarcane showing that the response of positive changes in crude on sugarcane was not the same as negative changes while null of symmetry stands accepted for the other two crops.

The next table, i.e., Table 4, discusses the results of short-run relation along with the error correction toward equilibrium. The results reveal that a rise in crude *(regressor D(Crude$^+$)* enables a rise in both sugarcane and wheat prices while a fall in crude *(regressor D(Crude$^-$)* has no impact on prices of any of the three energy crops. These results were also confirmed when short-run symmetry was proved only for sugarcane and wheat.

ECM (−1) coefficient for sugarcane is −0.005, which is both negative and statistically significant ("*p*" value is 0.008) showing stable equilibrium; however, speed of adjustment toward equilibrium is rather slow at 0.5% per period.

The last table, i.e., Table 5 discusses model diagnostics and table has five columns, column (1) lists down all the diagnostics, viz. stationarity, heteroscedasticity, and serial correlation while columns

Table 4
Short-run relation and error correction

	Regressand					
	D (wheat)		D (sugarcane)		D (soyabean)	
Regressors	Coeff.	*p* val	Coeff.	*p* val	Coeff.	*p* val
D(Crude$_t$)	–	–	0.013	0.035	0.023	0.061
D(Crude(−1))	–	–	0.009	0.027	–	–
D(Crude(−2))	–	–	0.002	0.176	–	–
D_{1t}	0.002	0.034	0.008	0.0264	0.023	0.001
D(Wheat(t)	–	–	–	–		
D(Wheat(−1))	0.077	0.000				
D($Sugarcane_t$)	–	–	–	–		
D(Sugarcane(−1))	–	–	0.235	0.000		
D($Crude^+$)	0.332	0.015	0.035	0.012	−0.523	0.667
D($Crude^-$)	0.812	0.124	0.025	0.250	0.198	0.221
ECM(−1)	−0.324	0.453	−0.005	0.008	−0.003	0.419
Short-run asymmetry	Null rejected		Null rejected	Null accepted		

Note (1): Short-run asymmetry is given by $\sum_{i=1}^{n}\left(\beta_{6A,i}^{+}\right)=\sum_{i=1}^{n}\left(\beta_{6B,i}^{-}\right)=0$ from Equation (3(a))

Table 5
Model diagnostics

(1)		(2)		(3)		(4)		(5)	
Stationary test no. 1 @									
ADF unit root with break point		**Crude**		**Wheat**		**Sugarcane**		**Soyabean**	
1. Coefficient "*p*" values		*Level*	*1st diff*	*Level*	*1st diff*	*Level*	*1st diff*	*Level*	*1st diff*
2. Table result null (accepted/rejected)	1	0.1443	<0.01	0.454	<0.01	0.448	<0.01	0.9828	<0.01
3. "Break date" identified	2	Accept	Reject	Accept	Reject	Accept	Reject	Accept	Reject
	3	28.04.20	–	24.04.20	–	21.01.11	–	24.01.11	–
Stationary test no. 2% Dickey fuller GLS		***Crude***		***Wheat***		***Sugarcane***		***Soyabean***	
		Level	*1st diff*	*Level*	*1st diff*	*Level*	*1st diff*	*Level*	*1st diff*
1. | Computed "*t*" values |	1	2.3494	32.949	0.4158	4.9586	1.616	3.7307	1.2608	3.2523
2. Table result null (accepted/rejected)	2	Reject	Reject	Accept	Reject	Accept	Reject	Accept	Reject
3. Critical at 5% (absolute value)	3	1.940954							
BPG heteroscedasticity test #		***Crude***		***Wheat***		***Sugarcane***		***Soyabean***	
1. Observed R^2	1	0.2737		0.186		0.342		0.795	
2. Probability χ^2	2	0.609		0.665		0.532		0.372	
B G serial corr. test **		***Crude***		***Wheat***		***Sugarcane***		***Soyabean***	
1. *F* statistics	1	0.5621		0.9861		0.6634		0.9324	
2. Prob *F* (2,2422)	2	0.3351		0.2866		0.4834		0.3937	

Note (1): @ ADF equation with single break is given as $\Delta Y_{V,t}=\beta_{1,v}+\beta_{1,v}{}^{*} D_{v,t}+(\beta_{2,v}-1)Y_{v,t-1}+\sum_{i=1}^{m}\beta_{3i,v}\Delta Y_{v,t-i}+\beta_{4,v}t+u_{v,t}$; *(v=1,2,3 &4) "v" denotes variables: crude, sugarcane, soyabean, and wheat,* $D_{v,t}$ *is the intercept dummy representing a single break in intercept.* $Y_{v,t-1}$ *reveals the stationarity of variable "v" and has* $(\beta_{2,v}-1)$*as its coefficient,* $\beta_{4,v}$ *is the coefficient of trend variable "t", and* $u_{v,t}$*. is the random error term. Null: non-stationarity time series.*

Note (2):% DFGLS stationary equation is given as $\Delta\ddot{Y}_{v,t}=\beta_1\ddot{Y}_{v,(t-i)}+\sum_{j=1}^{m}\beta_j\Delta\ddot{Y}_{v,(t-j)}+uv,_t$, $\ddot{Y}_{v,t}$ *is the de-trended variable with coeff.* β_1 *which tests for the variable stationary, "v"' = 1,2,3, and 4.* $\Delta Y_{v,(t-i)}$ *being the augmentation term added "m" times to take care of serial correlation. The de-trended data exclude intercept and time variable. Null hypothesis: Time series has a unit root*

Note (3): # B.P.G Heteroscedasticity test is given by $n.R^2_{aux}\sim\chi^2_{m-1}$. R^2 *is computed for auxiliary equation:* $u_t^2=\delta_1+\delta_2X_{2t}+\delta_3X_{3t}+\ldots+\delta_kX_{kt}$, *Null: no heteroscedasticity*

*Note (4): ** B G serial Cor. test is given as* $u_t=\beta_1+\beta_2Y_{t-1}+\beta_3Y_{t-2}+\ldots\ldots+\beta_pY_{t-p}+\rho_1u_{t-1}+\rho_2u_{t-2}+\ldots\ldots+\rho_mu_{t-m}+e_t$

Null : $\rho_1=\rho_2=\ldots\rho_m=0$ *(no serial cor. between residuals). Accept the null if* $R^2(n-p)<\chi^2n$

2, 3, 4, and 5 give the results for these diagnostics. For diagnostics stationarity, results are displayed both at level and at 1st differences while for other diagnostic tests these are displayed at level only. For stationarity, we have applied two tests: Dickey Fuller generalized least squares (DFGLS) and augmented Dicky Fuller (ADF) with a single break. The results from ADF with breakpoint revealed that all the variables were stationary only at 1st difference while DFGLS test results showed that except for crude all other variables were stationary at 1st difference, crude being stationary both at level and 1st difference. Thus, mixed nature of stationary results in terms of I(0) and I(1) reinforces the use of ARDL co-integration technique.

Next, we tested for heteroscedasticity by applying BPG heteroscedasticity test and the results accepted null of homoscedasticity for all the variables. For testing serial correlation, we applied BGLM serial correlation test and here too null of no serial correlation gets accepted for all variables. Lastly, we tested for the stability of variables by constructing cumulative sum of the residuals (CUSUM) stability plots and these are depicted in Figures 9, 10, 11, and 12. The stability of fitted models stands proved as all the plots are within the upper and lower critical lines.

Figure 9
CUSUM plot: Soyabean

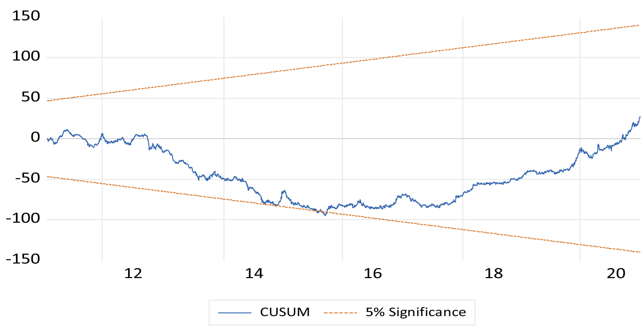


Figure 10
CUSUM plot: Sugarcane

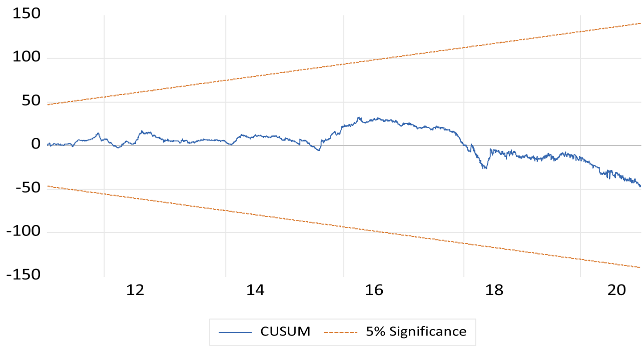


Figure 11
CUSUM plot crude

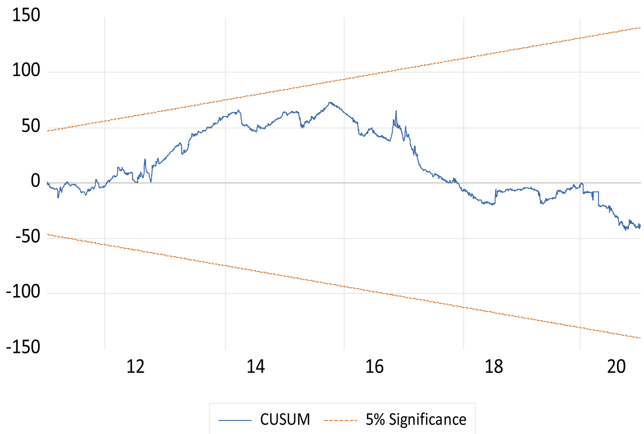


Figure 12
CUSUM plot wheat

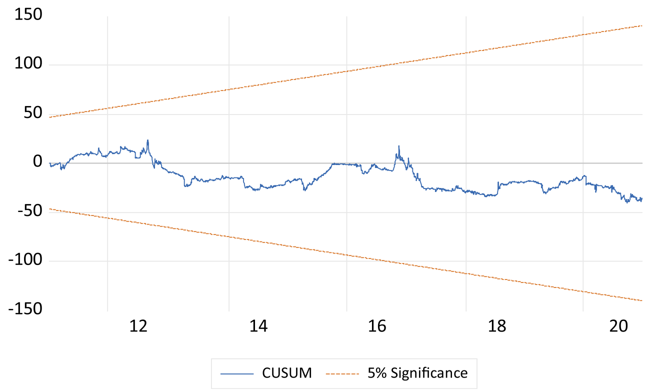


Table 6
Ethanol supplies and blending: Existing and proposed for India

Year	Supply of ethanol	Blending %
2014–15	67.4 crore liters	2.33
2017–18	150.5 crore liters	
2020–21	332 crore liters	8.5
2025 projections	1016 crore liters	20

6. Conclusion, Study Limitation, and Policy Recommendations

To conclude, the present study investigated the co-integrating relation between crude and three energy crops, namely soyabean, wheat, and sugarcane for India for a period of 10 years, ranging from Jan 2011 to Dec 2020 by taking log-transformed daily closing spot prices. The dynamic relation was established using linear and NARDL co-integrating techniques. The study also tested for asymmetric impact of crude on energy crops.

The study results showed that co-integration using ARDL was established only for sugarcane with other variables acting as forcing variables. The critical region for sugarcane improved from 5% to 1% when dummy variable representing single break was added in the ARDL model. Further asymmetric impact of crude on sugarcane was visible both in short and in long run. The long-run study results showed that the impact of crude on sugarcane was contemporaneous and also at first lag while no impact of any other variable on sugarcane was visible from the results.

Among the other study results, the short-run results were seen to be working only in one direction, i.e., a rise in crude impacting both sugarcane and wheat while no impact for a fall in crude on their prices. The coefficient of ECM (−1) for sugarcane was −0.005, this being negative and significant reflecting stability of long-run equilibrium with slow speed of adjustment at 0.5% per period. The above results also satisfied the diagnostics in terms of stationarity, stability, serial correlation, and heteroscedasticity.

Further, this being an India-specific study where concept of biofuels has not picked up like in US or Brazil markets, it has its own limitations, e.g., data on ethanol supplies, blending, etc. are available only for recent period with only one or two reliable sources to assist such kind of a study. This was the primary reason why the study had to focus on data collection from single source, MCX Website (www.mcxindia.com) while many other prominent studies do collect data from multiple sources and then obtain their averages, e.g., a study by Eissa and Al Refai (2019) has taken average of crude prices of West Texas Intermediate, Dated Brent, and Dubai Fateh. However in spite of being a single source data, we performed a quick check about crude price compatibility between our source and other commonly used data sources by researchers and the correlation was found to be very high, thereby ruling out any doubt regarding the source of data. Furthermore, a lot of research studies on commodities from India do rely on the same data source.

Furthermore, as revealed by literature review, most of the existing studies on crude–energy nexus have focused on countries like US, Brazil, and some European Countries where biofuel products are already available, have gained popularity, and also enjoy good demand while the current study has been carried out for a country, India, where things are at a very early stage with respect to biofuels. However, in spite of this difference, the study does provide useful, interesting, and largely unexplored insight and facts, which can be of great use to policy makers. This is also important as the country has ambitious plans with respect to biofuels with biofuel targets being advanced by few years with annual targets to be achieved in a planned time bound manner. Then, some researchers strongly feel that any kind of co-integration study requires a minimum period of 25 years to achieve reliable results; however, viewpoint being stressed upon here is that the same depends upon type of model and frequency of data. We have chosen ARDL model, which gives robust results even when the sample size is not very large and moreover ours being a daily price data, a 10-year period of study from 2011 to 2020 as considered in our study therefore is quite reasonable to develop a relation between energy crops and crude.

Thus, broad conclusion we draw from above is that in spite of certain limitations our results do provide an initial indication of a co-integration between crude and sugarcane, which for India is also the main crop supplied to bioethanol industry. Also, crude impacting sugarcane in long run and also having an asymmetric impact on sugarcane are some important takeaways, which cannot be ignored and may be extremely useful for policy makers while designing future policies on energy fuels. In light of the above, study would like to make a few recommendations: first, as the government moves toward promotion of biofuel policies aiming at an ambitious target of 20% ethanol blending by 2025 and with sugarcane being both a staple crop and main ingredient for bioethanol, India's agricultural producers shall have to decide on whether to choose food or fuel as a final destination for their crops, a debate very common in other countries. In this context, the policy makers are expected to harmonize and synergize energy and agricultural policies and also need to develop a mechanism so that biofuel policies are not blindly followed in India, thereby creating a food crisis situation like the one seen in early 2000. If we go by the projections of Govt of India's policy document: Roadmap for Ethanol Blending in India 2020–25, then by 2025 to achieve a blending target of 20%, the country would be requiring 1016 crore liters of ethanol (see Table 6), which would require 7.3 lakh metric tons of sugar for that year (assuming 1 ton of sugar produces 70 liters of ethanol).

Now with India exporting 40 lakh tons of sugar annually, meeting above target of ethanol using sugar or molasses by diverting exports would not be a problem for the country but the sacrifice of export revenues from the crop would be unavoidable. Further, since a part of sugarcane production is still mainly dependent upon rainfall, things may not go exactly as planned and therefore it is suggested that all biofuel policies must be supported by a pre-warning and a crisis response mechanism.

Another important consideration is that a rise in crude prices could trigger a rise in prices of other crops through a chain reaction resulting in a food inflation. Food inflation in India in the past has been mainly on account of external reasons like uncertain weather conditions but the same due to spillover effect of energy crops is something the country has not seen before. Hence, government must monitor the prices of biofuel crops and intervene whenever any sudden surge is visible due to crude price increase after ruling out other reasons for rise in prices. Another concern for government would be to keep a watch on area under cultivation under the biofuel crops as the farmers might shift land use from other agricultural crops to more profitable energy crops. Then risk of diverting forest land for cultivation of these energy crops cannot be ruled out and would require a strong environmental regulation to overcome such a possibility. The government thus must keep a close watch on such undesirable outcomes while promoting biofuel crops.

Further, from an investor's perspective, the association between crude and sugarcane prices might help in forecasting one set of prices based upon available information on prices of another. This would also imply that for investors in agricultural commodity markets, crude movement becomes an important risk factor and those strategizing portfolio hedging may not be able to achieve the desired result by diversifying into these energy crops. Further as seen from the return plots (Figures 5, 6, 7, and 8), the lowest 10-year return on all the three energy crops was seen during the early days of Covid-19 pandemic period much in line with the crude's lowest return, which entails a cautionary approach while investing in energy crops. Then, after analyzing biofuel movements against variable crude we further conclude that these biofuels especially sugarcane do not appear to qualify as a "safe haven" asset during a crisis, something which may not be good news for investors. This is important because of two reasons, first the recurrence of crisis has now become quite a regular phenomenon and second, investors are also quite keen in knowing more about new "safe haven" assets especially when the so-called traditional "safe haven" assets appear to have become less responsive during a crisis, which too have now become a global phenomenon with larger intensity.

Ethical Statement

This study does not contain any studies with human or animal subjects performed by any of the authors.

Conflicts of Interest

The authors declare that they have no conflicts of interest to this work.

Data Availability Statement

Data are available on request from the corresponding author, Rakesh Shahani, by email.

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