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Asymmetric impact of energy and non-energy agricultural commodity prices on the clean energy market

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Abstract

This study investigates agricultural commodity prices' asymmetric short and long-run impact on the clean energy prices index. To explore whether energy and non-energy agricultural commodities impact the clean energy prices index similarly or differently. Agricultural commodities are categorized into two main groups. The NARDL method was applied to estimate asymmetric long-run and short-run analysis on a daily data set from 3rd March 2005 to 12th December 2021. The main results showed that agriculture commodities had a positive impact on the clean energy price index. All agricultural commodity prices showed a positive impact except rice, with an inverse impact of the previous day's prices and no impact for the same day and oil also showed an inverse impact on the first lag, and the other lags were impacting positively. In the long run, both groups' commodity prices directly impacted the clean energy prices index. Further, the impact of rice prices was asymmetrical on its second lag of negative partial sums. The impact of oil prices was also observed as asymmetric. The findings of this study are important for the investors of clean energy markets, managers, policymakers, and regulatory bodies.

Keywords: Agricultural Commodities, Clean Energy, NARDL, Energy commodities, Non-Energy Commodities.

1. Introduction

Clean energy is produced from sources with zero emission and from natural renewable resources for instance solar, hydel, wind nuclear, geothermal, and bio energy (Dincer & Acar, 2015); Pang et al. (2015). It generates hundreds of billions of dollars in macroeconomic grids. It is anticipated to grow rapidly worldwide. There are many reasons that the world is trying to switch to alternative sources of energy, for instance to decrease energy dependence on fossil oil energy sources, climate change, global warming to mitigate atmospheric deterioration.

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Its resources are cost efficient because most of them are naturally replenishable. Since last few decades world paying more focus to adopt the less polluting energy alternatives which can undermine the pollution related human health problems and mitigate the climate deterioration (Haines et al., 2007). Agricultural developments and technological use in agriculture directly for cropping and form management has increased dependence of this sector on fossil fuel energy. Agricultural sector indirectly also uses oil and fossil fuels just like fertilizer and pesticides manufacturing (Woods et al., 2010). This agricultural dependence on fossil oil sourced energy is the reason to increase cost of production of agricultural commodities and a reason for atmospheric deterioration . Technological use in agriculture increases production yield along with increase in cost of production. Alternatively, decrease in technology use also will decrease the yield of agricultural commodities. The decrease in output creates demand supply gap, which can increases agricultural commodity prices. Maghyereh and Abdoh (2021) narrate oil prices and energy are anticipated to drive the earnings on investments in the clean energy and the allied clean energy technology sectors. These interrelationships will also have significant repercussions for the future growth of clean energy production therefore, it enlightens investors and assists governments to plan a suitable and inclusive energy strategies that reflect the circumstances in other allied markets. This scenario of agricultural commodity prices coupling with oil prices and technology supports the argument to use energy mix and to add alternative energy sources like clean energy. The mixed energy grid in agriculture can help to control the commodity prices up to the usage of alternative energy inclusion in agricultural sector. The shifting of agriculture sector's energy usage from fossil fuel energy to clean and energy will help to control the global prices of agricultural commodities and inflation. Clean energy slightly decreases total factor emission and increases global economic output efficiency (Pang et al., 2015). Clean energy technologies aims to achieve efficient cost effective and environmental friendly solution of the energy requirements (Dincer & Acar, 2015).

This study has categorized agricultural commodities into two subgroups, energy agricultural and non-energy agricultural commodities. There are eight major agricultural commodities which are traded in commodity markets i.e. corn, soybean, wheat, sugar, rice, cotton, coffee, and coca. Out of these eight Corn, sugar, and soybean are used to produce ethanol and biodiesel, these three are included as energy agricultural commodities and the remaining all are included in non-energy agricultural commodities subcategory. The investigation of the nonlinear short term and long-term relationship between agriculture energy and non-energy commodities can provide understanding in policy formulation for decoupling fossil energy and agricultural commodity prices nexus. Due to the agriculture sector dependence on fossil energy sources, it gets affected by the variations in fossil energy prices. The fossil energy market prices and agricultural commodity prices have a significant role in shaping clean energy market dynamics (Maghyereh & Abdoh, 2021). Clean energy is emerging as an alternative to fossil sourced energy (Ayres & Ayres, 2009; Barreto, 2018; Payam & Taheri, 2018). Clean energy technologies now a days playing pivotal role in sustainability in environmental resilience and in mitigation of the environmental deteriorating effects of fossil form of energy. By examining their influence, researchers can reveal important insights into market behavior, price associations, and risk management strategies, which are vital for investors, stakeholders, and policymakers alike. The traditional models are not efficient to capture complex asymmetric nexus among clean energy and agricultural commodities. Nonlinear autoregressive distributed lag model (NARDL) is efficient to discover asymmetric effects, where the impact of decreases or increases in commodity market prices on clean energy consequences differs in direction of magnitude (Shin et al., 2014). This model is efficient to capture the short run relationship between the constructs. In the scenario of agricultural commodities and clean energy immediate reactions in the response of the agricultural prices variations insights are valuable for managers and investors seeking to optimize resources allocation and manage short term risk. By scanning the long-term dynamics, researchers can gauge the sustainability of clean energy investments, advise policy decisions aimed at progressing long-term energy security and environmental sustainability.

There is no evidence found in literature that had investigated the impact of energy and non-energy agricultural commodities prices on clean energy market and the comparison of the impacts of both categories on it. The focus of this study is to investigate the asymmetric impact of energy and non-energy agricultural commodity prices on the clean energy market prices gauging index. Gorton et al. (2012) emphasized that commodity futures prices and risk vary across commodities and is dynamic and time varying. The oil prices and energy input prices volatility significantly transmits to the agricultural commodities, raw material prices indices, metal and manufacturing indices (Kirikkaleli & Güngör, 2021). The volatility in oil prices and high rises directly and indirectly affects the cost of production of agriculture that causes rise in the prices. Another cause world climate awareness and hard policies for oil, fossil dependent energy and carbon emission, on the other hand incentivized mechanism for clean and renew able energy sources like green energy taxes (Sun et al., 2020). These are the reasons agriculture is switching to clean energy as an alternative to fossil fuel energy. There are vast literature available on studies of commodities prices co-movements with energy indices, oil prices, energy price indices, metal indices and carbon emission (Kirikkaleli & Güngör, 2021; Naeem et al., 2021). The nonlinear spillover between green bonds and agricultural commodities crude oil, metal, natural gases (Kassouri et al., 2021).The green stocks, clean energy, high tech. stocks are same (Naeem et al., 2021). There are at least three contributions of our study, firstly a novel viewpoint on the relationship between clean energy and agricultural commodities' both categories. The segregation of the asymmetric impact of both categories is worthwhile for the understanding enhancement of complex dynamics among these both sectors and fills that gap in literature. Secondly using NARDL model empirical analysis, study stipulates interesting concrete insights regarding the differential impacts of non-energy and energy agricultural commodities on the clean energy market prices. The empirical findings corroborate not only the theoretical framework but also offer practical implications which can help in decision making process in the energy and agricultural sectors. The traditional models fail to estimate the asymmetric short term and long-term impact. When variables exhibit mixed stationary like at the I(0) and I(I) cointegration. The traditional linear models' assumptions limit their applicability. For instance, multiple regression model requires all variable must be cointegrated at I(0) level, VAR model required all variables must be cointegrated at first difference. In this condition the family of ARDL model is applicable for mixed stationery with the limit that no variable should be cointegrated at I(II) level. We applied NARDL model to capture the asymmetric effects in short run and long run. For the comparison of the impacts of both agricultural commodities on the clean energy market. Thirdly by identifying the distinct impacts of energy and non-energy agricultural commodities on the clean energy market, the research offers valuable guidance for designing policies that promote sustainable energy transitions while considering the implications for agricultural markets and energy sector. The major results of both the categories of agricultural commodities show positive impact on the clean energy market prices. Interestingly only the rice showed the asymmetric impact. WTI oil has shown major influence on the clean energy prices. While both categories of agricultural commodities exhibited long run as well as short run impact on clean energy prices.

This study captures the asymmetric impact of both energy and non-energy agricultural commodities on the clean energy market. The comparison of influence of both agricultural commodities categories on clean energy provides interesting and notable insights, that how prices of each category impact clean energy market. The dynamic relationship between agricultural commodities' categories and clean energy market are useful for policymakers like energy regulatory bodies, government, environmental protection agencies and a guide for investors to help in investment decisions. The findings are helpful for investors for both sectors in investment decisions. Furthermore, the behavior of clean energy in the response of price changes in agricultural commodities can help them for taking robust short-term and long-term investment decisions. We employed the NARDL model which strengthens the methodological rigor in study. This model is specifically suitable for capturing the asymmetric short run and long run impact of the constructs when variables are cointegrated on different levels. By using this advanced econometric model our study strengthens robustness of its findings and contributes to the advancement of the econometric methodology to explore the nexus between energy markets and agriculture economics.

2. Literature Review

Working is the father of the understanding of the price relationship between cash and future commodities (Working, 1948, 1949). He formulated a generally acceptable model of cash-future price relationship where intertemporal price relationship, or spot-future and nearby-distant price differences, both positive and negative are viewed as price of storage. These price spreads provide incentives or disincentives to the store and hedge commodities. Intertemporal price relationships are determined by the net cost of carrying stocks. The future price for any delivery month is equal to the current spot price plus the cost storage, which includes physical outlay costs, interest charges and possibly a risk premium. The positively sloped nonlinear storage curve associates larger carry price spread relationship and vice versa (Garcia & Leuthold, 2004). The future prices will depend on an equilibrium convenience yield obtained from competition between potential stores of the commodity. The equilibrium convenience yield contains inherent information about production technologies and consumer preferences in the commodity market. (Hilliard & Reis, 1998).

The commodities future price at the start of the day is considered as zero as the price changes during trading in day is satisfies the CAPM model (Black, 1976). The two hypothesis prevails concerning the motives for hedging of cost. The first was proposed by J. M. Keynard and J. R. Hicks, who stated that hedgers compensate speculators for taking on risk by paying a risk premium, with the goal of minimizing risk. According to the Keynes-Hicks hypothesis, demand, supply, and spot prices in commodities markets should all be expected to be constant for a few months under typical circumstances. Additionally, there is a lack of confidence among traders regarding these expectations, as the futures price, for example, for a delivery date of one month is certain to fall short of the spot price that traders anticipate would hold one month from now. The other Holbrook Working Hypothesis holds that hedging is not just done to reduce risk but also to simplify company decisions, save expenses, and anticipate profiting from a favorable change in the spot-futures price connection. The need for energy is growing worldwide, with a major reliance on sources supplied from fossil fuels. A paradigm shift from fossil fuels to green energy and renewable energy sources, such as corn and sugarcane, which are considered sources of bio-ethanol and soybeans, which are sources of biodiesel, has occurred as a result of these sources' unexpected extinction and the world's search for alternative energy sources (Srirangan et al., 2012). The climate change, energy security and fossil fuels unpredictable demise had created interest investors to invest in the reliable alternative energy sources like renewable energy, clean energy and biofuels (Sadorsky, 2021). While in the context of our study resource dependency theoretical (RDT) framework, is applicable in the connection of the energy prices variations external pressure on agricultural sector forces to switch from fossil energy sources to alternative energy sources. As Pfeffer and Salancik, (1978) postulates how organizations depend on external resources for survival and growth. In this context RDT framework assumptions fits on our study how agricultural sector prefers to substitute the external resources to be cost efficient and environmentally friendly for the purpose to contribute to adopt the environmental deterioration controlling policies.

Kuang, (2021) established that investors in oil energy equities can gain from risk divergence through both green bonds and clean energy stocks. Green bonds, on the other hand, reduce risk, whilst clean energy equities typically increase the risk of the global portfolio equity indices. (Naeem et al., 2021) determined the nonlinear relationship between Islamic index returns and Islamic gold prices. During normal market condition gold to be diversified for Islamic stock indices and Islamic equity sectors. Aumeboonsuke (2021) reported that Thailand stock market is responsive to commodities like gold, metals, auricular commodities, oil and energy prices. Sun et al. (2021) unearthed that there is bidirectional causality between agricultural commodities. Both the commodities remain unaffected from the shocks during Covid19 pandemic. Dawar et al. (2021) reported in their findings that clean energy dependence decreasing form crude oil returns while lagged effect of WTI is significant on clean energy returns generally pointing towards the clean energy stocks reacts differently to latest information of oil returns in different markets. Further claimed asymmetry during negative oil prices while no impact of oil prices during positive increase in oil prices on clean energy stocks. These findings indicated that the patterns of return, volatility, and shock spillover are remarkably diverse. Furthermore, they discovered the benefits of dynamic diversification for energy-related stock markets from energy commodities, particularly heating oil. It is also clear that SPGO and SPGCE stocks have the highest average ideal weight and hedging effectiveness for one another, suggesting that SPGO's poor performance is significantly offset by SPGCE's strong performance. (Asl et al., 2021). The energy prices have positive significant effect on agricultural food prices from any oil prices stocks evidence of linkage between energy and agricultural commodities. Also found the impact of biofuel prices on agricultural food prices Taghizadeh-Hesary et al. (2019) Changes in energy prices can affect agricultural production in two ways: either directly through energy consumption or indirectly through energy-related inputs like fertilizer. Energy taxes and subsidies, as well as changes in the natural gas and oil markets, can all have an impact on the energy costs that American farmers and ranchers must pay. Regardless of the cause of the increase in energy prices, higher production expenses associated to agriculture would typically result in decreased agricultural output, higher agricultural product prices, and lower farm income (Sands et al., 2011). The ability of agricultural commodity to act as hedge in the contrast of oil returns (Tiwari et al., 2021). Empirically investigated that effect of oil supply shocks on the returns of clean energy firms concentrated on the short term while there was long run shocks of the aggregate demand (Maghyereh & Abdoh, 2021).

3. Material and Methods

The quantitative secondary data are used for the analysis of our study. Daily data from 3rd March 2005 to 6th December 2021 extracted from source yahoo finance for all agricultural commodities and WTI oil prices. Data for agricultural commodities and oil prices were available for a much longer time horizon but samples were selected to align the commodities data with the clean energy index data, that is available from 3rd March 2005 and onwards. The Figure 1. represents the daily prices of agricultural commodities and the clean energy index. The US WilderHill PBW Clean Energy Index data is also extracted from yahoo finance. It serves as the foundation for the Invesco WilderHill Clean Energy ETF (Fund). Typically, the fund allocates no less than 90% of its total assets to common stock shares, which make up the index. The Index is a prominent standard that traces the performance of clean energy companies in the United States. Contains firms involved in various sectors such as clean technology development, renewable energy production and energy efficiency. The index specifies significant insights into the trends and growth within the clean energy industry. The index mirrors the mounting importance of sustainable energy solutions in concentrating environmental concerns and advancing directed towards a low-carbon future. Investors and researchers consider the index as a trustworthy gauge of the market dynamics and financial performance of clean energy prices, suggesting a broad glimpse of the sector's progression over time. The equities of American publicly traded companies that are involved in conservation and cleaner energy expansion make up the index. Every quarter, the fund and the index are reconfigured and rebalanced. All the variables described in Table 1. are converted into returns for the purpose of normality by applying equation 1 below.

$$LnRt = ln(P\_t / P\_(t-1)) \qquad (1)$$

Table No 1. Variable Description

Variable	Notation	Unit of Measurement
WilderHill PBW Clean Energy Index	CNEN	Index Points
Corn Prices	CRN	USD
Soybean Prices	SOY	USD
Sugar Prices	SGR	USD
Coca Prices	CC	USD
Coffee Prices	COF	USD
Cotton Prices	CTN	USD
Wheat Prices	WHT	USD
Rough Rice Prices	RCE	USD
OIL Prices	Oil	USD

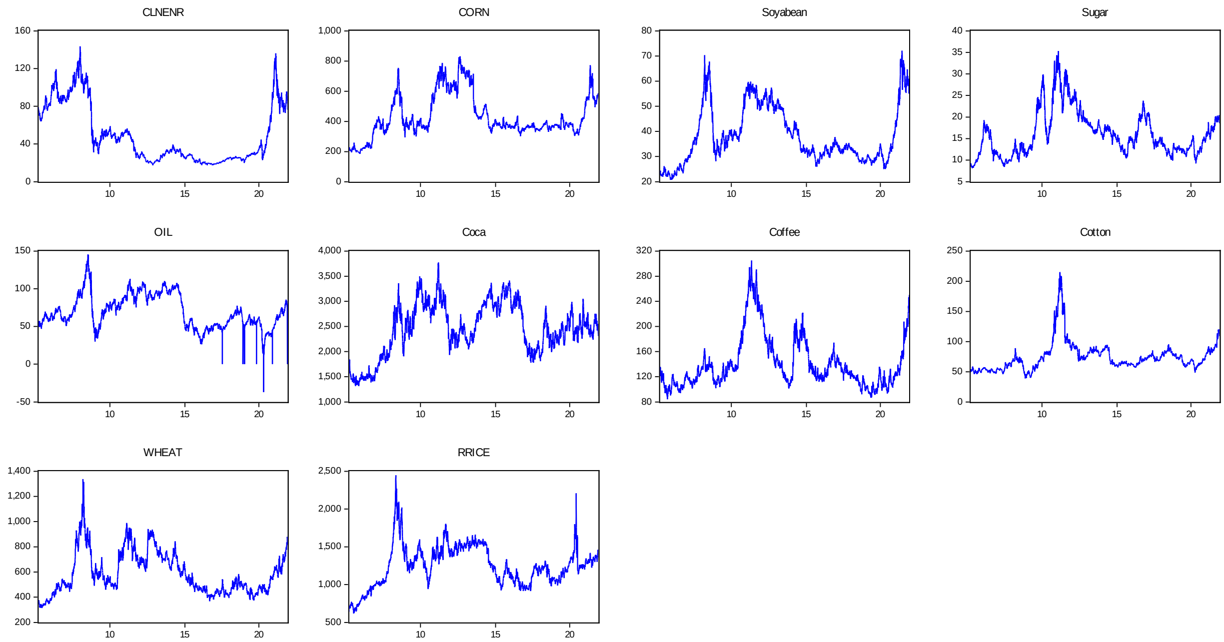

Figure 1. Clean Energy and Agricultural Commodities Prices

3.1 Nonlinear autoregressive distributed lag NARDL Model

NARDL (Nonlinear autoregressive distributed lag) model is employed to estimate the relationship of positive and negative partial sum squares respectively. Any financial time series data analysis must begin with a unit root test since the results of these tests are crucial in determining the best statistical approach to apply. Data normality, scatterness, and central values can all be inferred using descriptive statistics. In order to determine the kind and degree of associations between the variables, correlation was also examined. In the end diagnostic tests are used to evaluate the model's significance and robustness. Time series data are utilized for analysis, but because of problems with variable integration, linearity, leverage effects, and time variance, time series data analysis is very complex. As a result, one way to decide a model is to look at the findings of the unit root test. Nkoro and Uko (2016) argued that the existence of a long-term relationship is indicated by the theory's requirements that means and variances be constant, or, to put it another way, that they be independent of their lags or previous values and are not time variants; however, time series data do not typically exhibit this feature. Time series data may have these issues because of leverage effects, volatility clustering, and leptokurtic features. These are the primary factors influencing data integration. The estimations of t-statistic, R^2, F-statistic, and DW-Stat values become extremely significant when the conventional regression OLS test is applied to non-stationary data; nonetheless, those would be deceptive and unreliable parameters since spurious regression may arise.

As the (Nkoro & Uko, 2016) stated that the ARDL model fails if any variable is assimilated on I(2) but works when all the variables are integrated on I(0), I(1), or a combination of the two integrations. Additionally, he suggests that the NARDL Cointegration Bound test (Wald) can be used to find long-term relationships if the "F-statistic" value is greater than the bands value; on the other hand, if the F-statistic value is less than the lower band, this indicates that there is no long-term link (Nkoro & Uko, 2016) proposed re-parametrization of the integrations to ECM to validate the short run dynamics of relationship in order to further verify the short run affiliation. This study examines the asymmetric long- and short-term effects of energy- and non-energy-related agricultural commodities on the clean energy market using the Nonlinear Autoregressive Distributed Lags model (NARDL). NARDL model developed by Shin et al. (2014) When time series explanatories have an asymmetric effect on the dependent variable, NARDL is relevant. The partial +ve and -ve sums represent a deeper breakdown of the explanatory variables. When the partial +ve and partial -ve sums of a variable affect the dependent variable in different directions or magnitude, it is referred to as asymmetric. According to Larsson and Haq (2016) the family of ARDL models became more familiar as a result of addressing the determination of both short-term and long-term interactions between the sets of independent and dependent variables at the same time. They added that their econometric model is strong enough to yield improved findings when testing for both short- and long-term interactions on medium- and large-sized data. Spurious regression for non-stationary variables is the primary issue in time series data analysis, and the ARDL family has addressed this issue to a large degree. In comparison to other models such as the Granger causality model, VAR model, and VECM, NARDL yields superior findings for both short- and long-term relationships. The following equations describe the long-run models for Panel A and B, respectively: equations 2 and 3.

$$\begin{aligned}
LnCNEN = \alpha_\circ &+ \sum_{i=1}^{p} \alpha_1 \Delta LnCNEN_{t-i} + \sum_{i=0}^{q} \alpha_2 \Delta LnCRN^{+}_{t-i} + \sum_{i=0}^{q} \alpha_3 \Delta LnCRN^{-}_{t-i} \\
&+ \sum_{i=0}^{q} \alpha_4 \Delta LnSOY^{+}_{t-1} + \sum_{i=0}^{q} \alpha_5 \Delta LnSOY^{-}_{t-1} + \sum_{i=0}^{q} \alpha_6 \Delta LnSGR^{+}_{t-1} \\
&+ \sum_{i=0}^{q} \alpha_7 \Delta InSGR^{-}_{t-1} + \sum_{i=0}^{q} \alpha_8 \Delta InOil^{+}_{t-1} + \sum_{i=0}^{q} \alpha_9 \Delta InOil^{-}_{t-1} \\
&+ \rho LnCNEN_{t-1} + \varphi_1^{+} LnCRNx^{+}_{t-1} + \varphi_2^{-} LnCRN^{-}_{t-1} + \varphi_3^{+} SOY^{+}_{t-1} + \varphi_4^{-} SOY^{-}_{t-1} \\
&+ \varphi_5^{+} LnSGR^{+}_{t-1} + \varphi_6^{-} LnSGR^{-}_{t-1} + \varphi_7^{+} LnOil^{+}_{t-1} + \varphi_8^{-} InOil^{-}_{t-1} \\
&+ \mu_t \qquad (2)
\end{aligned}$$

$$LnCNEN = \alpha_\circ + \sum_{i=1}^{p} \alpha_1 \Delta LnCNEN_{t-i} + \sum_{i=0}^{q} \alpha_2 \Delta LnCOF_{t-i}^{+} + \sum_{i=0}^{q} \alpha_3 \Delta LnCOFx_{t-i}^{-} + \sum_{i=0}^{q} \alpha_4 \Delta LnCC_{t-1}^{+} + \sum_{i=0}^{q} \alpha_5 \Delta LnCC_{t-1}^{-} + \sum_{i=0}^{q} \alpha_6 \Delta LnCTN_{t-1}^{+} + \sum_{i=0}^{q} \alpha_7 \Delta LnCTN_{t-1}^{-} + \sum_{i=0}^{q} \alpha_8 \Delta LWHT_{t-1}^{+} + \sum_{i=0}^{q} \alpha_9 \Delta LnWHT_{t-1}^{-} + \sum_{i=0}^{q} \alpha_{10} \Delta LnRC_{t-1}^{+} + \sum_{i=0}^{q} \alpha_{11} \Delta LnRC_{t-1}^{+} + \sum_{i=0}^{q} \alpha_{12} \Delta LnOil_{t-1}^{-} + \sum_{i=0}^{q} \alpha_{13} \Delta LnOil_{t-1}^{-} + \rho LnCNEN_{t-1} + \varphi_1^{+} LnCOF_{t-1}^{+} + \varphi_2^{-} LnCOF_{t-1}^{-} + \varphi_3^{+} LnCC_{t-1}^{+} + \varphi_4^{-} LnCC_{t-1}^{-} + \varphi_5^{+} LnLnCTN_{t-1}^{+} + \varphi_6^{-} LnCTN_{t-1}^{-} + \varphi_7^{+} InWHT_{t-1}^{+} + \varphi_8^{-} InWHT_{t-1}^{-} + \varphi_9^{+} LnRC_{t-1}^{+} + \varphi_{10}^{-} LnRC_{t-1}^{-} + \varphi_{11}^{+} LnOil_{t-1}^{+} + \varphi_{12}^{-} LnOil_{t-1}^{-} + \mu_t (3)$$

The differenced variables with the summation signs show the error correction dynamics, and variables with φ_s show the long-run relationship . Ln with each variable indicates that the variables natural log has been taken. After estimating the lag length, the long-run relationship is examined with the help of a test named NARDL bounds test. In the above-given model, the null hypothesis for the bounds test is H_0: $\varphi 1 = \varphi 2 = \varphi 3 = ... = \varphi 12 = 0$, which indicates that the existence of long run co-integration. Rejection of the null hypothesis, in this case, indicates that independent variables are co-integrated with dependent variable. Once the results confirm that there is co-integration, the short-run analysis is conducted by the following ECM, equation 4 and 5 for panel A and B respectively given below:

$$LnCNEN = \alpha_\circ + \sum_{i=1}^{p} \alpha_1 \Delta LnCNEN_{t-i} + \sum_{i=0}^{q} \alpha_2 \Delta LnCRN_{t-i}^{+} + \sum_{i=0}^{q} \alpha_3 \Delta LnCRN_{t-i}^{-} + \sum_{i=0}^{q} \alpha_4 \Delta LnSOY_{t-1}^{+} + \sum_{i=0}^{q} \alpha_5 \Delta LnSOY_{t-1}^{-} + \sum_{i=0}^{q} \alpha_6 \Delta LnSGR_{t-1}^{+} + \sum_{i=0}^{q} \alpha_7 \Delta InSGR_{t-1}^{-} + \sum_{i=0}^{q} \alpha_8 \Delta InOil_{t-1}^{+} + \sum_{i=0}^{q} \alpha_9 \Delta InOil_{t-1}^{-} + n\, ECM_{t-1} + \mu_t \quad (4)$$

$$
\begin{aligned}
LnCNEN = \alpha_{\circ} &+ \sum_{i=1}^{p} \alpha_1 \Delta LnCNEN_{t-i} + \sum_{i=0}^{q} \alpha_2 \Delta LnCOF_{t-i}^{+} + \sum_{i=0}^{q} \alpha_3 \Delta LnCOFx_{t-i}^{-} \\
&+ \sum_{i=0}^{q} \alpha_4 \Delta LnCC_{t-1}^{+} + \sum_{i=0}^{q} \alpha_5 \Delta LnCC_{t-1}^{-} + \sum_{i=0}^{q} \alpha_6 \Delta LnCTN_{t-1}^{+} \\
&+ \sum_{i=0}^{q} \alpha_7 \Delta LnCTN_{t-1}^{-} + \sum_{i=0}^{q} \alpha_8 \Delta LWHT_{t-1}^{+} + \sum_{i=0}^{q} \alpha_9 \Delta LnWHT_{t-1}^{-} \\
&+ \sum_{i=0}^{q} \alpha_{10} \Delta LnRC_{t-1}^{+} + \sum_{i=0}^{q} \alpha_{11} \Delta LnRC_{t-1}^{+} + \sum_{i=0}^{q} \alpha_{12} \Delta LnOil_{t-1}^{-} \\
&+ \sum_{i=0}^{q} \alpha_{13} \Delta LnOil_{t-1}^{-} + n\, ECM_{t-1} + \mu_t (5)
\end{aligned}
$$

Where the lag lengths, p and q, are chosen based on the AIC criteria. The ECM shows how quickly short-term adjustments are made in the direction of the long-term equilibrium relationship. The clean energy index variance was then observed using the decomposition of variances technique, which explains both shockwaves to explanatory factors and shockwaves to the index itself. Lastly, the LM test was employed to diagnose serial correlation in order to validate and verify the diagnostic results. CUSUM test statistics are used to assess the stability of the model.

4. Results and Findings

This study contains asymmetric investigation of the impact of agricultural commodity prices on the US clean energy index. Result would be reported in the sequence by descriptive statistics, correlation for variables association strength and direction. Unit root test results than main model NARDL results followed by the diagnostics. Table 2. below reports a descriptive statistics summary of the selected variables for analysis. The oil showed the highest return in a day, and the clean energy exhibited lowest return, which is negative, while from commodities soybean showed highest return. These findings of return can be observed in Figure 2. When the highest loss in a single day is shown by rice followed by the oil while the lowest one by wheat. The highest profit in a single day exhibited by oil while the lowest one by soyabean. The skewness results in evidence that series of Oil, Rice, Coca are symmetrical while Clean Energy, Corn Soy are moderately skewed. Data series of Coffee, Cotton and Sugar are highly skewed. If the kurtosis value is 3 then data are said to be Mesokurtic. Greater than 3 are leptokurtic less than 3 Platykurtic. Only coffee stand Mesokurtic while the coca, soyabean and wheat shown platykurtic properties and the remain exhibited leptokurtic fait tails. The P value of the Jarque-Bera test also significant that rejects the null hypothesis for all series that the data is not normally distributed. The above results support that data are not normally distributed which is the evidence of symmetries, which supports the nonlinear ARDL model's application.

Table No 2. Descriptive Statistics

	CNEN	CC	COF	CRN	CTN	OIL	RC	SOY	SGR	WHT
Mean	-0.000003	0.0000513	0.0002177	0.0002961	0.0002347	0.0003406	0.0001963	0.0002828	0.0002275	0.0002090
Median	0.0011013	0.0004101	0.0003585	0.0003373	0.0002216	0.0008573	0.0000000	0.0000000	-0.000506	-0.000275
St. Dev.	0.0240354	0.0196917	0.0223683	0.0208442	0.0197824	0.0301231	0.0175314	0.0160061	0.0228551	0.0207508
Minimum	-0.145550	-0.111829	-0.147212	-0.251976	-0.199382	-0.281382	-0.2997029	-0.092784	-0.170283	-0.089948
Maximum	0.1663459	0.1149131	0.1618105	0.1651853	0.1052745	0.4258324	0.1020731	0.0750465	0.1442942	0.1537061
Kurtosis	5.3679151	2.2844379	3.1718024	11.1029902	6.0353493	28.8507207	29.1590378	2.7520261	4.0480960	2.3171476
Skewness	-0.466275	-0.214781	0.112314	-0.710369	-0.459440	1.154718	-1.593571	-0.103603	-0.112116	0.1735812
Count	3593	3593	3593	3593	3593	3593	3593	3593	3593	3593
J. Bera	548.6	105.2	2120.6	376.2	16407.0	64.6	127.2	359.3	753.0	422.6
Prob	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0

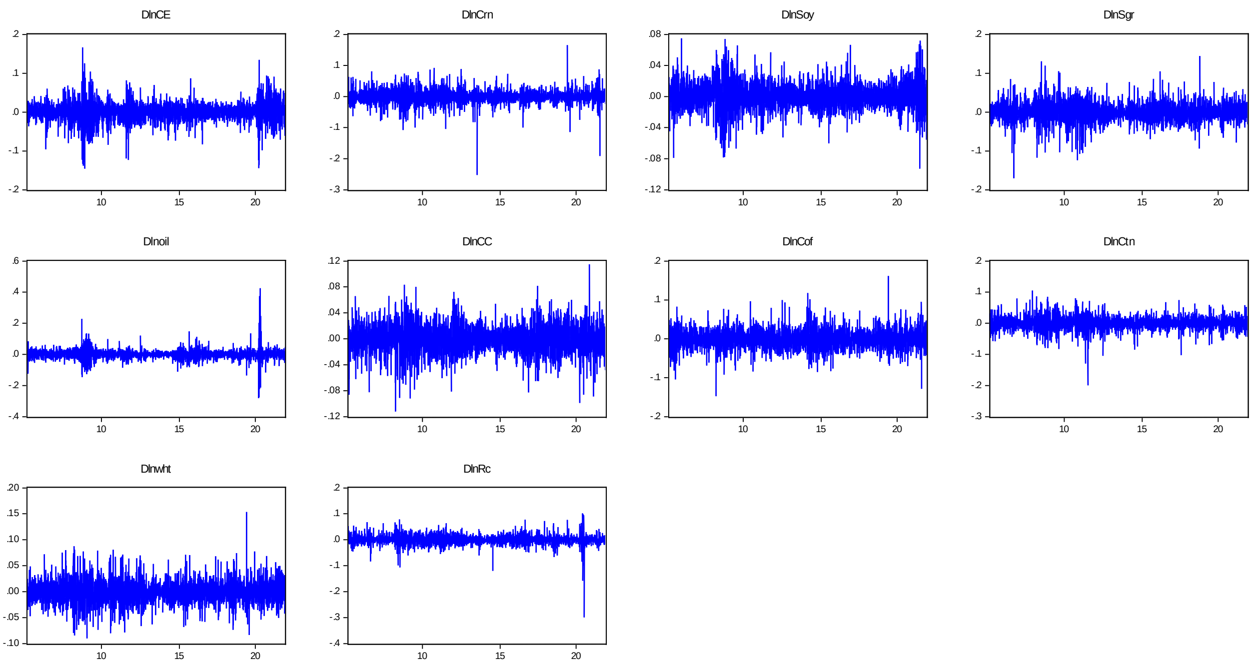

Figure No 2. Clean Energy and Agricultural Commodities Returns

Table 3. below reports correlations of variables results are displayed. It is quite interesting and favorable that all variables shown low are moderate but positive association among them. There is not any highly correlated variable that can create problems of misspecification and problems like multicollinearity in the analysis further.

Table No 3. Correlation Matrix

	CNEN	CC	COF	CRN	CTN	OIL	RC	SOY	SGR	WHT
CNEN	1.000									
CC	0.147	1.000								
COF	0.163	0.185	1.000							
CRN	0.090	0.064	0.114	1.000						
CTN	0.235	0.147	0.200	0.121	1.000					
OIL	0.310	0.172	0.188	0.072	0.219	1.000				
RC	0.032	0.027	0.080	0.223	0.089	0.040	1.000			
SOY	0.206	0.103	0.155	0.465	0.190	0.166	0.208	1.000		
SGR	0.145	0.164	0.262	0.096	0.211	0.204	0.065	0.123	1.000	
WHT	0.089	0.046	0.104	0.576	0.108	0.024	0.212	0.381	0.089	1.000

Stationarity test results are reported in Table 4. below, ADF test was applied to check the unit root on time series data, on I(0) level integration only coca and rice two series were stationary, and the other variables shown unit root. While on I(I) first difference all the variables are stationary at 1% CI level.

Table No 4. Unit Root Test Results (ADF Test)

Level	I(0)	I(I)
Variable	**T-Statistic**	**T-Statistic**
CNEN	-1.595	-39.214***
CC	-2.972***	-59.975***
COF	-1.812	-61.686***
COR	-2.303	-58.708***
CTN	-2.363	-53.117***
SOY	-1.711	-58.751***
SGR	-2.563	-61.245***
WHT	-2.466	-58.235***
RCE	-3.534***	-60.686***
Oil	-2.344	-48.348***

Note: (*, **, ***) three denotes significance at 10%, 5% & 1% respectively

Table 5. reports results, it has been observed that all agricultural commodity prices almost behaved in the similar trend on clean energy index prices and exhibited positive impact. Only asymmetry has been noted in the Oil prices in both energy and non-energy agricultural panels and rice shown asymmetrical impact. Further the R-square value is 0.73 and 0.75 of the models for Panel A and B, which shows the goodness of fit and explanatory power of the constraints. The spread of the R square and adjusted R squares are also below 0.01 which also strengthens the suitability of the models. The DW test score is close to 2 which evidence there is not any problem of serial correlation in the result estimates.

Table No 5. NARDL Results

Dependent Variable: DLNCE			Dependent Variable: DLNCE		
Method: NARDL Panel A			**Method: NARDL Panel B**		
Selected Model: ARDL(1, 0, 0, 0, 0, 0, 0, 0, 1)			**Selected Model: ARDL(3, 0, 0, 0, 0, 0, 0, 3, 3, 0, 0, 2, 0)**		
Variable	**Coefficient**	**Std. Error**	**Variable**	**Coefficient**	**Std. Error**
DLNCE(-1)	0.025520	(0.015844)	DLNCE(-1)	0.019271	(0.016377)
DLNCRN_POS	-0.009870	(0.020339)	DLNCE(-2)	0.024615	(0.016363)
DLNCRN_NEG	-0.011856	(0.020318)	DLNCE(-3)	-0.036751***	(0.016363)
DLNSOY_POS	0.228540***	(0.026893)	DLNCC_POS	0.075683***	(0.019497)
DLNSOY_NEG	0.232278***	(0.026815)	DLNCC_NEG	0.074753***	(0.019516)
DLNSGR_POS	0.070013***	(0.016888)	DLNCOF_POS	0.070230***	(0.017408)
DLNSGR_NEG	0.070485***	(0.016861)	DLNCOF_NEG	0.070171***	(0.01)7413
DLNOIL_POS	0.182878***	(0.014876)	DLNCTN_POS	0.178739***	(0.019742)
DLNOIL_NEG	0.254302***	(0.016103)	DLNCTN_NEG	0.177986***	(0.019760)
DLNOIL_NEG(-1)	-0.072598***	(0.017235)	DLNOIL_POS	0.154115***	(0.017661)
C	0.003736***	(0.001279)	DLNOIL_POS(-1)	0.053370***	(0.026101)
			DLNOIL_POS(-2)	0.002984	(0.026312)
			DLNOIL_POS(-3)	0.036579	(0.019235)
			DLNOIL_NEG	0.257368***	(0.019929)
			DLNOIL_NEG(-1)	-0.107140	(0.028802)
			DLNOIL_NEG(-2)	0.041146	(0.028645)
			DLNOIL_NEG(-3)	0.055665***	(0.018448)
			DLNWHT_POS	0.064641***	(0.018563)
			DLNWHT_NEG	0.068167***	(0.018478)
			DLNRC_POS	-0.042041	(0.028209)
			DLNRC_POS(-1)	0.099922***	(0.035528)
			DLNRC_POS(-2)	-0.058191***	(0.026759)

Dependent Variable: DLNCE			Dependent Variable: DLNCE		
			DLNRC_NEG	-0.002900	(0.025497)
			C	0.006974***	(0.001555)

R-squared	0.731356	R-squared	0.752786
Adjusted R-squared	0.728930	Adjusted R-squared	0.747320
F-statistic	54.13669	F-statistic	27.95258
Prob(F-statistic)	0.000000	Prob(F-statistic)	0.000000
Durbin-Watson stat	2.016769	Durbin-Watson stat	2.007941

Table 6. below shows an F-bound test confirming the existence of Cointegration in both energy and non-energy agricultural commodity prices with clean energy prices. Cointegration existence can be confirmed from the F-static value that is greater than the upper bounds in all slabs in the table below.

Table No 6. F Bound Test Results

NARDL	Significance level	Lower Bound	Upper Bound	F Statistic	K	Cointegration
Panel A	10%	1.95	3.06	381.9127	8	*Cointegration*
	5%	2.22	3.39			*Cointegration*
	2.50%	2.48	3.7			*Cointegration*
	1%	2.79	4.1			*Cointegration*
Panel B	10%	4.78	4.94	3 95.07131	12	*Cointegration*
	5%	5.73	5.77			*Cointegration*
	2.50%	6.68	6.84			*Cointegration*
	1%	7.84	5.59			*Cointegration*

Table 7. below exhibiting NARDL long run results, the long run results. Long run results are portrayed, all energy and non-energy agricultural commodity prices along with oil prices shown direct relationship with the clean energy index in long run.

Table No 7. Long run Cointegration Results

Panel A		Panel B	
Variable	**Coefficient**	**Variable**	**Coefficient**
DLNCRN_POS	-0.010129 (0.020872)	DLNCC_POS	0.076227*** (0.019685)
DLNCRN_NEG	-0.012167 (0.020850)	DLNCC_NEG	0.075291*** (0.019704)
DLNSOY_POS	0.234525*** (0.027742)	DLNCOF_POS	0.070734*** (0.017645)
DLNSOY_NEG	0.238361*** (0.027660)	DLNCOF_NEG	0.070675*** (0.017651)
DLNSGR_POS	0.071847*** (0.017320)	DLNCTN_POS	0.180024*** (0.020466)
DLNSGR_NEG	0.072331*** (0.017293)	DLNCTN_NEG	0.179265*** (0.020483)
DLNOIL_POS	0.187667*** (0.015321)	DLNOIL_POS	0.248822*** (0.025978)
DLNOIL_NEG	0.186462*** (0.015383)	DLNOIL_NEG	0.248813*** (0.026055)

C	0.003834*** (0.001314)	DLNWHT_POS	0.065105*** (0.018787)
		DLNWHT_NEG	0.068657*** (0.018702)
		DLNRC_POS	-0.000313 (0.025702)
		DLNRC_NEG	-0.002920 ((0.025681)
		C	0.007024*** (0.001573)

Table 8. below shows the Error correction term which is known as speed of adjustment towards long run Cointegration from the short run. In both panels the error term is significant because ECT term should be between 0 and -1 in some cases it may be accepted up to -2. Therefore, in both panels error term is between 0 and -1 are closer to the -1. The ECT term confirms here short run relationship in the agricultural commodities as the speed of adjustment towards long run equilibrium after short term shocks.

Table No 8. Error Correction Term

NARDL	**Coefficient**	**Std. Error**	**t-Statistic**	**Prob.**
Panel A CointEq (-1)	-0.974480	0.015844	-61.505111	0.0000
Panel B CointEq (-1)	-0.992865	0.027604	-35.967678	0.0000

The results of the LM test to confirm the presence of autocorrelation in the residuals are shown in Table 9. for every model, the LM test was used to confirm the serial correlation problem. The particular lag length criteria, which were determined using VAR based on SIC criteria, were used to verify the results. The diagnosis was used to determine whether or not residuals exhibit serial correlation. Panel A and B results indicate F Static insignificant value larger than 0.05. The null hypothesis, which states that there is no autocorrelation in the residuals, cannot be rejected based on the P value.

Table No 9. Diagnostic test Results

Breusch-Godfrey Serial Correlation LM Test:	**Panel A**	**Panel B**
F-statistic	0.711158	0.094733
Obs*R-squared	0.715400	0.095181
Prob. F	0.3991	0.7583
Prob. Chi-Square	0.3977	0.7577

The Figure 3 & 4. CUSUM graphs depict model stability, CUSUM results showing that model is stable. Because residuals line has not crossed upper and lower bands in both panels.

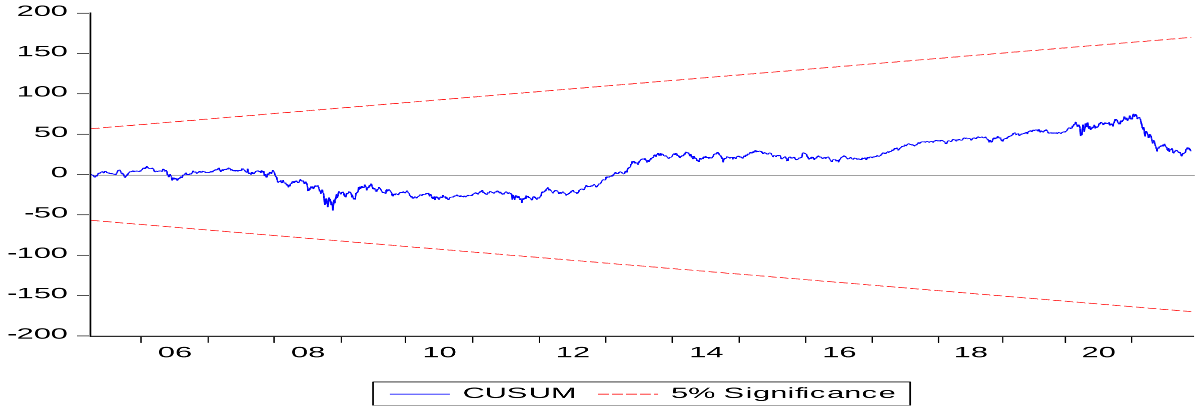

Figure No 3. Panel A CUSUM diagram of energy agricultural commodities and Clean Energy Index

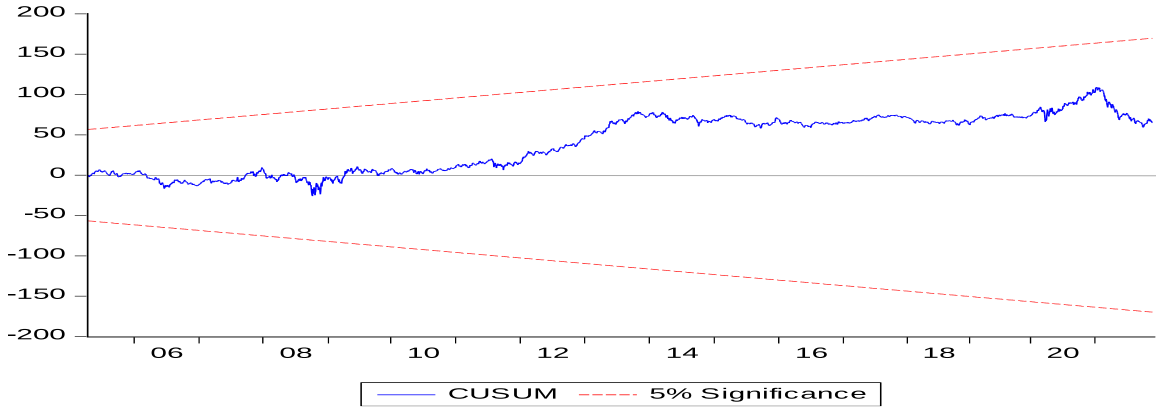

Figure No 4. Panel A CUSUM diagram of non- energy agricultural commodities and Clean Energy Index

5. Conclusion

The main purpose of this study is to inspect the impact of energy and non-energy agricultural commodity prices on US clean energy prices index. The focus of study was extended to find the asymmetric long run and short run impact of agricultural commodity future prices on clean energy stock prices. The eight major agricultural commodities were selected as a sample for this study. Those eight commodities traded in the commodity future market of Chicago USA. Agricultural commodities were categorized into two groups i.e. energy agricultural and non-energy agricultural commodities. The agricultural commodities used are source of biofuels were categorized as energy commodities and the remaining as non-energy commodities. Corn, soybean and sugar are included in energy agricultural commodities and cocoa, coffee, wheat, rice and cotton as non-energy agricultural commodities. Oil prices were used as the control variable to avoid the model misspecification issues. Time horizon of study was from 3rd March 2005 to 12th December 2021 daily data total 3593 observations were per variable. The NARDL method was applied to estimate long run and short run asymmetric and impact of commodities future prices on clean energy prices index.

Energy agricultural commodities prices show a direct impact on clean energy prices. Soy shown also positive impact on first lag while the other commodities only impact on current day not past day's impact. On the other side non-energy agricultural commodity prices shown direct impact on current day except rice which shown no impact. While oil prices shown same positive impact and inverse impact on first lag, while turned positive impact till lag 4. The rice previous day prices shown positive impact on clean energy prices consistent with (Sands et al., 2011). It could be perceived from the above results as agricultural commodity prices increases that have parallel impact on clean energy prices. The insight supports our idea that clean energy is an alternative to fossil energy for the agricultural sector. Long run positive impact observed from both categories' energy and non-energy agricultural commodities on clean energy market. The asymmetric effect is evidenced by rice prices and oil prices on clean energy market. Clean energy past prices impact was also asymmetric on its own.

The above findings are useful for the investors of clean energy. The short-term findings as a guide for portfolio managers as the prices of fossil fuels fluctuates which is an indication for them to rebalance their portfolio to decide increase and decrease of the proportion of agricultural commodity futures and the clean energy stocks. The findings are useful for policymakers like governments whose are interested to draw policies to reduces pollution and carbon emissions can decide to provide tax exemptions, on clean energy adoptions to agriculture former and subsidized technological support for the adaptation of the clean energy to increase the proportion of clean energy into energy mix of the agricultural sector.

Our study offers the basis for the research for the agricultural commodities and the clean energy, it may be extended to the other commodity sectors, like metals, industrial materials. This study is limited to the daily data, while it could provide interesting insights for the intraday high frequency data and its dynamic analysis or the event study of the different crises like the COVID-19 crises, US-China trade tension time period, global financial crises 2008.

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