INFLUENCE OF CRUDE OIL ON SOYBEAN OIL FUTURE AND PRICE FORECASTING OF CME SOYBEAN OIL FUTURE

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ABSTRACT

Soybean Oil is second largest source of vegetable oil in the world, due to its rich source of protein it is considered as a natural alternative to meat and dairy proteins, with sustained economic growth, increasing awareness about the health benefits of Soy oil, preference for healthy food, affordability to consume quality products and the rapidly increasing urban population, the demand for Soybean oil is expected to continue to expand..

Crude Oil is a highly sensitive indicator relative to the expansion or contraction of the economy. given that oil is consumed in virtually every aspect of our lives, from the food we eat to the products and services we buy, the demand side of the equation is a tell-tale sign of economic strength or weakness, Sharp decline in oil prices has been suggestive of downturns in economic activity, a drop in inflation, and a subsequent decline in interest rates, on the other hand sustained growth in Crude oil price has been indicative of sustained economic growth. Crude oil is also one of the important input materials for production and distribution of Soy Oil, The increasing Crude oil price also drives up the demand for biofuels, Soybean / Soyoil is one of the raw material for the biofuel. Thus Crude oil plays the role of both macro and micro factor for determining the price of Soy Oil.

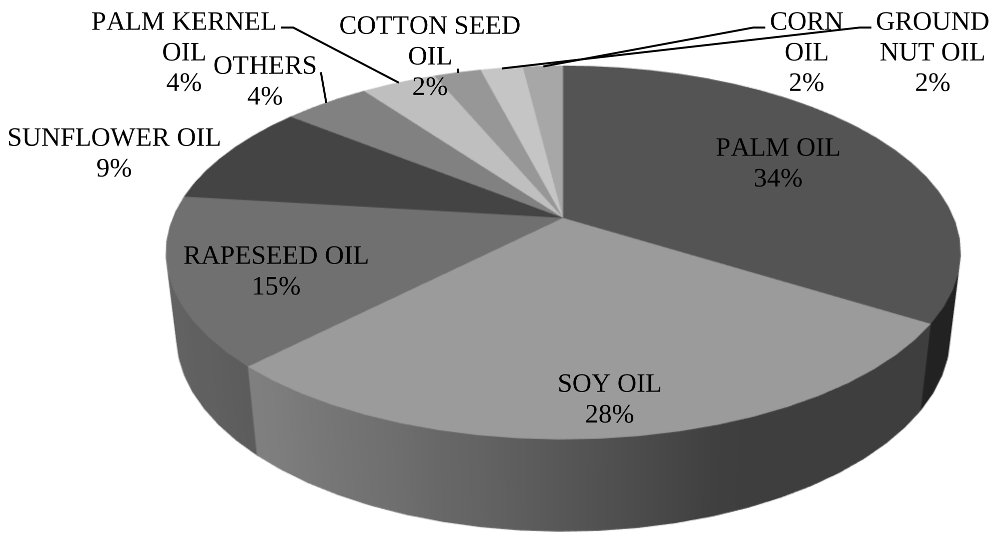
This Study, analyses the dynamic interactions between changes in Crude oil price and Soybean oil future price fluctuations and arrives at the forecasting model.

KEY WORDS *:- CME SOYBEAN OIL FUTURE, NYMEX US CRUDE, PRICE FORECASTING, ECONOMETRIC MODEL COINTEGRATION , ERROR CORRECTION MODEL, MACRO AND MICRO FACTOR.*

1. INTRODUCTION

Soybean is one of the most important and fastest growing oil-bearing crops in the world. During 1981-2011, the world's soybean area grew at an annual rate of 2.6 percent and production by 4 percent which are higher than the growth in area and production of most other food crops. Soybean accounts for 37 percent of the global area under oilseeds, and contributes 28 percent to vegetable oil production. The crop's adaptability to varied agro ecological environments viz the tropics, subtropics and temperate - has been responsible for its rapid spread across the globe (Sharma 2011).

FIGURE - 1- GLOBAL CONSUMPTION PATTERN OF VEGETABLE OIL



SOURCE: FAO, UNITED NATION 2016

Globally, annual per capita soy oil consumption is estimated around at 3 kg. However, when Disaggregated, consumption levels differ widely, with average consumption levels in industrialized countries almost three times that observed in developing nations. Also the share of soybean oil in total vegetable oil consumption or total oils/fats intake varies considerably between regions and countries, depending on numerous factors such as the availability of locally produced oils, consumer habits and preferences, local and international market prices and national trade policies. Overall, during the last two decades, two oils, soybean oil and palm oil, have strengthened their position vis-a-vis all other oils and fats, with palm oil recording the fastest growth rates. The two oils are close substitutes and both products are widely traded - at comparable price levels on the global market.(Source: FAO, United Nations 2016)

Regarding vegetables oils/fats in general, available statistics indicate that consumption trends do increase faster in poor countries than in middle- and high-income countries, and national studies seem to confirm that extra income enhances fat intake of the poor more than that of the rich. Consequently, in the long term (i.e. by the year 2030), FAO anticipates oil crop products to account for as much as 45 out of every 100 extra kcal added to average diets in developing countries, which implies a continuation and intensification of recent trends. Relatively high income elasticities of demand explain why there is considerable scope for increasing average per capitat consumption of vegetable oils in developing countries. Soy oil, together with palm oil, is well placed to play a central role in this expansion. In general, oilseeds and their products are intensively traded commodities - and soybean is no exception in this regard. Globally, close to 30 % of oilseeds produced enter trade and in the case of oils the share exceeds 40 % (compared to less than 20 % for the majority of other grains). During the last decade, global trade in soybeans, soyoil and soymeal has expanded by an average 6-7 % per year. Within the soy complex, beans account for about half of the total value of trade. The shares of soymeal and soy oil amount to 35% and 15 % respectively, while that of soya foods is negligible. Soyoil occupies a key position in global vegetable oil trade both in volume and value terms. (Source: - United Nations, FAO 2016)

The widespread consumption of soy oil and soy meal rests on the exportation of soybeans and their products by a few major producing countries to a large number of importing countries. The key producing countries export a combination of beans and their two sub products, depending on the requirements of the market and domestic policies. A main feature of the export market is its high level of concentration, with five countries (two developed and three developing) accounting for over 90 % of the market. The main competitors are USA, Brazil and Argentina. Overall, over the last 10-15 years, developing country imports of soybeans and derived products have roughly tripled in volume terms. This group of countries contributed to about three quarter of the expansion in global trade, reaching market shares of over 50 % and 70 % for, respectively, soymeal and soyoil in recent years. The extraordinary growth experienced by global trade in soybeans and products has been driven by economic expansion in developing countries, with Africa and in particular Asia playing a central role. Among developing countries, the contribution of imported soybean products to the rising average intake of dietary energy and protein has been of utmost importance. Typically, imports have expanded where domestic demand has expanded faster than production. As a result, the contribution of net imports to domestic consumption has risen in numerous developing countries in recent years, in some cases involving big upward leaps in import volumes, with corresponding surges in import bills. Outstanding examples include China and India. In the former, roughly one third of domestically consumed soymeal originates from imported soybeans, while in the latter almost 40 % of domestic vegetable oil supply is covered by imports.(Source : United Nation FAO 2016)

Global soybean production to continue to expand, at 1.5% p.a and the Global Soybean market in value terms that accounted for $136.23 billion in 2017 and is expected to reach $236.49 billion by 2026 growing at a CAGR of 6.3% during the forecast period. Preference for healthy food, increasing awareness of the health benefits of soybean and high demand for soybean oil are some of the factors fueling the market growth. (Source: OECD-FAO Agricultural Outlook 2018-2027)

Crude Oil is a highly sensitive indicator relative to the expansion or contraction of the economy. given that oil is consumed in virtually every aspect of our lives, from the food we eat to the products and services we buy, the demand side of the equation is a tell-tale sign of economic strength or weakness, Sharp decline in oil prices has been suggestive of downturns in economic activity, a drop in inflation, and a subsequent decline in interest rates, on the other hand sustained growth in Crude oil price has been indicative of sustained economic growth.(Fowowe, 2016),

Crude oil is one of the important input materials for production and distribution of Soy Oil, increase in price of Crude oil increases the cost of production and distribution (Baffes, 2013). The increasing Crude oil price also drives up the demand for biofuels, Soybean / Soyoil is one of the raw materials for the biofuel (Rafiq and Bloch, 2016). Thus Crude oil plays the role of both macro and micro factor for determining the price of Soy Oil.

2. LITERATURE REVIEW

2.1 NYMEX CRUDE Oil - MACRO & MICRO FACTOR DRIVING THE PRICE OF CME US SOYBEAN OIL PRICE

As one of the most important raw materials and fundamental energies, oil is of great importance to production and its price changes affect almost all aspects of the economy, (Hochman 2012).
Among many factors affecting the price of agri Commodity, crude oil price is one of the most important elements in affecting agricultural price variations,(Pal and Mitra 2017). Wang and McPhail (2014) investigated the impacts of energy price shocks on U.S. agricultural productivity growth and commodity price, this study found that energy price shocks give a negative impact on productivity growth in the short run (1 year), further, energy shocks and agricultural productivity shock's, the agricultural commodity prices to fluctuate. Recently, Wang et al. (2014) has analyzed the impact of oil price shocks on agricultural commodity prices. The responses of agricultural commodity prices to oil price changes depend greatly on oil supply shocks, aggregate demand shocks or other oil-specific shocks mainly driven by precautionary demand.

Fowowe, (2016), Ahmadi et al. (2016), Baumeister and Kilian, (2014); Hochman et al., (2012), Rising oil price resulting from increasing economic activities usually boosts the demand for food and hence the prices of many agricultural commodities. Abbot *et al*. (2008) looked into the relationship between rising crude oil prices and an increase in the United States current account deficit, the steady increase in oil prices and the decrease in the value of the United States dollar resulted in higher Soybean and corn prices in the United States as the decreased dollar resulted in cheaper Soybean and corn exports in places like China and India. Food price responds positively to a shock in oil price and the response is persistent and significant throughout. Food price response to a negative oil price shock is negative most of the periods. The effect of a negative oil price shock is quantitatively smaller than that of the positive oil price, thus supporting an asymmetric effect, (Goodness C. Aye 2015**).** Crude oil price change is a good predictor of food commodity price changes besides non-oil factors (Zaid 2011). The crude oil prices all across the globe have a significant impact on global economies directly or indirectly. However, the increase in the crude oil prices results in increase in almost all the consumable and non-consumable commodities (Sharma, 2012).

The increasing oil price drives up the demand for biofuels, leading to a positive shift in the prices of corn, soybeans and other agricultural products (Rafiq and Bloch, 2016), (Natanelov et al., 2011), thus Oil price affects the fluctuations of corn, soybean, and cotton markets,
(Nazlioglu, 2011), (Mutuc et al., 2010) and the effects of oil price changes vary across economies and over time, (Ji and Fan, 2016); (Liu, 2014); (Wang et al., 2014); (Nazlioglu, (2011), (Tyner, 2008). the co-integration between crude oil and biofuel crop prices, mainly for maize, sorghum, soybean, and soybean oil, is a signal of the linkage between the biofuel industry and petroleum prices. (Ziad 2011**).** The agricultural sector has become part of the energy-supply equation by providing feedstocks to produce biofuels. For instance, during 2007-2011, an average 20% of the 7,740 trillion British thermal units (tBtu) of renewable energy production in the United States was derived from biofuels but during 1981-1985, biofuels accounted for less than 1% of the 6,082 tBtu of renewable energy production. From 2007-2011, average annual U.S. fuel ethanol production exceeded 10.8 billion gallons, whereas during 1998-85, average annual ethanol production was around 370 million gallons. Global production of biofuels was over 29 billion gallons in 2011, six times the amount produced in 2000. As shown in Figure 1, the United States has been the leading producer of biofuel since 2006, followed by Brazil and EU-27 (EIA, 2014).

The interaction between energy and agriculture has undergone a number of major structural transformations over the last few decades. As agricultural production becomes more mechanized, energy becomes one of its principal inputs as it affects the level and scale of many agricultural inputs. Some models suggest that the direct energy component of agriculture alone is four to five times higher than for manufacturing sectors (Baffes, 2013). As an energy-intensive sector, agriculture plays a big role on the demand-side of the energy equation. The sector is directly affected by high and volatile world oil prices that in turn affected the cost of agricultural production (Nazlioglu & Soytas, 2011). Higher oil price raises the agricultural production costs and hence the prices of farming products, thus the mature agricultural future markets display co-movements with crude oil in the long run, (Zhang and Qu, 2015), (Tyner, 2010). The prices of vegetable, fruit, live products, special crops, and secondary product all display strong co-movements with oil price thus the local correlations between crude oil and agri commodity prices vary in the time-frequency sphere, (Xiangcai Meng 2018).

Thus US Crude Oil traded in NYMEX (New York Mercantile Exchange) is both micro and macro factor influencing the price of Soy oil future.

Considering growing significance of Soy Oil in terms of consumption and listed commodity for trading, few scholastic studies have been carried out to arrive at price forecasting model

Rajesh Panda (2014**)**, identified the forecasting model that best replicates the actual situation so as to minimize the speculative gains, Findings reveal that the proposed model of ARIMA (1, 1, 0) with additive seasonality predicts the nature of fluctuation and explains the underlying seasonality. It was found that the model has the ability to be used by traders, harvesters to minimize the scope for speculation and assume the change in prices of soybean seed for near future. It was also found that the model has the potential to be used by regulators to predict the future prices and to minimize the role of speculators who may otherwise destabilize the market pricing mechanism. Lei Cui (2001**),** determined the micro economic variable affecting the price of Soy bean and forecast the price of Soy bean and Canola price, Simultaneous equation system was used for studying the farm-level soybean prices. Findings reveal that the soybean prices are positively affected by: animal units (AF), wholesale corn oil price (PCOO), and real expenditures on food (E), time trend variable (T), the variable cost of growing soybeans and stock changes of soybeans, soybean oil and soy meal. Farm-level price of soybeans was also found to be negatively affected by one-year lagged farm level soybean price and one-year lagged farm level wheat price and one-year lagged soybean acreage, finally based on one-year lagged information of the economic variables, the price for soybeans was obtained, Forecast results suggest that with economic structure, we may roughly capture the price movements of soybean price.

2.2 ECONOMETRIC MODELS TO EVALUATE INTEGRATION BETWEEN MACRO FACTORS AND AGRI COMMODITY PRODUCT AND PRICE FORECASTING

The most recent trend to test integration across market and macro factor is the use of volatility based models, which measure the level of integration by estimating the spillover of volatility between two markets/two variables (Engle and Susmel, 1993). Proponents of volatility based models assert that if markets and macro factors are integrated, then market volatility is affected by volatility in macro factor. In other words, the transformation in macro factors is transmitted into markets. Thus, in order to gauge the level of integration between markets and macro factors, one can empirically measure the magnitude of volatility transfer from macro factor to market.

A study of empirical literature such as Bernard and Durlauf (1996) and St. Aubyn (1999) suggests that one of the way to assess the convergence (or divergence) in prices of interdependent markets is by performing pair wise stationary tests on the price differences of the two series. The difference of the price series of markets should not contain any unit root (i.e. stationary) to meet the convergence criteria. The Augmented Dickey Fuller (ADF) test (Dickey and Fuller, 1979) and the Kwiatkowski Phillips Schmidt and Shin (KPSS) test (Kwiatkowski et al., 1992) are generally used to test for convergence (or divergence) between the prices series of the two markets.

Most common method for forecasting in time series analysis is the regression model, however it can only be used when all the dependent and independent variables in the time series are stationary at the level, stationary data series generally have means that never changes with time, any other statistics (like variance) can change, When all (dependent and independent) time series are non-stationary, the regression results are simply misleading (Eduard and Stefan, 2009). Generally, spurious regression occurs when the variables being regressed are integrated variables of order one i.e., I(1), in which case they are not stationary, but stationary if differenced once (Wen-Jen Tsay 1999). Almost all economic variables are integrated of the order one, I(1), hence expected to lead to spurious regression. Some of the examples of the spurious regression results are explained in (Darlauf and Phillips, 1988, Granger and Newbold, 1974 and Ogaki and Choi, 2001). Spurious results lead us towards wrong, illogical and unacceptable conclusion.

Engle and Granger, (1987) introduced the co-integration technique as a solution of spurious regression due to non-stationary time series. According to Granger the non-stationary time series are cointegrated, if their linear combination is a stationary process. To estimate the long run equilibrium relationship parameters for this Engle and Granger presented an Error Correction Mechanism (ECM). ECMs are a theoretically-driven approach useful for estimating both short-term and long-term effects of one time series on another. The term error-correction relates to the fact that last-period's deviation from a long-run equilibrium, the *error*, influences its short-run dynamics. Thus ECMs directly estimate the speed at which a dependent variable returns to equilibrium after a change in other variable. The residuals of equilibrium regression can be used for error correction model when there is only one variable and single equation is to be arrived and for VECM (Vector Error Correction Model) when there are more than 2 Variables and multiple equation is to be arrived in matrix form based on restricted VAR .

However the assumption that all the dependent and independent variable in the time series which is stationary at the level one is also cointegrated, may not be true, Johansen's (1988, 1991) maximum eigenvalue and trace tests for cointegration under the empirically relevant situation of near-integrated variables, helps us determine if the series is cointegrated or not , if the series is not cointegrated than using Monte Carlo techniques, un resistricted Var Module is used as a remedy for spurious regression (Erik 2007) if the time series is not co-integrated use of ECM or VECM model can result in the erroneous conclusion.

In order to maintain the robustness of the model and remedy spurious regression, cointegration model can only be used for the time series that are stationary at 1st difference, if the time series has data stationary in combination at level and 1st difference, ARDL (the autoregressive distributed lag) approach is used, process of ARDL involves conducting bound test for in the unrestricted model and adop ARDL approach to the estimation of level of relationship (Pearson et al., 2001). Auto regressive Distributed lag model is a model for time series data in which a regression equation is used to predict current values of a dependent variable based on both the current values of an explanatory variable and the lagged (past period) values of this explanatory variable.

When all variables are integrated of different order and at least one variable is integrated of order 2 then Autoregressive models is employed. Autoregressive models are models that simply include the lag of dependent variable as independent variable (Chaudhry 2012). The autoregressive model specifies that the output variable depends linearly on its own previous values and on a stochastic term (an imperfectly predictable term); thus the model is in the form of a stochastic difference equation. In machine learning, an autoregressive model learns from a series of timed steps and takes measurements from previous actions as inputs for a regression model, in order to predict the value of the next time step.

3. NEED FOR STUDY

There are several scholastic studies that establish relationship between the agri commodity Price and economic factors influencing it, but then these studies are limited to identifying the short term and long term effect of individual macro factor on the agri commodity and are more into explaining the phenomena that has already taken place. However there is dearth of scholastic research that analyses the effect of combination of micro and macro factors that affects the price of Soy Oil Future and arrives at the forecast model that derives the price of Soy Oil Future from the micro and macro factor.

Some of the forecasting model that has been developed through Scholastic studies are on time series analysis of historical behavior of the Soy oil price or on the micro economic factors, these forecast are short term in nature and thus difficult to predict the possible price of the Soy oil future in long run at different levels of macro variable and hence is of very limited application.

Market Participants in Soy Oil Future consists of investors in the form of famers, processors; intermediaries dealing with Physical Soy bean and Soy Oil, and Speculator who without having the physical Soy bean or Soy Oil, deal with it in CBOT Market for Short term gain. These market percipients look for direction of price moment of Soy oil Futures with reference to the factor that influences the price.

The importance of the research stems from the fact that the Price Forecast model with macro factors as the determinants enables effective price risk management of Soy oil for the market participants, enables government to make policy decisions and enables Traders / Investors to estimate demand / supply and increase / decrease in price of Soy Oil Future.

3.1 RESEARCH OBJECTIVES

Following are the objectives of the study:-

1) To analyze the impact of NYMEX US Crude oil on Soybean Oil Futures price in CME (Chicago Mercantile Exchange) and to determine if there is any cause and effect relationship in long run and short run.

2) To determine US Crude Oil's ability to predict US Soybean Oil price in CME with use of econometric model.

3.2 RESEARCH METHODOLOGY

The Study shall be based on Empharical analysis to determine cause and effect relationship between US Crude Oil and US Soybean oil futures in CME using monthly secondary data for a period of twenty eight years from FY 1990 to FY 2018. The Study also aims at developing appropriate model to forecast the price of US Soybean Oil Future in CME based on different level of US Crude oil price.

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3.2.1 Secondary Data

Following shall be the source of secondary data for the period of over 28 years from FY 1990 to FY 2018:-

1. Soy Oil Future data shall be collected from CME (Chicago Mercantile Exchange)

2. US Crude Oil Data shall be collected from NYMEX (New York Mercantile Exchange)

3.2.2 Research Techniques & Statistical tools applied

Following are the research techniques and Statistical tools that shall be applied in the study:-

1. Unit root test, Granger Causality test and other statistical tools.

2. Co integration test and Econometric model in the form of Error Correction Model

3.2.3 Research Hypothesis

Following shall be the research hypothesis used in the study:-

HYPOTHESIS 1
H0: Unit root is present in time series and hence data is not stationary
Ha: Unit root is not present in time series and hence data is stationary

HYPOTHESIS 2

H0: The regression equation is Spurious
Ha: The regression equation is not Spurious

HYPOTHESIS 3

H0: Unit root is present in time series of the residue , hence residue data is not stationary, thus variables are not having a long run relationship.

Ha: Unit is root not present in time series of the residue and hence residue data is not stationary, thus variables are not having a long run relationship.

HYPOTHESIS 4
H0: Dependent and independent variable are not co integrated
Ha: Dependent and independent variable are co integrated.

HYPOTHESIS 5

H0: NYMEX US Crude does not have the information / ability to predict Price of CME US Soybean oil Future price through econometric model.

Ha: NYMEX US Crude has the information / ability to predict Price of CME US Soybean oil Future price through econometric models.

3.4 RESEARCH TECHNIQUES USED IN THE PAPER

3.4.1 DATA STATIONARITY

Most forecasting methods assume that a distribution has stationarity. For example, auto covariance and autocorrelations rely on the assumption of stationarity. An absence of stationarity can cause unexpected or bizarre behaviors, like t-ratios not following a t-distribution or high r-squared values assigned to variables that aren't correlated at all.

Stationary series generally have means that never changes with time. Any other statistics (like variance) can change.

Trend-stationary models fluctuate around a deterministic trend (the series mean). These deterministic trends can be linear or quadratic, but the amplitude (height of one oscillation) of the fluctuations neither increases nor decreases across the series.

It can be difficult to tell if a model is stationary or not. If we aren't sure about the stationary of a model, a hypothesis test can help, one of the most widely used test for testing data stationary is Unit root tests / Augmented Dickey-Fuller (ADF) test.

3.4.2 COINTEGRATION

The two series are said to be cointegrated if they move together over time, and the distance between them is stable. Co-integration reflects the presence of a long-run equilibrium towards which the economic system converges over time, Variables are found to be co-integrated, if there exists a linear, stable and long-run relationship among variables, such that the disequilibrium errors would tend to fluctuate around zero mean.

3.4.3 ERROR CORRECTION MODEL (ECM)

If all the variables are stationary at 1st difference, there is only one endogenous variable, and if a set of variables are found to be cointegrated then a suitable estimation technique is a ECM (Error Correction Model) which adjusts to both short run changes in variables and deviations from equilibrium in long run.

An error correction model belongs to a category of multiple time series models most commonly used for data where the underlying variables have a long-run stochastic trend, also known as co integration. ECMs are a theoretically-driven approach useful for estimating both short-term and long-term effects of one time series on another. The term error-correction relates to the fact that last-period's deviation from a long-run equilibrium, the *error*, influences its short-run dynamics. Thus ECMs directly estimate the speed at which a dependent variable returns to equilibrium after a change in other variables.

4. DATA COLLECTION, ANALYSIS AND RESULTS

4.1 HYPOTHESIS – 1 - TEST OF STATIONARITY AT 1ST DIFFERENCE

4.1.1 - TABLE 1: UNIT ROOT TEST - US Soybean Oil

Null Hypothesis: D(SOY_OIL) has a unit root
Exogenous: Constant
Lag Length: 1 (Automatic - based on SIC, maxlag=16)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-11.94762	0.0000
Test critical values:	1% level	-3.449108	
	5% level	-2.869701	
	10% level	-2.571187	

*MacKinnon (1996) one-sided p-values.

4.1.2 - TABLE 2 - UNIT ROOT TEST - NYMEX US Crude Oil

Null Hypothesis: D(CRUDE_OIL) has a unit root
Exogenous: Constant
Lag Length: 0 (Automatic - based on SIC, maxlag=16)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-14.42086	0.0000
Test critical values:	1% level	-3.449053	
	5% level	-2.869677	
	10% level	-2.571174	

*MacKinnon (1996) one-sided p-values.

Since Enger Granger Critical value at 5% and 10% level is -3.34 and -3.04 and the test statistics for both CME US SOYBEAN OIL AND NYMEX US CRUDE OIL is at -11.94 and -14.42 higher than the critical value and the both are significant, we can reject Null Hypothesis and accept alternate Hypothesis that the the variables are stationary at 1st difference and hence are integrated of order one I (I).

4.2 HYPOTHESIS – 2

TABLE – 3 – REGRESSION EQUATION

Dependent Variable: SOY_OIL
Method: Least Squares
Date: 03/31/19 Time: 18:21
Sample: 1990M01 2018M12
Included observations: 348

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	14.40287	0.614802	23.42683	0.0000
CRUDE_OIL	0.319710	0.010931	29.24869	0.0000

R-squared	0.712023	Mean dependent var	29.64784
Adjusted R-squared	0.711191	S.D. dependent var	11.31817
S.E. of regression	6.082493	Akaike info criterion	6.454437
Sum squared resid	12800.86	Schwarz criterion	6.476576
Log likelihood	-1121.072	Hannan-Quinn criter.	6.463251
F-statistic	855.4858	Durbin-Watson stat	0.152233
Prob(F-statistic)	0.000000		

Since R- squared is higher than Durbin – Watson Stat , We can reject the null hypothesis and accept the alternate hypothesis , hence the regression equation is spurious.

4.3 - HYPOTHESIS - 3

TABLE – 3 - Unit root test of residual

Null Hypothesis: U has a unit root
Exogenous: Constant
Lag Length: 0 (Automatic - based on SIC, maxlag=16)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-3.703292	0.0044
Test critical values:	1% level	-3.448998	
	5% level	-2.869653	
	10% level	-2.571161	

*MacKinnon (1996) one-sided p-values.

Enger Granger Critical value at 10% level is -3.04, since test statistic is higher than the critical value , We can reject the null hypothesis and accept the alternate hypothesis that the residue is stationary.

If residue of the model is stationary, the estimated model is not spurious, it also means that the variables are cointegrated and these 2 variables have long run equilibrium relationship and the whole model is long run model and the 0.31 in the regression equation in Table 3 is long run co-efficient of US Crude oil and it is significant. Since the variables are co integrated we can run Error Correction Model.

4.4 . HYPOTHESIS –4

TABLE -4 – ECM EQUATION

Dependent Variable: DSOY_OIL
Method: Least Squares
Date: 03/31/19 Time: 18:51
Sample (adjusted): 1990M02 2018M12
Included observations: 347 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.011874	0.120468	0.098566	0.9215
DCRUDE_OIL	0.191165	0.024191	7.902183	0.0000
U(-1)	-0.062357	0.020007	-3.116778	0.0020

R-squared	0.162710	Mean dependent var	0.024150
Adjusted R-squared	0.157842	S.D. dependent var	2.445138
S.E. of regression	2.243882	Akaike info criterion	4.462900
Sum squared resid	1732.042	Schwarz criterion	4.496179
Log likelihood	-771.3131	Hannan-Quinn criter.	4.476151
F-statistic	33.42473	Durbin-Watson stat	2.210347
Prob(F-statistic)	0.000000		

Crude Oil is long run co-efficient as P Value is significant

U(-1), one period lag of the residual from the previous regression model (Table 3) is the error correction term , the value of U(-1) at 6.2% implies that the error correction term corrects the disequilibrium of the system at a speed of 6.2% on a monthly basis, speed of adjustment is , adjusting with previous period disequilibrium at the rate 6.2%, since the error correction term is negative and significant , we can reject null hypothesis and accept the alternate hypothesis that the there is long run equilibrium relationship between the two variables.

4.5 -HYPOTHESIS – 5

In table 4 since R squared value is lower than Durbin Watson stat, the model is not spurious model or a non sense model and hence we can accept the model. we can reject the null hypothesis and accept the alternate hypothesis that NYMEX US Crude does has the information / ability to predict Price of CME US Soybean oil Future price through econometric model.

Estimation Model Equation is :-

DSOY_OIL = C(1) + C(2)*DCRUDE_OIL + C(3)*U(-1)

By Substituting Coefficients the final Error Correction Model Equation is :-

DSOY_OIL = 0.0118740716754 + 0.191165021061*DCRUDE_OIL - 0.0623567834285*U(-1)

5. CONCLUSION

In this study, we reviewed the existing theoretical and empirical literature on the dependence of CME US Soybean oil future with NYMEX US Crude oil, mainly focusing on the transmission mechanism of volatility from NYMEX CRUDE To CME US SOY OIL FUTURE. Various econometric models used in studying commodity market linkage with macro factors were also analyzed briefly. In line with the steps identified in the literature review for application of appropriate econometric model, both dependent and independent variables were found to be stationany at 1st difference, variables were also found to be cointegrated and having long run equilibrium relationship. Appropriate econometric model, error correction model was applied and model for forecasting the price of CME US Soyabean Oil future was developed, the Durbin Watson test confirmed the validity of the model and the model equation results to be not spurious.

6. BENEFITS OF THE RESEARCH

Research work helps traders in developing investment strategy. enables market participants in formulating hedging strategy as a part of risk management process., the research also facilitates government in making appropriate policy decision to mitigate the risk of price rise of Soy Oil and enables importers and exporters to mitigate the risk by analyzing the effects of NYMEX US CRUDE on the prices of CME US Soybean Oil. For academicians, the research finding would pave the way to explore predictability of Soy bean Oil Future with other asset class like interest rates, real estate, Commodities like Gold and etc.

7. LIMITATION OF THE STUDY

Research has considered only the official economic factor value as published by CME and NYMEX on a monthly basis. Hence any intervening change other than change in monthly price of Soy Oil Future cannot be measured and only selected econometric models is applied based on their merits and feasibility in forecasting Soy Oil Future Price. In Future research, much more effective econometric model can be used to predict the price of Soy oil future, much more effectively.

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