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Co-Integration and Causality between Equity and Commodity Futures: Implications for Portfolio Diversification

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Co-Integration and Causality between Equity and Commodity Futures: Implications for Portfolio Diversification

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Abstract- This paper examines the long term statistical relationship of commodity future prices with equity prices using various tools including Augmented Dickey Fuller Test, Vector Auto Regression and Johansen's Cointegration technique. The paper also investigates the short term dynamics of prices by testing for the existence and direction of inter-temporal Granger-causality between the indices. The analysis shows that there is no long term cointegration between the commodity future prices and equity prices therefore, an investor with long term investment horizon would benefit by including commodity futures to a traditional portfolio.

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I. Introduction

Strategic asset allocation is one of the most important set of decisions for a portfolio manager. Asset allocation is the amount of exposure (positive or negative) to a certain class of asset in the portfolio. Before doing the asset allocation the first step is to decide on the types of asset to be included in the portfolio. The theory says that an asset that has low or negative correlation with other assets existing in the portfolio should be included. But correlation being a short term estimate; the key issue for an investor is how to consider the long term movements between the asset prices (Kasa, 1992). In standard risk –return models, any long term trends in the data is removed by differencing the prices of the assets. Although these trends are implicit in the returns data, but then these risk- return models does not include the decisions based on long term common trends in the price data (Alexander, 1999). To incorporate this long term impact in portfolio construction, the paper uses cointegration technique developed by Johansen (1988, 1991, 1992b) and Johansen and Juselius (1990) to test the long term co-movement of commodity future prices with equity prices.

Correlation and cointegration although related, are two different concepts. Correlation having a short term implication reflects comovements that are liable to instabilities over time. So, correlation based portfolio strategies require frequent re-balancing. In contrast, cointegration measures long run co-movements in prices that may occur even through periods when static correlations appear low. The high correlation of returns does not essentially imply high cointegration in the prices (Alexander, 1999). Thus, diversification decisions based on cointegrated assets may be more effective in the long term. By including the assets that are not cointegrated would result in a more effective portfolio that does not require frequent re-balancing of the portfolio. While constructing a portfolio, high correlation among assets cannot be taken as a sufficient measure for long term diversification benefits, there is a need to enhance the standard risk-return modeling methodologies to take account of common long term trends among the asset prices. To complement this, the paper extends the traditional models by including a preliminary stage in which the asset prices are analyzed, and then augments the correlation analysis to include both short term and long term dynamics.

The aim of the paper is to estimate the long and short run relation of asset prices applying the principle of cointegration, vector error correction approach and granger causality to time series analysis.

II. Review of Literature

Relatively, a number of empirical studies validate the low correlation among commodity futures and other asset classes over certain periods of time (Bodie & Rosansky, 1980; Erb & Harvey, 2006; Gorton & Rouwenhorst, 2006; Buyuksahin et al., 2010; Chong & Miffre, 2010) and these studies concluded that the return of an equal weight commodity futures portfolio was comparable to a stock portfolio. Following, Ankrim & Hensel (1993), Lummer & Seigel (1993), Satyanarayan & Varangis (1996), have shown that commodity futures provide a good diversification to the portfolio of equity & bond. Anson (1999) found out that commodity futures can prove to be a valuable asset for risk-averse investor, but the amount of investment in commodity futures depends upon certain factors like utility functions, level of risk tolerance & portfolio composition.

Simon (2013) has modeled the conditional relationships between the Goldman Sachs Total Return Commodity Index and Sub-Indexes and the S&P 500

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index using the bivariate GARCH framework and the results indicate that while the diversification benefits of commodities have diminished over the sample period, the estimated conditional correlations remain low enough for commodities to provide meaningful diversification benefits to equity investors.

Buyuksahin et al.(2010) empirically investigated the relationship between ordinary, as well as extreme, returns on passive investments in commodity and equity markets using Johansen's Cointegration technique and identified that commodities provide substantial diversification to opportunities to passive equity investors.

Perhaps one of the more important contributions to the literature is that of Gorton and Rouwenhorst (2006). They construct their own commodity futures index for the period 1959 – 2004 and examine how this compares with returns from stock and bond indices. They concluded that the average annualized return on the collateralized futures index was very similar to that on the S&P 500 over the whole period and both assets outperformed corporate bonds. They also found that the relative performance varied over time and that "the diversification benefits of commodities work well when they are needed most". Hence, one conclusion reached was that commodity futures are useful in creating diversified portfolios with respect to the idiosyncratic component of returns.

Becker and Finnerty (2000) stated, with reference to the period from 1970 to 1990, that the risk and return of a portfolio composed of stocks and bonds had increased with the inclusion of commodities in asset allocation. They specify that this increase had been more valid in the 1970s compared to the following decade, due to high inflation in the first part of the study period.

Bodie and Rosansky (1980) analyzed the returns of an equal weight commodity futures portfolio, and showed that the results obtained with medium and long-term portfolios were comparable to stock portfolios.

Kasa (1992) is one of the first ones to use the multivariate cointegration method proposed by Johansen and Juselius (1990) to analyze co-movements in stock markets and found a common stochastic trend for the period 1974 – 1990 between the U.S., Japan, England, Germany and Canada. Arshanapalli and Doukas (1993) had used cointegration techniques to test the linkage and dynamic interactions among stock market movements and reported that The U.S. stock market has a considerable influence on the French, German and English markets in the post-crash period. On the same line of research, Meric and Meric (1997) analyzed changes in the co-movements of the 12 largest equity markets in Europe and the U.S. after the 1987 market crash and found that the benefits of international diversification decreased considerably in these developed markets after the crash.

Wong et al. (2005) investigated the long run equilibrium relationship and short run dynamics between the Indian market and 3 developed countries (U.S., U.K. and Japan) for the period 1991- 2003 and found that the Indian market follows these markets and is therefore integrated with them in the long run.

In essence, we are not interested in finding or explaining relationships between economies, but we are rather trying to find assets that move on their own in the long term, so that they can increase the portfolio performance.

III. Research Methodology

The paper provides detailed empirical evidence on the extent to which the prices of commodity futures and equity market move in sync so that the investor is able to take better investment decisions. We take the perspective of a passive investor when analyzing the relationship between commodity future and equity investments. Modern portfolio theory suggests that the relevant information matrix for such an investor includes the expected asset returns, the variability of these returns, as well as cross-asset correlations (Buyuksahin et al., 2010).

Additionally, leads or lags in the time series make correlations almost useless. For example, if we lag by one or two days some of the daily time series, that we will be using in the empirical part of the paper, the effect on the correlation between the series will be significant, the correlation might even turn from positive to negative. On the other side, the effect on the common long term relationship between the series will be minimal. Cointegration allows for short term divergence between two different time series, meaning that in a day to day basis, the series does not necessarily have to go up or down at the same time, one might go up while the other goes down, thus there is no need for the two series to move in daily synchrony at all. In the long run, however the two price series cannot wander off in opposite directions for very long without coming back to their long term equilibrium.

The distinction between stationary and non stationary time series is extremely important because stationarity is a precondition to make statistical inferences. If the mean or variance of our time series change with time, then it is impossible to generalize results from regressions made for a specific period of time into a different period of time. So, it is necessary to identify if our time series is stationary or not before any statistical inference can be made.

If we perform regression analysis on time series where the dependent, independent, or both variables have a unit root process, then the results will have no economic significance, in particular, the estimates will be biased and hypothesis tests will be invalid. This is the problem of spurious regression which was first reported back in 1926 by Yule. In order to confirm the (stationary) nature of the series, we perform the Augmented Dickey-Fuller test under the unit root test to identify whether or not the series is stationary. To analyze long-term cointegration, we use the daily settlement prices for all the indices.

Our study of testing whether there is a long-run statistical relationship between commodity futures and equity markets depend on the methods of Johansen's cointegration analysis. The idea for the analysis is that if two series each follow upward trend, then, in general, they will diverge in the long run. Our approach will comprise of four parts: (1) testing for a unit root in each price indices, (2) testing for the number of cointegrating vectors in the systems of asset prices, provided the null hypothesis of a unit root for every price index is not rejected, (3) testing the vector autoregression between the assets, and (4) testing the causality effect among the two assets.

1. Unit Root Test: To test for a unit root in each series, we employ the Augmented Dickey-Fuller (ADF) (Dickey and Fuller, 1981) methodology. The tests are conducted with and without a deterministic trend (t). The general form of ADF test is estimated by the following regression

$$\Delta Y_t = \alpha_0 + zt + a_1 Y_{t-1} + \sum_{i=1}^{p} \alpha_i \Delta Y_{t-1} + \varepsilon_t$$

where $\alpha 0$ is constant, t is a deterministic trend, and enough lagged differences (p) are included to ensure that the error term becomes white noise. If the autoregressive representation of Yt contains a unit root, the t-ratio for a1 should be consistent with the hypothesis, a1=0. However, the ADF test loses power for sufficiently large values of p.

2. Cointegration Test: To investigate the existence of a long-term relationship between real and financial variables, we explore existence of any significant long-run relationships among the variables in our model. If the real and financial variables are cointegrated with one another, then this will provide statistical evidence for the existence of a long-run relationship. Though, a set of economic series are not stationary, there may exist some linear combination of the variable which exhibit a dynamic equilibrium in the long run (Engle and Granger 1987). We employ the maximum-likelihood test procedure established by Johansen and Juselius (1990) and Johansen (1991).

Specifically, if Yt is a vector of n stochastic variables, then there exists a p-lag vector auto regression with Gaussian errors of the following form:

$$\Delta Y_t = k + \Gamma_1 \Delta Y_{t-1} + \ldots + \Gamma_{p-1} \Delta Y_{t-p+1} + \Pi Y_{t-1} + z_t$$

where Γ1, ... Γp-1 and Π are coefficient matrices, zt is a vector of white noise process and k contains all deterministic elements.

The focal point of conducting Johansen's cointegration tests is to determine the rank (r) of matrix Γ k. In the present application, there are three possible outcomes. First, it can be of full rank, (r = n), which would imply that the variables are stationary processes, which would contradict the earlier finding of non-stationarity. Second, the rank of k can be zero (r = 0), indicating that there is no long-run relationship among the variables. In instances when Γ k is of either full rank or zero rank, it will be appropriate to estimate the model in either levels or first differences, respectively. Finally, in the intermediate case when there are at most r cointegrating vectors 0≤ r ≤ n (i.e., reduced rank), it suggests that there are (n -r) common stochastic trends.

The number of lags used in the vector auto-regression is chosen based on the evidence provided by Akaike's Information Criterion. The cointegration procedure yields two likelihood ratio test statistics, referred to as the maximum eigenvalue (λ-max) test and the trace test, which will help determine which of the possibilities is supported by the data.

3. VAR and Granger Causality: If the variables are found to be not cointegrated in long run, then the next step is to employ vector autoregression followed by the granger causality. The vector auto regression (VAR) is commonly used for forecasting systems of interrelated time series and for analyzing the dynamic impact of random disturbances on the system of variables. The optimum lag length is identified using Akaike Information Criteria (AIC). The VAR approach sidesteps the need for structural modelling by treating every endogenous variable in the system as a function of the lagged values of all of the endogenous variables in the system.

Consider two time-series variables, yt and xt. Generalizing the discussion about dynamic relationships to these two interrelated variables yields a system of equations:

$$y_t = \beta_{10} + \beta_{11} y_{t-1} + \beta_{12} x_{t-1} + v_t^y$$
$$x_t = \beta_{20} + \beta_{21} y_{t-1} + \beta_{22} x_{t-1} + v_t^x$$

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The equations describe a system in which each variable is a function of its own lag, and the lag of the other variable in the system.

IV. Data & Empirical Analysis

The daily prices for asset classes from Indian Capital market, viz., Equity (S&P CNX Nifty), and Commodity futures (MCX COMDEX) are examined for the period June 2005 to December 2011. Daily data was preferred because any transmission mechanism between the stock markets in the ECM (Error Correction Model) is most likely to occur within few days. Monthly data was our backup option. A drawback in using daily data is that we will most likely face Autoregressive Conditional heteroskedastic (ARCH) residuals - the variance of the residuals in one period is dependent on their variance in the previous period. It is possible that monthly data will correct or eliminate the ARCH residuals; therefore, we performed cointegration analysis using monthly data, however, the ARCH processes of the residuals were not eliminated – although decreased slightly for some series. The estimation results from monthly data were generally the same as the results obtained from daily data.

a) *Correlation Test*

The short term estimation of the relationship between the variables can be studied using the cross-correlation coefficients (as shown in Table 1). For the asset to be included in a portfolio, it should have low or negative correlation with other assets existing in the portfolio.

The MCX COMDEX also demonstrates a significant low correlation with the equity during the analyzed period. Thus, commodity futures have the potential to reduce risk in a portfolio of stocks.

Table I : Correlation Matrix for the asset classes (2005-2011)

Asset Class	S&P CNX Nifty	NSE G-Sec	NSE TB	MCXCOMDEX
S&P CNX Nifty	1.00000			
NSE G-Sec	-0.01138	1.00000		
NSE TB	-0.18278	-0.02050	1.00000	
MCXCOMDEX	0.36436**	-0.35956**	-0.12306	1.00000

** denotes significance at the 1% level (2-tailed)

b) *Unit Root Tests*

To analyse the long term relation among the variables we use Johansen Cointegration Analysis. But, before running this analysis the data is checked for stationarity. As discussed in the above section, Figure 1 depicts the line graph for Equity and Commodity Futures at level, showing that the two indices are not stationary. Figure 2 depicts the line graph of log of Commodity Futures [D (CF)] and log of Equity [D (Equity)], showing that the two indices are stationary at their first difference.

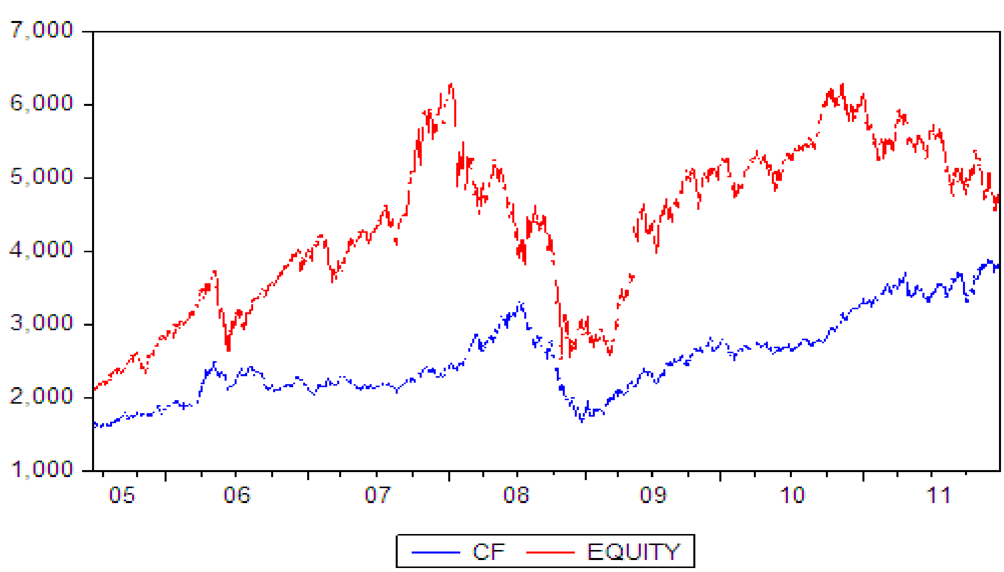

Figure 1: Line graph of Commodity Futures and Equity.

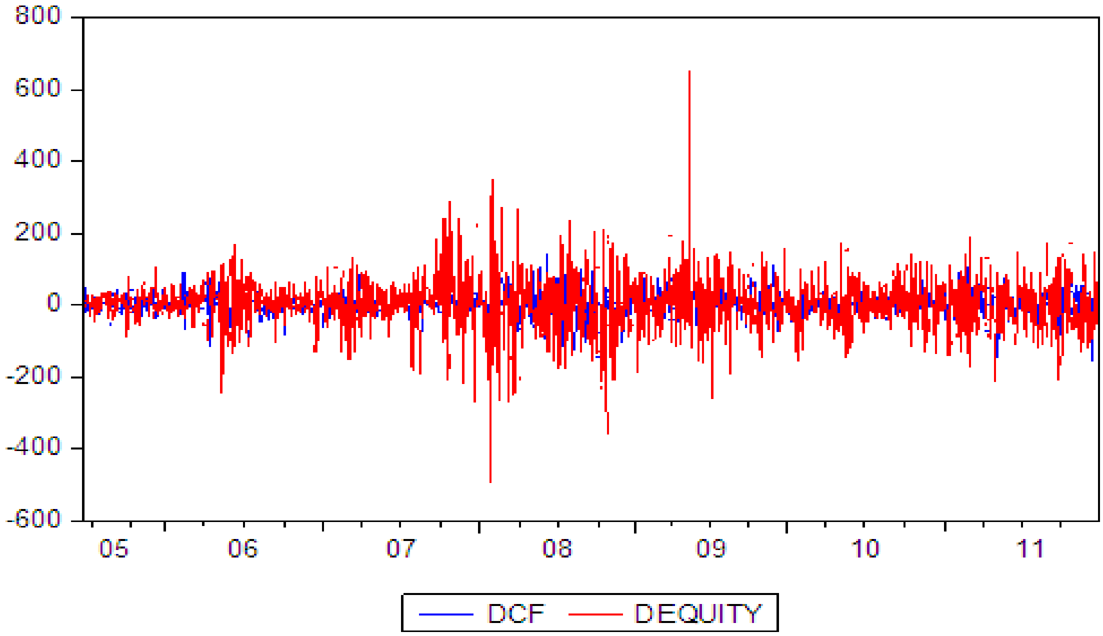

Figure 2: Line Graph of D (CF) and D (Equity).

Further, the study tests the stationarity by running Augmented Dickey Fuller test (ADF) on log of price indices. The optimal lag length is determined using minimum Akaike Information Criteria (AIC). The null hypothesis in case of ADF test is that the series under reference has a unit root, which implies that the series are not stationary in nature. A probability value of below 0.05 does not accept the null hypothesis at 5% level of significance and implies that the series under reference are stationary at 5% level of significance.

The probability value of less than 0.05 for log of commodity futures D (CF) and log of Equity, D(Equity) as presented in Table 2A and 2B, implying that the null hypothesis is not accepted and the variable does not have a unit-root, which confirms that the series is stationary meaning that both the indices are integrated of the order 1, I(1). The stationarity is verified at all the three conditions, i.e.,no intercept - no trend, intercept but no trend, no intercept but trend. Since the series are observed to be stationary in nature after the first differential, further econometric analysis can be performed on the log prices of indices.

Table 2A : Unit Root results for D (CF)

Null Hypothesis: D(CF) has a unit root
Exogenous: Constant
Lag Length: 0 (Automatic - based on SIC, maxlag=23)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-37.22596	0.0000
Test critical values:	1% level	-3.434307	
	5% level	-2.863175	
	10% level	-2.567688	

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

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Table 2B : Unit Root results for D(Equity)

Null Hypothesis: D(EQUITY) has a unit root
Exogenous: Constant
Lag Length: 0 (Automatic - based on SIC, maxlag=23)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-36.92791	0.0000
Test critical values:	1% level	-3.434307	
	5% level	-2.863175	
	10% level	-2.567688	

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

c) *Cointegration Test*

We applied Johansen and Juselius (1990) multivariate cointegration tests to determine the number of cointegrating relations, r. The results are shown in Table 3A and 3B.

Table 3A : Results of Johansen Cointegration between Commodity Futures & Equity

Series: CF EQUITY
Lags interval (in first differences): 1 to 4

Unrestricted Cointegration Rank Test (Trace)

Hypothesized No. of CE(s)	Eigenvalue	Trace Statistic	0.05 Critical Value	Prob.**
None	0.005067	13.73898	15.49471	0.0904
At most 1 *	0.003676	5.774479	3.841466	0.0163

Trace test indicates no cointegration at the 0.05 level
* denotes rejection of the hypothesis at the 0.05 level
**MacKinnon-Haug-Michelis (1999) p-values

Unrestricted Cointegration Rank Test (Maximum Eigenvalue)

Hypothesized No. of CE(s)	Eigenvalue	Max-Eigen Statistic	0.05 Critical Value	Prob.**
None	0.005067	7.964500	14.26460	0.3823
At most 1 *	0.003676	5.774479	3.841466	0.0163

Max-eigenvalue test indicates no cointegration at the 0.05 level
* denotes rejection of the hypothesis at the 0.05 level
**MacKinnon-Haug-Michelis (1999) p-values

Unrestricted Cointegrating Coefficients (normalized by b'*S11*b=I):

CF	EQUITY
-0.001071	0.001262
0.002539	-0.000612

Unrestricted Adjustment Coefficients (alpha):

D(CF)	1.569698	-1.278129
D(EQUITY)	-3.062121	-3.749438

1 Cointegrating Equation(s):	Log likelihood	-16563.05
Normalized cointegrating coefficients (standard error in parentheses)		
CF	EQUITY	
1.000000	-1.178339	
	(0.30654)	

Table 3B : Results and critical values for the λ_{trace} and λ_{max} test for CF and Equity

Lag: 2						
Ho	λtrace	CV (trace,5%)	Prob.	λmax	CV (max,5%)	Prob.
r=0	13.73898	15.49471	0.0904	7.964500	14.26460	0.3823
r≤1	5.774479	3.841466	0.0163	5.774479	3.841466	0.0163

Table 2A shows the results of Johansen Cointegration analysis run among the variables. The results are further compiled in Tables 2B. Johansen Cointegration results can be studied either on the basis of Trace value or Max Eigen value. From the above table, trace value indicates that there is no cointegration at level as p-value of 0.0904 is more than 0.05 and critical value(15.495) is more than the trace statistic(13.739), therefore we accept the null hypothesis that there is no cointegration equation among the variables. On the similar lines, Max-eigen value also indicates no cointegration by accepting the null hypothesis that there is zero cointegration equations among the variables, with p-value 0.3823 more than 0.05 and critical value(14.264) is more than the max eigen statistics (7.964). Therefore, both the tests indicate that there is no cointegration among equity and commodity futures.

d) Vector Autoregression

Since the above results show that there is no cointegration among the two variables, therefore we run the vector autoregression among CF and Equity to identify the cause and effect relationship. The results are shown in Table 4A and 4B.

Table 4A : Vector Autoregression estimates among CF and Equity

Vector Autoregression Estimates Standard errors in ( ) & t-statistics in [ ]		
	CF	EQUITY
CF(-1)	1.054101	0.204671
	(0.02556)	(0.06309)
	[41.2393]	[3.24394]
CF(-2)	-0.058845	-0.210345
	(0.02553)	(0.06302)
	[-2.30501]	[-3.33800]
EQUITY(-1)	0.007831	1.052822
	(0.01031)	(0.02545)
	[0.75965]	[41.3748]
EQUITY(-2)	-0.005175	-0.054759
	(0.01034)	(0.02552)
	[-0.50052]	[-2.14558]
C	1.717696	24.03004
	(3.65195)	(9.01439)
	[0.47035]	[2.66574]

R-squared	0.997015	0.995221
Adj. R-squared	0.997007	0.995209
Sum sq. resids	1458921.	8889045.
S.E. equation	30.52250	75.34105
F-statistic	130765.8	81530.88
Log likelihood	-7597.055	-9016.550
Akaike AIC	9.677983	11.48510
Schwarz SC	9.695040	11.50216
Mean dependent	2529.031	4367.760
S.D. dependent	557.9515	1088.462
Determinant resid covariance (dof adj.)	5163154.	
Determinant resid covariance	5130341.	
Log likelihood	-16594.82	
Akaike information criterion	21.13917	
Schwarz criterion	21.17328	

Table 4B : OLS for CF and Equity

Estimation Method: Least Squares

	Coefficient	Std. Error	t-Statistic	Prob.
C(1)	1.054101	0.025561	41.23928	0.0000
C(2)	-0.058845	0.025529	-2.305007	0.0212
C(3)	0.007831	0.010309	0.759652	0.4475
C(4)	-0.005175	0.010340	-0.500521	0.6167
C(5)	1.717696	3.651948	0.470351	0.6381
C(6)	0.204671	0.063093	3.243942	0.0012
C(7)	-0.210345	0.063015	-3.338005	0.0009
C(8)	1.052822	0.025446	41.37481	0.0000
C(9)	-0.054759	0.025522	-2.145576	0.0320
C(10)	24.03004	9.014388	2.665743	0.0077

Determinant residual covariance 5130341.

Equation: CF = C(1)*CF(-1) + C(2)*CF(-2) + C(3)*EQUITY(-1) + C(4)
*EQUITY(-2) + C(5)
Observations: 1571

R-squared	0.997015	Mean dependent var	2529.031
Adjusted R-squared	0.997007	S.D. dependent var	557.9515
S.E. of regression	30.52250	Sum squared resid	1458921.
Durbin-Watson stat	1.996879		

Equation: EQUITY = C(6)*CF(-1) + C(7)*CF(-2) + C(8)*EQUITY(-1) + C(9)
*EQUITY(-2) + C(10)
Observations: 1571

R-squared	0.995221	Mean dependent var	4367.760
Adjusted R-squared	0.995209	S.D. dependent var	1088.462
S.E. of regression	75.34105	Sum squared resid	8889045.
Durbin-Watson stat	2.002214		

From the table 3B, we can identify that for the equation CF = C(1)*CF(-1) + C(2)*CF(-2) + C(3)*EQUITY(-1) + C(4) *EQUITY(-2) + C(5), the coefficients C3 (0.4475) and C4 (0.6167) are insignificant, therefore, Equity does not cause CF. For the second equation EQUITY = C(6)*CF(-1) + C(7)*CF(-2) + C(8)*EQUITY(-1) + C(9) *EQUITY(-2) + C(10), the coefficients C6 and C7 are significant with 0.0012 and 0.0009 being less than 0.05, thereby meaning that CF does cause Equity. These results confine to the results given by cointegration analysis.

e) Granger Causality Test

Further, we run the Granger Causality among the variables, to identify the direction of causality in the variables. Results of Granger Causality test are reported in Table 5. We test the null hypothesis that one series does not Granger Cause another series at the conventional levels of significance. As in the below table, p-value of 0.1565 > 0.05, accepts the null hypothesis that equity doesnot granger cause commodity future. For the next hypothesis, we accept the alternate hypothesis that commodity futures granger cause equity as p-value of 0.0029 <0.05. We can say that there is a unidirectional relationship between commodity futures-equity.

Table 5 : Pairwise Granger Causality Test for CF and Equity

Null Hypothesis:	Lags	Obs	F-Statistic	Prob.
EQUITY does not Granger Cause CF	4	1569	1.66108	0.1565
CF does not Granger Cause EQUITY			4.04775	0.0029

So for the given data it is identified that there is no long run relation between commodity future prices and equity prices and that there is a unidirectional relation between CF and Equity.

V. Concluding Remarks

The paper has undertaken an examination of cause and effect between equity and commodity futures so that commodity futures could be considered as a diversification tool for investors to earn an extra return by using the data across 2005-2011. This is done by evaluating the short and long run relationship between the two variables. Since the introduction of commodity futures in India is of late (2003), therefore the data available for analysis is not very large. The analysis shows that there is a very low correlation among the two variables and no cointegration between equity and commodity futures results in no long term relation between the two variables meaning that the two series do not share a common stochastic drift. So if a passive investor includes commodity futures to the traditional portfolio mix of equity and bond, he would be able to earn high return in lieu of low risk. Thus, the results of the analysis do support the diversifying properties of commodity futures. The paper can be considered for future research by verifying the diversifying properties of commodity futures globally. The extension of this study could look at the behavior of commodity futures as an asset class during inflationary conditions.

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