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Interdependence & Integration between Futures and Spot Market: Empirical Evidence in India

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Abstract: ***The objective of this paper is to study the co-integration technique is used to determine the existence of any such relation in the two markets during 20th Nov 2009 and 31st Dec 2014. The major findings of this study that Futures prices tend to influence spot prices or; spot prices tend to lead futures prices. Nifty Futures market leads the Nifty index cash market; a lead-lag relation can be traced during the mentioned time period. This paper indicates that the two markets have a bidirectional causal relationship between spot and futures prices.***

Keywords: Lead-Lag Relationship, Jarque-Bera Test, Co-integration Analysis, Augmented Dickey-Fuller Test and Ganger Causality Test.

INTRODUCTION

Stock index futures contracts are usually priced using the forward pricing model which, given perfect capital markets and non-stochastic interest rates and dividend yields, implies that contemporaneous rates of returns of the futures contract and the underlying index portfolio should be contemporaneously correlated. Relevant new information should be theoretically impounded simultaneously into both the futures and cash prices and therefore, price movements in one market should neither lead nor lag the prices in the other market. However, on small time intervals (high frequency) it is often noticed that some price series consistently lead other closely related prices. Such lead-lag relations indicate that one market processes new information faster than the other market. Due to arbitrage restrictions that link these markets, lead and lag correlation coefficients between price change series will generally be small although it is possible that one market consistently leads or lags the other. Several studies examine temporal relationships between futures and cash index returns. The results frequently suggest that the futures returns lead the cash return and that this effect is stronger when there are more stocks included in the index. But the relationship is not completely unidirectional: the cash index may also affect the futures although this lead is almost always much shorter. The purpose of the present research is to examine the lead-lag relationship between Nifty futures index and Nifty spot index will be investigated. Granger's Co-integration Analysis Model will be applied to study the interrelationship between the two markets.

LITERATURE REVIEW

Vazakidis Athanasios (2010) studies the relationship between the spot price index and the futures price index in the Greek market. The objective of this study is to examine if the daily change in prices futures market has some information which is useful to predict the change in price in the spot market and vice versa. In other words, is the derivatives market playing the more important role of 'Price Discovery'? This study uses the GARCH model to examine the relationship between the returns on the volatility of the stock and the futures indices. Further, the study uses Granger causality test on the sample of data as a structural equation model in order to investigate the relationship between stock returns, futures returns, stock index volatility, and futures index volatility. The study claims to have unearthed interactions as well as causal effects (unidirectional and bidirectional) running between the market indices and their volatilities. As far as the outcome of the Granger causal test is concerned, the author found bi-directional causal effects between spot and futures returns. However, the effect running from spot returns is rather weaker. Further, the study finds stronger evidence suggesting that the stock index futures market leads the spot market at 1% level of significance.

Yiu-Kuen Tse and Wai-Sum Chan (2010) have investigated the lead–lag interaction between the futures and spot markets. Their work studies the intraday data on S&P500 using the threshold regression model which has become popular only recently. The researchers find that the lead effect of the futures market over the spot market is stronger when there is more market-wide information. Further, the lead effect of the cash market over the futures market is weaker when there is more market-wide information. The highlight of this research is the effort to establish a lead relationship base on market-wide information. One of the key observations of this research is that the lead effect of the spot market is stronger in periods of directionless trading than in periods of good or bad markets.

Sah and Omkarnath (2005) examined the nature and extent of the relation between NSE-50 Futures and volatility of S&P CNX Nifty. They used Granger causality test to study the relationship between volatility and futures market activity. The sample data consisted of daily closing prices of S&P Nifty and turnover from June 12, 2000, through March 25, 2004, for near month and from June 12 through January 29, 2004, for a middle month and far month contracts. Their empirical study suggested that futures market activity destabilized the underlying market. The direction of causation was bi-directional in the case of near month; however, causality ran from Nifty Futures to the volatility of S&P Nifty in the case of far month contract.

Mukherjee and Mishra (2006) used intraday data from April to September 2004 to investigate the lead-lag relationship between Nifty spot index and Nifty futures. They found that there was a strong bidirectional relationship among returns in the futures and the spot markets. The spot market was found to play a comparatively stronger leading role in disseminating information available to the market and therefore said to be more efficient. The results relating to the informational effect on the lead-lag relationship exhibit that though the leading role of the futures market wouldn't strengthen even for major market-wide information releases, the role of the futures market in the matter of price discovery tends to weaken and sometimes disappear after the release of major firm-specific announcements.

Shinhua Liu (2010) has studied the behaviour of stocks which have options available. The author asserts that in lesser mature markets, the introduction of options can skew the market in any direction. The author has studied the impacts of equity options in Japan. In particular, the study talks about the impact of an option listing on the behaviour of underlying stocks' key parameters such as price, trading volume, and volatility. The study finds no significant change to the long-term trading volume following the listings of options in Japan, relative to the control sample. The author argues that the reason for the absence of a volume increase could be a spillover of the volume effect from the sample to the control.

Natividad Blasco, Pilar Corredor, Rafael Santamarı (2010) have examined the presence or absence of informed trading in the options market and for the possible impact of this trading on underlying asset prices. The key test in the research is to observe if options trading affects underlying asset prices. The researchers have used GARCH as the conditional volatility model. Further, the researchers examine if volume occurs because of a release of news. The scope of the research is further sharpened to cover only private information. There is very little research done in this area earlier to directly prove or disprove the claims of information affecting volume though the concept by itself might seem obvious. The test findings disclose that potentially informed trading in options markets is channeled basically through out-of-the-money options. The exception is volatility trading which primarily involves at-the-money options owing to their liquidity. However, in either case, the researchers argue that transactions are broken up or fragmented into intermediate size trades.

EMPIRICAL TESTING OF THE LEAD-LAG RELATIONSHIP

In the study made here the entire estimation procedure has been divided into three interrelated steps: first, normality test; second, unit root test; third, Cointegration test. The econometric methodology first examines the stationarity properties of each time series of consideration. The present study uses Augmented Dickey-Fuller (ADF) unit root test to examine the stationarity of the data series. It consists of running a regression of the first difference of the series against the series lagged once, lagged difference terms and optionally, a constant and a time trend.

Normality Test (Jarque Bera statistics)

Following (Gujarati, 2003) we used the Jarque-Bera (JB) test to check the normality of data. We compute descriptive statistics of individual variables to check normality. We take values of skewness and kurtosis from descriptive statistics. The scale of normally distributed data is that its skewness must b equal to 0 and kurtosis equals to 3. So we assume our null hypothesis that our variable has S=0 and K=3, and in the case of rejection of null hypothesis, we drive that variables are not normally distributed. JB = n [S2 /6 + (K-3)2 /24] Here no denotes no. of observations is skewness and k is kurtosis.

Jarque-Bera is a test statistic for testing whether the series is normally distributed. The test statistic measures the difference of the skewness and kurtosis of the series with those from the normal distribution.

The statistic is computed as:

$$JB = \frac{N}{6}S + \frac{N}{24}K$$

Or

$$JB = \frac{N-k}{6}\left(S^2 + \frac{1}{4}(K-3)^2\right)$$

Where S is the skewness, K is the kurtosis, and k represents the number of estimated coefficients used to create the series. (Lawford, 2004)

	Future Price	Future Return	Spot Price	Spot Return
Mean	5875.987	0.030943	5861.306	0.038537
Median	5663.900	0.048900	5657.075	0.031500
Maximum	8618.613	5.951900	8582.288	3.397100
Minimum	4581.063	-4.605600	4587.100	-3.669700
Std. Dev.	901.1762	0.917929	889.0820	0.880645
Skewness	1.388880	-0.016582	1.390723	-0.068789
Kurtosis	4.316932	5.588706	4.315900	4.192238
Jarque-Bera	498.1078	353.2774	499.0445	75.91893
Probability	0.000000	0.000000	0.000000	0.000000
Sum	7433124.	39.14290	7414553.	48.74920
Sum Sq. Dev.	1.03E+09	1065.037	9.99E+08	980.2765
Observations	1265	1265	1265	1265

It can be observed from the above table that the corresponding p-value of the Jarque Bera statistics is 0.00000 for future Price, future return, spot price and spot return. Since p-value is more than 5 percent ($p < 0.05$), we reject the null hypothesis and accept the alternative hypothesis that future price, future return, spot price and spot return are not normally distributed.

Unit Root Test (Augmented Dickey–Fuller (ADF) Test)

To check whether a time series is stationary or non-stationary we used unit root test. Any data series is said to be stationary if its mean and variance remain constant over a period of time. After undertaking unit root we further confirm stationary of Nifty index and Nifty futures index by carrying out ADF Test.

Augmented Dickey-Fuller test is a modified version of Dickey Fuller Test. In order to statistically check whether our time series variables are stationary or not we used Augmented Dickey Fuller test. In this test, we compare the T-test with a critical value of studied variable to determine stationary in its time series.

The Augmented Dickey Fuller test is one of the most used for unit root tests in time series analysis. It is based on the following model, where p is the lag.

$$\Delta Y_t = \alpha + \beta_t + \gamma Y_{t-1} + \partial_1 \Delta Y_{t-1} + \ldots\ldots.. + \partial_{p-1} \Delta Y_{t-p+1} + \in_t$$

The statistic calculated is a negative number. The null hypothesis that a unit root exists is rejected if the calculated test statistic is more negative than the critical values at different significance levels. In other words, the absolute value of the calculated ADF test statistic is greater than the absolute critical values at different significance levels.

Augmented Dickey-Fuller Test on Future Return

Null Hypothesis: Future Return has a unit root
Exogenous: Constant
Lag Length: 0 (Automatic - based on SIC, max lag=22)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-27.92572	0.0000
Test critical values:	1% level	-3.435311	
	5% level	-2.863619	
	10% level	-2.567926	

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

Augmented Dickey-Fuller Test Equation
Dependent Variable: D(FR)
Method: Least Squares
Date: 01/15/16 Time: 21:27
Sample (adjusted): 2 1265
Included observations: 1264 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
FR(-1)	-0.763874	0.027354	-27.92572	0.0000
C	0.023785	0.025122	0.946774	0.3439

R-squared	0.381932	Mean dependent var	0.000273
Adjusted R-squared	0.381442	S.D. dependent var	1.135014
S.E. of regression	0.892671	Akaike info criterion	2.612383
Sum squared resid	1005.639	Schwarz criterion	2.620519
Log likelihood	-1649.026	Hannan-Quinn criteria.	2.615440
F-statistic	779.8457	Durbin-Watson stat	1.967211
Prob(F-statistic)	0.000000		

Augmented Dickey-Fuller Test on Spot Return

Null Hypothesis: Spot Return has a unit root
Exogenous: Constant
Lag Length: 1 (Automatic - based on SIC, max lag=22)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-22.99636	0.0000
Test critical values:	1% level	-3.435315	
	5% level	-2.863620	
	10% level	-2.567927	

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

Augmented Dickey-Fuller Test Equation
Dependent Variable: D(SR)
Method: Least Squares
Date: 01/15/16 Time: 21:30
Sample (adjusted): 3 1265
Included observations: 1263 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
SR(-1)	-0.764390	0.033240	-22.99636	0.0000
D(SR(-1))	0.087562	0.028033	3.123569	0.0018
C	0.028449	0.023616	1.204648	0.2286

R-squared	0.356871	Mean dependent var	-0.000962
Adjusted R-squared	0.355851	S.D. dependent var	1.044205
S.E. of regression	0.838068	Akaike info criterion	2.486937
Sum squared resid	884.9703	Schwarz criterion	2.499149
Log likelihood	-1567.500	Hannan-Quinn criter.	2.491525
F-statistic	349.5863	Durbin-Watson stat	2.003971
Prob (F-statistic)	0.000000		

Null Hypothesis H_0: Spot Return has a unit root (Non-Stationary)
Alternative Hypothesis H_1: Spot Return has no unit root (Stationary)
Condition:
If $p>0.05$, Null Hypothesis is accepted and Alternative Hypothesis is rejected.
If $p<0.05$, Null Hypothesis is rejected and Alternative Hypothesis is accepted.

Since all the P-values of the four market indexes are significantly less than 5% level, the null hypothesis that the future return and spot return have unit root is rejected. The alternative hypothesis that future return and spot return have no unit root is accepted. The unit root test indicates that both future return and spot return are stationary.

Co-Integration Test (Granger Causality Test)
Granger (1969) revolutionized the concept of causality by moving it from the domain of philosophy into a quantifiable science such as statistical hypothesis testing. This was a big step forward from regressions which pointed to mere correlation; to hypothesis testing to determine if one time series is useful in forecasting another. Granger causality states that if a time series or signal X_1 causes X_2, then the past values of X_1 hold information, over and above the information held in the past values of X_2 alone, which help predict X_2. In this context of two-time series X_1 and X_2

$$X_1(t) = \sum_{j=1}^{p} A_{11,j} X_{1(t-j)} + \sum_{j=1}^{p} A_{12,j} X_{2(t-j)} + E_1(t)$$

$$X_2(t) = \sum_{j=1}^{p} A_{21,j} X_{1(t-j)} + \sum_{j=1}^{p} A_{22,j} X_{2(t-j)} + E_2(t)$$

Here, p is referred to as the lag of the model. In other words, refers to the number of time periods that need to be backtracked to forecast. In this model, there exists causality if some of the coefficients $A_{12,j}$ in predicting $X_1(t)$ or some of the coefficients $A_{21,j}$ in predicting $X_2(t)$ are non-zero.

The lag is the period over which it is expected that the time series might exhibit memory. In other words, it is the duration of the time series during which the regressor variables can exhibit an influence on the regressand. We have assumed a lag of 1 day. This is because, with the onset of technology, it is extremely unlikely for the market to retain any advantage/ memory beyond a day.

We ran the Granger Causality test on the time series 'Option-Return' and 'Spot Return'. The causality test was run with a lag of 2 time period. The null hypothesis is that $A_{12,1}$ and $A_{21,1}$ are zero so that $X_1(t)$ and $X_2(t)$ are not caused by $X_{2\,(t-1)}$ and $X_{1\,(t-1)}$ respectively.

The output of the Granger Causality test is given below:

Pair-wise Granger Causality Tests
Date: 04/03/16 Time: 20:36
Sample: 1 1265
Lags: 2

Null Hypothesis:	Obs	F-Statistic	Prob.
FR does not Granger Cause FP	1263	2.54951	0.0785
FP does not Granger Cause FR		0.99698	0.3693
SP does not Granger Cause FP	1263	42.0684	0.0000
FP does not Granger Cause SP		5.58799	0.0038
SR does not Granger Cause FP	1263	32.1910	0.0000

FP does not Granger Cause SR		6.35188	0.0018
SP does not Granger Cause FR	1263	32.1783	0.0000
FR does not Granger Cause SP		7.83555	0.0004
SR does not Granger Cause FR	1263	33.7486	0.0000
FR does not Granger Cause SR		6.12264	0.0023
SR does not Granger Cause SP	1263	5.29672	0.0051
SP does not Granger Cause SR		0.35823	0.6990

There are four null hypotheses for four legs of the test:

1. Future Return does not Granger Cause Future Price: This hypothesis is accepted based on the probability value for the statistic (0.0785) at 5% level of significance.
2. Future Price does not Granger Cause Future Return: This hypothesis is accepted based on the probability value for the statistic (0.3693) at 5% level of significance.
3. Spot Price does not Granger Cause Future Price: This hypothesis can be rejected based on the probability value for the statistic (0.0000) at 5% level of significance.
4. Future Price does not Granger Cause Spot Price: This hypothesis can be rejected based on the probability value for the statistic (0.0038) at 5% level of significance.
5. Spot Return does not Granger Cause Future Price: This hypothesis can be rejected based on the probability value for the statistic (0.0051) at 5% level of significance.
6. Future Price does not Granger Cause Spot Return: This hypothesis can be rejected on the probability value for the statistic (0.0018) at 5% level of significance.
7. Spot Price does not Granger Cause Future Return: This hypothesis can be rejected based on the probability value for the statistic (0.0000) at 5% level of significance.
8. Future Return does not Granger Cause Spot Price: This hypothesis can be rejected based on the probability value for the statistic (0.0004) at 5% level of significance.
9. Spot Return does not Granger Cause Future Return: This hypothesis can be rejected based on the probability value for the statistic (0.0000) at 5% level of significance.
10. Future Return does not Granger Cause Spot Return: This hypothesis can be rejected based on the probability value for the statistic (0.0023) at 5% level of significance.
11. Spot Return does not Granger Cause Spot Price: This hypothesis can be rejected based on the probability value for the statistic (0.0051) at 5% level of significance.
12. Spot Price does not Granger Cause Spot Return: This hypothesis is accepted based on the probability value for the statistic (0.6990) at 5% level of significance.

Hence, we conclude that, based on the observed data, Spot return granger causes option to return and option return granger causes spot returns.

CONCLUSION

The future market trading in Indian financial markets was introduced in June 2000 and options index was commenced from June 2001 and subsequently, the options and futures on individual securities trading were commenced from July 2001 and November 2001, respectively. The futures trading on stock indexes has grown rapidly since inception and provides important economic functions such as price discovery, portfolio diversification and opportunity for market participants to hedge against the risk of adverse price movements. Hence, the movements of spot market price have been largely influenced by the speculation, hedging and arbitrage activity of futures markets. Thus, understanding the influence of one market on the other and role of each market segment in price discovery is the central question in market microstructure design and has become increasingly important research issue among academicians, regulators and practitioners alike as it provides an idea about the market efficiency, volatility, hedging effectiveness and arbitrage opportunities, if any. Price discovery is the process of revealing information about future spot prices through the future markets.

The essence of the price discovery function hinges on whether new information is reflected first in changes of future prices or changes of spot prices. Hence, there exists a lead-lag relationship between spot and futures market by information dissemination. All the information available in the marketplace is immediately incorporated in the prices of assets in an efficient market. So, new information disseminating into the market should be reflected immediately in spot and futures prices simultaneously. This will lead to perfect positive contemporaneous co-movement between the prices of those markets and there will be no systematic lagged response and therefore no arbitrage opportunity.

This prediction arises directly from the Cost of Carrying (COC) model. In addition, if there are economic incentives for traders to use one market over the other, a price discovery process between the two markets is likely to happen. This implies that futures and spot market prices are inter-related and can be traced under different market frictions through price discovery mechanism. Accordingly, there exist diversified theoretical arguments pertaining to the causal relationship between spot and futures markets by information dissemination and raises the major question that which market price reacts first (lead) whether; Futures prices tend to influence spot prices or; Spot prices tend to lead futures prices or; A bidirectional feedback relationship exists between spot and futures prices.

The main arguments in favour of futures market lead spot market are mainly due to the advantages provided by the futures market includes higher liquidity, lower transaction costs, lower margins, ease leverage positions, rapid execution and greater flexibility for short positions. Such advantages attract larger informed traders and make the futures market to react first when market- wide information or major stock-specific information arrives. Thus, the future prices lead the spot market prices.

We empirically examine the dynamics between CNX Nifty and Nifty Futures in terms of their relationship and causality between them. First of all, we converted the closing values into natural logarithm to get the log values. After getting two natural logarithms, time series we checked for normality of data by using Jarque-Bera test. After confirming the non-normal distribution of data we went for stationary or non-stationary time series. For checking and confirming stationarity we used two methods; first, we used simple graph method and then Augmented Dicket-Fuller Test. Both tests showed stationarity of time series data at level. The results of coefficient of correlations tell us that there is negative relationship exists between CNX Nifty and Nifty Futures. After affirming correlation we tested for cause and effect relationship by implementing Granger Causality Test which proved the bidirectional causal relationship between CNX Nifty and Nifty Futures.

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