A Study of Efficiency of Index Futures, Lead-Lag Relationship, and Speed of Adjustments in India Using High-Frequency Data

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Abstract

We conducted a rigorous analysis to find out the speed of adjustments in futures and spot indices on NSE NIFTY 50 in short-run as a part of examining the efficiency of the financial futures market in India. Towards that, we undertook the analysis of long-run and short-run efficiencies separately and used Engle – Granger's error correction mechanism (ECM) so that a clear picture of short-run efficiency in terms of speed of adjustments could emerge. The rigour manifested in the analysis of up to 412538 data points that bred from the choice of five different time intervals spanning from 1-minute to 120-minutes. Most of the price discovery took place in the futures market, and the spot market followed it mostly with a lag of 9 minutes. However, it took 35 minutes to completely return to the desired relationship once a drift had taken place. The increase in the speed of adjustments, as compared to the speed documented in previous studies, could be attributed to the large-scale adoption of the high-frequency (i.e. algorithmic) trading in recent times. Our findings suggested that traders can effectively use the near month contract of Nifty 50 Futures to hedge their open positions in the index or any other stock. At the same time, the market also offers an opportunity to arbitrageurs as the integration did not take place before 9 minutes.

Keywords : Futures market, index futures, market efficiency, high-frequency data, co-integration, hedging

JEL Classification Codes : G10, G14, G19

Paper Submission Date : September 24, 2019 ; Paper sent back for Revision : February 18, 2020 ; Paper Acceptance Date : March 10, 2020

Hedging is the prime objective behind introduction of futures market, which requires that the futures market exhibits long-run as well as short-run efficiency. The efficiency of the futures market is studied as the level of integration of returns in the two market segments of spot and futures with the desired relationship between the two. Fama (1970) developed the efficient market hypothesis (EMH), which states that the informational efficiency of spot market can be examined as a function of the flow of new information that can be modelled as taking a 'random walk.' With that, a lot of interest sprouted to study the efficiency of the stock markets across the world. Later on, with the introduction of the futures market, we have got in it a benchmark for the spot price, and vice - versa, making it possible to study the efficiency of futures market in relation to the spot market.

The price of financial futures contract today that expires at a future date t denoted as (Fo, t) is the price at which

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DOI : 10.17010/ijf/2020/v14i4/151705

the contract will be settled at that future date. In a perfect market, it turns out to be the expectation of the spot price at time *t* denoted by (*St*).

Thus, $Fo,t = E\,(St)$ (1)

The specific theoretical relationship between *Fo, t* and *St*, under the cost of carry model assuming continuous compounding, is stated as $Fo,\ t = So \cdot e^{rt}$, where *r* stands for risk-free rate of return and *t* stands for the time to maturity of the futures contract. If, for some reasons, at a given point of time, the modelled relationship is not observed, then the arbitrage process will again restore it. Since the market is made up of numerous players, and that not all of them have the same forecasting ability, the conceptualized relationship will always not be so sacrosanct. In other words, the actual price would randomly revolve around the conceptualized price as shown in Eq. (2), which is presented as a testable model :

$$Fo,\ t = So \cdot e^{rt} + \varepsilon \quad (2)$$

As far as the methodology for the study of efficiency of the futures segment of the stock market is concerned, the initial research took the route of testing the intercept and slope of the regression equation for the desired relationships (e.g., Frenkel, 1979 ; Goss, 1986 ; Huang, 1984). However, such procedures would prove unreliable if the price series are not stationary, which is generally the case with financial series. As a result, later on, there has been a shift from it in favour of testing cointegration and analyzing the residuals. For example, see MacDonald and Taylor (1988), Baillie (1989), Hakkio and Rush (1989), Chowdhury (1991), Barnhart and Szakmary (1991), Beck (1994), Brenner and Kroner (1995), and Laws and Thompson (2004).

Literature Review

Scholars have used both low frequency as well as high-frequency data to test the market efficiency and study the lead-lag relationship. We have reviewed only relevant studies that used high-frequency data.

The majority of the studies conducted over the last 50 years in different countries found that the futures led the spot, which implies that the price discovery occurs more significantly in the futures markets. Some of the old leading studies that deserve mention are discussed here first. Herbst, McCormick, and West (1987), who analyzed value line and S&P 500 based on the data of 1982 from USA, found that futures tend to move to the leading side of the spot index. Chan (1992) investigated the S&P 500 futures based on samples of two periods, one from August 1984 – June 1985 and second from January – September 1987, using 5-minutes data and found strong evidence that futures led the cash index. Gwilym and Buckle (2001) investigated the FTSE100 stock market index and futures and options contracts using hourly data from 1993 – 1996 and found that both the index futures and index options contracts led the cash index by up to 1 hour. This result is similar to Abhyankar (1995), who also found 1-hour lead in the futures market in FTSE-100 during 1986 – 1990.

Many recent studies also support the leading role of futures market in the price discovery process. For example, Fassas and Siriopoulos (2019) studied price discovery and volatility transmission between cash and futures market in the Athens exchange. They found evidence in support of leading role of futures market. Likewise, Hao, Xiong, He, and Ma (2019) investigated the price discovery in three Chinese stock index futures. They found that the futures market led the price discovery after substantial regulations in 2015. However, it is noteworthy here that Pathak, Ranajee, and Kumar (2014) reviewed empirical evidence on price discovery in the equity derivatives market around the globe. They documented that there was not a complete consensus among researchers about the direction and speed of adjustments.

In India, such studies began after the introduction of financial futures in 2000. Raju and Karande (2003) studied the price discovery in both the futures and spot markets. They found that the futures market responded to deviations from equilibrium, but the price discovery occurred in both futures and spot markets. However, their period of study was only the initial period spanning over not more than 3 years soon after the introduction of futures. Then, Vipul (2005) studied temporal variation in futures mispricing using high-frequency data from January 1, 2002 – November 24, 2004 and asserted that the NSE spot and futures segments provided significant opportunities of arbitrage due to mispricing. Bhatia (2007) studied long-run and short-run relationships between the Nifty 50 spot and futures index using 5-minutes data, and concluded that though the price discovery happened in both segments of the market, the futures index led price discovery by 10 – 25 minutes. Debashish and Mishra (2008) also examined NIFTY futures in the Indian market using hourly data during July 2001 – June 2008, and documented that the futures market led the cash market. Gupta and Singh (2009) investigated price discovery and arbitrage efficiency of Indian equity futures and cash markets during April 2003 – March 2007 using high-frequency data. They found that the futures market dominated the information transmission process to the extent of 5 – 55 minutes in majority of individual stocks. Sadath, Hiremath, and Kamaiah (2012) studied the expiration effects of stock futures on the price and volume of underlying stocks. They observed positive abnormal returns coupled with abnormal volume in the stock futures market during the last few days before the settlement date.

Shankar, Sankar, and Kumar (2015) analyzed the relationship between liquidity, volatility, and path dependency of mispricing in single stock futures. They concluded that size of the mispricing reduced with increase in liquidity and decrease in volatility. Nandan, Agrawal, and Jindal (2015) investigated the mispricing in the stock futures. They found that most of the futures contracts were underpriced due to short selling restrictions in the spot market. Inani (2017) revisited the price discovery relationship between spot and futures of S&P CNX Nifty index of India during January 2011 – August 2015 using 1- minute data. The author documented that the futures market was more efficient as compared to the spot market, and provided precise plausible reasons like lower transaction costs, leverage benefit, and ease of short selling in futures market.

Some researchers, in recent times, have examined other allied aspects of futures markets in India (for example, see Ashraf & Biag, 2019 ; Dikshita & Singh, 2019 ; Kaura, Kishor, & Rajput, 2019 ; Kaur & Singh, 2019).

Most of these studies mainly examined the lead-lag relationship between spot and futures markets once the cointegration of price series is established. Moreover, most of the studies asserted long-run efficiency of financial futures market; however, that is only the necessary condition. The sufficient condition for the use of futures contracts for hedging lies in the speed of adjustments between the two price series in the short-run. Therefore, this paper rigorously analyzes the aspect of speed of adjustments.

Tests of Efficiency

In this section, we review the established test procedures for inferring about whether there exists the expected relationship between the spot price and the futures price as conceptualized in eq. (1). The relationship can be examined for long-run as well as short-run. Accordingly, two different sets of tests are used namely, the test of long-run efficiency and test of short-run efficiency.

(1) Test of Long-run Efficiency - Cointegration Analysis : These tests are carried out using the log transformation of price data. Since the log of current spot price (*So*) is supposed to be an unbiased estimate of the log of futures price [i.e. the future dated spot price (*St*)], the efficiency tests can be carried out by modelling the following causal relationship :

$$S_t = \alpha + \beta F_t + \varepsilon_t \quad (3)$$

The standard approach stipulates that in order for the futures market to be efficient, eq. (3) must satisfy the following three interrelated conditions :

(i) S (*i.e. spot*) and F (i.e. futures) must be integrated to the same order.

(ii) S and F must be cointegrated.

(iii) For the cointegrating equation, the estimated slope coefficient (i.e. β) should be equal to 1, and the constant (i.e. α) should be 0. This requires that for the cointegrating equation, there should not be unit root in the error term.

(2) Test of Short - run Efficiency - Error Correction Mechanism : Once the long-run cointegration is established, then it is possible to conduct the test of short-run efficiency. This test is based on Granger representation theorem that treats the error term in the co-integrating equation as the equilibrating error term that corrects the deviations in the co-integrating equation. The test models the log-transformed spot returns as a function of log-transformed futures returns and the lagged residuals in the co-integrating equation. It is obvious that as the two price series are differenced stationary, and that the residuals provide for the error made in the previous period to correct the imbalance in the current period, the beta coefficient of the lagged error correction term would exhibit the short-run relationship in terms of feedback interaction between the two series.

Research Methodology

(1) The Sample : This study is based on NIFTY 50 index futures.

(2) Type, Source of Data, and Time Frame : We purchased the tick-by-tick data from DotEx International Limited for a period of 2 years, that is, from July 2014 – June 2016.

(3) The Sampling Units : The near month contract is considered because of its higher liquidity.
The number of observations considered for different time intervals are shown below :

Time Intervals	Pairs of NIFTY 50 Spot & Futures
1 Minute	183730
15 Minutes	12249
30 Minutes	5880
60 Minutes	2940
120 Minutes	1470

(4) Techniques of Data Analysis : As discussed earlier, the analysis requires examining as to how far the three conditions of efficiency are met by the futures market. Towards that ; first, OLS regression is performed to establish long-run efficiency. Then, Engle – Granger (Engle & Granger, 1987) test is conducted for the error correction mechanism (ECM). It is noteworthy here that the Johansen test does the twin jobs of examining the long-run as well as short-run efficiency in a single procedure. However, it is observed that when there are only two variables, the Engle – Granger test does a better job than Johansen's test (for example, see Brooks, Rew, & Ritson, 2001 ; Gonzalo & Lee, 1998 ; Hjalmarsson & Österholm, 2010). Stock and Watson (1993) noted that Johansen's approach is sensitive to the lag length used in the vector error correction mechanism (VECM) and to the sample-ending point. Therefore, if such specifications are not handled correctly, the results could be misleading. Hence, we resort to examining the long-run and short-run efficiencies separately using the tests that do not require any such specifications.

Data Analysis and Results

The analysis is conducted for five different time frequencies, that is, 1 - minute, 15 - minutes, 30 - minutes, 60 - minutes, and 120 - minutes. Thus, there are five sets of analysis. To form a preliminary view about the stationarity of price series, graphs of log-transformed data for 1-minute interval are developed on the level as well as first differenced data as shown in Figure 1 and Figure 2, respectively.

Figure - 1 Nifty 50 at Level Data (Log-transformed)

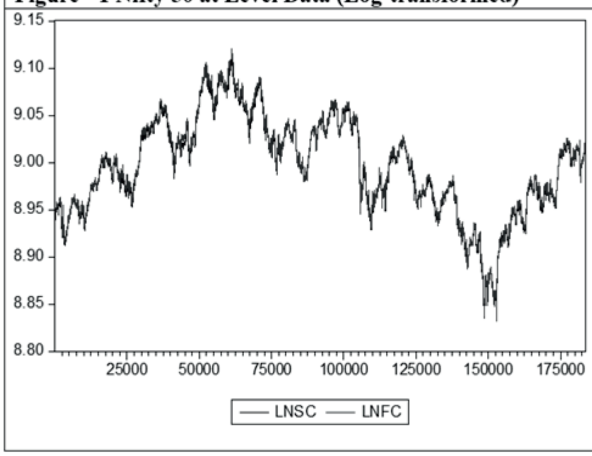
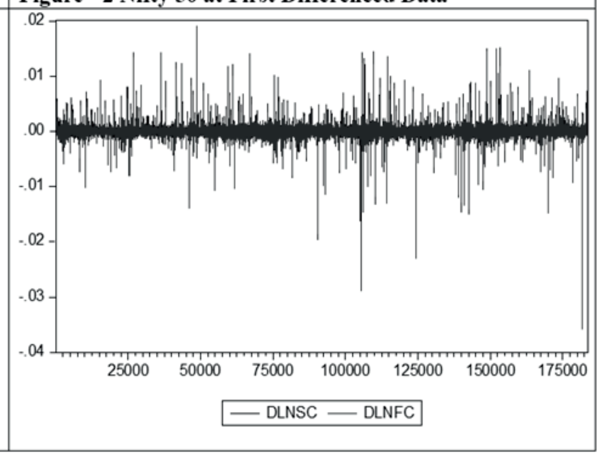


Figure - 2 Nifty 50 at First Differenced Data



The analysis is conducted in Eviews 6 using the following steps :

↘ **Step 1 :** To satisfy the first condition, we conducted the ADF test. It was conducted separately for the log-transformed values of the spot price series and the futures price series on the level data as well as on the first differenced data for all five-time intervals. Further, to make it a more insightful test, it was performed on three different variants, namely, 'none' (standing for the plain data without assuming any intercept or trend), 'intercept' (recognizing only the presence of intercept but ignoring any trend), and 'trend and intercept' (that recognizes the presence of both: the trend as well as the intercept).

The unit root results of spot and futures on NIFTY 50 are provided in Table 1, which shows that the level data are non-stationary for all the three variants for the spot series as well as the futures series. Against that, the results of analysis based on the first-differenced data shows stationarity, which indicates the cointegration between the log-transformed spot and futures price series. Hence, they can be analyzed for examining the long-run equilibrium relationship outlined in eq. (3).

↘ **Step 2 :** The long - run relationship is examined by running OLS. Table 2 shows the results of regression analysis for all the five time intervals, which are significant. Though the R^2 values are close to 1, suggesting a very strong long-run relationship for the coefficient values of more than 0.98, the Durbin – Watson statistic is in the lower range from 0.01 – 0.30, which alarms for a positive auto-correlation within the individual price series.

Table 1. Augmented Dickey – Fuller (ADF) Test Results for Unit Roots – NIFTY 50

	Spot						Futures					
Time Interval	Level			First Differenced (Returns)			Level			First Differenced (Returns)		
	None	Intercept	Intercept and Trend	None	Intercept	Intercept and Trend	None	Intercept	Intercept and Trend	None	Intercept	Intercept and Trend
	Augmented Dickey – Fuller (ADF)											
1 Minute	0.394	–2.064	–2.301	–303.352	–303.352	–303.351	0.562	–1.955	–2.180	–432.988	–432.988	–432.987
p - value	0.798	0.260	0.433	0.000*	0.000*	0.000*	0.838	0.307	0.500	0.000*	0.000*	0.000*
15 Minutes	0.396	–2.069	–2.308	–107.147	–107.144	–107.140	0.572	–1.924	–2.150	–107.274	–107.272	–107.268
p - value	0.798	0.258	0.429	0.000*	0.000*	0.000*	0.840	0.321	0.517	0.000*	0.000*	0.000*
30 Minutes	0.403	–2.050	–2.286	–75.258	–75.254	–75.249	0.373	–2.112	–2.365	–75.881	–75.876	–75.871
p - value	0.800	0.266	0.441	0.000*	0.000*	0.000*	0.792	0.240	0.398	0.000*	0.000*	0.000*
60 Minutes	0.397	–2.085	–2.322	–53.872	–53.865	–53.857	0.368	–2.141	–2.394	–55.007	–55.000	–54.992
p - value	0.798	0.251	0.421	0.000*	0.000*	0.000*	0.791	0.229	0.382	0.000*	0.000*	0.000*
120 Minutes	0.397	–2.087	–2.325	–24.758	–24.753	–24.746	0.369	–2.133	–2.387	–38.450	–38.441	–38.429
p - value	0.798	0.250	0.420	0.000*	0.000*	0.000*	0.791	0.232	0.386	0.000*	0.000*	0.000*

Note. *indicates 1% level of significance.

Table 2. OLS Regression Results (As per Equation - 3)

	1 Minute	15 Minutes	30 Minutes	60 Minutes	120 Minutes
Time Interval	Coefficient (*t*-Stat)	Coefficient (*t*-Stat)	Coefficient (*t*-Stat)	Coefficient (*t*-Stat)	Coefficient (*t*-Stat)
C	0.0941	0.095	0.0943	0.0938	0.0917
	(121.6251)*	(31.5777)*	(21.7956)*	(15.3059)*	(10.5153)*
LNFC	0.9893	0.9892	0.9893	0.9893	0.9896
	(11502.49)*	(2957.855)*	(2058.109)*	(1452.971)*	(1020.691)*
DW	0.012402	0.070434	0.101152	0.172853	0.301728
R^2	0.998613	0.998604	0.998614	0.99861	0.998593

Note. *indicates 1% level of significance.

➯ **Step 3 :** Now, we analyze the residuals obtained from eq. (3) by the ADF unit root test to check the stationarity. The hypothesis of unit root in the residuals (named as series *RES* in the analysis) is rejected with a *tau* value of –23.92 ($p < 0.01$) as reported in Table 3, meaning thereby that the residuals do not exhibit autocorrelation ; and thus, it is a stationary series. Therefore, now we can consider the results in Table 2, providing evidence of long-run co-integrating relationship. Both the beta and the intercept are statistically highly significant. As a result, the β values of more than 0.98 in the cointegration equations stand for the very high degree of long-run equilibrium relation between the two series across all time intervals. Finally, the results of eq. (3) by adding 1-lagged residuals as one of the independent variables are presented in Table 4.

➯ **Step 4 :** As far as the test of short-run efficiency is concerned, Granger representation theorem states that there exists a corresponding error correction representation. To estimate ECM, we use eq. (4) and eq. (5) in which

Table 3. ADF Test on Residuals (Generated from Equation - 3) of Engle – Granger Cointegration

Time Interval	NIFTY 50
1 Minute	–23.92289
p - value	0.000*
15 Minutes	–14.84516
p - value	0.000*
30 Minutes	–12.30605
p - value	0.000*
60 Minutes	–11.47473
p - value	0.000*
120 Minutes	–10.89841
p - value	0.000*

Note. *indicates 1% level of significance.

Table 4. Error Correction Model for Differenced Log Series at Lag 0 (As per Equation - 4)

	1 Minute	15 Minutes	30 Minutes	60 Minutes	120 Minutes
Time Interval	Coefficient (*t*-Stat)	Coefficient (*t*-Stat)	Coefficient (*t*-Stat)	Coefficient (*t*-Stat)	Coefficient (*t*-Stat)
C	0.000	0.000	0.000	0.000	0.000
	(0.1229)	(0.0376)	(0.1754)	(0.1764)	(0.1709)
D(LNFC)	0.8497	0.9142	0.9348	0.9428	0.951
	(869.6227)*	(375.9089)*	(333.2962)*	(261.815)*	(199.7608)*
RES(–1)	–0.0059	–0.0338	–0.0489	–0.0835	–0.1458
	(–23.7872)*	(–14.7333)*	(–12.3101)*	(–11.4257)*	(–10.7797)*
DW	2.484414	2.421756	2.287675	2.232743	2.181369
R^2	0.804617	0.920469	0.949776	0.958937	0.964569

Note. *indicates 1% level of significance.

lagged estimated residuals $(\hat{e}_{t-1})$ from the cointegration equation (for long-run equilibrium) and lagged changes in the spot and futures indices have been included to see the short-run adjustment in the equilibrium prices of spot indices.

$$\Delta S_t = \alpha_1 + \alpha_s \hat{e}_{t-1} + \text{lagged}\,(\Delta S_t, \Delta F_t) + \varepsilon_t \qquad (4)$$

$$\Delta F_t = \alpha_1 + \alpha_s \hat{e}_{t-1} + \text{lagged}\,(\Delta S_t, \Delta F_t) + \varepsilon_t \qquad (5)$$

Here, we estimate the error correction model assuming four different sets of lags, that is, lag-0, up to lag-4, up to lag-35, and up to lag-100. The only reason to extend lags up to 100 was to check the optimum level of lags for short-run adjustments for each time interval in the price series. Due to space constraints, we report the results for only the first 10 lags, 20^{th} lag, and 35^{th} lag.

At the same time, going by the standard procedure, initially, we have also tried to see the relationship of spot and futures by adding the difference in the log-transformed prices of futures (i.e. returns). The results are given in Table 5 and Table 6. It can be seen that the constant is almost zero for all variants as expected under the economic theory. Further, the residuals at lag-1 are close to zero but significant at the 5% in all time intervals, which implies that there is a little correction required in spot index to adjust to the long-run equilibrating values. This observation is substantiated by the fact that the optimum number of lags reduces with an increase in the time interval. As evident from Table 2, the beta coefficients showing long-run relationships in those ECM equations are significant in all time intervals. Further, it is noticeable that the coefficient values of return on futures [denoted as *D (LNFC)*] are increasing with an increase in the time interval. For example, in the case of 1 - minute observations, a 1% increase in the return on NIFTY 50 futures index results into on an average 0.85% increase on its spot return; while for 120-minutes interval, it results into on an average 0.96% increase. This result can be interpreted as : the short-run relationship between the futures and the spot is getting stronger with an increase in the time interval. The error term that represents the lagged value of the residuals [denoted as *RES*(*−1*)] shows that the speed of adjustment increases with an increase in the interval. Of course, for time intervals of 1-minute to 30-minutes, it is very slow (i.e. the coefficients are ranging between –0.006 to –0.05) in case of 1-minute, 15-minutes, and 30-minutes based data. However, it increases in case of long interval based data for 60-minutes and 120-minutes data to –0.08 and –0.15, respectively. This again is equally obvious because the magnitude of mean reversion

Table 5. Error Correction Model for NIFTY 50 Returns at Lag 4 (As per Equation - 4)

	1 Minute	15 Minutes	30 Minutes	60 Minutes	120 Minutes
Time Interval	Coefficient (*t*-Stat)	Coefficient (*t*-Stat)	Coefficient (*t*-Stat)	Coefficient (*t*-Stat)	Coefficient (*t*-Stat)
C	0.000	0.000	0.000	0.000	0.000
	(0.0754)	(–0.1081)	(0.113)	(0.1096)	(0.109)
D(LNFC)	0.8501	0.9137	0.9346	0.9428	0.9491
	(877.781)*	(375.05)*	(334.68)*	(263.95)*	(202.47)*
D(LNFC(–1))	0.0567	0.0127	0.0159	0.0233	0.0241
	(58.555)*	(5.209)*	(5.696)*	(6.508)*	(5.14)*
D(LNFC(–2))	0.0015	0.0098	0.0133	0.0114	0.0191
	(1.5283)	(4.037)*	(4.769)*	(3.181)*	(4.08)*
D(LNFC(–3))	–0.0014	0.0043	0.0061	0.0077	0.0193
	(–1.4272)	(1.758)***	(2.18)**	(2.146)**	(4.115)*
D(LNFC(–4))	0.0008	0.0089	0.0051	0.0048	–0.0081
	(0.7965)	(3.642)*	(1.82)***	(1.355)	(–1.72)***
RES(–1)	–0.0055	–0.0326	–0.0468	–0.0803	–0.1417
	(–22.48)*	(–14.18)*	(–11.81)*	(–11.05)*	(–10.57)*
DW	2.49527	2.43446	2.31134	2.267409	2.23812
R^2	0.808106	0.920735	0.950322	0.959757	0.966047

Note. * indicates 1% level of significance.

** indicates 5% level of significance.

*** indicates 10% level of significance.

would be higher for higher time intervals. Further, it should be noted that all the coefficients of residuals are negative, which reveals that mostly downward adjustments take place in the short-run in the spot index. Further, it is noticeable that the results in case of other time intervals are consistent with the results observed in case of 1-minute interval based analysis [see Table 4 (up to lag-0) and Table 5 (up to lag-4)]. Against all their merits, this model has one very big demerit in the sense that Durbin – Watson value stands drastically above the ideal level of 2.00 ; thus, it renders the models less dependable. Therefore, we chose to work with eq. (4) and eq. (5) up to lag-35, where, as shown in Table 6 and Table 7, the results are equally satisfactory, and at the same time, the Durbin – Watson value comes very close to its optimum level of 2.00, suggesting that with this model, there are neither negative nor positive autocorrelations.

Table 6. Error Correction Model for Change in Log Transformed of NIFTY 50 Spot Index at Lag 35 (As per Equation - 4)

Error Correction Model			Nifty 50 Spot Explained by Futures and Lags		
	1 Minute	15 Minutes	30 Minutes	60 Minutes	120 Minutes
Time Interval	Coefficient (*t*-Stat)	Coefficient (*t*-Stat)	Coefficient (*t*-Stat)	Coefficient (*t*-Stat)	Coefficient (*t*-Stat)
C	0.000	0.000	0.000	0.000	0.0001
	(0.5393)	(0.8317)	(0.3191)	(0.403)	(0.3844)
D(LNSC(–1))	–0.1757	–0.1411	–0.2101	–0.1719	0.066
	(–31.6014)*	(–4.1331)*	(–3.3813)*	(–1.6706)***	(0.3682)
D(LNSC(–2))	–0.1172	–0.1397	–0.031	–0.0516	–0.1389
	(–20.1872)*	(–3.9645)*	(–0.4905)	(–0.4974)	(–0.7711)
D(LNSC(–3))	–0.089	–0.0343	–0.0166	0.0129	0.2379
	(–15.1728)*	(–0.9689)	(–0.263)	(0.1245)	(1.3244)
D(LNSC(–4))	–0.0478	–0.0176	–0.0509	–0.1104	0.2168
	(–8.1193)*	(–0.4972)	(–0.8056)	(–1.0663)	(1.21)
D(LNSC(–5))	–0.035	–0.0548	0.0075	0.0143	0.0987
	(–5.9406)*	(–1.5458)	(0.1184)	(0.1383)	(0.5526)
D(LNSC(–6))	–0.0405	–0.0585	0.0014	0.1774	0.2103
	(–6.8613)*	(–1.6505)***	(0.0228)	(1.7147)***	(1.1818)
D(LNSC(–7))	–0.0424	–0.0043	–0.0148	–0.0801	0.3429
	(–7.1795)*	(–0.1218)	(–0.2357)	(–0.776)	(1.9357)***
D(LNSC(–8))	–0.028	–0.0155	–0.0453	–0.0554	0.1722
	(–4.7416)*	(–0.4382)	(–0.7209)	(–0.5371)	(0.9753)
D(LNSC(–9))	–0.0364	0.0085	0.0451	0.036	0.2154
	(–6.158)*	(0.2398)	(0.7167)	(0.3498)	(1.2266)
D(LNSC(–10))	–0.0061	–0.0431	0.0104	–0.0828	0.1453
	(–1.0242)	(–1.2161)	(0.1659)	(–0.8065)	(0.8322)
D(LNSC(–20))	–0.0066	0.0072	–0.0651	0.0054	0.2287
	(–1.1189)	(0.204)	(–1.0411)	(0.0535)	(1.3903)
D(LNSC(–35))	–0.0166	0.0163	–0.0035	–0.0572	0.0118
	(–3.0206)*	(0.4893)	(–0.0598)	(–0.6127)	(0.0822)
D(LNFC(–1))	0.2004	0.1718	0.2262	0.171	–0.0374

	(38.1421)*	(5.2817)*	(3.7898)*	(1.7211)***	(–0.2137)
D(LNFC(–2))	0.1084	0.1425	0.0578	0.0649	0.2112
	(19.5699)*	(4.243)*	(0.9522)	(0.6466)	(1.1976)
D(LNFC(–3))	0.0813	0.0482	0.0089	0.032	–0.2091
	(14.513)*	(1.4253)	(0.146)	(0.3191)	(–1.1884)
D(LNFC(–4))	0.0426	0.0272	0.0332	0.1095	–0.2374
	(7.5796)*	(0.8043)	(0.545)	(1.0911)	(–1.353)
D(LNFC(–5))	0.0369	0.0569	0.0293	0.0362	–0.0263
	(6.558)*	(1.6801)***	(0.4823)	(0.3606)	(–0.1506)
D(LNFC(–6))	0.0358	0.0685	0.0135	–0.1604	–0.2563
	(6.3487)*	(2.0223)**	(0.2229)	(–1.6005)	(–1.4723)
D(LNFC(–7))	0.0376	–0.0103	0.0164	0.0913	–0.3608
	(6.6669)*	(–0.3035)	(0.2706)	(0.9127)	(–2.0795)**
D(LNFC(–8))	0.0246	0.0101	0.0369	0.0402	–0.1363
	(4.355)*	(0.2996)	(0.6087)	(0.4026)	(–0.7879)
D(LNFC(–9))	0.0363	–0.0162	–0.0234	–0.0185	–0.2215
	(6.4381)*	(–0.4786)	(–0.3871)	(–0.1853)	(–1.2881)
D(LNFC(–10))	0.0004	0.044	0.0112	0.0817	–0.1596
	(0.0663)	(1.301)	(0.1857)	(0.822)	(–0.9333)
D(LNFC(–20))	0.0091	0.0038	0.0455	0.006	–0.2447
	(1.6063)	(0.1117)	(0.7567)	(0.0616)	(–1.527)
D(LNFC(–35))	0.0164	–0.0149	0.0216	0.0455	–0.0353
	(3.113)*	(–0.4689)	(0.3775)	(0.5035)	(–0.2524)
RES(–1)	–0.0012	–0.0005	–0.0131	–0.012	–0.1479
	(–2.046)**	(–0.0527)	(–0.6026)	(–0.2339)	(–1.2161)
DW	2.000136	1.99971	1.999502	1.999855	1.998285
R^2	0.010254	0.011623	0.016007	0.025439	0.067965

Note. * indicates 1% level of significance.

** indicates 5% level of significance.

*** indicates 10% level of significance.

While using eqs. (4) and (5), comparing the results obtained for different time intervals at 5% alpha, we find that there are lags in case of shorter time intervals to the order of 1 lag for 30-minutes interval, 2 lags for 15-minutes interval, and 35 lags in 1-minute interval. However, we do not find a single lag in cases of 60 and 120-minutes intervals because the entire short-run adjustment had taken place before reaching to 60 minutes and so on to 120 minutes. Therefore, though we conducted the analysis even for as many as 100 lags (not reported here), getting insights from these results finally makes us settled down at 35 lags. Specifically, as reported in Table 6, at 35 lags in case of spot, the estimate of α_s (–0.0012) is very small and close to 0, and it is significant at the 5% level. This implies that there is very little correction required in the spot index to adjust to the long-run equilibrium value as a large part of the adjustment takes place in the first 9 minutes. Of course, it takes as much as 35 minutes to completely adjust. Since the value of α_s coefficient is negative, it indicates that whatever correction takes place in spot market in the short-run is a downward adjustment. As far as the adjustments in the futures prices are concerned, as found in Table 7, almost all required adjustments take place in the first 5 minutes. However, some

Table 7. Error Correction Model for Change in Log Transformed of NIFTY 50 Futures Index at Lag 35 (As per Equation - 5)

Error Correction Model	Nifty 50 Future Explained by Spot and Lags				
	1 Minute	15 Minutes	30 Minutes	60 Minutes	120 Minutes
Time Interval	Coefficient (*t*-Stat)	Coefficient (*t*-Stat)	Coefficient (*t*-Stat)	Coefficient (*t*-Stat)	Coefficient (*t*-Stat)
C	0	0	0	0	0.0001
	(0.5735)	(0.8478)	(0.2985)	(0.3735)	(0.3517)
D(LNSC(–1))	0.1409	0.1275	–0.0239	–0.0122	0.2459
	(23.9234)*	(3.5527)*	(–0.3689)	(–0.1138)	(1.3251)
D(LNSC(–2))	0.0372	–0.0409	0.0391	0.0013	–0.0697
	(6.0549)*	(–1.1032)	(0.593)	(0.0117)	(–0.3736)
D(LNSC(–3))	0.0002	0.0211	0.0186	0.0562	0.2489
	(0.035)	(0.5668)	(0.2812)	(0.5207)	(1.3377)
D(LNSC(–4))	0.0176	0.0197	–0.0274	–0.0938	0.2991
	(2.8286)*	(0.5283)	(–0.4153)	(–0.8701)	(1.6116)
D(LNSC(–5))	0.0186	–0.0313	0.0331	0.0047	0.1441
	(2.9846)*	(–0.8404)	(0.5026)	(0.0441)	(0.7783)
D(LNSC(–6))	0.0042	–0.0427	0.0242	0.1549	0.2191
	(0.6643)	(–1.1456)	(0.3667)	(1.4384)	(1.1887)
D(LNSC(–7))	–0.0041	0.019	–0.0008	–0.0542	0.4035
	(–0.657)	(0.5094)	(–0.0122)	(–0.5041)	(2.1988)**
D(LNSC(–8))	0.0064	–0.0027	–0.0307	–0.0404	0.2201
	(1.0257)	(–0.0714)	(–0.4671)	(–0.3759)	(1.2033)
D(LNSC(–9))	–0.0053	0.0216	0.0725	0.058	0.1944
	(–0.8417)	(0.5797)	(1.1048)	(0.5414)	(1.0689)
D(LNSC(–10))	0.0241	–0.0327	0.0042	–0.0873	0.1735
	(3.8392)*	(–0.8791)	(0.0641)	(–0.8169)	(0.9593)
D(LNSC(–20))	0.0017	0.014	–0.0684	0.0148	0.2827
	(0.2724)	(0.3787)	(–1.0473)	(0.1412)	(1.659)***
D(LNSC(–35))	–0.0157	0.0197	–0.0083	–0.0351	0.0203
	(–2.704)*	(0.564)	(–0.1343)	(–0.3612)	(0.1368)
D(LNFC(–1))	–0.1305	–0.0853	0.0365	–0.0022	–0.2346
	(–23.451)*	(–2.495)**	(0.5863)	(–0.0212)	(–1.2939)
D(LNFC(–2))	–0.0454	0.0374	–0.0238	–0.0005	0.1245
	(–7.739)*	(1.0584)	(–0.375)	(–0.0044)	(0.6816)
D(LNFC(–3))	–0.0045	–0.0116	–0.0349	–0.0174	–0.2436
	(–0.7565)	(–0.3261)	(–0.5488)	(–0.1661)	(–1.3367)
D(LNFC(–4))	–0.0211	–0.0192	0.001	0.0862	–0.3126
	(–3.5423)*	(–0.539)	(0.0164)	(0.8251)	(–1.720)***
D(LNFC(–5))	–0.0126	0.0258	–0.0008	0.0357	–0.0714
	(–2.106)**	(0.7244)	(–0.0127)	(0.342)	(–0.3942)
D(LNFC(–6))	–0.003	0.0417	–0.0101	–0.1561	–0.2689

	(–0.5004)	(1.1704)	(–0.1591)	(–1.4964)	(–1.4907)
D(LNFC(–7))	0.0042 (0.7108)	–0.0345 (–0.9701)	–0.0032 (–0.0497)	0.072 (0.6921)	–0.4242 (–2.361)**
D(LNFC(–8))	–0.0073 (–1.2292)	–0.0079 (–0.2219)	0.0219 (0.3455)	0.0277 (0.2661)	–0.1836 (–1.0245)
D(LNFC(–9))	0.0075 (1.2589)	–0.0348 (–0.9788)	–0.0542 (–0.8563)	–0.0421 (–0.4064)	–0.1991 (–1.1177)
D(LNFC(–10))	–0.0279 (–4.668)*	0.0306 (0.8586)	0.0144 (0.227)	0.0905 (0.8742)	–0.1898 (–1.0715)
D(LNFC(–20))	–0.0001 (–0.017)	–0.0013 (–0.0375)	0.0473 (0.7517)	–0.0071 (–0.0697)	–0.2933 (–1.767)***
D(LNFC(–35))	0.0149 (2.6761)*	–0.0207 (–0.6202)	0.0219 (0.366)	0.0215 (0.2284)	–0.0457 (–0.316)
RES(–1)	0.0015 (2.467)**	0.0206 (2.1241)**	0.0209 (0.9229)	0.0532 (0.997)	–0.0562 (–0.4463)
DW	2.000133	2.000133	1.999734	2.000266	1.998606
R^2	0.004259	0.009466	0.012589	0.022575	0.064748

Note. * indicates 1% level of significance.

** indicates 5% level of significance.

*** indicates 10% level of significance.

minor short term adjustments take place up to lag 15. This implies that there would be spillover effect in the first 15-minutes time intervals. Of course, the complete adjustment takes place in 35 minutes.

Discussion and Conclusion

We have opted for conducting the inquiry as per the standard theoretical framework, but with a rigorous approach of data analysis by way of examining different time intervals for the short-run speed of adjustments. The results across all the five time frequencies clearly show that the two price series are not only integrated, but are also in an equilibrium state where the futures price influences the spot price to the extent of about 99%. This is consistent with the findings of the majority of studies across the globe (for example, see Abhyankar, 1995 ; Herbst et al., 1987 ; Gwilym & Buckle, 2001; Inani, 2017 ; Fassas & Siriopoulos, 2019). However, as far as the efficiency of futures market in India is concerned, there have been mixed findings so far. Against that, our results unequivocally prove an excellent state of long-run efficiency in the case of NIFTY 50 Index Futures in the near month. We think that the key lies in the depth of the futures market, evident in its trade volumes due to its leverage effect as well as low transaction cost.

As far as the lead-lag relationship is concerned, we find that the futures segment of the market leads the price discovery. Our results are consistent with the majority of the studies (for example, Bhatia, 2007 ; Debashish & Mishra, 2008). However, Mukherjee and Mishra (2006) found that the spot led the futures.

As far as the speed of adjustments is concerned, ECM analysis shows that the large part of short-run price adjustments takes place in the first 9 minutes. Of course, it takes about 35 minutes for complete adjustments. Our finding on the speed of adjustment is again encouraging when compared to the findings of similar previous studies in India that documented up to 55 minutes (for example, Gupta & Singh, 2009). We think that the reason behind reduction in the adjustment time can be attributed to large-scale adoption of high-frequency (i.e. algorithmic) trading coupled with increased volume in the market in recent years.

Research Implications

As the market exhibits excellent long-run efficiency, no further interventions are required from the market regulator. However, as far as the short-run efficiency is concerned, the adjustment duration of 9 – 35 minutes can be considered as offering good opportunities to arbitrageurs for making risk-free profits by exploiting imbalances in the spot and futures prices. Further, such an opportunity would become still more attractive in the case of mid and far months as the market liquidity in those time segments is supposed to be lesser than that in the near month. It is reasonable to expect that if such arbitrage actions are carried out, the short-run efficiency of the market may eventually increase, which may be manifested in the reduction of the adjustment period.

Limitations of the Study and the Way Forward

We have examined the efficiency of NIFTY 50 futures based on only the near month data. So, similar studies can be conducted for mid and far months. Particularly, the speed of short-run adjustments is a positive function of the level of market liquidity. Therefore, our findings should not be generalized for futures contracts for mid and far months as these time segments do not exhibit the same level of market liquidity. The same argument also applies to other indices as well as individual stocks as they do not enjoy the same level of liquidity as the NIFTY 50 futures does. Therefore, these aspects offer the potential for future research in India.

Our study also offers an opportunity to researchers to simulate a day trading strategy involving going long on futures and short on spot when an upward trend in futures is building up over a period of 2 – 3 minutes. If the trend is downward, then opposite positions should be taken. Since our study shows that it takes 9 – 35 minutes for restoring the equilibrium between the two price series, the positions should be squared off in the next block of time ranging between 6 – 32 minutes. The practitioners may also examine its implications in real-life situations.

The high-frequency data used in this work are a priced product of NSE's DotEx International. The data came in zipped file format, which had more than 10 layers of zipping. Therefore, it was a daunting task to download minute-by-minute data for the two-year period and then arrange the same in usable form. That took us a lot of time to complete our project and bring out this paper. With high-frequency data, this seems to be probably a common reason for delayed publication of many such studies that use relatively a longer period data.

Authors' Contribution

Deepak Danak conceived the research problem and developed the analytical framework. Nikunj Patel conducted the data analysis. Both of the authors discussed the results and contributed to the final manuscript.

Conflict of Interest

The authors certify that they have no affiliation with or involvement in any organization or entity with any financial interest or non-financial interest in the subject matter or materials discussed in this manuscript.

Funding Acknowledgment

This research paper is an outcome of a Minor Research Project funded by Nirma University, Ahmedabad, Gujarat (India). The authors are thankful to the University for providing financial support.

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Appendix

The following abbreviations are used in the tables.

LNSC	Log transformed NIFTY Spot close.
LNFC	Log transformed NIFTY Futures close.
RES	Residuals
D(*LNSC*)	Difference Log transformed NIFTY Spot close.
D(*LNFC*)	Difference Log transformed NIFTY Futures close.
DW	Durbin – Watson statistic

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