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Informational leadership of rubber futures market in India: exploration using data with different temporalities

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Abstract The informational efficiency of a commodity futures market is critical in determining resource allocation; an unbiased futures market that leads in information assimilation is considered efficient. Using the daily and monthly forecast series data on rubber futures trading, the informational efficiency of the National Multi Commodity Exchange is investigated. The results obtained from the two datasets are contradictory because of 'pseudo price discovery' in the futures market. The futures price is found to be highly dependent on the prevailing spot price; therefore, forecasts of future spot prices should be based on the prevailing spot price.

Keywords Commodity futures, pricing efficiency, forecast interval

JEL classification G130, G140

The true value of an asset, including of a commodity, is arrived at in a dynamic setting. This process, which involves many factors on both the demand and supply sides, is termed price discovery. Price discovery is one of the primary functions of a futures market. The leverage and low transaction cost inherent in a futures market, along with the breadth of participation in such a market, is supposed to give it informational leadership; the price discovery function is derived from such leadership (Tse 1998). The recent literature considers the price discovery function of a futures market, or its informational efficiency, the primary indicator of its efficiency. Informational superiority—the relative sensitivity of prices to new and relevant information—justifies the existence of a futures market. Informational efficiency makes the convergence between spot and futures prices easy and natural, and hedging effective. The absence of informational efficiency creates the possibility of added price risk; without it, a futures market may be detrimental to the interest of hedgers.

Market efficiency—the ability of prices to convey information at different levels (Fama 1970)—can be weak, semi-strong, or strong. If all the information conveyed by past prices is contained in the prevailing market price, the market efficiency is weak. If all the public information regarding the future is embedded into the price, the efficiency of the market is semi-strong. If the price contains all the public and private information, the market efficiency is strong. A random walk is characterized by price changes which are independently and identically distributed with mean zero. If the price behaves like a random walk—the price changes unpredictably—the efficiency of the market is weak.

But prices do change completely unpredictably; the current price is the best available prediction of the next period's price; it is difficult to define semi-strong and strong forms of efficiency, as there is no consensus on what information should be considered public and private; and, therefore, empirically analysing these forms of efficiency is difficult. The easiest way to understand informational efficiency in the spot and futures markets is to check the lead–lag relationships between the prices, as is done through the vector error correction model (VECM) and the Granger 'causality' and price discovery share methods. All these techniques deal with weak market efficiency; only the price information is modelled, and all other fundamental information on demand and supply ignored.

An efficient futures market provides unbiased estimates of future spot prices a considerable time ahead of the actual spot transaction. That requires the informational efficiency of a commodity futures market to be analysed for quite a long forecast interval, say a month or two at least. Using daily data to analyse the pricing efficiency of a commodity futures market ignores the lag between decision-making and the actual occurrence of the transaction and undermines the significance of the forecast interval. In a financial market, the concept of forecast interval is not as important as it is in an agricultural commodity market where there is a time gap between planting and harvesting or a real storage cost between harvesting and final marketing. Unfortunately, most studies of the commodity futures market in India use daily data on spot and futures prices to analyse pricing efficiency (Ghosh 2009). An elementary investigation into informational efficiency in a futures market analyses whether the futures price is an unbiased estimate or forecast of the spot price at maturity, and it investigates which among the two price series, spot and futures, is weakly exogenous. To test the hypotheses, the basic model employed in the literature is the regression of cash prices on lagged observations of futures prices for the relevant contract month (Tomek and Gray 1970; Kofi 1973; Martin and Garcia 1981). If the price series is non-stationary, the method of ordinary regression using spot and futures prices can lead to spurious results (Elam and Dixon 1988; Brenner and Kroner 1995), as the conventional F test for market efficiency is invalid. Any attempt to make them stationary by differencing leads merely to the estimation of short-term relations; long-run relations are not captured. In the presence of random walk, researchers use co-integration analysis and error correction models developed by Engle and Granger (1987).

Generally, price series are non-stationary, and co-integration is seen in the case of spot and futures; therefore, most recent empirical studies utilize error correction models (Behera 2015; Haq and Rao 2014; Carter and Mohapatra 2008; Chopra and Bessler 2005; He and Holt 2004; McKenzie et al. 2002; Yang et al. 2001). With non-stationary prices, the co-integration theory (Engle and Granger 1987; Johansen 1988, 1991) provides a more comprehensive approach by considering the behaviour of futures and cash prices in the short and long run. A convenient representation of co-integrated behaviour that separates the short-term adjustment component from the long-term equilibrium component is the error correction model (Johansen 1988; Hendry 1995).

Following the convention of financial market studies, the pricing efficiency analysis of commodity futures markets often uses daily data. This is especially true of the literature on Indian commodity markets—many studies apply the VECM on daily data (Samal 2017; Aggarwal et al. 2014; Atma and Rao 2013). In the case of financial derivatives, it is normal to use daily data to technically analyse price discovery, and such analysis often uses time series techniques like VECM or more sophisticated measures like price discovery share, an extension of the VECM that uses residuals from the VECM as input. In a commodity market, the forecasting power is the most important indicator of pricing efficiency (Stein 1981). Criticizing the over-emphasis of pricing efficiency analysis on random walk or stochastic nature of futures prices, Stein (1981, 223) notes that 'there is a tenuous connection between the stochastic nature of speculative price and measures of economic welfare, but there is a direct connection between the forecast errors and economic welfare'. Most studies on commodity futures markets in the US allow for a considerable forecast interval; this interval makes the studies relevant and prevents them from being merely technical exercises (Figuerola-Ferretti and Gonzalo 2010; McKenzie et al. 2002). Using two datasets of different frequencies—unlike in the literature on Indian commodity markets—helps compare informational efficiency.

This study analyses the informational leadership of the rubber futures market in India by using both daily and monthly data series and comparing the results from these datasets. It provides an insight into the real cost of ignoring the forecast interval in analysing informational efficiency. Rubber futures contracts were actively traded at the National Multi Commodity Exchange of India[1] (NMCE), the first national-level commodity exchange of India, from 2003 to 2018 By considering time series techniques –VECM, Granger

[1] The NMCE merged with the Indian Commodity Exchange (ICEX, icexindia.com) in 2017.

causality, and price discovery share—this paper analyses whether the futures market for rubber in India has informational leadership or informational efficiency.

Data

The data source is the website of the NMCE, which provides extensive data on the daily spot and futures prices for the basis variety[2] for both individual contracts and combined nearby series. This analysis considers contracts that matured during the period from April 2003 to March 2018.

Rubber is a storable commodity; therefore, the selection of a forecast interval is a matter of convention and convenience. In Indian commodity futures exchanges, trading starts only four or five months before a contract matures. Beyond that period, trade volumes are very low; therefore, we avoid higher forecast intervals. The literature allows for a forecast interval, and we consider all the possible observations by including forecast intervals ranging from one month to four months and arrange spot and futures prices according to the forecast intervals.

For a contract that is to mature on 15 April,[3] for example, the closing futures price on 15 March forms the forecast for a one-month forecast interval. Similarly, the closing futures price on 15 February forms the forecast for two-month forecast interval and so on. This forms the monthly forecast series for the analysis. In addition, we model daily spot and futures prices to know the differences in results obtained using datasets with alternative frequencies. The daily data comprise daily spot and futures prices taken from the nearby series. A nearby series is formed by rolling over to the next immediate contract once a given contract expires. The website of the NMCE provides nearby daily data with the option for selecting the rollover day.

Analytical approach

Vector error correction model (VECM)

We use the concepts of unbiasedness and weak exogeneity to analyse informational efficiency in the context of the spot and futures markets for a commodity. An unbiased futures market makes over-estimations as frequently and intensively as it makes under-estimations of future spot prices, and both these cases occur randomly and unpredictably. The concept of weak exogeneity is related to leadership in bringing information. A weakly exogenous market or price has to make fewer corrections in its course over time to develop a long-term equilibrium relationship with the related market(s) or price(s). In the long run, therefore, a weakly exogenous market can be considered superior in assimilating information into prices. This paper uses the VECM to analyse both unbiasedness and weak exogeneity. The spot and futures prices were found to be integrated of order one and co-integrated for all the forecast intervals considered. Therefore, we estimate the VECM separately for different forecast intervals, and extend the VECM estimation to the daily series of spot and futures prices, as in this case also the spot and futures prices are co-integrated.

$$\Delta P_t = \delta_o + \sum A_i^* \Delta P_{t-i} + \alpha(\beta P_{t-1} + \beta_o) + e_t \qquad \ldots(1)$$

where Δ is a difference operator, P_t is a 2 × 1 vector of dependent variables (cash and futures prices), and Δ_0 is 2 × 1 vector of coefficients for intercept. Each A_i* represents a 2 × 2 matrix of coefficients on lagged differenced cash and futures prices. Co-integration relations are represented by the 2 × r matrices, α and β, where r denotes the number of co-integrating relations in the system. The coefficients of intercepts in the levels of cash and futures prices are represented by the 2 × 1 vector, β_0. Finally, e_t denotes a 2 × 1 vector of mutually orthogonal random price disturbances, assumed to be serially uncorrelated with zero mean and constant variance. The short-run dynamics of the system are governed by the matrix of lagged coefficients, A*. The coefficients in vectors α and β represent the long-run components of the model.

An unbiased futures market generates a co-integrating vector β of (1, –1) in Equation 1. The equation was estimated without a trend term. The hypothesis of unbiasedness has been tested formally as linear restriction tests by using χ^2-test statistic. For futures prices to be efficient and accurate predictors of cash prices, it is necessary that futures prices lead cash prices

[2] The basis variety of rubber futures contract at the NMCE is ribbed smoked sheet 4.

[3] At the NMCE, a contract for a month expires on the 15th of that month. If the 15th of that month is a holiday, the contract expires on the day immediately preceding it.

in the long run. To test this property, we turn to the statistical concept of weak exogeneity. A series is regarded as being weakly exogenous if it leads other series in the long run without being influenced by other series. The weakly exogenous series, therefore, can be used as a predictor or explanatory variable for explaining variations in the ‘non-exogenous’ series (Zapata and Rambaldi 1997; Yang et al. 2001). We can test the hypothesis of weak exogeneity by examining the error correction coefficients, α. If one of the series has a zero error correction coefficient—its corresponding element in α is insignificantly different from zero—the series is regarded as weakly exogenous and as the leader in terms of information assimilation.

Price discovery share

Two more recent methods of analysing price discovery are the information share (IS), given by Hasbrouck (1995), and the component share (CS), given by Gonzalo and Granger (1995). Both methods are built on the VECM, but they differ in approach. Gonzalo and Granger (1995) focus on the proportion of each market’s innovation that contributes to the common efficient price, while Hasbrouck (1995) focuses on the proportion of the variance in the common efficient price that can be attributed to individual markets. Both IS and CS are based on the innovations in the two markets and their contributions in discovering the price.

The IS has two estimates for each market; one shows the upper bound and the other the lower bound. The upper bound is obtained by placing the given market first in the VECM modelling and the lower bound by placing it second (for the derivation of the basic equations, see Figuerola-Ferretti and Gonzalo (2010)).The Akaike information criterion is used for selecting the optimum lag length for estimating the price discovery share. The price discovery share approach has been used only for the daily data as it requires a large number of observations, a condition which is not satisfied with the monthly forecast series (Aggarwal, Jain, and Thomas 2014). These measures serve the important purpose of substantiating the findings obtained from the VECM estimation.[4]

Granger ‘causality’ analysis

Another extensively used method for analysing the informational superiority of a futures or spot market is Granger ‘causality’ (Granger 1969). This technique is used to analyse the lead–lag pattern in time series econometrics. We apply this technique to know which of the two price series leads the other in initiating changes. We estimate two models, an unrestricted model and a restricted model. A simple F test is used to determine whether the added variable in the unrestricted model results in significantly smaller sum of squared residuals.

The unrestricted model: $\Delta S_t = \alpha + \beta\, \Delta \mathrm{f}_{t\text{-}1} + \gamma\Delta S_{t\text{-}1} + e_t$ …(2)

The restricted model: $\Delta S_t = \alpha + \gamma\Delta S_{t\text{-}1} + e_t$ …(3)

If by adding the change in futures price as an explanatory variable the sum of squared errors is significantly smaller than from the restricted model, we conclude that futures price changes lead spot price changes. A second set of equations is also estimated, but in these the change in futures price is the dependent variable and the change in spot price is the added independent variable in the unrestricted model. From these, we can test if spot price changes lead futures price changes.

Results and discussions

Rubber futures trade at the NMCE

The NMCE started rubber futures trading in India in 2003. The basis variety of rubber traded at NMCE is ribbed smoked sheet 4; the basis centre is Cochin, Kerala; and the contract size is one tonne. Trading has been a success in terms of volume and delivery; it was interrupted only for four monthly contracts in 2008 from September to December. Rubber futures trading failed at other exchanges, like the Multi Commdocity Exchange of India and the National Commodities and Derivatives Exchange, because the trade volumes were low. In fact, trading in rubber futures in India has been practically confined to the NMCE. Trade was almost continuous at the NMCE during the entire study period (2003–18). Also, the volume has been considerable, at an average of 81,700 tonne per contract (Figure 1).

Globally, the delivery of any commodity through futures exchange platform forms a very low proportion

[4] The IS and CS shares have been obtained through the pdshare tool in the ifrogs package developed for the statistical package R by the finance research group at the Indira Gandhi Institute of Development Research, Mumbai.

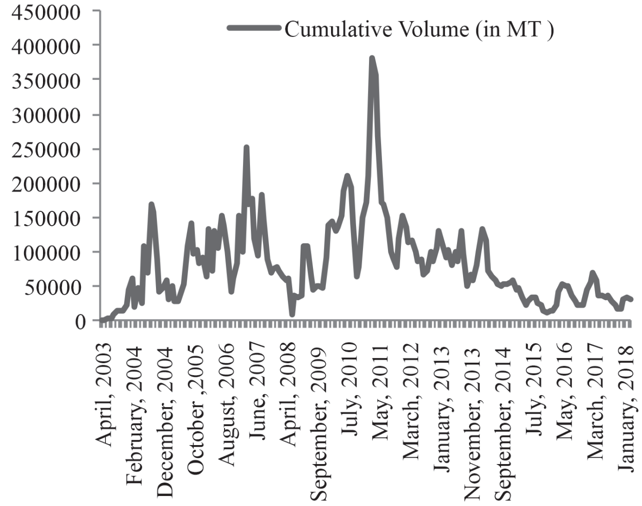

Figure 1 Contract-wise cumulative volume (in MT) of rubber futures trade at NMCE
***Source* NMCE website**

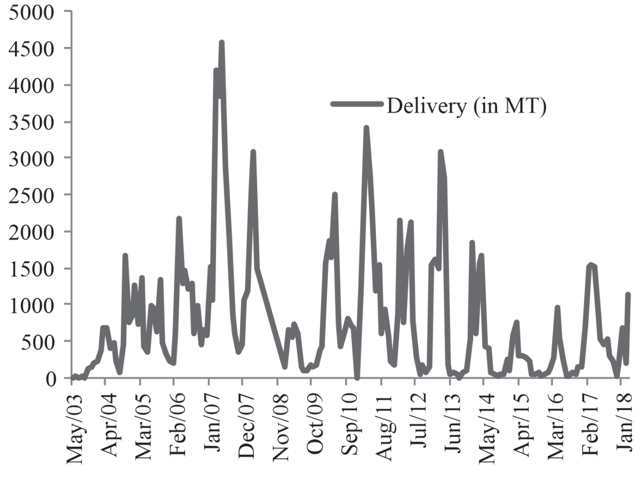

Figure 2 Contract-wise delivery (in MT) of rubber at NMCE
***Source* NMCE website**

of the total trade; the global average is only 2% of the trade volume. At the NMCE, the average delivery of rubber per contract was around 800 tonnes, the maximum being 4,583 tonnes for the May 2007 contract. On an average, only 1% of the total volume was delivered over the exchange platform at NMCE during the study period. Although it is just 50% of the global average of 2%, it is not very low in absolute terms (Figure 2).

Test for stationarity of rubber spot and futures prices

We conducted the Augmented Dickey–Fuller (ADF) test to know whether prices can be considered in an analysis of a long-run relationship between spot and futures prices. We used log-transformed series of both spot and futures prices. The Bayesian information criterion (BIC) has been used for lag selection. For the ADF test, the null hypothesis is that there is a unit root in the series or that the series is a random walk. The results of stationarity test are reported in Table 1.

The stationarity has been tested for each pair of spot and futures prices arranged according to the forecast interval from one to four months and for a daily series of spot and futures prices. From the ADF test, the unit root null hypothesis is not rejected for any of the price series. However, it is rejected at the first difference, leading to conclude that all series are integrated of order one. The spot and futures prices of rubber at the NMCE for all the forecast intervals show co-movement, which is an indication of the existence of co-integration (Figure 3). Figure 3(e) shows the daily spot and futures prices from the nearby series.

Co-integration analysis for rubber spot and futures prices

Since all the spot and futures prices are of order one, we require co-integration in each pair of spot and futures prices to establish a long-run relationship between these. In the absence of co-integration, a long-run time series analysis may lead to spurious conclusions. The results of co-integration are presented in Table 2. The Johansen test procedure has been used for the analysis, with the BIC for lag selection. From the Johansen procedure, we conclude that there is co-integration between the two series if we reject the hypothesis of 'no co-integrating vectors' (r=0) and at the same time the hypothesis of 'one co-integrating vector' (r=1) is not rejected.

From Table 2 we observe that for all forecast intervals there is strong co-integration between spot and futures prices at the NMCE, as the null hypothesis of no co-integration has been rejected, whereas the hypothesis in favour of co-integration has not been rejected. In addition to the monthly series, the nearby daily series of spot and futures prices are also co-integrated. As rubber is a storable commodity, the storage cost acts as a link between spot and futures prices and thus cannot drift apart for a considerable period of time. The storage theory states that at any point of time the

Table 1 Stationarity test results for rubber spot and futures prices at NMCE

Forecast interval	Series	Level/first difference	Trend specification	ADF test statistic	Order of integration
1 Month	Spot	Level	With trend	–1.098	I (1)
		First difference	Without trend	–7.471***	
	Futures	Level	With trend	–1.256	I (1)
		First difference	Without trend	–4.993***	
2 Months	Spot	Level	With trend	–1.451	I (1)
		First difference	Without trend	–11.118***	
	Futures	Level	With trend	–1.376	I (1)
		First difference	Without trend	–4.793***	
3 Months	Spot	Level	With trend	–1.489	I (1)
		First difference	Without trend	–15.119***	
	Futures	Level	With trend	–1.589	I (1)
		First difference	Without trend	–7.245***	
4 Months	Spot	Level	With trend	–1.361	I (1)
		First difference	Without trend	–11.900***	
	Futures	Level	With trend	–1.616	I (1)
		First difference	Without trend	–13.083***	
Daily series	Spot	Level	With trend	–1.705	I (1)
		First difference	Without trend	–33.266***	
	Futures	Level	With trend	–1.774	I (1)
		First difference	Without trend	–44.169***	

Source Estimated by the authors.
Note *** indicates the rejection of null hypothesis at 1% level of significance.

Table 2 Co-integration between spot and futures prices of rubber at NMCE

Forecast interval	Lags selected	No. of co-integrating vectors	Trace test statistic	'*P*' value for the trace statistic	Maximum Eigen value test statistic	'*P*' value for the maximum Eigen value
1 Month	1	0	119.94	0.00*	117.76	0.00*
		1	2.18	0.14#	2.18	0.14#
2 Months	2	0	98.17	0.00*	95.84	0.00*
		1	2.33	0.13#	2.33	0.13#
3 Months	3	0	83.91	0.00*	82.25	0.00*
		1	1.66	0.19#	1.66	0.19#
4 Months	1	0	32.15	0.00*	30.74	0.00*
		1	1.41	0.24#	1.41	0.24#
Daily series	3	0	324.83	0.00*	320.40	0.00*
		1	4.4233	0.68#	4.4233	0.68#

Source Estimated by the authors
Note *Indicates rejection of null hypothesis given in column 3 at 5% level of significance, # indicates failure to reject null hypothesis given in column 3 at 5% level of significance.

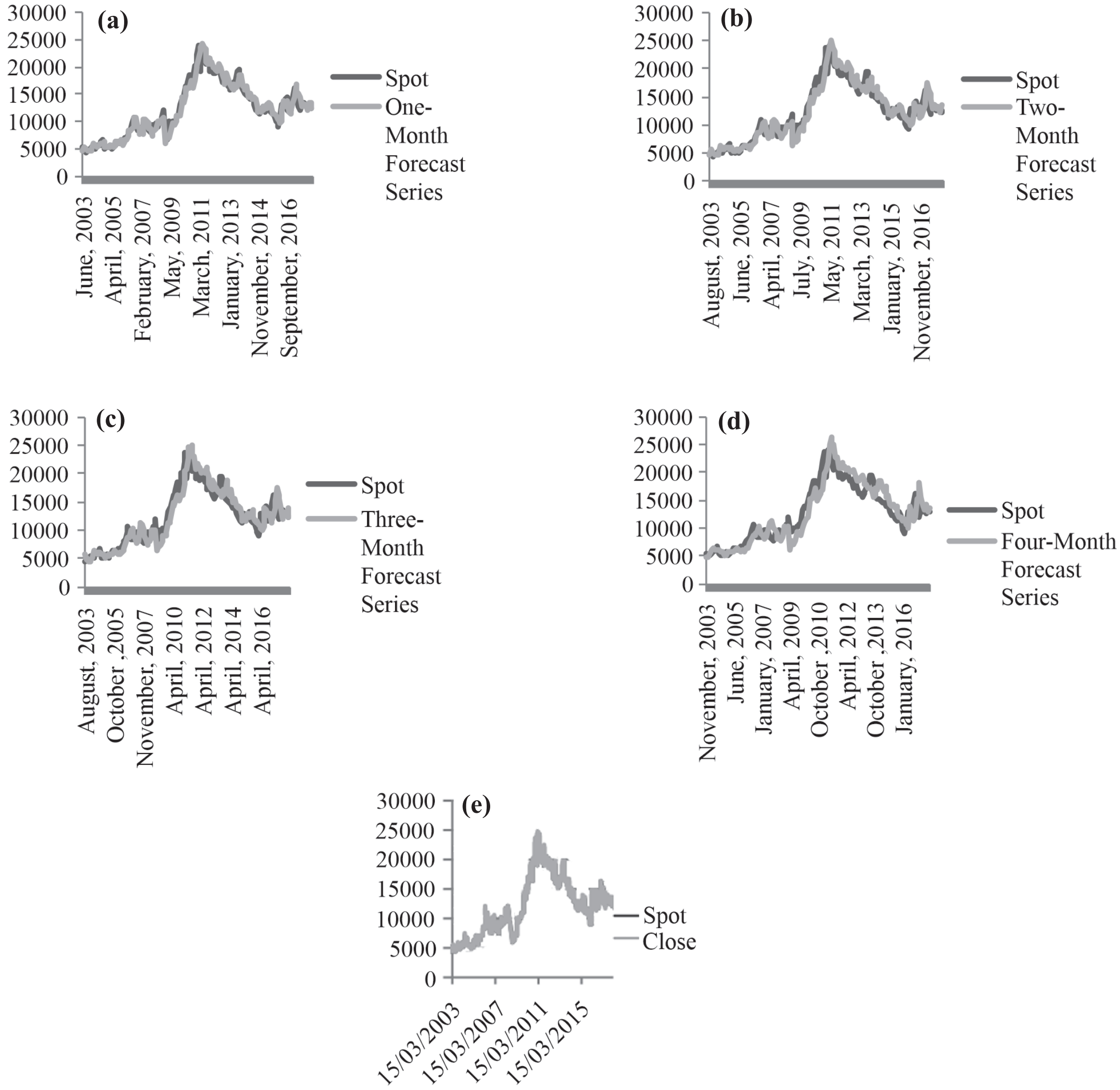

Figure 3 Spot and futures prices of rubber for different forecast intervals at NMCE
Source **NMCE website**

futures price would be spot prices plus the net cost of carriage of the commodity from the given day to the day of maturity. Any deviation from the storage equilibrium path will be corrected through arbitration and, for the same reason, such deviations cannot persist for long.

Unbiasedness and informational leadership of rubber futures market

The results of the VECMs for the forecast intervals from one to four months and for the daily series are reported in Table 3. The co-integrating vector is denoted as (β_S, β_F), where the first element represents the co-integration term for spot market and the second element for futures market. For an unbiased futures market, the value of co-integrating vector should be (1, –1). The hypothesis of unbiasedness has been tested using likelihood ratio (LR) test that uses χ^2-test statistics for joint restriction of $\beta_S = 1$ and $\beta_F = -1$.

In our case, the unbiasedness hypothesis could not be rejected for any of the forecast intervals from one month to four months at 5% level of significance. The error correction model using daily data of spot and futures prices of rubber gives a slightly different picture (Table 3). The LR test rejects the hypothesis of unbiasedness, that is, (β_F, β_S) = (1, –1). The concept of

Table 3 Error correction mechanism in rubber at NMCE

Coefficients	Forecast interval				
	1 Month	2 Months	3 Months	4 Months	Daily series
No. of observations	168	167	162	141	4,078
Lags based on BIC	4	3	5	2	4
Co-integrating vector (β_S, β_F)	(1, –0.996)	(1, –0.996)	(1, –1.019)	(1, –0.976)	(1, –1.008)
LR (χ^2) Test '*P*' Value for H_0: (β_S, β_F) = (1, –1)	0.779	0.884	0.568	0.592	0.000***
Spot error correction coefficient (α_S)	0.009	–0.074	–0.235**	0.001	–0.141***
Futures error correction coefficient (α_F)	–0.756***	–0.474***	–0.387***	–0.367***	0.067***
Autocorrelation (up to 12 lags)	Significant for lag 2	Nil	Significant for lags from 5 to 11	Significant for lag 1	Nil

Source Estimated by the authors.
Note ***Shows significance at 1% level, ** shows significance at 5%, * shows significance at 10%.

unbiasedness has practical implications in the context of the monthly forecast series and, therefore, is more important than in the context of the daily series. An analyst considering only a daily data series of spot and futures prices may conclude that the market is biased, although including the monthly forecast series would alter the picture entirely. Since the unbiasedness hypothesis is more relevant for spot and futures prices with a considerable forecast interval, we conclude that the rubber futures market is unbiased for practical purposes.

Further, we examine which market leads the other in incorporating price information by comparing the error correction terms from the VECM. For error correction to be meaningful, at least one of the error correction coefficients should be negative. We observe such a well-behaving error correction for all of the forecast intervals. The error correction term of the futures market is significantly different from zero for all of the monthly forecast series, while it is significant for the three-month forecast interval in the case of spot prices. In all the cases, the error correction term for the futures market is highly significant and takes a larger absolute numerical value than the spot error correction terms. This means that the futures price adjusts to the spot price for the co-integration to occur between the two prices. The conclusion is obvious: the spot market is weakly exogenous with less error correction, whereas the futures price corrects error for bringing long-run equilibrium.

With the daily series of spot and futures prices, the error correction terms are highly significant, and the error correction terms of the spot price are slightly stronger than of the futures price; this may be taken as an indication that futures prices lead spot prices. The spot and futures markets correct, respectively, 14% and 7% of their errors to revert to the co-integrating equilibrium path, whereas the futures market needs to correct only around 7% of its error to be back in co-integrating equilibrium. Thus, with daily data, we do not realize the contradictions in the results as the informational superiority of the futures market exists only for a very short time. In terms of information assimilation in the long run, the spot market leads the futures market.

Price discovery shares of spot and futures markets

The Hasbrouck IS and Gonzalo–Granger CS were calculated by using the nearby series data on spot and futures prices. The futures market clearly dominates over the spot market in price discovery (Table 4), and the result is invariant to the measures considered. Both the IS and the CS are larger for futures markets, with a clear margin over the spot market. Both the upper and lower bounds of the IS are greater for the futures market than for the spot market. The upper bound for the futures market is as high as 97% whereas for the spot market it is 73%. Similarly, the CS is 68% for the futures market and 32% for the spot market. Thus, the daily data unequivocally show the superiority of the futures market. These results for price discovery are similar to those obtained from the VECM using daily data, and that is not surprising as the shares have been derived from the residuals of the VECM.

Table 4 Price discovery shares for spot and futures markets of rubber at NMCE

Lag specification (in days)	Hasbrouck information share—lower and upper bounds (%)		Component share (%)	
	Spot	Futures	Spot	Futures
4*	3–73	27–97	32	68

Source Estimated by the authors.
Note *Lags fixed by Akaike information criterion.

Table 5 Granger 'causality' test results of spot and futures price changes for rubber at NMCE

Data series description	Null hypothesis				Nature of relationship
	Spot price change does not Granger cause futures price change		Futures price change does not Granger cause spot price change		
	P value	Decision	*P* value	Decision	
Nearby daily series	0.079	Do not reject	$<2.2e^{-16}$	Reject	Futures to spot
One-month forecast series	$5.773e^{-15}$	Reject	0.088	Do not reject	Spot to futures
Two-month forecast series	$3.512e^{-11}$	Reject	0.312	Do not reject	Spot to futures
Three-month forecast series	$1.345e^{-12}$	Reject	0.322	Do not reject	Spot to futures
Four-month forecast series	$1.051e^{-05}$	Reject	0.181	Do not reject	Spot to futures

Source Estimated by the authors.
Note 'Decisions' are based on 5% level of significance.

Granger 'causality' test of spot and futures price changes for rubber

In Table 5 we present results of the Granger 'causality' test. With monthly data series for forecast intervals of one to four months, the spot market has a clear edge in initiating a change. In all these four cases, the null hypothesis—a change in the spot price does not Granger 'cause' a change in the futures price—is rejected. In all these cases, the reverse null hypothesis—no causality exists from futures price change to spot price change—is not rejected. This confirms the contradictions in results obtained from the daily data and from the monthly forecast series. All the four monthly forecast series lead unequivocally to the conclusion that spot price changes lead futures price changes. Conversely, with the nearby series of daily data, the null hypothesis—a change in the futures price does not Granger 'cause' a change in the spot price—is rejected. That establishes the domination of the futures market in leading the spot market. At the same time, the reverse null hypothesis—a change in the spot price causes a change in the futures price—is not rejected. The daily data show that the market that leads the spot market in initiating price changes or in determining the direction of movement. This finding is in line with the results from the price discovery share analysis with daily data.

Further, we delved into the details of Granger 'causality' analysis using monthly forecast series by considering the details of vector auto regression (VAR) as part of doing the 'causality' test (Appendix tables A1–A4). By analysing alternative cases of changes in spot and futures prices as the dependent variable, we find that the futures price change in a given month is highly dependent on the spot price change for that month. For example, in the case of a two-month forecast interval, the futures price change has a high significant relation with spot price change lagged by two months. The VAR result shows that the spot price change lagged by two months, that is, spot price change in February is seen to be having a high stake in explaining futures price change in February. This feature is present for all the forecast intervals (shaded rows in Tables A1–A4). The impulse response functions (Appendix figures A1–A5) show that the impact of a shock in spot prices on futures prices lasts longer than the effect of a shock in futures prices on spot prices.

Figure 4 Monthly average price of rubber (in INR per 100 kg) 2003–18
***Source* NMCE website**

The VAR part of the 'causality' analysis further shows that most of the time, the futures price change depends on its own lagged values and the lagged values of spot price change for all of the forecast intervals. In this sense, spot price changes are more independent as we get a significant relation with lagged values much less frequently than futures price changes. This shows that spot prices are more efficient in weak form than futures prices. Finally, the R^2 of alternative VAR equations for all of the forecast intervals are very low when the dependent variable is the spot price change. When the dependent variable is futures price change, R^2 is very high and significant.

Using data of different temporalities leads to a contradiction in the results on the informational efficiency of the rubber futures market. One possible factor is 'pseudo-price discovery', when the futures market takes cues from spot price trends to arrive at estimation of future price. The futures market moves ahead of the spot market in deciding price directions even without any superior forecasting ability over the spot market. In reality, the spot price is taking an independent course in the long run, influenced by several demand and supply side factors, whereas the futures price is derived simply from the spot price without any allowance for the future state of affairs. This is what is unequivocally revealed to us through the daily forecast series, with which we found that futures market is biased, but it leads in information assimilation.

The daily data show that the futures market is biased and, at the same time, informationally efficient. An informationally efficient market can never be biased in the long run; thus, the daily data provide an ambiguous answer on informational efficiency. As the monthly data series eliminate influences in the very short run, its results can be cleaner than from the daily data series. The findings from the monthly forecast series regarding the unbiasedness property of futures prices even in the absence of any price leadership reveals the ingenuity of traders in basing their expectations on the spot price. This is partly due to the secular trends in spot price movements, which made expectations true most of the time. Spot prices were on the rise in the initial years of our study period; thereafter the trend started reversing (Figure 4). Even the new trend has shown consistency, making forecasting a somewhat easy job for futures market traders.

Conclusions

We studied the informational efficiency of rubber futures contracts traded at the NMCE using two alternative datasets, the first involving the monthly forecast series of spot and futures prices and the second the daily series of these prices. Efficiency has been defined in terms of unbiasedness and weak exogeneity. The unbiasedness property has been tested using the VECM, the weak exogeneity or informational leadership has been analysed using VECM, price discovery share, and Granger 'causality' techniques.

We found differences in the results of the two alternative datasets analysed. The analysis of monthly data leads to the conclusion that the futures market is unbiased, but not weakly exogenous, whereas the analysis of daily data says that the futures market is biased and it has informational efficiency. The probable reason is pseudo-price discovery, a scenario of price leadership by the futures market without any superior forecasting ability in the very short run. A spot market dealer who makes predictions of future spot price can rely on the prevailing spot price rather than turning to the futures market, as futures prices are found not to have any informational superiority over spot prices.

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Appendix

Table A1 VAR result for one-month forecast interval

Lagged price change	Estimate	Std. error	*t*-value	Pr (>|*t*|)
	Estimation results for spot price change (dspot) as the dependent variable			
constant	0.006701	0.006623	1.012	0.3133
Spot price change_1	–0.06754	0.087985	–0.768	0.4439
Futures price change_1	0.176029	0.099959	1.761	0.0802*
Spot price change_2	–0.20137	0.101777	“1.979	0.0497**
Futures price change_2	0.202218	0.114296	1.769	0.0788*
Spot price change_3	–0.26947	0.120433	–2.237	0.0267**
Futures price change_3	–0.08192	0.119212	–0.687	0.493
Spot price change_4	–0.02386	0.12105	–0.197	0.844
Futures price change_4	–0.00405	0.113489	–0.036	0.9716
Spot price change_5	–0.15098	0.113688	“1.328	0.1861
Futures price change_5	0.114723	0.096235	1.192	0.2351
Spot price change_6	0.023901	0.103574	0.231	0.8178
Futures price change_6	0.094696	0.080165	1.181	0.2393
	Degrees of freedom			153
	R^2			0.13
	Estimation results for futures price change (dclose) as the dependent variable			
constant	0.003916	0.005614	0.698	0.486455
Spot price change_1	0.578856	0.074576	7.762	1.11E–12***
Futures price change_1	–0.55952	0.084726	–6.604	6.23E–10***
Spot price change_2	0.587722	0.086266	6.813	2.06E–10***
Futures price change_2	–0.3888	0.096878	–4.013	9.35E–05***
Spot price change_3	0.354586	0.10208	3.474	0.000668***
Futures price change_3	–0.2843	0.101044	–2.814	0.005543***
Spot price change_4	0.325871	0.102602	3.176	0.001806***
Futures price change_4	–0.21509	0.096194	–2.236	0.0268**
Spot price change_5	0.169041	0.096363	1.754	0.081396*
Futures price change_5	–0.18814	0.081569	–2.307	0.022424**
Spot price change_6	0.212209	0.08779	2.417	0.016815**
Futures price change_6	–0.2326	0.067948	–3.423	0.000794***
	Degrees of freedom			153
	R^2			0.40

Notes ***Shows significance at 1% level, ** shows significance at 5%, * shows significance at 10%.

Table A2 VAR result for two-month forecast interval

Lagged price change	Estimate	Std. error	t-value	Pr (>|t|)
Estimation results for spot price change (dspot) as the dependent variable				
Constant	0.007046	0.007042	1.001	0.319
Spot price change_1	–0.12462	0.090918	–1.371	0.173
Futures price change_1	0.136042	0.108219	1.257	0.211
Spot price change_2	–0.11988	0.089112	–1.345	0.181
Futures price change_2	–0.11396	0.108424	–1.051	0.295
Spot price change_3	–0.10435	0.107301	–0.972	0.332
Futures price change_3	–0.01711	0.107108	–0.16	0.873
Spot price change_4	–0.05229	0.109131	–0.479	0.633
Futures price change_4	0.061687	0.101322	0.609	0.544
Spot price change_5	–0.08073	0.104796	–0.77	0.442
Futures price change_5	0.123878	0.085293	1.452	0.148
Spot price change_6	0.037062	0.101803	0.364	0.716
Futures price change_6	–0.04275	0.087793	–0.487	0.627
Degrees of freedom				151
R^2				0.09
Estimation results for futures price change (dclose) as the dependent variable				
Constant	0.004458	0.005777	0.772	0.44144
Spot price change_1	0.060827	0.074584	0.816	0.41604
Futures price change_1	–0.28562	0.088777	–3.217	0.00158***
Spot price change_2	0.534371	0.073102	7.31	1.45E–11***
Futures price change_2	–0.17257	0.088945	–1.94	0.05422*
Spot price change_3	0.367226	0.088024	4.172	5.08E–05***
Futures price change_3	–0.21725	0.087865	–2.473	0.01452**
Spot price change_4	0.186086	0.089525	2.079	0.03935**
Futures price change_4	–0.08317	0.083119	–1.001	0.3186
Spot price change_5	0.171379	0.085969	1.994	0.04801**
Futures price change_5	–0.19415	0.069969	–2.775	0.00622***
Spot price change_6	0.136372	0.083513	1.633	0.10457
Futures price change_6	–0.1911	0.07202	–2.653	0.00882***
Degrees of freedom				151
R^2				0.36

Note ***Shows significant at 1% level, ** shows significance at 5%, * shows significance at 10%.

Table A3 VAR result for three-month forecast interval

Lagged price change	Estimate	Std. error	*t*-value	Pr (>|*t*|)
Estimation results for spot price change (dspot) as the dependent variable				
Constant	0.006532	0.006754	0.967	0.335
Spot price change_1	–0.14311	0.088785	–1.612	0.109
Futures price change_1	–0.09813	0.101302	–0.969	0.334
Spot price change_2	0.009978	0.085243	0.117	0.907
Futures price change_2	–0.09382	0.085081	–1.103	0.272
Spot price change_3	–0.09784	0.085235	–1.148	0.253
Futures price change_3	0.111768	0.085745	1.303	0.194
Spot price change_4	0.042982	0.100023	0.43	0.668
Futures price change_4	0.068664	0.086418	0.795	0.428
Degrees of freedom				154
R^2				0.06
Estimation results for futures price change (dclose) as the dependent variable				
Constant	0.003333	0.005675	0.587	0.55789
Spot price change_1	–0.04553	0.074602	–0.61	0.54259
Futures price change_1	–0.15894	0.085119	–1.867	0.06377*
Spot price change_2	0.05516	0.071626	0.77	0.44241
Futures price change_2	0.102074	0.071489	1.428	0.15537
Spot price change_3	0.525753	0.071619	7.341	1.15E–11***
Futures price change_3	–0.11465	0.072048	–1.591	0.11359
Spot price change_4	0.337089	0.084044	4.011	9.41E–05***
Futures price change_4	–0.19094	0.072613	–2.63	0.00942***
Degrees of freedom				154
R^2				0.33

Note ***Shows significant at 1% level, ** shows significance at 5%, * shows significance at 10%.

Table A4 VAR result for four-month forecast interval

Lagged price change	Estimate	Std. error	t-value	Pr (>|t|)
Estimation results for spot price change (dspot) as the dependent variable				
Constant	0.005934	0.007084	0.838	0.4038
Spot price change_1	–0.03716	0.090682	–0.41	0.6827
Futures price change_1	–0.0254	0.083618	–0.304	0.7619
Spot price change_2	–0.09646	0.091082	–1.059	0.2917
Futures price change_2	0.130593	0.084263	1.55	0.1238
Spot price change_3	–0.11819	0.09372	–1.261	0.2097
Futures price change_3	0.217206	0.084299	2.577	0.0112**
Spot price change_4	0.001263	0.096308	0.013	0.9896
Futures price change_4	–0.02323	0.081968	–0.283	0.7774
Spot price change_5	–0.08262	0.097915	–0.844	0.4005
Futures price change_5	–0.09397	0.082368	–1.141	0.2562
Spot price change_6	0.039107	0.09427	0.415	0.679
Futures price change_6	–0.02406	0.08258	–0.291	0.7713
Spot price change_7	–0.07621	0.096093	–0.793	0.4293
Futures price change_7	0.035154	0.082515	0.426	0.6708
Degrees of freedom				121
R^2				0.12
Estimation results for futures price change (dclose) as the dependent variable				
Constant	0.002366	0.007371	0.321	0.74881
Spot price change_1	0.090175	0.094355	0.956	0.34113
Futures price change_1	–0.24817	0.087005	–2.852	0.0051***
Spot price change_2	0.278493	0.094771	2.939	0.00395***
Futures price change_2	–0.07725	0.087676	–0.881	0.38005
Spot price change_3	0.256999	0.097516	2.635	0.0095***
Futures price change_3	–0.13819	0.087714	–1.575	0.11776
Spot price change_4	0.453548	0.100209	4.526	1.42E–05***
Futures price change_4	–0.22785	0.085288	–2.671	0.00859***
Spot price change_5	0.141573	0.101881	1.39	0.1672
Futures price change_5	–0.22084	0.085704	–2.577	0.01118**
Spot price change_6	0.240596	0.098088	2.453	0.0156**
Futures price change_6	–0.04669	0.085925	–0.543	0.58784
Spot price change_7	0.328646	0.099985	3.287	0.00133***
Futures price change_7	–0.15461	0.085857	–1.801	0.07423*
Degrees of freedom				121
R^2				0.27

Notes ***Shows significant at 1% level, ** shows significance at 5%, * shows significance at 10%.

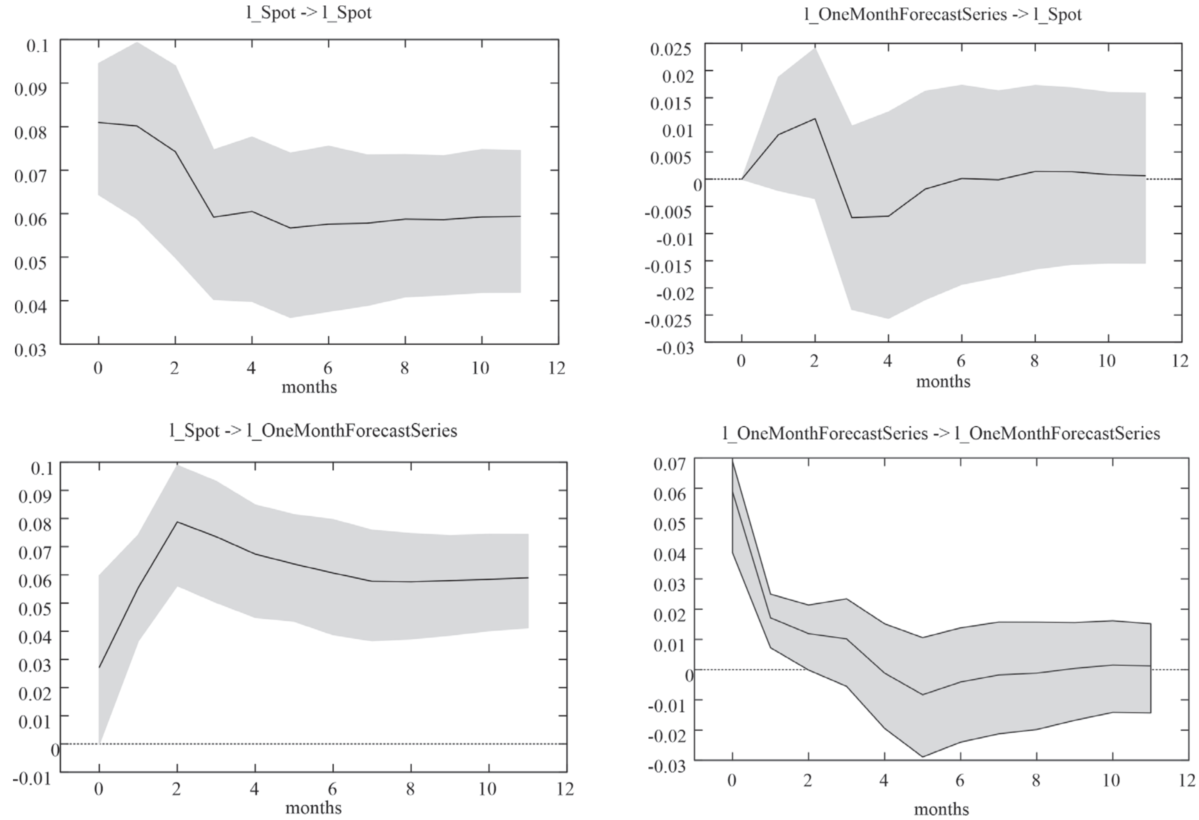

Figure A1 Impulse response function for one-month forecast interval

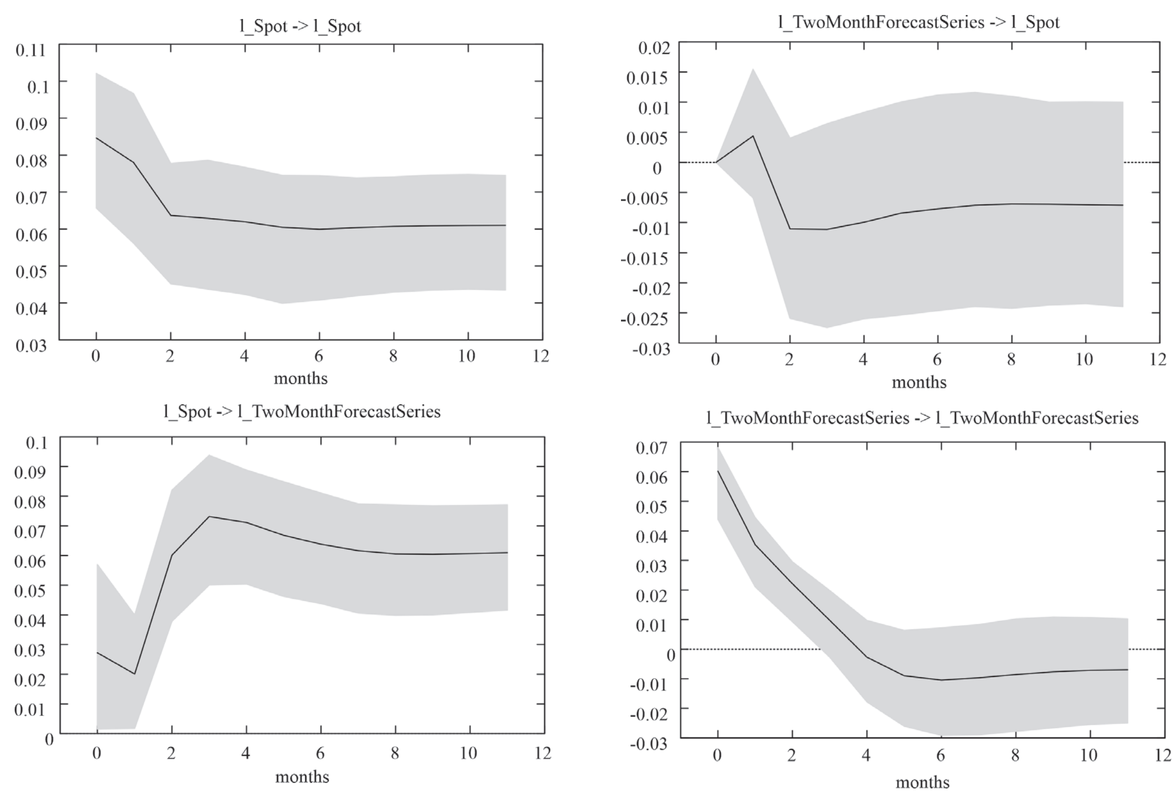

Figure A2 Impulse response function for two-month forecast interval

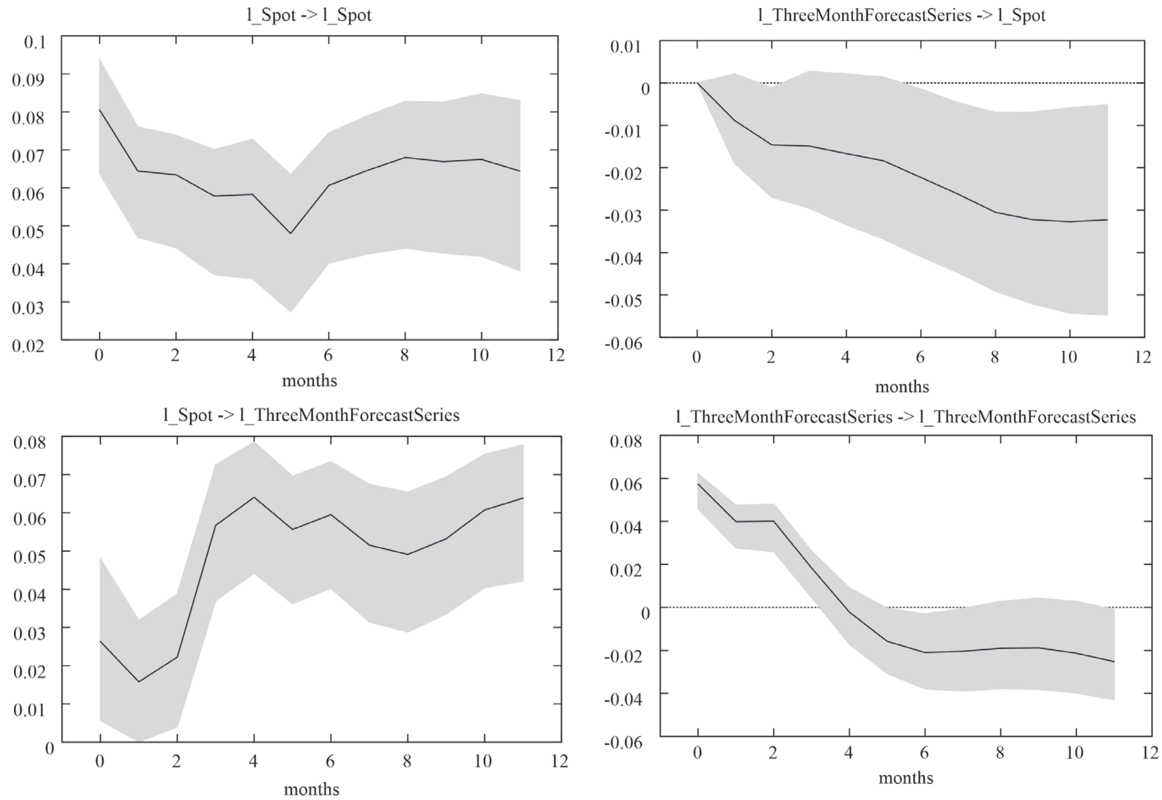

Figure A3 Impulse response function for three-month forecast interval

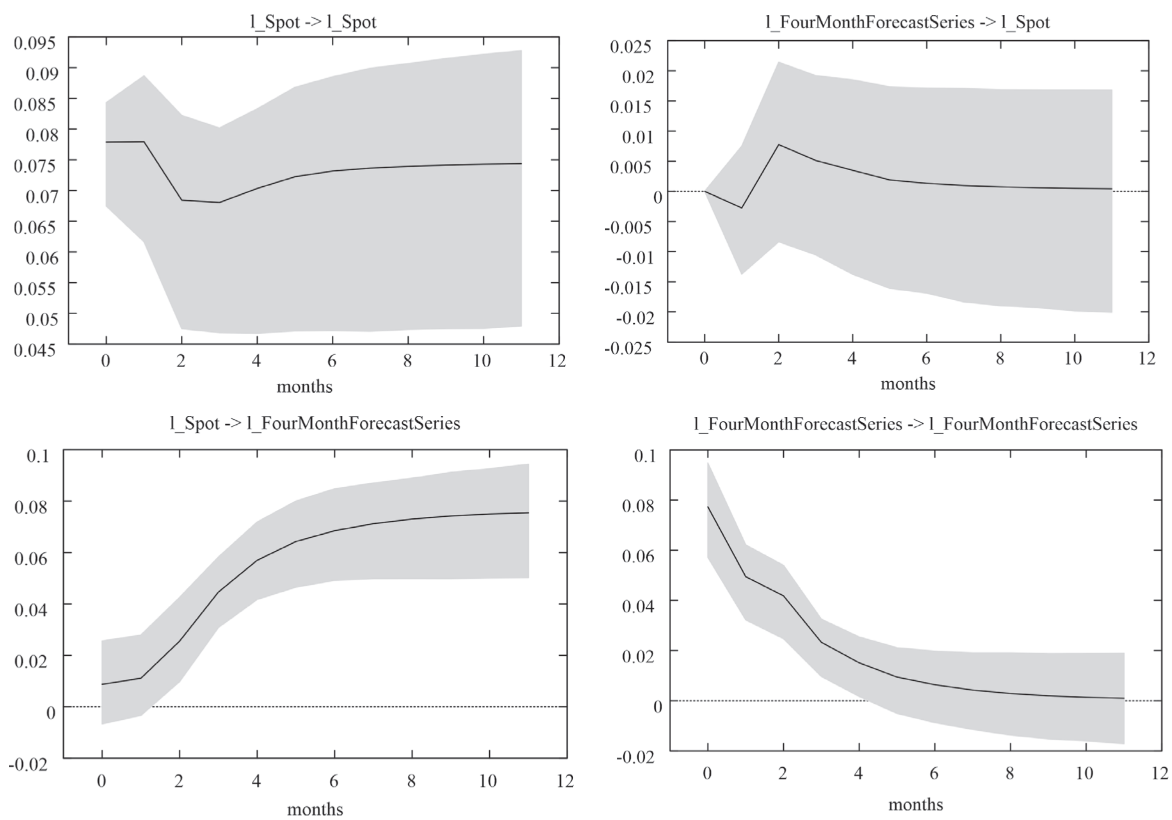

Figure A4 Impulse response function for four-month forecast interval

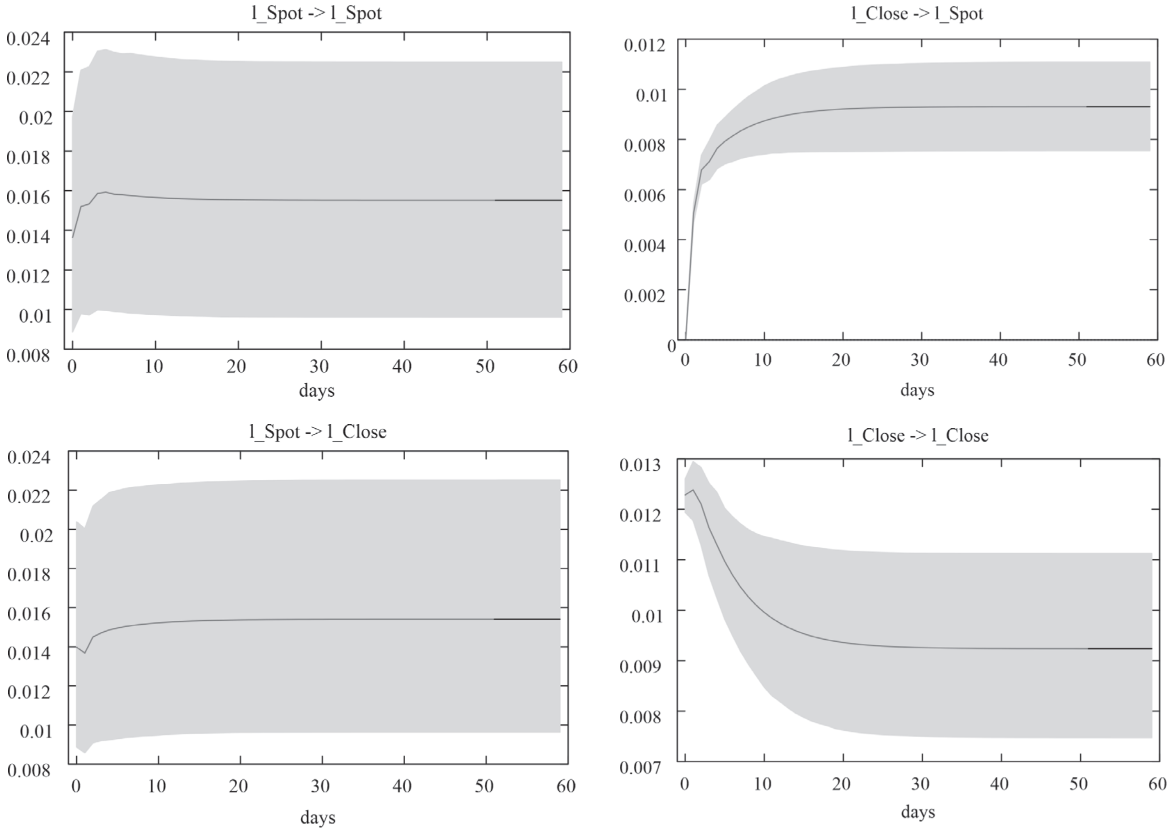

Figure A5 Impulse response function for daily spot and futures prices