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Crude oil futures to manage the price risk of natural rubber: Empirical evidence from India

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Abstract: The trading of natural rubber derivatives in the Indian commodity exchanges was banned several times in the past. Hence, in India, the derivatives on natural rubber are not traded actively and regularly. We have examined the possibility of a forecast model and a cross hedge tool for the natural rubber price by using crude oil futures in India. Results of the Johansen cointegration test proved that there is no cointegration equation in the model; hence, there is no scope to develop long-run models or error correction models. We have developed a vector autoregressive [VAR(2)] model to forecast the rubber price, and we examined the possibility of a cross hedge for natural rubber further by using the Pearson correlation coefficient and Granger causality test. We have extended our research to a structural VAR analysis to examine the effect of crude futures and exchange rate shocks on the natural rubber price. Our results showed that there is a short-term relationship between the crude oil futures price, the exchange rates of the US dollar to the Indian rupee, the Malaysian ringgit to the Indian rupee and the Thai baht to the Indian rupee; and the natural rubber price in India. The effort of policymakers to cause the Indian rupee to appreciate against the Thai baht and Malaysian ringgit may increase the natural rubber price in India. Natural rubber traders, growers and consumers can use crude futures to hedge the price risk. The Indian Rubber Board can suggest the VAR(2) model to predict the short-run price for natural rubber.

Keywords: cointegration; cross hedge; exchange rates; oil future; vector autoregressive model

India is the second largest consumer and fourth largest producer of natural rubber in the world. At present in India, there are two substitutes available for natural rubber – they are synthetic rubber and reclaimed rubber. Hawaldar et al. (2019) suggested that Indian customers associate the marked price with quality. Car tire makers in India are slowly switching to synthetic rubber, which is the final product of different petrochemical raw materials. However, there is still demand for rubber in India because of India's exports of natural rubber. In a recently released rubber policy report (GoI 2019), the officials of the Indian Ministry of Commerce and Industry stated that many macroeconomic factors influence the price of natural rubber in India because this commodity is traded in the international markets. Raju (2016) opined that the value of the Indian rupee (INR)

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in the foreign exchange market and the prices of crude and synthetic rubber are the major reasons for natural rubber price fluctuations in India. The demand-supply gap, rainfall and crude price show a positive relationship with natural rubber prices in the world market (Arunwarakorn et al. 2019). Using a generalised supremum augmented Dicky-Fuller methodology, Su et al. (2019) concluded that oil price, climatic imbalances, and exchange rates are the main cause of volatility in rubber prices. The volatile rubber price market adversely affects the performance of Indian rubber-based industries, rubber traders and rubber growers.

Nambiar and Balasubramanian (2016) opined that the volatile rubber price in India has resulted in the poor lifestyle of many rubber farmers and workers. An appropriate hedging tool and an appropriate forecast model may help different stakeholders in the rubber industry in India to manage price risk. However, to our knowledge, there is no study specifically using multivariate analysis with respect to natural rubber price risk management. Hence, this gap makes the following research agenda worthwhile. In this regard, an appropriate hedging tool and an appropriate forecast model may help different stakeholders in the Indian rubber industry to manage the price risk. With the help of econometric time series data analysis, we examined the possibility of a forecast model and a cross hedge tool for natural rubber prices in India. The crude oil futures price series and the exchange rates of the US dollar (USD) to the INR, the Malaysian ringgit (MYR) to the INR and the Thai baht (THB) to the INR are used to develop a multivariate vector autoregressive (VAR) model. An industry and trade summary on synthetic rubber from the United States International Trade Commission (Misurelli and Cantrell 1997) stated that synthetic rubber is made of three petrochemicals – namely, butadiene, styrene and acrylonitrile. Moreover, the price of crude oil was discussed in many academic studies as the price determinant for natural rubber. Furthermore, a lot of natural rubber is imported from Thailand and Malaysia. The authors of some of the studies already mentioned (Burger et al. 2002; Arunwarakorn et al. 2019) have stated that the exchange rate is also a natural rubber price determinant. Most international trade, including crude oil trade transactions, takes place in USD. Hence the crude oil futures price, USD_INR, THB_INR and MYR_INR series are taken as the influencing variables in the VAR model.

The VAR model is a bivariate or multivariate model popularly used in econometrics to develop forecasting models using more than one dependent variable (Brooks 2008). The predictions made using VAR give better results compared with those obtained with ordinary least squares (OLS) and other univariate time series models because the VAR model is not just using its lags; it also uses combinations of white noise terms (Sims 1972). A post-VAR estimation Granger causality test will be performed to check whether y_1 cause y_2 or y_2 cause y_1 (y_1 and y_2 are two return series; this test simply addresses the correlation between variables $y_1 \wedge y_2$ (Brooks 2008). This empirical study provides the most suitable bivariate VAR model used to predict the price of natural rubber in India. With the help of Pearson correlation and Granger causality tests, we also examine the feasibility of a cross hedge tool for the natural rubber commodity by using crude oil futures in India.

Literature review. Raju (2016) highlighted the fact that in the past two decades, natural rubber prices have exhibited a high level of volatility. Moreover, the factors that generated this significant instability of natural rubber prices are the collapse of the oil price and the decrease in synthetic rubber prices. Datta et al. (2019) investigated relevant aspects of the process of production and the productivity of natural rubber in Tripura, which is the second largest producer of natural rubber in India. These researchers concluded that not only the production and productivity but also the profitability and sustainability of natural rubber plantations are highly correlated with the quality of selected planting materials. Zwart and Blandford (1989) investigated the nexus between international price stability and domestic agricultural policies and argued that increasing volatility is a major concern for agricultural producers.

According to Joseph et al. (2018), there has long been the preconceived opinion that natural resource wealth retards economic growth, whereas the innovation system approach reveals that it does not affect a growing and diversified economy. Tran (2020) found that the risks associated with rubber production include the following categories: natural disasters, price fluctuations, the instability of the legislative framework, widespread illness, disease and epidemics, farming techniques, and quantifiable damages affecting the rubber industry. Goh et al. (2016) suggested that rubber price volatility is an important risk that affects producers, consumers, traders and others, so accurately predicting rubber prices would significantly contribute to the decision-making process.

Various univariate and multivariate time series models are used worldwide to develop appropriate forecast models. A good number of studies (Lekshmi 1996; Pareed and Kumaran 2017; Khin et al. 2019) have ap-

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peared so far to identify the price determinants of natural rubber, and efforts are also made to develop forecast models for natural rubber prices in Malaysia, China and the world market. Using the OLS method, Kannan (2013) stated that, in India, export quantity, inventory levels and domestic prices are the determinants of natural rubber production. Tulasombat et al. (2015), Arunwarakorn et al. (2019) and Burger et al. (2002) used the regression method in their studies and stated that the exchange rate is the key determinant for rubber price and export quantity of rubber in Thailand, Indonesia and Malaysia. Zahari et al. (2017) used the Box--Jenkins methodology to develop an appropriate price forecast model for natural rubber in Malaysia.

Some researchers have conducted empirical studies. For example, Khin et al. (2019) used a vector error correction model (VECM) methodology and concluded that the crude oil price, exchange rates and Shanghai natural rubber price showed a significant correlation with the natural rubber price in Malaysia. Some researchers in the Indian context also mentioned that crude oil price is the major price determinant for natural rubber. Since the Second World War, the cost of crude has been fluctuating in the market, so the price of natural rubber has also been volatile. In India, the price of natural rubber is not stable, and the reasons for this volatility are crude oil prices, synthetic rubber prices and global consumption (Lekshmi 1996; Pareed and Kumaran 2017).

Khin et al. (2019) used a VECM to study the consumption patterns of natural rubber and stated that the exchange rate of the importing countries is the major determinant of consumption. The VAR model is used in other streams of finance and management as well. For example, Gatarek and Johansen (2014) used the cointegrated VAR model to compute the optimal hedge ratio for a portfolio, and their results revealed that the causality was high in the short run compared with that in the long run. Moreover, Hossain et al. (2015) used the Granger causality test to develop a forecast model for different indices of the Dhaka Stock Exchange and to find the causality between different microvariables and the Dhaka Stock Exchange price. Kumar (2017) conducted an empirical study based on the Granger causality test and VAR model to understand the lead-lag relationship between the gross domestic product and foreign tourist arrivals in India and stated that the gross domestic product caused the foreign tourist arrivals and not *vice versa*.

Nkcubeko Nomsobo and Roscoe van Wyk (2018) and Citak (2018) conducted empirical studies based on VAR models to examine the effect of short-term interest rates on bank funding costs in South Africa and to investigate the relationship between the exchange rate and tourism trade in Turkey, respectively. Pablo and Arias (2019) used VAR and VECM methodology to investigate the relationship between the consumer price index and the producer price index for six countries in South America and concluded that causality exists between the consumer price index and the producer price index in the economies of Peru and Paraguay. Su et al. (2019) used time-varying parameter VAR with stochastic volatility to understand the effect of the US factors on the oil market. Su et al. (2019) investigated the causalities between oil and agricultural commodity prices and concluded that time-varying positive bidirectional causality exists between oil and agricultural prices over certain sub-periods. Charfeddine and Kahia (2019) used a panel VAR model to examine the effect of financial development and renewable energy consumption on economic growth and carbon dioxide emissions. Barbaglia et al. (2020) used a threshold VAR (*t*-VAR) model to examine the volatility spillovers between energy and agricultural commodities.

MATERIAL AND METHODS

We collected daily closing prices of natural rubber for this multivariate time series analysis for the sample period starting from 2nd January 2012 to 18th December 2019 (Natural Rubber Price in India 2020). Natural rubber price data were available only from 2012, which necessitated the sample period used in the study. Data on crude oil futures were collected for nearest to maturity dates for each contract during the study period from Crude Oil Futures (2020). The data on the exchange rates of the USD, MYR and THB with the INR were collected from Exchange Rates (2020). We used the VLOOKUP function in Microsoft Excel 2007, adjusted the data and eliminated a few missing observations.

The initial research on forecasting was performed using a linear regression model. Multiple regression models were used in many studies when multiple dependent variables were available. VAR methodology resembles the multiple regression models. However, in the VAR model, all the variables are treated as endogenous variables, and there are no exogenous variables. The value of each endogenous variable is the function of its own lagged values and the past values of all other endogenous variables in the VAR system.

The basic requirement for any time series analysis is that the series must be stationary to avoid useless predictions or spurious regressions. The line plot of the series will give an initial clue regarding the stationar-

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ity of the data series. Nevertheless, using some formal method of hypothesis testing is advised to confirm the stationarity of the series. The augmented Dickey-Fuller unit root test is widely used by researchers to check the stationarity of financial time series (Brooks 2008; Gujarati et al. 2009). Once both the series used in the model are stationary with first-order differencing, it is necessary to conduct a formal cointegration test to check the long-run effect of each endogenous variable on the endogenous variable of interest. If the cointegration test proves the presence of cointegration, then the VECM has to be used (Mills and Patterson 2009). We used the Johansen cointegration test, and the test proved that there was no long-term effect of crude futures on the price of natural rubber in India. Hence, error correction methodology was necessary, so we used VAR methodology.

We developed a multivariate VAR model; the endogenous variables in the model are the crude oil futures price, USD_INR, MYR_INR, THB_INR and natural rubber price. The following equations show the general form of the bivariate VAR model:

$$NR_t = \beta_{NR0} + \beta_{NR1} NR_{t-1} + \ldots + \beta_{NRk} NR_{t-k} + \\ + \infty_{NRk} CF_{t-1} + \ldots + \alpha_{NRk} CF_{t-k} + u_{NRt} \tag{1}$$

$$CF_t = \beta_{CF0} + \beta_{CF1} CF_{t-1} + \ldots + \beta_{CFk} CF_{t-k} + \\ + \infty_{CFk} NR_{t-1} + \ldots + \alpha_{CFk} NR_{t-k} + u_{CFt} \tag{2}$$

where: NR – natural rubber price, which is dependent on its own lagged values and the lagged values of the crude oil futures price (CF); u_{NRt} – white noise error term; CF – crude oil future price, which is dependent on its own lagged values and the lagged values of the natural rubber price (NR); u_{CFt} – white noise error term; t – time index; k – number of lags

The challenge was to decide on the optimal number of lags (k) for the model; taking higher-order lags than the optimal lag will result in increased forecast errors of the VAR, and selecting lower lags will produce autocorrelated errors (Hossain et al. 2015). Two methods proposed to decide on the lag length for the VAR are cross-equation restrictions and information criteria. However, the first method has some limitations, so many researchers have used the information criteria method to decide on the VAR lag length (Brooks 2008; Gujarati et al. 2009). Using the EViews 10 package, we ran the VAR with the default lag length, and post-estimation, we used the lag length criteria function under the lag structure option. These functions in EViews give the Akaike information criterion (AIC), Schwarz criterion (SC) and a few other information criteria to decide on the appropriate lag length. The Durbin-Watson statistic of the autocorrelation of residuals was estimated to verify the quality of the regression estimation. To find the effect of the crude oil futures price, USD_INR, MYR_INR and THB_INR shocks on the price of natural rubber in India, we processed the impulse response function graph.

Narayan et al. (2008) stated that the reduced form of the standard VAR will not allow investigators to impose short run or long run restrictions based on economic theory. Imposing only long-run restrictions is allowed in a VECM. The interest of the researcher is to impose restrictions based on economic theory, and that is possible only with structural vector autoregression (SVAR) (Brooks 2008). Hence, we extended our empirical analysis to develop an SVAR. Brooks (2008) stated that the VAR in the primitive form of Equations (1–2) can be written as follows:

$$Y_t = AY_{t-1} + \ldots + A_p Y_{t-p} + \psi D_t + \varepsilon_t \tag{3}$$

where: Y – $n \times 1$ vector of the endogenous variables mentioned in Equations (1–2); A and D – time invariant matrices; p – lag order of the model; ε_t– $n \times 1$ vector of the reduced form of white noise error terms in Equations (1–2).

Restricting the coefficient on the basis of economic theory requires that either α_{NRk} or α_{CFk} from Equations (1–2) has to be set to zero. Such a SVAR model is presented in the following form:

$$AY_t = A_1^* Y_{t-1} + \ldots + A_P^* Y_{t-p} + B_{\varepsilon t} \tag{4}$$

where: A – matrix of the contemporaneous terms of Equations (1–2) to model the relationships; B – matrix containing the structural parameters of the VAR model.

The SVAR model of this empirical study includes the natural rubber price, crude futures price, USD_INR, MYR_INR and THB_INR. Recursive structural VAR was considered with short-run restrictions. In academic research, the accumulated and the normal response to SVAR shocks are presented graphically (Narayan et al. 2008; Chaudhry et al. 2013).

We performed the Granger causality test and also estimated the Pearson correlation coefficient to examine the possibility of a cross hedge for the natural rubber price by using crude oil futures.

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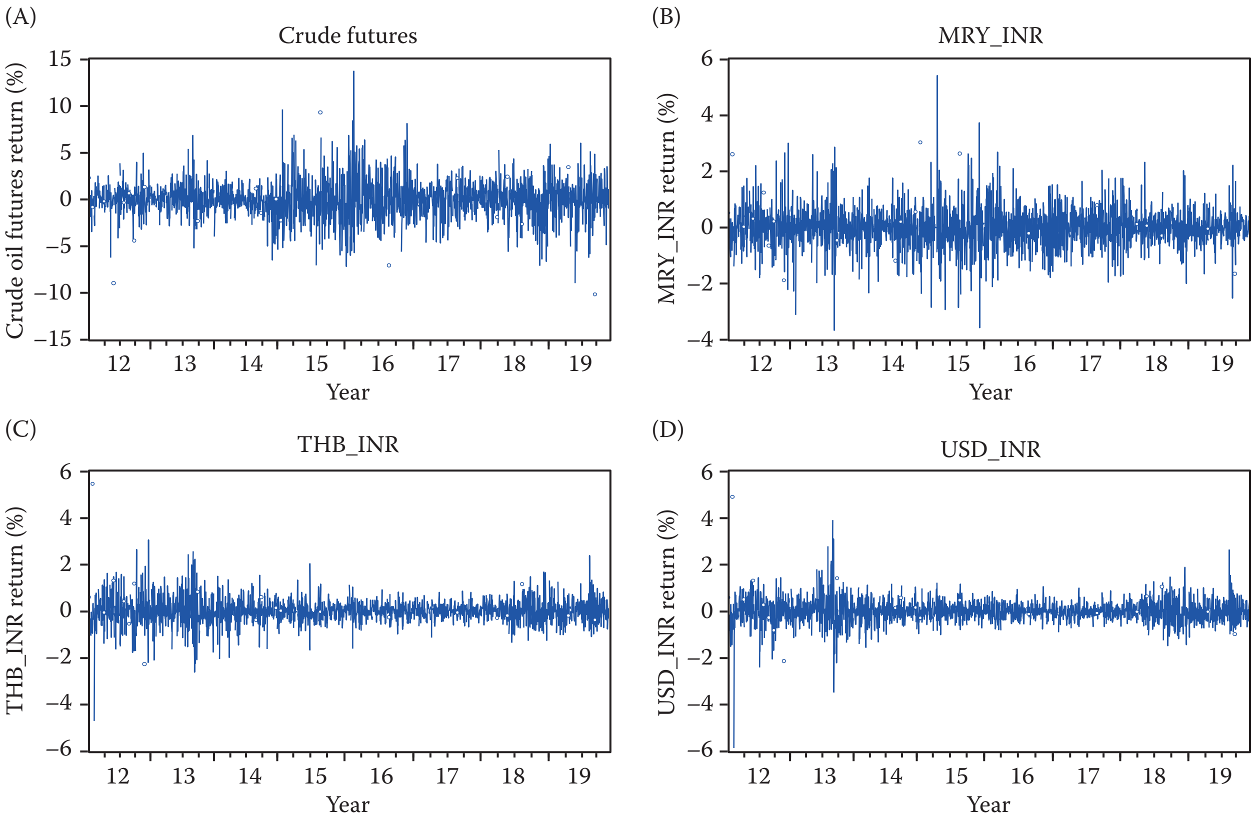
RESULTS AND DISCUSSION

First of all, we needed to make the series stationary to avoid spurious regression. Most financial and economic time series follow an upward trend and become stationary with a first-order difference. Figure 1 shows that all the selected series for the model, that is, rubber prices, crude oil futures, USD_INR, MYR_INR and THB_INR, were stationary after a first-order difference and did not follow any particular trend.

Table 1 presents the augmented Dickey-Fuller test results for the natural rubber price, crude oil futures price, USD_INR, MYR_INR and THB_INR series. All series in their level form are not stationary because the probability values in Panel A of Table 1 are greater than 0.05. In Panel B, the absolute critical values are less than the absolute *t*-statistic value and the probability values are less than 0.05 for all the return series. Hence, we can reject the null hypothesis and can confirm that the series are stationary after the first difference. The next step in VAR methodology is to select an appropriate lag length; for this, we used the EViews econometrics package.

Using the EViews 10 package, we estimated the VAR by taking a default lag length of 2, with the assumption that the optimal lag length is 2. Using post-estimation in EViews, we asked for lag length criteria by using the lag structure function under the view but-



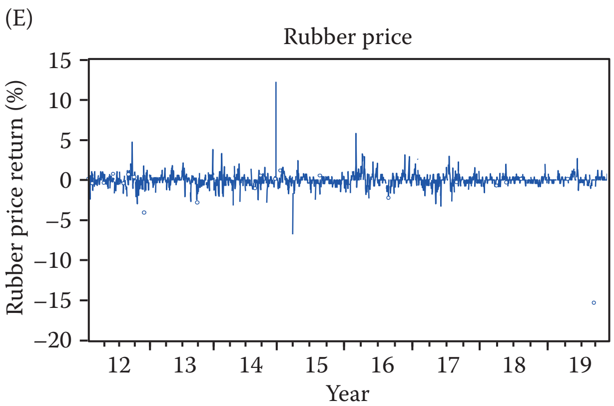


Figure 1. Line plot of 1st differenced (A) crude oil futures price series, (B) MRY_INR, (C) THB_INR, (D) USD_INR, and (E) natural rubber price series

USD_INR – United States Dollar/Indian Rupee exchange rate; THB_INR – Thai Baht/Indian Rupee exchange rate; MRY_INR – Malaysian Ringhit/Indian Rupee exchange rate

Source: Authors processing using Crude Oil Futures (2020), Exchange Rates (2020) and Natural Rubber Price in India (2020)

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Table 1. Augmented Dickey-Fuller test for the level and return series of natural rubber price, crude oil futures price, USD_INR, MRY_INR and THB_INR exchange rate

Augmented Dickey-Fuller test statistic		Crude futures		Rubber price		THB_INR		USD_INR		MRY_INR	
		t-statistic	prob.	*t*-statistic	prob.	*t*-statistic	prob.	*t*-statistic	prob.	*t*-statistic	prob.
Panel A: Level series		–1.609	0.478	–2.384	0.147	–0.253	0.929	–1.465	0.551	–1.529	0.519
Test critical values (level)	1%	–3.434	–	–3.434	–	–3.434	–	–3.434	–	–3.434	–
	5%	–2.863	–	–2.863	–	–2.863	–	–2.863	–	–2.863	–
	10%	–2.568	–	–2.568	–	–2.568	–	–2.568	–	–2.568	–
Panel B: Return series		–43.626	0.000	–30.406	0.0001	–36.839	0.000	–49.990	0.000	–37.498	0.000
Test critical values (level)	1%	–3.434	–	–3.434	–	–3.434	–	–3.434	–	–3.434	–
	5%	–2.863	–	–2.863	–	–2.863	–	–2.863	–	–2.863	–
	10%	–2.568	–	–2.568	–	–2.568	–	–2.568	–	–2.568	–

Null hypothesis: Series have a unit root; USD_INR – United States Dollar/Indian Rupee; THB_INR – Thai Baht/Indian Rupee; MRY_INR – Malaysian Ringhit/Indian Rupee; prob. – probability
Source: Authors' estimations using Crude Oil Futures (2020), Exchange Rates (2020) and Natural Rubber Price in India (2020)

ton (Brooks 2008). EViews provides various information criteria values to determine the optimal lag order. We extracted the popular information criteria values from the EViews output, and they are the AIC, SC, and Hannan-Quinn criterion (HQC).

Table 2. VAR lag order selection criteria

Lag	AIC	SC	HQ
0	–34.72	–34.71	–34.72
1	–35.09	–35.01*	–35.06
2	–35.13*	–34.97	–35.07*
3	–35.12	–34.88	–35.03
4	–35.11	–34.80	–34.99

*Lag order selected by the criterion; AIC – Akaike information criterion; SC – Schwarz criterion; HQ – Hannan Quinn
Source: Authors' estimations using Crude Oil Futures (2020), Exchange Rates (2020) and Natural Rubber Price in India (2020)

In Table 2, SC shows lag 1 as an appropriate lag; alternatively, AIC and HQC show second-order lag as an optimal lag. As both HQC and AIC identified lag 2 as the optimal lag, the majority are in favour of lag 2 compared with lag 1 on the basis of SC.

Table 3 shows the cointegration test results of the natural rubber price; the crude oil futures price; and the USD_INR, MYR_INR and THB_INR exchange rate series. There is not enough evidence to reject the null hypothesis that there is no cointegration equation. The *P*-values for both the trace and maximum Eigen value tests are greater than 0.05. The trace statistic, 44.337, is less than the critical value at 5%, and even the maximum eigenvalue statistic, 17.797, is less than its critical value at 5%; hence, from the Johansen cointegration test, we confirmed that there was no cointegration equation in this model. Hence, we proceeded with the estimation of the short-term VAR model and not the long-run error correction models.

Table 3. Johansen cointegration test estimates

Hypothesised No. of CE(s)	Unrestricted cointegration rank test (trace)			Unrestricted cointegration rank test (maximum Eigen value)		
	trace statistic	0.05 critical value	prob.	max. Eigen statistic	0.05 critical value	prob.
None	44.337	69.819	0.851	17.797	33.877	0.888
At most 1	26.540	47.856	0.871	13.550	27.584	0.852
At most 2	12.991	29.797	0.892	8.660	21.132	0.859
At most 3	4.330	15.495	0.875	4.213	14.265	0.836
At most 4	0.117	3.841	0.732	0.117	3.841	0.732

CE – cointegration equation; prob. – probability
Source: Authors' estimations using Crude Oil Futures (2020), Exchange Rates (2020) and Natural Rubber Price in India (2020)

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With this multivariate VAR system with lag length 2, we had five endogenous variables and lag length *k* (2). Hence, we have 5 × 2 + exogenous intercept $c = 1$ regressors for each equation in the system. In this multivariate VAR, there are five equations and a total of 55 estimates in the output. However, our interest is to examine whether a natural rubber price forecast is possible by using crude oil future prices and the USD_INR, MYR_INR and THB_INR exchange rates.

Table 4 provides the regression estimate coefficients with the standard error, *t*-statistics, and *P*-values with 95% confidence levels. A total of 55 coefficients is estimated; 23 of 55 were statistically significant with a 95% confidence level. Coefficients for the rubber price with other endogenous variables were extracted from the VAR and presented because other coefficients were beyond the scope of this study. The coefficients for the first lags of the rubber price with crude oil futures was 0.0281, and for both lags with the rubber price itself were 0.313 and 0.0671; all of these were significant with *P*-values of 0.0027, 0.0000, and 0.0039. The coefficients for the rubber price with other endogenous variables in the VAR system were not statistically significant. Therefore, these regression coefficients and significant coefficients of VAR estimates indicate that the price of natural rubber in India is dependent on crude oil future prices and that the price of natural rubber can be predicted by following crude oil price movements. It is also clear that the USD_INR, MYR_INR and THB_INR exchanges rates do not influence the price of natural rubber in India. The equation given by the VAR system to forecast the natural rubber price is shown as Equation (5). As Equation (5) contains both significant and non-significant coefficients, VAR equations with only significant equations are shown in Equation (6).

As usual, R^2 in the model summary table (Table 5) indicates the goodness of fit, and this value is 12.54%. In other words, these statistics indicate the proportion of variance in natural rubber price that can be explained by our coefficients. The Durbin-Watson statistic was used to test whether the residual series of the estimated model were serially correlated, and the test value, 2.002863, is equal to 2, which indicates that the residuals in the series are free from autocorrelation. The null hypothesis of the Lagrange multiplier (LM) test was that there is no autocorrelation in the VAR estimation residuals. The *P*-values of 0.485 and 0.077 in Table 5 are greater than 0.05, so the null hypothesis is accepted, which confirms that the residuals of the estimated VAR were not serially correlated. Hence, the estimated VAR model is a good fit, and this model may be used for the short-term prediction of the natural rubber price in India.

Table 4. VAR(2) regression estimations

Other variable	Rubber price	Prob.
Crude futures (–1)	0.0281 –0.0094 (2.99786)	0.0027
Crude futures (–2)	–0.0145 –0.0095 (–1.53200)	0.1256
MRY_INR (–1)	–0.0360 –0.0323 (–1.11697)	0.2640
MRY_INR (–2)	0.0070 –0.0322 (0.21570)	0.8292
Rubber price (–1)	0.3131 –0.0233 (13.41330)	0.0000
Rubber price (–2)	0.0671 –0.0233 (2.88406)	0.0039
THB_INR (–1)	–0.011 –0.053 (–0.20990)	0.8340
THB_INR (–2)	–0.051 –0.053 (–0.96708)	0.3340
USD_INR (–1)	0.049 –0.049 (1.00509)	0.3150
USD_INR (–2)	0.080 –0.049 (1.62967)	0.1030
C	0.000 0.000 (–0.70544)	0.4810

USD_INR – United States Dollar/Indian Rupee; THB_INR – Thai Baht/Indian Rupee; MRY_INR – Malaysian Ringhit/ Indian Rupee; Prob. – probability; *C* – intercept

Source: Authors' estimations using Crude Oil Futures (2020), Exchange Rates (2020) and Natural Rubber Price in India (2020)

Figure 2 shows the response of the natural rubber price to a unit shock in the crude oil futures price, USD_INR, MYR_INR and THB_INR. The blue line

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$$\begin{aligned} \textit{Rubber price} = {} & C(23)\times \textit{Crude futures}(-1) + C(24)\times \textit{Crude futures}(-2) + \\ & + C(25)\times MRY_{INR(-1)} + C(26)\times MRY_{INR(-2)} + C(27)\times \textit{Rubber price}(-1) + \\ & + C(28)\times \textit{Rubber price}(-2) + C(29)\times THB_{INR(-1)} + C(30)^{*} THB_{INR(-2)} + \\ & + C(31)\times USD_{INR(-1)} + C(32)\times USD_{INR(-2)} + C(33) \end{aligned} \tag{5}$$

$$\begin{aligned} \textit{Rubber price} = {} & C(23)\times \textit{Crude futures}(-1) + C(27)\times \textit{Rubber price}(-1) + \\ & + C(28)\times \textit{Rubber price}(-2) + C(33) \end{aligned} \tag{6}$$

Table 5. Fitness summary for our estimated equation

LM test						
Lag	LRE* statistic	*df*	prob.	Rao's *F*-statistic	*df*	prob.
1	24.60502	25	0.4847	0.984314	(25, 6 885.1)	0.4847
2	35.65228	25	0.0770	1.427399	(25, 6 885.1)	0.0770
R-squared			0.125356			
Adjusted *R*-squared			0.120658			
SE of regression			0.008126			
Durbin-Watson statistic			2.002863			
Mean dependent variable			–0.000205			
SD dependent variable			0.008666			
Sum squared residual			0.122952			

*Edgeworth expansion corrected likelihood ratio statistic; LM – Lagrange multiplier; LRE – likelihood ratio statistic; SE – standard error; prob. – probability

Source: Authors' estimations using Crude Oil Futures (2020), Exchange Rates (2020) and Natural Rubber Price in India (2020)

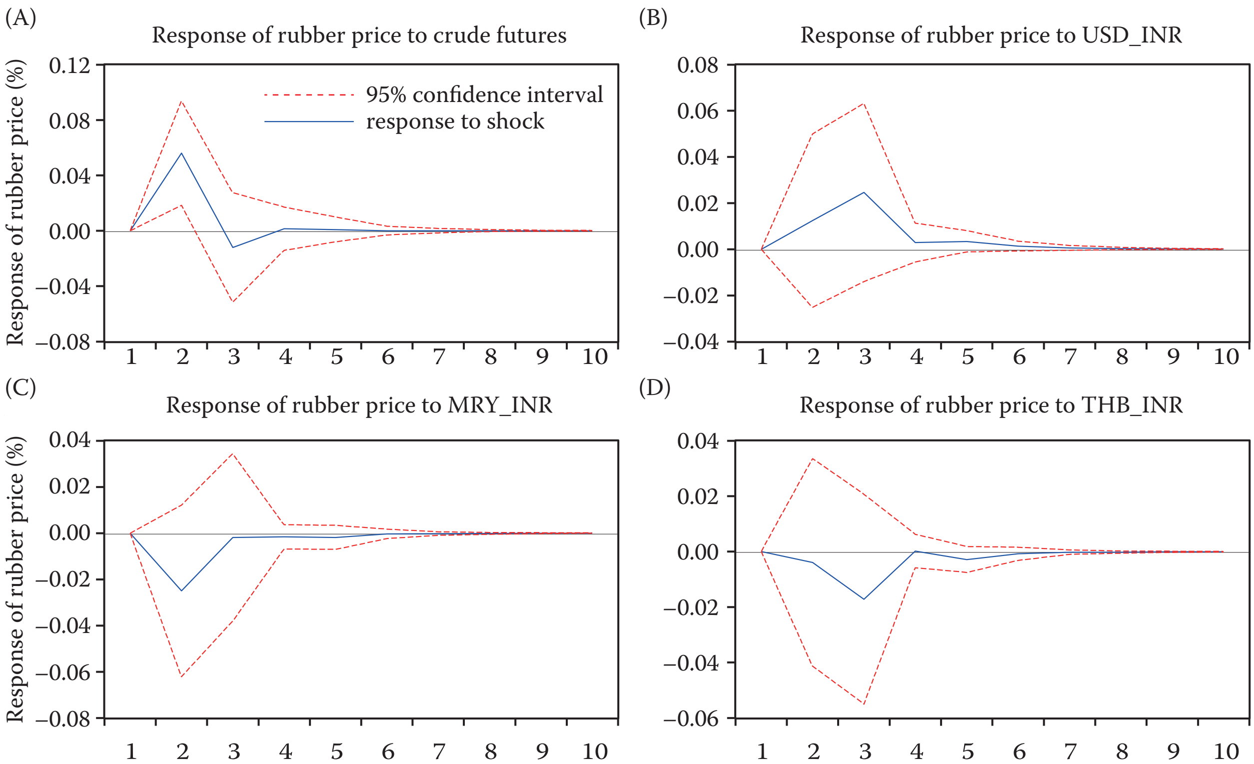

Figure 2. Impulse response of rubber price to (A) crude future, (B) USD_INR, (C) MRY_INR and (D) THB_INR shocks

USD_INR – United States Dollar/Indian Rupee exchange rate; THB_INR – Thai Baht/Indian Rupee exchange rate; MRY_INR – Malaysian Ringhit/Indian Rupee exchange rate

Source: Authors' processing using Crude Oil Futures (2020), Exchange Rates (2020) and Natural Rubber Price in India (2020)

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is the impulse response function, and the red lines are 95% confidence intervals; the general rule is that the impulse response function should always lie within the 95% confidence intervals. The responses to the crude futures price shock are positive and sharp at the beginning, increase and then sharply decrease further until they die off after the sixth lag. The response for the USD_INR shock is also positive, whereas the responses for MYR_INR and THB_INR are negative.

The impulse responses and accumulated responses to structural VAR shocks are plotted in Figure 3 and Figure 4, respectively. A positive crude futures shock would increase the natural rubber price in India. We found that a positive USD_INR disturbance would also increase the natural rubber price in India. However, even though India imports natural rubber from Malaysia and Thailand, the positive MYR_INR and THB_INR shocks would decrease the price of natural rubber in India.

Our second objective in this study was to examine the possibility of a cross hedge tool for natural rubber prices with crude oil futures. Correlation between the commodity price series and futures price series is a prerequisite for a cross hedge strategy (Hull 2015). Highly correlated commodity futures can be selected to cross hedge any particular underlying asset, and sometimes the choice becomes obvious (Chance 2000). Our VAR regression already proved that the crude futures price in India is one of the price determinants for the commodity of natural rubber. The Pearson correlation is widely used academically to examine the possibility of a cross hedge.

In Table 6, the Pearson correlation of the natural rubber price series with the crude futures price, USD_INR, MYR_INR and THB_INR series are given for both the price series and the return series. The rubber price is positively correlated with crude futures and the MYR_INR at *r*-values of 0.63 and 0.38, respectively. The correlation coefficient of natural rubber with USD_INR and THB_INR are negative, with *r*-values of –0.70 and –0.41, respectively. Furthermore, the Granger causality test results also support the argument that the crude oil futures price in India causes natural rubber prices with a *P*-value of 0.00.

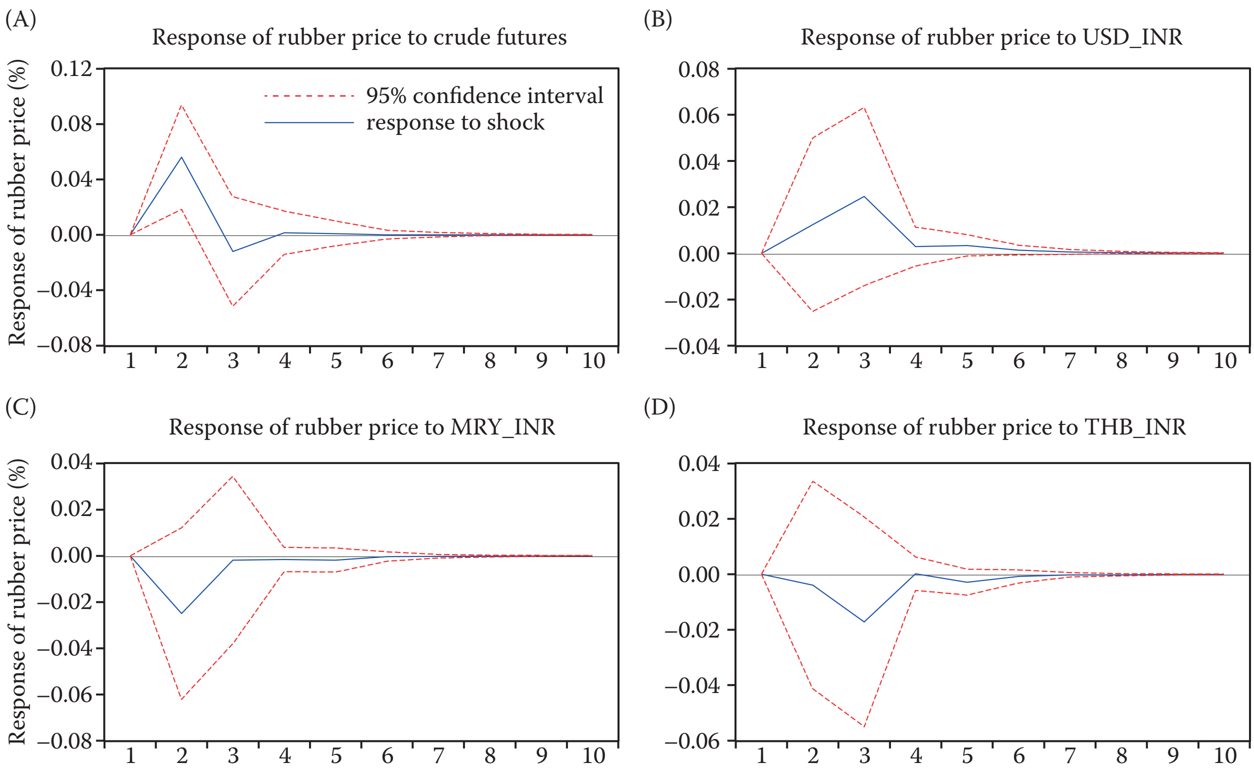

Figure 3. Impulse response of rubber price to (A) crude future, (B) USD_INR, (C) MRY_INR and (D) THB_INR structural VAR shocks

USD_INR – United States Dollar/Indian Rupee exchange rate; THB_INR – Thai Baht/Indian Rupee exchange rate; MRY_INR – Malaysian Ringhit/Indian Rupee exchange rate; VAR – vector autoregressive

Source: Authors' processing using Crude Oil Futures (2020), Exchange Rates (2020) and Natural Rubber Price in India (2020)

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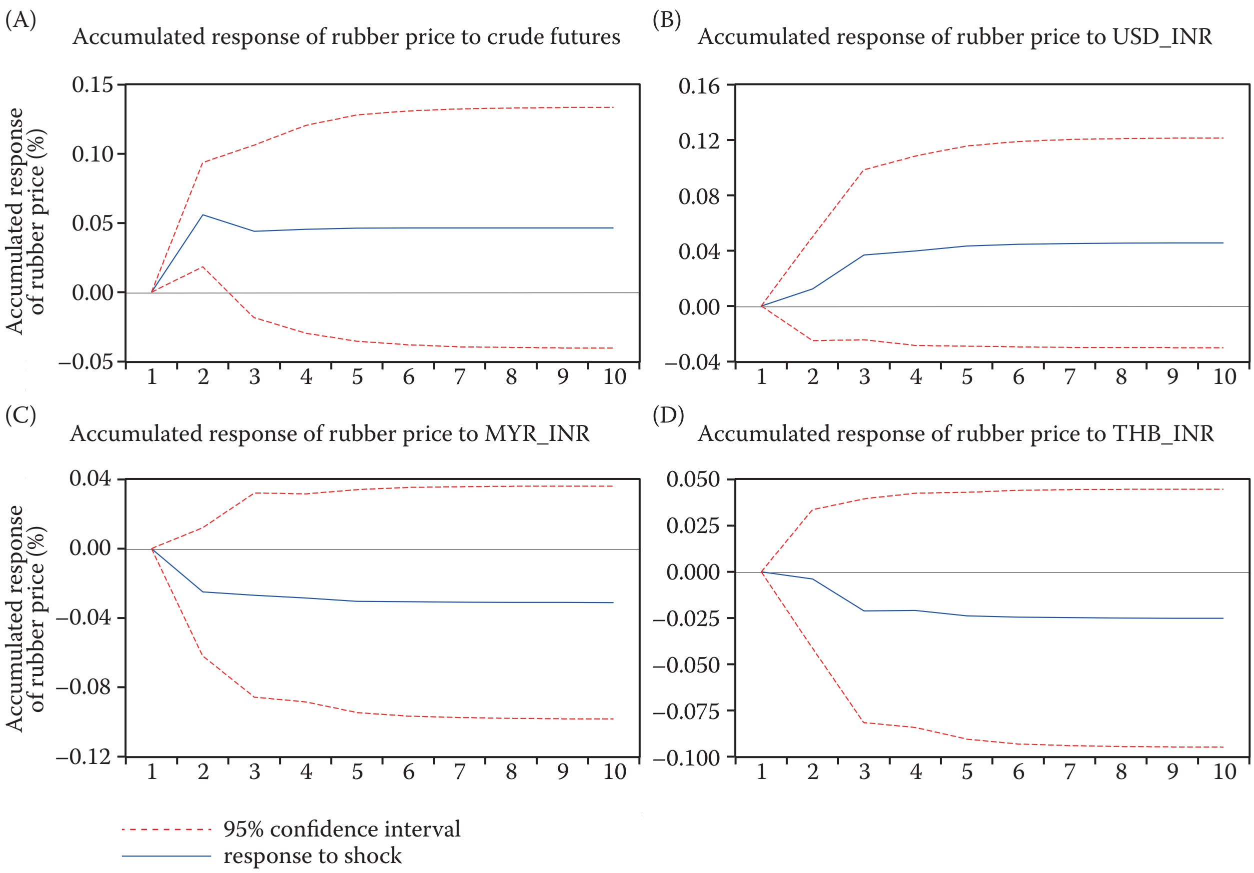

Figure 4. Accumulated response of rubber price to (A) crude futures, (B) USD_INR, (C) MRY_INR and (D) THB_INR structural VAR shocks

USD_INR – United States Dollar/Indian Rupee exchange rate; THB_INR – Thai Baht/Indian Rupee exchange rate; MRY_INR – Malaysian Ringhit/Indian Rupee exchange rate; VAR – vector autoregressive

Source: Authors' processing using Crude Oil Futures (2020), Exchange Rates (2020) and Natural Rubber Price in India (2020)

Table 6. Pearson correlation coefficients and Granger causality test results

Independent variable	Correlation coefficients with rubber price		Granger causality test results	
	price series	return series	Chi-square	prob.
Crude futures	0.63	0.13	11.54	0.00
USD_INR	−0.70	−0.03	3.15	0.21
MRY_INR	0.38	0.04	1.68	0.43
THB_INR	−0.41	−0.01	0.94	0.63

prob. – probability

Source: Authors' processing using Crude Oil Futures (2020), Exchange Rates (2020) and Natural Rubber Price in India (2020)

CONCLUSION

The volatility of the natural rubber price has adversely affected the lifestyle of rubber growers in India. Indian commodity exchanges have seen pressure from tire makers to ban natural rubber futures, and the government of India has banned the futures on natural rubber many times in the past. Hence, the commodity of natural rubber is not traded actively and regularly in the Indian commodity exchanges. Speculation in the commodity derivatives market is a major concern for tire makers and policymakers. However, crude futures are actively traded in the Indian commodity derivatives market, and the crude futures price is the

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crucial price determinant for natural rubber. Hence, the players in the natural rubber industry, like growers, traders and users, can use the crude futures as a price risk management tool.

Using VAR methodology, we developed a forecast model to predict the daily price of natural rubber in India. The Johansen cointegration test estimates proved that long-run models cannot be developed because there is no cointegration equation in the model. The VAR(2) multivariate model indicates that the natural rubber price in India is influenced by the crude oil futures price, and the equation given by the system is as follows:

$$\begin{aligned} \textit{Rubber price} &= C\left(23\right)\times \textit{Crude futures}\left(-1\right)+ \\ &+C\left(27\right)\times \textit{Rubber price}\left(-1\right)+ \\ &+C\left(28\right)\times \textit{Rubber price}\left(-2\right)+C\left(33\right) \end{aligned} \tag{7}$$

The accumulated responses to shocks in the SVAR analysis showed that the crude futures and USD_INR exchange rates have a significant positive effect on the prices of natural rubber in India. The MYR_INR and THB_INR exchange rates have a negative effect over the short-term horizon. The efforts of policymakers to cause the INR to appreciate against the MYR and THB may increase the natural rubber price in India. Furthermore, using the Pearson correlation and Granger causality tests, we confirmed the possibility of a cross hedge tool for the natural rubber commodity price by using crude oil futures in India. These types of forecast models and cross hedge tools will help traders, corporations and growers to manage the price risk. Furthermore, using OLS or multivariate generalised autoregressive conditional heteroscedasticity models, one can produce an optimal hedge ratio for this cross hedge.

REFERENCES

Arunwarakorn S., Suthiwartnarueput K., Pornchaiwiseskul P. (2019): Forecasting equilibrium quantity and price on the world natural rubber market. Kasetsart Journal of Social Sciences, 40: 8–16.

Barbaglia L., Croux C., Wilms I. (2020): Volatility spillovers in commodity markets: A large *t*-vector autoregressive approach. Energy Economics, 85: 1–11.

Brooks C. (2008): Econometrics Introduction. 2nd Ed. New York, USA, Cambridge University Press: 290–308.

Burger K., Smit H., Vogelvang B. (2002): Exchange rates and natural rubber prices, the effect of the Asian crisis. In: Exploring Diversity in the European Agri-Food System, Zaragoza, Spain, 28–31 Aug, 2002: 1–22.

Chance D.M. (2000): Derivatives and Risk Management. 5th Ed. USA, Harcourt College Publishers: 401–420.

Charfeddine L., Kahia M. (2019): Impact of renewable energy consumption and financial development on CO_2 emissions and economic growth in the MENA region: A panel vector autoregressive (PVAR) analysis. Renewable Energy, 139: 198–213.

Chaudhry A., Kalim S., Bukhari H. (2013): A structural VAR analysis of the impact of macroeconomic shocks on Pakistan's textile exports. Economic Modelling, 32: 302–315.

Citak F. (2018): Exchange rate and Turkish tourism trade. International Journal of Economics and Financial Issues, 8: 206–213.

Crude Oil Futures (2020): Crude oil futures. [Dataset]. Multi Commodity Exchange of India Ltd. Available at https://www.mcxindia.com/market-data/bhavcopy (accessed Mar 15, 2020).

Datta H., Debnath H., Shil P. (2019): Production and productivity of natural rubber: A study on growth-trends of rubber plantation in Tripura. International Journal of Management, 10: 115–131.

Exchange Rates (2020): USD/INR: Historical Data. [Dataset]. Available at https://finance.yahoo.com/quote/USDINR%3DX/history?p=USDINR%3DX (accessed May 23, 2021).

Gatarek L., Johansen S. (2014): Optimal hedging with the vector autoregressive model. Tinbergen Institute Discussion Paper, 22: 1–20.

Goh H.H., Tan K.L., Khor C.Y., Ng S.L. (2016): Volatility and market risk of rubber price in Malaysia: Pre- and post--global financial crisis. Journal of Quantitative Economics, 14: 323–344.

GoI (2019): National Rubber Policy 2019. Department of Commerce, Ministry of Commerce and Industry, Government of India (GoI): 1–25.

Gujarati D.N., Porter D.C., Gunasekar S. (2009): Basic Econometrics. 5th Ed. Mumbai, India, Mc Graw Hill Education: 821–831.

Hawaldar I.T., Ullal M.S., Birau F.R., Spulbar C.M. (2019): Trapping fake discounts as drivers of real revenues and their impact on consumer's behavior in India: A case study. Sustainability, 11: 1–20.

Hossain A., Kamruzzaman M., Ali M.A. (2015): Vector autoregressive (VAR) modeling and projection of DSE. Chinese Business Review, 14: 273–289.

Hull J.C. (2015): Option Futures and Other Derivatives. 9th Ed. New York, USA, Pearson: 50–60.

Joseph K.J., Thapa N., Wicken O. (2018): Innovation and natural resource-based development: Case of natural rubber sector in Kerala, India. Innovation and Development, 8: 125–146.

https://doi.org/10.17221/28/2021-AGRICECON

Kannan M. (2013): The determinants of production and export of natural rubber in India. Journal of Economics and Finance, 1: 41–45.

Khin A.A., Leh Bin R.L., Keong O.C., Yie F.W., Jye Liang N. (2019): Crittical factors of the natural rubber price instability in the world market. Humanities & Social Sciences Reviews, 7: 199–208.

Kumar N.P. (2017): Tourism led growth the case of India. South Asian Journal of Management Research, 9: 751–757.

Lekshmi S., Moganakumar S., Tharian G.K. (1996): The trend and pattern of natural rubber price in India: An exploratory analysis. Indian Journal of Natural Rubber Research, 9: 82–92.

Mills T.C., Patterson K. (2009): Palgrave Handbook of Econometrics. Vol. 2. London, United Kingdom, Palgrave Macmillan: 266–275.

Misurelli D., Cantrell R. (1997): Industry & Trade Summary. Synthetic Rubber. Washington, D.C., USA, U.S. International Trade Commission (USITC) Publication: 1–27.

Nambiar R.S., Balasubramanian P. (2016): A study on the impact of fall in ruber prices with respect to farmers in Kottayam district. International Journal of Applied Business and Economic Research, 14: 10463–10478.

Narayan P., Narayan S., Prasad A. (2008): A structural VAR analysis of electricity consumption and real GDP: Evidence from the G7 countries. Energy Policy, 36: 2765–2769.

Natural Rubber Price in India (2020): Daily Market Price. [Dataset]. The Rubber Board (Ministry of Commerce & Industry, Government of India). Available at http://indiannaturalrubber.com/market_price_daily.aspx (accessed Mar 15, 2021).

Nkcubeko Nomsobo A., Roscoe van Wyk B. (2018): The impact of short-term interest rates on bank funding costs. Journal of Economics and Behavioral Studies, 10: 141–148.

Pablo J., Arias M. (2019): Relationship between the consumer price index and the producer price index for six South American countries. Apuntes Del CENES, 37: 39–74.

Pareed A.O., Kumaran M.P. (2017): Price volatility and its impact on rubber cultivation in India – An analysis of recent trends. Journal Academic Research in Economics, 9: 293–312.

Raju K.V. (2016): Instability in natural rubber prices in India: An empirical analysis. IOSR Journal of Economics and Finance, 7: 24–28.

Sims A.C. (1972): Money, income, and causality. American Economic Review, 62: 540–552.

Tran T.L. (2020): Risk assessment of the economic efficiency of rubber production: Case of smallholder rubber production in QuangBinh Province, Vietnam. African Journal of Agricultural Research, 16: 567–573.

Tulasombat S., Bunchapattanasakda C., Ratanakomut S. (2015): The effect of exchange rates on agricultural goods for export: A case of Thailand. Information Management and Business Review, 7: 1–11.

Su C.-W., Liu L., Tao R., Lobont O.R. (2019): Do natural rubber price bubbles occur? Agricultural Economics, 2: 67–73.

Zahari F.Z., Khalid K., Roslan R., Sufahani S., Mohamad M., Rusiman M.S., Ali M. (2017): Forecasting natural rubber price in Malaysia using ARIMA. Journal of Physics, 995 (Conference Series): 1–7.

Zwart A.C., Blandford D. (1989): Market intervention and international price stability. American Journal of Agricultural Economics, 71: 379–388.

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