Forecasting Butyl Price : A Case of India's Tire Industry

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Abstract

In this work, a modest attempt was taken to forecast Butyl prices in setting market prices of tires more accurately because it is an important issue for managers of firms in the tire industry. In this context, two types of models were taken into consideration on the basis of sources of information (i.e. analogous time series or conventional time series). A linear regression model and a Box – Jenkins autoregressive integrated moving average (ARIMA) model were fitted to data on Exxon Butyl price (EBP), Russian Butyl price (RBP), and Crude oil price (RBRTE). Results showed that the ARIMA model was superior to the regression model in case of predicting Butyl prices. Marketing practitioners will benefit from the findings of this work in various aspects such as in setting tire prices more precisely. Moreover, the findings should assist managers in managing inventory costs more accurately. This study showed how a significant improvement can be achieved at a much lower cost and with a much lesser effort for forecasting Butyl prices in case of the tire industry.

Keywords : **Butyl, prices, ARIMA, regression, prediction**

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Predicting is an important issue in many aspects of managers' lives (Canitz, 2016 ; Hyndman & Athanasopoulos, 2018). They usually invest enormous amount of time in various activities to forecast strategic variables to minimize risk in outcomes (Albuquerque & Bronnerberg, 2012 ; Ramanathan, 2012). This exercise indeed is needed because the poor forecast can navigate managers to under/over investing in important factors leading to lousy firm performance (Aribarg, Arora, & Kang, 2010). Previous research used very complicated approach in this context, which is not so easy to apply in reality (Armstrong, 2012). That is why, we do believe that more research is needed so that the managers are able to forecast more accurately with less effort.

In this work, we make a modest attempt to predict Butyl prices (i.e., Exxon and Russian as the case may be) since it accounts for around 70% cost of production in case of tires which, in fact, vigorously influences on setting market prices. It is to be noted that there is a great deal of uncertainty involved in predicting this macro-economic variable in reality (Draganska & Klapper, 2011 ; Hoshmand, 2010). Here, we want to reduce that uncertainly in predicting Butyl prices, which would be a great help to business practitioners in framing pricing policies more precisely (Beal & Wilson, 2015 ; Currie & Rowley, 2010).

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Literature suggests that forecasting practices have come a long way and have also improved over time academically. At the same time, practitioners' knowledge about forecasting methods and their usefulness have increased substantially (Armstrong, 2001 ; Chintagunta, Hanssens, & Hauser, 2016). However, managers should keep in mind that many forecasting problems are usually more complex than they appear at the first time. This degree of complexity determines whether more sophisticated approach or simple traditional approach is required (Chase Jr., 2013 ; Fildes, Nikolopoulos, Crone, & Syntetos, 2008).

It is worthy to mention that choosing an appropriate forecasting method is a daunting task. It partially depends on situations as well as partially depends on analysts' skills, experience, and orientation (Henderson, Storeygard, & Weil, 2012 ; Mela, 2011). For instance, for long-term forecasting of environmental variables such as raw material costs, an econometric approach would be more appropriate (Brockwell & Davis, 2016 ; Luan & Sudhir, 2010). On the other hand, for short-term forecasting such as market share, an exponential smoothing method is more relevant (Brockwell & Davis, 2016).

What we understood from literature is that the forecasting process is more data-driven than theory-driven. Which is why, a few researchers have dealt with this issue methodically in the past (Narayanan & Nair, 2013 ; Ni, Neslin, & Sun, 2012). We, in this paper, attempt to fill this research gap by providing a framework of how to predict Butyl prices (the costliest component in tire) methodically on behalf of marketing managers of a big tire company in India.

Prediction of Butyl prices are subject to a lot of uncertainty since there only two alternatives (e.g., Exxon Russian) that are available to managers (Danese & Kalchschmidt, 2011). Hence, we wanted to explore an econometric method, that is, standard regression analysis using Crude oil as predictor (Armstrong, 2012). However, prediction of Butyl price depends on various factors. It is not always easy to identify all tentative predictors of Butyl prices. Furthermore, this problem is compounded due to high multicollinearity among predictors. That is, a standard regression model may not be the right one to predict Butyl prices more accurately (Klindokmai, Neech, Wu, Ojiako, Chipulu, & Marshall, 2014).

To overcome this limitation, we also considered an autoregressive integrated moving average (ARIMA) model which uses past observations to predict future Butyl prices without predictors (Singh, 2016 ; Yang, Zhao, Erdem, & Zhao, 2010). With the above backdrop, we want to address two managerially relevant objectives in this work. Specifically :

- To forecast Butyl prices for a period of 5 years in setting tire prices in advance ; and
- To understand whether regression model or ARIMA model fits better to the data.

From a managerial point of view, we think that a deep insight into the findings of these objectives should help managers to respond quickly to the changes in Butyl prices and in fixing prices objectively. This sort of insight also tells managers how to allocate funds between supply and demand generating activities optimally. On the other hand, from an academic point of view, it is important to understand how variations in the cost of the most important raw material influence the pricing policy of the product. There are not many research studies that have dealt with a relationship like this in the past. A good insight into this issue adds value to our understanding of marketing science as well (Armstrong, 2012). Here, we deal with a problem of forecasting methodically ; hence, it definitely adds value to the area of forecasting in business in general and marketing in particular. These are the unique aspects of this research as far as our limited knowledge is concerned.

Research Design

Our research is not about building and testing new methods, but to apply two established approaches, that is, the causal model and the univariate time series econometric model to predict Butyl prices. To do so, we implement a deductive methodology instead of inductive one. We selected a case study approach which includes quantitative data. A single participating firm from the motorcycle tire industry was taken into consideration to apply both the approaches to predict Butyl prices for the purpose of formulating pricing policy on behalf of the marketing managers of the company under study.

Research Hypotheses

To make prediction issues simple and actionable, we formulated a few hypotheses on the tentative association/relationship between the variables of interest. These hypotheses were conceptualized through an in-depth discussion with the managers of the firm under study. If these hypotheses are confirmed, then the selection of a right model would be very easy for the purpose of prediction of Butyl prices in practice. We present our hypotheses in both null and alternative forms :

- **H_{01} :** Butyl price and Crude oil price do not move together in the same direction.
- **H_{a1} :** Butyl price and Crude oil price move together in the same direction.
- **H_{02} :** Crude oil price does not influence prediction of Butyl price.
- **H_{a2} :** Crude oil price does influence prediction of Butyl price.
- **H_{03} :** Past prices do not influence current Butyl price.
- **H_{a3} :** Past prices do influence current Butyl price.

Models

Here, we consider two types of models, that is, the causal model and the time-series econometric model to test our hypotheses as mentioned above. To be more precise, we consider a simple linear regression model in causal category to test the hypothesis (H_2) and ARIMA model in time - series econometric category to test the hypothesis (H_3) (Montgomery, Jennings, & Kulachi, 2015).

In addition of testing the hypothesis (H_3), the ARIMA model does help us to test one more hypothesis with respect to past prediction errors. In this context, we would like to test the null hypothesis of 'prediction errors in past don't help to predict current Butyl price more precisely' against the alternative hypothesis of 'prediction errors in past help to predict current Butyl price more precisely.' We denote this hypothesis as H_4 throughout the paper. However, for testing the hypothesis (H_1), we use simple Pearson correlation coefficient model (Armstrong, 2012).

Database

To estimate our models, data were needed. Which is why, we gathered monthly data on Exxon Butyl price (EBP), Russian Butyl price (RBP), and Crude oil prices (RBRTE) from the internal records of the firm in question. It is wise to note that EBP is American Butyl and RBP is Russian Butyl and these two were competitors at the time of this study. A company can use any of these two or both in production of tires. Here, RBRTE, that is, crude oil price is considered as the only driver of Butyl prices as per the opinion of managers as well as literature suggested. It is worthy to mention that the period of study is 6 years from 2012 – 2018. This means that our data file contained 72*3 observations. To get primary idea about the characteristics of variables, we estimated descriptive statistics (i.e. mean, standard deviation, and coefficient of variation) of each variable and the results are shown in Table 1.

We did more preliminary analyses, such as we neutralized seasonal variations in our monthly data by dividing respective month's seasonal indices (shown in Table 2) to ensure that the model fits don't influence due to a

Table 1. Summary Statistics of *RBP, EBP,* and *RBRTE*

Variable	Mean	*SD*	*CV*
RBP	4334	1262	0.29
EBP	4070	518	0.12
RBRTE	94.81	22.87	0.24

Note. *RBP* = Russian Butyl price, *EBP* = Exxon Butyl price, *RBRTE* = Crude oil price, *SD* = Standard Deviation, *CV* = Coefficient of Variation.

Table 2. Seasonal Indices

Variable	Nov.	Dec.	Jan.	Feb.	March	April	May	June	July	August	Sep.	Octo.
RBP	0.95	0.92	0.93	0.98	1.01	1.02	1.00	1.07	1.01	1.04	1.05	0.96
RBRTE	0.96	0.96	0.98	1.02	1.03	1.07	0.99	0.98	1.02	1.01	0.99	0.95
EBP	1.00	1.01	0.98	1.00	0.96	1.00	0.99	0.99	1.01	1.00	1.01	1.00

Note. *RBP* = Russian Butyl Price, *EBP* = Exxon Butyl Price, *RBRTE* = Crude oil price.

particular month (Brockwell & Davis, 2016 ; Hanssens, Parsons, & Schultz, 2009). In addition, we deleted some records due to having much bigger standard deviations (i.e. more than three *SD*) to ensure that the model's fit is not overly determined by outliers (Brockwell & Davis, 2016 ; Hanssens et al., 2009). However, we don't interpret the figures on both the tables due to space constraints. In the end, we used a purified data file consisting of 70*3 observations for subsequent analyses.

Methods of Data Analyses

To achieve our goals, we analyze the data into several steps. Specifically :

At first, we calculate the Pearson correlation coefficients between Exxon Butyl price (EBP) & Crude oil price (RBRTE) and Russian Butyl price (RBP) & RBRTE to see the degree of strength of the associations between the two variables. The signs and magnitudes of the coefficients along with the *p*-values are reported in Table 3.

Next, we fit a linear regression model to 70*2 data points on Exxon Butyl price (EBP) and RBRTE (Agarwal, Sahoo, & Agarwal, 2019 ; Banerjee & Mandal, 2018). The mathematical form of this model is,

$$EBP_t = \alpha + \beta_{EB} RBRTE + u_t \ , \qquad (1)$$

where, EBP_t = Exxon Butyl price at time t ; $RBRTE_t$ = Crude oil price at time t ; α = Intercept ; β_{EBP} = Response coefficient of EBP to $RBRTE$; and u_t = Random disturbance term at time t.

We utilize an OLS estimation algorithm to estimate all parameters on the above eq. (1). The ratio of β_{EBP} to its standard error is nothing but *t*-value. To facilitate interpretation, we calculate the elasticity of *EBP* to *RBRTE* by multiplying β_{EBP} by a ratio of mean of *EBP* to mean of *RBRTE*. The results are shown in Table 4.

We then fit our data on *EBP* and *RBP* one by one to a time-series econometric model called auto-regressive integrated moving average (ARIMA) model (Gebre & Singh, 2016 ; Sarkar, Jha, & Mukherjee, 2018). The general mathematical form of this model is shown below :

$$\Delta y_{i,t} = \alpha + \beta_k \Delta y_{i,t-k} + \lambda_k \Delta e_{i,t-k} + u_{it} \ , \qquad (2)$$

where $\Delta y_{i,t}$ = First differenced i^{th} Butyl price (Exxon or Russian as the case may be) at time t ; $\Delta y_{i,t-k}$ = First differenced k^{th} lagged of i^{th} Butyl price (Exxon or Russian as the case may be) at time $t-k$; $\Delta e_{i,t-k}$ = First differenced k^{th} lagged error term of i^{th} Butyl price (Exxon or Russian as the case may be) at time $t-k$; (β_k , λ_k) = a vector of response coefficients ; and $u_{i,t}$ = a random disturbance term of i^{th} Butyl price (Exxon or Russian as the case may be) at time t.

Technically, the above eq. (2) is called ARIMA (p , d , q) model, where p is the number of autoregressive terms, d is the number of differences needed to make the data series stationary, and q is the number of moving average terms (i.e. the number of lagged forecast errors in the prediction model). We used ACF and PACF graphs to look for AR and MA terms (not shown here), respectively. Subsequently, we took a tentative AR (3) MA (2) model. Moreover, we differenced only once to make the data series stationary. This implies that the best estimates are coming from ARIMA (3, 1, 2) model.

We test this model on data of Butyl prices.

➭ First, we fit our tentative ARIMA (3, 1, 2) to 70 data points on Russian Butyl price (RBP), that is, we regress RBP on its own past up to three lags and past prediction error up to two lags. The outcomes are presented in Table 5.

➭ Second, we fit the same model to 70 data points on Exxon Butyl price (EBP) and follow the same methodology. Results are not reported here due to space constraints and high degree of repetition.

In the end, we do prediction of Exxon and Russian Butyl prices through eq. (3) and eq. (4), respectively by using the estimated coefficients of AR 1, AR 2, AR 3, MA 1, and MA 2 :

$$EBP_t = \beta_1 \Delta EBP_{t-1} + \beta_2 \Delta EBP_{t-2} + \beta_3 \Delta EBP_{t-3} + \lambda_1 \Delta e_{t-1} + \lambda_2 \Delta e_{t-2} \quad (3)$$

$$RBP_t = \beta_1 \Delta RBP_{t-1} + \beta_2 \Delta RBP_{t-2} + \beta_3 \Delta RBP_{t-3} + \lambda_1 \Delta e_{t-1} + \lambda_2 \Delta e_{t-2} \quad (4)$$

It is worthy to mention that all the parameters and notations on eq. (3) and eq. (4) tell their stories by themselves.

Results and Discussion

This section deals with the outcomes we obtained through analysis of data. First, we present and discuss the results of correlation analysis followed by the outcomes from regression and time series analyses, respectively.

When we look at Table 3, we find that the correlation coefficients between Butyl prices and Crude oil price (RBTRE) are positive, which means that Butyl prices and Crude oil prices are moving together in the same direction. Coming to the sizes of the coefficients, we observe that it is 43 times more in case of Exxon Butyl than in case of Russian Butyl. As far as the statistical test is concerned, we find that the correlation coefficient between

Table 3. Pearson Correlation Coefficients between Butyl Price and Crude Oil

Variable vs. Variable	Size	p
EBP vs. *RBRTE*	0.390*	<0.001
RBP vs. *RBRTE*	0.009	0.950

Note. *p < 0.01, *RBP* = Russian Butyl Price, *EBP* = Exxon Butyl Price, *RBRTE* = Crude oil price.

Exxon Butyl price and RBTRE is significant at $p < 0.05$ or better. However, we do observe that it is not significant at any conventional significance level in case of Russian Butyl price. These evidences suggest that the hypothesis (H_{a1}) is partially confirmed (i.e. null hypothesis H_{01} is rejected), that too only in case of Exxon Butyl instead of in both the cases. The most important point that we should take away is that the managers who are currently using Russian Butyl should not consider the Crude oil price as a proxy of Russian Butyl price.

Coming to the regression analysis, Exxon Butyl price (EBP) is regressed on Crude oil price (RBRTE) only since the correlation coefficient between Russian Butyl price (RBP) and RBRTE is not significant as we observe. The results are posted in Table 4. These results (in Table 4) simply have two parts, that is, model's validation statistics and the size of the effect and its related issues.

We report three validation statistics (i.e. R^2, DW, and MAPE) for choosing our model. It is to be noted that R^2 value indicates the degree at which the model fits to data. We can see from Table 4 that the R^2 (0.60) value is reasonably high, which means that the model gives a fit to data and it explains around 60% of the variation in EBP. On the other hand, the Durbin – Watson statistic tests whether the error terms are auto-correlated or not. We see that the DW value is less than 2 but more than 1.86, which testifies that there is no autocorrelation problem in our data set. Furthermore, we use mean absolute percentage error (MAPE) to assess the regression model's predictive power. Its value is 12.4%, which means that our regression model is supposed to predict Exxon Butyl price at 87.6% accuracy level, at least for the short-term.

We turn our attention to the response coefficient (in Table 4) of Crude oil, which we find to be positive and significant at $p < 0.01$ (one-tailed tests).That is, H_{02} is rejected. This evidence supports the alternative hypothesis (H_{a2}) against the null hypothesis of 'Crude oil price doesn't influence Exxon Butyl price.' Hence, we make a conclusive statement that the relationship between Exxon Butyl price and Crude oil price is significant and positive. Coming to 'size of the effect,' we utilize the elasticity of EBP to RBRTE, which is 0.55 in this case. This value indicates that when there is a 1% change happening in RBRTE, 0.55% change is supposed to happen in EBP. This elasticity coefficient is easily understandable and does provide a clue of how sensitive EBP to RBRTE is, which is quite useful information in decision making of predicting Butyl prices.

Coming to the results of ARIMA (3,1,2) model. The results deal with the coefficients of AR1, AR2, AR3, MA1, and MA2. The values of these coefficients are reported in Table 5. The results reveal that the coefficients of AR1 and AR2 are significant at $p <.01$ or better and the coefficient of AR3 is significant at $p < .10$ or better. Which is

Table 4. Estimates of the Regression Analysis between *EBP* and *RBRTE*

Variable	Coefficient	Std. E	*p*	Elasticity	R^2	DW	MAPE (%)
Constant	1722.30*	254.70	<0.001	0.55	0.60	1.89	12.40
RBRTE	23.56*	2.54	<0.001				

Note. *p <0.01, DW = Durbin – Watson statistic, MAPE = Mean absolute percentage error.

Table 5. Results of ARIMA (3, 1, 2) on Russian Butyl Price

Predictor	Coefficient	*p*	MAPE (%)
AR1	1.63*	<0.001	2.15
AR2	–1.14*	<0.001	
AR3	0.18**	0.084	
MA1	1.51*	<0.001	
MA2	–0.97*	<0.001	

Note. *p< 0.01, **p< 0.10, MAPE = Mean absolute percentage error.

why, we reject the null hypothesis H_{03}. This evidence confirms our third hypothesis of 'substantial coefficients' against the null hypothesis of 'zero coefficients.' Signs of the coefficients of AR1 and AR3 are positive and AR2 is negative. As far as the absolute magnitudes are concerned, AR1 has the highest magnitude followed by AR2 and AR3, respectively. That is, the magnitudes of coefficients are monotonically declining from AR1 through AR3, which means that the immediate past has more impact on current prices than distance pasts.

When we turn our attention to MA terms, we find that MA1 and MA2 are significant at $p < 0.01$ or better. Hence, we reject the null hypothesis H_{04}. That is, the past prediction errors up to two periods influence the current period's Russian Butyl price. The signs of these coefficients are mixed. MA1 has a positive coefficient and MA2 has a negative coefficient. Between these two, the magnitude of the coefficient of MA1 is higher than MA2, that is, recent past has higher influence than the distant past as the case of AR terms.

The estimated MAPE is only 2.15%, which means that the ARIMA (3, 1, 2) model gives a good fit to Russian Butyl price and would be able to predict its price at 97.75% accuracy level. Next, we attempt to test our ARIMA model's forecasting power in both cases.

Putting the estimated values of all parameters on eq. (3) and eq. (4), we forecast the Exxon and Russian Butyl prices, respectively. However, we forecast prices for a period of five-months in advance from the last observation 73 of our sample data. We then wait for actual prices of both the Butyls to compare forecasted values to realized values. Observation-wise, the forecasted prices, the actual prices, and the absolute percentage error (APE) are shown in Table 6.

Table 6. Forecasting Power of ARIMA (3, 1, 2) Model

Observation	Forecasted		Actual		APE (%)	
	EBP	*RBP*	*EBP*	*RBP*	*EBP*	*RBP*
73	8.10	7.98	8.23	7.88	1.50	1.20
74	8.12	7.98	8.27	7.89	1.75	1.10
75	8.32	7.98	8.54	7.80	2.50	2.30
76	8.63	7.99	8.92	7.74	3.60	3.20
77	8.70	8.00	9.10	7.70	4.55	3.09

Note. *RBP* = Russian Butyl Price, *EBP* = Exxon Butyl Price, *APE* = (Actual – Forecasted)/Actual*100.

We observe a close correspondence between actual and forecasted Butyl prices since the APE ranges are from 1.10% – 3.20% in case of Russian Butyl ; whereas, it is 1.50% – 4.55% in case of Exxon Butyl, which is less than 5% (i.e. acceptable error percentage in this case). It clearly shows the forecasting power of ARIMA (3, 1, 2) model outside the sample observations. In a nutshell, the ARIMA model is capable of predicting Butyl prices on an average at 97% accuracy level at least up to five periods, as we find in this study.

Conclusion

In this work, we make a modest attempt to predict Butyl prices on behalf of marketing practitioners in setting the tire prices since it plays an important role in this matter. We consider two types of models to uncover the hidden relationship between and within the variables under study. To be more precise, we fit regression model and ARIMA model to data on Exxon Butyl price, Russian Butyl price, and Crude oil price. We find that both the models are useful to predict Butyl prices with different accuracy levels.

We would like to present some interesting insights of our findings very briefly such as : (a) Crude oil is a strategic variable to predict Exxon Butyl price, but not to predict Russian Butyl price ; (b) up to three lags (lag 1, lag 2, and lag 3) of and up to two shocks (lag 1 and lag 2) provide statistical significant information for predicting

Butyl prices ; and (c) the regression model is only applicable for predicting Exxon Butyl price and ARIMA model is applicable in both cases.

This work couples insights with data experimentation methodology in selecting models to predict behavior of strategic variables in setting prices within a reasonable standard error. That is why, this work definitely adds value to marketing practices in general and in tire industry in particular. This research predicts Butyl prices and waits for five months to get the actual market prices. It then compares the forecasted prices to the actual market prices, which is very rare in academic research. These are the two unique contributions of this research to the field of pricing.

Managerial Implications

Our findings do have some important implications for marketing practitioners. First, using the findings of this work, managers should be able to project revenues from each unit of sale as well as number of units needed to be sold to maximize overall revenues by framing a dynamic pricing policy. By doing so, managers would be able to develop a 'mini income statement' leading to a better allocation of marketing resources on each market.

Second, our findings should assist managers in framing three possible scenarios such as worst-case, most-likely-case, and best-case scenarios. These help them in capturing a broad range of likely outcomes about future unit sales, various costs of production, various inventory costs at distributer's/retailer's points, and other marketing actions.

Third, our approach should help managers in implementing the Kaizen philosophy of cost reduction in case of Butyl – the costliest component in tires, which indeed helps to assess and gain a competitive advantage by setting right prices in markets since most brands almost target similar segments and adopt a cost-plus pricing method in India.

Fourth, managers should use our findings in developing market-based assets such as better relationship with channel members (i.e. wholesalers and retailers), providing right margin per unit through better inventory control coupled with right pricing policy.

Last but not the least, the findings of this work should assist managers to reduce information asymmetry between marketing and production functions, which indeed would enhance total operational efficiency of a firm.

Limitations of the Study and Directions for Further Research

Our work does have some limitations too. First, we don't take into consideration all components in tires since we do consider that the fluctuations in all other attributes are constant, which would definitely not be so practical, leading to formulation of a sub - optimal pricing policy. Researchers should take a holistic approach to solve this problem in the future. Second, we don't attempt to establish a causal relationship between market price and Butyl price, which is required to set price more accurately. Researchers should explore this research avenue to expand this work in the future.

Last but not the least, we use two different approaches and use them independently. Researchers can make an attempt to combine both the causal model and the time series model in predicting Butyl prices. Researchers should also use multiple autoregressive integrated moving average (MARIMA) model to predict Butyl prices in the future.

Authors' Contribution

There are three authors in this paper. All authors contributed more or less equally. Mehir Baidya conceived the idea and designed research. Bipasha Maity did the literature review, identified objectives, framed research hypotheses, and gathered data. P. Srinivasan analyzed the data and prepared tables. Mehir Baidya wrote the manuscript, modified it, as well as organized the manuscript.

Conflict of Interest

There is no conflict of interest in the subject matter or materials discussed in this manuscript among authors or any stakeholder.

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