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Modelling and Forecasting Commodities Prices in Emerging Market: Lessons from the Preceding Super Cycle

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Abstract
Futures trading is one of the oldest methods of trading and investing in commodities. History of commodities futures trading in India is interrupted, flabbergasted and disrupted unlike commodities future trading in Chicago Mercantile Exchange (CME), Chicago Board of Trade (CBOT), or London Metal Exchange (LME) where futures trading has been taking place uninterrupted for over a century. Prohibiting of futures trading in India in a large part of the last few decades has ensured research on commodities trading in India is still at an embryonic stage. In this study, we model Commodity prices of select Agriculture (Barley, Jeera, Sugar, and Pepper), Metal (Aluminium, Copper, Lead, and Gold), and Energy commodities (Crude Oil) in Indian Commodity Markets. Data during the Super-cycle period of commodities in India from 2003 to 2013 is used for the study and modeled using the state-space specification. The results of the study suggest that state-space specification and Kalman filter provides preeminent estimates for modeling and forecasting Indian commodity prices during the Super-cycle period. The results of the study provide crucial insights for pension funds, alternate investment funds, hedge funds and sovereign wealth funds worldwide to strategize better in the next expected super-cycle period of commodities post Covid-19 with burgeoning demand from developing economies of Asia and Africa.

Keywords: Commodity Market, India, Spot Price, Futures prices, Seasonality, State Space Model, Kalman Filter.

1. Introduction
Trading of Commodities in India can be traced back 2500 years ago as stated in Kautilya's Arthashastra book of Economics written by Chanakya in the Sanskrit language who was the teacher to the founder of the Mauryan empire between 322 and 185 BC. The evolution of modern-day commodity derivative markets in India can be traced back to the 17th century. Gelderblom and Jonker (2005) argue that financial futures were traded on shares of the Dutch East Indian Company in the 17th century itself unlike the contradicting perspective of Anderson, Larson, and Varangis (2001) that modern futures markets have their origins in the 18th century about Japanese rice futures trading in Osaka.

Commodity exchanges in India have evolved with a large number of regional exchanges designed and established during the period of first and second world wars in different parts of the country. By 1930, India had over 300 commodity exchanges dealing in different commodities in different parts of the country which were regional and/or local. Interestingly, trading was shepherded both in options and futures back then however nonexistence of a Central Regulator for commodities handicapped the system plaguing the system with clearing and settlement woes for the participants of these exchanges. Studies in literature point out that participants of developed markets have deciphered commodity price dynamics better owing to data availability on uninterrupted futures trading in exchanges such as the Chicago Mercantile Exchange (CME), Chicago Board of Trade (CBOT) or London Metal Exchange (LME) for over a century. Though commodity futures trading commenced in a similar time frame in India, structural bottlenecks and lack of a central regulator coupled with prohibiting of futures trading in

India in large part of the last few decades have ensured that research on commodities trading in India is still at an embryonic stage.

Commodity markets in India over the decades have encountered bottlenecks for market microstructure, restrictions on the free movement of commodities in various States/Provinces of the country, the actuality of market imperfections such as Minimum Support Price (MSP) for essential commodities as announced by the Government, superfluous political interloping and infrastructure concerns related to derisory warehousing facilities to name a few. The recent merger of the Securities Exchange Board of India (SEBI) and Forward Market Commission (FMC) has gotten in more depth and width to the market ensuing better price discovery in the Indian commodities market. Initiatives by SEBI in connotation with exchanges to carry in further farmers to rationalized trading platform discarding middle man Mittal, Hariharan, and Subash (2018) are expected to further aid the commodities market participants in India.

In this study, we model Commodity prices of select Agriculture (Barley, Jeera, Sugar, and Pepper), Metal (Aluminium, Copper, Lead, and Gold), and Energy commodities (Crude Oil) in Indian Commodity Markets. Data during the Super-cycle period of commodities in India from 2003 to 2013 is used for the study and modeled using the state-space specification. The results of the study suggest that state-space specification and Kalman filter provides preeminent estimates for modeling and forecasting Indian commodity prices during the Super-cycle period Fernández, González, and Rodriguez (2018). The proposed Modeling framework used in the study can be embraced by market participants to value commodity derivatives and mitigate risk optimally. The results of the study provide crucial insights for pension funds, alternate investment funds, hedge funds and sovereign wealth funds worldwide to strategize better in the next expected super-cycle period of commodities post Covid-19 with burgeoning demand from developing economies of Asia and Africa. The rest of the paper is structured as follows: In section 2 we describe the data, model, and methodology used in our study. In section 3 we present our empirical findings and discuss and conclude our study in section 4 Literature Review

2. Research Methodology

2.1 Data

The study ruminates both spot and futures prices of select Agriculture (Barley, Jeera, Sugar, and Pepper), Metal (Aluminium, Copper, Lead and Gold), and Energy commodities (Crude Oil) in Indian Commodity Markets. Weekly data for the period from January 2003 to December 2013 is considered as super-cycle period when commodity prices escalated across the spectrum of Agriculture as well as metals Pindyck (2001). Data of mid-week i.e. of Wednesday is considered similar to Sorensen (2002) to negate any kind of the beginning of the week and end of the week influences and in the process remove undesirable noises of the data.

2.2 Data Source

Data for our study has been sourced from the Multi-Commodity Exchange (MCX) of India and National Commodities and Derivatives Exchange (NCDEX). The study considers both spot and futures data with similar dates. Metal and Energy Commodities are the most aggressively traded contracts in MCX. Weekly Spot and Futures Data of Metal (Aluminium, Copper, Lead and Gold) and Energy commodities (Crude Oil) is sourced from MCX. Agricultural Commodities in India are most aggressively traded in NCDEX. Data of Agriculture commodities (Barley, Jeera, Sugar, and Pepper) is sourced from NCDEX for our study.

2.3 Econometric Model

The key objective of this study is to model Commodity prices of select Agriculture (Barley, Jeera, Sugar, and Pepper), Metal (Aluminium, Copper, Lead, and Gold), and Energy commodities (Crude Oil) in Indian Commodity Markets during the Super-cycle period. Modeling of commodity price literature advocates different models for addressing the disparate scope of commodity price series. Studies by Schwartz (1997) and Schwartz and Smith (2000) highlight the state-space framework for modeling commodity prices using Kalman filter as an appropriate tool for estimating commodity price models because Kalman filtering eases execution requirements and handles glitches similar to missing data very effortlessly. Though estimation is fairly complex for including contracts with non-linear pricing like Options, it offers a conjoint dais for addressing diverse issues Zhao and Wan (2018).

The state-space models are considered to be relatively more inclusive and detailed than simple autoregressive models. Ribeiro and Oliveira (2011) put forward a hybrid model for forecasting the prices of agricultural commodities which is built upon two approaches: one is artificial neural networks (ANNs) and the other is Kalman filter. The rationale and motivation for considering Kalman filter and state-space models are due to Ribeiro and Oliveira (2011) study which shows that the Kalman filter's structure is adequate and appropriate in unfolding any stochastic process comprising convenience yield and is suitable athwart commodities markets. Cortazar, Millard, Ortega, and Schwartz (2019) in their study forecasted oil spot prices and also articulated the leeway of modeling oil prices forecast with futures data. Similar to Cortazar *et al.* (2019) study we model and forecast both futures and spot price data.

The general state-space model with two arbitrary functions gt and ht can be represented as:

$$Y_t = F_t(\theta_t \upsilon_t) \quad (1)$$

$$\theta_t = G_t(\theta_{t-1}\omega_t) \quad (2)$$

Equation 1 is referred to as observation or signal equation and Equation 2 is referred to as State or System equation. These set of equations together is referred to as local level models. Dynamic Linear Models (DLM) is an imperative class of state-space models and we specify these models also with Equations 3 and 4.

$$Y_t = F_t\theta_t + \upsilon_t, \upsilon_t N_m \sim (0, V_t) \quad (3)$$

$$\theta_t = G_t\theta_{t-1} + \omega_t, \omega_t N_p \sim (0, W_t) \quad (4)$$

Where,

- G_t and F_t have known matrices and the (v_t) and (w_t) are two independent white noise sequences with a mean value of Zero and known covariance matrices V_t and W_t correspondingly
- $\theta_0$is assumed to follow Gaussian distribution, $\theta_0 \sim N_p(m_0, C_0)$for non-random vector m_0 and matrix C_0, and it is independent on (v_t) and (w_t)

$$y_t = \mu_t + \upsilon_t, \qquad \upsilon_t \sim NID(0, \sigma_\upsilon^2) \quad (5)$$

$$\mu_t = \mu_{t-1} + \omega_t, \qquad \omega_t \sim NID(0, \sigma_\omega^2) \quad (6)$$

For t = 1,2,.......n

Where

μt is the unobservable level at time t
υt is the observation disturbance at time t
ωt is the level(state) disturbance at time t

Subsequently, the Level (State) equation is analogous to random walk representation and is usually termed as a Random walk plus noise model where noise specifies the asymmetrical component υt.

If level disturbances in Equation 6 are all fixed on ωt = 0 for all t = 1, 2, 3, ...,n in that scenario Equation 6 would turn out to be deterministic in nature and the local level model will be abridged to a single equation 5.

If μt in equation 5 is allowed to vary over time, the model is referred to as Stochastic level

The local level trend model is a variation of the local level model by adding a slope component νt.

$$y_t = \mu_t + \upsilon_t, \qquad \upsilon_t \sim NID(0, \sigma_\upsilon^2) \quad (5)$$

$$\mu_t = \mu_{t-1} + \beta_{t-1} + \omega_{1,t}, \qquad \omega_{1,t} \sim NID(0, \sigma_{\omega 1}^2) \quad (7)$$

$$\beta_t = \beta_{t-1} + \omega_{2,t}, \qquad \omega_{2,t} \sim NID(0, \sigma_{\omega 2}^2) \quad (8)$$

for t = 1,2,.......,n

The local linear trend model has two state equations One is helpful for modelling level and the other for slope. The slope βt is rather akin to the regression slope coefficient but permits to vary over time. So it is also called as drift.

$$\theta = \begin{pmatrix} \mu_t \\ \beta_t \end{pmatrix}, G = \begin{pmatrix} 1 & 1 \\ 0 & 1 \end{pmatrix}, W = \begin{pmatrix} \sigma_{\omega 1}^2 & 0 \\ 0 & \sigma_{\omega 2}^2 \end{pmatrix}, F = \begin{pmatrix} 1 & 0 \end{pmatrix}$$

Fixing the residuals ($\upsilon_{1,t}$ =0 and $\omega_{i,t}$=0) provides a deterministic local linear trend model.

Both level and slope are allowed to vary under the Stochastic model. Model without assuming the parameter values can be estimated under the Bayesian framework.

If seasonal effects are permitted in the model, we get Equation 9.

$$y_t = \mu_t + \upsilon_t\,, \qquad \upsilon_t \sim NID(0, \sigma_\upsilon^2)(5)$$

$$\mu_t = \mu_{t-1} + \omega_{1t}\,, \qquad \omega_{1t} \sim NID\left(0, \sigma_{\omega 1,t}^2\right) \quad (6)$$

$$\gamma_{1,t} = -\gamma_{1,t-1} - \gamma_{2,t-1} - \gamma_{3,t-1} - \cdots - \omega_{2,t-1}\,, \qquad \omega_t \sim NID(0, \sigma_{\omega 2}^2) \quad (9)$$

where

$\gamma_{2,t} = \gamma_{1,t-1}$
$\gamma_{3,t} = \gamma_{2,t-1}$
for t=1,….n where $\gamma_t = \gamma_{1,t}$denotes the seasonal components. The noise component in Equation 9 permits the seasonal change over time.

Other Assumptions related to Modeling State Space models include:

- Under the deterministic level and seasonal under local level model we assume νt and ωt are equal to zero
- Under the stochastic level and seasonal under the local level model we allow both of them to vary
- Under stochastic level and deterministic seasonal under the local level model, we assume ωt equal to zero.

In the case of non-Gaussian series, the modified observation equation can be specified as

$$\prod_{i}^{p} p_i\left(y_{i,t}|\delta_t\right) \qquad (10)$$

with $\delta_{i,t} = F_{i,t}\theta_t$being one of the following

If observations yi,1,…….yi,n are distributed as:

- $N(\mu_t, u_t)$, then $\delta_t = \mu_t$. Note that now variances are defined using *u*, not *H*. If the correlation between gaussian observation equations is needed, one can use $u_t = 0$ and add correlating disturbances into state equation
- *Poisson*$(u_t\lambda_t)$, where u_t is offset term, then $\delta_t = \log(\lambda_t)$
- *binomial*$(u_t\ \pi_t)$, then $\delta_t = log[\pi_t/(1-\pi_t)]$, where π_t is the probability of success at time t
- *gamma*(u_t,μ_t), then $\delta_t = \log(\mu_t)$, where $\mu[t]$ is the mean parameter and u is the shape parameter
- *Negative binomial*$(u_t\ ,\mu_t)$ (with expected value μ_t and variance $\mu_t + \mu_t^2/u_t$, then $\delta_t = log[\mu_t]$. For exponential family models $u_t = 1$ as a default. For completely Gaussian models, the parameter is omitted

State estimation is deliberated as a step for predicting the value of future observations. For one-step-ahead forecasting i.e. predicting the next observation Y_{t+1}based on the data$y_1, \ldots, y_t$, we estimate the next value θ_{t+1} of the state vector, and it's used as the basis for computing the forecast for Y_{t+1}. The one-step-ahead state predictive density is$p(\theta_{t+1} \mid y_1, \ldots, y_t)$ and it is based on the filtering density ofθ_t. From this, one acquires one-step-ahead predictive density $f(y_{t+1} \mid y_1, \ldots, y_t)$. Estimating the evolution of the system i.e. State vector θ_{t+k} for k ≥ 1 and making k-steps-ahead forecasts for Y_{t+k}. The state-prediction is unravelled by computing the k-steps-ahead state predictive density $p(\theta_{t+k} \mid y_1, \ldots, y_t)$ and cantered on this density, one can compute the k-steps-ahead predictive density $f(y_{t+k} \mid y_1, \ldots, y_t)$ for the future observation at time t + k. The conditional mean$E(Y_{t+1} \mid Y_1, \ldots, Y_t)$ provides an optimal one-step-ahead point forecast of the value of Y_{t+1}, minimizing the conditional expected square prediction error. As a function of k, $E(Y_{t+k} \mid Y_1, \ldots, Y_t)$ is usually called the forecast function.

Let us denote with D_t the information provided by the first t observations, $Y_1, \ldots, Y_t$. One of the benefits of state-space models is the Markovian structure of the state dynamics and the conventions on conditional independence for the observables leading to the fact that filtered and predictive densities can be computed by a recursive algorithm.

Starting from$\theta_0 \sim p_0(\theta_0) = p(\theta_0 \mid D_0)$ one may be able to recursively compute, for t = 1, 2, . . .

- the one-step-ahead predictive density for θ_t given D_{t-1}, based on the filtering density $p(\theta_{t-1} \mid D_{t-1})$ and the transition model
- the one-step-ahead predictive density for the next observation
- the filtering density $p(\theta_t \mid D_t)$ using Bayes rule with $p(\theta_t \mid D_{t-1})$ as the prior density and the likelihood $f(y_t \mid \theta_t)$

In our study, we follow a step by step procedure to find out the suitable model for Agriculture (Barley, Jeera, Sugar, and Pepper), Metal (Aluminum, Copper, Lead, and Gold), and Energy commodities (Crude Oil) in the Indian Commodity Markets.

3. Empirical Findings

To model Commodity prices of select Agriculture (Barley, Jeera, Sugar, and Pepper), Metal (Aluminium, Copper, Lead, and Gold) and Energy commodities (Crude Oil) in Indian Commodity Markets using data of super-cycle period of commodities in India between 2003 to 2013, we potentially can employ the following models categorized as local level model, local linear trend model, local level model with seasonal and nonlinear- non-Gaussian models. According to the literature, Commodity prices can be modelled under a) Local-level Model by investigating Deterministic Level and Stochastic level. B) Local linear trend model by investigating Deterministic level and slope, Stochastic level and slope and Stochastic level and deterministic slope. c) The local-level model with seasonal components by investigating using Deterministic level and seasonal, Stochastic level and seasonal and Stochastic level and deterministic seasonal and d) Nonlinear- Non-Gaussian models. However, some of the models may be straightforwardly precluded owing to their rudimentary properties. As an illustration, the deterministic level model is not suitable for modeling commodity price series.

One of the conspicuous approaches in the literature to model commodity prices is that of state-space using Kalman filter. In our study, we model all the select commodities (both spot and future) using the state-space specification and Kalman filter and the coefficients are estimated using the Maximum Likelihood procedure. Table 1 presents Model estimation basic statistics for Agricultural Commodities and Table 2 presents Model estimation basic statistics for Metals and Gold. The model estimation results express that estimated coefficients are statistically significant at one percent level. We did happenstance the fact that the Stochastic seasonal model exhibited seasonal variation in the case of barley, Sugar, and lead. However, a meticulous inspection showed that allowing for dummy or trigonometric models delivered insignificant seasonal coefficients while expending weekly data. This obligated us to comprehend that weekly data may not be appropriate for toting an additional seasonal state in the specified models.

Table 1. Model estimation basic statistics for Agricultural Commodities

	Barley	Jeera	Guar (Jaggery)	Pepper
Stochastic level				
OERV	3.302864e-08	7.184766e-10	3.402458e-05	1.621058e-11
SEEV	0.00100362	0.0006706176	0.001826666	0.001132374
MLEIV	6.722028	8.87801	7.013466	8.950612
Deterministic level and slope				
Coefficients	6.7892 and 0.0013	8.909 and 0.002	7.2894 and 0.0013	8.61159448 and
Error Variance	0.022549	0.018796	0.015161	0.03802418
Stochastic level and slope				
OERV	1.076965e-08	4.660239e-10	3.627604e-05	7.035936e-11
LEEV	0.001004828	0.0005895749	0.001819609	0.001122871
SEEV	9.565125e-17	1.189473e-05	2.521578e-11	9.258171e-19
Stochastic level and deterministic slope				
OERV	0.006638241	4.573724e-09	0.00862351	
LEEV	0.001004594	0.0006697476	0.001819485	0.001122437
MLEILS	6.722028	8.87801	7.013466	8.950612
MLEISS	0.001502057	0.001539107	0.002808999	0.00346552

Stochastic level and seasonal				
OERV	0.006732182	4.875374e-09	0.007723510	3.848959e-09
LEEV	0.002187562	2.968608e-11	0.001819485	1.637415e-11
SzEEV	0.0003592764	0.0006693368	7.013466	0.001133516
Stochastic level and deterministic seasonal				
OERV	0.02296905	0.02293878	0.02295442	0.02292424
LEEV	0.1057372	0.1060151	0.1058714	0.106149

Note: *Observation equation error variance (OERV); Level equation error variance (LEEV); Slope equation error variance (SEEV); Seasonal equation error variance (SzEEV); MLE of the initial value of level state (MLEILS); MLE of the initial value of slope state (MLEISS)*

Table 2. Model estimation basic statistics for Metals and Gold

	Aluminum	Copper	Gold	Lead	Crude
Stochastic level					
OERV	1.114458e-10	1.256363e-09	6.373081e-10	9.265161e-09	0.0001763699
SEEV	0.001028956	0.001739356	0.0006648634	0.00308933	0.002076606
MLEIV	4.629863	4.865224	9.192889	4.667206	7.675546
Deterministic level and					
Coefficients	4.67636676 and -	5.3686 and 0.0018	8.9624 and 0.0040	4.4935 and 0.0007	7.8509 and 0.0016
Error Variance	0.02233927	0.0483710	0.005224	0.046548	0.03635
Stochastic level and slope					
OERV	3.359361e-10	5.089304e-10	9.718779e-09	1.188643e-09	0.0001741163
LEEV	0.001031707	0.001709881	0.0006571363	0.003099562	0.002080605
SEEV	2.839746e-13	7.478439e-07	1.624911e-13	8.063967e-22	5.466195e-10
MLEILS	4.629863				
MLEISS	-3.016657e-05	4.979304e-09	1.424396e-07	0.02100242	0.000080986
Stochastic level and deterministic slope					
OERV	1.707418e-11	0.00173541	0.0006570298	0.003099544	0.002078867
LEEV	0.001031628	4.865224	9.192889	4.667206	7.675546
MLEILS	4.629863	0.002839205	0.003087949	0.0002130462	0.002152463
Stochastic level and seasonal					
OERV	1.565336e-09	8.317233e-09	1.624396e-08	0.0007063968	0.0001907874
LEEV	0.001018252	7.727068e-11	0.0006508755	0.003674626	0.002068797
SzEEV	1.403396e-12	0.00175149	1.65004e-13		1.788887e-11
Stochastic level and deterministic seasonal					
OERV	0.02294949	0.02292974	3.467775e-08	0.0229682	0.02293087
LEEV	0.1059166	0.1060983	0.0006509846	0.105745	0.1060879

Note: *Observation equation error variance (OERV); Level equation error variance (LEEV); Slope equation error variance (SEEV); Seasonal equation error variance (SzEEV); MLE of the initial value of level state (MLEILS); MLE of the initial value of slope state (MLEISS)*

Modeling and One-Step Ahead Forecasting has been performed using Weekly data for the period from January 2003 to December 2013 which is considered as super-cycle period when commodity prices escalated across the spectrum of Agriculture as well as metals. Data of mid-week i.e. of Wednesday is considered similar to Sorensen (2002) to negate any kind of the beginning of the week and end of the week influences and in the process remove undesirable noises of the data. Out of the select commodities deliberated in our study, we found that Aluminium, Copper, Lead, and Crude showed a significant impact of the 2008-2009 Global Recession. Nevertheless, prices rebounded back to their preceding state and don't demonstrate any impact comparable to structural change emphasizing the mean reversion characteristic of commodity prices. Commodities such as Gold, Jeera, Pepper, and Sugar do not express any noteworthy impact of the 2008-2009 financial crisis. Furthermore, these commodities confirmed long term upward trend Fernández *et al.* (2018). We found seasonal deviations while investigating monthly data for gold, barley, Sugar, and Jeera. Table 3 presents the One-Step Ahead Forecasting Performance of the Model. The forecasting performance of the estimated models is found to be respectable. The sum of squared residual or its average is astoundingly small in most of the cases. Only for lead, the errors are rather high. The calibrated and estimated models having stochastic specifications do well paralleled to deterministic ones for selected commodities.

Table 3. One-Step Ahead Forecasting Performance of the Model

Commodity		No. of observations	Residual				
			Values	Total	Average	Squared Total	Squared Total Average
Aluminum	Spot	378	Log	-0.05914	-0.00016	0.389361	0.001033
			Antilog	0.942577	0.999843	1.476038	1.001033
	Future	378	Log	0.042489	0.000113	0.428854	0.001138
			Antilog	1.043405	1.000113	1.535496	1.001138
Copper	Spot	409	Log	0.616678	0.001511	1.266124	0.003103
			Antilog	1.852762	1.001513	3.547078	1.003108
	Future	409	Log	0.636682	0.00156	1.191688	0.002921
			Antilog	1.890198	1.001562	3.292635	1.002925
Lead	Spot	246	Log	41.18282	0.168093	1696.025	0.0282553
			Antilog	1.614716	-0.7745	3.229432	-1.5489
	Future	246	Log	42.68361	0.174933	1821.89	0.0306015
			Antilog	1.6302611	-0.757128	3.260522	-1.514257
Gold	Spot	358	Log	-0.73507	-0.00206	0.540321	0.0000042
			Antilog	0.479474	0.997943	1.716558	1.0000042
	Future	358	Log	-0.73202	-0.00205	0.535855	0.0000042
			Antilog	0.480936	0.997952	1.708908	1.0000042
Crude	Spot	410	Log	0.630845	0.001542	0.397965	0.0000024
			Antilog	1.879198	1.001544	1.488793	1.0000024
	Future	410	Log	0.707102	0.001729	0.499993	0.000003
			Antilog	2.028105	1.00173	1.648709	1.000003
Barley	Spot	312	Log	0.088991	0.000286	0.007919	0.0000001
			Antilog	1.093071	1.000286	1.007951	1.0000001
	Future	312	Log	0.161248	0.026001	0.000519	0.0000003
			Antilog	1.174976	1.026342	1.000519	1.0000003
Jeera	Spot	407	Log	0.95093	0.002342	0.904268	0.0000055
			Antilog	2.588116	1.002345	2.470123	1.0000055
	Future	407	Log	0.805274	0.001983	0.648466	0.0000039
			Antilog	2.237309	1.001985	1.912605	1.0000039
Sugar	Spot	352	Log	0.307357	0.000878	0.094468	0.0000008
			Antilog	1.359826	1.000879	1.099074	1.0000008

	Future	352	Log	0.42289	0.001208	0.178836	0.0000015
			Antilog	1.526367	1.001209	1.195825	1.0000015
Pepper	Spot	450	Log	1.521151	0.003388	2.313899	0.0000115
			Antilog	4.577489	1.003394	10.11378	1.0000115
	Future	450	Log	1.394821	0.003107	1.945526	0.0000097
			Antilog	4.034254	1.003111	6.997315	1.0000097

An assessment of the performance of the models directs that the forecasts are very close to the actual values for most of the commodities. Figure 1 shows the One-Step Ahead Forecasting Performance of the Model with Residuals for Metals and Crude. Figure 2 presents the One-Step Ahead Forecasting Performance of the Model with Residuals for Agricultural Commodities. The results of the study suggest that state-space specification and Kalman filter provides preeminent estimates for modeling and forecasting Indian commodity prices during the Super-cycle period. The results of the study provide crucial insights for pension funds, alternate investment funds, hedge funds and sovereign wealth funds worldwide to strategize better in the next expected super-cycle period of commodities post Covid-19 with burgeoning demand from developing economies of Asia and Africa.

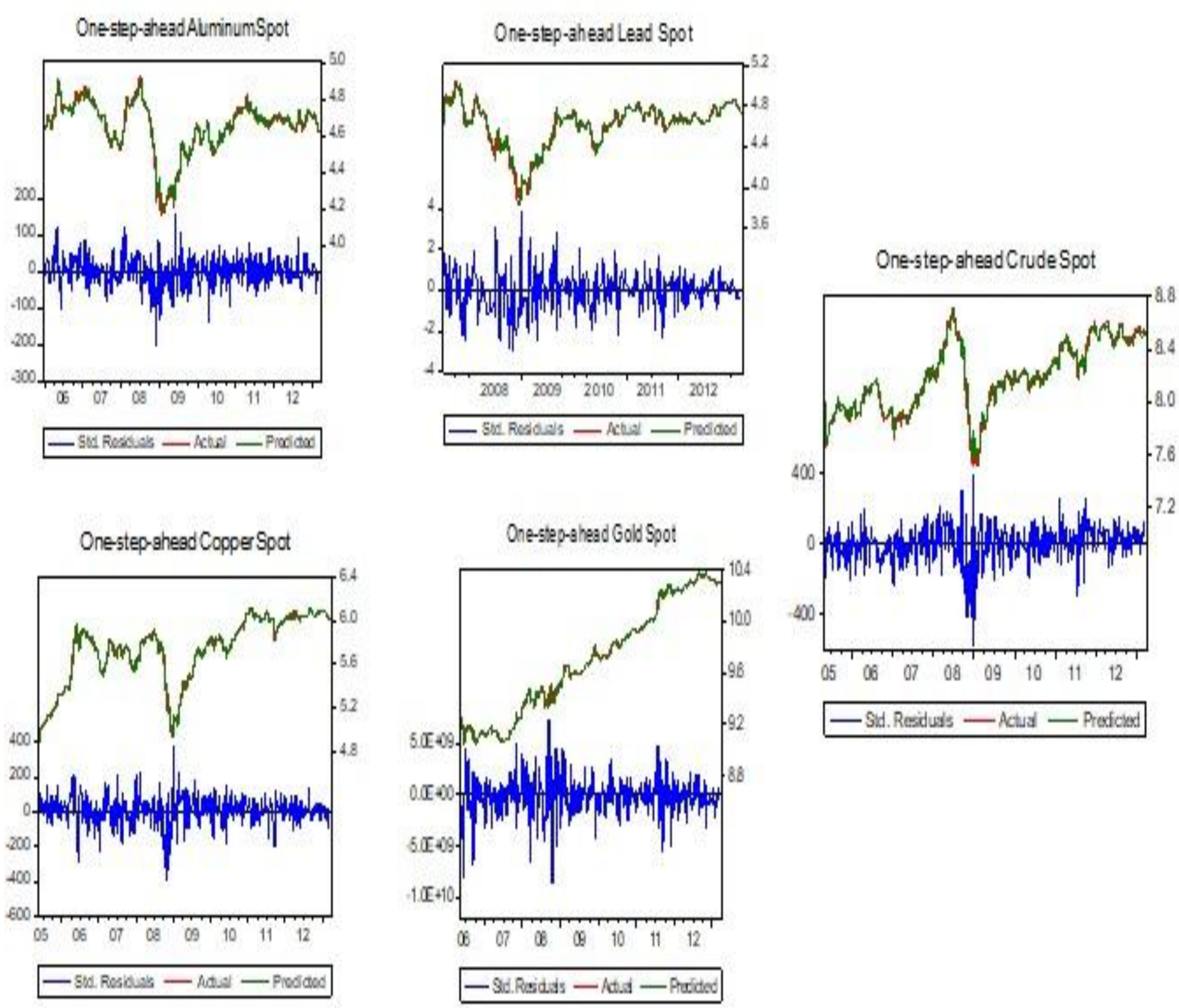

Figure 1. One-Step Ahead Forecasting Performance of the Model with Residuals for Metals and Crude

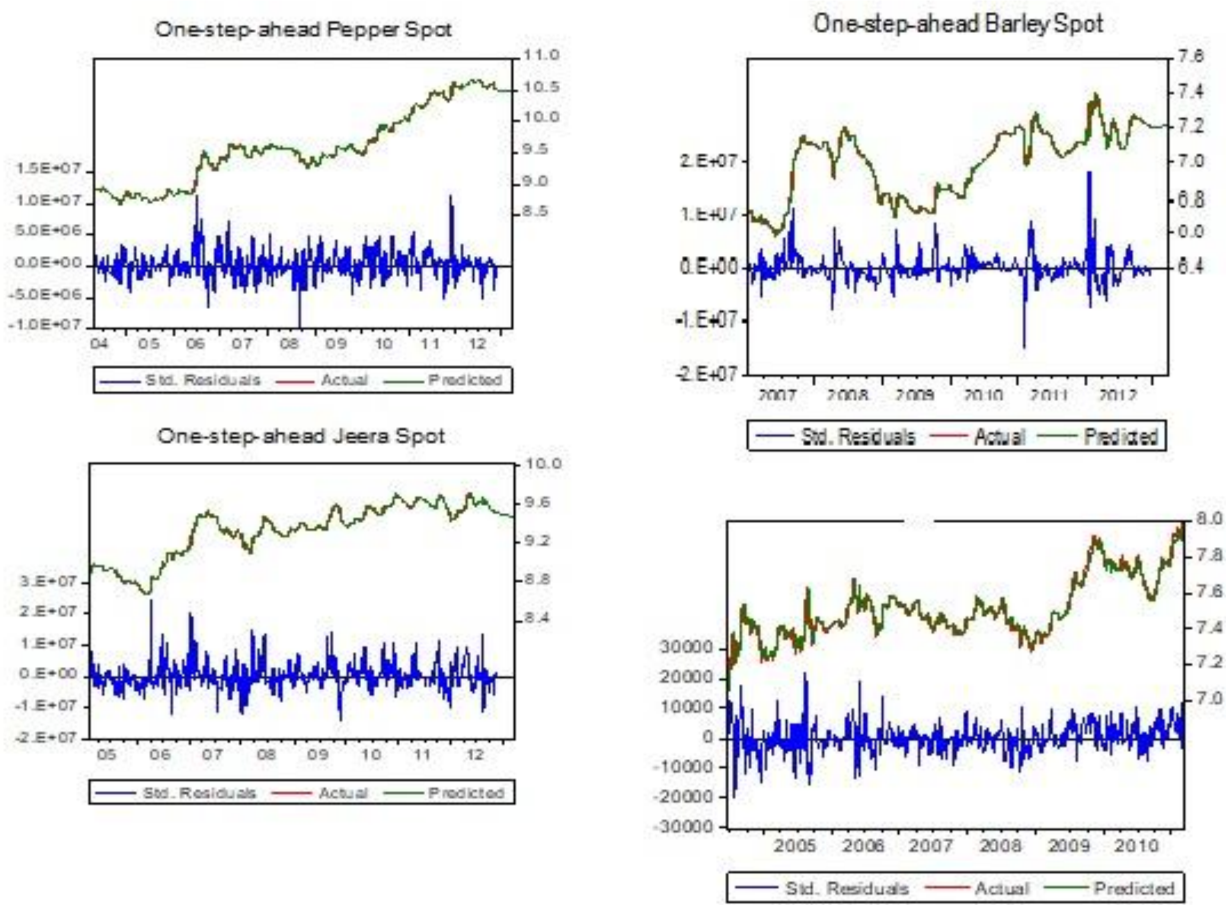

Figure 2. One-Step Ahead Forecasting Performance of the Model with Residuals for Agricultural Commodities

4. Conclusion

Commodity markets in India over the decades have encountered bottlenecks for market microstructure, restrictions on the free movement of commodities in various States/Provinces of the country, the actuality of market imperfections such as Minimum Support Price (MSP) for essential commodities as announced by the Government, superfluous political interloping and infrastructure concerns related to derisory warehousing facilities to name a few. As a result, the history of commodities futures trading in India is interrupted, flabbergasted and disrupted unlike commodities future trading in Chicago Mercantile Exchange (CME), Chicago Board of Trade (CBOT), or London Metal Exchange (LME) where futures trading has been taking place uninterrupted for over a century.

In this study, we modeled Commodity prices of select Agriculture (Barley, Jeera, Sugar, and Pepper), Metal (Aluminium, Copper, Lead, and Gold), and Energy commodities (Crude Oil) in Indian Commodity Markets by considering data during the super-cycle period of using the state-space specification and Kalman filter. The results of the study suggest that the estimated State-space models and Kalman filter provide preeminent estimates for modeling and forecasting commodity prices. This is a critical insight for Investors such as pension funds, alternate investment funds, hedge funds, and sovereign wealth funds worldwide to strategize better while allocating Capital in the next expected super-cycle period of commodities post-COVID-19 with burgeoning demand from developing economies of Asia and Africa.

The present study does not account for inventory positions. Studies in the future can explore incorporating data related to inventory positions of commodities for bringing a holistic picture. Studies using high-frequency data post-COVID-19 may bring an interesting picture to the world of commodity modeling and forecasting literature in the future.

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