

Spillover Effects of Covid-19 Induced Lockdown on Onion Prices in India

ABSTRACT

In a normal situation onion prices vary in a highly unprecedented way in India. So, it is worth noticing the effect of an uncertain situation on onion prices. In this article an efficient Artificial Intelligence (AI) tool, i.e., Support Vector Regression (SVR) has been used to predict the price fluctuation of onion over the lockdown period, unlock condition and the period including the pre-pandemic situation. Results obtained are compared with prediction of traditional Multiple Linear Regression (MLR) model. Several metrics such as R^2 , Root Mean Squared Error (RMSE), Mean Absolute Deviation (MAD), and Relative Mean Absolute Percentage Error (RMAPE) have been used for this purpose. The result of Machine Learning (ML) algorithm indicates that in the nationwide lockdown condition pandemic indicator variables are having more than 70% influence on the onion price variability. The effect is reduced to near about 60% in unlock condition and if considering the whole year data this effect is near about 45%. The results also indicate that ML algorithm is more efficient to capture the variability than the traditional model.

Keywords: AI; Covid-19; Lockdown; Volatility; MLR; SVR

1. INTRODUCTION

Nationwide lockdown in pan India affected the food chain, distribution and consumption. This affected several agricultural commodities world-wide which therefore created remarkable price changes, social, economic and policy crisis (Chen et al., 2019; Shiferaw, 2019; Su et al., 2019; Vo et al., 2019; Chang et al., 2020; Goodell et al., 2020 and 2021; Sharif et al., 2020). Changes in agricultural prices occur mainly due to several endogenous factors like demand and supply relationship, crude oil price, and monetary policies (Durevall et al., 2013; Paul and Ghosh, 2014; Fowowe, 2016; Mitra et al., 2019; Wei Su et al., 2019; Abedi and Zaionchik, 2020; Liu et al., 2020; Yeasin et al., 2020; Li et al., 2020 and 2021). External factors related to agricultural price changes are directly connected to natural shocks and climate changes (Jebabli et al., 2014; Bhardwaj et al., 2015; Priyanka and paul, 2017; Klomp and Hoogezand, 2018; Seok et al., 2018, and Yi et al., 2019; Chatzopoulos et al., 2020; Siddig et al., 2020; Paul et al., 2022). Rapid spread of the disease caused sheer decline of global economy (Verikios, 2020, Wu et al., 2020; Mofijur et al., 2021). Cariappa et al. (2021) studied impact on prices of agricultural items due to the lockdown. Panic purchase during incarcerated condition caused food wastage and increase in prices caused food losses in supply chain. Hung et al. (2021) studied connectedness between crude oil price and agricultural markets during covid-19 outbreak. It has been found by wavelet coherence analysis that the effect is more conspicuous during covid-19 crisis than pre-covid era and there is heterogeneity in the degree of spill-over effect over several markets. In the study of Cariappa et al. (2022) it can be found that observed price changes in wheat were due to the coincidence of wheat harvesting period and lockdown due to covid-19 pandemic. It was also found that pandemic induced shock could cause disaster if government had not bolstered by staggered procurement and provided logistic supports. Just and Echaust (2022) provided insights on transmission of return spill over among agricultural commodities due to combined

40 effect of covid-19 induced pandemic and Russia-Ukraine war. Sharing views regarding the
41 risks of the disease created unnecessary panic and anxiety among people (Loureiro and
42 Allo, 2020; Naseem et al., 2020; Zou et al., 2020; Islam et al., 2020; Nicomedes and Avila,
43 2020). Liu et al. (2022) used text mining tool and time dependent variance autoregressive
44 model to study the negative sentiments of online micro blogs to agricultural commodity
45 prices. They found interesting positive relationships with livestock and vegetable products,
46 negative relationships with fruits, and negative at the early but positive relationships at
47 middle and late stages with aquatic products. Martey et al. (2022) studied the effects of
48 covid-19 shock on adoption of sustainable agricultural practices among farmers. Paul et al.
49 (2022) pointed out impact of covid-19 shocks on vegetable prices and tried to predict daily
50 price of brinjal in 17 markets of Odisha, India. Paul and Yeasin (2022) also applied
51 Generalized Autoregressive Conditional Heteroscedastic (GARCH) model to investigate the
52 effects of covid-19 pandemic on prices of major pulses in India. Tiwari et al. (2022)
53 employed a new technique related to Variance Autoregressive (VAR) model to measure the
54 spillover effect between energy and agricultural commodity prices. Zahraee et al. (2022)
55 evaluated the impact of covid-19 induced disruptions on resilience of supply chain of
56 agricultural sector.

57 Machine learning techniques are proven to be effective in capturing volatility in time series
58 datasets especially, in agricultural price series (Das et al., 2020, Garai et al., 2023). Support
59 Vector Machine (SVM) has recently been widely in use by researchers in the field of time
60 series modelling. It is an unsupervised learning technique where input variables are provided
61 with very few information about the results. The 'Vapnik ϵ -insensitive Loss Function' was
62 introduced by Vapnik et. al (1992) which clarifies the use of SVR technique in the domain of
63 regression and time-series problems. Non-linear dynamics present in the price structure of
64 agricultural products allow SVR to be implemented for prediction. Extreme price fluctuation
65 of onion in one of the major consumer markets i.e. the Delhi market has been observed in
66 2020, the year of Corona pandemic. Due to lockdown condition rural people could not
67 transport their agricultural products to nearby markets for around 2 months which may be a
68 reason for price change and their deteriorating economic condition (Imai et al., 2020). In this
69 situation an efficient AI tool namely support vector regression (SVR) has been applied to
70 model the daily price of onion and investigate the effect of pandemic on onion price in Delhi.

71

72 **2. MATERIAL AND METHODS**

73

74 **2.1 DATA**

75

76 Daily price of Onion (Y) in Delhi has been collected from the National Horticultural Research
77 and Development Foundation (NHRDF) website for the year of 2020 from 1st of January to
78 27th of October. Dataset is divided into two parts: data of lockdown period (25th March-31st
79 May) and another is of Unlock period (1st June-27th October). Dataset of Covid-19 infection
80 is also collected for this time period on a daily basis from the website
81 <https://www.kaggle.com/sudalairajkumar/covid19-in-india>.

82 Firstly, Pearson's correlation coefficient (CC) was computed to see if there is significant
83 correlation among the onion prices with number of daily covid-19 infected (CO), number of
84 daily deaths due to covid-19 infection (D) and number of daily cured (CU) individuals after
85 covid-19 infection. Secondly, suitable statistical test was conducted to check for presence of
86 any non-linearity pattern in the datasets. MLR and SVR models have been fitted to these
87 datasets taking onion prices as dependent variable and others as predictors to predict onion
88 price for the whole year, lockdown and unlock condition.

89

90 **2.2 TRADITIONAL MLR MODEL**

91

92 A tradition MLR model can be represented as

$$93 \widehat{y}(t_n) = a_0 + a_1CU + a_2D + a_3CO \quad (1)$$

94 where $\widehat{y}(t_n)$ is the predicted onion price (equation 1). CU, D, CO are the potential predictors
95 and a_i 's are the regression parameters used in the MLR model. The a_i values are estimated
96 from the data given. In order to prevent overfitting of the data and to find the optimal (final)
97 regression model, a stepwise regression algorithm (Draper and Smith, 1998) is employed to
98 select significant predictors from all the candidate variables in this study. Finally, the
99 predicted prices are computed.

100

101 **2.3SVR**

102

103 SVM got extensive popularity in the field of classification, regression, and dimensionality
104 reduction. It simply utilizes a hyperplane to linearly separate a series into two classes.
105 Optimal hyperplane can be obtained by- a) convex hull, b) maximizing the margin between
106 two parallel boundaries.

107 In linear case training set $(x_1, y_1), (x_2, y_2), \dots (x_n, y_n)$; $x \in R_n, y \in \{+1, -1\}$ is classified by
108 hyperplane: $(w \cdot x) + b = 0$ such that margin between nearest vectors to this is maximized.
109 $(w \cdot xi) + b \geq +1$ if $yi = 1$, or $(w \cdot xi) + b \leq -1$ if $yi = -1$, where w and b are weight and
110 bias respectively.

111 Non-linear datasets are mapped into higher dimensional feature space for linear separation.

112 Nonlinear SVR is represented as (equation 2):

$$113 f(x) = w^T \varphi(x) + b \quad (2)$$

114 Where $\varphi(\cdot): R^n \rightarrow R^{n_h}$, which is a non-linear mapping function for linear separation. The
115 following function (equation 3) is maximized:

$$116 R(C) = \frac{1}{2} \|w\|^2 + C \left[\frac{1}{N} \sum_{i=1}^N L_\varepsilon(y_i, f(x_i)) \right] (3)$$

117 where $x_i \in R^n$ and $w \in R^{n_h}$ is the weight vector. Both C and ε are arbitrary hyper-parameters.

118 'Regularized term', i.e., $\frac{1}{2} \|w\|^2$ measures the flatness of the function in equation 3. 'Empirical

119 error', i.e., $\frac{1}{N} \sum_{i=1}^N L_\varepsilon(y_i, f(x_i))$ is estimated by 'Vapnik ε -insensitive Loss Function' (equation

120 4), given by:

$$121 L_\varepsilon(y_i, f(x_i)) = \begin{cases} |y_i - f(x_i)| - \varepsilon & |y_i - f(x_i)| \geq \varepsilon \\ 0 & |y_i - f(x_i)| < \varepsilon \end{cases} (4)$$

122 where y_i denotes actual value and $f(x_i)$ is the estimated value at i^{th} period.

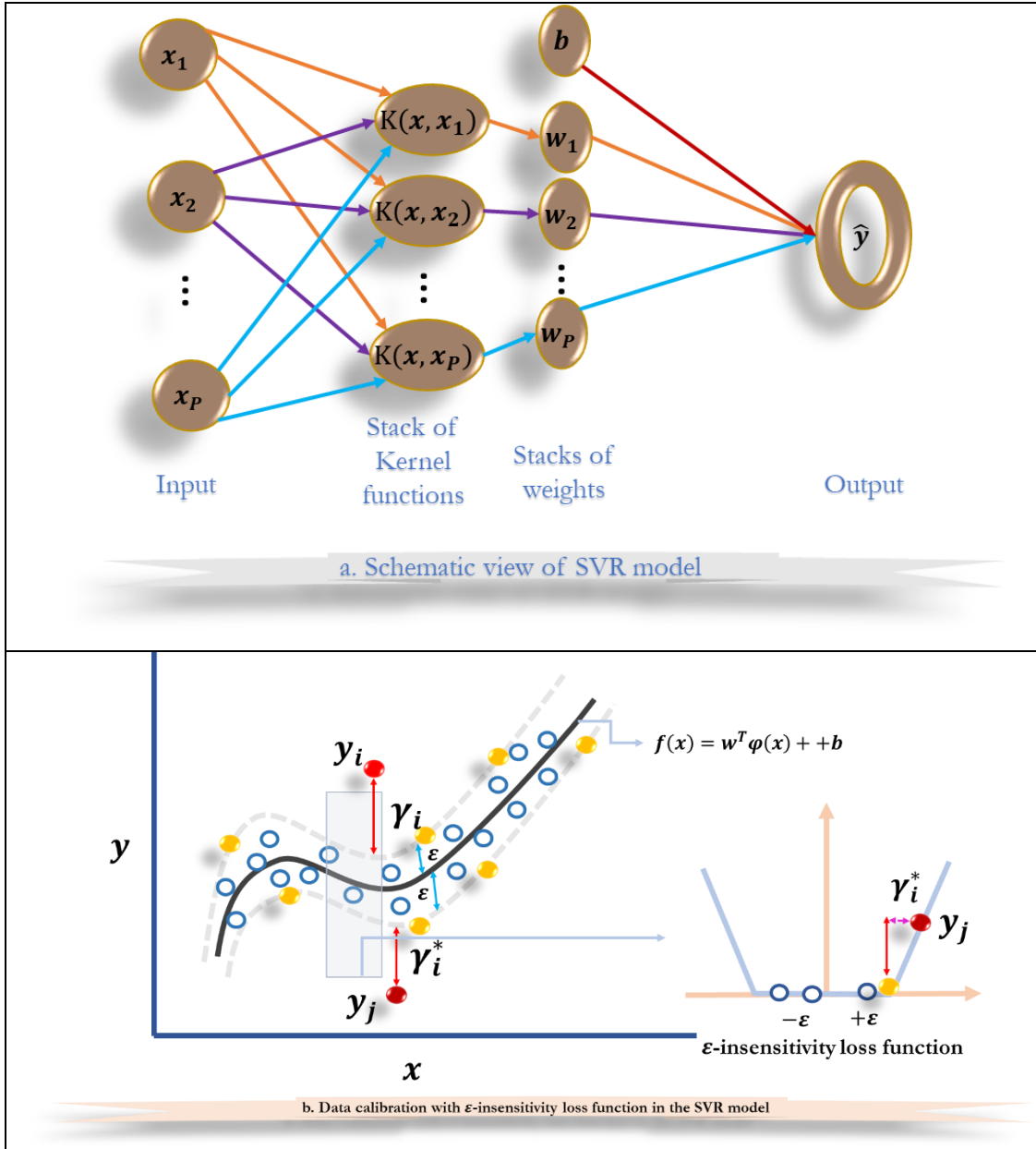


Fig. 1. SVR model

123

124 Then the $R(C)$ can be reframed as (equation 5):

125
$$R(C) = \frac{1}{2} \|w\|^2 + C \left[\frac{1}{N} \sum_{i=1}^N (\gamma_i + \gamma_i^*) \right] \quad (5)$$

126 Subjected to the constraints:
$$\begin{cases} w^T \varphi(x_i) + a - y_i \leq \epsilon + \gamma_i^* \\ y_i - w^T \varphi(x_i) - a \leq \epsilon + \gamma_i \\ \gamma_i \gamma_i^* \geq 0 \quad i = 1, 2, \dots, N \end{cases}$$

127 where γ_i and γ_i^* are positive slack variables measuring distance from actual values, y_i and
 128 corresponding 'boundary values of the ϵ -tube'. The primal Lagrange function (equation 6) for
 129 solving this problem:

130
$$L = \frac{1}{2} \|w\|^2 + C \left[\sum_{i=1}^N (\gamma_i + \gamma_i^*) \right] - \sum_{i=1}^N \alpha_i (w^T \varphi(x_i) + a - y_i + \epsilon + \gamma_i^*) - \sum_{i=1}^N \alpha_i^* (y_i -$$

 131
$$w^T \varphi(x_i) - a + \epsilon + \gamma_i) - \sum_{i=1}^N (\eta_i \gamma_i + \eta_i^* \gamma_i^*) \quad (6)$$

132 Where w , a , γ_i and γ_i^* are primal variables, and α_i , α_i^* , η_i , and η_i^* are nonnegative Lagrange
 133 multipliers. Karush-Kuhn-Tucker (KKT) condition (Vapnik et al., 1992) is used to solve the
 134 problem. Partially differentiating (equation 6) we get:

$$\frac{\partial L}{\partial b} = \sum_{i=1}^N (\alpha_i^* - \alpha_i) = 0$$

$$\frac{\partial L}{\partial w} = w - \sum_{i=1}^N (\alpha_i^* - \alpha_i) \varphi(x_i) = 0$$

$$\frac{\partial L}{\partial \xi_i^*} = C - \alpha_i^* - \eta_i^*; i = 1, 2, \dots, N$$

135 Kernel Functions are used by SVR to transform the input dataset into required form.
 136 Mathematically a Kernel function can be represented as (equation 7)

$$137 K(x, y) = \begin{cases} 1, & \langle f(x), f(y) \rangle > \epsilon \\ 0, & \text{otherwise} \end{cases} \quad (7)$$

138 where K is the kernel function, x, y are n dimensional inputs. f is a map from n -dimension to
 139 m -dimension space. In figure 1 (a) schematic diagram of SVR model has been represented
 140 and in figure(b) ϵ -insensitive Loss Function is introduced. Some commonly used kernel
 141 functions are linear, polynomial, Radial Basis Function (RBF), sigmoid kernel, etc.
 142 Introducing the 'Kernel function' ($K(x_i, x_j)$) [i.e., inner product of $\varphi(x_i)$ and $\varphi(x_j)$], the final
 143 form of the equation of nonlinear SVR will be (equation 8):

$$144 f(x) = \sum_{i=1}^N (\alpha_i - \alpha_i^*) K(x_i, x_j) + b \quad (8)$$

145 However, efficiency of nonlinear SVR models depends on the hyper-parameters. The most
 146 efficient technique to optimize them is real valued Genetic Algorithm (GA). Albeit, due to the
 147 capacity of escaping local minima Particle Swarm Optimization (PSO) technique is
 148 extensively used.

149 MLR and SVR models have been fitted to the mentioned datasets taking onion prices as
 150 dependent variable and others as predictor variables for the whole year, lockdown and
 151 unlock conditions.

152

153 3. RESULTS AND DISCUSSION

154

155 3.1 DATA DESCRIPTION

156

157 Total 301 observations were obtained for each of the 4 datasets mentioned in this study.
 158 Minimum onion price in Delhi market was 567 rupees/Quintal (Rs/Q) and maximum price of
 159 4550 Rs/Q was observed during the stipulated time period. Average price during this period
 160 was 1650 Rs/Q with a standard deviation (SD) of 964 and Coefficient of Variation (CV) as
 161 58.4%. 1st, 2nd (Median), and 3rd quartile (Q) values of prices were 916, 1310 and 2000
 162 Rs/Q respectively. It can be observed from table 1 that price dataset was positively skewed
 163 and leptokurtic in nature. Maximum number of daily confirmed cases was 4473 with an
 164 average case of 1194. Dataset is slightly positively skewed with a platykurtic feature.
 165 Maximum number of cured cases in a day was 437. Average number of cured cases was 20
 166 with a SD of 33 and CV of 165%. The dataset is highly positively right tailed and possesses
 167 extreme leptokurtic nature. Maximum number of deaths observed in a day was 7725.
 168 Average number of death cases was 1088 with SD and CV values were 1357 and 125%.
 169 Dataset related to death cases is positively skewed and leptokurtic in nature.

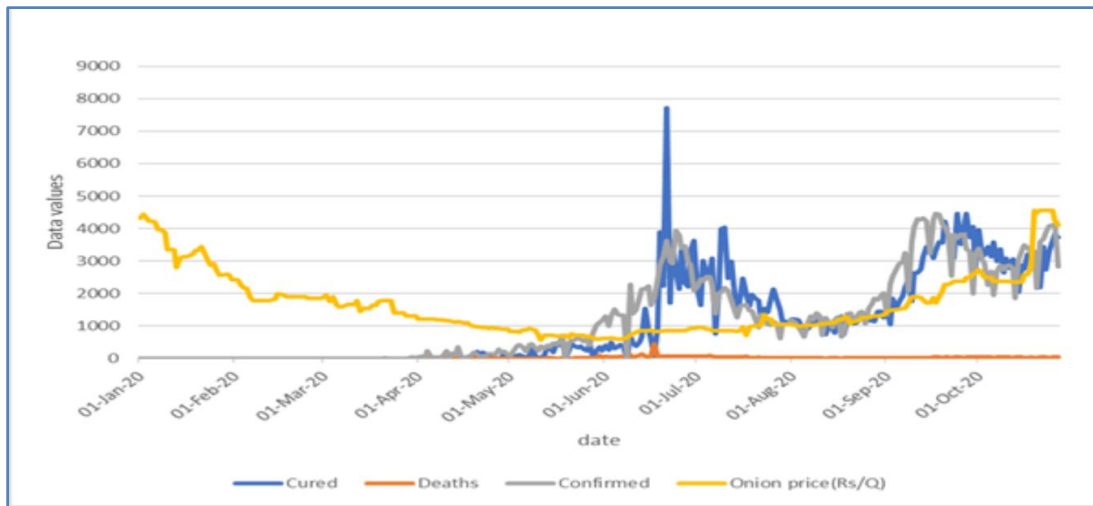
170

Table 1. Descriptive statistics of the full data set

	Y	CU	D	CO
N	301	301	301	301
Min	567	0	0	0
1st Q	916	0	0	1

Median	1310	13	375	674
Mean	1650	20	1088	1194
3rd Q	2000	34	1973	2089
Max	4550	437	7725	4473
Range	3983	437	7725	4473
SD	964	33	1357	1334
CV (%)	58.4	165	125	112
Skewness	1.34	6.82	1.18	0.86
Kurtosis	1.29	78.22	0.98	-0.53

171



172

Fig. 2. Line charts describing the pattern of different variables

173

174

175

176

177

178

179

180

181

182

183

184

Time plots of 301 observations covering onion price patterns and covid-19 related figures are represented in figure 2. Pearsonian correlation measure is useful for an overall view of the relation of any two datasets. Relation between each of the predictor variables, i.e., CU, D and CO with price dataset has been found by calculating CC values between them and represented in table 2. For checking the significance of each of the correlation measure t-test was applied and calculated statistics value and corresponding degrees of freedom (df) have been mentioned in table 2. Correlation measures were calculated for each of the variables on the full data, only lockdown period data and unlock condition data separately and represented in table 2.

Table 2. Correlation coefficient values (CC) of different predictor variables with onion market arrival prices (Rs/Q)

Predictors	CC			t-value and df			p-value		
	Full	Lockdown	Unlock	Full	Lockdown	Unlock	Full	Lockdown	Unlock
CU	0.14	-0.66	0.52	2.41, 299	-7.11, 66	7.35, 147	0.02	<0.0001	<0.0001
D	-0.17	-0.48	-0.13	2.93, 299	-4.44, 66	-1.56, 147	0.004	<0.0001	0.12
CO	0.11	-0.76	0.57	1.86, 299	-9.50, 66	8.49, 147	0.06	<0.0001	<0.0001

185

186

187

188

189

It can be observed that CC values are higher in case of lockdown data. In unlock situation number of deaths due to Corona does not affect much to onion prices but other two predictors are affecting significantly to the onion price data. By observing CC values, it can be concluded that predictors have less influence on price series for the full-length data. Brock-Dechert-Scheinman (BDS) test (Brock et al., 1996) had been applied to all the four

190 variables. BDS test is a two-tailed test. The null hypothesis (H_0) and alternative hypothesis
 191 (H_1) of the BDS test are as follows:

192 H_0 = Time series is linear (data series are identically and independently distributed,
 193 i.e., i.i.d)

194 H_1 =Time series is nonlinear (presence of nonlinear dependency)

195 It is proved from table 3 that all the variables are having non-linear pattern in the given time
 196 period.

197

Table 3. BDS test results for four variables

Statistics	Embedding dimension								Conclusion (at 1% level)
	2				3				
	Value				Value				
	Y	CU	D	CO	Y	CU	D	CO	
eps [1]	65.54	42.40	46.22	54.81	103.90	64.50	63.28	89.81	Nonlinear with maximum embedding dimension- 3
eps [2]	43.54	38.93	26.88	47.79	50.70	47.91	31.36	58.75	
eps [3]	34.37	33.74	21.17	40.06	35.42	37.60	20.97	44.73	
eps [4]	27.81	24.08	7.05	33.74	26.93	26.18	7.01	35.81	

198

199

200

3.2 FITTING INTO MLR AND SVR MODELS

201

202

203

204

205

206

207

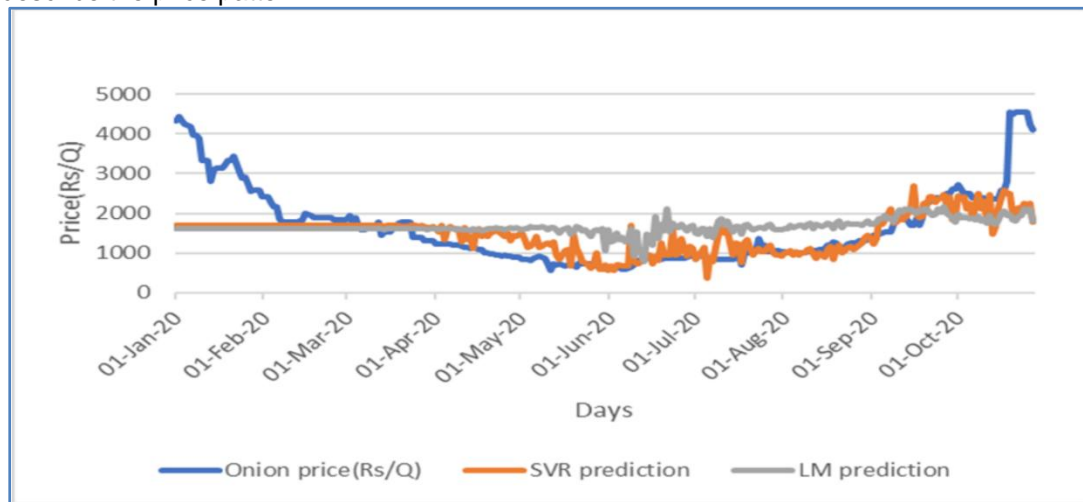
208

209

210

211

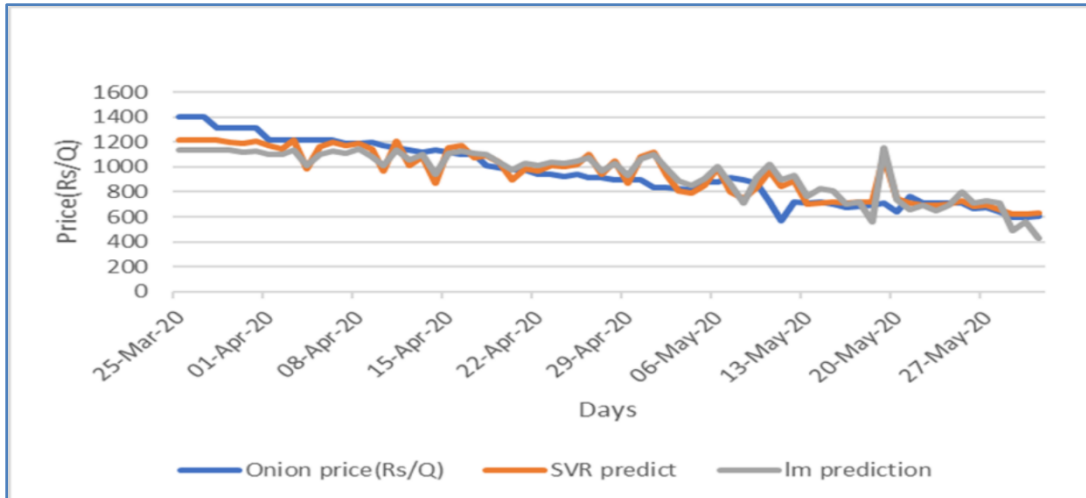
MLR model had been fitted into 3 datasets to predict onion prices on 3 different time frames. A glimpse of impact of covid-19 pandemic on onion prices can be observed by doing so. However, non-linear ML model, i.e., SVR was applied on the series to capture its predictability during 3 different scenarios. Figure 3 represents line charts of predictions of MLR and SVR models on complete series. How the two models performed during the lockdown period can be observed in figure 4. Predictions of these models on onion prices at the unlock situations can be visualized in figure 5. It can be seen from figure 2 and figure 4 that prices of last few days could not be predicted by both of the models. This simply implies that at unlock condition as time passed on dependence of covid-19 related statistics on onion price structure gradually decreased. Hence, there are other influential factors to describe the price pattern.



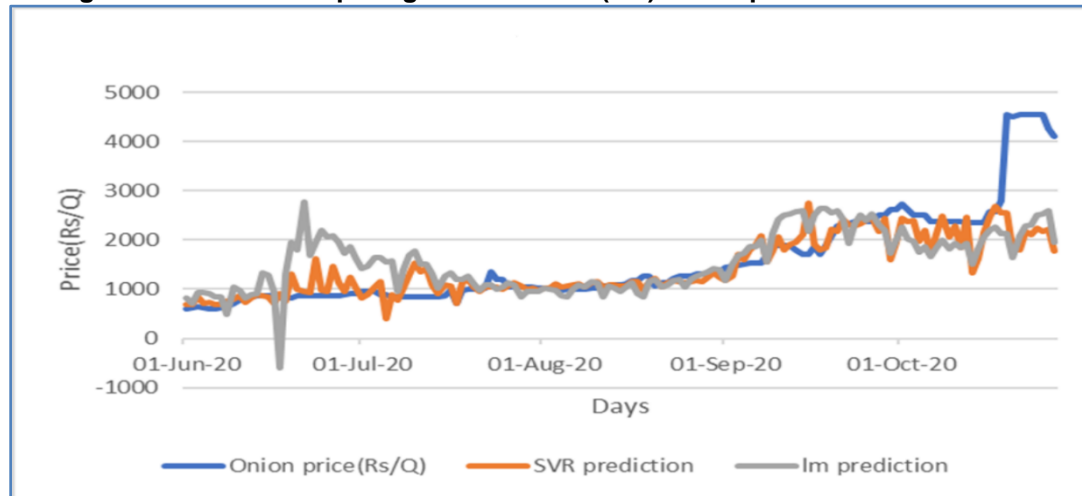
212

213

Fig. 3. Line charts comparing SVR and MLR(LM) model prediction on full dataset



214
215 **Fig.4. Line charts comparing SVR and MLR(LM) model prediction in lockdown**



216
217 **Fig.5. Line charts comparing SVR and MLR(LM) model prediction in unlock**

218 Comparison statistics are represented for three series on prediction performance of MLR
219 and SVR models in table 4. R^2 in a regression model plays very important role which
220 indicates the percentage variability of predictand explained by predictor variables. Error or
221 residuals in prediction is a very important keyword meaning the failure of a model to predict
222 a variable precisely. This is used to produce several metrics of model evaluation. RMSE is
223 the squared root of the average mean squared error. However, MAD is calculated by
224 averaging the absolute error values. Similarly, Relative Absolute Error (RAE) values are
225 calculated for each observation by dividing the absolute error values by actual observation.
226 Thus, RMAPE is obtained by averaging out the RAEs over the whole series followed by
227 multiplication of a cent. In the full data set R^2 values are 8.31 and 45.21 for MLR and SVR
228 models respectively. This means SVR can explain percentage variation in the series more
229 accurately than MLR. Albeit, R^2 value of such a low quantity cannot be considered a good fit
230 for a statistical model, in lockdown condition the predictor variables can explain most of the
231 variability in the onion price series.

232 **Table 4. Comparative performance of prediction models on different datasets**

Comparative measures	Full		Lockdown		Unlock	
	MLR	SVR	MLR	SVR	MLR	SVR
R^2 (%)	8.31	45.21	62.78	74.90	38.18	59.94

RMSE	922	756	143.5	118.23	752	643
MAD	707	445	114	84	502	313
RMAPE (%)	52	25	13	9	35	17

233 A significant improvement in prediction has been achieved by utilizing ML algorithm. A steep
234 increase of 19.31% in R^2 value is achieved by fitting the series into SVR model in lockdown
235 condition. Although, number of observations was less in case of lockdown, 74.90% R^2 value
236 has been acquired by fitting the data into SVR model. The spillover effect of covid-19
237 lockdown was sustained in unlock situation as the statistics related to the disease are
238 capable of explaining the price variability of onion at that time period also. It is obvious that
239 there are many factors which are causing onion price volatility. The previous statement is
240 true because onion price variability could not be explained by using only covid-19 statistics.
241 That's why the R^2 , RMSE, MAD and RMAPE values were quite unsatisfactory when the
242 MLR and SVR models were used to fit price series on whole series. Nevertheless, these
243 metrics prove that SVR performs better than MLR. The statistical metrics used in this study
244 confirms that SVR model is better in capturing the price volatility of onion for the lockdown
245 condition than MLR model. Similar comment can be passed on for unlock condition. These
246 statements are indicating that the specified ML algorithm used in the study, i.e., SVR
247 outperforms in all aspects to capture price volatility of onion price either in a normal or crisis
248 situation. RMAPE value less than 10% is considered an outstanding fit for a model. This was
249 achieved by SVR model in lockdown condition. MLR was also capable to predict the series
250 during the period. It is quite interesting to note that at last few days of unlock condition both
251 MLR and SVR were incapable of predicting the price series using the chosen predictor
252 variables. This indicates that effect of covid-19 pandemic on onion prices was decreasing
253 and other related price factors were reasons for the price volatility.

254
255
256

4. CONCLUSION

257 Price of perishable agricultural food products is fully dependent on every day transport and
258 supply chain. In the lockdown condition rural people could not be able to market their
259 agricultural products to nearby markets properly due to unavailability of proper transportation
260 facility. Due to less supply, price of food products might have increased in a normal condition
261 but effect of corona virus (covid-19) was so severe that a reverse price scenario had been
262 observed due to less demand during the lockdown condition. In this study the effect of covid-
263 19 was studied on onion prices. MLR and SVR models were applied to fit confirmed, cured
264 and death cases due to covid-19 and onion prices data series during pre-pandemic,
265 nationwide lockdown and unlock condition in India. Price trend of onion series had effectively
266 been captured by the SVR and outperformance of this AI tool was noticed over the
267 traditional MLR tool. It is clear from table 4 considering the result of ML algorithm that in the
268 nationwide lockdown condition pandemic indicator variables were having more than 70%
269 influence on the onion price variability. The effect was reduced to near about 60% in unlock
270 condition and if considering the whole year data, this effect was near about 45%. The results
271 also indicate that ML algorithm was more efficient to capture the variability than the
272 traditional model. During covid-19 pandemic, panic buying situation was observed among
273 people. They stored essential commodities before the lockdown and for this reason price
274 hike might be noticed. On the other hand, rural farmers had to go for distress sell also. This
275 trend might be observed on other daily food essentials like potato, egg etc. which were
276 marketed by rural people on a daily basis but hampered due to the pandemic and they had
277 suffered for this. Therefore, it is worth analysing the impact of covid-19 on other food items
278 using several other AI tools.
279

280 **ACKNOWLEDGEMENTS**

281

282 The authors are thankful to ICAR-IASRI for providing infrastructural support to carry out this
283 research.

284

285

286 **AUTHORS' CONTRIBUTIONS**

287

288 'S.G.' designed the study, performed the statistical analysis, and wrote the first draft of the
289 manuscript. 'R.K.P.' edited the manuscript and 'A.K.P.' reviewed the manuscript. All authors
290 read and approved the final manuscript."

291

292 Conference disclaimer:

293 Some part of this manuscript was previously presented and published in the conference:
294 Indian Society of Agricultural Statistics (ISAS) 2022, during 14-16 Nov, 2022 in J&K. Web
295 Link of the proceeding: <http://isas.org.in/IsasConference/aboutConference>

296

297 **REFERENCES**

298

299 **Abedi, A., & Zaionchik, L. (2020). The Fundamentals of Financial Forecasting Condition of**
300 **Oil Production Enterprise. *ICEMT, Atlantis Press, 87-90.***

301 Bhardwaj, S.P., Paul, R.K., and Singh, K.N. (2015). Price forecast an instrument for
302 improvement in agricultural production and marketing in Rajasthan-A case study of
303 rape & mustard seeds. *Jour. Ind. Soc. Ag. Statistics*, **29**(2), 155-163.

304 Brock, W. A., Scheinkman, J. A., Dechert, W. D. and Le, B. (1996). A test for
305 independence based on the correlation dimension. *Econom. Rev.*, **15**, 197-235.

306 Cariappa, A.A., Acharya, K.K., Adhav, C.A., Sendhil, R., and Ramasundaram, P. (2022).
307 COVID-19 induced lockdown effects on agricultural commodity prices and consumer
308 behaviour in India—Implications for food loss and waste management. *Socio-*
309 *Econ. Plan. Sci.*, **82**, 101160.

310 Cariappa, A.A., Acharya, K.K., Adhav, C.A., Sendhil, R., Ramasundaram, P., Kumar, A.,
311 Singh, S., and Singh, G.P. (2022). COVID-19 induced lockdown effect on wheat
312 supply chain and prices in India—Insights from state interventions led
313 resilience. *Socio-Econ. Plan. Sci.*, 101366.

314 Chang, C.L., McAleer, M., and Wong, W.K. (2020). Risk and financial management of
315 COVID- 19 in business, economics and finance. *J. Risk Financ. Manag.*, **13**, 102.

316 Chatzopoulos, T., P´erez Dom´ınguez, I., Zampieri, M., and Toreti, A. (2020). Climate
317 extremes and agricultural commodity markets: a global economic analysis of
318 regionally simulated events. *Weather. Clim. Extremes*, **27**, 100193.

319 Chen, Z.M., Wang, L., Zhang, X.B., and Zheng, X. (2019). The co-movement and
320 asymmetry between energy and grain prices: evidence from the crude oil and corn
321 markets. *Energies*, **12**(7), 1373.

322 Das, T., Paul, R.K., Bhar, L.M. and Paul, A.K. (2020). Application of Machine Learning
323 Techniques with GARCH Model for Forecasting Volatility in Agricultural Commodity
324 Prices. *Jour. Ind. Soc. Ag. Statistics*, **74**(3), 187-194.

325 Draper, Norman R. and Smith, H. (1998). [Wiley Series in Probability and Statistics] Applied
326 Regression Analysis, DOI:10.1002/9781118625590.

327 Durevall, D., Loening, J.L., and Ayalew Birru, Y. (2013). Inflation dynamics and food prices in
328 Ethiopia. *J. Dev. Econ.*, **104**, 89–106.

329 Fowowe, B. (2016). Do oil prices drive agricultural commodity prices? Evidence from South
330 Africa. *Energy*, **104**, 149–157.

331 Garai, S., Paul, R. K., Rakshit, D., Yeasin, M., Emam, W., Tashkandy, Y., and Chesneau, C.
332 (2023). Wavelets in combination with stochastic and machine learning models to
333 predict agricultural prices. *Mathematics*, **11**(13), 2896.

334 Goodell, J.W. (2020). COVID-19 and finance: agendas for future research. *Finance Res.*
335 *Let.*, 101512.

336 Goodell, J.W., and Goutte, S. (2021). Co-movement of COVID-19 and Bitcoin: evidence
337 from wavelet coherence analysis. *Finance Res. Let.*, **38**, 101625.

338 Gurung, B., Paul, R.K., and Ghosh, H. (2014). Fitting exponential smooth transition
339 autoregressive nonlinear time-series model using particle swarm optimization
340 technique. *Jour. Ind. Soc. Ag. Statistics*, **68**(3), 327-332.

341 Hung, N.T. (2021). Oil prices and agricultural commodity markets: Evidence from pre and
342 during COVID-19 outbreak. *Res. Policy*, **73**, 102236.

343 Imai, K. S., Kaicker, N., and Gaiha, R. (2020). "The Covid-19 Impact on Agricultural Prices in
344 India. Discussion Paper Series DP2020-25, Research Institute for Economics &
345 Business Administration, Kobe University, revised Oct 2020.

346 Islam, M.S., Ferdous, M.Z., and Potenza, M.N. (2020). Panic and generalized anxiety during
347 the COVID-19 pandemic among Bangladeshi people: an online pilot survey early in
348 the outbreak. *J. Affect. Disord.*, **276**, 30–37.

349 Jebabli, I., Arouri, M., and Teulon, F. (2014). On the effects of world stock market and oil
350 price shocks on food prices: an empirical investigation based on TVP-VAR models
351 with stochastic volatility. *Energy Econ.*, **45**, 66–98.

352 Just, M. and Echaust, K. (2022). Dynamic spillover transmission in agricultural commodity
353 markets: What has changed after the COVID-19 threat? *Econ. Let.*, **217**, 110671.

354 Klomp, J., and Hoogezand, B. (2018). Natural disasters and agricultural protection: a panel
355 data analysis. *World Dev.*, **104**, 404–417.

356 Li, T., Rong, L., and Zhang, A. (2021). Assessing regional risk of COVID-19 infection from
357 Wuhan via high-speed rail. *Transport Pol.*, **106**, 226–238.

358 Li, X., Wu, P., and Wang, W. (2020). Incorporating stock prices and news sentiments for
359 stock market prediction: a case of Hong Kong. *Inf. Process. Manag.*, **57**, 102212.

360 Liu, L., Tan, S., and Wang, Y. (2020). Can commodity prices forecast exchange rates?
361 *Energy Econ.*, **87**, 104719.

362 Liu, Y., Liu, S., Ye, D., Tang, H. and Wang, F. (2022). Dynamic impact of negative public
363 sentiment on agricultural product prices during COVID-19. *J. Retail. Consum.*
364 *Serv.*, **64**, 102790.

365 Loureiro, M.L., and Allo, M. (2020). Sensing climate change and energy issues: sentiment
366 and emotion analysis with social media in the U.K. and Spain. *Energy Pol.*, **143**,
367 111490.

368 Martey, E., Etwire, P.M., Adzawla, W., Atakora, W., and Bindraban, P.S. (2022). Perceptions
369 of COVID-19 shocks and adoption of sustainable agricultural practices in
370 Ghana. *J. Environ. Manage.*, **320**, 115810.

371 Mitra, D., Paul, R.K., Udgata, A.R., Paul, A.K., and Bhar, L.M. (2019). Spatio-temporal
372 models for forecasting of rice and wheat yields in India. *Jour. Ind. Soc. Ag.*
373 *Statistics*, **73**(3), 181-188.

374 Mofijur, M., Fattah, I.M.R., Alam, M.A., Islam, A.B.M.S., Ong, H.C., Rahman, S.M.A., Najafi,
375 G., Ahmed, S.F., Uddin, M.A., and Mahlia, T.M.I. (2021). Impact of COVID-19 on the
376 social, economic, environmental and energy domains: lessons learnt from a global
377 pandemic. *Sustain. Prod. Consum.*, **26**, 343–359.

378 Naseem, U., Razzak, I., Musial, K., and Imran, M. (2020). Transformer based deep
379 intelligent contextual embedding for twitter sentiment analysis %. *J. Future Gener.*
380 *Comput. Syst.*, 113.

381 Nicomedes, C.J.C., and Avila, R.M.A. (2020). An analysis on the panic during COVID-19
382 pandemic through an online form. *J. Affect. Disord.*, **276**, 14–22.

383 Panwar, S., Kumar, A., Sarkar, S.K., Paul, R.K., Gurung, B., and Rathore, A. (2016).
384 Forecasting of common carp fish production from ponds using nonlinear growth
385 models-a modelling approach. *Jour. Ind. Soc. Ag. Statistics*, **70**(2), 139-144.

386 Paul R.K., Yeasin, M., and Paul, A. (2022). The volatility spillover of potato prices in different
387 markets of India. *Curr. Sci.*, **123**(10), 482-487

388 Paul, R.K., and Himadri, G. (2014). Development of out-of-sample forecasts formulae for
389 ARIMAX-GARCH model and their application. *Jour. Ind. Soc. Ag. Statistics*, **68**(1),
390 85-92.

391 Paul, R.K., and Yeasin, M. (2022). COVID-19 and prices of pulses in Major markets of India:
392 Impact of nationwide lockdown. *Plos one*, **17**(8), e0272999.

393 Paul, R.K., Yeasin, M., Kumar, P., Kumar, P., Balasubramanian, M., Roy, H.S., Paul, A.K.,
394 and Gupta, A. (2022). Machine learning techniques for forecasting agricultural
395 prices: A case of brinjal in Odisha, India. *Plos one*, **17**(7), e0270553.

396 Priyanka, A. and Paul, R.K. (2017). Wavelet based hybrid approach for forecasting volatile
397 potato price. *Jour. Ind. Soc. Ag. Statistics*, **71**(1), 7-14.

398 Seok, J.H., Kim, G., Reed, M.R., and Kim, S.-E. (2018). The impact of avian influenza on the
399 Korean egg market: who benefited? *J. Pol. Model.*, **40**, 151–165.

400 Sharif, A., Aloui, C., and Yarovaya, L. (2020). COVID-19 pandemic, oil prices, stock market,
401 geopolitical risk and policy uncertainty nexus in the US economy: fresh evidence
402 from the wavelet-based approach. *Int. Rev. Financ. Anal.*, 101496.

403 Shiferaw, Y.A. (2019). Time-varying correlation between agricultural commodity and energy
404 price dynamics with Bayesian multivariate DCC-GARCH models. *Phys. Stat. Mech.*
405 *Appl.*, **526**, 120807.

406 Siddig, K., Stepanyan, D., Wiebelt, M., Grethe, H., and Zhu, T. (2020). Climate change and
407 agriculture in the Sudan: impact pathways beyond changes in mean rainfall and
408 temperature. *Ecol. Econ.*, **169**, 106566.

409 Su, C.W., Wang, X.Q., Tao, R., and Oana-Ramona, L. (2019). Do oil prices drive agricultural
410 commodity prices? Further evidence in a global bio-energy context. *Energy*, **172**,
411 691–701.

412 Tiwari, A.K., Abakah, E.J.A., Adewuyi, A.O. and Lee, C.C. (2022). Quantile risk spillovers
413 between energy and agricultural commodity markets: Evidence from pre and during
414 COVID-19 outbreak. *Energy Econ.*, **113**, 106235.

415 Vapnik, V., and Bottou, L. (1992). Local Learning Algorithms. AT&T Bell Laboratories,
416 Holmdel, NJ 07733 USA.

417 Verikios, G. (2020). The dynamic effects of infectious disease outbreaks: the case of
418 pandemic influenza and human coronavirus. *Soc. Econ. Plann. Sci.*, **71**, 100898.

419 Vo, D.H., Vu, T.N., and McAleer, M. (2019). Modeling the relationship between crude oil and
420 agricultural commodity prices. *Energies*, **12**(7), 1344.

421 Wei Su, C., Wang, X.-Q., Tao, R., and Oana-Ramona, L. (2019). Do oil prices drive
422 agricultural commodity prices? Further evidence in a global bio-energy context.
423 *Energy*, **172**, 691–701.

424 Wu, Y., Kwakkenbos, L., Henry, R.S., Tao, L., Harb, S., Bourgeault, A., Carrier, M.-E., Levis,
425 B., Sun, Y., Bhandari, P.M., Carboni-Jiménez, A., Gagarine, M., He, C., Krishnan,
426 A., Negeri, Z.F., Neupane, D., Mouthon, L., Bartlett, S.J., Benedetti, A., Thombs,
427 B.D., Culos-Reed, N., El-Baalbaki, G., Hebblethwaite, S., Patten, S., Varga, J.,
428 Bustamante, L., Duchek, D., Ellis, K., Rice, D., Dyas, L., Fortuné, C., Gietzen, A.,
429 Guillot, G., Lewis, N., Nielsen, K., Richard, M., Sauvé, M., and Welling, J. (2020).
430 Validation of the COVID-19 fears questionnaires for chronic medical conditions: a
431 scleroderma patient-centered intervention network COVID-19 cohort study. *J.*
432 *Psychosom. Res.*, **139**, 110271.

433 Yeasin, M., Singh, K.N., Lama, A. and Paul, R.K. (2020). Modelling Volatility Influenced by
434 Exogenous Factors Using an Improved GARCH-X Model. *Jour. Ind. Soc. Ag.*
435 *Statistics*, **74**, 209-216.

- 436 Yi, L., Tao, J., Tan, C., and Zhu, Z. (2019). Avian influenza, public opinion, and risk spillover:
437 measurement, theory, and evidence from China's broiler market. *Sustainability*, **11**,
438 1–44.
- 439 Zahraee, S.M., Shiwakoti, N., and Stasinopoulos, P. (2022). Agricultural biomass supply
440 chain resilience: COVID-19 outbreak vs. sustainability compliance, technological
441 change, uncertainties, and policies. *Cleaner Logistics and Supply Chain*, **4**, 100049.
- 442 Zou, X., Yang, J., Zhang, W., and Han, H. (2020). Collaborative community-specific
443 microblog sentiment analysis via multi-task learning. *Expert Syst. Appl.*, 114322.