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On the effects of COVID-19 on food prices in India: a time-varying approach

Lotanna E. Emediegwu*,† and Obianuju O. Nnadozie‡,§

†*Department of Economics, Policy and International Business, Manchester Metropolitan University, Manchester, UK;* ‡*Department of Economics, University of Benin, Benin, Nigeria;* §*Department of Economics, University of Ibadan, Ibadan, Nigeria*

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Abstract

Since the inception of the novel coronavirus, immense research efforts have been made to understand how several economic indicators, including food security, would be affected. With India racing behind the United States in terms of daily infection rate and being a country with challenging food security issues, it is important to investigate how the presence of the pandemic has influenced the dynamics of food prices in the country. This paper considers seven price series from 167 markets across the five regions in India as well as the growth rate of COVID-19 infection. The paper uses a time-varying autoregressive model to investigate the nonlinear dynamics of food prices in relation to the pandemic in India. The resultant models reveal strong asymmetric properties with shock-inflicted persistence, which appear not to converge over the simulation period. Moreover, in terms of the location of the burden of the pandemic impact, we find a food product divide.

Keywords: COVID-19, food prices, India, time-varying autoregressive model

JEL classification: C58, I19, Q11

1. Introduction

Coronavirus disease 2019 (COVID-19),[1] caused by severe acute respiratory syndrome coronavirus 2 (SARS-CoV-2), was first identified in the Chinese city of Wuhan on 31 December 2019. Due to its rapid spread across the world, the World Health Organization assigned it a 'pandemic' status on 11 March 2020.[2] In addition to raising the morbidity and mortality levels, the COVID-19

*Corresponding author: E-mail: l.emediegwu@mmu.ac.uk

1 Everywhere else, we may refer to the disease as covid or coronavirus.

2 As of 29 October 2021, covid infection had been confirmed in over 220 countries and territories.

pandemic and the associated measures deployed to control contagion triggered a historic halt in economic activities. Unsurprisingly, the pandemic generated massive disruption in global and regional food supply chains and could potentially worsen the food crisis in many countries. However, less is reported about the effect of the COVID-19 pandemic on food prices.

Few attempts have been made to examine the impact of COVID-19 on food prices in different settings. For instance, Amare *et al.* (2021) apply a difference-in-difference approach to investigate the implication of the pandemic for food security and labour market participation in Nigeria. They find that both infection rates and restrictions designed to contain the spread of the pandemic significantly raise local food prices in Nigeria. However, this study employs an aggregate measure of food price. In the same vein, Yu *et al.* (2020) analyse the impact of COVID-19 on four food prices in three (out of the 23) provinces in China. Using fractionally integrated Generalized AutoRegressive Conditional Heteroskedasticity (FIGARCH) model, they find that the pandemic has no significant impact on rice and wheat flour prices in China. However, they report mixed results for pork prices and a significantly positive effect on cabbage prices.

Furthermore, Çakır, Li and Yang (2021) adopt a difference-in-difference technique to assess the response of wholesale prices of fruits and vegetables to the COVID-19 pandemic using data for the United States and China. While they report a decline in wholesale prices of fruits and vegetables in China, they find no significant effect of the pandemic on the prices of fruits and vegetables in the United States.

Akter (2020) assesses whether the COVID-19-related stay-at-home restrictions affected seven food categories in 31 European countries, with data spanning January–May 2020. The empirical results, obtained from a series of difference-in-difference regression models, reveal that the severity of stay-at-home restrictions increased overall food prices by 1 per cent in March and April 2020 compared to January and February 2020. Similarly, using dynamic panel data model, Agyei *et al.* (2021) find that COVID-19 infections adversely affect the prices of maize, sorghum, and imported and local rice in sub-Saharan Africa. However, they find that lockdowns were associated with an increase in the price of maize only but had no effect on sorghum and imported and local rice prices.

There are very few studies that have attempted to explore whether the COVID-19 pandemic and subsequent containment measures affected food prices in India. Mahajan and Tomar (2021) document that the COVID-19 lockdown resulted in a decline in product availability and arrival in online retail and wholesale markets, respectively, although its effects on the prices of vegetables, fruits, and edible oils were marginal. On their part, Lowe, Nadhanael and Roth (2021) find a sizeable fall in food arrivals in the wholesale markets but a rise in wholesale food prices consequent on the announcement of the lockdown, albeit, with full recovery within 2 months. Also, Narayanan and Saha (2021), evaluating the potential impacts of the COVID-19 lockdown on urban food markets in India, report that there is heterogeneity across commodities and cities. Retail food prices in many urban cities in India rose sizeably with the price increases being more pronounced in smaller cities compared to more populated ones. Specifically, the study attests to a substantial increase in the prices of pulses, oils, potatoes, tomatoes and onions.

This paper seeks to add to the evidence by analysing the effect of COVID-19 on food prices in India. India is of particular interest given that it has the second-highest growth rate of COVID-19 infection after the United States.[3] It is also considered one of the countries that imposed the longest and strictest lockdowns (Mishra and Rampal, 2020). Moreover, the country still grapples with the challenges of food insecurity despite the important role of agriculture in India's economy. Food prices and their volatility have been linked with food insecurity, malnutrition, and other health outcomes, as well as poverty, especially in developing countries (Amolegbe *et al.*, 2021; De Hoyos and Medvedev, 2011). Hence, an investigation into the pandemic–prices nexus can be useful in explaining the food security situation in India.

Our second and most significant contribution is in terms of the methodology we employ. We employ a time-varying approach to account for structural instability, a critical feature of prices, especially when observed over long time spans. Previous studies focusing on the impact of the pandemic on food prices use standard linear models, such as linear regressions, to model price changes. One main shortfall inherent in these econometric strategies is the assumption of a linear relationship between commodity prices and some exogenous shocks, such as COVID-19. The use of linear models adds some intricacies to the linkage between COVID-19 signals and food prices. For example, price behaviour can differ between the pre-pandemic and pandemic eras. Furthermore, there is compelling evidence from Deaton and Laroque (1992), Deaton (1999) and Balagtas and Holt (2009) that the behaviour of many agricultural commodities prices follows a nonlinear regime dependence. Given these two reasons, the use of standard linear models may not correctly model the relationship between price movements and some exogenous shocks, like the global pandemic and the attendant restrictions. Consequently, we utilise a time-varying autoregressive (TVAR) model to investigate the nonlinear dynamics of food prices in relation to the pandemic status in India as well as to further control for potentially complex dynamic relationships between the two variables.

Moreover, while previous Indian studies consider food prices of a subset of India (e.g. Narayanan and Saha, 2021; Mahajan and Tomar, 2021), this study takes a holistic approach by considering all the regions in India. The food prices data are gathered from more than 160 markets across the country, while the covid data are from the Center for Systems Science and Engineering (CSSE) at the Johns Hopkins University. In addition to the covid index used, our sample's temporal length ensures that we capture the food price variations in a typical year other than just occurrences in a limited part of the year as done in previous studies. Furthermore, using the entire regions in India rather

3 As of 29 October 2021, over 246 million people worldwide have been infected with the virus, with almost 5 million deaths. The most severely affected countries are the United States, India, and Brazil, in that order.

than only a single region or few cities allows for substantial heterogeneity in our model.

We find that parameter constancy is mostly rejected for prices of perishable products like onions. On the other hand, our results show that prices of cereal crops, sugar and milk are affected by the pandemic in India. Besides, most nonlinear models exhibit strong asymmetric properties with shock-inflicted persistence, which appear not to converge over the simulation period. Consequently, the price dynamics differs between pre-structural and post-structural regimes.

The rest of the paper is ordered as follows: Section 2 considers several channels through which the pandemic can affect food prices. Data description and model specification are considered in Section 3. The main results are discussed in Section 4, and finally, Section 5 concludes the paper with some policy recommendations.

2. COVID-19 and food prices: potential mechanisms

From a theoretical perspective, the price of any commodity may likely change with changing demand and supply conditions. Hence, food prices are expected to react to massive disruptions in the demand and supply of food products caused by the COVID-19 pandemic and its associated containment measures. On the supply side, COVID-19 restrictions, such as lockdowns, will reduce food availability. Although exemptions were granted to agricultural workers in India to ensure the continuity of food production, voluntary stay-at-home as a protective mechanism, shielding by infected farm workers, as well as deaths from covid infection led to farm labour shortages (Jaacks *et al.*, 2021; Ceballos, Kannan and Kramer, 2020). Besides, the closure of national and international borders further reduces food availability in India since food importation was halted as important trading partners such as Russia and Ukraine introduced trade restrictions on some food or agricultural products (ITC, 2022).[4] This shortage has adverse implications for food availability, which, in turn, results in rising food prices.[5]

Also, national- and state-level restrictions of movement massively affected the transportation sector, which is a critical sector in the food system value chain (Maliszewska, Mattoo and Van Der Mensbrugghe, 2020). Transport cost has risen dramatically in many Indian states due to social distancing measures: ergo, the increased cost of transporting food commodities from the point of production to the consumers. Also, the movement of factors of production and raw materials to farms where they are needed is affected by disruption in the transportation sector. Consequently, barriers to transportation owing to the COVID-19-induced restrictions may prevent farmers from reaching their

4 Although India was able to sustain food production during the pandemic, it still relies heavily on imports and food aids to feed over 190 million undernourished people in the country (FAO, 2022). Hence, even in the face of steady food production, declining food imports still affect the overall food availability negatively.

5 Several studies (e.g. Zilberman *et al.*, 2013; Ajanovic 2011) have highlighted the negative relationship between food availability and food prices.

farms or cause wastage of harvested farm produce since these cannot get to the final consumers. This mismatch between demand and supply creates some form of artificial scarcity, thereby impacting food prices. In addition, the possibility of hoarding (non-perishable) food for the sake of profiteering by intermediaries along the retail value chain would restrict supply and affect prices.

On the demand side, the uncertainty owing to the novelty of the pandemic and the limited knowledge of the duration of lockdowns elicits panic buying of essential goods, including the ones with extended shelf lives. Given the inelastic character of food demand, this sharp increase in demand has implications for the prices of food items. Consequently, local markets are stressed because demand is high, but food supply is scarce and expensive (Emediegwu, 2020).

Summarily, while there are several channels through which COVID-19 shocks can influence food prices, our intention is not to quantitatively unpack the individual channels, rather we employ a reduced-form framework to analyse the general pass through effect of the pandemic on food prices in India.

3. Model specification and data description

3.1. Data sources

3.1.1. Food prices data

We use daily data for selected food prices and covid case count in India. As measures of food prices, we use daily average nominal prices from several markets across India. The food price data set comes from the Ministry of Consumer Affairs, Food and Public Distribution in India. The Price Monitoring Division (PMD) in the Department of Consumer Affairs receives the prices of food commodities daily from the State Civil Supplies Departments of the respective State Governments.[6] Based on data availability, we consider seven daily food price series from 167 markets across the five regions in India (see, Figure 1).[7] To ensure accuracy, we remove 10 markets where the series has missing observations for more than five consecutive days. Unlike Lowe, Nadhanael and Roth (2021), where wholesale prices were used, all our food prices are collected at the retail level to ensure that the pass through of the pandemic to household welfare is captured.[8]

For each price series, we calculate the daily $\boldsymbol{Pr_t}$ as the national average of all market prices weighted by market population, where the population weights are the Year 2000 population count extracted from the Gridded Population of the World (GPWv4) data set at 0.5 degree resolution (CIESIN, 2018).

6 The PMD in the Department of Consumer Affairs is responsible for monitoring the prices of selected essential commodities. The activities of the division include monitoring of the retail and wholesale prices and spot and future prices of selected essential commodities on a daily basis and are reported on this website: https://fcainfoweb.nic.in/reports/report_menu_web.aspx.

7 The five regions in India are North, West, East, South, and North-Eastern regions. See Supplementary Table A2 in the Appendix for the number of markets per region. We considered seven food prices: rice, wheat, sugar, milk, tomato, groundnut oil and onion.

8 It is important to state that using retail prices for our analysis ensures that we capture local welfare and not global trade activities such as food exportation.

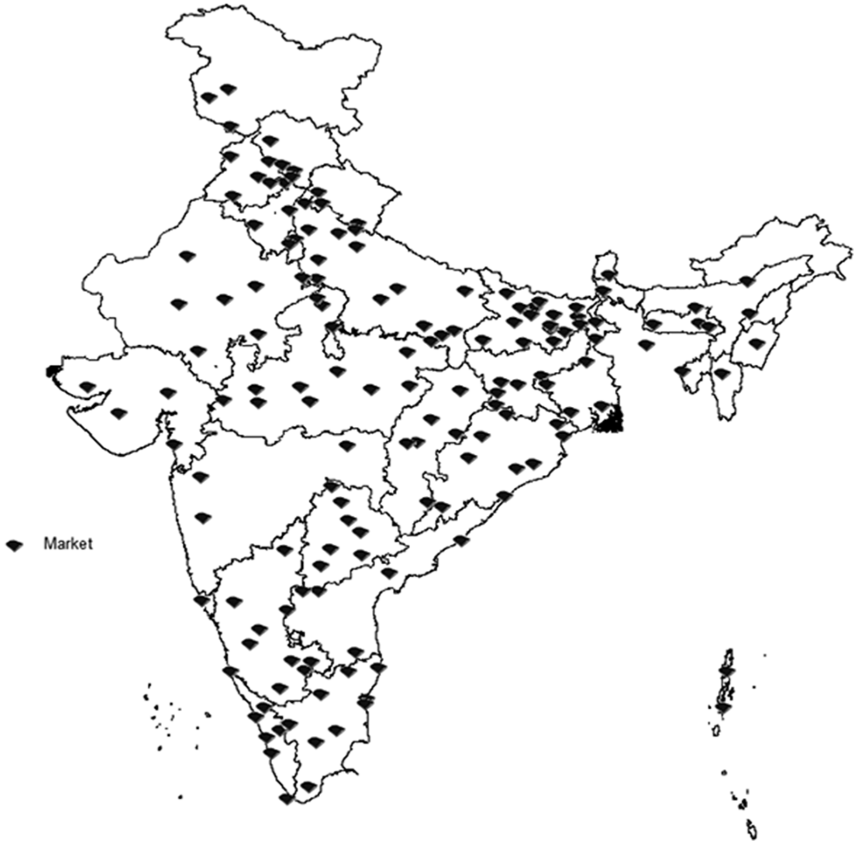

Fig. 1. Food market locations across India.
Note: Each dark shade represents a local market where data for food commodities are collected.

The weighted construction allows us to account for possible heteroskedasticity in the data. Besides, the use of population as weight helps ensure that the pass through of the COVID-19 shock funnels directly to the economy. We transformed the nominal prices (in local currencies—Indian rupee) to their day-on-day logarithmic values to ease the interpretation of the impulse responses in percentage terms.[9]

3.1.2. COVID-19 data

We draw Indian COVID-19 data from the COVID-19 Data Repository by the CSSE at Johns Hopkins University.[10] Among other country-level variables, the

9 Like most developing nations, India does not have an up-to-date daily official exchange rate (local conversion units per US$), hence the use of prices in local currency as done in other studies (e.g. Dillon and Barrett (2015), Minot (2014)).

10 Data is accessible via https://github.com/CSSEGISandData/COVID-19.

data set contains the daily count of covid cases from 30 January 2020 and is updated daily as new information becomes available.[11] Our sample, however, ends on 30 June 2021. The dataset is obtained from daily officially reported confirmed case counts reported to the Ministry of Health and Family Welfare in India.[12]

To account for the pandemic's progress, we use the growth rate of covid infection (GRI) in Carleton *et al*. (2020) as

$$GRI_t = \log(C_t) - \log(C_{t-1})$$

where C_t refers to cumulative covid cases in India at time *t*. GRI_t measures the rate at which infection is transmitted among the populace. In principle, $C_t - C_{t-1}$ refers to the number of new covid cases in the last one day.[13] The use of growth rate rather than covid count is based on policy preference, as the former is one of the main metrics which policymakers use to decide what sort of policy to adopt (UK Government, 2020).

3.2. Model specification

Let Pr_t be designated as the measure of food prices in time *t* and allow it to follow a simple linear AR model augmented with weekly dummy variables and GRI entering as an exogenous forcing variable:[14]

$$Pr_t = \boldsymbol{\alpha}'\boldsymbol{x_t} + \varepsilon_t \tag{1}$$

where $\boldsymbol{x_t} = (1, Price_{t-1}, \ldots, Price_{t-p}, GRI_t, \ldots, GRI_{t-q}, , w_{1,t}, \cdots, w_{n,t})'$, $w_{j,t}, j = 1, \ldots, n$ are deterministic variables, which include weekly dummies; $\boldsymbol{\alpha}$ are estimable set of parameters, and ε_t is white noise process. Since the procedures for testing the structural instability in the subsequent steps are sensitive to residual serial correlation, we control for autocorrelation in ε_t by following a bottom-up sequential investigatory approach to determine *p*. Furthermore, the choice of *q* is determined by the sample-size-corrected Akaike information criterion (AICc).

Following, we conduct unit roots tests since the structural instability test and the use of TVAR model require stationary time series. The Augmented Dickey–Fuller (ADF) and Kwiatkowski–Phillips–Schmidt–Shin (KPSS) tests in Supplementary Table A1 in the Appendix show that most prices series follow

11 The first case of COVID-19 in India was reported on 30 January 2020, in the state of Kerala.

12 The national figure here is the aggregation of reported confirmed cases in the states.

13 Several papers, such as Emediegwu (2021), Chernozhukov, Kasahara and Schrimpf (2021), use a longer lag period to account for the period between when an infection occurs and when a positive test detects it. However, Emediegwu (2021) and Carleton *et al*. (2020) show that there is no significant difference in the number of lags. Moreover, there is no unanimity on the number of lag days to use in calculating the growth rate. Also, with the advancement in medical science and technology, positive tests can be detected within a day of contracting the virus.

14 The time dummies control any time-related effects that are not already in the model such as the Public Distribution System (PDS) monthly programme where free food grains were provided to more than 800 million beneficiaries across the five regions in India.

a unit root process ($I(1)$).[15] Moreover, we also employ the Zivot–Andrews (ZA) test, which allows for a structural break in the time series while testing for unit roots. The ZA test is necessary because the ADF and KPSS tests assume away nonlinearity and structural break in the series, which may not be the case. Although results from the ZA test are largely similar to those from the previous tests, still there are few series $I(0)$ which previously followed a unit root process. It is important to note, as stated in Haldrup *et al.* (2013), that even the ZA test does not address all the challenges of unit root test in the presence of nonlinearity and structural breaks: hence, our decision rule is to model a price series in levels if any of the three unit root tests reject the null hypothesis of the unit root. Otherwise, the series are difference stationary. To avoid the bad control scenario and in the spirit of Emediegwu, Wossink and Hall (2022) and Angrist and Pischke (2008), we do not control for factors (e.g. daily oil prices) that may be jointly correlated with food prices and covid infection rates.

We also adopt Lundbergh, Teräsvirta and Van Dijk's (2003) testing approach to ascertain the presence or otherwise of parameter constancy in the model.[16] Where the test fails to reject the null hypothesis of parameter constancy, an AR model (as in equation 1) is estimated. On the other hand, where the test rejects the null hypothesis of parameter constancy, we will estimate a TVAR model presented below:

$$Pr_t = \boldsymbol{\alpha}_0'\boldsymbol{x}_t\left(1 - \mathcal{L}\left(\bar{t}, \psi_\vartheta, \vartheta\right)\right) + \boldsymbol{\alpha}_1'\boldsymbol{x}_t\mathcal{L}\left(\bar{t}, \psi_\vartheta, \vartheta\right) \tag{2}$$

where $\mathcal{L}\left(\bar{t}, \psi_\vartheta, \vartheta\right)$ is a transition function (hereafter abbreviated as $\mathcal{L}\left(\bar{t}\right)$) with $\bar{t}$ as the state (transition) variable that regulates the transition by determining the state of nature at time t. ψ is the smoothness (or speed-of-adjustment) parameter that governs the occurrence of structural shifts, and ϑ denotes the location parameter, which reflects the period in time when the parameter instability in the price series set in. Other variables and parameters are as defined in equation (1).

Based on data, the transition function can either take a logistic (LTVAR) or exponential (ETVAR) function of $\bar{t} = t/T$ written as

$$\mathcal{L}_{LTVAR}\left(\bar{t}, \psi_\vartheta, \vartheta\right) = \left[1 + \exp\left\{-\psi\left(\frac{\bar{t} - \vartheta}{\sigma_{\bar{t}}}\right)\right\}\right]^{-1}, \psi > 0; \vartheta \epsilon \left[\tau_{\bar{t}}, 1 - \tau_{\bar{t}}\right] \tag{3}$$

$$\mathcal{L}_{ETVAR}\left(\bar{t}, \psi_\vartheta, \vartheta\right) = 1 + \exp\left\{-\psi\left(\frac{\bar{t} - \vartheta}{\sigma_{\bar{t}}}\right)\right\}^2, \psi > 0; \vartheta \epsilon \left[\tau_{\bar{t}}, 1 - \tau_{\bar{t}}\right] \tag{4}$$

15 As shown in Supplementary Table A1 in the Appendix, the result holds for both without and with trend.

16 The approach in Lundbergh, Teräsvirta and Van Dijk (2003) is similar to that in Teräsvirta (1994) for testing the presence of nonlinearity in a smooth transition autoregressive (STAR) model. The main difference between the STAR model and the TVAR model is that the transition variable in the former is either an exogenous variable or a lagged endogenous variable, while the transition variable in the latter is a function of time. More technical details of the difference between both models are documented in Van Dijk, Teräsvirta and Franses (2002).

where $\sigma_{\bar{t}}$ is the standard deviation of $\bar{t}$; the restriction $\psi > 0$ is an identification restriction; $\tau_{\bar{t}}$ is the truncation factor normally pegged at the 15th and 25th percentiles of the transition variable in (3) and (4), respectively. We standardise ψ by $\sigma_{\bar{t}}$ to render the smoothness parameter unit-free.[17] Depending on the value ψ, in the logistic function, the TVAR model can reduce to certain sub-models. For example, as ψ becomes larger, the logistic function $\mathcal{L}\left(\bar{t}, \psi_{\vartheta}, \vartheta\right)$ approximates into a dummy function, I[$\bar{t} > \vartheta$], where the transition between pre- and post-structural change becomes sharp rather than smooth. In such a scenario, (3) and (2) reduce to a two-regime threshold autoregressive (TAR) model. On the other extreme, as $\psi \rightarrow 0$, $\mathcal{L}_{LTVAR}\left(\bar{t}, \psi_{\vartheta}, \vartheta\right) \rightarrow 0.5$, and in the limit, (2) reduces to a linear AR model.

Furthermore, we constrict the slope parameters, η, between 2 and 100 and between one and ten in the logistic and exponential functions, respectively.[18] The empirical strategy permits the impact of the pandemic to be transmitted into food prices dynamics in India. Finally, we estimate the parameters of the TVAR model via nonlinear least squares as described in Lundbergh, Teräsvirta and Van Dijk (2003).[19]

4. Results and discussion

4.1. Parameter constancy tests and diagnostics

The main results, together with the maximum number of lags and the delay parameter of the preferred model for each price series, are recorded in Table 1. The results show that the parameter stability is rejected against (2) for rice, wheat, milk and sugar. The results show that tomato, onion and groundnut oil prices are not affected by the pandemic but rather by past prices. However, while onion and groundnut prices are affected by past prices linearly, tomato prices are affected nonlinearly by past prices. Rice and wheat prices series preferred the ETVAR to LTVAR; the reverse is the case for the other nonlinear price series. This result is qualitatively similar to what is gotten using mortality rate instead of infection rate as shown in Supplementary Table A3 in the Appendix.[20]

In general, we find that prices of perishable food products do not experience structural instability due to the pandemic, while storable food products show parameter instability over the period under consideration. These results are in line with earlier findings by Narayanan and Saha (2021) and Mahajan and Tomar (2021) that pulses, most edible oils, sugar and salt register significant increases during the period of the pandemic lockdown in India. On the contrary, they find that prices of tomatoes and onions do not exhibit a sustained increase over the same period. Further, our results also align with those

17 Standardising the smoothness parameter is an important process to avoid certain estimation problems like overestimation and slow convergence (Van Dijk, Teräsvirta and Franses, 2002).

18 Where the slope value is greater than the upper bound, a TAR model will result.

19 Lundbergh, Teräsvirta and Van Dijk (2003) expanded Teräsvirta's (1994) STAR approach to allow for time-varying parameters.

20 In a similar fashion as GRI, the growth rate of mortality is derived as *log(Dt) – log(Dt – 1)*, where *Dt* refers to cumulative covid deaths in India at time *t*.

Table 1. Model choice and investigation

Series	*Model*	p	q	n	$\hat{\psi}_{\vartheta}$	$\hat{\vartheta}$	Associated date of structural change t/T	*AICc*
Rice	ETVARDL	7	7	44	10.00 (2.87)	0.59 (0.01)	30 November 2020	−1.816
Wheat	ETVARDL	7	6	44	6.45 (1.20)	0.54 (0.01)	5 November 2020	−1.034
Sugar	LTVARDL	5	0	26	2.00 (1.04)	0.44 (0.08)	14 September 2020	−4.833
Milk	LTVARDL	8	1	34	50.95 (90.35)	0.70 (0.01)	26 January 2021	−3.260
Tomato	LTVAR	2		18	100.00 (327.78)	0.31 (0.01)	10 July 2020	−0.473
Onion	AR	1		7				−1.240
Groundnut oil	AR	8		14				−2.717

Note: p and q are the selected autoregressive and distributed lag lengths, respectively; w and n denote the delay parameter of the transition function used to test for regime dependency and number of estimated parameters, respectively; $\hat{\psi}_{\vartheta}$ and $\hat{\vartheta}$, respectively, represent estimated speed-of-adjustment and location parameters (values in parentheses are standard errors).

in Çakır, Li and Yang (2021), where they find no significant effect of the pandemic on the prices of fruits and vegetables in the United States.[21] On the other hand, they find that prices of the same products reduced in China during the COVID-19 pandemic.

One intuition coming from these results is that these massive price changes due to the pandemic are human-driven rather than production-driven. Agents hoard non-perishable goods to create some form of artificial scarcity during lockdowns in a bid to jack up prices (Vercammen, 2020). Barriers to transportation owing to the COVID-19-induced restrictions, as well as the uncertainty surrounding the gravity of the pandemic and the duration of the lockdown, may lead to stockpiling of food products for either subsistence or profiteering motives. However, this artificial scarcity-creating mechanism impacts prices of food products that are durable, hence the price adjustment in storable food products like wheat, rice, etc. On the other hand, where wastage is envisaged, prices will unlikely adjust during the pandemic as seen in the non-significant impact of the pandemic on perishable products like tomatoes.[22,23]

21 Since fruits and vegetables are perishable products, they are 'economically' similar to the perishable products in our study.

22 It is important to note that the reason stated here could be country-dependent. For example, Çakır, Li and Yang (2021) attribute the resiliency of the fruits and vegetable market in the United States during the pandemic to an effective supply chain response and not to the physiological signature of the products. However, they do not conduct the same analysis for durable products. Hence, it is difficult to conclude that food price non-adjustment during the pandemic was due to a resilient supply chain structure, rather than (or in addition to) the properties of the crop.

23 This is the point expressed in Deaton and Laroque (1996) that rational speculators may be unwilling to cover the cost of holding commodity stocks where there exists failure of the commodity real prices to trend upwards.

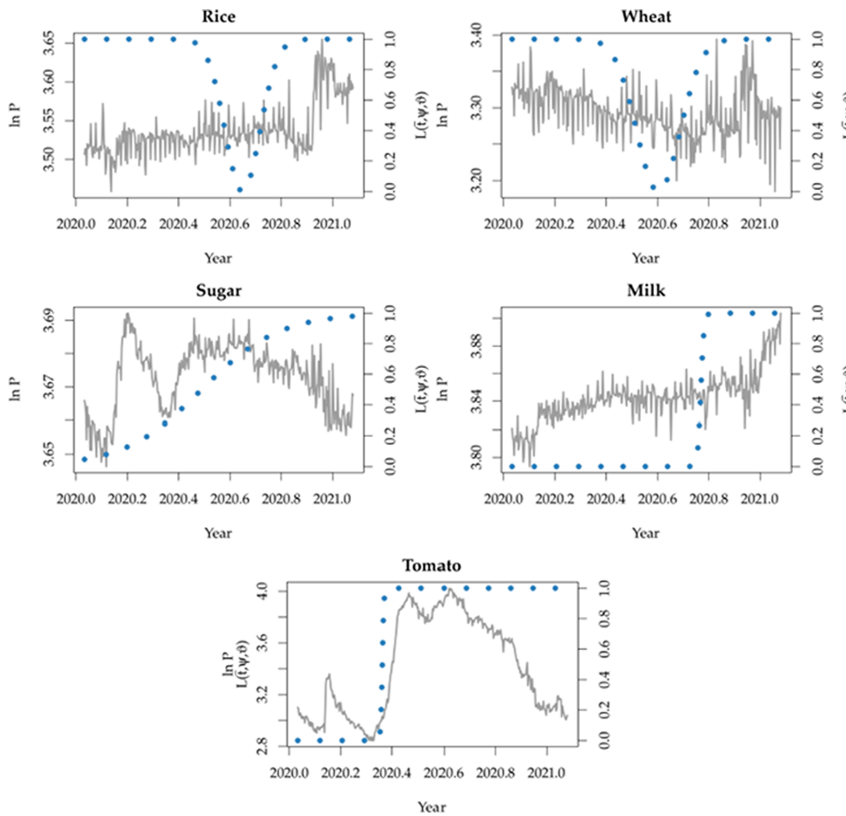

Fig. 2. Observed values and transition function versus time.
Note: The figure showcases natural log of food price series plus their associated estimated transition functions. The solid grey lines represent the series, while the dotted line denotes the time-varying transition function over time.

Table 1 also shows the character of the transition function variables. The estimated location parameter, $\widehat{\vartheta}$, reflects the period in time when the parameter instability in the price series set in. On the other side, the estimated speed-of-adjustment parameter, $\widehat{\psi}_{\vartheta}$, dictates the time frame for the parameter change. For further insight, Figure 2 reveals the estimated transition functions for the time-varying models, assuming values close to unity after the occurrence of the alteration of the price dynamics. Specifically, the transition function of time suggests that the structural change is centred around November 2020 for rice and wheat, earlier for sugar and tomato, and later for milk. These periods are domiciled within the first-wave era, indicating that the food market had begun to experience some structural shocks, even before the commencement of the second wave in March 2021.

Further, the values of the speed-of-adjustment parameters $\widehat{\psi}_{\vartheta}$ in Table 1 reveal that these changes are not smooth (with the exception of wheat and sugar

Table 2. Model and residual diagnostics

Series	*Model*	p_{PC}	p_{RA}	p_{ARCH}	$\hat{\sigma}_{\varepsilon}^{2}$	*SP*	*SK*	*EK*
Rice	ETVARDL	0.72	0.30	0.06	0.21	3.39×10^{-07}	−0.04	1.4
Wheat	ETVARDL	0.01	0.59	0.75	0.46	1.39×10^{-10}	−0.29	1.87
Sugar	LTVARDL	0.56	0.08	0.31	0.00	6.57×10^{-07}	0.53	1.25
Milk	LTVARDL	0.26	0.07	0.25	0.05	2.57×10^{-05}	−0.04	1.23
Tomato	LTVAR	0.06	0.11	0.07	0.46	3.39×10^{-11}	0.02	3.39
Groundnut oil	AR	0.08	0.67	0.25	0.05	4.64×10^{-10}	−0.34	2.95
Onion	AR	0.17	0.83	0.06	0.21	5.22×10^{-09}	0.48	2.75

Note: p_{PC}, p_{RA} and p_{ARCH} represent the probabilities associated with the hypothesis of (no remaining) parameter constancy, residual autocorrelation and AR conditional heteroskedasticity, respectively. $\hat{\sigma}_{\varepsilon}$ and is residual standard deviation, *N* is sample size, *SP* is the *p*-value of the Shapiro test for normality of residuals, and *SK* and *EK* are skewness and excess kurtosis, respectively.

prices) but abrupt. However, the changes are completed before the end of the sample period, as shown in Figure 2. Following the insignificant estimates of some $\widehat{\psi}_{\vartheta}$, we investigate the diagnostics. Table 2 reveals that the conventional diagnostics for checking the appropriateness of a TVAR model design are in order. For example, the associated *p*-values indicate no remaining parameter constancy, residual autocorrelation, or neglected heteroskedasticity.[24]

Figure 3 showcases further gains of nonlinear models by comparing the residuals from the estimated nonlinear model and those from the linear model used for parameter constancy testing. The benefits from the nonlinear models are most evident after a major spike in infection rate, such as the second-wave era of March 2021; otherwise, benefits from fitting the time-varying models seem to be slight.

4.2. Generalised impulse response function

It is elusive to attempt to interpret the estimated parameters of a time-varying model (except the transition function parameters); therefore, we turn to the dynamic characteristics to better appreciate the models. We employ the generalised impulse response functions (GIRFs) developed in Koop, Pesaran and Potter (1996) and the methods in Lundbergh, Teräsvirta and Van Dijk (2003) to investigate the dynamic behaviour of the models over time.[25,26] For a given shock $s_t = \Gamma$and history $\Psi_{t-1} = \lambda_{t-1}$, we define *GI* as

$$GI_{pr}(h, \Gamma, \lambda_{t-1}) = E(Pr_{t+h} | \lambda_t = \Gamma, \Psi_{t-1} = \lambda_{t-1}) - E(Pr_{t+h} | \Psi_{t-1} = \lambda_{t-1}) \quad (5)$$

24 Computational details of these diagnostic terms, in a nonlinear context, are documented in Van Dijk, Teräsvirta and Franses (2002).

25 We follow similar computational steps in generating the GIRFs as reported in Lundbergh, Teräsvirta and Van Dijk (2003) and Ubilava (2017).

26 The use of GIRFs is occasioned by the invariance of nonlinear models to idiosyncratic shocks that may affect the underlying dynamics of a stochastic process. Consequently, the conventional extrapolation means of generating impulse response functions for linear models is inapplicable in this case.

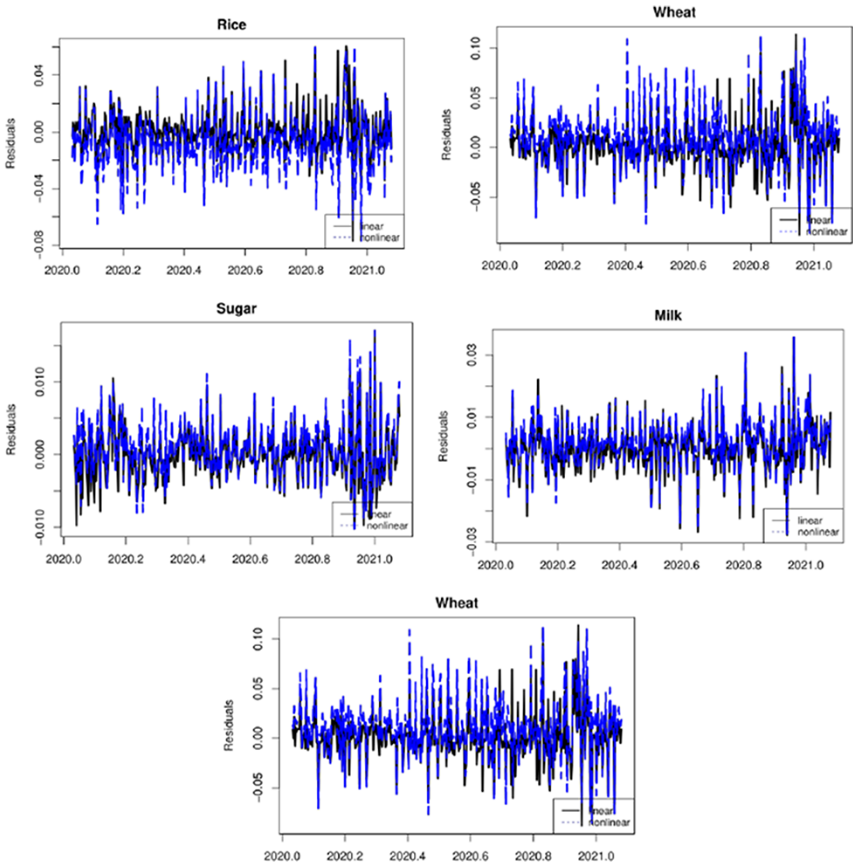

Fig. 3. Residuals of estimated TVAR(DL) models and the corresponding linear AR(DL) model.
Note: The selected AR and distributed lag lengths for each country model are found in Table 1.

where $h = 0,1,\ldots,30$ (number of days in a typical month). We generate two sets of histories λ_{t-1} (without replacement), periods before and after the structural change in each price series, numbering 100 for each history to control for asymmetry. For each history, 100 initial shocks are randomly drawn from a normal distribution bounded by $0.5\hat{\sigma}_{\Gamma}$ and $1.5\hat{\sigma}_{\Gamma}$, where $\hat{\sigma}_{\Gamma}$ is the estimated standard deviation of the residuals from the TVAR model. For each set of history and initial shock, we compute 2500 replicates of a 31-step iterative forecast sequence with and without the initial shock in the first horizon and employ randomly drawn residuals from the estimated TVAR model as noise elsewhere. For each horizon, the conditional expectations of the price models with and without the initial shock are generated from the 2500 replicates. Hence, a GIR estimate is derived as a difference of the two averages, as shown in equation (5). Besides, since food price series are modelled as $I(1)$ series, we integrate the GIRs over the length of the horizon to estimate the effect of GRI on log levels of food prices as shown:

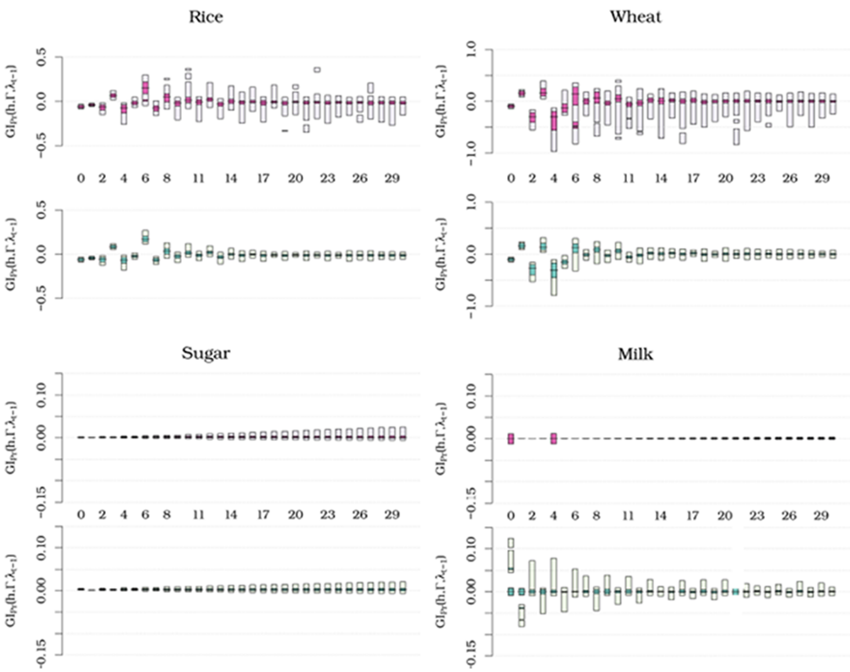

Fig. 4. GIRFs of time-varying models of food prices.
Note: The figure features 50 per cent (dark), 75 per cent (fair) and 90 per cent (light) HDRs for GIRFs in the TVAR models. The GIRFs in each plot are associated with an average 1-standard-deviation shock before (upper panel) and after (lower panel) the respective estimated structural change.

$$GI_{pr}(h,\Gamma,\ \lambda_{t-1}) = \sum_{f=0}^{h} GI_{\Delta pr}(f,\Gamma,\ \lambda_{t-1}) \tag{6}$$

Finally, we use 50 per cent, 75 per cent and 90 per cent highest-density regions (HDRs), generated using the density quantile method described in Hyndman (1995, 1996) to showcase a graphical representation of the GIRF distributions graphically.

Figure 4 presents the estimated GIRFs of the time-varying models. It shows price dynamics before and after the estimated structural change. It is important to state that we concern ourselves with 'unconditional' GIRFs based on all histories before/after the structural change. The figure highlights that the effect of the shock on most food prices in India that follow nonlinear processes is stronger in pre-structural change (upper panel) than post-structural change (lower panel), while the reverse is the case for milk prices. These uneven HDR shapes justify the existence of asymmetry between the pre- and post-structural change eras in some food prices. On the other hand, this asymmetry is not observed for sugar prices as the shock's effect is equally dispersed.

Further, the effect of shock is both amplified and early in several price series. For example, the impact of the shock on wheat prices is felt immediately but after almost a week (7 days) for rice prices. Likewise, it is felt immediately after a post-structural change shock to milk prices. However, the impacts are persistent for some prices in the pre-structural change (e.g. rice and wheat prices) as they do not appear to fade out at the end of the history length. On the other hand, the effect of a 1-standard-deviation-positive shock tends to return to zero after the initial impact following a shock in the pre-structural change period (except sugar).

5. Conclusion

This study applies a time-varying approach to assess the effect of COVID-19 on food prices in India. Specifically, we consider the prices of seven food categories. Our findings suggest that the pandemic has no significant impact on the prices of tomatoes, onions and groundnut oil but resulted in instability in the prices of rice, wheat, milk and sugar. Overall, we find that prices of perishable food products do not experience structural instability due to the pandemic, while storable food products show parameter instability over the period under consideration. A plausible explanation for this result is that the sizeable price changes experienced during the pandemic may have been driven by human factors, especially hoarding of non-perishable commodities, rather than actual production shortages. Our results are also robust to alternative specifications using mortality rate rather than infection rate.

The findings in this research will help policymakers in India and other nations with similar economic and political structures to have adequate tools to work with when determining how pandemics affect food prices. Given the severity of the impact of rising food prices on living standards, governments must develop or sustain programmes that are geared towards food availability and affordability. For example, the Public Distribution System (PDS) in India is a programme managed by the Department of Food and Public Distribution, which provides subsidised food grains every month to around 810 million people, which is two-thirds of its country's population. The impact of such large-scale intervention programmes on the welfare of the citizens during the pandemic can be an interesting avenue for further research.[27] However, in terms of food price shocks, some studies opine that government's interventions in food markets are often counterproductive. These interventions, especially under unpredictable commerce as experienced during the pandemic, may exacerbate rather than curb price volatility (Deaton, 1999; Deaton and Laroque, 1996).

The detailed number of price series considered offers a microscopic view of how important food prices in India are affected by the COVID-19 incidence: hence, decision-making can be more commodity-centric. Further, our work

27 Here, our focus is on market food prices, and since the PDS programme does not work through market boards, its impact on market prices is questionable. Moreover, the rationing system employed in the programme introduces significant operational inefficiencies and corruption in terms of timeliness, who gets food and how much food they get: hence, many households still resort to the market to get sufficient food on time (Ramaswami and Balakrishnan, 2002; Umali-Deininger and Deininger, 2001; Balakrishnan and Ramaswami, 1997).

provides evidence that a 'one-jacket' solution may not fit all in response to global shocks. A detailed work like this is necessary to help relevant stakeholders understand how the recent pandemic affects individual food prices. Such understanding becomes relevant in preparedness for future pandemics and in ensuring food security.

While this paper contributes to the literature on food price dynamics, certain caveats are noteworthy. Food classes that are not affected by the COVID-19 pandemic do not imply stable prices. It only means that the pandemic does not affect them in any significant manner. For example, while we argue that the COVID-19 pandemic does not impact the prices of tomatoes and onions, these prices might exhibit some instability in the face of daily weather shocks. The above scenario is one way of saying 'no one jacket fits it all' as no one cause can fully explain all the dramatic changes in local (and global) food prices behaviour. The trends and activities we see are caused by the interaction and interruption of several forces. While disentangling the individual effects of each channel is problematic, it will be a profitable venture to investigate which drivers are more active in determining food price fluctuations in India. For example, the principal drivers affecting the price of rice might be different from that of milk. This disparity in driving forces could be an interesting area for further research.

Supplementary data

Supplementary data are available at *ERAE* online.

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