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

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Abstract

Since the inception of the novel coronavirus virus, 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 (TVAR) 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

1 Introduction

COVID-19[1], caused by severe acute respiratory syndrome coronavirus 2 (SARS-CoV2), was first identified in the Chinese city of Wuhan on December 31, 2019. Due to its rapid spread across the world, the World Health Organization (WHO) assigned it a "pandemic" status on March 11, 2020.[2] In addition to raising the morbidity and mortality levels, the COVID-19 pandemic and the associated measures deployed to control contagion triggered

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[1]Everywhere else, we may refer to the disease as covid or coronavirus.
[2]As of October 29, 2021, covid infection had been confirmed in over 220 countries and territories.

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 insecurity 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 labor 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) analyze the impact of COVID-19 on four food prices in three (out of the 23) provinces in China. Using fractionally integrated GARCH (iGARCH) 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.

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% in March and April 2020 compared to January and February 2020. Similarly, using dynamic panel data model, Agyei et al. (2021) find that the number of COVID-19 infections adversely affects the prices of maize, sorghum, and imported and local rice in sub-Saharan Africa. However, they find that lockdown was associated with an increase in the price of maize only and had no effect on sorghum, imported, and local rice prices.

This paper seeks to analyze 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 after the United States.[3] It is also considered one of the countries that imposed the longest and strictest lockdowns (Mishra & 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 & Medvedev 2011). Hence, an investigation into the pandemic-food 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

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

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 regression and vector autoregression (VAR), 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 behavior can differ between the pre-pandemic and pandemic era. Furthermore, there is compelling evidence from Balagtas & Holt (2009), Deaton (1999), Deaton & Laroque (1992) that the behavior of many agricultural commodities prices follows a nonlinear regime-dependence. Given these two reasons, the use of standard linear models like VAR may not correctly model the relationship between price movements and some exogenous shock, like the global pandemic and the attendant restrictions. Consequently, we utilize 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 similar studies consider either food prices of a subset of a country or at country-level, this study takes a holistic approach by considering all regions in India. The food prices data are gathered from more than 160 markets across the county, while the covid data is from the Center for Systems Science and Engineering (CSSE) at 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 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 in the pre-pandemic regime differ from those during the pandemic era.

The rest of the paper is ordered as follows: Section 2 considers several channels through which the pandemic affects 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 to ensure continuity of food production, voluntary stay-at-home as a protective mechanism or shielding by infected farmworkers, as well as deaths from covid infection, would lead to farm labor shortages (Jaacks et al. 2021, Ceballos et al. 2020). Besides, the closure of borders further reduces food availability since food importation is halted. This shortage has direct adverse consequences for food production, which, in turn, results in rising food prices.

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 et al. 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, barrier to transportation owing to the COVID-19 induced restrictions may prevent farmers from reaching their 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 limited knowledge of the duration of lockdown 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 ENSO shocks can influence food prices, our intention is not to quantitatively unpack the individual channels, rather we employ a reduced-form framework to analyze the general pass-through effect of the COVID-19 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 dataset 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[4]. Based on data availability, we consider seven daily food price series from 167 markets across the five regions in India (see, Figure 1).[5,6] To ensure accuracy, we remove ten markets where the series has missing observations for more than five consecutive days. All the food prices are collected at retail level to ensure that pass-through of the pandemic to household welfare is captured.

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) dataset at 0.5 degree resolution (CIESIN 2018). The weighted construction allows us to account for possible heteroskedasticity in the data. Besides, the use of population as weight helps ensure that pass-through of the COVID-19 shock funnels directly to the economy. We transformed the nominal prices (in local currencies - Indian rupee (INR)) to their day-on-day (DoD) logarithmic values to ease the interpretation of the impulse-responses in percentage terms.[7]

3.1.2 COVID-19 Data

We draw Indian COVID-19 data from COVID-19 Data Repository by the Center for Systems Science and Engineering (CSSE) at Johns Hopkins University.[8] Among other country-level variables, the dataset contains the daily count of covid cases from January 30, 2020 and is updated daily as new information becomes available.[9] Our sample,

[4]The Price Monitoring Division (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`

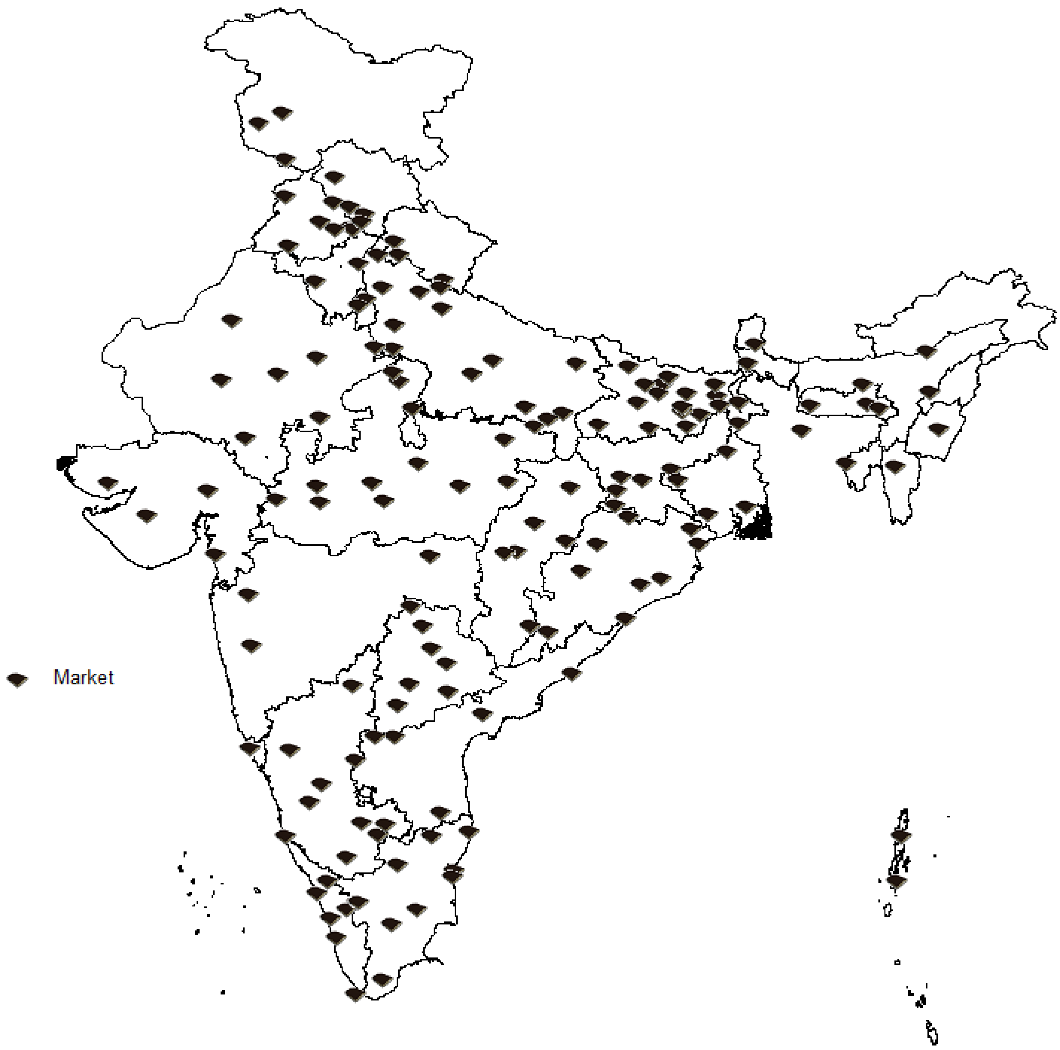
[5]The five regions in India are North, West, East, South, and North-Eastern regions. See Table 4 in the Appendix for the number of markets per region.

[6]We consider seven food prices: rice, wheat, sugar, milk, tomato, groundnut oil, and onion.

[7]As most developing nations, India does not have 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 & Barrett (2015), Minot (2014)).

[8]Data is accessible *via* `https://github.com/CSSEGISandData/COVID-19`

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



Note: Each dark shade represents a local market where data for all the food commodities are collected.

Figure 1: Food Market Locations across India

however, ends on June 30, 2021. The dataset is obtained from daily officially reported confirmed case counts reported to the Ministry of Health and Family Welfare in India.[10]

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 amongst the populace. In principle, $C_t - C_{t-1}$ refers to the number of new covid cases in the last one day.[11] Our decision to use growth rate rather than case count is due to policy preference. Growth rate is one of the main metrics policymakers monitor to make decisions on policy direction. 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:

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

where $\boldsymbol{x}_t = (1, Price_{t-1}, ..., Price_{t-p}, GRI_t, ..., GRI_{t-q},, w_{1,t}, ..., w_{n,t})'$, $w_{j,t}, j = 1, ..., n$ 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 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 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 ADF and KPSS tests in Table 3 in the Appendix show that most prices series follow a unit root process (*I(1)*).[12] Moreover,

[10]The national figure here is the aggregation of reported confirmed cases in the states.

[11]Several papers, such as Emediegwu (2021), Chernozhukov et al. (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), 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 growth rate. Also, with the advancement in medical science and technology, positive tests can be detected within a day of contracting the virus.

[12]As shown in Table 3, the result holds for both without and with trend.

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 are *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 unit root. Otherwise, the series are difference stationary*.* To avoid the *bad control* scenario and in the spirit of Angrist & Pischke (2008), Hsiang et al. (2013), 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 et al. (2003) testing approach to ascertain the presence or otherwise of parameter constancy in the model.[13] 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:

$$Pr_t = \boldsymbol{\alpha_0'} \boldsymbol{x_t}(1 - \mathcal{L}(\bar{t}, \psi_\vartheta, \vartheta)) + \boldsymbol{\alpha_1'} \boldsymbol{x_t} \mathcal{L}(\bar{t}, \psi_\vartheta, \vartheta) \tag{2}$$

where $\mathcal{L}(\bar{t}, \psi_\vartheta, \vartheta)$ is a transition function (hereafter abbreviated as $\mathcal{L}(\bar{t})$) with $\bar{t}$ as the state (transition) variable that regulates 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

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

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

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 percentile of the transition

[13]The approach in Lundbergh et al. (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 et al. (2002).

variable in the (3) and (4), respectively. We standardize ψ by $\sigma_{\bar{t}}$ to render the smoothness parameter unit-free.[14] 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 $\mathcal{L}(\bar{t}, \psi_\vartheta, \vartheta)$ 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 as scenario, (3) and (2) reduces to a two-regime threshold autoregressive (TAR) model. On the other extreme, as $\psi \to 0$, $\mathcal{L}_{LTVAR}(\bar{t}, \psi_\vartheta, \vartheta) \to 0.5$, 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.[15] Finally, 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 (NLS) as described in Lundbergh et al. (2003).[16]

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 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 its past prices. Rice and wheat prices series preferred the ETVAR to LTVAR; the reverse is the case for the other nonlinear price series. 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. One intuition coming from this result 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. This result is qualitatively similar to what is gotten using mortality rate instead of infection rate as shown in Table

[14]Standardizing the smoothness parameter is an important process to avoid certain estimation problems like overestimation and slow convergence (Van Dijk et al. 2002).

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

[16]Lundbergh et al. (2003) expanded Teräsvirta (1994) STAR approach to allow for time-varying parameters.

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)	November 30, 2020	-1.816
Wheat	ETVARDL	7	6	44	6.45 (1.20)	0.54 (0.01)	November 5, 2020	-1.034
Sugar	LTVARDL	5	0	26	2.00 (1.04)	0.44 (0.08)	September 14, 2020	-4.833
Milk	LTVARDL	8	1	34	50.95 (90.35)	0.70 (0.01)	January 26, 2021	-3.260
Tomato	LTVAR	2		18	100.00 (327.78)	0.31 (0.01)	July 10, 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; $\hat{\psi}_{\vartheta}$ and $\hat{\vartheta}$ respectively, represent estimated speed-of-adjustment and location parameters (values in parenthesis are standard errors).

Table 2: **Model and Residual Diagnostics**

Series	*Model*	p_{PC}	p_{RA}	p_{ARCH}	$N\hat{\sigma}^2_{\varepsilon}$	*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}, p_{ARCH} represent the probabilities associated with hypothesis of (no remaining) parameter constancy, residual autocorrelation, and autoregressive 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, *SK* and *EK* are skewness and excess kurtosis, respectively.

5.[17,18]

Table 1 also shows the character of the transition function variables. The estimated location parameter, $\hat{\vartheta}$, 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, $\hat{\psi}_{\vartheta}$. 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 centered 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, $\hat{\psi}_{\vartheta}$ in Table 1 reveal that these changes are not smooth (with exception of wheat and sugar prices) but abrupt. However, the change is completed before the end of the sample period, as shown in Figure

[17]Data for Indian covid mortality is obtained from the same source as covid cases (see, Subsection 3.1).

[18]In similar fashion as GRI, the growth rate of mortality is derived as $log(D_t) - log(D_{t-1})$, where D_t refers to cumulative covid deaths in India at time t.

2. Following the insignificant estimates of some $\hat{\psi}_{\vartheta}$, 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.[19]

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 mostly evidence 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 Generalized Impulse Response Function (GIRF)

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 generalized impulse response functions (GIRFs), developed in Koop et al. (1996) and the methods in Lundbergh et al. (2003) to investigate the dynamic behavior of the models over time.[20,21] For a given shock $s_t = \Gamma$ and history $\Psi_{t-1} = \lambda_{t-1}$, we define GI as

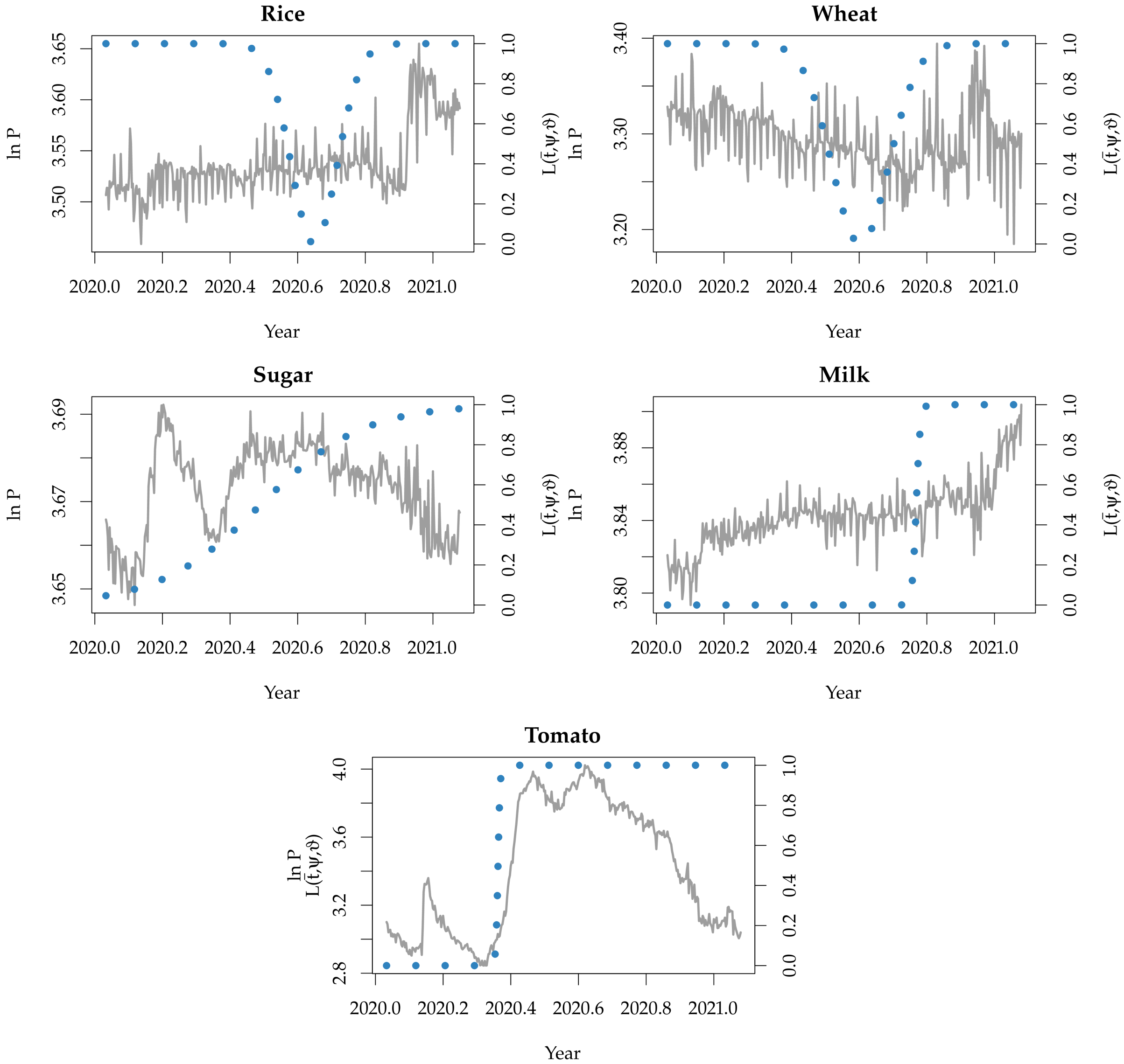
$$GI_{Pr}(h, \Gamma, \lambda_{t-1}) = E(Pr_{t+h}|\lambda_t = \Gamma,\ \Psi_{t-1} = \lambda_{t-1}) - E(Pr_{t+h}|\Psi_{t-1} = \lambda_{t-1}) \tag{5}$$

where $h = 0,\ 1,\ ...,\ 30$ (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 employing 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 modeled as *I(1)* series, we integrate the GIRs over the length of the horizon to

[19] Computational details of these diagnostic terms, in a nonlinear context, are documented in Van Dijk et al. (2002)

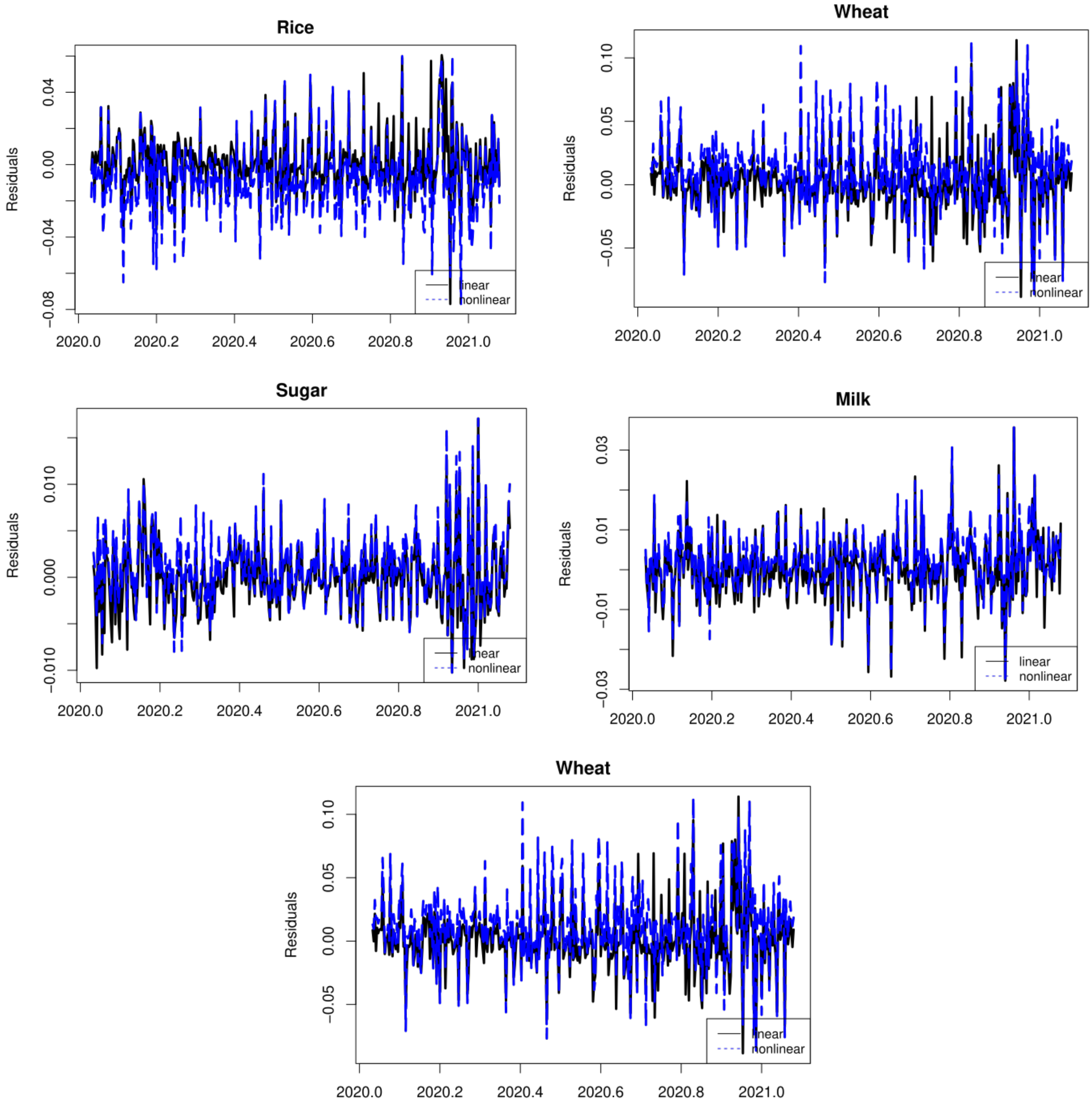
[20] We follow similar computational steps in generating the GIRFs as reported in Lundbergh et al. (2003) and Ubilava (2017)

[21] 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 (IRFs) for linear models is inapplicable in this case.



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.

Figure 2: **Observed Values and Transition Function Versus Time**



Note: The selected autoregressive and distributed lag lengths for each country model are found in Table 1.

Figure 3: **Residuals of estimated TVAR(DL) models and corresponding linear AR(DL) model**

estimate the effect of GRI on log-levels of food prices as shown:

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

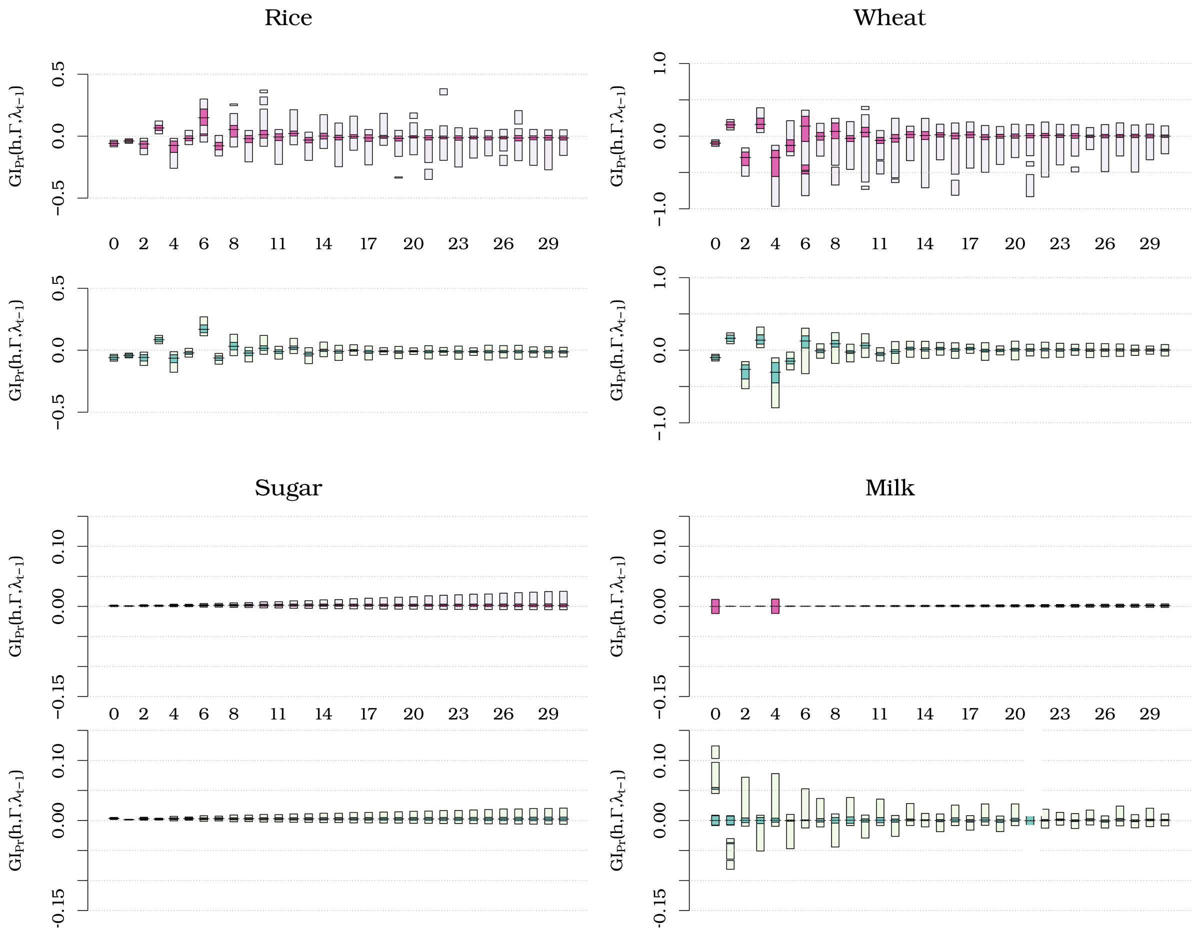
Finally, we use 50%, 75%, and 90% highest-density regions (HDRs), generated using the density quantile method described in Hyndman (1995, 1996) to showcase a graphical representation of the GIRFs distributions graphically.

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 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 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 one-standard-deviation positive shock tends to return to zero after the initial impact following a shock in pre-structural change period (except sugar).

5 Conclusion

This study applies the 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 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 sizable 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 robust to the specification using mortality rate rather than infection rate.



Note: The Figure features 50% (dark), 75% (fair) and 90% (light) highest density regions (HDRs) for generalized impulse response functions (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.

Figure 4: **GIRFs of Time-Varying Models of Food Prices**

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. 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 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 managing food security.

While this paper contributes to the literature on food price dynamics, certain caveats are noteworthy. First, 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 behavior. The trends and activities we see are caused by interaction and interruption of several factors. 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 fluctuation 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.

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A Additional Tables

Table 3: Unit Root Tests of log prices

	ADF		KPSS		**Z-A**	
	No Trend	Trend	No Trend	Trend	No Trend	Trend
			Levels			
Rice	-0.600	-2.724	4.613	0.786	-4.537	-5.016
Wheat	-1.188	-2.618	4.220	0.528	-3.731	-4.377
Groundnut oil	4.757	0.775	3.527	1.181	-0.941	-2.110
Sugar	-2.045	-2.062	1.749	0.852	-5.697	-5.925
Tomato	-3.992	-3.976	0.141	0.120	-4.457	-5.074
Milk	0.632	-1.227	4.507	1.016	-3.063	-3.916
Onion	-3.532	-3.729	0.867	0.132	-4.335	-4.546
			First difference			
Rice	-13.505	-13.500	0.021	0.021	-13.606	-13.622
Wheat	-13.986	-13.983	0.017	0.017	-14.133	-14.135
Groundnut oil	-11.118	-12.569	1.256	0.014	-12.704	-12.709
Sugar	-5.764	-5.783	0.106	0.085	-15.117	-15.117
Tomato	-6.233	-6.242	0.057	0.034	-6.504	-6.579
Milk	-13.846	-15.353	0.056	0.016	-15.528	-15.615
Onion	-5.673	-5.676	0.050	0.041	-6.509	-6.619
CV	**-2.863**	**-3.412**	**0.463**	**0.146**	**-4.930**	**-5.080**

Notes: All tests were conducted at levels and with a constant term. The choice of the lag lengths is based on Akaike Information Criteria (AIC) for the ADF and Z–A tests, while the bandwidths in the KPSS test were determined using the Newey-West method. Critical values (CV) at 5% significance level for the ADF test is based upon MacKinnon (1996); the values for the KPSS test are from Kwiatkowski et al. (1992); and critical values for Z–A are based on Zivot & Andrews (2002).

Table 4: **Summary of Sampled Markets**

Region	*No of markets*
North	36
West	32
East	39
South	40
North-East	10
Total	***157***

Table 5: **Model Choice and Investigation - Mortality Rate**

Series	*Model*	*p*	*q*	*n*	$\hat{\psi}_\vartheta$	$\hat{\vartheta}$	*AICc*
Rice	AR	7		20			-1.831
Wheat	ETVAR	7		44	1.00	0.40	-1.049
					(0.33)	(0.02)	
Sugar	LTVARDL	4	0	38	26.51	0.59	-4.878
					(49.49)	(0.02)	
Milk	LTVAR	5		38	100.00	0.68	-3.284
					(204.48)	(0.01)	
Tomato	LTVARDL	12	0	54	2,02	0.15	-0.518
					(1.46)	(0.21)	
Onion	AR	1		14			-1.260
Groundnut oil	AR	8		21			-2.759

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; $\hat{\psi}_\vartheta$ and $\hat{\vartheta}$ respectively, represent estimated speed-of-adjustment and location parameters (values in parenthesis are standard errors).