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Abstract

Our study builds on a few econometric studies of the Covid-19 impact on food prices in India. The period covered is March-June 2020 during which a national lockdown was imposed and its subsequent relaxation (Unlock 1). Wholesale and retail prices and the wedge between them are analysed in detail, focusing on three Indian states, Maharashtra, Jharkhand and Meghalaya. The importance of this study lies in using rigorous panel models (the Hausman-Taylor model with fixed or random effects) and a dynamic panel SGMM model. The latter allows us to establish causality between severity of the Covid-19 pandemic and a few food commodities' prices. Thus new insights emerge that could help mitigate the severity of economic stress and hardships.

Key words: Covid-19 pandemic, food prices, panel models, lockdown, Maharashtra, Jharkhand, Meghalaya.

JEL codes: E 31, E 61, E 65.

I. Introduction

The first positive Covid-19 case was registered in India on 30 January 2020 in Kerala of a student who had returned from China. While there were only three cases in India till the end of February 2020, the number of cases started increasing rapidly in early March. India reported its first death due to Covid-19 on 13 March 2020, soon after which the Indian government sealed its international borders, suspended all visas to India, banned domestic travel by rail as well as air, and eventually announced a complete lockdown of the country to prevent community spread of the virus. As of 25th October 2020, the total coronavirus infection cases in India were 7,866,740 (the second next to USA) with death numbers 118,593 9 (the third next to USA and Brazil).[1] Though both daily cases and death numbers showed signs of slowing in September, there still exist risk for the second wave and thus a huge impact of the pandemic - both direct and indirect – on the Indian society. Hence sound policies to mitigate such impact need careful analysis. Among numerous issues on the Covid-19 impact, our focus here is on the price effect of the pandemic. Using the national panel data from March-June 2020, this study will examine carefully whether there is any association between the Covid-19 pandemic and the wholesale and retail prices of a number of food commodities, such as rice and onions.

Covid-19 pandemic has already impacted negatively agricultural production, sales, prices and income of farmers in India which has caused a huge disruption to the country's food systems and livelihoods (Harris et al. 2020). Harris et al. undertook a telephone survey with 448 farmers in four states, Jharkhand, Assam, Andhra Pradesh, and Karnataka during 5-12 of May, 2020, and found that a majority of farmers experienced negative impacts on production, sales, prices and incomes. Price reductions were reported by over 80% of farmers, and reductions by more than half for 50% of farmers. FAO (2020) also reported a huge loss in agricultural production in India, but rather emphasised a surge in food prices: 'food prices skyrocketed across the nation as transportation services were halted and fresh supplies were unavailable. Urban residents all over India found it difficult to buy groceries as the commodities became scarce in the beginning of the pandemic. The major reason was panic buying and hoarding among the people'. Globally, the Covid-19 impact on food prices is likely to depend on crops or items as well as the extent to which food supply chains are disrupted (Laborde et al., 2020).[2] However, Reardon et al. (2020) observe that "COVID-19 is likely to increase food prices, both as a cause and consequence of food shortages. Restrictions on food supply chains (FSCs) logistics will increase transaction costs and thus consumer prices.

[1] Source: www.worldmeters.info (accessed on 25 October 2020).
[2] 'Since the onset of the pandemic, world wheat prices have been quite volatile…, but prices have declined by around 10% between January and early July. By contrast, world market prices of rice rose around 20% between January and April and became highly volatile in May' (IFPRI, 2020, cited by Laborde et al., 2020, p. 502).

Speculative hoarding may occur and trigger price increases" (Reardon et al, 2020, page 80). ADB (2020) has also noted significant price increases in staple prices in developing Asian countries.

While the effect of the Covid-19 pandemic on agricultural production and food supplies is complex as it may vary across different products and different regions, it is important to understand how the pandemic and the government lockdown policies influence food supply chains and the agricultural market – its functioning and access. To understand the effect of the Covid-19 pandemic on food systems, it is necessary to analyse how it affects farm gate prices – the price of an agricultural product sold minus selling costs –by type of farmer (e.g. by operated land size), commodity, type of selling channel (e.g. local traders, the regulated market, government agencies), or by geographical regions at different times depending on the severity of Covid-19 and resulting policies or regulations set by central/state governments. The gap between these prices and consumer prices will vary considerably. Negi et al. (2018) have shown that farmers' access to transportation (i.e. roads) and information about the government-set minimum support prices (MSP), (i.e. access to mobile phones, landline phones and internet) enables them to obtain better price terms from informal as well as formal channels. Their econometric analysis is based on the National Sample Survey Organization's (NSSO) Situation Assessment Survey of Agricultural Households conducted in 2013.

Chatterjee and Kapur (2016) examined the sources of price variations in detail by using the monthly price data at district levels over 10 years (2005-2014). The authors estimated the effect of the presence of government procurement at district levels on the agricultural commodity price (i.e. paddy and wheat) measured as a relative difference from MSP and found that procurement had a positive effect on relative price of paddy and a negative effect on the price of wheat. They also examined whether the competition between *mandis* nearby (across state borders) resulted in higher prices to farmers. They showed the impact of one additional *mandi* in the neighbourhood to be an increase between 1% and 6% in price.[3]

To our knowledge the only detailed study of the impact of Covid-19 pandemic on agriculture prices in India during March-May 2020 is by Seth et al. (2020). Its merits are that it analyses producer and consumer price changes in a large number of agricultural commodities in 11 cities, from March 1, 2020 to May 31, 2020, relative to the same period in 2019. Seth et al. (2020) found that cereal prices remained stable relative to last year and across the weeks following lockdown. This stability is explained through India's cereal-centric policies, which resulted in huge stockpiles of grains across the country. On the other hand, among the non-cereal food groups (e.g. pulses, vegetables, and eggs), pulses have exhibited a consistent increase in the retail prices across cities, and the prices have not stabilized after more than a month of lockdown. An increase in demand for pulses due to panic buying and disruptions in the supply chain plausibly contributed to the rising trend in prices. The disruptions in the supply chain include the inability of farmers to mo0ve produce to APMCs due to the lack of transport. Further, stock replenishment was reported to have been affected due to reduced availability of labour.[4] Potato retail prices increased for all cities relative to last year and across weeks after the lockdown. Onion retail prices more than doubled in almost all the cities studied, relative to last year. The price rise was due to decreased deliveries that occurred because of transportation bottlenecks. However, these conclusions by Seth et al. (2020) may not be robust as their analysis primarily draws upon the comparison of means in a descriptive analysis, without a t-test or rigorous time series econometric analyses.[5]

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[3] Only a summary of the results was given by the authors.

[4] How the labour shortage due to the Covid-19 pandemic influenced wholesale and retail prices is important, but it is difficult to obtain the labour supply data at state levels. However, in our separate analysis (Imai et al., 2020), we found that the Covid-19 pandemic has had little effect on market arrivals, implying that the production systems have not been severely influenced. Employment policies can also mitigate the shortage of labour supplies (Walter, 2020) and thus affect commodity prices indirectly with regional variations. However, as the data are unavailable, we assume that our insertion of unobservable state-level fixed effects captures the different policy effects at the state level.

[5] Seth et al.'s (2020) assessment of impact of the price changes on nutrition also needs to be supported by more formal analyses. It rests on the premise that a disproportionate rise in prices of non-cereals may divert consumer spending toward staples (that is, wheat and rice), resulting in inadequate intakes of protein-rich food groups. However, the analysis need to take account of

Although the Covid-19 pandemic has had a widespread and profound impact on food supply chains and commodity prices, there are just a few rigorous econometric analyses. An exceptionally rich and analytically rigorous study (Varshney et al.2020) assesses the impact of the spread of COVID-19 and the lockdown on wholesale prices and quantities traded in agricultural markets. It compares whether these impacts differ across non-perishable (wheat) and perishable commodities (tomato and onion), and the extent to which any adverse impacts are mitigated by the adoption of a greater number of agricultural market reform measures. It uses granular data set comprising daily observations for 3 months (i.e April-June 2020, relative to the same period in 2019) from nearly 1000 markets across five states and uses a double- and triple- difference estimation strategy. Indeed, as the authors rightly claim, this study is probably one of the first to estimate the causal impacts of COVID-19 on food prices. Wheat saw a decrease in price differentials in June, but the overall impact across the 3 months was insignificant. This is likely because government procurement operations helped anchor wheat prices at the MSP. Prices for tomatoes fell in May, but there was no statistically robust impact otherwise. Also, onion prices were unaffected—this may reflect the concentrated nature of its supply, and the relatively dispersed nature of its demand.

In comparison, all the market arrival impact magnitudes were positive and significant, especially for the two perishable goods. That the magnitudes of differentials in market arrivals were much higher than those in prices suggests that supply constraints began easing beginning in May. In the case of the perishables, the positive coefficients on market arrivals may well be a reflection of distress sales and/or the need to address cash flow constraints. Together, these results suggest that while there were undoubtedly short-term disruptions in agricultural markets, they were also relatively resilient, in the sense that market arrivals were quick to recover after

dietary diversification that is associated with food prices, income/expenditure, household characteristics and its location, and time-related changes transmitted through prices and expenditure, and residually through life-style, activity patterns, and improvements in the epidemiology of disease environment (Kaicker et al., 2014).

the initial month, and that possible distress sales did not result in a disproportionate fall in prices.

The methodology used is, however, debatable. Running double and triple differences on wholesale prices and *mandi* arrivals, respectively, raises the concern whether the results on the prices might be different if instrumented *mandi* arrivals are used as an explanatory variable[6].

Our study is to our knowledge the first one to estimate the effects of the Covid-19 on food commodity prices based on both dynamic and static panel models. Given the scarce literature, the present analysis is significant for its analytical rigour and innovative methodology. The rest of the paper is organised as follows. The next section states the hypotheses and defines the variables we use in this study. This is followed by specifications of our econometric models. Section IV reports and discusses the results based on our econometric results. The final section summarises the results with policy lessons.

II. Hypotheses, Data, and Econometric Models

We will examine the following hypotheses based on the state-level weekly panel data on commodity prices (based on the data collated from Price Monitoring Division of the Department of Consumer Affairs[7]) as well as the weekly panel data of the Covid-19 cumulative severity ratio (CSR) as a proxy for the pandemic, after controlling for the state-level time-variant and time-invariant determinants, drawing upon and extending Negi et al. (2018) and Chatterjee and Kapur (2016).

The Price Monitoring Cell (PMC) in the Department of Consumer Affairs was created in 1998, with the task of monitoring prices of 14 essential commodities across 18 centres in the

[6] Another interesting study, Mahajan and Tomar (2020), quantifies the level of disruption in the food supply chains in India due to COVID-19 induced lockdown. While the methodology is rigorous, a limitation is that the analysis is confined to data from one of largest online grocery retailers in India. Overall, the study tracks 789 products across three cities (Delhi, Chennai and Kolkata). It evaluates the impact across four product categories, vegetables and fruits (i.e., perishables, and edible oils), and cereals and pulses (i.e., non-perishables). For an appraisal, see Kaicker, Gaiha and Aggarwal (2020).
[7]https://fcainfoweb.nic.in/reports/report_menu_web.aspx

country (PMC, 2011). PMC is the only organization in the country collating and disseminating absolute prices (retail and wholesale) of select essential commodities on an almost real time basis every day (ibid., 2011). Retail and wholesale prices are collected by 49 centres for 22 commodities either by online networking (26 centres), by email (8 centres) or by fax (19 centres) based on their connections to the common vendors (ibid., 2011). Weekly *mandi* prices are updated every Friday by email. The prices are then carefully checked by the PMC staff. Quality and variety of the item for which prices are reported remain same for each centre though these may vary from one centre to another. We have constructed the panel data of wholesale and retail prices based on the prices data collated by PMC. Given that the prices are reported for the average quality of the item for a given centre, the data are comparable across time. There remains an issue of cross-sectional comparison of the price data (e.g. due to the different methods of data collection or differences in the average quality), but it is unlikely that the nature of the price data significantly varies across different regions. For the purpose of our study, this dataset is undoubtedly the best source which we could use. Given the time-consuming nature of the data construction, we have created the centre-state-weekly panel data for retail and wholesale prices of rice, onions, potatoes and tomatoes.[8] Not only the effect of the pandemic on the consumer price and on the farm gate price but also its effect on the difference between the consumer and the farm gate prices will also be estimated.

A new indicator 'relative severity' proposed by the World Bank is used to illustrate the unequal distribution and progression of covid-19 deaths across states[9]. The relative severity ratio is defined as the ratio of the total deaths attributable to Covid-19 over a given period to

[8] While the choice of these four commodities is primarily guided by the availability of data, they are important in terms of both supply and demand. On the production side, rice is the second (15.3% in the total food production), potatoes the sixth (4.3%), onion the tenth (2.0%) and tomatoes the 12th (1.7%) largest food commodities in India in terms of the quantity (https://beef2live.com/story-top-50-produced-foods-india-89-120768, based on FAOSTAT in 2018). This reflects the importance of these commodities in demand as these are important ingredients for the Indian cuisine and rich in carbohydrate and vitamins.

[9] For details, see Schellenkens and Sourrowuille (2020). Kaicker, Imai and Gaiha (2020) examined the determinants of the Covid -19 severity ratio in India.

the expected total deaths from all causes under the counterfactual assumption that the pandemic had not taken place over a base period of the same length. Comparison with pre-pandemic mortality patterns provide a state- specific measure of the severity of the pandemic, and the excess burden on the health system

Algebraically,

$$Cumulative\ Severity\ Ratio_t = \frac{Cumulative\ Covid\ Deaths_t}{(\frac{No.of\ Deaths\ in\ a\ pre\ pandemic\ year}{365} * Length\ of\ Pandemic_t)} \quad (2)$$

where,

$$Length\ of\ Pandemic_t$$
$$= No.of\ Days\ between\ Date\ of\ First\ Covid\ Linked\ Death\ and\ t\ in\ the\ Region$$

The Covid-19 data are obtained from Ministry of Health and Family Welfare, India. The data on past mortality patterns is based on the State-wise Number of Registered Deaths in 2017 from the Ministry of Health and Family Welfare, Government of India. For the purpose of the Cum-SR, the number of reported deaths in 2017 is scaled down from annual estimates to the length of the pandemic in each state, calculated as the number of days since the first death in the state till the cut-off date for this analysis, i.e. 21 June 2020. For instance, in Maharashtra, the first death was reported on 17 March 2020, implying the length of the pandemic as 97 days. The expected total deaths under the no-pandemic situation is calculated as the total number of deaths in each region in 2017 * 97 days / 365.[10]

More specifically, we will test the following hypotheses, focusing on Maharashtra, Jharkhand and Meghalaya.

[10]A question is whether the death numbers in 2017 would serve as a valid counterfactual. First, the national level death rate has been fairly stable and gradually declining from 7.4 to 7.3 deaths/1,000 population since 2012 and the year 2017 is not an exceptional year. Second, while India has experienced frequent and widespread droughts, there were no major droughts in 2017. The death numbers in 2017 would thus serve as a reasonable counterfactual for the present analysis of Covid-19 (https://www.indexmundi.com/, accessed on 18 July 2020).

Hypothesis 1: The Covid-19 pandemic negatively influenced the weekly commodity price (namely, rice, onions, potatoes and tomatoes) in India.

Hypothesis 2: The Covid-19 pandemic negatively influenced the gap between the consumer price and the whole sale price in India.

Hypothesis 3: The Covid-19 pandemic negatively influenced the weekly commodity price (namely, rice, onions, potatoes and tomatoes) –in comparison with the rest of India.

Hypothesis 4: The Covid-19 pandemic negatively influenced the gap between the consumer price and the wholesale price in Maharashtra (or Jharkhand or Meghalaya) –in comparison with the rest of India.

$$\log Wholesale\ Price^{k}{}_{ijt} = \beta_0 + \beta_1\, log\ CSR\ (Cumulative\ Severity\ Ratio)_{jt} + \beta_2 Share\ of\ small\ farmers_j + \beta_3 Road\ availability\ _j + \beta_4\, Information_j + \beta_5 Temperature_{jt} + \beta_6 Rainfall_{jt} + Phase\ Dummies_t\ \beta_7 + State\ Dummies_{jt}\ \beta_8 + \mu_i + e_{ijt} \ldots\ldots\ldots(1)$$

As in Equation (1) $\log Wholesale\ Price^{k}{}_{ijt}$, the wholesale price of crop *k*, rice, onions, potatoes, or tomatoes[11], is estimated by the measure of Covid-19 pandemic severity together with various other determinants. Here *i* stands for centres (1 to 107), *j* for states (1 to 31) and *t* for weeks (Week 1 starting on 15 March 2020 to Week 14 starting on 14 June 2020).[12]As the

[11]Our selection of crops is based on the availability of comprehensive price data.
[12] Descriptive statistics are reported in Appendix Table 1.

price data at centre levels within a state can be correlated, the standard errors of all the estimations are clustered at state levels (i.e. robust and clustered standard errors).

The same specification will be used to estimate $\log Retail\ Price^{k}{}_{ijt}$ and $Price\ Gap^{k}{}_{ijt}$ as in Equation (1)' and Equation (1)". [13]

$$\log Retail\ Price^{k}{}_{ijt} = \beta_0 + \beta_1\, log\ CSR\ (Cumulative\ Severity\ Ratio)_{jt} + \beta_2 Share\ of\ small\ farmers_j + \beta_3 Road\ availability\ _j + \beta_4\, Information_j + \beta_5 Temperature_{jt} + \beta_6 Rainfall_{jt} + Phase\ Dummies_t\ \beta_7 + State\ Dummies_{jt}\ \beta_8 + \mu_i + e_{ijt} \ldots\ldots\ldots (1)'$$

$$Price\ Gap^{k}{}_{ijt} = \beta_0 + \beta_1\, log\ CSR\ (Cumulative\ Severity\ Ratio)_{jt} + \beta_2 Share\ of\ small\ farmers_j + \beta_3 Road\ availability\ _j + \beta_4\, Information_j + \beta_5 Temperature_{jt} + \beta_6 Rainfall_{jt} + Phase\ Dummies_t\ \beta_7 + State\ Dummies_{jt}\ \beta_8 + \mu_i + e_{ijt} \ldots\ldots\ldots (1)''$$

Our main explanatory variable is $log\ Cumulative\ Severity\ Ratio_{jt}$, the logarithm of Cumulative Severity Ratio (CSR) of Covid-19. We also control for $Share\ of\ small\ farmers_j$, that is the share of small and marginal farmers in 2017-18 at state levels[14]. This reflects differential farm-gate prices between large farmers and small farmers. Negi et al. (2018) found that smallholder farmers tend to sell more to local traders and input

[13]The price gap is defined as the difference of the retail price and the wholesale price. It is not in log as in a few cases it shows negative values.

[14]This is based on "Catalogues/Answers Data of Rajya Sabha Questions for Session 247/State-wise Percentage of Small and Marginal farmers and Women farmers under PMFBY during 2017-18" (From : Ministry of Agriculture and Farmers Welfare) (available from http://www.mospi.gov.in/statistical-year-book-india/2017/190).

dealers at lower prices, while large farmers can sell in the regulated market at higher prices. So the expected sign is negative.

We also control for $Road\ availability_{\ j}$, and access to highways. As we are not able to match the road data at centre levels, we proxy it by the share of national and state highway length in each state's area.[15] Another control variable is $Information_j$, that is, State-wise Number of Inhabited Villages Covered With Mobile Service and Without Mobile Service in India in 2019.[16]The inclusion of these variables follows Negi et al. (2018) who argue that farmers' access to transportation and information enables them to obtain better price and so expected signs are positive.[17]

The model also controls for the daily data on temperature and rainfall from MERRA (Modern-Era Retrospective analysis for Research and Applications – Version 2 web service). It delivers time series of temperature (at 2m), relative humidity (at 2m) and rainfall. The data source is a NASA atmospheric reanalysis of the satellite era using the Goddard Earth Observing System Model (GEOS-5) and focuses on historical climate analyses for a broad range of weather and climate time scales (GMAO, 2015).

To capture time effects, the model also has 4 dummy variables for Phase 2, Phase 3, Phase 4 and Phase 5 of the lockdowns announced by the Government of India. The first lockdown spanned a period of 21 days from 25 March 2020 to 14 April 2020, where nearly all factories and services were suspended, barring "essential services". The second lockdown started on 15 April 2020 and continued till 3 May 2020, with conditional relaxations for regions where the Covid-19 spread had been contained. With additional relaxations, the phase three of the

[15] This is based on the data of Ministry of Statistics and programme implementation, Government of India, http://www.mospi.gov.in/statistical-year-book-india/2017/190.
[16] The data are based on Indiastat (https://www.indiastat.com/table/telecommunication-data/28/mobile/169/1343759/data.aspx).
[17] It has been suggested that the quality and the availability of the local health system – on which data are unavailable - would influence the demand for these commodities and resilience to the Covid-19 pandemic, but we assume that the unobservable state-level fixed effects as well as the access to mobile phones capture these aspects to some extent.

lockdown was from 4 May 2020 to 17 May 2020, and the fourth phase was from 18 May 2020 to 1 June 2020. Phase 5 of the lockdown (1 June 2020 to 30 June 2020), also known as Unlock 1.0, was the first phase of the reopening in stages, with an economic focus.[18]

As an extension, a vector of the lockdown phase dummy variables is interacted with a vector of dummy variables for Maharashtra, Jharkhand, and Meghalaya to capture the effect of phases in these states. μ_i is an unobservable effect at centre levels and e_{it} is an independent identically distributed error term. While we estimate both Fixed Effects and Random Effects models, we present only the results of Random Effects model as the Fixed-Effects model cannot include time-invariant variables. [19]

As a robustness check, given that the severity of Covid-19 pandemic is potentially endogenous, for instance, because a sudden increase of food prices would worsen the pandemic while the pandemic affects the prices, we will apply the Hausman-Taylor model as well as the System GMM to the same data.

In the Hausman-Taylor model, Equation (1) can be rewritten by grouping the covariates into the four vectors, time-variant and exogenous variables (X_{it}^1) (e.g., $Temperature_{jt}$ and $Rainfall_{jt}$, lockdown phase dummies), time-variant and endogenous variables (X_{jt}^2) (e.g., ($log\ CovidCases_{jt-1}$, and its interaction with state dummies), time-invariant and exogenous variables (Z_i^1) (e.g.,$Information_i$, $Road\ availability\ _i$) and time-invariant and endogenous variables (Z_i^2) (e.g.$Share\ of\ small\ farmers_i$,).

[18] Responses to the COVID-19 pandemic are considerably different across different states (*Lancet*, 2020). For instance, Kerala declared high alert in early February (*The Economic Times*, 2020). It drew on its experience with the Nipah virus in 2018 to use extensive testing, contact tracing, and community mobilisation to contain the virus. In fact, it has also set up thousands of temporary shelters for migrant workers (*Lancet*,2020, p. 1315). Odisha's exposure to previous natural disasters meant precautions were already in place and Maharashtra has decided to close the school and the public facility on 13-14 March and used drones to monitor physical distancing during lockdown and applied a cluster containment strategy (ibid., 2020). Our insertion of state-level unobservable fixed effects can capture overall difference in lockdown policies.

[19] A statistically not significant Hausman test statistic implies that there is no significant difference in parameter estimates between random and fixed effects models, implying that the assumption for random effects model that there is no correlation between the error term (e_{it}) and the state-level individual term (μ_i) is likely to hold, that is, the test favours random effects model in most cases. In a few cases the Hausman test is statistically significant, but this does not necessarily imply that the fixed-effects model should be chosen over the random-effects model as this is based on the comparison of a subset of estimated coefficients. The Breusch -Pagan Lagrangian multiplier test for random effects is not significant, which suggests that between OLS and random effects model, the latter should be chosen.

Equation (1) is written as:

$$\log Wholesale\ Price^{k}{}_{ijt} = \gamma_0 + X_{jt}^1\gamma_1 + X_{jt}^2\gamma_2 + Z_j^1\gamma_3 + Z_j^2\gamma_4 + \mu_i + e_{ijt} \text{ .... } (3)$$

Here it is assumed that, unlike Random-Effects model, the individual effect can be correlated with endogenous variables ($E\left(\mu_i \middle| X_{jt}^2,\ Z_j^2\right) \neq$) and it is uncorrelated with exogenous variables ($E\left(\mu_i \middle| X_{jt}^1, Z_j^1\right) = 0$). Hausman and Taylor (1981) suggest an instrumental variable (IV) estimator which premultiplies equation (2) by $\Omega^{-1/2}$ where Ω is the variance covariance term of the error component, $\mu_i + e_{it}$, and performs 2SLS using instruments $\left[Q, X_{jt}^1, Z_j^1\right]$ in which Q is the within transformation matrix (i.e. based on demeaning transformation) with $\tilde{y} = Qy$ having a typical element $\tilde{y} = y_{jt-}\overline{y_i}$ and $\overline{y_j}$ is the individual mean (where y_{jt} is $\log CSR_{jt}$in our case) (Baltagi et al., 2003, p. 363). This is equivalent to applying 2SLS to the random effects model where the vector of time-invariant endogenous regressors,Z_i^2, is instrumented by deviations from the means of time-variant regressors, the mean of exogenous time-variant regressors and exogenous time-invariant regressors$\left[\widetilde{X_{it}^1}, \widetilde{X_{it}^2}, \overline{X_i^1} Z_i^1\right]$. Equation (1) is identified in our case because the number of regressors in $X_{it}^1$is much larger than that in Z_i^2 (Baltagi, et al., 2003). Our use of weather variables (part of X_{jt}^1) is crucial for identifications in this context. This makes sense empirically as fluctuations in weather occur outside the model of commodity price determinations. Baltagi et al. (2003) suggested a pretest estimator based upon two Hausman tests (i.e., FE versus RE and FE versus HT) where the RE estimator should be preferred if the standard Hausman test between FE and RE estimators is not rejected, while the HT estimator should be preferred if the choice of exogenous regressors is not rejected based on the second Hauaman test between FE and HT estimators. The HT estimator is likely to be a consistent estimator model except the two cases (wholesale price of potato, retail price of tomato) where the Hausman test suggests that the FE estimator is more consistent. However, as the FE model cannot have a time-invariant variable, we present the results of the RE and HT models for all the cases.

To capture the dynamics in the price determination process, we extend the model by estimating the dynamic model or System GMM which allows the model to include the time-invariant explanatory variables, unlike First Difference GMM (Roodman, 2009).However, as Roodman suggests that System GMM is not suitable for the panel with a small N and a large T (the number of time units), we follow Roodman (2009, p. 87) to “collapse” the instruments to have a common set of instruments for different time periods, rather than varying them for each time period and limit the number of lags in defining the instruments (up to the third lags). We have also applied the forward orthogonal deviations transform (Arellano and Bover, 1995). Here the log of CSR and its interactions with state dummies and the lagged dependant variable are treated as endogenous.

$$\log Wholesale\ Price^{k}{}_{ijt} = \beta_0 + \beta_1 \log Wholesale\ Price^{k}{}_{ijt-1} + \beta_2\ log\ CSR\ (Cumulative\ Severity\ Ratio)_{jt} + \beta_3 Share\ of\ small\ farmers_j + \beta_4 Road\ availability\ _j + \beta_5\ Information_j + \beta_6 Temperature_{jt} + \beta_7 Rainfall_{jt} + Phase\ Dummies_t\ \beta_8 + State\ Dummies_{jt}\ \beta_9 + \mu_i + e_{ijt} \ldots\ldots\ldots(4)$$

Equations (3) and (4) will be applied to the retail prices and the price gap of rice, onions, potatoes and tomatoes.

III. Results

A. Panel Unit Root Tests

As the long time-series data of prices can be non-stationary, we have restricted the periods to only after the Covid-19 pandemic started in India so that we can identify its effect on whole sale, retail prices and their gaps by phased geographical spreads of the Covid-19 pandemic. In Table 1 we apply Levin–Lin–Chu (LLC) (Levin et al., 2002) and Im-Pesaran-Shin (IPS) tests (Im et al, 2003). LLC tests the null hypothesis that each time series contains a unit root against the alternative hypothesis that each time series is stationary in which the lag order is permitted to vary across individuals. IPS test is not as restrictive as the LLC test, since it allows for heterogeneous coefficients. The null hypothesis is that all individuals follow a unit root process against the alternative hypothesis allowing some (but not all) of the individuals to have unit roots. We apply the specifications with and without a time trend. We determine the number of lags by Akaike Information Criteria (AIC).[20]

Table 1 shows that wholesale price, retail price and the price gap are panel stationary except two cases (IPS test with the time trend for wholesale prices of onions and tomatoes). So we are justified to use the static panel models. We have also carried out the unit root tests for the Covid-19 Cumulative Severity Ratio which is also stationary. Though the results are not shown, all the variables in the models are I(0).

Table 1. Results of Unit-root Tests

			Levin-Lin-Chu (LLC) no trend		Levin-Lin-Chu (LLC) with trend		Im-Pesaran-Shin (IPS) no trend		Im-Pesaran-Shin (IPS) no trend	
Panel structure		N (no of centres)	108		108		108		108	
		T (no of periods)	14		14		14		14	
		Panel means	No		No		No		No	
Rice	Wholesale	Average lags *a	3.76		3.6		2.16		3.06	
	Price	adjusted t or W-t-bar*b	-103	***	-29.62	***	55.1	***	-35.36	***
			I(0)		I(0)		I(0)		I(0)	
Rice	Retail Price	Average lags	3.79		1.7		2.4		2.39	
	Price	t (adjusted)	-95.99	***	-17.92	***	-11.6	***	-45.42	***
			I(0)		I(0)		I(0)		I(0)	
Rice	Price Gap	Average lags	3.01		1.79		1.85		2.69	

[20] We have also applied other alternatives of panel unit root tests and the results are broadly similar.

			Levin-Lin-Chu (LLC) no trend		Levin-Lin-Chu (LLC) with trend		Im-Pesaran-Shin (IPS) no trend		Im-Pesaran-Shin (IPS) no trend	
	Price	t (adjusted)	-6.11	***	-30.51	***	-38	***	-13.83	***
			I(0)		I(0)		I(0)		I(0)	
Onion	Wholesale	Average lags	3.79		3.27		1.72		**2.79**	
	Price	t (adjusted)	-38.78	***	-12.39	***	7.96	***	-0.31	***
			I(0)		I(0)		I(0)		I(1) [*c3]	
Onion	Retail Price	Average lags	4.18		3.22		1.86		2.43	
	Price	t (adjusted)	-53.75	***	-7.77	***	-5.73	***	-2.07	**
			I(0)		I(0)		I(0)		I(0)	
Onion	Price Gap	Average lags	3.69		3.04		1.59		2.37	
	Price	t (adjusted)	-32.28	***	-9.59	***	-7.85	***	-7.78	***
			I(0)		I(0)		I(0)		I(0)	
Potato	Wholesale	Average lags	3.57		2.9		1.75		2.6	
	Price	t (adjusted)	-250	***	-15.6	***	-12.4	***	-11.69	***
			I(0)		I(0)		I(0)		I(0)	
Potato	Retail Price	Average lags	3.71		2.86		1.74		2.35	
	Price	t (adjusted)	-45.86	***	-9.54	***	-10.5	***	-8.49	***
			I(0)		I(0)		I(0)		I(0)	
Potato	Price Gap	Average lags	3.34		3.07		1.47		2.45	
	Price	t (adjusted)	-18.88	***	-32.26	***	-12.6	***	-4.29	***
			I(0)		I(0)		I(0)		I(0)	
Tomato	Wholesale	Average lags	3.67		3.14		1.7		2.46	
	Price	t (adjusted)	-54.53	***	-11.5	***	-4.24	***	3.35	
			i(0)		i(0)		i(0)		I(1)[*d]	
Tomato	Retail Price	Average lags	3.32		3.21		1.64		2.53	
	Price	t (adjusted)	-11.37	***	-14.46	***	-2.93	***	-2.73	***
			I(0)		I(0)		I(0)		I(0)	
Tomato	Price Gap	Average lags	3.5		3.23		1.64		2.52	
	Price	t (adjusted)	-35.28	***	-55.41	***	-21.3	***	-23.76	***
			I(0)		I(0)		I(0)		I(0)	
log CSR		Average lags	1.53		0.53		1.76		1.36	
(Covid-19 Severity)		t (adjusted)	-7.04	***	-7.86	***	-4.66	***	-60.45	***
			I(0)		I(0)		I(0)		I(0)	

Notes: a. Lags are determined by Akaike Information Criteria (AIC).

*b. adjusted t is reported for LLC and W-t-bar is reported for IPS.

*c. The first difference is I(0) with w-t-bar -2.7, statistically significant at 1% level.

*d. The first difference is I(0) with w-t-bar -13.4, statistically significant at 1% level.

Source: Authors' calculation based on the data collected by the Price Monitoring Cell (PMC) in the Department of Consumer Affairs.

B. Covid-19 impact on commodity prices and price gaps

Next, we have estimated Equations (1), (3) and (4) for the wholesale price, the retail price and the price gap of rice, onions, potatoes and tomatoes.

Table 2 shows the results for rice without the interaction terms between state dummies and CSR. The first panel in Appendix Table 2 shows the results with the interaction terms. Below we focus mainly on how the Covid-19 pandemic influenced prices and the price gap. The results of Hausman tests suggest that in all the three cases there is little difference in estimated coefficients between the Fixed Effects and the Random Effects models as well as between the Fixed Effects and the Hausman-Taylor models. These results imply that the Hauman-Taylor model estimator is a consistent estimator.

Specification tests (serial correlation tests for AR(1), AR(2) and the Hansen over-identification test) for SGMM suggest that the dynamic panel models are correctly specified. The number of instruments is well below the number of 'groups' (or the number of N) as recommended by Roodman (2009).

- The Covid-19 pandemic (captured by log CSR) is positively and significantly associated with wholesale price of rice (confirmed by the Random Effects model and the Housman Taylor model, the first two columns of Table 2). It shows that on average a 10 % increase in the severity is associated with 0.04% increase in wholesale prices of rice at their conditional means, other things being equal. The association is not very large in terms of the magnitude than in the cases of the other food commodities, suggesting that the rice market is resilient to the Covid-19 shocks.
- To establish causality, we treat log CSR as an endogenous variable in the model. While log CSR is treated as endogenous in the model and the over-identifying test suggests that the instruments are excluded from the model, we need to rely on SGMM or the dynamic model to see if the association is causal as it takes account of the past development of CSR as instruments. The estimated coefficient of SGMM is positive and not statistically significant. The result is in line with those of the Random Effects model and the Hausman Taylor model,

but we cannot conclude that the positive association between the Covid-19 pandemic and wholesale price of rice is causal.

- However, an interesting and important result emerges once we insert the interaction term between state dummies and log CSR. It is confirmed that in Maharashtra the effect of the Covid-19 pandemic on wholesale price is significantly higher than in other states. As the interaction term is statistically significant in SGMM, the relationship is not only robust but also causal (as we treat the interaction terms as endogenous in SGMM). It could be because the pandemic has been severer in Maharashtra than elsewhere and it caused a significant disruption to supply or distribution systems in Maharashtra.
- The association between the Covid-19 pandemic and the wholesale price is higher in Meghalaya as well (only in Random effects model).
- The Covid-19 pandemic is positively associated with the retail price of rice but the estimates are not statistically significant (the second panel of Table 2). However, it is evident that in Maharashtra the Covid-19 pandemic is positively associated with the retail price of rice and the causal relation is established (Appendix Table 2).
- The Covid-19 pandemic had no impact on the gap between retail and wholesale prices of rice. However, in Maharashtra, the Covid-19 pandemic increased the price gap significantly. This may be because the surge in retail prices was not fully reflected in wholesale prices of rice in Maharashtra.
- On other explanatory variables, access to highway is positively correlated with wholesale and retail prices (Hausman-Taylor model). This is consistent with Negi et al. (2018). However, access to information has no role in raising the prices.
- We find through the dynamic panel model that the lagged price and the price gap strongly influence their current values.

- It is notable that, based on Random Effects and Hausman Taylor Models, both wholesale and retail prices of rice are higher in Phase 2 than in Phase 1 on average but they fell marginally in Phases 3 and 4. No significant effects of Phase dummies on the price gap are found.

Table 2. Associations of COVID-19 Pandemic with Wholesale Prices, Retail Prices and Price Gap of Rice

Dependent Variable	Wholesale Price (log)			Retail Price (log)			Price Gap		
Explanatory Variables	Random-Effects	Hausman-Taylor	SGMM	Random-Effects	Hausman-Taylor	SGMM	Random-Effects	Hausman-Taylor	SGMM
log CSR† [a]	**0.004**	**0.004**	0.002	0.002	0.002	0.003	-0.04	-0.043	0.03
(Covid-19 Severity)	**(3.28)[bcf]** ***	**(3.73)** ***	(0.81)	(1.33)	(1.50)	(1.32)	(1.24)	(1.41)	(0.70)
log Share of	-0.032	-0.032	0.035	-0.054	-0.05	0.059	-0.79	-0.791	1.411
Small farmers †	(0.13)	(0.21)	(0.19)	(0.23)	(0.36)	(0.28)	(0.79)	(0.84)	(0.32)
Access to	0.123	**0.123**	-0.014	0.109	**0.109**	-0.02	0.05	0.053	-0.44
Highways	(1.53)	**(1.99)** **	(0.21)	(1.48)	**(1.93)** *	(0.35)	(0.17)	(0.21)	(0.25)
Access to	-0.079	-0.079	0.167	-0.088	-0.09	0.143	-0.54	-0.515	1.494
Mobile Phones	(0.29)	(0.40)	(0.60)	(0.38)	(0.51)	(0.63)	(0.46)	(0.37)	(0.27)
Temperature	-0.001	-0.001	0.003	-0.001	-0	0.001	0	0.002	**-0.07**
	(1.44)	(1.20)	(1.23)	(0.90)	(0.95)	(0.43)	(0.06)	(0.10)	**(2.26)** **
Rainfall	0	0	0.002	0.001	0.001	0.001	0.02	0.018	-0.03
	(0.05)	(0.06)	(1.57)	(1.40)	(1.44)	(0.82)	(1.74) *	(1.75) *	(1.57)
D_Phase2 [d e]	**0.015**	**0.015**	**-0.024**	**0.017**	**0.017**	-0.02	0.08	0.088	0.216
	(3.84) ***	**(3.50)** ***	**(1.83)** *	**(4.14)** ***	**(3.80)** ***	(1.32)	(0.68)	(0.61)	(1.29)
D_Phase3	**0.009**	**0.009**	**-0.027**	0.012	0.012	-0.02	0.08	0.087	0.238
	(2.13) **	**(2.04)** **	**(2.20)** **	(1.65)	(1.61)	(1.57)	(0.36)	(0.36)	(1.08)
D_Phase4	**0.009**	**0.009**	**-0.035**	0.012	0.012	-0.02	0.07	0.073	0.376
	(1.76) *	**(1.69)** *	**(1.94)** *	(1.66)	(1.66)	(1.43)	(0.30)	(0.30)	(1.74) *
D_Phase5	0	0	-0.041	0.003	0.003	-0.03	0.01	0.021	0.36
	(0.06)	(0.06)	(1.84) *	(0.29)	(0.31)	(1.35)	(0.06)	(0.10)	(1.52)
l_wholesal~e									
L1.			**0.938**						
			(11.08) ***						
l_retailpr~e									
L1.						**0.921**			

											(13.0)	***						
price_gap																		
L1.																	**0.812**	
																	(10.7)	***
_cons	4.066		4.065		-0.64		4.073		4.071		0.029		2.67		2.474		20.53	
	(0.00)		(11.79)		(1.41)		(10.52)		(0.00)		(0.06)		(0.41)		(0.42)		(2.09)	
No of Observations(N)	1498		1498		1498		1498		1498		1498		1498		1498		1498	
No of centres(N)	107		107		107		107		107		107		107		107		107	
No of states (clusters)	31		31		31		31		31		31		31		31		31	
No of weeks(T)	14		14		14		14		14		14		14		14		14	
Wald chi2	77.25	***	30827	***	1795	***	46.93	***	36268	***	1630	***	8.88		574	***	409	***
R squared within	0.063		-		-		0.039		-		-		0.01		-		-	
R squared between	0.076		-		-		0.074		-		-		0.02		-		-	
R squared overall	0.076		-		-		0.072		-		-		0.02		-		-	
Breusch and Pagan Test (p value)	0	***	-		-		0	***	-		-		0	***	-		-	
Hausman Test *g (p value)	0.997		0.911				0.999		0.635				0.67		0.536			
AR(1)					0.024	**					0.018	**					0.009	***
AR(2)					0.222						0.451						0.225	
Over-Id test*h (p value)			0.17		0.84				0.13		0.33				0.21		0.959	

Notes: a. Variables marked by † are treated as endogenous in the Hausman Taylor Model and the SGMM model.

b. *** = Significant at 1% level. ** = Significant at 5% level. * = significant at 10% level.

c. The numbers in brackets show z values. They are based on robust standard errors.

d. State dummies for all the states have been included in the regressions.

However, the results are shown only for Jharkhand Maharashtra.

e. D_ stands for a dummy variable (taking 1 or 0).

f. Statistically significant cases are highlighted as bold numbers.

g. The Hausman tests were carried out between FE and RE and FE and Hausman-Taylor (Baltagi et al., 2003).

h. The Hansen test for SGMM.

Source: Authors' calculation based on the data collected by the Price Monitoring Cell (PMC) in the Department of Consumer Affairs.

Table 3 presents the results where we estimated the effect of the Covid-19 pandemic on the wholesale and retail prices and their gaps for onions. The Hausman test between the Fixed effects and the Hausman-Taylor models suggests that the choice of strictly exogenous regressors in the latter is not rejected and thus the Hausman-Taylor estimator is consistent. The SGMM model is also correctly specified as corroborated by the specification test results. To summarise the results:

- The Covid-19 pandemic is positively and significantly associated with both wholesale prices and the retail prices of onions (Random effects model and Hausman-Taylor Model). A 10% increase in the Covid-19 severity ratio is associated with 0.14-0.15% increase in wholesale and retail prices of onions. Importantly, we have found a positive and significant coefficient (at the 10 % level) for wholesale prices. This implies that there is a significant causal relationship between the Covid-19 pandemic and onion wholesale prices. The estimated coefficient is not significant, but with a z value 1.64 (close to the 10% significance level). However, the pandemic does not influence the price gap of onions.
- The second panel of Appendix Table 2 shows that the correlation between the Covid-19 pandemic and onion prices is weak in Jharkhand.
- On the other hand, the effect of the Covid-19 pandemic on the price gap of onions is significantly higher in Maharashtra than elsewhere. This is reflected in the estimated coefficients of the interaction between log CSR and the Maharashtra dummy. The pandemic effect is significantly high for retail prices, but not for wholesale prices of onions. That may reflect that, while retail prices of onions rose as a result of the pandemic, this is not fully reflected in the wholesale prices.
- In Meghalaya the correlation between the pandemic and both wholesale and retail prices of onions is higher than elsewhere if we follow the results of the Random-Effects model or the Hausman-Taylor model. However, these results are not robust as the coefficient is negative and significant for the wholesale price and not significant for the retail price in the case of SGMM model.
- Negi et al. (2018) show that infrastructure – or road access – together with information access - empower farmers to bargain better price in selling their products. Consistent with Negi et al.'s argument, access to highways has a positive and significant association with wholesale prices and the price gap. Information, in terms of access to mobile phones, is, however, negative and significant, which is inconsistent with Negi et al. (2018).

- Weather variables are associated with prices of onions (Random effects and Hausman-Taylor models), but we cannot infer any causality as they are statistically not significant in the SGMM model.
- The estimates of phase dummies suggest that on average wholesale and retail prices of onions as well as the gap between them have decreased from Phase 1 to Phase 5.

Table 3. Associations ofCOVID-19 Pandemic with Wholesale Prices, Retail Prices and Price Gap of Onion

Dependent Variable	Wholesale Price (log)						Retail Price (log)						Price Gap					
Explanatory Variables	Random-Effects		Hausman-Taylor		SGMM		Random-Effects		Hausman-Taylor		SGMM		Random-Effects		Hausman-Taylor		SGMM	
log CSR † [a] (Covid-19 Severity)	**0.014**		**0.015**		**0.02**		**0.015**		**0.015**		0.013		0.07		0.05		-0.024	
	(2.41) [bcf]	**	**(3.39)**	***	**(1.67)**	*	**(3.01)**	***	**(3.84)**	***	(1.64)		(1.46)		(1.22)		(0.26)	
log Share of Small farmers † [a]	-0.107		-0.109		1.331		-0.114		-0.114		1.435		0.132		0.155		17.512	
	(0.59)		(0.81)		(0.31)		(1.16)		(1.29)		(0.30)		(0.06)		(0.10)		(0.36)	
Access to Highways	0.057		0.057		0.809		**0.128**		**0.128**		0.829		2.053		**2.046**		10.349	
	(0.69)		(1.11)		(0.45)		**(2.34)**	**	**(2.59)**	**	(0.41)		(1.51)		**(2.20)**	**	(0.48)	
Access to Mobile Phones	**-1.504**		**-1.52**		0.012		**-1.363**		**-1.361**		-0.237		-2.286		-2.088		-8.562	
	(5.88)	***	**(7.41)**	***	(0.01)		**(8.38)**	***	**(11.15)**	***	(0.13)		(0.44)		(0.45)		(0.34)	
Temperature	**-0.016**		**-0.016**		-0.008		**-0.014**		**-0.014**		-0.005		-0.031		-0.026		0.082	
	(4.31)	***	**(6.03)**	***	(0.78)		**(4.76)**	***	**(6.82)**	***	(0.52)		(0.96)		(1.00)		(0.71)	
Rainfall	**0.003**		**0.003**		0.012		0.002		**0.002**		0.009		-0.007		-0.007		0.056	
	(2.28)	**	**(2.48)**	**	(1.69)	*	(1.36)		**(1.75)**	*	(1.58)		(0.38)		(0.42)		(0.78)	
D_Phase2 [d e]	**-0.188**		**-0.191**		-0.173		**-0.151**		**-0.151**		-0.129		-0.098		-0.054		-0.267	
	(5.31)	***	**(8.12)**	***	(1.62)		**(5.39)**	***	**(7.39)**	***	(1.52)		(0.46)		(0.22)		(0.42)	
D_Phase3	**-0.375**		**-0.378**		-0.201		**-0.313**		**-0.313**		-0.144		**-0.738**		**-0.691**		-0.514	
	(7.32)	***	**(11.51)**	***	(1.81)	*	**(7.77)**	***	**(11.23)**	***	(1.58)		**(2.44)**	**	**(2.12)**	**	(0.89)	
D_Phase4	**-0.463**		**-0.467**		-0.236		**-0.385**		**-0.385**		-0.177		**-0.898**		**-0.852**		-0.865	
	(8.38)	***	**(13.24)**	***	(1.63)		**(8.92)**	***	**(13.62)**	***	(1.50)		**(3.36)**	***	**(2.84)**	***	(1.12)	
D_Phase5	**-0.583**		**-0.589**		-0.311		**-0.487**		**-0.486**		-0.221		**-0.906**		**-0.833**		-0.801	
	(14.80)	***	**(18.83)**	***	(1.73)	*	**(14.30)**	***	**(19.19)**	***	(1.56)		**(4.96)**	***	**(3.20)**	***	(0.87)	
l_wholesal~e																		
L1.					**0.683**													
					(4.14)	***												
l_retailpr~e																		

L1.											**0.716**							
											(4.16)	***						
price_gap L1.																	**0.596**	
																	(4.56)	***
_cons	7.932		8.032		5.849		7.789		7.774		4.819		20.8		19.17		5.989	
	(7.15)		(9.94)		(0.98)		(9.00)		(12.73)		(0.81)		(1.98)		(2.49)		(0.09)	
No of Observations(N)	1498		1498		1498		1498		1498		1498		1498		1498		1498	
No of centres(N)	107		107		107		107		107		107		107		107		107	
No of states (clusters)	31		31		31		31		31		31		31		31		31	
No of weeks(T)	14		14		14		14		14		14		14		14		14	
Wald chi2	609	***	26684	***	7847	***	981	***	66029	***	9435	***	71.35	***	483	***	365	***
R squared within	0.643		-		-		0.633		-		-		0.039		-		-	
R squared between	0.308		-		-		0.513		-		-		0.106		-		-	
R squared overall	0.461		-		-		0.574		-		-		0.092		-		-	
Breush and Pagan Test (p value)	0	***	-		-		0	***	-		-		0	***	-		-	
Hausman Test [g] (p value)	0.05	**	0.927				0.499		0.556				0.0003	***	0.990			
AR(1)					0	**					0	***					0.003	***
AR(2)					0.587						0.587						0.397	
Over-Id test [h] (p value)			0.595		0.563				0.13		0.448				0.598		1	

Notes: a. Variables marked by † are treated as endogenous.

b. *** = Significant at 1% level. ** = Significant at 5% level. * = significant at 10% level.

c. The numbers in brackets show z values. They are based on robust standard errors.

d. State dummies for all the states have been included in the regressions.

However, the results are shown only for Jharkhand Maharashtra.

e. D_ stands for a dummy variable (taking 1 or 0).

f. Statistically significant cases are highlighted as bold numbers.

g. The Hausman tests were carried out between FE and RE and FE and Hausman-Taylor (Baltagi et al., 2003).

h. The Hansen test for SGMM.

Source: Authors' calculation based on the data collected by the Price Monitoring Cell (PMC) in the Department of Consumer Affairs.

Table 4 reports the results in which the effect of the Covid-19 pandemic on wholesale and retail prices of potatoes and their gaps are estimated. The Hausman tests between the Fixed Effects and the Random Effects estimators suggest that the former is consistent for all the three cases. However, the Hausman tests between the Fixed Effects and the Hausman-Taylor estimators imply that the latter (HT) is a consistent estimator for retail price (based on the 5% threshold) and price gap as the choice of the strictly exogenous variables is not rejected, while the Fixed Effects estimator is consistent for wholesale prices. While our preferred model remains HT, the results for wholesale prices need to be interpreted with caution. The SGMM model is found to be correctly specified. To summarise the results briefly:

- The Covid-19 pandemic is positively associated with wholesale and retail prices (the Random Effects and Hausman-Taylor models), but there is no significant association found in the SGMM model. Therefore, we cannot conclude any causal relation between the pandemic and prices or the price gap.
- The association of the Covid-19 pandemic with retail price of potatoes is stronger in Maharashtra where, as a result, the price gap is found to be more pronounced, as shown in the third panel of Appendix Table 2. This pattern is reversed in Jharkhand and Meghalaya where the Covid impacts on the retail price and the price gap are weaker for potatoes.
- We found the results for control variables which are broadly similar to those for onions (e.g. a negative association with mobile phones).
- Contrary to the results for rice and onions, Phase dummies are not statistically significant for potatoes.

Table 4. Associations of COVID-19 Pandemic with Wholesale Prices, Retail Prices and Price Gap of Potato

Dependent Variable	Wholesale Price (log)			Retail Price (log)			Price Gap		
Explanatory Variables	Random-Effects	Hausman-Taylor	SGMM	Random-Effects	Hausman-Taylor	SGMM	Random-Effects	Hausman-Taylor	SGMM
log CSR † [a] (Covid-19 Severity)	**0.015** [bcf]	**0.016**	0.01	**0.013**	**0.014**	0.003	0.037	0.018	0.089
	(2.29) **	**(3.65)** ***	(1.20)	**(2.27)** **	**(3.24)** ***	(0.48)	(0.71)	(0.38)	(1.31)
log Share of Small farmers †	0.144	0.143	-1.624	0.019	0.019	-0.595	-2	-1.98	-12.584
	(0.63)	(1.06)	(0.52)	(0.12)	(0.18)	(1.08)	(1.27)	(1.41)	(1.11)
Access to Highways	0.126	0.127	-0.184	0.139	0.139	0.221	1.009	1.001	-1.082
	(0.96)	(1.23)	(0.19)	(1.25)	(1.50)	(1.91) *	(0.99)	(1.56)	(0.29)
Access to Mobile Phones	**-0.865**	**-0.875**	-0.845	**-0.821**	**-0.825**	-0.75	-2.934	-2.743	-1.237
	(2.35) **	**(3.43)** ***	(0.68)	**(2.93)** ***	**(5.03)** ***	(1.03)	(0.80)	(0.88)	(0.10)
Temperature	0.004	0.004	-0.002	0.003	0.003	0.002	-0.009	-0.005	-0.056
	(1.26)	(1.73) *	(0.19)	(0.94)	(1.27)	(0.36)	(0.27)	(0.17)	(0.45)
Rainfall	0.003	0.003	0.007	0.002	0.002	0.005	-0.01	-0.01	0.045
	(4.80) ***	(4.86) ***	(1.01)	(3.60) ***	(3.72) ***	(1.72) *	(0.93)	(0.96)	(0.60)
D_Phase2 [de]	0.051	0.049	-0.029	0.053	0.052	-0.015	0.39	0.431	0.322
	(1.84) *	(2.64) **	(0.67)	(2.16) **	(3.05) ***	(0.47)	(1.17)	(1.36)	(0.44)
D_Phase3	0.015	0.012	-0.035	0.026	0.025	-0.023	0.408	0.454	0.18
	(0.71)	(0.73)	(0.71)	(1.29)	(1.48)	(0.74)	(1.28)	(1.50)	(0.33)
D_Phase4	-0.02	-0.023	-0.059	-0.012	-0.012	-0.056	0.163	0.207	-0.046
	(0.85)	(1.27)	(0.81)	(0.61)	(0.77)	(1.49)	(0.49)	(0.69)	(0.05)
D_Phase5	0.016	0.013	-0.069	0.031	0.03	-0.039	0.409	0.478	-0.212
	(0.47)	(0.56)	(0.76)	(1.16)	(1.53)	(0.85)	(1.27)	(1.64)	(0.23)
l_wholesal~e									
L1.			0.85						
			(5.56) ***						
l_retailpr~e									
L1.						0.855			

											(9.50)	***						
price_gap																		
L1.																	0.542	
																	(6.38)	***
_cons	1.953		2.005		0.286		2.701		2.725		0.14		9.915		8.496		14.206	
	(1.71)		(2.48)		(0.05)		(2.92)		(4.01)		(0.07)		(0.82)		(0.88)		(0.43)	
No of Observations(N)	1498		1498		1498		1498		1498		1498		1498		1498		1498	
No of centres(N)	107		107		107		107		107		107		107		107		107	
No of states (clusters)	31		31		31		31		31		31		31		31		31	
No of weeks(T)	14		14		14		14		14		14		14		14		14	
Wald chi2	132.33	***	19832	***	2364	***	98.86	***	54788	***	1815	***	21.16	**	651	***	223.1	***
R squared within	0.199		-		-		0.19		-		-		0.015		-		-	
R squared between	0.061		-		-		0.132		-		-		0.066		-		-	
R squared overall	0.086		-		-		0.145		-		-		0.053		-		-	
Breush and Pagan Test (p value)	0	***	-		-		0	***	-		-		0	***	-		-	
Hausman Test [g] (p value)	0	**	0.0002***				0.0002	***	0.080*				0.004	***	0.999			
AR(1)					0	***					0	***					0.017	**
AR(2)					0.027	**					0.22						0.128	
Over-Id test [h] (p value)			0.2614		0.818				0.459		0.144				0.657		0.616	

Notes: 1. Variables marked by † are treated as endogenous.

2. *** = Significant at 1% level. ** = Significant at 5% level. * = significant at 10% level.

3. The numbers in brackets show z values. They are based on robust standard errors.

4. State dummies for all the states have been included in the regressions.

However, the results are shown only for Jharkhand Maharashtra.

5. D_ stands for a dummy variable (taking 1 or 0).

6. Statistically significant cases are highlighted as bold numbers.

7. The Hausman tests were carried out between FE and RE and FE and Hausman-Taylor (Baltagi et al., 2003).

8.The Hansen test for SGMM.

Source: Authors' calculation based on the data collected by the Price Monitoring Cell (PMC) in the Department of Consumer Affairs.

Table 5 presents the results for tomatoes. The Hausman test results suggest that the Random effects model is preferred over Fixed effects model for the price gap, while the Fixed effects model is preferred for wholesale and retail prices. However, the Hausman test between the Fixed effects and the Hausman-Taylor models suggests that the choice of strictly exogenous variables in the latter is not rejected and the latter is preferred for wholesale prices and the price gap, but the hypothesis is rejected for the retail price where the Fixed Effects model is preferred. Therefore, the results for the retail price of the static models need to be interpreted with caution. Specification test results justify the dynamic panel model results.

- The Covid-19 pandemic is positively associated with wholesale and retail prices (the Random Effects and Hausman-Taylor models), but there is no significant association found in the SGMM model, which implies that there is no significant causality from the pandemic to prices.
- The size of the coefficients is relatively large for tomatoes: - for instance, a 10% increase in the severity ratio is on average associated with a 0.43-0.49% increase in wholesale prices and a 0.39-0.41% increase in retail prices.
- What is striking is that the Covid-19 pandemic is significantly and positively associated with the price gap of tomatoes in the static panel models. The estimated coefficient of CSR is positive in the dynamic panel model, but it is not statistically significant.
- If we follow the results of the Random Effects model, we find that the Covid-19 impact on retail and wholesale prices is significantly higher in Maharashtra than elsewhere. The pandemic is also strongly associated with the price gap in Maharashtra. This pattern is *reversed* in Jharkhand and Meghalaya.

Table 5. Associations of COVID-19 Pandemic with Wholesale Prices, Retail Prices and Price Gap of Tomato

Dependent Variable	Wholesale Price (log)			Retail Price (log)			Price Gap		
Explanatory Variables	Random-Effects	Hausman-Taylor	SGMM	Random-Effects	Hausman-Taylor	SGMM	Random-Effects	Hausman-Taylor	SGMM
log CSR † [a] (Covid-19 Severity)	**0.043** [bcf]	**0.049**	-0.018	**0.039**	**0.041**	-0.002	**0.135**	**0.115**	0.116
	(3.45) ***	**(5.80)** ***	(1.24)	**(3.66)** ***	**(6.14)** ***	(0.20)	**(2.07)** **	**(1.78)** *	(1.12)
log Share of Small farmers†	0.332	0.326	0.414	0.251	0.249	-0.073	0.438	0.46	-0.856
	(1.04)	(1.24)	(0.20)	(0.93)	(1.10)	(0.08)	(0.28)	(0.29)	(0.08)
Access to Highways	0.044	0.047	0.258	0.103	0.104	0.195	1.186	1.179	3.339
	(0.44)	(0.74)	(0.43)	(1.39)	(1.86) *	(0.80)	(1.34)	(1.33)	(1.10)
Access to Mobile Phones	**-2.195**	**-2.252**	-0.057	**-1.934**	**-1.956**	-0.43	-3.53	-3.329	-4.503
	(4.64) ***	**(5.26)** ***	(0.03)	**(4.78)** ***	**(5.68)** ***	(0.60)	(0.87)	(0.83)	(0.57)
Temperature	-0.033	-0.034	-0.018	-0.027	-0.028	-0.016	-0.055	-0.051	-0.109
	(3.72) ***	(5.92) ***	(2.50) **	(4.02) ***	(6.64) ***	(3.20) ***	(1.60)	(1.45)	(1.51)
Rainfall	0.005	0.005	-0.004	0.003	0.003	0.001	-0.008	-0.008	0.043
	(3.27) ***	(3.37) ***	(0.51)	(2.58) **	(2.67) ***	(0.22)	(0.61)	(0.58)	(0.93)
D_Phase2 [de]	0	-0.014	0.109	0.002	-0.004	0.058	-0.001	0.042	0.216
	(0.01)	(0.37)	(1.45)	(0.03)	(0.12)	(1.47)	(0.00)	(0.13)	(0.55)
D_Phase3	-0.091	-0.106	0.152	-0.079	-0.084	0.074	-0.23	-0.182	0.061
	(1.69) *	(2.84) ***	(1.98) **	(1.62)	(2.52) **	(1.82) *	(0.60)	(0.47)	(0.16)
D_Phase4	-0.127	-0.142	0.16	-0.124	-0.129	0.063	-0.725	-0.679	-0.161
	(2.05) **	(3.19) ***	(1.61)	(2.25) **	(3.43) ***	(1.20)	(2.26) **	(2.08) **	(0.33)
D_Phase5	-0.11	-0.132	0.291	-0.113	-0.121	0.143	-0.668	-0.595	-0.32
	(1.32)	(2.70) ***	(2.06) **	(1.56)	(2.95) ***	(1.87) *	(1.62)	(1.43)	(0.48)
l_wholesal~e									
L1.			0.946						
			(11.12) ***						
l_retailpr~e									
L1.						0.872			
						(16.64) ***			

price_gap									
L1.									0.7
									(14.04) ***
_cons	12.761	13.121	6.229	11.602	11.737	5.632	26.102	24.537	42.714
	(4.83)	(7.68)	(1.97)	(5.54)	(9.20)	(3.30)	(2.33)	(2.20)	(1.90)
No of Observations(N)	1498	1498	1498	1498	1498	1498	1498	1498	1498
No of centres(N)	107	107	107	107	107	107	107	107	107
No of states (clusters)	31	31	31	31	31	31	31	31	31
No of weeks(T)	14	14	14	14	14	14	14	14	14
Wald chi2	97.05 ***	9576 ***	878 ***	71.52 ***	20855 ***	1815 ***	19.12 **	404.2 ***	270.3 ***
R squared within	0.165	-	-	0.157	-	-	0.02	-	-
R squared between	0.315	-	-	0.385	-	-	0.066	-	-
R squared overall	0.265	-	-	0.309	-	-	0.054	-	-
Breush and Pagan Test (p value)	0 ***	-	-	0 ***	-	-	0 ***	-	-
Hausman Test [g] (p value)	0 ***	0.818		0.008 ***	0.012**		0.153	0.593	
AR(1)			0 ***			0 ***			0.005 ***
AR(2)			0.633			0.576			0.167
Over-Id test [h] (p value)		0.2614	0.084 *		0.299	0.041 **		0.185	0.856

Notes: a. Variables marked by † are treated as endogenous.

b. *** = Significant at 1% level. ** = Significant at 5% level. * = significant at 10% level.

c. The numbers in brackets show z values. They are based on robust standard errors.

d. State dummies for all the states have been included in the regressions.

However, the results are shown only for Jharkhand Maharashtra.

e. D_ stands for a dummy variable (taking 1 or 0).

f. Statistically significant cases are highlighted as bold numbers.

g. The Hausman tests were carried out between FE and RE and FE and Hausman-Taylor (Baltagi et al., 2003).

Source: Authors’ calculation based on the data collected by the Price Monitoring Cell (PMC) in the Department of Consumer Affairs.

IV. Conclusions

Using the national panel data in India from March-June 2020, we find positive associations between the Covid-19 pandemic and the wholesale prices and the retail prices of food commodities, such as rice and onions. The causal associations are established by the dynamic panel data based on SGMM model in a few cases. For instance, the Covid-19 pandemic increased the wholesale price of onions significantly for all-India.

We have also found that in Maharashtra which experienced a surge of the Covid-19 pandemic, retail prices of commodities and the price gap increased significantly. The dynamic panel model confirms that the Covid-19 pandemic raised both wholesale and retail prices of rice significantly in Maharashtra.

An interesting and important result for rice emerges once we insert the interaction term between state dummies and log CSR. It is confirmed that in Maharashtra the effect of the Covid-19 pandemic on wholesale price is significantly higher than in other states. As the interaction term is statistically significant in SGMM, the relationship is not only robust but also causal. It could be because the pandemic has been severer in Maharashtra than elsewhere and it caused a significant disruption to supply or distribution systems in Maharashtra.

The Covid-19 impact on retail and wholesale prices of tomatoes is significantly higher in Maharashtra than elsewhere. The pandemic is also strongly associated with the price gap in Maharashtra. This pattern is *reversed* in Jharkhand and Meghalaya.

Our analysis makes a significant contribution to the paltry literature on the Covid-19 impact by carrying out a detailed econometric analysis on food prices. We use detailed wholesale and retail food prices from a large number of *mandis* and retail outlets during different nation-wide lockdown phases and Unlock 1. Our analysis breaks new ground by using rigorous econometric models including dynamic models to arrive at robust inferences.

There are a few limitations arising from patchy and incomplete data on correlates of food commodities' price behaviours and their dynamics. We do not, for example, have direct measures of shares of food commodities marketed by size of farm, the costs of production, marketed surplus, and prices received from local buying agents, direct selling to *mandis* and government agency. Even if wholesale prices rise, it does not necessarily follow that small farmers receive higher farm gate prices. Further, although the recent *rabi* harvest was good, we do not know what was the approximate benefit to different categories of farmers. However, despite these limitations, some useful findings emerge.

The effects of different phases of the lockdowns are varied. For example, both wholesale and retail prices of rice are higher in Phase 2 than in Phase 1 on average but they fall marginally in Phases 3 and 4. No significant effects of Phase dummies on the price gap are found. Our estimates suggest that on average wholesale and retail prices of onions as well as their gap have decreased from Phase 1 to Phase 5. In sharp contrast, both wholesale and retail prices of rice are higher in Phase 2 than in Phase 1 on average but they fall marginally in Phases 3 and 4. No significant effects of Phase dummies on the price gap are found. On the contrary, lockdowns do not have significant effects on the prices of potatoes.

In brief, broad brush treatments of changes in food commodity prices based on pre-pandemic and pandemic means have only descriptive value. It is misleading to draw inferences about the effects of the lockdowns on wholesale and retail prices from such descriptions. Our panel data analysis casts serious doubts on the inferences offered. Although the NDA regime has undertaken several important policy initiatives, it is too soon to assess their effectiveness.

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Appendix Table 1. Descriptive Statistics of the Variables

Variable		Mean	Std. Dev.	Min	Max	Observations
log wholesale price	overall	3.40	0.23	3.02	4.11	N =1512
(rice)	between		0.23	3.02	4.11	n =108
	within		0.04	3.09	3.84	T =14
log retail price	overall	3.51	0.22	3.14	4.17	N =1512
(rice)	between		0.21	3.19	4.17	n =108
	within		0.05	3.20	3.95	T =14
price gap	overall	3.42	1.89	0.00	13.00	N =1512
(rice)	between		1.60	0.62	10.47	n =108
	within		1.02	-1.08	10.83	T =14
log wholesale price	overall	2.92	0.41	1.39	4.09	N =1512
(onion)	between		0.30	2.06	3.87	n =108
	within		0.28	1.93	3.73	T =14
log retail price	overall	3.21	0.32	2.30	4.09	N =1512
(onion)	between		0.21	2.57	3.84	n =108
	within		0.23	2.35	3.97	T =14
price gap	overall	5.95	4.33	-10.00	29.96	N =1512
(onion)	between		3.88	-1.79	25.77	n =108
	within		1.96	-5.33	20.45	T =14
log wholesale price	overall	2.95	0.29	1.79	3.81	N =1512
(potato)	between		0.26	2.30	3.59	n =108
	within		0.13	2.36	3.45	T =14
log retail price	overall	3.20	0.25	2.56	3.91	N =1512
(potato)	between		0.22	2.75	3.68	n =108
	within		0.12	2.65	3.67	T =14
price gap	overall	5.32	3.27	-2.50	32.14	N =1512
(potato)	between		2.81	-0.36	16.73	n =108
	within		1.69	-5.03	23.49	T =14
log wholesale price	overall	2.64	0.49	1.07	4.38	N =1512
(tomato)	between		0.40	1.75	4.32	n =108
	within		0.28	1.53	3.70	T =14
log retail price	overall	2.99	0.41	1.79	4.38	N =1512
(tomato)	between		0.33	2.06	4.32	n =108
	within		0.24	2.15	3.90	T =14
price gap	overall	5.92	4.59	-2.50	35.23	N =1512
(tomato)	between		4.00	0.00	28.13	n =108
	within		2.27	-4.11	23.03	T =14
log CSR	overall	-4.23	3.09	-9.21	0.97	N =1391
(Covid-19 Severity)	between		1.98	-9.21	-1.10	n =107

	within		2.37	-11.85	2.78	T =13
log Share of Small farmers	overall	-0.26	0.66	-6.91	0.00	N =1512
	between		0.66	-6.91	0.00	n =108
	within		0.00	-0.26	-0.26	T =14
Access to Highways	overall	-2.47	0.51	-3.51	0.56	N =1512
	between		0.51	-3.51	0.56	n =108
	within		0.00	-2.47	-2.47	T =14
Access to Mobile Phones	overall	-0.06	0.10	-0.50	0.00	N =1512
	between		0.10	-0.50	0.00	n =108
	within		0.00	-0.06	-0.06	T =14
Temperature	overall	301.69	5.15	275.16	311.13	N =1391
	between		4.22	282.45	306.21	n =107
	within		2.98	291.04	310.27	T =13
Rainfall	overall	3.06	5.46	0.00	34.61	N =1391
	between		2.32	0.22	12.62	n =107
	within		4.95	-8.64	27.79	T =13
D_Phase2	overall	0.19	0.34	0.00	1.00	N =1391
	between		0.04	0.13	0.21	n =107
	within		0.34	-0.02	1.05	T =13
D_Phase3	overall	0.15	0.30	0.00	1.00	N =1391
	between		0.00	0.15	0.15	n =107
	within		0.30	0.00	1.00	T =13
D_Phase4	overall	0.15	0.30	0.00	1.00	N =1391
	between		0.00	0.15	0.15	n =107
	within		0.30	0.00	1.00	T =13
D_Phase5	overall	0.20	0.37	0.00	1.00	N =1391
	between		0.00	0.20	0.20	n =107
	within		0.37	0.00	1.00	T =13

Appendix Table 2. Results with the interaction terms between State dummies and the cumulative COVID-19 severity ratio

	Dependent Variable / Explanatory Variables	Wholesale Price (log) Random-Effects		Hausman-Taylor		SGMM		Retail Price (log) Random-Effects		Hausman-Taylor		SGMM		Price Difference Random-Effects		Hausman-Taylor		SGMM	
Rice	log CSR (Covid-19 Severity)	**0.004**		**0.004**		0.001		0.002		0.002		0.003		-0.042		-0.05		0.043	
		(2.79)	***	**(3.16)**	***	(0.45)		(1.02)		(1.15)		(1.35)		(1.26)		(1.52)		(1.06)	
	D_Jharkhand	-0.001		-0.001		-0.004		0		0		-0.004		0.033		0.04		-0.009	
	*log CSR	(0.73)		(0.64)		(1.31)		(0.38)		(0.46)		(1.45)		(1.43)		(1.97)	**	(0.16)	
	D_Maharashtra	**0.009**		**0.009**		**0.009**		**0.006**		0.006		**0.007**		**-0.161**		-0.14		**-0.117**	
	*log CSR	**(8.56)**	***	**(2.19)**	**	**(4.84)**	***	**(5.01)**	***	(1.24)		**(4.10)**	***	**(6.73)**	***	(0.71)		**(2.27)**	**
	D_Meghalaya	**0.005**		0.004		-0.006		**0.008**		0.008		-0.004		**0.131**		0.12		0.069	
	*log CSR	**(3.88)**	***	(1.14)		(0.89)		**(6.17)**	***	(1.30)		(0.84)		**(4.99)**	***	(1.23)		(0.75)	
Onions	log CSR (Covid-19 Severity)	**0.013**		**0.015**		0.014		**0.014**		**0.013**		0.012		0.067		0.02		-0.042	
		(2.30)	**	**(3.26)**	***	(1.52)		**(2.59)**	**	**(3.10)**	***	(1.59)		(1.39)		(0.45)		(0.33)	
	D_Jharkhand	**-0.019**		**-0.028**		0.002		- 0.009		-0.013		-0.001		**0.09**		**0.17**		-0.092	
	*log CSR	**(4.42)**	***	**(7.13)**	***	(0.17)		(2.38)	**	(3.92)	***	(0.14)		**(1.87)**	*	**(4.93)**	***	(0.40)	
	D_Maharashtra	**-0.025**		**-0.031**		**-0.006**		**0.036**		0.038		**0.006**		**0.474**		*0.61*		0.216	
	*log CSR	**(3.85)**	***	**(3.07)**	***	**(0.48)**		**(7.53)**	***	(5.51)	***	**(0.48)**		**(9.67)**	***	*###*	***	(1.00)	
	D_Meghalaya	**0.031**		**0.03**		**-0.042**		**0.029**		**0.033**		-0.024		**0.141**		0.25		0.121	
	*log CSR	**(5.81)**	***	**(2.71)**	***	**(2.02)**	**	**(7.59)**	***	**(3.22)**	***	(1.07)		**(2.59)**	**	(1.40)		(0.34)	
Potatoes	log CSR (Covid-19 Severity)	**0.015**		**0.016**		0.004		**0.013**		**0.013**		0.001		0.041		0.01		0.037	
		(2.19)	**	**(3.51)**	***	(0.50)		**(2.20)**	**	**(3.13)**	***	(0.20)		(0.89)		(0.15)		(0.48)	
	D_Jharkhand	-0.004		-0.006		**-0.022**		- **0.012**		**-0.013**		**-0.018**		**-0.223**		**-0.2**		-0.04	
	*log CSR	(0.90)		(1.82)	*	**(2.60)**	**	**(3.32)**	***	**(5.10)**	***	**(1.90)**	*	**(5.55)**	***	**(5.79)**	***	(0.25)	
	D_Maharashtra	-0.002		-0.003		0.002		**0.023**		**0.024**		-0.002		**0.843**		**0.96**		-0.06	
	*log CSR	(0.31)		(0.31)		(0.18)		**(5.80)**	***	**(3.00)**	***	(0.12)		**(24.75)**	***	**(3.03)**	***	(0.29)	
	D_Meghalaya	0.004		0.001		-0.027		- **0.007**		-0.01		**-0.021**		**-0.289**		**-0.27**		0.24	

	*log CSR	(1.04)		(0.27)		(1.69)	*	**(2.17)**	**	(1.14)		**(1.73)**	*	**(8.43)**	***	**(2.27)**	**	(0.98)	
Tomatoes	log CSR (Covid-19 Severity)	**0.042**		**0.048**		-0.012		**0.039**		**0.041**		-0.002		**0.151**		**0.12**		0.042	
		(3.27)	***	**(5.61)**	***	(1.00)		**(3.67)**	***	**(6.06)**	***	(0.17)		**(2.30)**	**	**(1.83)**	*	(0.27)	
	D_Jharkhand	**-0.009**		**-0.03**		-0.008		**- 0.025**		**-0.032**		0.043		**-0.3**		**-0.2**		1.246	
	*log CSR	**(1.76)**	*	**(5.99)**	***	(0.21)		**(5.37)**	***	**(7.77)**	***	(0.90)		**(5.93)**	***	**(5.26)**	***	(1.04)	
	D_Maharashtra	**0.072**		**0.061**		**0.024**		**0.025**		0.025		**-0.006**		**0.291**		0.42		-0.078	
	*log CSR	**(10.51)**	***	**(3.89)**	***	**(2.73)**	***	**(3.99)**	***	(1.56)		**(0.31)**		**(6.39)**	***	(1.00)		(0.23)	
	D_Meghalaya	-0.009		-0.014		-0.033		**- 0.014**		**-0.017**		-0.024		**-0.245**		**-0.27**		0.213	
	*log CSR	(1.49)		(1.57)		(1.10)		**(2.62)**	**	**(1.74)**	*	(0.85)		**(5.29)**	***	**(2.43)**	**	(0.43)	