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The Covid-19 impact on food prices in India

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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 then subsequently relaxed (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 the severity of the Covid-19 pandemic and the prices of certain food commodities. Thus new insights emerge that could help mitigate the severity of economic stress and hardship.

Keywords

Covid-19 pandemic, food prices, panel models, lockdown, Maharashtra, Jharkhand, Meghalaya

JEL Codes

E 31, E 61, E 65

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1. Introduction

The first positive Covid-19 case in India was registered on 30 January 2020 in Kerala and concerned a student who had returned from China. While there were only three cases in India until the end of February 2020, the number of cases started increasing rapidly in early March. India reported its first death as a result of Covid-19 on 13 March 2020, soon after which the government sealed its international borders, suspended all visas to the country, 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 25 October 2020, total cases of coronavirus infection in India were 7,866,740 (the second highest after the US), with 118,593 deaths (the third highest after the US and Brazil).[1] Although both daily cases and deaths showed signs of slowing in September, the risk of a second wave still exists, as does that of a huge impact from the pandemic – both direct and indirect – on Indian society. Hence sound policies to mitigate such an impact need careful analysis. Among numerous aspects of Covid-19's impact, our focus here is on the price effect of the pandemic. Using national panel data from March–June 2020, this study carefully examines whether there is any association between the pandemic and the wholesale and retail prices of a number of food commodities, such as rice and onions.

The Covid-19 pandemic has already negatively affected agricultural production, sales, prices and farmers' income in India, causing 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 – between 5 and 12 May 2020 and found that a majority had experienced negative impacts on production, sales, prices and incomes. Price reductions were reported by over 80% of farmers, and reductions of more than half by 50%. FAO (2020) also reported a huge loss in agricultural production in India, but emphasised rather 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 other items, as well as the extent to which food supply chains are disrupted (Laborde et al, 2020).[2] However, Reardon et al (2020, p 80) have observed 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. Speculative hoarding may occur and trigger price increases." The Asian Development Bank has also noted significant price increases in staple prices in developing Asian countries (ADB, 2020).

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 are influencing food supply chains and the agricultural market – its functioning and access. To understand the pandemic's effect on food systems, it is necessary to analyse how it affects farm gate prices

[1] Source: www.worldmeters.info. Accessed: 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, cited in Laborde et al, 2020, p 502).

– the price of an agricultural product sold minus selling costs – by type of farmer (eg by available land size), by commodity, type of selling channel (eg local traders, the regulated market, government agencies), or by geographical region at different times, depending on the severity of Covid-19 and the resulting policies or regulations set by central or state governments. The gap between these prices and consumer prices will vary considerably. Negi et al (2018) have shown that farmers' access to transportation (ie roads) and information about government-set minimum support prices (MSP) (via access to mobiles, landline phones and the 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 monthly price data at district levels over 10 years (2005–14). The authors estimated the effect of the presence of government procurement at district levels on the agricultural commodity price (ie paddy and wheat), measured as a relative difference from MSP, and found that procurement had a positive effect on the relative price of paddy and a negative effect on the price of wheat. They also examined whether the competition between *mandis* nearby[3] (across state borders) resulted in higher prices for farmers. They showed the impact of one additional *mandi* in the neighbourhood to be an increase of between 1% and 6% in price.[4]

To our knowledge the only detailed study of the impact of the 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 1 March to 31 May 2020, relative to the same period in 2019. These authors found that cereal prices remained stable relative to 2019 and across the weeks following lockdown. This stability was explained through India's cereal-centric policies, which resulted in huge stockpiles of grain across the country. On the other hand, among the non-cereal food groups (eg pulses, vegetables and eggs), pulses exhibited a consistent increase in retail price across cities, and these prices had not stabilised after more than a month of lockdown. An increase in demand for pulses as a result of panic buying and disruptions in the supply chain plausibly contributed to the rising trend in prices. The disruptions in the supply chain included the inability of farmers to move produce to Agricultural produce market committees (APMCs) because of the lack of transport. Further, stock replenishment was reported to have been affected as a result of reduced availability of labour.[5] Potato retail prices increased for all cities relative to 2019 and across weeks after the lockdown. Onion retail prices more than doubled in almost all the cities studied, relative to 2019. The price rise was the result of decreased deliveries because of transportation bottlenecks. However, Seth et al's (2020) conclusions

[3] *Mandi* stands for market place in Hindi.
[4] Only a summary of the results was given by the authors.
[5] How the labour shortage caused by the pandemic influenced wholesale and retail prices is important, but it is difficult to obtain relevant data at state levels. Nevertheless, in our separate analysis (Imai et al, 2020), we found that the pandemic has had little effect on market arrivals, implying that production systems have not been severely influenced. Employment policies may 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.

may not be robust, as their analysis primarily draws upon a comparison of means in a descriptive analysis, without a t-test or rigorous time-series econometric analyses.[6]

Although Covid-19 has had a widespread and profound impact on food supply chains and commodity prices, there are only a few rigorous econometric analyses of it. An exceptionally rich and analytically rigorous study (Varshney et al, 2020) assessed the impact of the spread of the disease and the lockdown on wholesale prices and quantities traded in agricultural markets. It compared whether these impacts differed across non-perishable (wheat) and perishable commodities (tomato and onion), and the extent to which any adverse impacts were mitigated by the adoption of a greater number of agricultural market reform measures. It used a granular dataset comprising daily observations for three months (April–June 2020), relative to the same period in 2019, from nearly 1000 markets across five states, and used 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 three months was insignificant. This is probably 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, which may reflect the concentrated nature of the supply of onions, and the relatively dispersed nature of demand for them.

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 from May onwards. 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, the latter were also relatively resilient, in the sense that market arrivals were quick to recover after the initial month, and that possible distress sales did not result in a disproportionate fall in prices.

The methodology used was, however, debatable. Running double and triple differences on wholesale prices and *mandi* arrivals, respectively, raises concerns about whether the results on the prices might be different if instrumented *mandi* arrivals were used as an explanatory variable.[7]

Our study is, to our knowledge, the first to estimate the effects of Covid-19 on food commodity prices based on both dynamic and static panel models. Given the scarce literature, the present

[6] Seth et al's (2020) assessment of the 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 towards staples (that is, wheat and rice), resulting in inadequate intakes of protein-rich food groups. However, the analysis needs to take account of the dietary diversification associated with food prices, income and expenditure, household characteristics and location, and time-related changes transmitted through prices and expenditure, and residually through lifestyle, activity patterns and improvements in the epidemiology of the disease environment (Kaicker et al, 2014).

[7] Another interesting study, Mahajan and Tomar (2020), quantifies the level of disruption in India's food supply chains as a result of the Covid-19-induced lockdown. While the methodology is rigorous, one 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 (ie perishables), edible oils, cereals, and pulses (ie non-perishables). For an appraisal, see Kaicker, Gaiha et al (2020).

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 used in this study. This is followed by specifications of our econometric models. Section 4 reports and discusses the findings based on our econometric results. The final section summarises the results and suggests policy lessons.

2. Hypotheses, data and econometric models

The hypotheses we examine are based on the state-level weekly panel data on commodity prices (themselves based on the data collated from the Price Monitoring Cell (PMC) of the Department of Consumer Affairs[8]), as well as on 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. In this way we are drawing upon and extending Negi et al (2018) and Chatterjee and Kapur (2016).

The PMC in the Department of Consumer Affairs was created in 1998, with the task of monitoring the prices of 14 essential commodities across 18 centres in the country (PMC, 2011). PMC is the only organisation in India collating and disseminating absolute prices (retail and wholesale) of select essential commodities on an almost real-time basis every day (PMC, 2011). Retail and wholesale prices are collected by 49 centres for 22 commodities – either by online networking (26 centres), email (eight centres) or by fax (19 centres) – based on their connections to the common vendors. Weekly *mandi* prices are updated every Friday by email. The prices are then carefully checked by the PMC staff. The quality and variety of the item for which prices are reported remain the same for each centre, although these may vary from one centre to another. We constructed the panel data of wholesale and retail prices based on the prices data collated by PMC. Given that 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 (thanks to the different methods of data collection or differences in the average quality), but it is unlikely that the nature of the price data varies significantly across different regions. For the purpose of our study, this dataset was undoubtedly the best source available. Given the time-consuming nature of the data construction, we created centre-state-weekly panel data for retail and wholesale prices of rice, onions, potatoes and tomatoes.[9] We estimated not only the effect of the pandemic on the consumer and farm gate prices but also on the difference between consumer and farm gate prices.

A new indicator, 'relative severity', proposed by the World Bank, is being used to illustrate the unequal distribution and progression of Covid-19 deaths across states.[10] The relative severity ratio is defined as the ratio of the total deaths attributable to Covid-19 over a given period to the expected total deaths from all causes under the counterfactual assumption that the

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[8] https://fcainfoweb.nic.in/reports/report_menu_web.aspx.

[9] While the choice of these four commodities was primarily guided by the availability of data, they are important in terms of both supply and demand. On the production side, rice is India's second (15.3% of total food production), potatoes its sixth (4.3%), onions its tenth (2%) and tomatoes its 12th (1.7%) largest food commodity in terms of quantity. See https://beef2live.com/story-top-50-produced-foods-india-89-120768, based on FAOSTAT for 2018. This reflects the importance of demand for these commodities, as they are important ingredients in Indian cuisine and rich in carbohydrates and vitamins.

[10] For details, see Schellekens and Sourrouille (2020). Kaicker, Imai et al (2020) have examined the determinants of the Covid -19 severity ratio in India.

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 were obtained from the Ministry of Health and Family Welfare. The data on past mortality patterns are based on the state-wise number of registered deaths in 2017 from the same ministry. For the purpose of the Cum-SR, the number of reported deaths in 2017 has been 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 until the cut-off date for this analysis, 21 June 2020. For instance, in Maharashtra, the first death was reported on 17 March, implying a pandemic length of 97 days. The expected total deaths under the no-pandemic situation was calculated as the total number of deaths in each region in 2017 * 97 days / 365.[11]

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

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

Hypothesis 2: The pandemic negatively influenced the gap between the consumer price and the wholesale price in India.

Hypothesis 3: The pandemic negatively influenced the weekly commodity price of rice, onions, potatoes and tomatoes of each of the three states (Maharashtra, Jharkhand and Meghalaya) in comparison with the rest of India.

Hypothesis 4: The 9 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.

$$\log Wholesale\ Price^k{}_{ijt} = \beta_0 + \beta_1 \log CSR\ (Cumulative\ Severity\ Ratio)_{jt} +$$
$$\beta_2 Share\ of\ small\ farmers_j + \beta_3 Road\ availability_j + \beta_4 Information_j +$$

[11]A question is whether the death numbers in 2017 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 2017 was 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 can thus serve as a reasonable counterfactual for the present analysis of Covid-19. https://www.indexmundi.com/. Accessed: 18 July 2020.

$\beta_5 Temperature_{jt} + \beta_6 Rainfall_{jt} + Phase\ Dummies_t\ \beta_7 + State\ Dummies_{jt}\ \beta_8 + \mu_i + e_{ijt}$.........(1)

As in Equation (1) $\log Wholesale\ Price^k{}_{ijt}$, the wholesale price of crop *k*, rice, onions, potatoes or tomatoes,[12] was estimated by the measure of Covid-19 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 to Week 14 starting on 14 June).[13] As the price data at centre levels within a state can be correlated, the standard errors of all the estimations are clustered at state levels (ie 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)".[14]

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

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

Our main explanatory variable was $log\ Cumulative\ Severity\ Ratio_{jt}$, the logarithm of the CSR of Covid-19. We also controlled for $Share\ of\ small\ farmers_j$, that is the share of small and marginal farmers in 2017–18 at state levels.[15] This reflects differential farm gate prices between large farmers and small farmers. Negi et al (2018) found that smallholder farmers tended to sell more to local traders and input dealers at lower prices, while large farmers could sell in the regulated market at higher prices. So the expected sign is negative.

We also controlled for $Road\ availability\ _j$, and access to highways. As we were not able to match road data at centre levels, we proxied these by each state's share of national and state highway length.[16] Another control variable was $Information_j$, that is, the state-wise number of villages with and without mobile phone service coverage in 2019.[17] The inclusion of these

[12] Our selection of crops was based on the availability of comprehensive price data.
[13] Descriptive statistics are reported in Appendix Table 1.
[14] The price gap is defined as the difference between the retail price and the wholesale price. It is not in log as, in a few cases, it shows negative values.
[15] This is based on the Ministry of Agriculture and Farmers' Welfare's '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' [available at http://www.mospi.gov.in/statistical-year-book-india/2017/190].
[16] This is based on data from the Ministry of Statistics and Programme Implementation [available at http://www.mospi.gov.in/statistical-year-book-india/2017/190].
[17] The data are based on Indiastat [available at https://www.indiastat.com/table/telecommunication-data/28/mobile/169/1343759/data.aspx].

variables follows Negi et al (2018), who argued that farmers' access to transportation and information enabled them to obtain better prices, and so expected signs are positive.[18]

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), which delivers time series of temperature (at 2m), relative humidity (at 2m) and rainfall. The data source was a NASA atmospheric re-analysis of the satellite data 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 four dummy variables for Phase 2, Phase 3, Phase 4 and Phase 5 of the lockdowns announced by the Indian government. The first lockdown spanned a period of 21 days, from 25 March to 14 April 2020, during nearly all factories and services were suspended, barring 'essential services'. The second lockdown started on 15 April and continued until 3 May, with conditional relaxations for regions where the spread of Covid-19 had been contained. With further relaxations, phase three of the lockdown ran from 4 to 17 May, and the fourth phase ran from 18 May to 1 June. Phase 5 of the lockdown (1–30 June), also known as Unlock 1.0, was the first stage of the phased reopening, with an economic focus.[19]

As an extension, a vector of the lockdown phase dummy variables was 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 estimated both fixed-effects and random-effects models, we present only the results of the random-effects model as the fixed-effects model cannot include time-invariant variables.[20]

As a robustness check, given that the severity of the pandemic is potentially endogenous – for instance, because a sudden increase in food prices would worsen the pandemic while the

[18] It has been suggested that the quality and availability of the local health system – about which data are unavailable – would influence the demand for these commodities and resilience to the pandemic, but we have assumed that the unobservable state-level fixed effects, as well as access to mobile phones, capture these aspects to some extent.

[19] Responses to the pandemic have varied considerably across different states ('India under COVID-19 lockdown.' *Lancet* , *395*, 1315). For instance, Kerala declared a high alert in early February. 'Coronavirus: over 3000 people still under observation, says govt' (*Economic Times*, 8 February 2020. [https://economictimes.indiatimes.com/news/politics-and-nation/coronavirus-over-3000-people-still-under-observation-says-govt/articleshow/74034608.cms]. Accessed: 29 November 2020). The state drew on its experience with the Nipah virus in 2018 to use extensive testing, contact tracing and community mobilisation to contain the virus. Indeed, it has also set up thousands of temporary shelters for migrant workers ('India under COVID-19 lockdown.' *Lancet 395*, p 1315). Odisha's exposure to previous natural disasters meant precautions were already in place and Maharashtra decided to close schools and public facilities on 13–14 March and used drones to monitor physical distancing during lockdown, as well as applying a cluster containment strategy ('India under COVID-19 lockdown.' *Lancet 395*). Our insertion of state-level unobservable fixed effects is able to capture overall difference in lockdown policies.

[20] A statistically insignificant Hausman test statistic implies that there is no significant difference in parameter estimates between random- and fixed-effects models, implying that the assumption for the 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 the 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 the OLS (Ordinary Least Squares) and the random-effects model, the latter should be chosen.

pandemic would affect prices – we applied the Hausman–Taylor model as well as the System GMM (Generalized Method of Moments) 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) (eg $Temperature_{jt}$and $Rainfall_{jt},$ lockdown phase dummies), time-variant and endogenous variables (X_{jt}^2) (eg $log\ CovidCases_{jt-1},$ and its interaction with state dummies), time-invariant and exogenous variables (Z_i^1) (eg $Information_i,\ Road\ availability\ _i$) and time-invariant and endogenous variables (Z_i^2) (eg $Share\ of\ small\ farmers_i$,).

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 in the 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 is uncorrelated with exogenous variables ($E\left(\mu_i \middle| X_{jt}^1, Z_j^1\right) = 0$). Hausman and Taylor (1981) have suggested an instrumental variable (IV) estimator which pre-multiplies 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 (ie based on demeaning transformation) with $\tilde{y} = Qy$ having a typical element $\tilde{y} = y_{jt-}\overline{y_\iota}$, 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$\left[\widetilde{X_{\iota t}^1}, \widetilde{X_{\iota t}^2}, \overline{X_\iota^1} Z_i^1\right]$. 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 pre-test estimator based upon two Hausman tests (ie 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 Hausman test between FE and HT estimators. The HT estimator is likely to be a consistent estimator model, except for 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 extended the model by estimating the dynamic model or SGMM, which allowed it to include the time-invariant explanatory variables, unlike First Difference GMM (Roodman, 2009). However, as Roodman suggests that SGMM is not suitable for a panel with a small N and a large T (the number of time units), we followed him (2009, p 87) by 'collapsing' the instruments to have a common set of instruments for different time periods, rather than varying them for each time period, and by limiting the number of lags in defining the instruments (up to the third lags). We also applied the transformation based on forward orthogonal deviations (Arellano & Bover, 1995). Here the log of CSR and its interactions with state dummies and the lagged dependent 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) are applied to the retail prices and the price gap for rice, onions, potatoes and tomatoes.

3. Results

3.1 Panel unit root tests

As the long time-series data of prices may be non-stationary, we restricted the periods to only after the Covid-19 pandemic started in India, so that we could identify their effect on wholesale and retail prices and their gaps by phased geographical spread of Covid-19. In Table 1 we applied 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. The 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 applied the specifications with and without a time trend. We determined the number of lags using Akaike Information Criteria (AIC).[21]

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

[21] We have also applied alternatives to panel unit root tests and the results are broadly similar.

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 price	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	
	Price	t (adjusted)	-6.11	***	-30.51	***	-38	***	-13.83	***
			I(0)		I(0)		I(0)		I(0)	
Onion	Wholesale price	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 price	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 price	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 were determined using 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' calculations based on data collected by the PMC in the Department of Consumer Affairs.

3.2 Covid-19 impact on commodity prices and price gaps

Next, we estimated Equations (1), (3) and (4) for the wholesale price, the retail price and the price gap for 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 pandemic influenced prices and the price gap. The results of Hausman tests suggest that in all three cases there was little difference in estimated coefficients between the fixed-effects and random-effects models and likewise between the fixed-effects and the Hausman–Taylor models. These results imply that the Hausman–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 were 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 the wholesale price of rice (confirmed by the random-effects model and the Hausman–Taylor model, the first two columns of Table 2). Table 2 shows that on average a 10% increase in Covid-19 severity is associated with a 0.04% increase in the wholesale prices of rice at their conditional means, other things being equal. The association is not as large as in the cases of the other food commodities, suggesting that the rice market is resilient to Covid-19 shocks.

- To establish causality, we treated 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. This 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 pandemic and the 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. This confirms that in Maharashtra the effect of the pandemic on the wholesale price was significantly higher than in the other two 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). This may be because the pandemic has been more severe in Maharashtra than elsewhere and caused significant disruption to supply and distribution systems in the state.

- The association between the pandemic and the wholesale price was higher in Meghalaya as well (but only in the random-effects model).

- The pandemic is positively associated with the retail price of rice but the estimates are not statistically significant (second panel of Table 2). However, it is evident that in Maharashtra the pandemic is positively associated with the retail price of rice and a causal relation is established (Appendix Table 2).
- Overall, the pandemic had no impact on the gap between the retail and wholesale prices of rice. However, in Maharashtra, it increased the price gap significantly. This may be because the surge in retail prices was not fully reflected in wholesale prices of rice in the state.
- On other explanatory variables, access to a highway is positively correlated with wholesale and retail prices (Hausman–Taylor model). This is consistent with Negi et al (2018). However, access to information had no role in raising the prices.
- We found through the dynamic panel model that the lagged price and the price gap strongly influenced their current values.
- It is notable that, based on the random-effects and Hausman–Taylor models, both wholesale and retail prices of rice were 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 were found.

Table 2: Associations of Covid-19 pandemic with wholesale and retail rice prices and the gap between them

Dependent Variable / Explanatory variables	Wholesale price (log) Random effects		Hausman–Taylor		SGMM		Retail price (log) Random effects		Hausman–Taylor		SGMM		Price gap Random effects		Hausman–Taylor		SGMM	
log CSR† [a] (Covid-19 severity)	**0.004**		**0.004**		0.002		0.002		0.002		0.003		-0.04		-0.043		0.03	
	(3.28)[bcf]	***	**(3.73)**	***	(0.81)		(1.33)		(1.50)		(1.32)		(1.24)		(1.41)		(0.70)	
log share of small farmers †	-0.032		-0.032		0.035		-0.054		-0.05		0.059		-0.79		-0.791		1.411	
	(0.13)		(0.21)		(0.19)		(0.23)		(0.36)		(0.28)		(0.79)		(0.84)		(0.32)	
Access to highways	0.123		**0.123**		-0.014		0.109		**0.109**		-0.02		0.05		0.053		-0.44	
	(1.53)		**(1.99)**	**	(0.21)		(1.48)		**(1.93)**	*	(0.35)		(0.17)		(0.21)		(0.25)	
Access to mobile phones	-0.079		-0.079		0.167		-0.088		-0.09		0.143		-0.54		-0.515		1.494	
	(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 [de]	**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 and SGMM models.*
[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.*
[e] *D_ stands for a dummy variable (taking 1 or 0).*
[f] *Statistically significant cases are highlighted in bold*
[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' calculations based on data collected by the PMC in the Department of Consumer Affairs.

Table 3 presents the results of our estimation of the effect of Covid-19 on the wholesale and retail onion prices and the gaps between them. 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; 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 the wholesale and retail prices of onions (random-effects model and Hausman–Taylor model). A 10% increase in the Covid-19 CSR is associated with a 0.14–0.15% increase in these prices. Importantly, we found a positive and significant coefficient (at the 10 % level) for wholesale prices. This implies that there is a significant causal relationship between the pandemic and wholesale onion prices. The estimated coefficient is not significant, but has a z value of 1.64 (close to the 10% significance level). However, the pandemic does not influence the price gap for onions.
- The second panel in Appendix Table 2 shows that the correlation between the pandemic and onion prices is weak in Jharkhand.
- On the other hand, the effect of the pandemic on the onion price gap 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 – perhaps a reflection of the fact that, while the 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 onion prices is higher than elsewhere, if we follow the results of the random-effects or Hausman–Taylor models. However, these results are not robust, as the coefficient is negative and significant for the wholesale price but not significant for the retail price in the case of the SGMM model.
- Negi et al (2018) show that infrastructure – or road access – together with access to information empowers farmers to bargain for a better price when 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 onion prices (random-effects and Hausman–Taylor models) but we cannot infer any causality, as they are not statistically significant in the SGMM model.
- The estimates of phase dummies suggest that on average the wholesale and retail onion prices, as well as the gap between them, decreased from Phase 1 to Phase 5.

Table 3: Associations of Covid-19 with wholesale and retail onion prices and the gap between them

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]	**0.014**		**0.015**		**0.02**		**0.015**		**0.015**		0.013		0.07		0.05		-0.024	
(Covid-19 severity)	**(2.41)** [bcf]	**	**(3.39)**	***	**(1.67)**	*	**(3.01)**	***	**(3.84)**	***	(1.64)		(1.46)		(1.22)		(0.26)	
log share of	-0.107		-0.109		1.331		-0.114		-0.114		1.435		0.132		0.155		17.512	
small farmers † [a]	(0.59)		(0.81)		(0.31)		(1.16)		(1.29)		(0.30)		(0.06)		(0.10)		(0.36)	
Access to	0.057		0.057		0.809		**0.128**		**0.128**		0.829		2.053		**2.046**		10.349	
highways	(0.69)		(1.11)		(0.45)		**(2.34)**	**	**(2.59)**	**	(0.41)		(1.51)		**(2.20)**	**	(0.48)	
Access to	**-1.504**		**-1.52**		0.012		**-1.363**		**-1.361**		-0.237		-2.286		-2.088		-8.562	
mobile phones	**(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	0 ***	-	-	0 ***	-	-	0 ***	-	-
(p value)									
Hausman test [g]	0.05 **	0.927		0.499	0.556		0.0003 ***	0.990	
(p value)									
AR(1)			0 **			0 ***			0.003 ***
AR(2)			0.587			0.587			0.397
Over-Id test [h]		0.595	0.563		0.13	0.448		0.598	1
(p value)									

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 are included in the regressions.
However, the results are shown only for Jharkhand and Maharashtra.
[e] D_ stands for a dummy variable (taking 1 or 0).
[f] Statistically significant cases are highlighted in bold.
[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' calculations based on data collected by the PMC in the Department of Consumer Affairs.

Table 4 reports the estimates of the effect of the pandemic on the wholesale and retail prices of potatoes and the gaps between them. The Hausman tests between the fixed-effects and random-effects estimators suggest that the former is consistent for all three cases. However, the Hausman tests between the fixed-effects and the Hausman–Taylor estimators imply that the latter 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 Hausman–Taylor, the results for wholesale prices need to be interpreted with caution. The SGMM model is found to be correctly specified. To summarise the 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. Therefore, we cannot infer any causal relation between the pandemic and prices or the price gap.
- The association of the pandemic with the retail price of potatoes is stronger in Maharashtra where, as a result, the price gap was 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 pandemic's impacts on the retail price and the price gap were weaker for potatoes.
- We found the results for control variables to be broadly similar to those for onions (eg a negative association with access to mobile phones).
- Contrary to the results for rice and onions, phase dummies are not statistically significant for potatoes.

Table 4: Associations of Covid-19 with wholesale and retail potato prices and the gap between them

Dependent variable / Explanatory variables	Wholesale price (log) Random effects		Hausman–Taylor		SGMM		Retail price (log) Random effects		Hausman–Taylor		SGMM		Price gap 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	0.144		0.143		-1.624		0.019		0.019		-0.595		-2	-1.98	-12.584
small farmers †	(0.63)		(1.06)		(0.52)		(0.12)		(0.18)		(1.08)		(1.27)	(1.41)	(1.11)
Access to	0.126		0.127		-0.184		0.139		0.139		0.221		1.009	1.001	-1.082
highways	(0.96)		(1.23)		(0.19)		(1.25)		(1.50)		(1.91)	*	(0.99)	(1.56)	(0.29)
Access to	**-0.865**		**-0.875**		-0.845		**-0.821**		**-0.825**		-0.75		-2.934	-2.743	-1.237
mobile phones	**(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: [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 and 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' calculations based on data collected by the 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 the 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 tomato 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 between the pandemic and 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 pandemic is significantly and positively associated with the price gap for 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 Covid-19's 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 with wholesale and retail tomato prices and the gap between them

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 and Maharashtra.

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

[f] Statistically significant cases are highlighted in bold.

[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' calculations based on the data collected by the PMC in the Department of Consumer Affairs

4. Conclusions

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

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

Where rice is concerned, an interesting and important result emerged once we had inserted the interaction term between state dummies and log CSR. This confirmed that in Maharashtra the effect of the pandemic on the wholesale price was significantly higher than in other states. As the interaction term is statistically significant in SGMM, the relationship is not only robust but also causal. Such a result could have occurred because the pandemic has been more severe in Maharashtra than elsewhere and it caused significant disruption to supply and distribution systems in the state.

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

Our analysis makes a significant contribution to the sparse literature on the pandemic's impact by carrying out a detailed econometric analysis of food prices. We used detailed wholesale and retail food prices from a large number of *mandis* and retail outlets during different nationwide 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 the 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 surpluses, and prices received from local buying agents, by direct selling to *mandis* or from government agencies. Even if wholesale prices rise, it does not necessarily follow that small farmers receive higher farm gate prices. Further, although the recent *rabi* harvest[22] was good, we do not know its approximate benefit to different categories of farmers. Nevertheless, despite these limitations, some useful findings emerge.

The effects of the different phases of the lockdowns were varied. For example, both wholesale and retail rice prices were higher in Phase 2 than in Phase 1 on average but

[22] Rabi harvest means agricultural crops that are sown in winter and harvested in the spring.

they fell marginally in Phases 3 and 4. No significant effects of phase dummies on the price gap were found. Our estimates suggest that on average wholesale and retail onion prices and the gap between them decreased from Phase 1 to Phase 5. In contrast, lockdowns do not have significant effects on the price 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 (rice)	overall	3.40	0.23	3.02	4.11	N =1512
	between		0.23	3.02	4.11	n =108
	within		0.04	3.09	3.84	T =14
log retail price (rice)	overall	3.51	0.22	3.14	4.17	N =1512
	between		0.21	3.19	4.17	n =108
	within		0.05	3.20	3.95	T =14
price gap (rice)	overall	3.42	1.89	0.00	13.00	N =1512
	between		1.60	0.62	10.47	n =108
	within		1.02	-1.08	10.83	T =14
log wholesale price (onion)	overall	2.92	0.41	1.39	4.09	N =1512
	between		0.30	2.06	3.87	n =108
	within		0.28	1.93	3.73	T =14
log retail price (onion)	overall	3.21	0.32	2.30	4.09	N =1512
	between		0.21	2.57	3.84	n =108
	within		0.23	2.35	3.97	T =14
price gap (onion)	overall	5.95	4.33	-10.00	29.96	N =1512
	between		3.88	-1.79	25.77	n =108
	within		1.96	-5.33	20.45	T =14
log wholesale price (potato)	overall	2.95	0.29	1.79	3.81	N =1512
	between		0.26	2.30	3.59	n =108
	within		0.13	2.36	3.45	T =14
log retail price (potato)	overall	3.20	0.25	2.56	3.91	N =1512
	between		0.22	2.75	3.68	n =108
	within		0.12	2.65	3.67	T =14
price gap (potato)	overall	5.32	3.27	-2.50	32.14	N =1512
	between		2.81	-0.36	16.73	n =108
	within		1.69	-5.03	23.49	T =14
log wholesale price (tomato)	overall	2.64	0.49	1.07	4.38	N =1512
	between		0.40	1.75	4.32	n =108
	within		0.28	1.53	3.70	T =14
log retail price (tomato)	overall	2.99	0.41	1.79	4.38	N =1512
	between		0.33	2.06	4.32	n =108
	within		0.24	2.15	3.90	T =14

price gap (tomato)	overall	5.92	4.59	-2.50	35.23	N =1512
	between		4.00	0.00	28.13	n =108
	within		2.27	-4.11	23.03	T =14
log CSR (Covid-19 severity)	overall	-4.23	3.09	-9.21	0.97	N =1391
	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

Data sources: Authors' calculation based on the data from the Price Monitoring Cell of the Department of Consumer Affairs, the Ministry of Health and Family Welfare, the Ministry of Agriculture and Farmers' Welfare's 'Catalogues/answers data, the Ministry of Statistics and Programme Implementation and Indiastat.

Table 2: Results with the interaction terms between state dummies and the Covid-19 CSR

	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)	

Data sources: Authors' calculation based on the data from the Price Monitoring Cell of the Department of Consumer Affairs, the Ministry of Health and Family Welfare, the Ministry of