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Abstract

Using the panel data on market arrivals and prices for the 17 Indian states from July 2019 to June 2020, the present study examines whether the growth of Covid-19 pandemic influenced fractional changes in market arrivals and prices. A point of departure of our analysis from the literature is that we take into account the dynamic and lagged interactions between the fractional changes in market arrivals and prices of food commodities, namely, rice, onion, potato, and tomato, and the growth rate in the severity ratio of the Covid-19 pandemic, using a panel VAR model based on the GMM. Our results suggest that there was virtually no effect of the Covid-19 pandemic growth on fractional changes in market arrivals while the former negatively influences fractional food price changes in the short run. However, once we consider feedback effects in the VAR model based on Impulse Response Functions, the overall elasticity of the fractional change in the market arrival with respect to the Covid-19 pandemic growth turns from weakly positive to zero in a relatively short term. The overall elasticity of the fractional change in the market price with respect to the Covid-19 pandemic growth turns from positive to zero or negative in onion and tomato, and from negative to zero in rice and potato. We also find a great deal of regional heterogeneity where, for instance, the negative effect of the pandemic growth on the fractional change in price is larger in Maharashtra, the state with the worst pandemic. While the effect of the pandemic growth is relatively short-lived, policymakers need to take into account dynamic effects over time given the complexity of the transmission mechanism.

Key words: Covid-19 pandemic, food prices, a panel VAR model, lockdown, India

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

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I. Introduction

A nearly one year has passed since the 1st of December 2019 when the first case of Covid-19 was confirmed in China (Wu et al., 2020) and more than nine months have passed since the first positive Covid-19 case was registered in India on 30 January, 2020, in Kerala. 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 (Kaicker, Imai and Gaiha, 2020). As of 12th November 2020, the total coronavirus infection cases in India were 8,727,900 (the second next to USA) with death numbers 128,380 (the third next to USA and Brazil).[1] Though both daily cases and death numbers showed signs of slowing in September, there still exists 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. The impact has had a huge negative impact – including direct and indirect - , but despite its importance we do not know exactly the extent to which the Covid-19 pandemic damaged the Indian economy and society or how various policy measures taken by the central and state governments have mitigated any negative impact of the pandemic. Among numerous issues, the present study investigates whether the Covid-19 pandemic affected agricultural market arrivals and prices by taking into account the dynamic interactions between

[1] Source: https://www.covid19india.org/ (accessed on 12 November 2020).

the *mandi* prices and the arrivals[2]. More specifically, we will use the weekly panel data of 17 Indian states from July, 2019, to June, 2020, and will examine whether there exist any causal associations between the Covid-19 pandemic growth and fractional changes in the agricultural market prices and the market arrivals of food commodities, namely, rice, onion, potato and tomato.[3] For this purpose, we use a Panel VAR (Vector Autoregressive) Model based on the GMM (the generalized method of moments) to allow the dynamic interdependence of fractional changes in *mandi* arrivals, prices, and the Covid-19 pandemic growth.

Covid-19 pandemic had a negative impact on agricultural production, sales, prices and income of farmers in India and it 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 4 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. Harris et al.'s study suggests that the immediate or short-term impact of the Covid-19 pandemic on prices and market arrivals was likely to be negative. 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. The major reason was panic buying and hoarding among the people'. Globally, the Covid-19 impact on food prices is likely

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[2] *Mandi* means market place.

[3] We focus on the first difference of these variables as some of the level variables of arrivals are non-stationary while price and the Covid-19 severity are stationary as we will discuss later in detail.

to depend on crops or items as well as the extent to which food supply chains are disrupted (Laborde et al., 2020).[4] 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. 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 food prices and market arrivals at the same time given the complexity of the system. In their admirably rich contribution, Varshney et al. (2020) assess the impact of the spread of COVID-19 and the lockdown on market prices and quantities traded in agricultural markets. They compare whether the impact differs 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. Varshney et al. use a granular dataset comprising daily observations for 3 months (i.e. April-June 2020, relative to the same month/period in 2019) from nearly 1000 markets across five states and use a double- and triple-difference estimation strategy. Indeed, as the authors rightly claim, this study is probably one

[4] '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).

of the first to estimate the causal impacts of COVID-19 on food prices. They found that wheat saw a decrease in price differentials in June, but the overall impact across the 3 months was non-significant. This is likely because government procurement operations helped anchor wheat prices at the minimum support price (MSP). Prices for tomatoes fell in May, but there was no statistically robust impact. 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 the initial month, and that possible distress sales did not result in a disproportionate fall in prices.

The methodology used is, however, debatable. First, it ignores the price-quantity interaction. Running double and triple differences on wholesale prices and *mandi* arrivals, respectively, raises the concern whether the results on the prices (or arrivals) might be different if instrumented *mandi* arrivals (or prices) are used as an explanatory variable[5]. Second, the main explanatory variable based on the Covid cases is misleading as it depends on the number of tests which are not randomly distributed across different states or districts. Their claim that

[5] 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).

there are states with relatively high Covid cases and those with relatively low cases is broadly valid, but this overlooks time-series variation or development of Covid cases or pandemic within the former (taking 1 in their analysis) and within the latter (taking 0). Third, they claim that the difference- in- difference approach is valid if the parallel trend assumption (based on the comparison between 2018 and 2019) is valid. In addition to the parallel trend assumption DID assumes that the treated and the controls are comparable in the sense that the macro-environment is similar, or there is no factor that will uniquely influence only the former, or only the latter. It is unlikely that this condition will be satisfied, for instance, under different weather conditions that they did not control for. Our study based on the weakly panel VAR covering the period from July 2019 to June 2020 attempts to overcome some of the limitations by taking account of the dynamic (and endogenous) interactions among prices, *mandi* arrivals, and the Covid-19 pandemic based on the severity measure.

Another 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 the 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 move produce to APMCs due to the lack of transport. Further, stock replenishment was reported to have been affected due to reduced availability of labour. 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.[6] The present study attempts a more rigorous study based on the panel data econometric method where the price-quantity interaction is fully modelled.

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 *mandi* level weekly panel data on commodity prices (based on the data collated from Price Monitoring Division of the Department of Consumer Affairs[7]), market arrivals (based on Agricultural Marketing Information Network) as well as the weekly panel data of the Covid-19 cumulative severity

[6] Seth et al.'s (2020) assessment of impact of the price changes on nutrition is thin. 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 needs to take account of 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).

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

ratio (CSR) as a proxy for the pandemic, after controlling for the state-level time-variant and time-invariant determinants.

Hypothesis 1: The Covid-19 pandemic growth negatively influenced the fractional change in market arrivals (namely, rice, onions, potatoes and tomatoes) in India after taking account of the interaction between price and market arrivals.

Hypothesis 2: The Covid-19 pandemic growth negatively influenced the fractional market price change (namely, rice, onions, potatoes and tomatoes) in India after taking account of the interaction between the price and the market arrivals.

Hypothesis 3: The Covid-19 pandemic growth negatively influenced the fractional change in market arrivals differently in Maharashtra (or Meghalaya, Uttar Pradesh, Madhya Pradesh, Rajasthan, Punjab, Haryana, Jharkhand or Meghalaya) –in comparison with the rest of India.

Hypothesis 4: The Covid-19 pandemic growth negatively influenced the weekly market price change differently in Maharashtra (or Meghalaya, Uttar Pradesh, Madhya Pradesh, Rajasthan, Punjab, Haryana, Jharkhand or Meghalaya) –in comparison with the rest of India.

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 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). *Mandi* 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 market prices based on the price 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 over 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 market prices of rice, onions, potatoes and tomatoes. 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.[8]

The market arrival data are Agricultural Marketing Information Network (AGMARKNET) which was launched by the Union Ministry of Agriculture and links around 7,000 agricultural wholesale markets in India with the State Agricultural Marketing Boards and Directorates for effective information exchange. This e-governance portal AGMARKNET, implemented by National Informatics Centre (NIC), facilitates generation and transmission of prices, commodity arrival information from agricultural produce markets, and web-based dissemination to producers, consumers, traders, and policy makers transparently and quickly. We have constructed the variable on *mandi* arrivals, the total quantity (in tonnes) of food commodities arrivals from agricultural produce markets. The weekly *mandi* arrival quantities have been collated at the state level for 17 states[9] of India for four food commodities, namely, potato, tomato, onion and rice. The time period is 1st July 2019 to 30th June 2020.

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[8] Appendix Table 1 provides a summary of descriptive statistics of the variables we use in this study.

[9] They are Andhra Pradesh, Assam, Chhattisgarh, Gujarat, Haryana, Himachal Pradesh, Jharkhand, Karnataka, Kerala, Madhya Pradesh, Maharashtra, Meghalaya, Odisha, Punjab, Rajasthan, Uttar Pradesh, and West Bengal. These states are selected on the basis of the data availability as there are relatively few missing observations for these states in our study period. They are by no means representative of India, but the share of GDP of the 17 states in India

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[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 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,

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

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.

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was 76.4% and the population share was 77.8% in 2017-2018, which implies that we cover major states in our dataset.

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

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.[11]

As we noted earlier, we estimate the following panel VAR model based on the GMM, which draws upon Abrigo and Love (2016). As suggested by Tomek and Myers (1993) who reviewed various econometric models of agricultural market behaviours (e.g. price, demand, supply) and public policies, the use of VAR model for hypothesis generation would be less controversial than other alternative econometric methods under the uncertainty where not all the variables are observed.

$$Y_{ijt} = Y_{ijt-1}A_1 + Y_{ijt-2}A_2 + Y_{ijt-3}A_3 + X_{jt}B + \mu_i + e_{it} \qquad (1)$$

where Y_{ijt} is a $(1 \times k)$ vector (where k is 3 or 2 in our study) of dependent variables (namely, the first differences of the logarithm of *mandi* arrivals and prices (and the first logged difference of Covid-19 severity ratio in Model A) and X_{jt} is a $(1 \times l)$ vector of exogenous explanatory variables (namely, weekly variables on temperature and rainfall at state levels and the Covid-19 severity ratio at state levels and various state dummies in Model B). The number of lags has been determined by statistical significance of lagged variables and it is 3 in our case. μ_i and e_{it} is a $(1 \times k)$ vector of panel fixed effects and idiosyncratic errors at *mandi* levels, respectively. The Covid-19 severity ratio is treated as an endogenous variable in Model A, while it is made exogenous in Model B where the state-level effect of the pandemic growth on the fractional change of *mandi* arrivals and prices is examined. i stands for *mandi* (1 to 93), *j* stands for state (1 to 17) and *t* stands for time, or week (1 to 52, or the first week of July 2019

[11]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).

to the last week of June 2020). More specifically, we estimate the following two versions of the panel VAR model.[12]

Model A:

$$d\log Mandi\ Arrivals^{k}{}_{ijt} = \alpha_1\, d\log Mandi\ Arrivals^{k}{}_{ijt-1} +$$

$$\alpha_2\, d\log Mandi\ Arrivals^{k}{}_{ijt-2} + \alpha_3\, d\log Mandi\ Arrivals^{k}{}_{ijt-3} +$$

$$\alpha_4\, d\log Mandi\ \ Price^{k}{}_{ijt-1} + \alpha_5\, d\log Mandi\ Price^{k}{}_{ijt-2} +$$

$$\alpha_6\, d\log Mandi\ \ Price^{k}{}_{ijt-3} + \alpha_7 d\log CSR\ (Cumulative\ Severity\ Ratio)_{jt-1} +$$

$$\alpha_8 d\log CSR\ (Cumulative\ Severity\ Ratio)_{jt-2} +$$

$$\alpha_9 d\log CSR\ (Cumulative\ Severity\ Ratio)_{jt-3} + \beta_1 Temperature_{jt} + \ \beta_2 Rainfall_{jt} +$$

$$Phase\ Dummies_t\ \beta_3 + \mu_i + e_{it} \ldots\ldots\ldots(2)$$

$$d\log Wholesale\ Price^{k}{}_{ijt} = \alpha_1\, d\log Mandi\ Arrivals^{k}{}_{ijt-1} +$$

$$\alpha_2\, d\log Mandi\ Arrivals^{k}{}_{ijt-2} + \alpha_3\, d\log Mandi\ Arrivals^{k}{}_{ijt-3} +$$

$$\alpha_4\, d\log Mandi\ \ Price^{k}{}_{ijt-1} + \alpha_5\, d\log Mandi\ \ Price^{k}{}_{ijt-2} +$$

$$\alpha_6\, d\log Mandi\ Price^{k}{}_{ijt-3} + \alpha_7 d\log CSR\ (Cumulative\ Severity\ Ratio)_{jt-1} +$$

$$\alpha_8 d\log CSR\ (Cumulative\ Severity\ Ratio)_{jt-2} +$$

[12] One issue is whether it is appropriate to use a (first-differenced) log linear specification for the panel VAR model where the underlying relationships among dependent variables may be non-linear. First, use of a non-linear function in a VAR model is feasible (e.g. Altissimo and Violante, 2001), but computationally demanding in our data settings. Second, if quadratic terms are inserted, they are not statistically significant, implying that there is no quadratic relationship. Also, plotting key variables does not show any particular form of non-linearity. We have thus decided to use a log linear specification in estimating a panel VAR. A linear panel VAR model cannot capture non-linearity among variables, but it can model non-linearity in a time dimension, as we discuss later.

$\alpha_9 d \log CSR\ (Cumulative\ Severity\ Ratio)_{jt-3} + \beta_1 Temperature_{jt} + \ \beta_2 Rainfall_{jt} +$

$Phase\ Dummies_t\ \beta_3 + \mu_i + e_{it}$ ……….(3)

$d \log CSR\ (Cumulative\ Severity\ Ratio)_{jt} = \alpha_1\, d \log Mandi\ Arrivals\ ^{k}{}_{ijt-1} +$

$\alpha_2\, d \log Mandi\ Arrivals\ ^{k}{}_{ijt-2} + \alpha_3\, d \log Mandi\ Arrivals\ ^{k}{}_{ijt-3} +$

$\alpha_4\, d \log Mandi\ \ Price^{k}{}_{ijt-1} + \alpha_5\, d \log Wholesale\ \ Price^{k}{}_{ijt-2} +$

$\alpha_6\, d \log Wholesale\ \ Price^{k}{}_{ijt-3} + \alpha_7 d \log CSR\ (Cumulative\ Severity\ Ratio)_{jt-1} +$

$\alpha_8 d \log CSR\ (Cumulative\ Severity\ Ratio)_{jt-2} +$

$\alpha_9 d \log CSR\ (Cumulative\ Severity\ Ratio)_{jt-3} + \beta_1 Temperature_{jt} + \ \beta_2 Rainfall_{jt} +$

$Phase\ Dummies_t\ \beta_3 + \mu_i + e_{it}$ ……….(4)

In estimating (2)-(4), the first difference is taken for dependent variables because the panel unit root test results show that some time-series data of *mandi* arrivals (in particular, rice) are not-stationary (or I(1)) while those of market prices and the Covid-19 severity ratio are stationary (or I(0)) (Tables 1 and 2). This means that these three variables are not co-integrated and we cannot examine their long-term association based on the co-integration or the error-correction model. If *mandi* arrivals in level are not stationary, we cannot estimate the panel VAR model. As the first differenced data of these time-series are strongly stationary (Table 2), we will examine the relationships of the first differences of these variables.[13]

[13] When we include the equation for the pandemic growth (Equation (4)) in a panel VAR, lagged variables of the fractional changes in *mandi* arrivals and prices need to be included. This captures in principle how market changes will affect the pandemic, for instance, through food shortages or worsening poverty.

Mandi arrivals is the aggregate amount of each commodity transacted in each market place and as such it represents the equilibrium point based on the producer supply and the consumer demand, both of which respond to *mandi* prices of each commodity, which is roughly same as wholesale prices[14], and are known daily to producers, retailers, and consumers. As both *mandi* arrivals and *mandi* prices are determined *ex post* to reflect both demand and supply, neither consumer nor producer theories are directly applicable to them. For instance, the suppliers consider daily or weekly whether and how much they should bring their products to the market depending on the price (where a price-quantity relation is broadly positive). On the other hand, buyers have stronger incentives to purchase more if the prices are getting lower (i.e. a negative price-quantity relationship) and so the short-term price-quantity relationship can be complex and possibly non-linear. For instance, Sharma and Singh (2014) showed that the relationship between *mandi* arrivals of pearl millet can be positive or negative across different markets within Rajasthan. There is also a long-term price-quantity association that is associated with a long-term planting and product decisions of producers which are influenced by the expected market price of commodities –predicted by the long-run weather forecast, in particular, of rainfall and other factors as well as the input prices. Consumers will adjust the components in the basket of various foods depending on their budget constraint in the middle/or mid- term. The application of the panel VAR to the first differenced *mandi* price and arrivals as well as the Covid-19 severity ratio by no means reflect all the complexities in the quantity-price relationships. However, an advantage of our approach based on the panel VAR for the first

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[14] In this study, we use ‘*mandi* prices’ or ‘market prices’, and ‘wholesale prices’ interchangeably. Wholesale price is a broader concept where all the prices retailers will pay to the wholesalers are averaged at a certain point of time (e.g. prices of some direct transactions between large farmers and retailers or supermarkets outside *mandi* are omitted), while the *mandi* prices are the average prices transacted between sellers and buyers at *mandi* or market places. However, *mandi* prices are used as a basis for constructing the wholesale prices of food commodities in India.

differenced variables is that we can capture a complex, dynamic and endogenous price-quantity association *over time* by analysing the effect of the Covid-19 pandemic growth on either price or quantity of agricultural products.

In Equations (1)-(3), the first differences of log (equivalent to the growth rate, or the fractional change) of *mandi* arrivals ($d\log Mandi\ Arrivals^{k}{}_{ijt}$), market price ($d\log Mandi\ Price^{k}{}_{ijt}$) and the Covid-19 severity ratio ($d\log CSR\ (Cumulative\ Severity\ Ratio)_{jt}$) for the k^{th} product in the i^{th} market, the j^{th} state in week *t* are estimated jointly by their lags up to the third lags. We have access to the data of *mandi* arrivals only as an aggregate of all the markets in each state, while we constructed the *mandi* level prices for all markets in our earlier study (Imai et al., 2020). So all the regressions are estimated at *mandi* levels where the standard errors are clustered at state levels to take account of the within state correlations of prices. Our main variable, $log\ Cumulative\ Severity\ Ratio_{jt}$, the logarithm of Cumulative Severity Ratio (CSR) of Covid-19, is also first differenced to examine how the pandemic growth affects the fractional changes in the market price and market arrivals.

The model also controls for the weekly data on temperature and rainfall at state levels from MERRA (Modern-Era Retrospective analysis for Research and Applications – Version 2 web service). We use the weather data of capital (or a major city) of each state as a proxy for those at state levels. 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). Weather also can affect the Covid-19 pandemic development. Ma et al. (2020) used the data on daily death numbers from Wuhan, China, in January-February in 2020 and found that death counts are positively associated with temperature and negatively with relative humidity, while Kaicker, Imai and Gaiha (2020) found that in India temperature is positively and significantly associated with the Covid-19 pandemic, but rainfall is not.

To capture time effects, the model also has 5 dummy variables for Phase 1, 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 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. We have controlled for the unobservable *mandi*-level fixed effects. This captures whether prices, arrivals and the severity of pandemic differs due to unobservable factors at market levels, such as, institutional factors or cultural factors which are unchanged in our study period.

Model B:

As an extension, Model B examines whether the effect of the Covid-19 severity ratio differs across different states due to different policies of lockdown or different degrees of market reforms. For instance, an Agriculture Produce and Livestock Marketing Act (APLMA) was introduced in 2017 with the aim to rebuild appropriate market infrastructure for the public and private sectors to benefit both farmers and consumers, where each state decides how it is applied locally depending on its circumstances (e.g. this deregulation will reduce marketing margins and lower food prices) (Varshney, et al., 2020). They used the market-level data for five states and argued that Uttar Pradesh and Rajasthan (adopted the market reform with high intensity (taking 1 in their triple difference model), and Madhya Pradesh, Punjab, and Haryana with low intensity (taking 0) depending on the number of adopted provisions in APLMA. They found that the states with market reforms tend to prevent prices from falling under the Covid-19 crisis, mainly for perishable goods (tomato, onion) not for non-perishable goods, such as wheat. Our recent studies focused on three states, namely, Maharashtra, Jharkhand, and Meghalaya (by using dummy variables for Maharashtra and Meghlaya depending on statistical significance) which showed highly contrasting development of the Covid-19 pandemic in analysing the causes for the pandemic and its effect on wholesale and retail prices (Kaicker, Imai, and Gaiha, 2020; Imai et al., 2020). Building upon these studies, the first difference of logged Cumulative Severity Ratio is interacted with a vector consisting of a set of seven state dummy variables (for Uttar Pradesh, Rajasthan, Madhya Pradesh, Punjab, Haryana, Maharashtra and Meghlaya) out of 17 states to capture the effect of phases in these states.[15] In Model B, the Covid-19 severity ratio and the interaction terms are treated as exogenous variables to avoid the specification becoming too complicated. Equations (5) and (6) are estimated where the first differences (in logarithm) of *mandi* arrivals and price are estimated by the panel VAR model where the first difference of the Covid-19 severity and the interaction terms are included as exogenous variables. D_state_j denotes a vector of state dummies for seven states and this is interacted with the first differences of the Covid-19 severity ratio. Everything else is same as in Model A. It should be noted that the identification of the state-level effect is similar to Varshney et al.'s (2020) methodology of triple differencing (Covid dummy * Year dummy * State dummy) though our identification is based on the time-series

[15] State-level unobservable fixed effects are included for all 17 states to identify the interacted effects for these seven states separately. Insertion of interaction terms only for a subset of the seven states will not change the main results as well as those of the interaction terms significantly.

variation (on a weekly basis, including the period prior to the pandemic) and the cross-sectional variation in continuous changes in the Covid severity after controlling for separate effects of phases and fixed effects at the *mandi* level.

$$d\log Mandi\ Arrivals^{k}{}_{ijt} = \alpha_1\, d\log Mandi\ Arrivals^{k}{}_{ijt-1} + \alpha_2\, d\log Mandi\ Arrivals^{k}{}_{ijt-2} + \alpha_3\, d\log Mandi\ Arrivals^{k}{}_{ijt-3} + \alpha_4\, d\log Mandi\ \ Price^{k}{}_{ijt-1} + \alpha_5\, d\log Mandi\, Price^{k}{}_{ijt-2} + \alpha_6\, d\log Mandi\ \ Price^{k}{}_{ijt-3} + \beta_1 d\log CSR\ (Cumulative\ Severity\ Ratio)_{jt} + D\_state_j \otimes \log CSR\ (Cumulative\ Severity\ Ratio)_{jt}\beta_2 + \beta_3 Temperature_{jt} + \beta_4 Rainfall_{jt} + Phase\ Dummies_t\ \beta_5 + \mu_i + e_{it} \ldots\ldots\ldots (5)$$

$$d\log Mandi\ Price^{k}{}_{ijt} = \alpha_1\, d\log Mandi\ Arrivals^{k}{}_{ijt-1} + \alpha_2\, d\log Mandi\ Arrivals^{k}{}_{ijt-2} + \alpha_3\, d\log Mandi\ Arrivals^{k}{}_{ijt-3} + \alpha_4\, d\log Mandi\ \ Price^{k}{}_{ijt-1} + \alpha_5\, d\log Mandi\, Price^{k}{}_{ijt-2} + \alpha_6\, d\log Mandi\ \ Price^{k}{}_{ijt-3} + \beta_1 d\log CSR\ (Cumulative\ Severity\ Ratio)_{jt} + D\_state\ {}_j \otimes d\log CSR\ (Cumulative\ Severity\ Ratio)_{jt}\beta_2 + \beta_3 Temperature_{jt} + \beta_4 Rainfall_{jt} + Phase\ Dummies_t\ \beta_5 + \mu_i + e_{it} \ldots\ldots\ldots (6)$$

Based on the results of panel VAR models, we have carried out Granger causality tests among endogenous variables to see the direction as well as the presence of causalities.

III. Results

(1) Panel Unit Root Tests

As the long time-series data of prices or arrivals or the Covid-19 severity ration can be non-stationary, we have carried out the panel unit root tests to see whether these variables are stationary or not. In Tables 1 and 2 we apply Levin–Lin–Chu (LLC) (Levin et al., 2002) and Im-Pesaran-Shin (IPS) tests (Im et al, 2003) for the level and the first differences of these variables. 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).[16]

Table 1. Results of Unit-root Tests (Level)

			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)	93	93	93	93
		T (no of periods)	52	52	52	52
		Panel means	No	No	No	No
Rice	Mandi Arrivals	Average lags [*1]	**2.13**	**2.43**	**2**	**2.22**
	(log)	adjusted t or W-t-bar[*2]	**8.12**	**6.78**	**4.66**	**-0.84**
			I(1)	**I(1)**	**I(1)**	**I(1)**
Rice	Mandi	Average lags	1.09	1.21	0.97	1.01

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

	Price (log)	t (adjusted)	-5.12 I(0)	***	-4.86 I(0)	***	-4.75 I(0)	***	-4.64 I(0)	***
Onion	Mandi Arrivals	Average lags *1	0.78		0.85		0.65		0.7	
	(log)	adjusted t or W-t-bar*2	-8.55 I(0)	***	-5.79 I(0)	***	-10.7 I(0)	***	-4.86 I(0)	***
Onion	Mandi	Average lags	0.5		1.11		0.52		0.93	
	Price (log)	t (adjusted)	-12.52 I(0)	***	-14.8 I(0)	***	-12.5 I(0)	***	-14.56 I(0)	***
Potato	Mandi Arrivals	Average lags *1	**0.52**		0.63		**0.52**		0.51	
	(log)	adjusted t or W-t-bar*2	**2.55** **I(1)**		-1.67 I(0)	**	**-1.48** **I(1)**		-1.98 I(0)	**
Potato	Mandi	Average lags	1.2		1.19		0.9		0.84	
	Price (log)	t (adjusted)	-8.18 I(0)	***	-9.77 I(0)	***	-12.2 I(0)	***	-12.32 I(0)	***
Tomato	Mandi Arrivals	Average lags *1	**0.77**		0.76		**0.59**		0.6	
	(log)	adjusted t or W-t-bar*2	**-1.37** **I(1)**		-4.95 I(0)	***	**-1.19** **I(1)**		-4.09 I(0)	***
Tomato	Mandi	Average lags	0.95		1.02		0.69		0.81	
	Price (log)	t (adjusted)	-7.53 I(0)	***	-6.34 I(0)	***	-11.7 I(0)	***	-7.35 I(0)	***
log CSR		Average lags	1.22		1.51		1.23		1.4	
(Covid-19 Severity)		t (adjusted)	-7.24 I(0)	***	-2.52 I(0)	***	-12.1 I(0)	***	-10.58 I(0)	***

Notes: 1. Lags are determined by Akaike Information Criteria (AIC).

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

*3. The threshold significance level is at 5%.

*4. Cases where the null hypothesis is rejected are highlighted in bold.

We focus on the cases with no trend (the first and the third columns in Table 1), we can conclude that *mandi* arrivals of rice, potato and tomato are likely to be I (1) while all the other variables are I(0) which would suggest that *mandi* arrivals and price of these commodities cannot be co-integrated. That is why we modelled the price-quantity and Covid-19 pandemic relationships with the focus on the first differences of these variables. We repeat the same tests for the first differences and find that they are I (0) or stationary.

Table 2. Results of Unit-root Tests (First Difference)

			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)	93		93		93		93	
		T (no of periods)	51		51		51		51	
		Panel means	No		No		No		No	
Rice	Mandi Arrivals (FD, log)	Average lags *1	2		2.01		1.62		1.62	
		adjusted t or W-t-bar*2	-45.98	***	-48.08	***	-53.72	***	-51.82	***
			I(0)		I(0)		I(0)		I(0)	
Rice	Mandi Price (log)	Average lags	0.87		1		0.68		0.79	
		t (adjusted)	-45.89	***	-42.93	***	-51.69	***	-48.15	***
			I(0)		I(0)		I(0)		I(0)	
Onion	Mandi Arrivals (log)	Average lags *1	0.76		0.88		0.68		0.71	
		adjusted t or W-t-bar*2	-58.42	***	-55.66	***	-58.29	***	-56.64	***
			I(0)		I(0)		I(0)		I(0)	
Onion	Mandi	Average lags	1.02		1.06		0.87		0.91	

	Price	t (adjusted)	-57.37	***	-53.21	***	-60.62	***	-57.16	***
	(log)		I(0)		I(0)		I(0)		I(0)	
	Mandi									
Potato	Arrivals	Average lags *1	0.72		0.63		0.52		0.51	
		adjusted t or W-t-								
	(log)	bar*2	-94.3	***	-48.08	***	-53.72	***	-51.82	***
			I(0)		I(0)		I(0)		I(0)	
Potato	Mandi	Average lags	1.2		1.25		1.09		1.12	
	Price	t (adjusted)	-52.19	***	-48.96	***	-57.71	***	-54.36	***
	(log)		I(0)		I(0)		I(0)		I(0)	
	Mandi									
Tomato	Arrivals	Average lags *1	0.78		0.93		0.52		0.57	
		adjusted t or W-t-								
	(log)	bar*2	-57.14	***	-53.49	***	-57.89	***	-55.91	***
			I(0)		I(0)		I(0)		I(0)	***
Tomato	Mandi	Average lags	0.67		0.86		0.64		0.7	
	Price	t (adjusted)	-56.84	***	-53.92	***	-58.38	***	-56.4	***
	(log)		I(0)		I(0)		I(0)		I(0)	
log CSR		Average lags	1.19		1.33		1.13		1.28	
(Covid-19										
Severity)		t (adjusted)	-55.98	***	-43.97	***	-67.99	***	-58.73	***
			I(0)		I(0)		I(0)		I(0)	

Notes: 1. Lags are determined by Akaike Information Criteria (AIC).

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

*3. The threshold signficance level is at 5%.

(2) Covid-19 impact on market arrivals and prices

Rice

Next, we have estimated Model A (Equations (2), (3) and (4)) and Model B (Equations (5) and (6) based on the GMM applied to the panel VAR model. The results for rice, onions, potato and tomato are given in Tables 3, 4, 5 and 6. Broadly speaking, rice is a non-perishable commodity while onions, potato and tomato are semi perishable and perishable commodities and the quality of rice deteriorates over time. Below, we primarily focus on the results related to the Covid-19 in light of our research hypotheses. Other results are only briefly noted.

Table 3 shows the results for rice for Model A and Model B. In the case of Model A where the Covid-19 is treated as endogenous, we find that the pandemic growth negatively and significantly influences *mandi* price growth with three lags (i.e., after three weeks) and positively and significantly influences *mandi* arrivals growth with 2 lags (i.e., after two weeks). However, as in the results of Granger causality test based on the panel VAR results shown at the bottom of Table 3, the pandemic growth does not significantly affect either fractional price change or change in arrivals. That is, we cannot conclude that the pandemic growth influences any change in market price or arrivals when it is treated as an endogenous variable.

Table 3. Associations among COVID-19 Severity Ratio, Market Arrivals and Wholesale Prices of Rice: Panel VAR model based on the GMM Robust Estimation, Weekly Data July 2019-June 2020

		Model A (Rice)				Model B (Rice)	
	Dep Vars Endogenous Vars	**Arrivals**	**Prices**	**Covid Severity Ratio**		**Arrivals**	**Prices**
Exp. Vars	FD log Mandi Arrivals						
Endogenous	L1.	-0.013	0.001	-0.398		-0.01	0.002
		(0.31) [a]	(1.25)	(1.47)		(0.35)	(1.34)
	L2.	**0.029**	-0.002	-0.16		**0.029**	-0.002
		(1.76) *b,f	(1.48)	(0.65)		**(1.77)** *	(1.33)
	L3.	0.014	-0.001	-0.079		0.014	-0.001
		(0.35)	(0.77)	(0.30)		(0.35)	(0.64)
	FD log Mandi Price						
	L1.	0.043	**0.092**	-1.666		0.057	**0.096**
		(0.23)	**(1.96)** *	(0.43)		(0.32)	**(2.00)** **
	L2.	0.012	**-0.063**	-0.898		0.026	**-0.063**
		(0.18)	**(2.10)** **	(0.21)		(0.37)	**(1.98)** **
	L3.	-0.007	-0.001	-0.668		-0.001	0
		(0.11)	(0.05)	(0.16)		(0.03)	(0.01)
	FD log Covid-19 Severity Ratio						
	L1.	-0.004	0.001	0.075			
		(0.57)	(1.48)	(0.61)			
	L2.	-0.001	-0.001	**0.359**			
		(0.29)	(1.31)	**(2.67)** ***			
	L3.	-0.005	**-0.001**	0.045			
		(1.04)	**(1.94)** *	(0.47)			
Exogenous	FD log Covid-19 Severity Ratio					0.004	**-0.001**

								(0.64)		**(1.80)**	*
	D_Maharashtra*FD Covid SR [c,d,e]							**-0.013**		**-0.004**	
								(1.91)	*	**(4.03)**	***
	D_Meghalaya* FD Covid SR							0.003		**0.003**	
								(0.39)		**(2.82)**	***
	D_Uttar Pradesh* FD Covid SR							**0.014**		**0.004**	
								(3.25)	***	**(4.92)**	***
	D_Madhya Pradesh* FD Covid SR							0.005		**-0.003**	
								(1.16)		**(2.63)**	**
	D_Rajasthan* FD Covid SR							0.039		**0.002**	
								(5.81)	***	**(2.07)**	**
	D_Punjab*FD Covid SR							0.012		**0.002**	
								(1.61)		**(2.07)**	**
	D_Haryana*FD Covid SR							0		**0**	
								(0.32)		**(1.77)**	*
	temperature	0.011		-0.001		**0.491**		0.007		0	
		(1.10)		(1.28)		**(3.17)**	***	(0.73)		(0.01)	
	rainfall	-0.004		0		**5.451**		-0.002		0	
		(1.15)		(0.24)		**(3.85)**	***	(0.77)		(0.46)	
	Phase1	-0.022		**0.008**		**7.179**		-0.009		0.006	
		(0.97)		**(3.12)**	***	**(3.89)**	***	(0.22)		(1.12)	
	Phase2	-0.039		0.007		**8.382**		-0.031		-0.001	
		(0.73)		(1.57)		**(4.50)**	***	(0.60)		(0.15)	
	Phase3	-0.017		0.001		**8.773**		0.004		-0.003	
		(0.42)		(0.34)		**(4.62)**	***	(0.07)		(0.39)	
	Phase4	-0.067		0.004		**6.21**		-0.048		-0.003	
		(1.36)		(1.01)		**(7.39)**	***	(0.91)		(0.32)	
	Phase5	-0.143		0.001		0		-0.128		-0.003	
		(2.42)	**	(0.25)		(0.00)		(2.44)	**	(0.43)	
	Constant							-0.003		-0.001	
								(0.37)		(0.77)	
	No. of observations	4371						4371			
	No of N	93						93			
	Average no. of T	47						47			
	Hansen's J (Over Identifying Restriction, p value)	1.00						1.00			
	No. of instruments	16						22			
Eigenvalue stability condition All the eigenvalues lie inside the unit circle		Yes.						Yes			
Panel VAR-Granger Causality Wald Test											
Arrivals (FD)		Yes/No	Chi2	Prob> Chi2				Yes/No	Chi2	Prob> Chi2	
	Price causes arrivals	No	0.145	0.986				No	0.282	0.963	
	Covid causes arrivals	No	1.824	0.610				-	-	-	
Wholesale Price (FD)											
	Arrivals cause price	No	4.258	0.235				No	4.175	0.243	
	Covid causes price.	No	4.620	0.202				-	-	-	
Covid (FD)											
	Arrivals cause Covid.	No	2.768	0.429				-	-	-	
	Price causes Covid,	No	0.427	0.935				-	-	-	

Notes: a. The numbers in brackets show z values. They are based on robust standard errors.

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

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

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

e. FD stands for First Difference.

f. Statistically significant cases are highlighted as bold numbers.

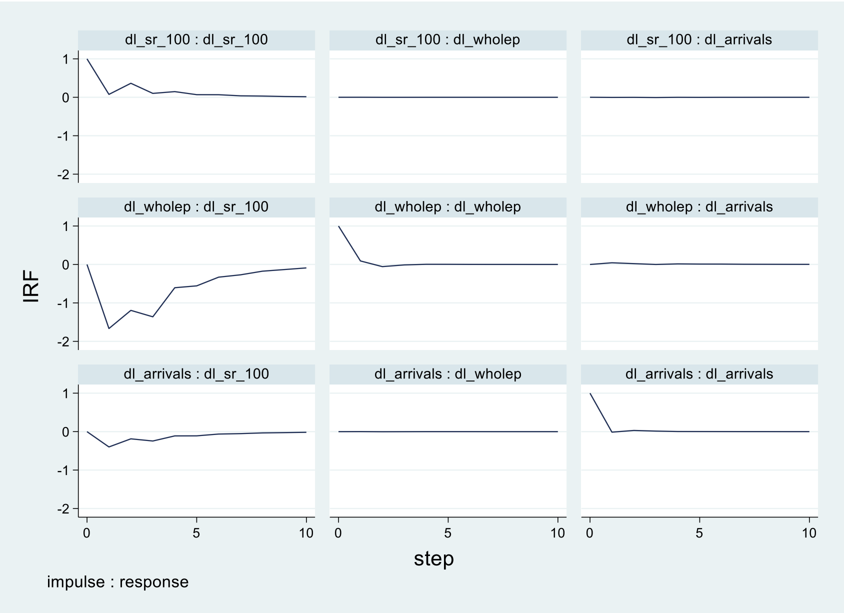
However, in Model B where the change in log Covid-19 severity ratio is treated as an exogenous variable, the estimated coefficient is negative and significant (for the 10 default states) [17]. Compared with default cases, negative effects of the pandemic are more pronounced in Maharashtra and Madhya Pradesh. Negative effects are mitigated in Haryana. Compared with other states, the negative effect of the pandemic on changes in market arrivals is larger in Maharashtra, but smaller in Uttar Pradesh where the market reform has been actively implemented (Varshney,et al., 2020). It is notable that in Maharashtra where the pandemic has been the most severe since its onset, the pandemic growth reduces the growth of market arrivals and prices in the short- run.

While we observe some statistically significant effects of own lags, we find no significant causality from price changes to arrival changes or *vice versa*. While both temperature and rainfall raise Covid-19 severity significantly, consistent with Ma et al. (2020), they are not associated with growth of prices or arrivals (Models A and B). The specifications are validated as Hansen's J statistic for over-identification test is statistically non-significant

Graphical representations of Impulse Response Function (IRF) also show that any negative effects of the pandemic growth on changes in the market prices is short-lived, lasting only 4 weeks (the second graph from the top in the left hand side, Figure 1). The graph of IRF on the dynamic relationship between the pandemic growth and the change in arrivals (the third graph on the left) implies that a slight negative effect of the pandemic disappears quickly. Figure 2 shows graphically that the dynamic association between arrivals and prices is weak.

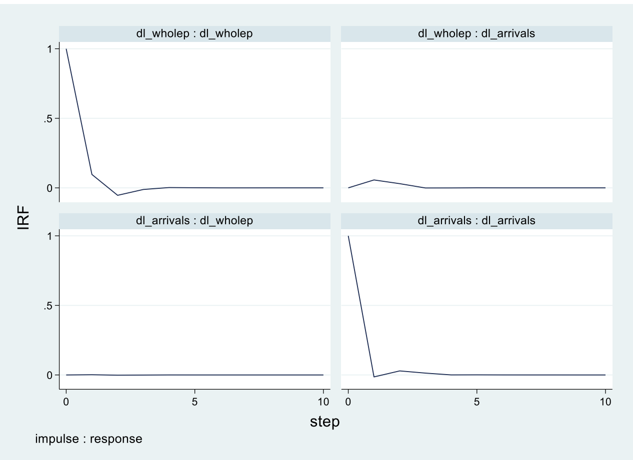
[17] Default cases are the average of 10 states, that is, Andhra Pradesh, Assam, Chhattisgarh, Gujarat, Himachal Pradesh, Jharkhand, Karnataka, Kerala, Odisha and West Bengal.

Figure 1. Graphs of Impulse Response Function (IRF) among COVID-19 Severity Ratio, Market Arrivals and Wholesale Prices of Rice



Note: Y axis is a response variable. X axis is an impulse variable.

Figure 2. Graphs of Impulse Response Function (IRF) among COVID-19 Severity Ratio and Market Arrivals of Rice



Note: Y axis is a response variable. X axis is an impulse variable.

Overall, we can conclude that, apart from a few states, such as Maharashtra, the Covid-19 pandemic growth does not strongly influence either rice price change or any change of market arrivals. We observe a weak negative effect of the pandemic growth on rice prices, but it will last only 5 weeks. A caveat, however, is that if the pandemic continues to grow, the negative effects will further accumulate over time.

Onion

The results of Models A and Model B for onion are shown in Table 4 as well as in Figures 3 and 4. It is notable that statistically significant and positive associations are observed between lagged fractional changes in price and in quantities and the current pandemic growth (the third column of Table 4). That could be due to the fact that food prices and availability have a strong association with food security that will directly influence the pandemic development. However, the lagged variables on the pandemic growth negatively influence price growth and positively affect quantity growth. The overall association of the pandemic growth on the changes in market prices and arrivals are positive as suggested by graphs on IRF (the middle and the bottom graphs on the left-hand side of Figure 3), consistent with Varshney et al. (2020). If we compare the graphical analyses for rice and onion, we find that for onion the overall association between the Covid-19 pandemic growth and price growth (or the elasticity of price growth with respect to the pandemic growth) is initially larger and *positive* (particularly for price) and gradually disappears, while for rice the initial association is negative and small and then weakens gradually.

The Granger causality shows that the Covid-19 pandemic growth causes (reduces) price, but not *mandi* arrivals, while both arrivals and price *cause* (or increase) the pandemic growth. Also, price changes cause (or increase) market arrivals, but not vice versa.

Table 4. Associations among COVID-19 Severity Ratio, Market Arrivals and Wholesale Prices of Onion: Panel VAR model based on the GMM Robust Estimation, Weekly Data July 2019-June 2020

		Model A (Onion)			Model B (Onion)	
	Dep Vars Endogenous Vars	**Arrivals**	**Prices**	**Covid Severity Ratio**	**Arrivals**	**Prices**
Exp. Vars	FD log Mandi Arrivals					
Endogenous	L1.	-0.015	-0.005	0.54	-0.014	-0.01
		(1.00)[a]	(0.62)	(1.59)	(0.92)	(0.78)
	L2.	-0.014	-0.012	0.354	-0.013	-0.01
		(1.05)	(1.51)	(0.97)	(0.96)	(1.52)
	L3.	-0.025	-0.007	**0.831**	-0.023	-0.01
		(1.66)	(0.84)	**(2.58)** **[b,f]	(1.57)	(1.04)
	FD log Mandi Price					
	L1.	0.034	**0.197**	**3.406**	0.043	**0.19**
		(1.03)	**(7.69)** ***	**(4.47)** ***	(1.29)	**(6.83)** ***
	L2.	-0.018	0.014	**2.157**	-0.011	0.008
		(1.37)	(1.05)	**(3.97)** ***	(0.70)	(0.53)
	L3.	**0.044**	**0.106**	**1.699**	**0.049**	**0.1**
		(3.22) ***	**(5.66)** ***	**(4.05)** ***	**(3.14)** ***	**(5.08)** ***
	FD log Covid-19 Severity Ratio					
	L1.	0.004	-0.002	-0.028		
		(1.21)	(0.63)	(0.25)		
	L2.	0.003	**-0.013**	**0.255**		
		(0.61)	**(2.83)** ***	**(2.34)** **		
	L3.	**0.003**	-0.005	0.039		
		(2.06) **	(1.51)	(0.44)		
Exogenous	FD log Covid-19 Severity Ratio				0.004	**-0.01**
					(1.07)	**(3.25)** ***
	D_Maharashtra*FD Covid SR [c,d,e]				0.005	**-0.01**
					(1.23)	**(2.77)** ***
	D_Meghalaya* FD Covid SR				-0.003	0
					(1.03)	(0.06)
	D_Uttar Pradesh* FD Covid SR				0	**-0.01**
					(0.09)	**(2.90)** ***
	D_Madhya Pradesh* FD Covid SR				0.009	-0
					(2.48) **	(0.52)
	D_Rajasthan* FD Covid SR				-0.004	0.001

								(1.21)		(0.29)	
	D_Punjab*FD Covid SR							-0.002		-0	
								(0.56)		(1.14)	
	D_Haryana*FD Covid SR							0.001		**0.002**	
								(1.22)		**(3.33)**	***
	temperature	-0.003	-0.004		**0.434**			-0.006		-0	
		(0.69)	(0.96)		**(3.02)**	***		(1.45)		(0.13)	
	rainfall	0.002	**0.005**		**5.586**			0.003		0.004	
		(1.01)	**(3.97)**	***	**(4.34)**	***		**(1.73)**	*	**(2.38)**	**
	Phase1	0.008	-0.019		**7.408**			**0.023**		**-0.03**	
		(0.52)	(1.16)		**(4.25)**	***		(1.14)		(1.42)	
	Phase2	-0.007	**-0.061**		**8.908**			0.021		**-0.1**	
		(0.36)	**(2.87)**	***	**(5.15)**	***		(0.74)		**(2.95)**	***
	Phase3	0.035	-0.04		**9.063**			**0.061**		-0.06	
		(1.06)	(1.38)		**(4.99)**	***		**(1.94)**	*	(1.50)	
	Phase4	0.002	-0.028		**6.574**			0.029		-0.06	
		(0.07)	(1.07)		**(7.78)**	***		(0.85)		(1.33)	
	Phase5	0.002	-0.016		0			0.022		-0.04	
		(0.09)	(0.80)		(0.00)			(0.85)		(1.21)	
	Constant							-0.01		-0.02	
								(1.72)		(1.85)	
	No. of observations	4371						4371			
	No of N	93						93			
	Average no. of T	47						47			
	Hansen's J (Over Identifying Restriction, p value)	1.00						1.00			
	No. of instruments	16						22			

Eigenvalue stability condition All the eigenvalues lie inside the unit circle		Yes.				Yes		
Panel VAR-Granger Causality Wald Test								
Arrivals (FD)		Yes/No	Chi2	Prob>Chi2		Yes/No	Chi2	Prob>Chi2
	Price causes arrivals	**Yes**	**13.88** ***	**0.003**		**Yes**	**13.21** ***	**0.004**
	Covid causes arrivals	No	5.28	0.152				
Wholesale Price (FD)								
	Arrivals cause price	No	2.448	0.485		No	2.527	0.470
	Covid causes price.	**Yes**	**11.55** ***	**0.009**				
Covid (FD)								
	Arrivals cause Covid.	**Yes**	**8.640** **	**0.034**				
	Price causes Covid,	**Yes**	**22.90** ***	**0.000**				

Notes: a. The numbers in brackets show z values. They are based on robust standard errors.

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

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

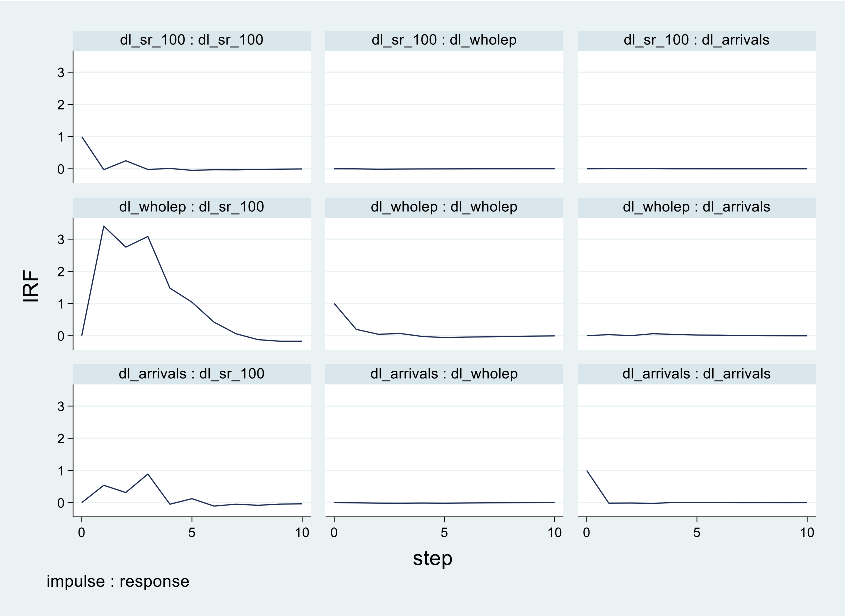
d. D_ stands for a dummy variable (taking 1 or 0).

e. FD stands for First Difference.

f. Statistically significant cases are highlighted as bold numbers.

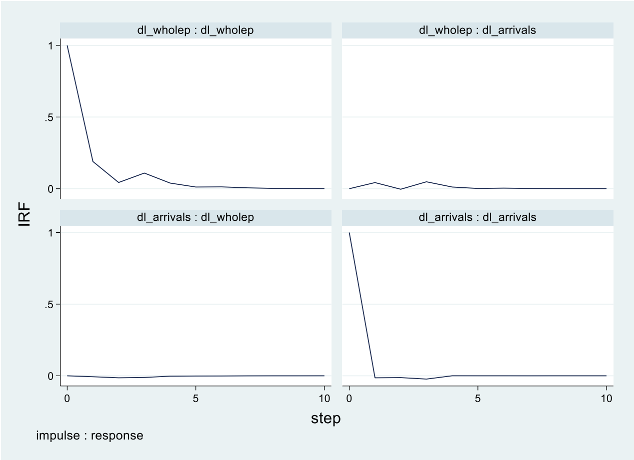
The results of Model B suggest that there is an overall negative effect of the pandemic growth on the fractional changes in onion market prices (for the default 11 states), but the negative effect on price changes is much larger in Maharashtra and Uttar Pradesh (the state with the market reform). The state-level effect of the pandemic growth on the fractional change in market arrivals is statistically not significant (except Madhya Pradesh where the effect is positive and significant relative to the 10 default states). Madhya Pradesh is another state that actively implemented the market reform, which may have prevented any decline of market transactions even during the Covid-pandemic. It is also noted that rainfall positively influences the changes in both price and quantity in Model B (and only prices in Model A). The Covid-19 pandemic tends to rise when rainfall and temperature are high. This is consistent with Ma et al. (2020). It is noted that from Figures 3 and 4 cross-effects between market prices and market arrivals are weak.

Figure 3. Graphs of Impulse Response Function (IRF) among COVID-19 Severity Ratio, Market Arrivals and Wholesale Prices of Onion



Note: Y axis is a response variable. X axis is an impulse variable.

Figure 4. Graphs of Impulse Response Function (IRF) among COVID-19 Severity Ratio and Market Arrivals of Onion



Note: Y axis is a response variable. X axis is an impulse variable.

Potato

The results on potato are given in Table 5 as well as Figures 5 and 6. We infer from the Granger causality test as well as the estimates of relevant coefficients based on Model A that (i) the Covid-19 pandemic growth reduced changes of market prices of onions significantly, but not those of market arrivals; and (ii) the cross-effect between price changes and changes in *mandi* arrivals are negative and the causality is from the former to the latter (not the other way around).

In Maharashtra, the effect of the pandemic growth is more negative than in other states as before, while in Utter Pradesh it has a more positive effect than other states. It is observed that the pandemic development had a more positive effect on change in market arrivals in Meghalaya and Uttar Pradesh, but the effect is negative in Madhya Pradesh, Rajasthan and Punjab. The variation in results does not match with the classification of the states according to the degree of implementation of market reforms made by Varshney et al. (2020) and so further investigations are necessary to understand the underlying factors of explaining this heterogeneity.

Table 5. Associations among COVID-19 Severity Ratio, Market Arrivals and Wholesale Prices of Potato: Panel VAR model based on the GMM Robust Estimation, Weekly Data July 2019-June 2020

		Model A (Potato)				Model B (Potato)	
	Dep Vars Endogenous Vars	**Arrivals**	**Prices**	**Covid Severity Ratio**		**Arrivals**	**Prices**

Exp. Vars	FD log Mandi Arrivals										
Endogenous	L1.	-0.008		-0.011		0.278		-0.01		-0.011	
		(0.38) [a]		(1.41)		(0.97)		(0.38)		(1.52)	
	L2.	-0.026		0.001		0.136		-0.03		0	
		(0.96)		(0.09)		(0.32)		(0.97)		(0.02)	
	L3.	-0.009		0.007		0.271		-0.01		0.005	
		(0.38)		(1.13)		(0.85)		(0.39)		(0.93)	
	FD log Mandi Price										
	L1.	**-0.084**	***	-0.006		0.028		**-0.09**		-0.009	
		(3.23)	[b, f]	(0.28)		(0.05)		**(3.29)**	***	(0.38)	
	L2.	-0.016		**-0.06**		-0.854		-0.02		-0.068	
		(0.81)		**(2.74)**	***	(1.62)		(0.93)		(2.98)	***
	L3.	0		-0.019		**-1.69**		-0		-0.027	
		(0.02)		(1.07)		**(2.14)**	**	(0.10)		(1.49)	
	FD log Covid-19 Severity Ratio										
	L1.	-0.001		-0.004		0.092					
		(0.34)		(1.52)		(0.74)					
	L2.	-0.004		**-0.013**		**0.363**					
		(1.17)		**(3.81)**	***	**(2.68)**	***				
	L3.	-0.001		**-0.005**		0.026					
		(0.27)		**(2.36)**	**	(0.26)					
Exogenous	FD log Covid-19 Severity Ratio							0		-0.002	
								(0.28)		(0.72)	
	D_Maharashtra*FD Covid SR [c,d,e]							-0		**-0.01**	
								(1.25)		**(2.99)**	***
	D_Meghalaya* FD Covid SR							**0.008**		0.002	
								(4.04)	***	(0.58)	
	D_Uttar Pradesh* FD Covid SR							**0.006**		**0.012**	
								(1.99)	**	**(4.34)**	***
	D_Madhya Pradesh* FD Covid SR							**0.01**		-0.004	
								(3.84)	***	(1.26)	
	D_Rajasthan* FD Covid SR							**-0.02**		0.008	
								(6.70)	***	(1.94)	*
	D_Punjab*FD Covid SR							**-0.02**		0.005	
								(7.23)	***	(1.62)	
	D_Haryana*FD Covid SR							-0		**0.001**	
								(1.91)	*	**(1.21)**	
	temperature	-0.001		**0.008**		**0.484**		-0		0.007	
		(0.41)		**(2.26)**	**	**(3.25)**	***	(0.12)		(1.08)	
	rainfall	0		**-0.002**		**5.396**		0		-0.002	
		(0.57)		**(1.75)**	*	**(4.02)**	***	(0.17)		(0.96)	
	Phase1	-0.007		**0.021**		**7.271**		-0.01		0.025	
		(0.67)		**(2.05)**	**	**(3.95)**	***	(0.57)		(1.16)	
	Phase2	-0.006		-0.029		**8.218**		-0.02		-0.046	
		(0.33)		(1.55)		**(4.64)**	***	(0.60)		(1.57)	
	Phase3	-0.019		**-0.047**		**8.693**		-0.02		-0.045	
		(0.82)		**(2.75)**	***	**(4.81)**	***	(0.72)		(1.42)	

	Phase4	0.016	**-0.063**	**6.19**		0.011	-0.064	
		(1.30)	**(2.80)** ***	**(7.69)** ***		(0.45)	(1.68) *	
	Phase5	0	-0.013	0		-0	-0.013	
		(0.02)	(0.90)	(0.00)		(0.16)	(0.50)	
	Constant					0.01	-0.007	
						(1.88) *	(1.00)	
	No. of observations	4465				4465		
	No of N	95				95		
	Average no. of T	47				47		
	Hansen's J (Over Identifying Restriction, p value)	1.00				1.00		
	No. of instruments	16				22		
Eigenvalue stability condition All the eigenvalues lie inside the unit circle		Yes.				Yes		
Panel VAR-Granger Causality Wald Test								
Arrivals (FD)		Yes/No	Chi2	Prob> Chi2		Yes/No	Chi2	Prob> Chi2
	Price causes arrivals	**Yes**	**13.16*****	**0.004**		**Yes**	**14.19*****	**0.003**
	Covid causes arrivals	No	1.55	0.670		-	-	-
Wholesale Price (FD)								
	Arrivals cause price	No	4.68	0.197		No	3.95	0.267
	Covid causes price.	**Yes**	**14.99*****	**0.002**		-	-	-
Covid (FD)								
	Arrivals cause Covid.	No	2.42**	0.491		-	-	-
	Price causes Covid,	**Yes**	**6.75***	**0.080**		-	-	-

Notes: a. The numbers in brackets show z values. They are based on robust standard errors.

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

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

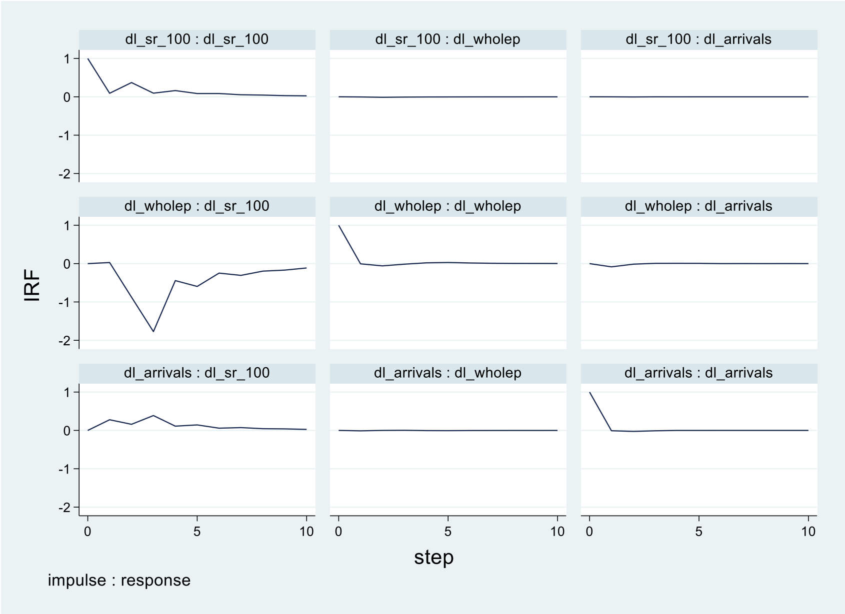
d. D_ stands for a dummy variable (taking 1 or 0).

e. FD stands for First Difference.

f. Statistically significant cases are highlighted as bold numbers.

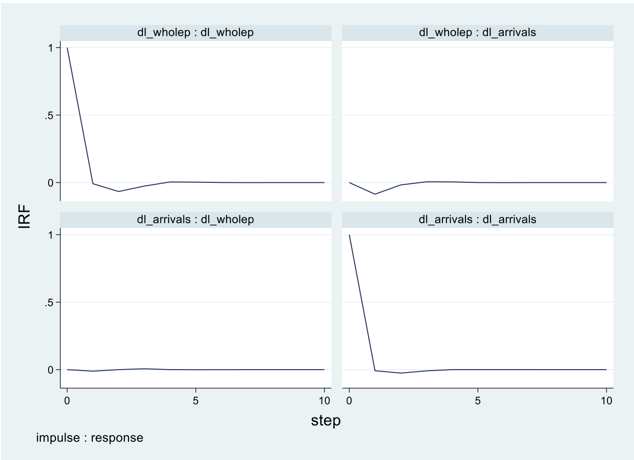
The graphs of IRF (Figures 5 and 6) show that (i) the negative effect of the pandemic growth on the fractional change of *mandi* prices weakens quickly in the second or the third steps (or after two or three weeks); (ii) there is a weak positive effect of the pandemic growth on market arrivals of potatoes for 3-4 weeks; and (iii) the cross-effects between *mandi* arrivals and prices are weak.

Figure 5. Graphs of Impulse Response Function (IRF) among COVID-19 Severity Ratio, Market Arrivals and Wholesale Prices of Potato



Note: Y axis is a response variable. X axis is an impulse variable.

Figure 6. Graphs of Impulse Response Function (IRF) among COVID-19 Severity Ratio and Market Arrivals of Potato



Note: Y axis is a response variable. X axis is an impulse variable.

Tomato

Finally, we have estimated Models A and B for a highly perishable commodity, tomatoes. The results are given in Table 6 and Figures 7 and 8. Similar to the case of onion (Table 4), the

Covid-19 pandemic growth negatively influences fractional changes in *mandi* prices of tomato with some lags (Model A, Table 6), while the lagged changes in *mandi* prices promoted the growth of the pandemic significantly, possibly due to the deteriorated food security. However, such relationships are not observed for *mandi* arrivals. Cross-effects between changes in *mandi* arrivals and prices are weak and not statistically significant. Granger causality tests reflect these results. That is, the causality is statistically significant in both directions between changes in *mandi* prices and the Covid-19 pandemic growth. Interestingly, the graphical analysis of IRF shows a non-linear relationship between the Covid-19 pandemic growth and price changes (Figure 7). Initially, the pandemic growth had a positive association with the fractional price change of tomato, but the effect turns negative in 4-6 weeks, after which it becomes positive again. Initial shortages in food may cause the price change to be more positive (e.g. panic buying, or the shortage of supply due to the lack of labour), but after some time adjustment takes place. A slight negative association between the pandemic growth and the fractional change in arrivals is observed in Figure 7.

Table 6. Associations among COVID-19 Severity Ratio, Market Arrivals and Wholesale Prices of Tomato: Panel VAR model based on the GMM Robust Estimation, Weekly Data July 2019-June 2020

		Model A (Tomato)							Model B (Potato)			
	Dep Vars	**Arrivals**		**Prices**		**Covid Severity**			**Arrivals**		**Prices**	
	Endogenous Vars					**Ratio**						
Exp. Vars	FD log Mandi Arrivals											
	L1.	-0.058		0.03		-0.291			-0.059		0.026	
		(1.15) [a]		(1.21)		(0.79)			(1.19)		(1.10)	
	L2.	**0.014**	***	0.03		-0.22			0.013		0.025	
		(3.44)	[b,f]	(1.12)		(0.57)			**(3.05)**	***	(0.97)	
	L3.	-0.034		0.02		-0.272			**-0.034**		0.019	
		(1.24)		(0.92)		(0.56)			(1.30)		(0.74)	
	FD log Mandi Price											
	L1.	0.004		**-0.14**		**2.929**			0.016		**-0.132**	
		(0.25)		**(3.27)**	***	**(5.38)**	***		(0.88)		**(1.97)**	**
	L2.	-0.005		**-0.22**		**2.983**			0.007		**-0.239**	
		(0.21)		**(4.79)**	***	**(4.44)**	***		(0.31)		**(2.95)**	***
	L3.	0.022		**-0.17**		**2.386**			**0.031**		**-00.191**	
		(1.64)		**(4.93)**	***	**(3.80)**	***		**(2.03)**	**	**(2.66)**	**

FD log Covid-19 Severity Ratio					
L1.	0	**-0.03**	0.005		
	(0.10)	**(2.71)** ***	(0.04)		
L2.	-0.002	**-0.04**	0.268		
	(1.26)	**(4.19)** ***	(1.89) *		
L3.	0	-0.01	0.061		
	(0.09)	(1.42)	(0.63)		
FD log Covid-19 Severity Ratio				**0.004**	-0.006
				(2.00) **	(0.52)
D_Maharashtra*FD Covid SR				**0.004**	**-0.084**
c, d, e				**(2.69)** ***	**(7.32)** ***
D_Meghalaya* FD Covid SR				**0.013**	0.011
				(8.55) ***	(1.03)
D_Uttar Pradesh* FD Covid SR				-0.004	**0.1**
				(0.93)	**(2.90)** ***
D_Madhya Pradesh* FD Covid SR				0.002	**-0.012**
				(1.26)	**(0.71)**
D_Rajasthan* FD Covid SR				0.007	**0.12**
				(1.21)	**(2.23)** **
D_Punjab*FD Covid SR				-0.003	**0.074**
				(0.61)	**(2.10)** **
D_Haryana*FD Covid SR				0.003	**-0.011**
				(3.97) ***	**(1.93)** *
temperature	0.001	**0.11**	**0.589**	-0.007	**0.113**
	(0.25)	**(2.88)** ***	**(3.01)** ***	(1.09)	**(2.10)** **
rainfall	0	**-0.03**	**5.933**	0.002	**-0.034**
	(0.22)	**(2.32)** **	**(3.41)** ***	(0.84)	**(1.69)** *
Phase1	0.006	**-0.2**	**8.618**	0.034	-0.22
	(0.41)	**(1.76)** *	**(3.67)** ***	(1.53)	(1.26)
Phase2	-0.009	**-0.47**	**10.408**	0.028	**-0.557**
	(0.37)	**(3.08)** ***	**(4.26)** ***	(0.87)	**(2.22)** **
Phase3	0.022	**-0.56**	**10.537**	0.069	**-0.604**
	(0.64)	**(3.65)** ***	**(4.42)** ***	(1.60)	**(2.30)** **
Phase4	-0.004	**-0.61**	**7.334**	0.044	**-0.659**
	(0.13)	**(3.68)** ***	**(6.78)** ***	(1.25)	**(2.51)** **
Phase5	-0.008	**-0.3**	0	0.026	**-0.337**
	(0.31)	**(4.10)** ***	(0.00)	(0.82)	**(2.02)** **
Constant				-0.036	0.111
				(4.33)	(1.67)
No. of observations	4418			4418	
No of N	94			94	
Average no. of T	47			47	
Hansen's J (Over Identifying Restriction, p value)	1.00			1.00	
No. of instruments	16			22	
Eigenvalue stability condition All the eigenvalues lie inside the unit circle	Yes.			Yes	

Panel VAR-Granger Causality Wald Test							
Arrivals (FD)		Yes/No	Chi2	Prob> Chi2	Yes/No	Chi2	Prob> Chi2
	Price causes arrivals	No	6.23	0.101	**Yes**	**6.46***	**0.091**
	Covid causes arrivals	No	4.00	0.261	-	-	-

Wholesale Price (FD)								
	Arrivals cause price	No	1.64	0.651		No	1.52	0.678
	Covid causes price.	**Yes**	**19.85*** **	**0.000**		-	-	-
Covid (FD)								
	Arrivals cause Covid.	No	0.756	0.860		-	-	-
	Price causes Covid,	**Yes**	**29.01*** **	**0.000**		-	-	-

Notes: a. The numbers in brackets show z values. They are based on robust standard errors.

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

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

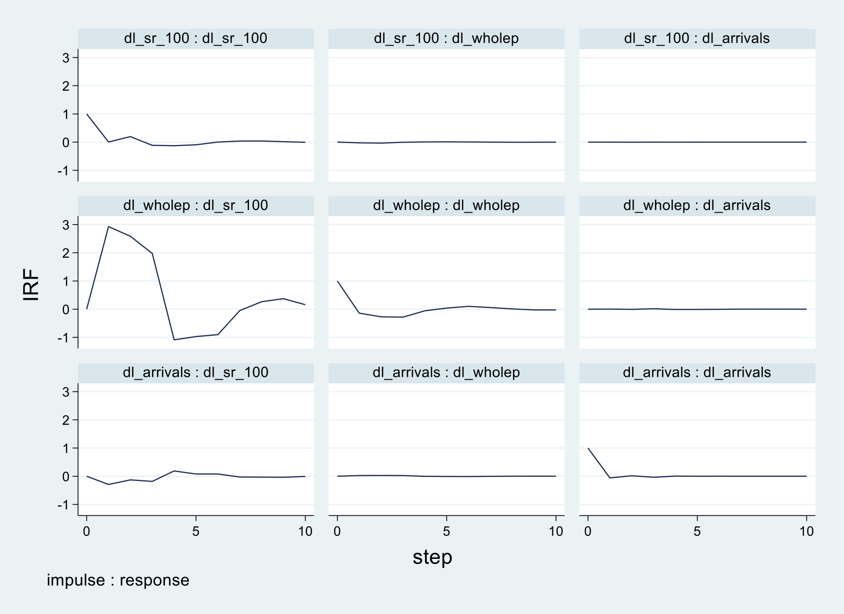
d. D_ stands for a dummy variable (taking 1 or 0).

e. FD stands for First Difference.

f. Statistically significant cases are highlighted as bold numbers.

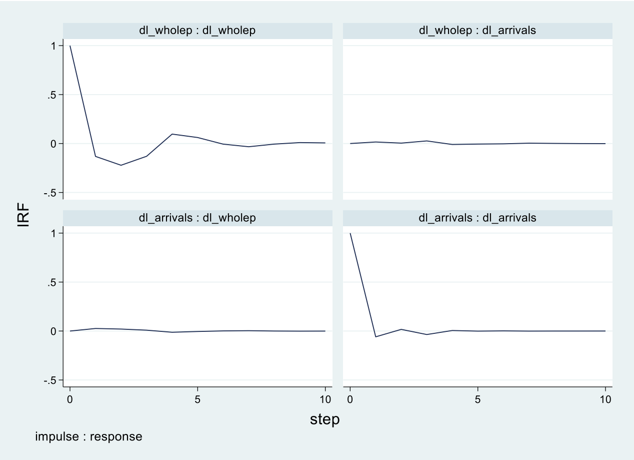
The results of Model B suggest that, while an overall effect of the pandemic growth on fractional changes in *mandi* arrivals is positive in the default states, but the positive effect is larger in Maharashtra and Meghalaya. On the other hand, while the overall effect of the pandemic growth on *mandi* price growth is not significant for the default states, the effect is more negative in Maharashtra, Madhya Pradesh and Haryarna and more positive in Uttar Pradesh, Rajasthan (both of which are active in implementing market reforms) and Punjab (which is less active in implementing reforms than Uttar Pradesh and Rajasthan, according to Varshney et al. 2020). Whether these state-level results are due to differences in agricultural policies or in the degree of adoption of market policies needs to be further investigated.

Figure 7. Graphs of Impulse Response Function (IRF) among COVID-19 Severity Ratio, Market Arrivals and Wholesale Prices of Tomato



Note: Y axis is a response variable. X axis is an impulse variable.

Figure 8. Graphs of Impulse Response Function (IRF) among COVID-19 Severity Ratio and Market Arrivals of Tomato



Note: Y axis is a response variable. X axis is an impulse variable.

IV. Conclusions

Using the panel data on *mandi* arrivals and prices in 17 Indian states from July 2019 to June, 2020, the present study examined whether the growth of Covid-19 pandemic influenced fractional changes in market (or *mandi*) arrivals and prices. A point of departure of our analysis from the previous literature is that we take into account the dynamic interactions among the fractional changes in *mandi* arrivals, the *mandi* price change of food commodities, namely, rice, onion, potato, and tomato, and the change in the severity ratio of the Covid-19 pandemic using a panel VAR model based on the GMM.

Firstly, we find that the Covid-19 pandemic growth decreases the fractional changes in *mandi* price of rice, onion, potato and tomato, but it does not affect the *mandi* arrivals, as implied by the estimated coefficients of the panel VAR model. The Granger causality test confirms that the causality runs from the Covid-19 pandemic growth to the fractional *mandi* price change for onion, potato and tomato, but there is no causality between the Covid-19 pandemic growth and the *mandi* arrival (fractional) changes.[18]

Secondly, however, once the feedback from the fractional change in *mandi* prices to the Covid-19 pandemic growth is taken into account, the graphical analysis based on the Impulse Response Functions suggests that the overall elasticity of the fractional change in the *mandi* price with respect to the pandemic growth turns from positive to zero or negative for onion and tomato, and from negative to zero for rice and potato. On the other hand, the overall elasticity of the fractional change in the *mandi* arrivals with respect to the pandemic growth turns from slightly positive to zero. The results are by and large consistent with Varshney et al. (2020), but our contribution is that we have incorporated the cross-dependence among growth paths of the Covid-19 severity, price and quantity in the market in estimating the pandemic impact.

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[18] At first sight the results appear to be inconsistent with Imai et al. (2020) who found a positive associations between the Covid-19 pandemic and the wholesale prices and the retail prices of food commodities, such as rice and onions. It should be noted that Imai et al. (2020) focus on the contemporaneous association between the pandemic and price in levels, where our present study focuses on lagged and causal associations between the variables in first difference after taking account of the complex price-quantity interdependence. It is noted that the first differenced variables of price is estimated by the Covid-19 severity with lags using the static model, as in Imai et al. (2020), the coefficient estimate becomes negative. That is, once pandemic occurs, this will raise commodity prices, but as the pandemic grows, the price change tends to slow down over time. In this sense, the two studies are not inconsistent and complementary.

Thirdly, we have found that a negative effect of the pandemic growth on the fractional change in *mandi* price is stronger in Maharashtra where the pandemic remained worst among all the Indian states (for all the commodities) but weaker in Utter Pradesh where the market reform was actively implemented (for rice, potato and tomato).

Our detailed analysis of the data suggests that, while the effect of the pandemic is relatively short-lived, it changes over time and the effect differs across different commodities and different regions. This might be due to success of market reforms, as argued by Varshney et al. (2020), but given the large negative effect of the pandemic growth on price changes in Maharashtra, careful monitoring of the dynamic effect of the pandemic growth on market price and arrivals is necessary to prevent any deterioration of food security.

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Appendix Table 1. Descriptive Statistics

Variable		Mean	Std. Dev.	Min	Max	Observations		Mean	Std. Dev.	Min	Max	Observations	
Rice								**Potato**					
log Mandi Arrivals	overall	7.54	2.01	-0.43	12.08	N =	4836	7.62	2.13	-0.73	11.89	N =	4836
	between		1.97	0.46	11.68	n =	93		2.08	-0.02	11.72	n =	93
	within		0.43	3.24	11.33	T =	52		0.48	2.21	11.12	T =	52
l_Mandi Prices	overall	3.38	0.22	2.99	4.11	N =	4836	3.35	0.62	1.39	4.94	N =	4836
	between		0.21	3.06	3.98	n =	93		0.23	2.65	4.02	n =	93
	within		0.08	3.01	3.88	T =	52		0.58	1.95	4.86	T =	52
log_Severity Ratio	overall	-6.15	2.06	-9.21	1.24	N =	4836	-6.16	2.06	-9.21	1.24	N =	4836
	between		0.56	-7.53	-5.30	n =	93		0.57	-7.53	-5.30	n =	93
	within		1.98	-9.93	0.44	T =	52		1.98	-9.93	0.38	T =	52
dlog Mandi Arrivals	overall	-0.01	0.24	-5.16	5.02	N =	4743	0.00	0.21	-2.95	3.99	N =	4743
	between		0.02	-0.09	0.03	n =	93		0.02	-0.06	0.12	n =	93
	within		0.24	-5.10	5.08	T =	51		0.20	-2.90	3.89	T =	51
dlog Mandi Price	overall	0.00	0.03	-0.52	0.31	N =	4743	0.00	0.17	-0.92	1.49	N =	4743
	between		0.00	-0.01	0.01	n =	93		0.01	-0.01	0.02	n =	93
	within		0.03	-0.52	0.31	T =	51		0.17	-0.93	1.47	T =	51
dlog_Severity Ratio	overall	0.00	1.14	-8.15	7.63	N =	4743	0.00	1.16	-8.15	7.63	N =	4743
	between		0.00	0.00	0.00	n =	93		0.00	0.00	0.00	n =	93
	within		1.14	-8.15	7.63	T =	51		1.16	-8.15	7.63	T =	51
temperature	overall	299	6.25	277	311	N =	4836	299	6.27	277	311	N =	4836
	between		4.34	289	308	n =	93		4.34	289	308	n =	93
	within		4.51	285	313	T =	52		4.54	285	313	T =	52
rainfall	overall	5.62	7.90	0.00	63	N =	4836	5.60	7.90	0.00	63	N =	4836
	between		5.53	0.72	29	n =	93		5.53	0.72	29	n =	93
	within		5.67	-4.11	59	T =	52		5.67	-4.13	59	T =	52
Phase1	overall	0.08	0.27	0.00	1.00	N =	4836	0.08	0.27	0.00	1.00	N =	4836
	between		0.00	0.08	0.08	n =	93		0.00	0.08	0.08	n =	93
	within		0.27	0.00	1.00	T =	52		0.27	0.00	1.00	T =	52
Phase2	overall	0.05	0.20	0.00	1.00	N =	4836	0.05	0.20	0.00	1.00	N =	4836
	between		0.00	0.02	0.05	n =	93		0.00	0.02	0.05	n =	93
	within		0.20	0.00	1.03	T =	52		0.20	0.00	1.03	T =	52

Phase3	overall	0.04	0.17	0.00	1.00	N =	4836	0.04	0.17	0.00	1.00	N =	4836
	between		0.00	0.00	0.04	n =	93		0.00	0.00	0.04	n =	93
	within		0.17	0.00	1.00	T =	52		0.17	0.00	1.00	T =	52
Phase4	overall	0.04	0.17	0.00	1.00	N =	4836	0.04	0.17	0.00	1.00	N =	4836
	between		0.00	0.00	0.04	n =	93		0.00	0.00	0.04	n =	93
	within		0.17	0.00	1.00	T =	52		0.17	0.00	1.00	T =	52
Phase5	overall	0.07	0.24	0.00	1.00	N =	4836	0.07	0.24	0.00	1.00	N =	4836
	between		0.01	0.00	0.07	n =	93		0.01	0.00	0.07	n =	93
	within		0.24	0.00	1.00	T =	52		0.24	0.00	1.00	T =	52

Variable		Mean	Std. Dev.	Min	Max	Observations		Mean	Std. Dev.	Min	Max	Observations	
Potato								**Tomato**					
log Mandi Arrivals	overall	7.66	2.01	-0.51	11.91	N =	4940	7.45	2.01	-0.43	11.92	N =	4888
	between		1.98	1.28	11.63	n =	95		1.94	0.07	11.47	n =	94
	within		0.40	3.61	9.52	T =	52		0.55	2.71	11.55	T =	52
l_Mandi Prices	overall	2.84	0.36	1.25	4.14	N =	4940	3.00	0.57	1.07	4.61	N =	4888
	between		0.29	1.96	3.50	n =	95		0.36	2.24	4.40	n =	94
	within		0.22	2.13	3.75	T =	52		0.44	1.38	4.17	T =	52
log_Severity Ratio	overall	-6.16	2.06	-9.21	1.24	N =	4940	-6.15	2.06	-9.21	1.24	N =	4888
	between		0.56	-7.53	-5.30	n =	95		0.56	-7.53	-5.30	n =	94
	within		1.98	-9.93	0.38	T =	52		1.98	-9.93	0.39	T =	52
dlog Mandi Arrivals	overall	0.00	0.20	-3.38	4.53	N =	4845	0.00	0.24	-4.42	4.73	N =	4794
	between		0.02	-0.06	0.08	n =	95		0.02	-0.10	0.09	n =	94
	within		0.19	-3.32	4.53	T =	51		0.24	-4.40	4.64	T =	51
dlog Mandi Price	overall	0.01	0.10	-0.85	0.69	N =	4845	0.00	0.20	-1.38	1.67	N =	4794
	between		0.00	0.00	0.02	n =	95		0.01	-0.03	0.01	n =	94
	within		0.10	-0.85	0.69	T =	51		0.20	-1.38	1.66	T =	51
dlog_Severity Ratio	overall	0.00	1.14	-8.15	7.63	N =	4845	0.00	1.13	-8.15	7.63	N =	4794
	between		0.00	0.00	0.00	n =	95		0.00	0.00	0.00	n =	94
	within		1.14	-8.15	7.63	T =	51		1.13	-8.15	7.63	T =	51
temperature	overall	299.23	6.27	277	311	N =	4940	299.18	6.22	277	311	N =	4888
	between		4.39	289	308	n =	95		4.33	289	308	n =	94
	within		4.50	285	313	T =	52		4.49	285	313	T =	52

rainfall	overall	5.55	7.85	0.00	63	N =	4940	5.66	7.86	0.00	63	N =	4888
	between		5.49	0.72	29	n =	95		5.51	0.72	29	n =	94
	within		5.64	-4.18	59	T =	52		5.64	-4.07	59	T =	52
Phase1	overall	0.08	0.27	0.00	1.00	N =	4940	0.08	0.27	0.00	1.00	N =	4888
	between		0.00	0.08	0.08	n =	95		0.00	0.08	0.08	n =	94
	within		0.27	0.00	1.00	T =	52		0.27	0.00	1.00	T =	52
Phase2	overall	0.05	0.20	0.00	1.00	N =	4940	0.05	0.20	0.00	1.00	N =	4888
	between		0.00	0.02	0.05	n =	95		0.00	0.02	0.05	n =	94
	within		0.20	0.00	1.03	T =	52		0.20	0.00	1.03	T =	52
Phase3	overall	0.04	0.17	0.00	1.00	N =	4940	0.04	0.17	0.00	1.00	N =	4888
	between		0.00	0.00	0.04	n =	95		0.00	0.00	0.04	n =	94
	within		0.17	0.00	1.00	T =	52		0.17	0.00	1.00	T =	52
Phase4	overall	0.04	0.17	0.00	1.00	N =	4940	0.04	0.17	0.00	1.00	N =	4888
	between		0.00	0.00	0.04	n =	95		0.00	0.00	0.04	n =	94
	within		0.17	0.00	1.00	T =	52		0.17	0.00	1.00	T =	52
Phase5	overall	0.07	0.24	0.00	1.00	N =	4940	0.07	0.24	0.00	1.00	N =	4888
	between		0.01	0.00	0.07	n =	95		0.01	0.00	0.07	n =	94
	within		0.24	0.00	1.00	T =	52		0.24	0.00	1.00	T =	52