International Food and Agribusiness Management Review
2025; DOI: 10.22434/IFAMR.1382

Received: 30 June 2025 / Accepted: 10 November 2025

Do supply chain bottlenecks affect perishable commodity prices? Evidence from the COVID-19 lockdown in India

RESEARCH ARTICLE

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Abstract

The COVID-19 lockdown caused severe supply-chain bottlenecks across India, disrupting the transport of agricultural commodities from farm to market, especially for perishable commodities such as vegetables. India exhibits widespread variation in vegetable production. West Bengal and Uttar Pradesh are leading states in vegetable production. However, agricultural commodities like vegetables vary in their levels of perishability; this study measures it using the cross-sectional variation in maximum storage days for 10 vegetables. This paper investigates how supply chain bottlenecks caused by lockdown stringency during the COVID-19 pandemic affected product prices in vegetable-producing states, using secondary panel data on daily wholesale price for all the wholesale markets in the two states, West Bengal and Uttar Pradesh. Using an interactive fixed-effects panel methodology, the paper finds that an increase in stringency leads to a significant increase in the price of vegetables. An increase in price due to stringency implemented during the lockdown is prominent for vegetables that have fewer storage days (high perishability) compared to those that can be stored for more days (low perishability). Doubling of stringency leads to 3% increase in prices for highly perishable commodities but reduces the prices by 1% for high storage vegetables. Further, the market's location at the epicentre of the production region reduces the impact of stringency on prices. The availability of cold storage facility at the location, and market reforms, and better logistic facilities in the state attenuate the impact of stringency on prices in the wholesale market. The study indicates that the market reforms, infrastructure development, like the creation of green corridors and multipurpose cold storage facilities, will be highly beneficial.

Keywords: COVID-19, market reforms, perishable products, supply-chain bottlenecks
JEL codes: Q11, Q130, Q19

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1. Introduction

Sustainable agriculture is a major feature of sustainable development. The COVID-19 lockdown saw widespread dumping of products by farmers across the world, in developed countries like the USA (New York Times, 2020), developing countries like India (Hindu, 2020) and less developed countries like Ethiopia (Ababulgu *et al*., 2022). Although the action was the same, the cause was different in the two scenarios. Whereas in the USA, it was a sharp decrease in demand due to the lockdown that caused the farmers in major production areas to dump their produce, in a developing or less developed country context like India or Ethiopia, it was frail supply chain management and the inability to reach wholesale markets in time that caused anguish among the farmers. In India, on the one hand, the farmers of major vegetable-producing areas were dumping their products due to their inability to reach the wholesale markets in time; the food prices rose three times during the COVID-19 lockdown compared to the normal rate in the wholesale markets (Hindustan Times, 2020). Food price inflation reduces the welfare of low-income earners, especially in a developing country context (Alam and Khatun, 2021; Anriquez *et al*., 2013; Anwar *et al*., 2023; Cariappa *et al*., 2022; Moturki, 2020; Short *et al*., 2018). Dietrich *et al*. (2022) found that for low- and middle-income countries, while prices in markets importing commodities rose, those exporting the commodities fell. This is worrisome as this can lead to food insecurity for the vulnerable population, especially, the producers of the commodities by reducing their income, and further creating a vicious circle of poverty. However, the impact of the COVID-19 lockdown on the wholesale market prices of major producing areas and for perishable commodities like vegetables has been little studied in the literature. The central objective of the study is to provide nuanced evidence on the impact of stringency on perishable commodity prices in the major producing areas.

I shed light on the impact of wholesale market prices in the major vegetable-producing areas of India, Uttar Pradesh and West Bengal, due to the lockdown stringency. To explore this issue, I document three key facts. First, I study the impact of stringency on wholesale prices of vegetables and whether the impact differs by maximum storage days. Second, I explore the linkage between the location of the wholesale market where the commodity is sold and the production capacity at that locality. Third, I show how the availability of cold storage facilities, logistic facilities, and market reforms previously adopted by the state will either amplify or attenuate the stringency effect.

The setting for this study is unique in answering these questions. India was one of the earliest countries that adopted strict stringency measures to curtail the spread of the pandemic compared to the daily active COVID-19 cases (Dietrich *et al*., 2022). Second, in developing and upcoming countries like India, the supply chain network is long and frail (Dietrich *et al*., 2022; Varshney *et al*., 2020). Third, there is a huge cross-sectional variation across states in India regarding the production capacity of vegetables; whereas some states are consumers of vegetables, others are producers of the same vegetable. Fourth, agricultural reforms have been adopted to a varying degree.

In a few ways, economic lockdown would impact the functioning of wholesale markets in a developing country like India. First, due to stringent interstate border restrictions, the transport of commodities would be impacted negatively. Secondly, the lockdown would lead to a shortage of skilled labour to handle the loading and unloading of commodities, which would lead to greater wastage. Thirdly, it would reduce the arrival of commodities from farm to market. Lowe *et al*. (2021) and Mahajan and Tomar (2021) found that following the economic lockdown, the wholesale market arrivals dropped by 69 and 20%, respectively. This effect would be aggravated for vegetables with fewer storage days. To avoid food shortage and food wastage, the impact of economic lockdown and supply chain management disruption on the prices of perishable commodities like vegetables in the major producing areas in a developing country context needs a special policy focus.

I have performed this exercise using secondary data on daily wholesale vegetable prices for all the wholesale markets for two major vegetable-producing states in the country, namely Uttar Pradesh and West Bengal.

Usually in India, there is a major heterogeneity across different states regarding vegetable production. Uttar Pradesh and West Bengal are the major producers of vegetables and together constitute about 30% of the nation's vegetable production (NHB, 2018). Similarly, there is heterogeneity across different types of vegetables consumed in a representative Indian consumer's food basket. In this study, I consider only ten vegetables, which are majorly consumed by an Indian household (see Figure 1) and have a wide cross-sectional variation regarding their maximum storage days (natural storage capacity). In Figure 1, except for ginger and garlic[1] (365 days), which are spices, all the other vegetables are represented. The lockdown stringency would disrupt the supply chain framework, and the impact would be larger for vegetables with fewer storage days.

First, I specifically studied the impact of stringency imposed during the COVID-19 lockdown across four categories of storage days: 7 days, 30 days, 180 days, and 365 days. Using the interactive fixed-effect methodology of panel data, I studied whether the wholesale markets of vegetable prices were differently impacted due to their perishability by the stringency measure adopted in these states during the lockdown by segregating different vegetable groups based on their storage days. I found that the prices of vegetables that have fewer storage days are more sensitive to stringency restrictions in comparison to those that have more storage days, though there is a positive impact on prices due to stringency restrictions.

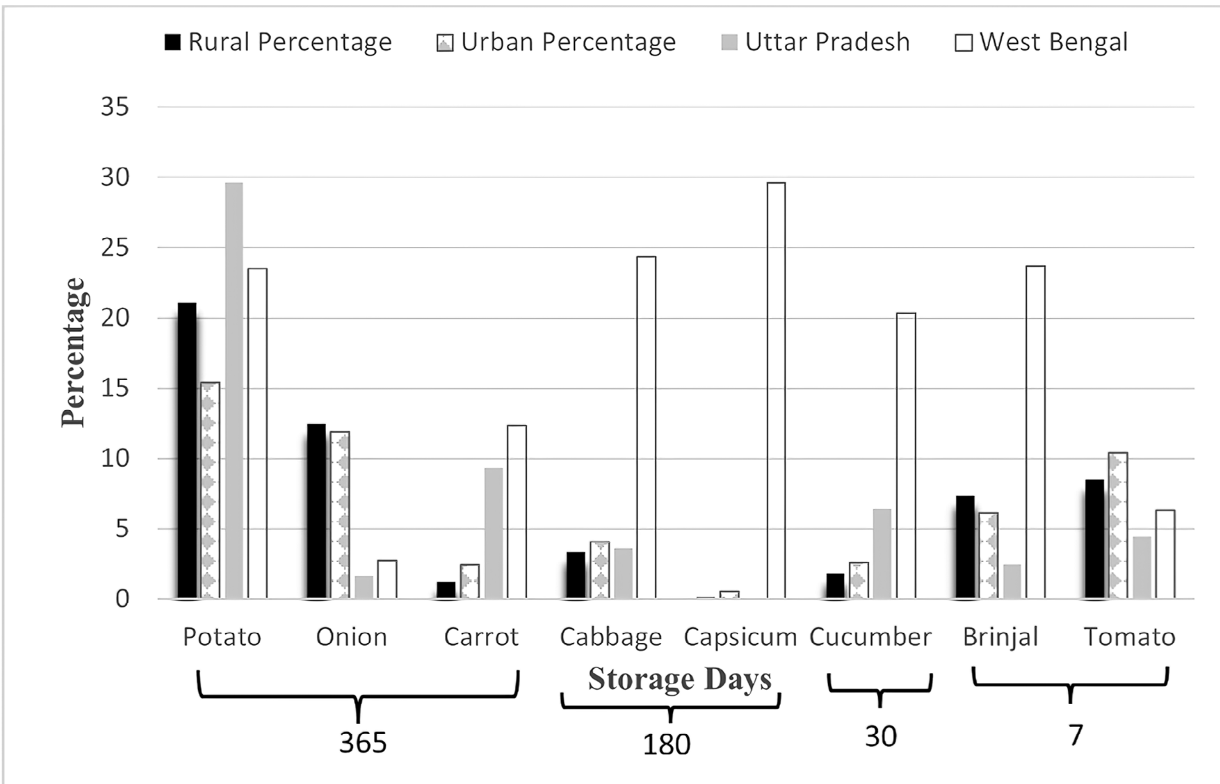

Figure 1. Monthly per-capita consumption and production of vegetables in two major producing states. Source: Based on author's compilation from Vegetable Statistics (2013) and www.apeda.gov.in.

[1] Information regarding the per-capita consumption of ginger and garlic was not available.

Second, I will demonstrate that wholesale markets in the epicentre of production will experience less sensitivity to restrictions in their prices than those in other districts. Third, I explore whether the availability of cold storage or warehousing facilities in the districts of each of these states can affect the prices during the lockdown. I find there is a significant effect of cold storage on the prices of the vegetables, but the magnitude is smaller. Lastly, I explore the effect of market reforms and logistic facilities in each state on the prices of agricultural commodities during the pandemic. I find that both logistic facilities and market reforms attenuate the impact of stringency.

This study makes several contributions. Firstly, this study explicitly explores the perishability of vegetables by their maximum storage capacity in days. Unlike previous studies (Liu and Yue, 2013; Mahajan and Tomar, 2021; Pan and Zheng, 2023; Paul and Birthal, 2021; Varshney *et al*., 2020), which consider vegetables as a broad category of perishable products, it stresses the wide heterogeneity of perishability across vegetables. Second, it considers the heterogeneity of vegetable production across states and districts in India, unlike existing studies, which ignore this aspect (Alam and Khatun, 2021; Ali and Khan, 2020 Bairagi *et al*., 2022; Emediegwu and Nnadozie, 2023; Narayana and Saha, 2020). I explicitly consider that some states are producers of vegetables and others are consumers of vegetables. It investigates the impact of restrictions on the major vegetable producing states, thereby, to some extent, indirectly assessing its impact on farmers in these exporting states. Lastly, it considers the impact of market reforms, logistic facilities and warehousing infrastructure, especially multi-purpose cold storage on the wholesale market prices of vegetables. To the best of the author's knowledge, these aspects have not been considered in the existing literature, and hence the study aims to contribute to the literature in this direction.

The rest of this study is planned as follows. Section 2 describes the relationship between stringency, perishability of the commodity, and prices in detail. Section 3 provides a theoretical background, and Section 4 explains the empirical framework used in this study. Section 5 explains the data, and Section 6 provides the results of the analysis. Section 7 provides the concluding remarks, along with the policy prescription from this study.

2. Background: stringency, perishability of commodity, and prices

2.1 COVID-19 stringency and agricultural commodity prices

The COVID-19 outbreak was considered a major worldwide pandemic, and India ranked first in the world for average excess deaths[2] (4734516) during 2020–2021 as per the World Health Organisation (WHO). Following this announcement, the international prices for wheat, corn, and barley increased by 22.8, 45.6 and 32.2%, respectively, for one year (Ayyildiz, 2022). India was one of the first few countries to adopt stringent measures to control the increase in active COVID-19 cases and deaths. During the first wave of COVID-19 (2020) as well as its second wave (2021), lockdowns were imposed, including restrictions on transport and movement of goods, to curb the spread of infection through social distancing. However, while in the first wave, the lockdown (25 March–31 May 2020) was centrally implemented nationwide and was introduced in four phases[3]; during the second wave, state-wise lockdown was implemented. There was a considerable cross-sectional variation across different states regarding its implementation (Hindu, 2021).

During the lockdown, complete closure of schools and colleges and severe restrictions on the movement of goods and transport were implemented. India was among the outlier countries that implemented stringent lockdown restrictions compared to the active COVID-19 cases, aiming to curtail the spread of the SARS-CoV-2 virus through social distancing (Mishra and Rampal, 2020; Mahajan and Tomar, 2021). As there was a huge variation in the different lockdown measures adopted across different states and during the two waves of

[2] Excess deaths caused due to COVID-19 alone after accounting for extra deaths due to other causes.
[3] 1st phase of lockdown: 25 March–14 April, 2020, 2nd phase of lockdown: 15 May–3 April 2020, 3rd phase of lockdown: 4–17 May 2020 and 4th phase of lockdown: 18–31 May 2020.

COVID-19, to maintain uniformity, I use the OxCGRT data (https://ourworldindata.org/covid-stringency-index) to measure the stringency of restrictions imposed in each state during the two different periods. The OxCGRT stringency index[4], which ranges from 0 (least restriction imposed) to 100 (stringent restriction imposed), effectively captures the lockdown restrictions in each state of India.

Figure 2 depicts the relationship between log(stringency index) in each state and the log(average commodity prices) of vegetables for the corresponding states in our study period, 2018–2021, respectively. Figure 2a depicts the stringency measures and vegetable prices in Uttar Pradesh, whereas Figure 2b depicts the stringency measures and prices in West Bengal. We can observe that during the first wave of lockdown, vegetable prices reduced in Uttar Pradesh; however, the prices increased in West Bengal.

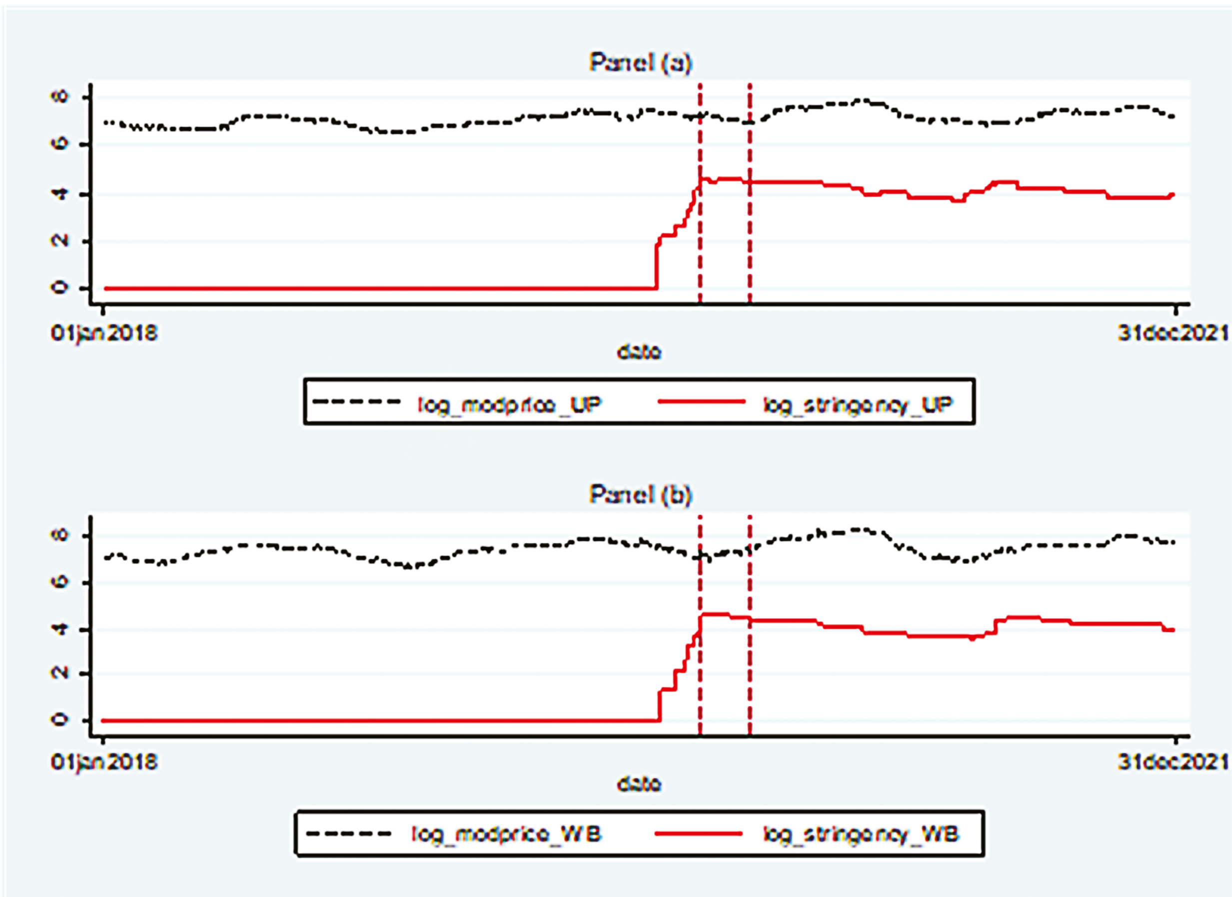

Figure 2. COVID-19 stringency and agricultural commodity price. (a) The mean of log(Modal prices) and log(stringency) in Uttar Pradesh. (b) The average of log(Modal prices) and log(stringency) in West Bengal. The dashed lines indicate the start and end of the lockdown in 2020. Average modal prices for all wholesale markets (Mandis) in both states are represented. Data source: Author's calculation based on COVID-19 stringency index from OxCGRT and wholesale prices of agricultural commodities from CEDA Agri Market Data.

[4] The stringency index is a linear combination of three other indexes, namely government response, containment and economic support.

The lockdown restricted the movement of goods and transport, and created various supply chain bottlenecks, leading to an increase in agricultural commodity prices. Few attempts have been made to study this empirically in different settings (Alam and Khatun, 2021; Ali and Khan, 2020; Ayyildiz, 2022; Balichar *et al*., 2022; Bairagi *et al*., 2022; Dietrich *et al*., 2022; Emediegwu and Nnadozie, 2023; Igua *et al*., 2024; Hung, 2021; Narayana and Saha, 2020; Varshney *et al*., 2020). Dietrich *et al*. (2022) found that due to stringency measures, the agricultural commodity prices increased more in integrated markets than in segmented markets. Applying the nonlinear autoregressive distributed lag (NADL) model, Ayyildiz (2022) found that there is a nonlinear and asymmetric relationship between the global fear index (fear caused by COVID-19) and agricultural commodity prices. The prices of agricultural commodities like corn barely responded to an increase in the global fear index compared to a decrease in the index. Yu *et al*. (2020), using time-series data and a fractionally integrated generalised autoregressive conditional heteroscedasticity (FIGARCH) model, studied the impact of lockdown restrictions on four staple food commodities in three provinces of China. They found that for a highly perishable commodity like cabbage, the lockdown restrictions caused a significant increase in prices. Further, they also found regional heterogeneity in the impact of lockdown restrictions on commodity prices across the three provinces.

In the Indian context, Emediegwu and Nnadozie (2023) use a time-varying approach to study the non-linear relationship between food prices at the retail level and the pandemic for 167 markets. Their study found that there was a structural shift in prices caused by the pandemic for rice, wheat, sugar and milk. Tomato, onion and groundnut were not affected by the pandemic but were affected by past prices. For six states of India, Bairagi *et al*. (2022) found that the price of rice and atta increased, whereas that of onions decreased significantly. Ali and Khan (2020), using a difference in weighted wholesale prices for Jammu and Kashmir, India, discovered that vegetables with high water content (>90%) showed a steep decline in prices during the lockdown; the prices of those with longer shelf life, like onion, increased. Their study finds prices of perishable vegetables declined by 19%. Mahajan and Tomar (2021) analysed online retail price data for 789 products in three Indian cities using the event management methodology. They showed that although the quantity arrival of commodities significantly declined due to lockdown restrictions, the online retail prices were not affected. Varshney *et al*. (2020) used COVID-19 caseloads to study the effect of lockdown in five Indian states for three commodities: wheat, onion, and tomatoes. They found that the prices initially rose for commodities due to the severe lockdown, but after the removal of restrictions, the prices started declining.

Although the former studies examined COVID-19 restrictions, they did not address the heterogeneity in the production of agricultural commodities, especially vegetables, across different Indian states. Hence the COVID-19 restrictions affected the exporting states (major producing states) for a particular commodity differently than the consuming states (least producing states). To the best of my knowledge, the effect on prices and indirectly on their agricultural income for exporters of commodities has not been explored. This study aims to fill these gaps in the literature.

2.2 Perishability and agricultural commodity prices

The perishability of a commodity can be measured using various proxies, for example, either by maximum storage capacity days (Bakas and Triantafyllou, 2020; Cuaresma, 20; Hung, 202121; Kopp and Mishra, 2022; Liu and Yue, 2013; Pan and Zheng, 2023; Varshney *et al*., 2020) or by moisture content (Ali and Khan, 2020). In this study, I will use the natural capacity to store vegetables to capture the perishability of the same: 7 days, 30 days, 180 days, and 365 days.

In Figure 3, the price of the vegetables in two major producing states, namely Uttar Pradesh and West Bengal, is plotted for 2018-2021, for various storage periods. Figure 3a represents 7 days, Figure 3b 30 days, Figure 3c 180 days, and Figure 3d 365 days for each state. The findings reveal that the volatility of commodity prices and the gap between average product prices of the two states decrease with greater storage capacity (lower perishability) of the commodity.

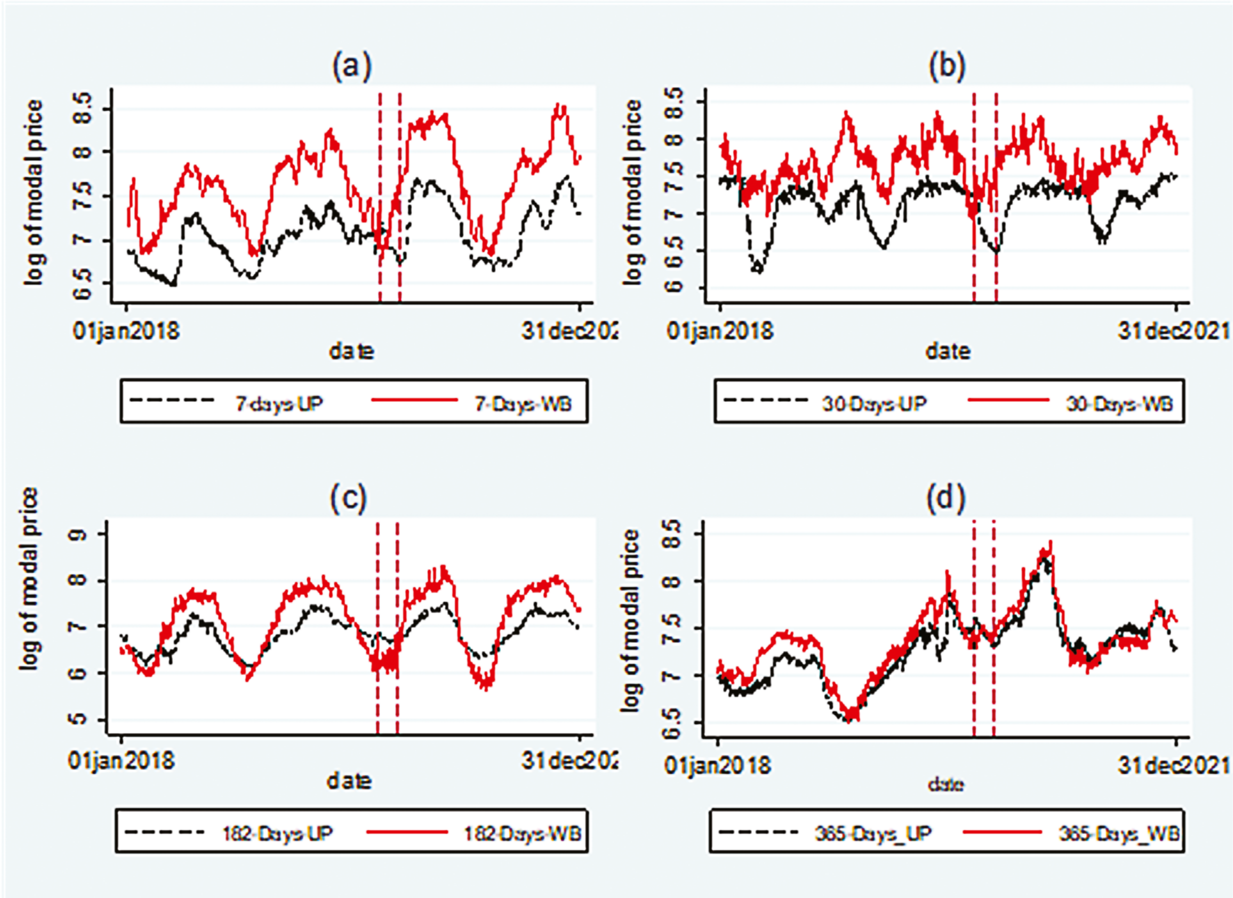

Figure 3. Storage Days and agricultural commodity price. (a) Mean of log(Modal prices) in Uttar Pradesh and West Bengal for 7 days. (b) Mean of log(Modal prices)) in Uttar Pradesh and West Bengal for 30 days. (c) Mean of log(Modal prices)) in Uttar Pradesh and West Bengal for 180 days. (d) Mean of log(Modal prices) in Uttar Pradesh and West Bengal for 365 days. The dashed lines indicate the start and end of the lockdown in 2020. Average modal prices for all wholesale markets (Mandis) in both states are represented. Data source: Author's calculation based on COVID-19 stringency index from OxCGRT and wholesale prices of agricultural commodities from CEDA Agri Market Data.

The literature on the impact of perishability on commodity prices is limited and ambiguous. Few empirical studies have explicitly considered the impact of perishability of commodities on prices of commodities (Mahajan and Tomar, 2021; Ali and Khan, 2020; Pan and Zheng, 2023; Liu and Yue, 2013; Kopp and Mishra, 2022). Pan and Zheng (2023); Liu and Yue (2013) used the storage capacity of the commodities as a measure of perishability, whereas Ali and Khan (2020) relied on the moisture content of the product.

Liu and Yue (2013), in their study on China, found that perishability negatively affects commodity trade by reducing product quality, and consequently lowering commodity prices. If there are trade delays, the commodities with lower storage days suffer more than those with higher storage days. Similarly, Pan and Zheng (2023) found that in China, perishability is directly proportional to price volatility. Their study compared the litchi (less storage capacity) market chain with the apple (more storage capacity) market and found that price volatility is transmitted from the farm gate to retail for perishable commodities. Kopp and Mishra (2022) found that in Nepal, the perishability of a commodity increases the market power and reduces farmers' welfare.

In the Indian context, Ali and Khan (2020) found that perishable commodities caused prices to fall by 19% during the COVID-19 pandemic in Jammu and Kashmir, which is an essentially vegetable-consuming state. Mahajan and Tomar (2021), found for India that due to lockdown, there is a marginal increase (0.06%) in the online prices of perishable commodities like vegetables and fruits, compared to pulses and cereals with longer longevity that see an increase in prices (2%).

However, to the best of the author's knowledge, the literature (except for Kopp and Mishra, 2022) has not explicitly explored the cross-sectional variation of perishability of commodities based on maximum storage days, nor considered that the storage duration of all vegetables (perishability) is not uniform. There is much heterogeneity across different vegetables based on their perishability. This study plans to fill this gap in the literature.

2.3 Agricultural reforms and agricultural commodity prices

In 2017, the Indian government introduced the Agricultural Produce and Livestock Marketing Act (APLMA) to initiate agricultural reforms to rebuild market infrastructure with the objective of benefiting both the farmers and consumers. The different Indian states have adopted various provisions of the APLMA to suit their local conditions and to benefit farmers. In this study, I will discuss two provisions that can benefit the vegetable producers under the APLMA and have been adopted in the two states in various forms, besides other provisions (refer to Table A3).

Delisting and deregulation of vegetables: Previously, under the APMC Act 2003, the farmers could sell their vegetables and products only in authorized markets (Mandis) and faced restrictions on selling outside their residential states. Under the current system, the APLMA delisting and deregulation of fruits and vegetables has been suggested, which will remove the restrictions on movement for farmers, and they will have the liberty to sell their product directly to consumers or at any location, including at the farm gate. Delisting also removes the market fee and the intermediaries' fees. This provides farmers with greater options to sell their products and increase their income even during COVID-19. Chatterjee (2023) found that removing the restriction of selling at local mandis can increase the farmer's income by increasing spatial competition. Varshney *et al*. (2020) found that the states that initiated greater reforms faced lower volatility in prices during the COVID-19 lockdown and higher prices of products in the mandis. West Bengal is one of the states that adopted this measure for the farmers' benefit, and Uttar Pradesh also delisted 46 fruits and vegetables to improve market competition.

Cold storage/warehouse deemed as market: The APLMA has suggested using warehouses and cold storage as deemed markets from where the farmers can directly sell their products. Such a provision allows the farmers to avoid transport and directly take their products to markets. Uttar Pradesh is the only Indian state that has proactively adopted this measure. This would attenuate the effect of restrictions in districts where cold storage is available in Uttar Pradesh, in comparison to West Bengal.

The literature on agricultural reforms on commodity prices is scant, and no study has explicitly studied the benefits of treating cold storage as a market. To the best of the author's knowledge, the literature (except for Varshney *et al*., 2020) has not explicitly explored the cross-sectional variation of perishability of commodities and delisting of fruits and vegetables.

3. Theoretical model

Yu *et al*. (2020) established the relation between COVID-19 and food prices. In this paper, we will extend their model to consider the effect of lockdown restrictions on perishable commodity prices. The model assumes that in a well-functioning market, equilibrium occurs when demand D_t equals supply S_t. Both demand and supply are determined by market prices P_t and restrictions on the movement of goods and services R_t. The restriction on the movement of goods and services is a continuous variable, which takes the form of different types of logistic bottlenecks in ordinary times and lockdown restrictions C_t during the COVID-19 pandemic.

$D_t\,(P_t, R_t) = S_t\,(P_t, R_t)$

where $R_t = R_o$ during normal times,

$= R_o + C_t$ during COVID-19 (1)

Equation (1) captures the fact that there were restrictions during normal times, but during the COVID-19 lockdown, there was additional restrictions to movement. The result of the model is provided in eqn (2). The derivation of results is provided in the appendix (refer to Section A1 in the Appendix).

$$\varepsilon_{P,R} = \frac{\varepsilon_{S,R} - \varepsilon_{D,R}}{\varepsilon_{D,P} - \varepsilon_{S,P}} \quad (2)$$

where $\varepsilon_{P,R}$ represents price elasticity with respect to restrictions on the movement of goods R_t. $\varepsilon_{D,R}$ and $\varepsilon_{S,R}$ are demand and supply elasticities in response to restrictions on movement R_t. Similarly, $\varepsilon_{D,P}$ and $\varepsilon_{S,P}$ are demand and supply elasticities in response to food price P_t. For normal goods, $\varepsilon_{D,P}$ <0, and $\varepsilon_{S,P}$ <0, hence, the sign of $\varepsilon_{P,R}$ will be determined by the sign of the numerator. The change in prices will be the difference in supply elasticity $\varepsilon_{S,R}$ and demand elasticity $\varepsilon_{D,R}$. With COVID restrictions, the equation boils down to Yu *et al*. (2020).

During COVID-19, major transport disruptions, magnified by the lack of proper infrastructure, like cold-chain facilities, mobile cold chain to transport fruits and vegetables, caused a major reduction in supply. During COVID-19, commodities with fewer storage days will face more supply disruptions due to restrictions C_t compared to commodities with more storage days, hence the elasticity will be negative, and as follows:

$$\left|\varepsilon_{S,R}\right|_{7-\text{days}} > \left|\varepsilon_{S,R}\right|_{30-\text{days}} > \left|\varepsilon_{S,R}\right|_{180-\text{days}} > \left|\varepsilon_{S,R}\right|_{365-\text{days}} \quad (3)$$

Demand elasticity can be expressed as $\varepsilon_{D,C} < 0$ when lockdown restrictions limit access to markets, leading to decline in demand, or $\varepsilon_{D,C} > 0$ when people start hoarding goods, fearing shortage of goods. Hoarding of goods with more storage days is probable; hence, it follows from eqn (2) that price elasticity with respect to restrictions will be higher for goods with fewer storage days than those with more storage days.

$$\varepsilon_{P,R\,7-\text{days}} > \varepsilon_{P,R\,30-\text{days}} > \varepsilon_{P,R\,180-\text{days}} > \varepsilon_{P,R\,365-\text{days}} \quad (4)$$

During normal times (non-COVID-19), commodities with fewer storage days will suffer more due to restrictions R_t.than commodities with more storage days, hence, the elasticity will be as follows

$$\left|\varepsilon_{S,R}\right|_{7-\text{days}} > \left|\varepsilon_{S,R}\right|_{30-\text{days}} > \left|\varepsilon_{S,R}\right|_{180-\text{days}} > \left|\varepsilon_{S,R}\right|_{365-\text{days}} \quad (5)$$

According to Liu and Yue (2013), consumers are more quality conscious due to degradation of quality of more perishable products, which is reflected in its demand elasticity $\varepsilon_{D,R} < 0$. Further, hoarding of goods with more storage days is probable, but hoarding those with fewer storage days is less probable. If the magnitude of demand elasticity is greater than supply elasticity, then from eqn (2), the prices of commodities will fall more under restrictions for goods with fewer storage days compared to those with more storage days.

$$\left|\varepsilon_{P,R}\right|_{7-\text{days}} < \left|\varepsilon_{P,R}\right|_{30-\text{days}} < \left|\varepsilon_{P,R}\right|_{180-\text{days}} < \left|\varepsilon_{P,R}\right|_{365-\text{days}} \quad (6)$$

From the theoretical model given above, we can conclude the following:

Proposition 1: During the COVID-19 pandemic, commodities with fewer(more) storage days were likely to have a higher (lower) price rise when facing supply chain bottlenecks due to movement restrictions imposed by the lockdown. The lack of cold chain facilities and transport disruption would cause a reduction in supply more than the demand, causing an increase in prices for vegetables with high perishability than for those with low perishability.

Proposition 2: During normal times, commodities with fewer(more) storage days will either have a lower (higher) rise in price or a higher (lower) fall in price when facing supply chain bottlenecks. This is because supply chain bottlenecks will cause degradation of the quality of perishable commodities, leading to a fall in demand for highly perishable commodities.

4. Empirical framework

Mahajan and Tomar (2021) and Varshney *et al*. (2020) address similar research questions and study the impact of supply chain disruptions caused by COVID-19 on food commodity prices. However, these studies had two serious limitations: first, they clubbed the vegetables into a single category of highly perishable commodities (low storage life). Although, as per the storage manual (NHB, 2001), vegetables have a high cross-sectional variation of perishability (natural life or maximum storage days), the number of storage days varies from 7 to 365 days. Henceforth, clubbing all the vegetables into a single category as low perishability would be erroneous.

Second, they ignore cross-sectional dependence across units during their empirical estimation. As shown in Table A1 in the Appendix, there is strong cross-sectional dependence across units in vegetables. Under such cross-sectional dependence across units, the estimates can be biased. An interactive fixed-effect methodology has been proposed by Bai (2009) to capture the unobserved heterogeneity in the error term.

4.1 Identification

The stringency adopted during COVID-19 is one of the causes that leads to differential outcomes in prices in agricultural markets. However, there are other factors like weather and policy changes that can act simultaneously confound the results. Henceforth, I use both time variation and cross-sectional variation to identify the effect of stringency on agricultural commodity prices. Over time, the stringency measures in the two states have changed, creating time variation, with differing degrees of stringency across states, which allows for cross-sectional variation (refer to Tables 1–3). Furthermore, I exploit the within variation of a commodity with a particular storage day sold in a particular market over time; therefore, my cross-sectional unit is a commodity sold in a particular market on a particular day.

A major concern in this analysis is that the stringency adopted by the government to contain the COVID-19 pandemic is an internal decision[5] and can be correlated with agricultural commodity prices. To overcome this problem, I adopt the following strategy.

To avoid the reverse causality problem, there were two choices: either using the COVID-19 caseload as an instrument for stringency or using past stringency as a proxy for the current period. Although Fear Index[6] is highly correlated with the stringency index, it directly affects the outcome variables (refer to Table A4);

[5] I thank the anonymous referee for highlighting this potential threat to identification and suggesting the two alternative approaches to address it.
[6] Salisu and Akani (2020) have developed a Fear Index based on morbidity and mortality of COVID-19 caseloads. Accordingly, a Fear Index was computed for two states, Uttar Pradesh and West Bengal, on the basis daily COVID-19 caseloads.

therefore, it cannot be validated as an instrument for stringency. I use the 15 days[7] preceding the existing stringency in individual states as a proxy for that period's stringency, which should be exogenous. The 15-day preceding information is considered, similar to Salisu and Akani (2020), who use a 14-day incubation period for constructing the Fear index.

Second, the government can change policy measures from time to time to adapt to the local conditions. However, such measures would affect all vegetables similarly, and therefore, the analysis would remain unaffected. If either the central or state government had relaxed the movement of highly perishable vegetables differently from those with more storage days, that would have created a problem in segregating the effect, but no such measures were taken.

The main equation of interest is given by

$$\log(\text{price})_{it} = \beta \log(\text{stringency})_{it-15} + u_{it};$$

and

$$u_{it} = \alpha_i + \gamma_t + \Lambda_i' F_t + \varepsilon_{it}\ (i = 1.2 \ldots .10, t = 1,2 \ldots .T) \ldots \ldots \quad (9)$$

where $\log(\text{price})_{it}$ represents the logarithmic value of price for a particular vegetable "i" in the Mandis on a particular day t. The independent variable is $\log(\text{stringency})_{it}$ the logarithmic value of stringency implemented during COVID-19 for the state in which the Mandi is located, for vegetable i on a particular day t. The term u_{it} has a factor structure with Λ_i' as a vector of factor loadings, and F_t as a vector of common structure. ε_{it} are idiosyncratic errors; Λ_i', F_t and ε_{it} are unobserved. The variable "α_i" captures the time-invariant individual characteristic of the product like the location of Mandis, while "γ_t" represents the time effect.

The coefficient β captures the impact of past stringency on vegetable prices. A positive value indicates that higher stringency has caused a supply shortage, leading to a higher price. On the other hand, a negative value would indicate that stringency led to quality deterioration, reducing the price. The logistic problem will be acute and cause quality deterioration with fewer storage days, compared to those with more storage days.

However, in the presence of cross-sectional dependence across units (refer to Table A1 in the Appendix), the estimates can be biased and inconsistent; therefore, an interactive fixed effect model as proposed by Bai (2009), should be adopted. Common shocks can cause cross-sectional correlations. An example of a common shock is the logistics problem that each state faces, which is unobservable in nature and can simultaneously affect both the stringency measure and the commodity price. Each commodity can be differently affected by common-shock logistics measures, largely due to its perishable nature and the location of Mandis where it is sold. Then, in an interactive fixed model, vector F_t captures common shocks like logistics and governance in each state, while the loading factor Λ_i' represents the degree of heterogeneity to which each commodity is affected by F_t. A limitation of this method is that no direct interpretation can be given to the common shock. The two-way fixed effect is a special case of the interactive fixed effect.

During the estimation of the interactive fixed-effect methodology, the first step is to determine the number of common shocks relevant to the model. To achieve this, I use the xtnumfac command in Stata, and based on Ahn and Horenstein (2013), I conclude that the number of factors is 1, which is considered a consistent method.

[7] I have also used the 30 days preceding stringency as proxy for current period stringency. The results are robust with direction, but magnitude drops further.

5. Data and variables

In this section, I describe the data sources and justify the variables chosen for this study. The data were compiled mainly from three different secondary sources. In India, Uttar Pradesh (15.4%) and West Bengal (15.03%) are the leading states in vegetable production; therefore, they are the natural candidates for our analysis (NHB, 2018). Hence, to maintain the comparability between the two states, I have selected 10 vegetables for which both states are leading producers, and gathered information available for both states from 1 January 2018 to 31 December 2021. Therefore, I have 1 257 571 unbalanced panel observations.

5.1 Perishability of vegetables

The perishability of commodities can be captured by various measures. One of the popular measures used in the literature (Pan and Zheng, 2023; Liu and Yue, 2013) is the storage life of the commodities. Vegetables exhibit a wide range of perishability, in terms of their maximum days of storage (natural life); some vegetables can be stored for a week, while others can be stored for a year (refer to Table A2). Warehousing, such as cold storage, cannot extend the natural life of vegetables. The information on the storage days of each vegetable was collected from the storage manual of the National Horticulture Bureau (2001). To capture a cross-sectional variation of perishability, ten commodities are chosen, whose storage days range from a week to a year, and these are significantly represented in the consumption basket of an Indian household (see Figure 1).

Table 1 reports the log(modal price) of the distribution of these ten vegetables across different categories of perishability. As can be observed from column (1) of Table 1, our data are skewed towards the tail end, with commodities having a maximum storage life of either a week (35%) or a year (52%). As expected, from column (2), the mean log(modal prices) of the commodities increases as their storage days (natural life) increase, because wastage is reduced and better markets can be explored with time.

5.2 Stringency during the COVID-19 lockdown

The data on stringency measures implemented during the COVID-19 lockdown in the two states were collected from the OxCGRT database. The OxCGRT data compile a stringency index for each state based on different stringency measures implemented by the state government, and it ranges between 0 (the least stringent condition) and 100 (the most stringent condition). The stringency index is a linear combination of three different indexes, namely the containment index, government response and the economic support index. In both states, the average past stringency index was 63 during the COVID-19 phase (1 January 2020–31 December 2021). Usually, stringency implemented by the government depends on internal decisions, so to avoid the reverse causality issue, a 15-day earlier stringency that existed for each state will be considered in this study for the current period. The average stringency in Uttar Pradesh is 66, slightly higher than West Bengal's 65.8, but West Bengal has a higher variation in stringency than Uttar Pradesh.

Table 1. Summary statistics of vegetable prices.

Storage time	No. of observations (1)	Mean (2)	SD (3)	Min (4)	Max (5)	No. of products (6)
7 days	439 721	7.16	0.57	4.33	9.75	2
30 days	93 375	7.17	0.57	4.80	9.62	2
180 days	77 353	6.81	0.56	4.71	8.72	1
365 days	647 122	7.27	0.70	2.08	9.83	5

The mean log(Prices) of vegetables by maximum storage days in our data (for West Bengal and Uttar Pradesh) are shown.

5.3 Prices

Price data were collected from the CEDA Agri Market database (https://ceda.ashoka.edu.in/agmarknet), which is a comprehensive database compiling and maintaining information on all the daily wholesale market prices for different vegetables. The daily prices of vegetables in CEDA are collected from the official Agmarknet data (https://agmarknet.gov.in/). The prices primarily considered in this study are the daily modal prices of ten vegetables for all the wholesale markets (Mandis) in the two selected states, Uttar Pradesh and West Bengal, for the study period 1 January 2018–31 December 2021. Mandis in India are markets where the farmers sell their products to intermediaries and are not operational daily, which provides an idea about the farm-gate arrivals.

Ideally, one would like to consider the actual equilibrium prices prevailing in the Mandi on its operating day. However, in its absence, I consider the modal price for the respective vegetables available for my analysis on that day. In the case of prices, Mandi data are available only for a limited number of products. Hence, to maintain comparability between the two states, ten vegetables are chosen. Table 2 presents the mean of log(modal prices) of the commodities before and during COVID-19. A comparative analysis of the mean before and during COVID-19 shows that the commodities were, on average, Rs. 470 more expensive during the pandemic across all categories of perishability. The coefficient of variation (CV) shows that the volatility of prices of agricultural commodities of 7 and 365 storage days increased during COVID-19, but that of 30-day and 180-day storage has decreased during the same time.

5.4 Warehousing facilities

In the trade literature (Liu and Yue, 2013; Ramizo and Hagiwara, 2025), perishable commodities are defined as those that require cold storage during transportation. In India, the availability of cold storage facilities poses a limitation. To supplement the above dataset, I have included information on cold storage facilities available in each district across their respective states, sourced from the National Horticulture Bureau dataset. Cold storage facilities can be broadly categorised as product-specific (potato cold storage) and generic storage (referred to as multipurpose cold storage, MPS). Only 25% of the cold storage is classified as MPS in India, while the remaining 75% is potato-specific. Uttar Pradesh is the leading state (with an average of 23 cold storages per district) and West Bengal is the second leading state (with an average of 20 cold storages per district) in terms of cold storage (refer to Tables 1–3). However, most cold storages in both states are potato-specific as these two states are the leading producers of potato in India.

Table 2. Summary statistics of vegetable prices before and during the COVID-19 pandemic.

Storage time	**Normal (before COVID-19)**			**COVID-19**		
	No. of observations (1)	**Mean (2)**	**SD (CV) (3)**	**No. of observations (4)**	**Mean (5)**	**StD (CV) (6)**
7 days	235 729	7.06	0.536 (7.6)	203 992	7.28	0.58 (7.9)
30 days	42 750	7.14	0.597 (8.4)	50 625	7.20	0.54 (7.5)
180 days	41 483	6.72	0.563 (8.4)	35 870	6.91	0.54 (7.8)
365 days	348 397	7.03	0.627 (8.9)	298 725	7.54	0.69 (9.2)

The mean *log(Prices)* of vegetables by maximum storage days for Normal and COVID-19 periods in our data (for West Bengal and Uttar Pradesh) are shown. The normal period is from 1 January 2018 to 31 December 2019; the COVID-19 period is 12 March 2020 to 31 December 2021. The coefficient of variation is reported in parentheses.

Table 3. Summary statistics of stringency; LEADS index and cold storage.

	No. of observations	Mean	SD	Min	Max
Lag Stringency Index (UP)	466 860	66.9	18.08	25	100
Lag Stringency Index (WB)	96 849	65.8	18.91	30.6	100
LEADS Index (UP)	488 388	3.17	0.08	3.08	3.3
LEADS Index (WB)	100 824	3.02	0.02	2.99	3
Cold Storage (UP)-All types	1 026 976	23.2	45.38	0	211
Cold Storage (UP)-MP types	1 026 976	19.6	33.34	0	129
Cold Storage (WB)-All types	230 595	26.2	28.8	0	96
Cold Storage (WB)-MP types	230 595	2.01	1.57	0	6

Data source: Author's calculation based on COVID-19 stringency index from OxCGRT, wholesale prices of agricultural commodities on CEDA Agri Market Data, storage days, and cold storage information from NHB storage manual. Cold storage denotes district-wise number of cold storages. All types include (both potato and multi-purpose) or multi-purpose cold storage.

In this study, I use multipurpose storage to perform additional analysis, as it can store different vegetables. It should be noted that Uttar Pradesh holds 67% of the total MPS cold storage in India, while West Bengal accounts for only 3%. The average number of MPS cold storage facilities in Uttar Pradesh is 26, compared to only 2 in West Bengal. However, in our data, only 3 out of 19 districts of West Bengal do not have any MPS cold storage facility, whereas 43 out of 71 districts in Uttar Pradesh lack such facilities. I will consider all types of cold-storage and multi-purpose cold storage in my analysis.

5.5 Logistic facilities (LEADS)

The data for logistics facilities for both states is captured by the Logistics Ease of Doing Business (LEADS) index. LEADS is a comprehensive index of infrastructure, logistic facilities and bottlenecks in each state of India. The LEADS index for the study period for Uttar Pradesh and West Bengal was compiled from the LEADS report. Uttar Pradesh has better logistics facilities and infrastructure, as suggested by its average LEADS index of 3.10 for 2018–2021, whereas West Bengal's average LEADS index is 2.90 for the same period (refer to Tables 1–3). Although West Bengal had higher growth (10%) than Uttar Pradesh (8%) in logistic facilities during the study period, in absolute terms, Uttar Pradesh is still ahead with 3.25 in 2021, whereas West Bengal was 3.04 in 2021.

5.6 Agricultural reforms

The data regarding agricultural reforms was collated from Varshney *et al*. (2020) and NITI Aayog (refer to Table A3 in the Appendix). As of 2019, the two states of this study had adopted the APLMA provisions in various degrees. Whereas Uttar Pradesh has adopted cold storage as a deemed market, West Bengal has incorporated the provision of delisting and deregulation. Later, in May 2020, Uttar Pradesh delisted 46 fruits and vegetables.

6 Results and analysis

In this section, I present the main results of the impact of restrictions on agricultural commodity prices.

6.1 Base results

Table 4 shows the estimation results based on Eq. (9) for the impact of restrictions on wholesale commodity prices of vegetables. In Table 4, each column represents the agricultural commodities segregated according to their maximum storage days. As one moves from column (1) to column (4) and from column (5) to column

Table 4. Effect of stringency on price of perishable agricultural commodities during the COVID pandemic.

	Full period (2020–2021)				**Smaller window (1 April–31 May 2020)**			
	(1) log(price) (7 days)	**(2) log(price) (30 days)**	**(3) log(price) (180 days)**	**(4) log(price) (365 days)**	**(5) log(price) (7 days)**	**(6) log(price) (30 days)**	**(7) log(price) (180 days)**	**(8) log(price) (365 days)**
Lag stringency	0.0350***	0.0252**	0.0435***	−0.0159***	−0.0272***	0.0333*	0.0419**	0.00885*
	[3.6]	[2.5]	[4.4]	[−1.6]	[−2.7]	[3.4]	[4.3]	[0.9]
	(0.0044)	(0.0078)	(0.0075)	(0.0024)	(0.0072)	(0.015)	(0.0143)	(0.0037)
No.of observations	196 297	47 633	33 532	286 246	18 638	5122	3352	26 564
No. of factors	1	1	1	1	1	1	1	1
Time effect	Y	Y	Y	Y	Y	Y	Y	Y
Commodity × Market effect	Y	Y	Y	Y	Y	Y	Y	Y

The dependent variable is log(Modal Prices) of the commodity in the wholesale market (Mandis). The estimates are based on an interactive fixed-effect methodology. All regressions include commodity and time fixed effects. The number of factors is chosen by using Ahn and Horenstein (2013) statistics. The full sample period is 12 March 2020–31 December 2021, and the narrow window is 1 April–31 May 2020, coinciding with Varshney *et al*. (2020). Standard errors are in parentheses. *, **, and *** denote significance at the 10%, 5% and 1% level, respectively. Some observations are lost for incorporating the lag-stringency of 15 days preceding. Effect on prices due to 1 SD increase using $100(\exp(\beta).1SD)^{-1}$ is in square brackets. Data source: Author's calculation based on COVID-19 stringency index from OxCGRT and wholesale prices of agricultural commodities on CEDA Agri Market Data and storage days from the NHB storage manual.

(8), the storage days increase from 7 days to 365 days, respectively. The full sample period is represented in columns (1) to (4), and the short window is represented in columns (5) to (8). First, I find that Lag (stringency index), measuring restrictions imposed during the full period of the pandemic, has a significant positive impact on the prices of agricultural commodities, except for agricultural commodities with 365 storage days. During a severe pandemic, the price of highly perishable commodities drops, but others increase.

A natural concern is whether the price increase was supply-driven or demand-driven. To examine this, I tested the Lag (stringency index) on the daily quantity of arrival of the same commodities in their respective markets during the same period. Table 5 shows the estimation results based on the impact of restrictions on the wholesale commodity quantity arrival of vegetables in their respective mandis. In Table 5, as one moves from column (1) to column (4) and from column (5) to column (8), the storage days increase from 7 days to 365 days, respectively. The full sample period is represented in columns (1) to (4), and the small window is represented in columns (5) to (8). Table 5 shows that during the severe pandemic (short window), there was no significant drop in the arrival of the commodities; on the other hand, the arrival of commodities with higher storage days (365 days) increased. This confirms that both states' high production capacity acted as a buffer during the severe pandemic period. However, when we consider the entire period of the pandemic, the quantity arrivals dropped. Therefore, we can conclude that during the pandemic, with an increase in stringency or restrictions of movements, supply was affected more than demand for all agricultural commodities, irrespective of their storage days. This evidence is consistent with previous empirical studies that found supply chain bottlenecks imposed during the pandemic due to stringency measures led to an increase in agricultural commodity prices (Mahajan and Tomar, 2021; Paul and Birthal, 2021; Yu *et al*., 2020).

Second, I find that, consistent with our first proposition, agricultural commodities' perishability (maximum storage capacity) is a determining factor in terms of their price responsiveness to stringency measures adopted in the form of restrictions during the pandemic. As one moves from columns (1)–(4), the responsiveness decreases with an increase in storage days, except for vegetables with 180 storage days. Comparing column

Table 5. Effect of stringency on daily quantity arrival of perishable agricultural commodities during the COVID pandemic.

	Full period (2020–2021)				**Smaller window (1 April–31 May 2020)**			
	(1) log(Quantity) (7 days)	**(2) log(Quantity) (30 days)**	**(3) log(Quantity) (180 days)**	**(4) log(Quantity) (365 days)**	**(5) log(Quantity) (7 days)**	**(6) log(Quantity) (30 days)**	**(7) log(Quantity) (180 days)**	**(8) log(Quantity) (365 days)**
Lag stringency	−0.0117	-0.0556^{***}	-0.133^{***}	-0.0484^{***}	0.00903	−0.0364	0.0445	0.0590^{***}
	(0.00863)	(0.0138)	(0.016)	(0.00837)	(0.0151)	(0.0338)	(0.0318)	(0.0179)
No. of observations	196 297	47 633	33 532	286 246	18 638	5122	3352	26 564
No. of factors	1	1	1	1	1	1	1	1
Time effect	Y	Y	Y	Y	Y	Y	Y	Y
Commodity × Market effect	Y	Y	Y	Y	Y	Y	Y	Y

The dependent variable is log(Quantity Arrival) of the commodity in the wholesale market (Mandis). The estimates are based on interactive fixed-effect methodology. All regressions include commodity and time fixed effects. The number of factors is chosen by using Ahn and Horenstein (2013) statistics. The full sample period is 12 March, 2020–31 December 2021, and narrow window is 1 April–31 May 2020, coinciding with Varshney *et al*. (2020). Standard errors are in parentheses. *, **, and *** denote significance at the 10%, 5% and 1% level, respectively. Some observations are lost for incorporating lag-stringency of 15 days preceding. Data source: Author's calculation based on COVID-19 stringency index from OxCGRT and wholesale prices of agricultural commodities on CEDA Agri Market Data and storage days from the NHB storage manual.

(1) to column (4), one observes that for commodities like tomato and brinjal, which can be stored for a week, the prices would increase by 3% due to the doubling of stringency restrictions. However, for commodities like onion and potato, whose storage capacity is 365 days, the prices would increase by only 1%. An increase of 1 SD causes approximately a 3% increase in prices of vegetables with low to medium storage days, but leads to a 2% decrease for vegetables with very high storage days in the entire pandemic period. Yu *et al*. (2020) similarly found in China that prices of highly perishable commodities like cabbage and pork were positively affected by the pandemic, while less perishable commodities like rice and wheat remained unaffected by the same restrictions.

Third, during the pandemic, there was probably a switch in demand from vegetables with high perishability to low perishability; therefore, the price of vegetables with 180 storage days increased, regardless of a reduction in the arrival quantity.

Result 1: (i) Perishability of commodities serves as a crucial factor in price determination; (ii) prices are more sensitive to restrictions for highly perishable commodities (which have fewer storage days) compared to less perishable commodities (which have more storage days).

Up to now, in this study I have considered both states to be homogeneous in their production capacity. However, some Indian states grow and export vegetables, whereas other states import the same vegetables. Hence, it is important to consider the heterogeneity in both production and consumption of the commodity under consideration.

6.2 Heterogeneity across states in vegetable production

In this section, I explore the heterogeneous vegetable production capacities across Indian states, which lead to varying impact on the prices of these commodities due to the stringency imposed during the pandemic. To capture this, I concentrate on the simple fixed effect model of Eq. (9). The simple fixed effect captures the influence of time-invariant characteristics like the location of wholesale markets where the commodity is sold in a district or state with high production capacity, in the determination of a product's price.

The state production capacity for the concerned commodity, compared to the rest of the country, would play a major role in price determination. For example, if the state is a major producer, it will export the commodity to other states, thereby serving as an internal exporter(producer) of the commodity.[8] However, if the state does not produce the commodity, it will import the commodity, thereby serving as an internal importer (consumer). I use NHB (2018) to determine the production capacity of a state. Further, as only five commodities of this study had detailed information regarding the major producing states and their respective districts, the analysis had to be further restricted to only these five commodities. The result of the analysis is provided in Table 6. A detailed analysis of all ten commodities of the study is presented in the appendix (refer to Table A5 in the Appendix). In Table 6, column (3) and column (5) indicate whether the individual state in our study is a producer or consumer of the concerned vegetables. Columns (4) and (6) indicate the impact of the state's production capacity on the log(modal price) of the commodity in the wholesale market. It is evident that the agricultural commodities' prices are affected by both storage days and whether the state is a producer of the commodity. The production capacity of the state reduces the impact of restrictions on commodity prices. In cases where the state is a major exporter to the other Indian states, the restriction in movement will lead to dumping in the local wholesale markets.

Potato is a staple vegetable in India, besides onion and tomato (refer to Figure 1), and both rural and urban populations spend a large percentage of their monthly expenditure on purchasing potatoes. In the case of

[8] Inter-state trade is very important in this context, but due to unavailability of public data on inter-state trade of commodities in our study, we cannot explore it empirically. The study cannot capture spatial spillover due to data limitation.

Table 6. Role of state's vegetable production capacity on price during the COVID-19 lockdown.

(1)	(2)	Uttar Pradesh		West Bengal	
		(3)	(4)	(5)	(6)
Commodity	**Perishable days**	**Producer/ consumer**	**Impact on log(Modal price)**	**Producer/ consumer**	**Impact on log(Modal price)**
Brinjal	7	Consumer (2.45)	−0.23(↓)	Producer (1^{st}, 23.72)	0.47 (↑)
Tomato	7	Consumer (4.44)	0.03(↑)	Consumer (7^{th}, 6.33)	0.48 (↑)
Garlic	365	Producer (4^{th}, 6.57)	1.23(↑)	Consumer (1.15)	1.39 (↑)
Onion	365	Consumer (1.63)	0.02(↑)	Consumer (7^{th},2.77)	0.32(↑)
Potato	365	Producer (1^{st}, 29.65)	−0.44 (↓)	Producer (2^{nd},23.51)	−0.29 (↓)

The average of log(Modal price) for the commodity concerned is mentioned along with whether the respective state is listed among the largest five producers of the commodity in India, with their respective rank and percentage of total production in the country. Otherwise, the state is considered a consumer of the commodity. The list of major producing states for the vegetable was collected from NHB (2018) and the percentage from www.apeda.gov.in). The average fixed effect value is mentioned, and an upward (downward) arrow indicates an increasing (decreasing) impact of the state on the respective commodity price. Data source: NHB (2018) and agriexchange.apeda.gov.in.

potato, where the two states are the largest producers and the product has a long storage life, restrictions on the movement lead to an increase in supply (dumping) in the local wholesale market, and as a result, suppress the product's price. In almost all scenarios, we see that being a producer rather than a consumer suppresses the price increase of the vegetable. This result supports Dietrich *et al*. (2022), who found that due to the imposition of stringency by the government, the exporting markets' prices drop.

The exception is brinjal: COVID-19 restrictions caused an increase in the price of the vegetable in West Bengal, the largest producer of the vegetable in India, whereas in Uttar Pradesh, the prices declined. A plausible reason is that due to the deregulation of vegetables and brinjal being highly perishable, the vegetable producers are more inclined to sell it at a nearby location than taking the risk of transporting the item to mandis during the pandemic. Consequently, in the mandis, the price of vegetables increases due to a decrease in the quantity arriving.

Even with similar perishability and Uttar Pradesh being a consumer state for both brinjal and tomato, the restrictions imposed caused an opposite impact on the price of brinjal compared to that of tomato. This can be explained by the fact that the demand for brinjal is primarily local (Kumar *et al*., 2011), and in Uttar Pradesh, the consumer's preference for brinjal is low, possibly causing a lower demand than supply.

However, a concern is that logistics and ease of doing business of a state may be driving the results. Hence, to accurately identify the location effect on the prices, I further segregate markets situated in major producing districts from those in other districts within the same state.

The location of the wholesale market where the commodity is exchanged plays an important role. If the market is close to the epicentre of the production of the commodity, then due to increased supply of the product, the price would reduce. Table 7 compares the major producing districts to other districts within the same state, focusing on the commodities and states of the major producers as mentioned in Table 5. The study compiles the list of major producing districts from NHB (2018). Table 7 presents the location effect

Table 7. Advantages of market located at the epicentre of production on vegetable commodity price.

(1)	(2)	Major producing districts		Other districts	
		(3)	(4)	(5)	(6)
Commodity	**Perishable days**	**State**	**Impact on log(Modal price)**	**State**	**Impact on log(Modal price)**
Brinjal	7	West Bengal (1^{st}, 23.72)	0.57 (↑)	West Bengal (1^{st}, 23.72)	0.24(↑)
Potato	365	West Bengal (2^{nd}, 23.51)	−0.33(↓)	West Bengal (2^{nd},23.51)	−0.26 (↓)
Potato	365	Uttar Pradesh (1^{st}, 29.65)	−0.47(↓)	Uttar Pradesh (1^{st}, 29.65)	−0.44(↓)

The average of log(Modal price) for the commodity concerned is mentioned for major producing districts and other districts of the same states. Details of major producing states of the vegetables with their respective rank and percentages are stated in parentheses. The list was collected from NHB (2018), and the percentage from www.apeda.gov.in. The average fixed effect value is stated; an upward (downward) arrow indicates an increasing (decreasing) impact of state on the respective commodity price. Data Source: NHB (2018) and agriexchange.apeda.gov.in.

on wholesale commodity prices in the markets, specifically comparing the major producing districts with other districts within the same state. Comparing column (4) and column (6), we find that just being at the epicentre of production dampens the price of agricultural commodities in wholesale markets, even after COVID-19 restriction is imposed. This empirical finding is similar to Mahajan and Tomar (2021), who find that the distance between the farmgate and market plays an important role in the agricultural food price determination during COVID-19 restrictions. An exception to this is brinjal, where the prices are higher in the major producing districts compared to other districts, likely due to deregulation of vegetables in West Bengal.

An interesting point to be observed is that in case of potato where both the states are its largest producers, the gap between major districts and other districts diminishes for Uttar Pradesh, but the gap remains for West Bengal. A plausible reason for this reduction in the gap can be the market reforms in Uttar Pradesh, where cold storage acts as a deemed market.

Result 2: The location of the wholesale market at the epicentre of production of the commodity reduces the impact of stringency on prices. Market reforms can narrow the gap between major producing districts and other districts.

In the following sections, I study the role of market reforms, cold storage, and logistic facilities in the two states, which can further play an important role.

6.3 Impact of cold storage/warehousing facilities and market reforms during COVID-19 lockdown

Cold storage and mobile cold-storage facilities are vital for perishable commodities like vegetables. However, in our country, cold storage facilities are limited in number. In this section, I explore the effect of warehousing facilities — both commodity-specific (potato cold storage) and multipurpose cold storage facilities found in different districts — on agricultural commodity prices. Furthermore, I study the impact of market reforms adopted in Uttar Pradesh and West Bengal on the commodity prices. Uttar Pradesh and West Bengal took different stances regarding market reforms. Whereas Uttar Pradesh allowed for the deregulation of 46 fruits and vegetables and treated cold storage as deemed markets, West Bengal only allowed for the deregulation of fruits and vegetables. Thus, in Uttar Pradesh, cold storage facilities themselves became another market and can act as intermediaries between the mandis and farmers. However, in West Bengal, farmers growing vegetables could sell their produce anywhere they wished, even at the farm gate.

Usually, cold storage facilities are of two types: product-specific (single commodity storage) and multipurpose (multiple commodity storage, MPS). In India, 75% of cold storage facilities are product-specific and built to store potato, while only 25% are multipurpose and can be used for different commodities (NHB MIS-Reports). As there is a direct need for multipurpose cold storage facilities that can be used uniformly for different commodities, although I perform the analysis for both potato cold-storage and multipurpose, I concentrate mainly on multipurpose. The result of the analysis is reported in Table 8. Table 8 presents the impact of stringency and cold storage facilities on agricultural commodity prices, showing the analysis for all types of cold storage facilities (potato cold storage), and for multi-purpose cold storage facilities. Columns (1)–(4) present the analysis for Uttar Pradesh commodities with various degrees of perishability, whereas Columns (5)–(8) present that of West Bengal.

Table 8 (All types of cold storage) presents mainly the contribution of potato cold storage facilities during the pandemic. As the storage period of potato is 365 days, therefore, I would concentrate on column (4) and column (8), respectively, for both the states. A few observations are obvious. First, due to the stringency, prices of vegetables with more storage days increased in West Bengal, whereas they dropped in Uttar Pradesh. This is mainly because the quantity of arrivals dropped significantly in West Bengal but not in Uttar Pradesh (refer to Table A6 in the Appendix). Second, the interaction of cold storage facilities with stringency being positive indicates that markets in districts with cold storage facilities received a greater quantity of high storage vegetables, leading to a decrease in prices of the commodity. Consequently, the cold storage attenuated the impact of stringency during the pandemic. This is quite intuitive, as most of the time the location of cold storages is not random and is clustered in districts with major production (ISTIP, 2015). Further, the presence of cold storage facilities would provide farmers with a choice of storing some of their products to sell them at a higher price later, rather than selling them immediately at spot market prices (Ateka and Mbeche, 2023). Hence, a portion of the supply available to market gets reduced due to being stored, increasing the impact on prices from cold storage facility availability due to restrictions.

Table 8 (Multi-purpose cold storage) presents mainly the impact of the multi-purpose cold storage facility availability during the pandemic. As one moves from column (1) to column (4) in Uttar Pradesh and column (5) to column (8) in West Bengal, the storage days of commodities increase and the prices of commodities decrease due to stringency, irrespective of their location. This is mainly led by a shrinking of supply, especially for highly perishable commodities (refer to Table A7 in the Appendix).

Second, as one moves from column (1) (column (5)) to column (4) (column (8)), it is observed that the availability of cold storage facilities reduces the prices of commodities in Uttar Pradesh but increases them in West Bengal. This is caused by the market supply drastically shrinking in districts with more cold storage facilities than in West Bengal, but comparatively increasing in Uttar Pradesh. A plausible reason is that in Uttar Pradesh, cold-storage facilities themselves acted as an extension of market yards, allowing farmers to sell their produce directly instead of incurring transport costs to travel to the market. The cold storage facility owner can further sell the produce to the mandis. However, in West Bengal, the farmers, instead of incurring both cold storage hiring costs and transport costs, due to deregulation and delisting of fruits and vegetables, can sell their products directly to customers or at other places. Thus, this will significantly reduce the supply of commodities in the markets. As cold storage is strategically located in districts that are major producers of the commodities, the impact on the mandis will be higher in such districts.

Third, a comparison of both modes of storage indicates that the impact of a multipurpose cold-storage facility is higher for commodities with low storage days than more storage days. This is intuitive as multipurpose can store generic items, whereas potato storage is commodity-specific. The magnitude of the impact is negligible due to the relatively low number of cold storage (MPS) facilities available in the two states.

Result 3: (i) Cold storage availability reduces the supply in the spot market and increases the prices of commodities due to stringency; (ii) cold storage acting as a market itself has the potential to increase the supply of commodities in markets, even during stringency.

Table 8. Impact of agricultural reforms (cold storage vs deregulation) on agricultural commodities price during the COVID pandemic.

Independent variable	**Uttar Pradesh**				**West Bengal**			
	(1) log(price) (7 days)	**(2) log(price) (30 days)**	**(3) log(price) (180 days)**	**(4) log(price) (365 days)**	**(5) log(price) (7 days)**	**(6) log(price) (30 days)**	**(7) log(price) (180 days)**	**(8) log(price) (365 days)**
All types of cold storage (potato + MPCS)								
Lag stringency	−0.000111	0.0000821	−0.0000191	−0.000602***	0.000558**	0.000458	0.00181***	0.000528***
	(0.000102)	(0.000138)	(0.000132)	(0.0000623)	(0.000265)	(0.000702)	(0.000375)	(0.000126)
Lag stringency × CS	−0.00000122**	0.0000124***	−0.00000583***	−0.0000132***	0.0000280***	0.0000014	0.0000317***	−0.00000778***
	(0.000000605)	(0.00000139)	(0.00000102)	(0.000000742)	(0.00000286)	(0.00000632)	(0.00000777)	(0.00000119)
Multi-purpose cold storage								
Lag stringency	0.0000696	0.0000413	−0.0000126	−0.000556***	0.000385	−0.00359***	0.00130***	−0.000015
	(0.000103)	(0.000139)	(0.000134)	(0.0000627)	(0.000268)	(0.000677)	(0.000433)	(0.000132)
Lag stringency × CS	−0.00000370***	0.0000162***	−0.00000728***	−0.0000183***	0.000470***	0.00209***	0.000695***	0.000179***
	(0.000000799)	(0.00000175)	(0.00000148)	(0.00000097)	(0.0000448)	(0.000103)	(0.000166)	(0.0000227)
No. of observations	163 008	41 097	28 386	234 368	33 289	6533	5141	51 878
No. of factors	1	1	1	1	1	1	1	1
Time fixed effects	Y	Y	Y	Y	Y	Y	Y	Y
Commodity × Market fixed effects	Y	Y	Y	Y	Y	Y	Y	Y

The dependent variable is log(Modal prices) of the commodity in the wholesale market (Mandis). The estimates are based on interactive fixed-effect methodology. All regressions include commodity and time-fixed effects. The number of factors is chosen by using Ahn and Horenstein (2013) statistics. The sample period is 12 March 2020–1 December 2021. Standard errors are in parentheses. *, **, and *** denote significance at the 10%, 5% and 1% level, respectively. Multi-purpose cold storages are generic in nature, whereas potato cold storage is product-specific. Data source: Author's calculation based on COVID-19 stringency index from OxCGRT, wholesale prices of agricultural commodities on CEDA Agri Market Data, storage days and cold storage information from NHB storage manual.

6.4 Impact of logistic infrastructure of states during COVID-19 lockdown

The logistic environment of a state encompasses a few pillars: logistic infrastructure, logistic services, and the regulatory environment, while others, like logistic services, will become dormant during the pandemic. The logistic infrastructure, like roads, cold storage availability, and existing capacity in the states, will play an important role in transporting agricultural commodities during the pandemic. The LEADS Index of a state is a comprehensive measure of the logistic facilities. As evident in Figure 4, the logistic facilities of Uttar Pradesh (3.25) are better than those of West Bengal (3.04).

In this section, I explore the impact of the logistic facilities of the states on the agricultural commodity prices. Ideally, states with better logistic infrastructure would benefit more during the pandemic, and the impact of stringency would get attenuated in the presence of higher LEADS. The result of the analysis is provided in Table 9. In Table 9, each column presents agricultural commodities segregated according to their maximum storage days. As one moves from column (1) to column (4) and from column (5) to column (8), the storage days increase from 7 days to 365 days, respectively. The full sample period is presented in columns (1) to (4), and the small window is presented in columns (5) to (8). First, it is evident that the impact of stringency is positive on agricultural commodity prices due to a shrinking of supply.

Second, the interaction term of LEADS and stringency captures the differential effect of logistic facilities on states facing similar stringency. As the interaction term between LEADS and stringency in most cases is negative, it indicates a plausibility that with an improvement of logistics, the supply of the vegetables is higher in markets, leading to a reduction in prices. The attenuation effect of logistics is greater for agricultural commodities with low storage days than with high storage days. The result is robust even in a small window.

Result 4: (i) With an improvement of logistics facilities, the impact of stringency gets attenuated, leading to a dampening of the prices of agricultural commodities; (ii) The attenuation effect is larger for highly perishable commodities than for low-perishable commodities.

6.5 Robustness checks

In this section, I examine the robustness of the base model used in this study, employing three robustness checks. First, I conduct a placebo test where I provide the COVID-19 stringency at normal times. Second,

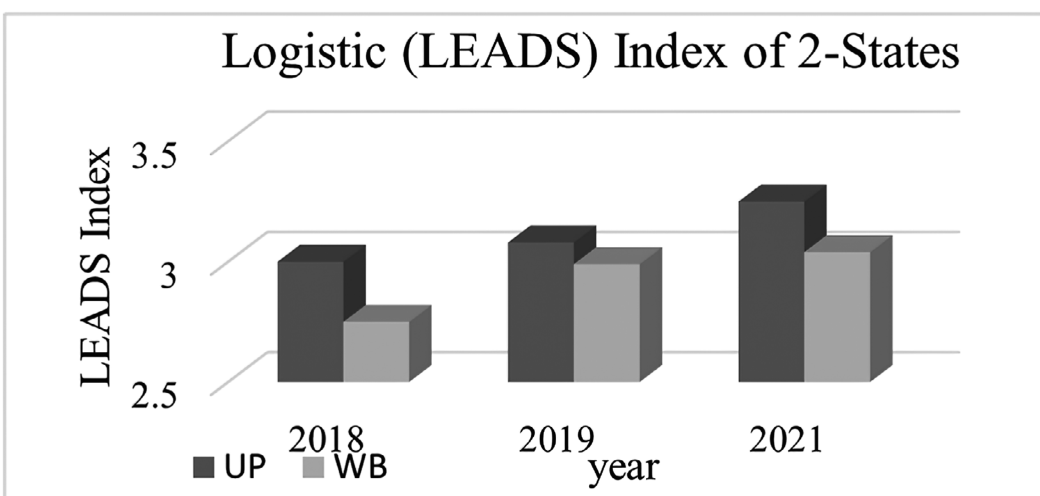

Figure 4. Comparison of logistics facilities of two states over the years. Source: Assorted Reports of LEADS.

Table 9. Effect of logistics facilities (LEADS) on agricultural commodities price during the COVID pandemic.

	Full period (2020–2021)				Smaller window (1 April–31 May 2020)			
	(1) log(price) (7 days)	**(2) log(price) (30 days)**	**(3) log(price) (180 days)**	**(4) log(price) (365 days)**	**(5) log(price) (7 days)**	**(6) log(price) (30 days)**	**(7) log(price) (180 days)**	**(8) log(price) (365 days)**
Lag stringency	0.132^{***}	0.0276^{***}	0.0226^{***}	-0.0167^{***}	0.110^{***}	0.0747^{***}	-0.0303^{**}	0.0425^{***}
	(0.00167)	(0.00324)	(0.0034)	(0.00105)	(0.0086)	(0.0198)	(0.0147)	(0.00363)
LEADS	1.750^{***}	0.405^{***}	-0.943^{***}	0.128^{***}	–	–	–	–
	(0.0373)	(0.0882)	(0.091)	(0.0349)	–	–	–	–
LEADS × Lag stringency	-0.0428^{***}	-0.00872^{***}	-0.00716^{***}	0.00531^{***}	-0.0360^{***}	-0.0242^{***}	0.0100^{**}	-0.0138^{***}
	(0.000542)	(0.00104)	(0.00109)	(0.00034)	(0.0028)	(0.00644)	(0.00479)	(0.00118)
No. of observations	196 297	47 633	33 532	286 246	18 638	5122	3352	26 564
No. of factors	1	1	1	1	1	1	1	1
Time effect	Y	Y	Y	Y	Y	Y	Y	Y
Commodity × Market fixed effect	Y	Y	Y	Y	Y	Y	Y	Y

The dependent variable is log(Modal prices) of the commodity in the wholesale market (Mandis). The estimates are based on interactive fixed-effect methodology. All regressions include commodity and time fixed effects. The number of factors is chosen by using Ahn and Horenstein (2013) statistics The full sample period is 12 March 2020–31 December 2021, and narrow window is 1 April–31 May 2020, coinciding with Varshney *et al*. (2020). Standard errors are in parentheses. *, **, and *** denote significance at the 10%, 5% and 1% level, respectively. Some observations are lost for incorporating the lag-stringency of 15 days preceding. LEADS index denotes logistic facilities of an individual state. Data source: Author's calculation based on COVID-19 stringency index from OxCGRT and wholesale prices of agricultural commodities on CEDA Agri Market Data, LEADS index from Assorted Logistic Report and storage days from the NHB storage manual.

I test the base result with a two-way fixed effect, and third, I test the base result of the full period with a smaller window.

To avoid the influence of seasonality on our findings presented in Table 4, I conduct a placebo test. The placebo stringency index is constructed for the normal period 2018–2019 by matching the measure of stringency from the COVID-19 period in a particular state on a specific date with those from normal times (on a dod basis). For example, the stringency for the same date in 2018 is matched with that of 2020; similarly, the stringency for 2019 is matched with that of 2021. As discussed in proposition 2, during normal periods, any restriction of movement will cause a decline in prices of commodities with the fewest storage days, or these prices will increase less than those with more storage days. The results are reported in Table 10. In Table 10, columns (1)–(4) represent different storage days arranged in increasing order. As one observes, the impact of placebo stringency on prices during normal periods, although significant, is negligible and increases with the storage days of the commodity. A comparison of Tables 4 and 10 reveals a trend opposite to that observed during the COVID-19 pandemic. A plausible reason for this is that, during normal periods, any form of restriction, like trade restrictions, will impact commodities with fewer (more) storage days more (less). Commodities with more storage days can be preserved for future use, but those with low storage days must be sold quickly as the consumers are quality conscious, leading to less (more) reduction in the prices of commodities with more (less) storage days.

Second, I compare two-way fixed effects with interactive fixed effects. The results of the two-way fixed effect, along with the interactive fixed effect, are reported in Table A7 in the Appendix. The results show that direction and sign are robust, but the magnitude and significance differ in two-way fixed effects. This is because the two-way fixed effect, although a special case of interactive fixed effects, it fails to capture the shock effect on various commodities differently in different markets.

Third, I compare the base result for the full period with those for a smaller window. For the choice of a smaller window, I use the same reference period (1 April–31 May 2020) as Varshney *et al*. (2020), which contains the initial period of lockdown when stringency was extreme. The results are represented in Table 4. In Table 4, columns (1)–(4) present the full period and columns (5)–(8) present the smaller window. Comparing the full period with a smaller period, I observe that the sign and significance are robust for both the smaller and full periods, except for vegetables with storage of 7 days and 365 days. This is intuitive as during the initial phase, the pandemic was severe and so was the stringency. Due to the immense lockdown restrictions, the quantity of arrivals in the market fell during that phase but recovered gradually in the full period, with some relaxation of restrictions.

Table 10. Effect of restrictions on price of agricultural commodities in normal times.

	(1) **7 days**	**(2)** **30 days**	**(3)** **180 days**	**(4)** **365 days**
Log(Placebo Stringency Index)	0	-0.009^{***}	-0.004^{***}	0.001^{***}
	(0)	(0.001)	(0.001)	(0)
No. of observations	235 729	42 750	41 483	348 397
No. of factors	1	1	1	1
Time effect	Y	Y	Y	Y
Commodity × Market effect	Y	Y	Y	Y

The dependent variable is log(Modal prices) of the commodity in the wholesale market (Mandis). The estimates are based on interactive fixed-effect methodology. All regressions include commodity and time-fixed effects. The number of factors is chosen by using Ahn and Horenstein (2013) statistics. The sample period is 2018–2019. Standard errors are in parentheses. *, **, and *** denote significance at the 10%, 5% and 1% level, respectively. Data source: Author's calculation based on COVID-19 stringency index from OxCGRT, wholesale prices of agricultural commodities from CEDA Agri Market Data and storage days from the NHB storage manual.

7. Discussion and conclusion

This paper quantifies the impact of economic lockdown and stringency measures imposed during the COVID-19 pandemic on agricultural commodity prices in the context of a developing country, using data sourced from primary agricultural markets. The study examines the storage capacity of different agricultural products and finds that storage capacity (perishability) is a driving factor for price rise during the pandemic. The price sensitivity is higher for commodities with less storage capacity (perishability) than for those with more storage capacity. This study focuses on markets located in major producing areas that export commodities in normal times. However, the locations that are dependent on imported goods usually, those markets will usually see a drastic rise in prices. Therefore, the results can be considered for locations that are export-dependent, especially for perishable commodities, but cannot be generalized for all markets or all kind of vegetables.

Further, using information on major producing states and districts for the commodities, I find that the state's production capacity and location of the wholesale market are driving factors for price fall. The advantage of being in the major production epicentre has been particularly evident during the pandemic in terms of price reduction by creating a buffer. The warehousing (cold storage), logistics facilities, and market reforms in each state play an important role in attenuating the effect of lockdown restrictions.

My study presents a few major policy implications. First, market reforms like deregulation and delisting of fruits and vegetables, with the cold chain acting as an extension of markets, can benefit the farmers by increasing competition. Second, an improvement in supply chain logistics, like cold storage, mobile cold chains, and e-commerce infrastructure in each state, will benefit both the producers and consumers, especially during such disasters. Third, creating green corridors for fast movement will reduce the loss of perishable commodities, as consumers are quality-conscious. The development of warehousing facilities, especially multipurpose cold storage facilities for only fruits and vegetables, is much needed. An investment in multipurpose cold storage instead of product-specific facilities, which can store different commodities, will develop resilience for such disasters. Fourth, the usage of innovative technology, like protective surface coating, should be adopted to extend the shelf life of vegetables and fruits. This will benefit both producers and consumers.

Acknowledgements

I thank the two anonymous referees and Editor Kevin Chen for their insightful comments.The author is grateful to Debabrata Dutta, Chiwa Koa, Shamim Mondal, Munmi Saikia and Indira Rajaraman for their invaluable inputs, which have enriched this study. The author also appreciates the help of colleagues from the Department of Economics and the staff of the Alliance University, especially Mr. Nagendra.

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Appendix

Table A1. Testing for strong cross-sectional dependence.

	CD (Pesaran, 2021)	CDw (Juodis and Reese, 2021)	CDw+ (Fan *et al.*, 2015)	CD* (Pesaran and Xie, 2021)
log(price)	2204.61	−0.63	5 100 000.00	323.49
	(0.00)	(0.53)	(0.00)	(0.00)
log(stringency)	3817.94	1.70	7 000 000.00	329.69
	(0.00)	(0.09)	(0.00)	(0.00)

P-values are in parentheses. Null hypothesis is weak cross-sectional dependence. Rejecting the null hypothesis indicates strong cross-sectional dependence.

Table A2. Details of commodities with storage days.

Commodity	Storage days considered in study	Maximum storage days as per NHB storage manual
Brinjal	7	About 1 week
Tomato	7	About 1 week
Capsicum	30	Less than a month
Cucumber (Kheera)	30	Less than a month
Cabbage	180	3–6 months
Carrot	365	6–12 months
Onion	365	6–12 months
Potato	365	6–12 months
Ginger	365	6–12 months
Garlic	365	6–12 months

Maximum storage days are stated when commodities are stored under recommended temperature, relative humidity, and controlled atmosphere. In this study, the maximum storage days have been considered when a range has been provided. Data Source: Storage Manual, NHB.

Table A3. Status of adoption of APLMA reforms in two states.

State	ProvisionsaAdopted
Uttar Pradesh	Single point levy of market fee, single unified trading license, E-trading, direct marketing, private markets, administrative reforms, declaring warehouse/cold storages as deemed market. Delisting and deregulation of 46 fruits and vegetables.
West Bengal	Single point levy of market fee, single unified trading license, E-trading, direct marketing, private markets, deregulation of marketing of fruits and vegetables.

Declaring cold storage as a deemed market allows farmers to sell products directly from cold storage instead of bringing them to the mandi. Deregulation of the marketing of fruits and vegetables involves delicensing and allows farmers to sell in places other than mandis. Data sources: NITI Aayog, Kaur (2020) and Varshney *et al*. (2020).

Table A4. Impact of Fear Index on agricultural commodity prices.

Independent variable	**(1) log(price) (7 days)**	**(2) log(price) (30 days)**	**(3) log(price) (180 days)**	**(4) log(price) (365 days)**
log(Fear Index)	0.0948***	0.0435***	0.0415***	0.0169***
	(0.00199)	(0.00447)	(0.00529)	(0.00113)
No. of observations	203 991	50 625	35 870	298 724
No. of factors	1	1	1	1
Time effect	Y	Y	Y	Y
Commodity × Market effect	Y	Y	Y	Y

The dependent variable is log(Modal prices) of the commodity in the wholesale market (Mandis). Fear Index was created as per Salisu and Akani (2020) using new COVID-19 cases in each state. The estimates are based on an interactive fixed-effect methodology. All regressions include commodity and time fixed effects. The number of factors is chosen by using Ahn and Horenstein (2013) statistics. The sample period is 12 March 2020–31 December 2021. Standard errors are in parentheses. *, **, and *** denote significance at the 10%, 5% and 1% level, respectively. Data sources: Author's calculation based on COVID-19 new cases, wholesale prices of agricultural commodities from CEDA Agri Market Data, and storage days from the NHB storage manual.

Table A5. Impact of state production capacity on vegetable commodity price.

(1) Commodities	**Uttar Pradesh**			**West Bengal**	
	(2) Storage days	**(3) Producer/ consumer**	**(4) Impact on average log(Modal price)**	**(5) Producer/ consumer**	**(6) Impact on average log(Modal price)**
Brinjal	7	Consumer (2.45)	−0.23(↓)	Producer (1st, 23.72)	0.47 (↑)
Tomato	7	Consumer (4.44)	0.03(↑)	Consumer (7th, 6.33)	0.48 (↑)
Capsicum	30	Consumer	0.49 (↑)	Producer (1st, 29.61)	1.42 (↑)
Cucumber	30	Consumer (7th, 6.45)	−0.19 (↓)	Producer (1st, 20.32)	0.42 (↑)
Cabbage	180	Producer (8th, 3.63)	−0.01 (↓)	Producer (1st, 24.38)	0.10(↑)
Carrot	365	Producer (4th, 9.37)	−0.57 (↓)	Producer (2nd, 12.32)	0.51(↑)
Garlic	365	Producer (4th, 6.57)	1.23(↑)	Consumer (1.15)	1.39 (↑)
Ginger	365	Consumer (0.19)	0	Producer (5th, 6.09)	1.15(↑)
Onion	365	Consumer (1.63)	0.02(↑)	Consumer (7th,2.77)	0.32(↑)
Potato	365	Producer (1st, 29.65)	−0.44 (↓)	Producer (2nd, 23.51)	−0.29 (↓)

The average of log(Modal price) for the commodity concerned is mentioned along with whether the respective state is listed among the largest five producers of the commodity in India, with their respective rank and percentage of total production in country. Otherwise, the state is considered as consumer of the commodity. The list of major producing states for the vegetable is collected from NHB (2018) and percentage from www.apeda.gov.in). The average fixed effect value is mentioned, an upward (downward) arrow indicates an increasing (decreasing) impact of state on the respective commodity price.

Table A6. Impact of agricultural reforms (cold storage vs deregulation) on agricultural commodities quantity arrival during the COVID pandemic.

Independent variable	**Uttar Pradesh**				**West Bengal**			
	(1) log(quantity) (7 days)	**(2) log(quantity) (30 days)**	**(3) log(quantity) (180 days)**	**(4) log(quantity) (365 days)**	**(5) log(quantity) (7 days)**	**(6) log(quantity) (30 days)**	**(7) log(quantity) (180 days)**	**(8) log(quantity) (365 days)**
All types of cold storage (potato+MPCS)								
Lag stringency	−0.000392**	−0.000361	−0.00184***	−0.000157	−0.00160***	0.00419***	0.000581	−0.00280***
	(0.000198)	(0.000324)	(0.000347)	(0.000198)	(0.000288)	(0.000741)	(0.00044)	(0.000287)
Lag stringency × CS	0.0000105***	−0.0000123***	0.0000114***	0.00000866***	−0.0000103***	−0.000148***	−0.0000373***	0.0000107***
	(0.00000125)	(0.00000364)	(0.00000252)	(0.00000187)	(0.00000307)	(0.0000113)	(0.0000112)	(0.00000251)
Multi-Purpose Cold Storage								
Lag stringency	−0.000547***	−0.000362	−0.00184***	−0.000136	−0.00133***	0.00024	−0.000574	−0.00238***
	(0.000199)	(0.000327)	(0.000352)	(0.000198)	(0.000292)	(0.000675)	(0.000484)	(0.000296)
Lag stringency × CS	0.0000212***	−0.000139***	0.0000132***	0.00000855***	−0.000289***	−0.000740***	0.000172	−0.0000837*
	(0.00000165)	(0.00000465)	(0.00000361)	(0.00000245)	(0.0000493)	(0.0000986)	(0.000184)	(0.0000455)
No. of observations	163 008	41 097	28 386	234 368	33 289	6533	5141	51 878
No. of factors	1	1	1	1	1	1	1	1
Time fixed effects	Y	Y	Y	Y	Y	Y	Y	Y
Commodity × Market fixed effects	Y	Y	Y	Y	Y	Y	Y	Y

The dependent variable is log(Quantity arrival) of the commodity in the wholesale market (Mandis). The estimates are based on interactive fixed-effect methodology. All regressions include commodity and time-fixed effects. The number of factors is chosen by using Ahn and Horenstein (2013) statistics. The sample period is 12 March 2020–31 December 2021. Standard errors are in parentheses. *, **, and *** denote significance at the 10%, 5% and 1% level, respectively. Multi-purpose cold storages are generic in nature, whereas potato cold storage is product-specific. Data sources: Author's calculation based on COVID-19 stringency index from OxCGRT, wholesale prices of agricultural commodities on CEDA Agri Market Data, storage days and cold storage information from the NHB storage manual.

Table A7. Additional robust checks: comparison of interactive and regular fixed effects.

	Full period (2020–2021) interactive fixed effect				**Full period (2020–2021) regular fixed effect**			
	(1) log(price) (7 days)	**(2) log(price) (30 days)**	**(3) log(price) (180 days)**	**(4) log(price) (365 days)**	**(5) log(price) (7 days)**	**(6) log(price) (30 days)**	**(7) log(price) (180 days)**	**(8) log(price) (365 days)**
Lag stringency	0.0350^{***}	0.0252^{**}	0.0435^{***}	-0.0159^{***}	0.0586^{*}	0.00776	0.179^{***}	-0.0366^{*}
	(0.00436)	(0.00782)	(0.00746)	(0.00242)	(0.0297)	(0.0406)	(0.0453)	(0.018)
No. of observations	196 297	47 633	33 532	286 246	196 297	47 633	33 532	286 246
No. of factors	1	1	1	1	–	–	–	–
Time effect	Y	Y	Y	Y	Y	Y	Y	Y
Commodity × Market effect	Y	Y	Y	Y	Y	Y	Y	Y

The dependent variable is log(Modal prices) of the commodity in the wholesale market (Mandis). The estimates are based on an interactive fixed-effect methodology. All regressions include commodity and time fixed effects. The number of factors is chosen by using Ahn and Horenstein (2013) statistics. The full sample period is 12 March 2020–31 December 2021. Standard errors are in parentheses, robust standard errors have been considered for regular fixed effect *, **, and *** denote significance at the 10%, 5% and 1% level, respectively. Some observations are lost for incorporating the lag-stringency of 15 days preceding. Data sources: Author's calculation based on COVID-19 stringency index from OxCGRT and wholesale prices of agricultural commodities on CEDA Agri Market Data and storage days from the NHB storage manual.

A1. Scientific model appendix

$D_t(P_t,R_t) = S_t(P_t,R_t)$,

where $R_t = R_o$ during normal times,

$= R_o + C_t$ during COVID-19. (1)

Taking the total derivative on both sides of Eq. (1) yields

$$\frac{\partial D_t}{\partial P_t}\mathrm{d}P_t + \frac{\partial D_t}{\partial R_t}\mathrm{d}R_t = \frac{\partial S_t}{\partial P_t}\mathrm{d}P_t + \frac{\partial S_t}{\partial R_t}\mathrm{d}R_t, \quad (2)$$

Rearranging Eq. (2), we have

$$\frac{\mathrm{d}P_t}{\mathrm{d}R_t} = \frac{\dfrac{\partial S_t}{\partial R_t} - \dfrac{\partial D_t}{\partial R_t}}{\dfrac{\partial D_t}{\partial P_t} - \dfrac{\partial S_t}{\partial P_t}}, \quad (3)$$

Using market equilibrium condition, $D_t = S_t$, Eq. (3) becomes

$$\frac{\mathrm{d}P_t R_t}{\mathrm{d}R_t P_t} = \frac{\frac{\partial S_t}{\partial R_t}\frac{R_t}{S_t} - \frac{\partial D_t}{\partial R_t}\frac{R_t}{D_t}}{\frac{\partial D_t}{\partial P_t}\frac{P_t}{D_t} - \frac{\partial S_t}{\partial P_t}\frac{P_t}{S_t}},$$

which can be rewritten as

$$\varepsilon_{P,R} = \frac{\varepsilon_{S,R} - \varepsilon_{D,R}}{\varepsilon_{D,P} - \varepsilon_{S,P}}$$