Department of Economics

DISCUSSION PAPER SERIES IN ECONOMICS

DP No. 28

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May 2020

Kanika Mahajan
Shekhar Tomar

https://www.ashoka.edu.in/ecodp

Here Today, Gone Tomorrow: COVID-19 and Supply Chain Disruptions *

Kanika Mahajan † Shekhar Tomar‡

Ashoka University ISB

Update: June 8, 2020

Abstract

This paper looks at the disruption in food supply chains due to COVID-19 induced economic shutdown in India. We use a novel dataset from one of the largest online grocery retailers to look at the impact on product stock-outs and prices. We find that product availability falls by 10 percent for vegetables, fruits, and edible oils, while there is a minimal impact on their prices. On the farm-gate side, it is matched by a 20 percent fall in quantity arrivals of vegetables and fruits. We then show that supply chain disruption is the main driver behind this fall. We compute the distance to production zones from our retail centers and find that the fall in product availability and quantity arrivals is larger for items that are cultivated or manufactured farther from the retail centers. Our results show that long-distance food supply chains have been hit the hardest during the current pandemic with welfare consequences for urban consumers and farmers.

JEL Codes: E20, E30, Q11, L81, Q54

Keywords: COVID-19, Supply chain disruptions, Food, Prices, Online data

*We thank Viral Acharya, Shoumitro Chatterjee, Amartya Lahiri, Abhinav Narayanan, Bharat Ramaswami, Zahra Siddique and Madhu Viswanathan for their comments and feedback. We thank Sharad Hotha, Sanchit Goel and Akash Sood for excellent research assistance. Shekhar Tomar also acknowledges the support from the Centre for Analytical Finance (CAF) in the collection of online data.

†Assistant Professor, Ashoka University. Email: kanika.mahajan@ashoka.edu.in

‡Assistant Professor, Indian School of Business, Hyderabad. Email: shekhar_tomar@isb.edu

1 Introduction

The COVID-19 pandemic has emerged as a significant health risk, and countries around the world have responded with partial shutdowns of their economies to slow the pace of infections. These measures have reportedly led to massive disruptions in the global and domestic supply chains. The restoration of supply chains to their pre-lockdown levels will require prompt policy intervention. In this context, the vulnerability of food supply chains to disruptions needs special policy focus. Any disruption in food availability has adverse health consequences through a reduction in diet diversity and nutritional intake, which can further increase people's susceptibility to infection (Short *et al.* (2018) and Anríquez *et al.* (2013)).[1] Reduced food availability with unmet demand could also result in price spikes (FAO (2020)). Both have important welfare implications, especially for poor households.

Consequently, an essential question for public policy is to measure the level of these disruptions and where they are more likely to occur (Inoue & Todo (2020) and Barrot *et al.* (2020)). Stringent lockdowns or a protracted epidemic can affect food supply in many ways. First, it can directly impact the transportation of food products. Second, it can impact the availability of packaged goods from food-processing industries as manufacturing activity slows down due to social distancing guidelines and labor shortages. Third, it can reduce future agricultural production by reducing current incomes.[2] These issues are more salient in a developing country context where food supply chains are long and fragile (Reardon *et al.* (2020) and Aggarwal (2018)), and millions live under poverty. Given this background, we quantify the level of disruption in the food supply chains in India due to COVID-19 induced lockdown.[3]

We do this exercise by using data on food availability at the retail and the farm-gate

[1]One of the critical lessons from the Spanish Flue of 1918 is that populations with severe malnutrition are more vulnerable to disease. For instance, Short *et al.* (2018) find that influenza-related mortality was higher in regions of India having greater malnutrition.

[2]Evidence from Ebola epidemic in Africa shows that restrictions on movements can lead to disruptions in food supply chains and eventually reduce production, and adversely affect food security (FAO (2020)).

[3]In 2018, India ranked 103 among 119 countries in the Global Hunger Index (GHI). Around 270 million people were living living under poverty in India in 2011-12.

level. Among all countries, India implemented one of the most stringent lockdowns to contain COVID-19 which could have put a strain on its supply chains.[4] The first nationwide lockdown was announced on March 24, 2020, and lasted until April 14, 2020. The first lockdown was unanticipated, both in terms of timing and duration. It curtailed all economic activities, including transportation of goods, except those deemed essential like food and medical supplies. The reduction in freight services combined with the restrictions on inter-state transportation could have disrupted the food supply chains, with a larger impact on products that are procured from far. We test this hypothesis by combining the food availability data with distance to production zones from the retail centers.

On the retail side, our data on product availability and prices comes from one of the largest online grocery retailers in India. The data is scraped daily and provides information on product stock-outs and sale price for in-stock products.[5] Overall, we track 789 products across three cities. We evaluate the impact across four product categories, vegetables and fruits, i.e., perishables, and edible oils, cereals, and pulses, i.e., non-perishables. We employ an event study framework to study the change in product availability and prices, using data for approximately 20 days before and after the first lockdown, which came into effect on March 25, 2020 (within 4 hours of the announcement). An event study framework can be used to obtain consistent estimates in this case since the exact date, severity, and geographic coverage of the lockdown were unknown. Additionally, we observe availability and prices at the product level, which allows us to control for time-invariant product characteristics.[6] On the farm-gate side, we use data on daily quantity arrivals of commodities (only vegetables and fruits) in the primary agricultural markets called *Mandis* to conduct a similar exercise.

We find that the online product availability of vegetables and fruits falls by 8 percent

[4]The total COVID-19 cases in India were less than 500 when it imposed the first lockdown.

[5]This data is being collected on an ongoing basis by the author, Shekhar Tomar, and hence pre-dates the spread of COVID-19.

[6]We use precise product level information, both before and after the lockdown, which allows a more uniform comparison. Such a comparison is not possible with standard datasets collected by government agencies. Department of Consumer Affairs, India collects data on daily retail and wholesale prices. However, it does not report product level information.

while it falls by 14 percent for edible oils. The impact on cereals and pulses is less pronounced. Since we capture the fall in product availability on the extensive margin, these results are likely to be a lower-bound on the total fall in availability. This is supported by the results based on *Mandi* data, where the quantity arrivals for vegetables and fruits fall by 20 percent for these cities.[7] At the same time, there is minimal change in online prices for all categories. Online prices are easy to monitor, and Indian government had strict guidelines against price gouging during the lockdown, which can explain the inaction on online prices. Our results are similar to Gagnon & Lopez-Salido (2020) and Cabral & Xu (2020), who also see minimal change in prices during such events for existing sellers. They argue that monitoring and fairness concerns can drive pricing decisions. These results lead us to the next question, why do we see a fall in the availability of products or increased stock-outs? Is it driven by a fall in supply or change in demand or both?

First, as a direct test of the supply chain disruption, we examine if the fall in availability is more pronounced for products whose production zone is farther spatially. There were media reports on a collapse in daily truck movement during the lockdown, as the state governments implemented strong border controls.[8] We thus hypothesize that transportation bottlenecks are likely to be larger for long-distance freight. To test this, we supplement our retail and farm-gate data with distance to production from each retail center. For edible oils, we use the exact distance between the closest manufacturing plant for each edible oil product-city pair. For vegetables and fruits, we construct an inverse distance index since their production is geographically dispersed across the country. In both cases, the fall in availability is more for products produced farther from the retail centers. In fact, in the case of *Mandis*, the entire fall in quantity arrivals is driven by commodities coming from far. These findings suggest that distance of retail center to production zone can be critical for food availability during a pandemic.

[7] There were many media reports on reduction in arrivals in primary agricultural markets in India. Source: The Wire.

[8] State governments closed down inter-state borders and thoroughly inspected vehicle movement during the first lockdown. Report Times of India.

Next, we look at the demand side. Since online grocery platforms in India cater to middle-upper income households, it is unlikely that their incomes were hit in the immediate aftermath of the lockdown. So the retailer reducing product availability due to lower demand is unlikely. The other potential demand channel leading to stock-outs could be panic buying by the customers. Again, this is unlikely, as the lockdown was announced on the evening of March 24 and came into force within 4-hours. Also, unlike brick and mortar shops, panic buying on online portals is less likely due to delivery constraints.[9] Nevertheless, we test for panic buying by exploiting the heterogeneity between products based on the pre-lockdown level listing on the website and perishability and show that it does not drive the observed fall in availability.

Lastly, we test for persistence in our results. We find that the availability of non-perishables bounces back after the end of the first lockdown, while the availability of perishables continues to remain low in the online data. The farm gate quantity arrivals of the perishables also continue to remain lower than their pre-lockdown levels. This again points to supply chain disruptions, which are likely to be larger for perishables since they are at a higher risk of spoilage than non-perishables, due to below normal operation of freight services.

We make several contributions to the literature. First and most generally, our work is closest to the studies that look at the impact of natural disasters like earthquakes, hurricanes and snowstorms (Cavallo *et al.* (2014), Heinen *et al.* (2019) and Gagnon & Lopez-Salido (2020)) on product availability and prices.[10] However, there are two key differences between COVID-19 induced lockdowns and such disasters. Most disasters are local and can have a heterogeneous impact on demand, based on location. They may or may not cause supply

[9] Additionally, e-commerce deliveries during the lockdown were allowed only through personnel having curfew passes, which took a few days to arrive post the first lockdown. See: Indian Express Report

[10] Cavallo *et al.* (2014) examine the effects of earthquakes in Chile and Japan on product availability and prices using online data. Heinen *et al.* (2019) evaluate the impact of hurricanes and floods in the Caribbean using monthly Consumer Price Index (CPI) data while Gagnon & Lopez-Salido (2020) use scanner data to study the impact of natural disasters in the US. Bellemare (2015) uses natural disasters to generate exogenous shifts in food prices to study the impact of food prices on social unrest.

chain disruption depending on the extent of the area affected by the shock. Also, for disasters like hurricanes and snowstorms, their occurrence and the resultant length of disruption can be predicted based on past experiences, leading to large anticipatory effects. Thus, the effect of lockdowns due to COVID-19 on product availability and prices can be different. In a recent paper, Cabral & Xu (2020) look at price gouging in China for medical supplies like masks and sanitizers. Our work directly contributes to this nascent literature that evaluates the effect of COVID-19 on product supply and prices.

Second, we study this question by using online retail data in conjunction with farm-gate arrivals. Thus, we combine multiple data sources in our analyses. Online retail data collection has been gaining traction over time for analyzing inflation trends (Cavallo & Rigobon (2016) and Cavallo (2018)). Previously, Cavallo *et al.* (2014) have used it to study the impact of earthquakes in Chile and Japan. They find a reduction in product availability but relatively stable prices, similar to what we find for India. In this context, we show how online data can be useful for policymakers to infer impact on a real-time basis, even in a developing country setting. This is highly relevant as the current pandemic has also upended the existing data collection systems in the developing countries which mostly rely on physical data collection. For instance, the National Statistical Office (NSO) in India deferred the release of inflation numbers for April 2020, as the lockdown affected the official price collection exercise.[11] Lastly, our work is connected to the literature that looks at how supply chain disruptions propagate. Carvalho *et al.* (2016) provide evidence for the role of input-output linkages in supply chain disruptions after the Great East Japan earthquake using firm-level data. We extend this work by highlighting the importance of spatial inter-connections and showing how the distance between production and final point of retail sale can dictate the impact on supply chains.

Our findings have important policy implications. We demonstrate that the supply chains for perishables are the most vulnerable to the current lockdowns. These have important

[11] To study the level of disruption in economic activity due to COVID-19, there are efforts to collect novel datasets with high frequency (Chetty *et al.* (2020)) even in advanced economies.

welfare consequences for consumers and producers. While product availability falls for urban consumers, it leads to income losses for farmers. Moreover, this impact on farmers is more pronounced for those located farther from retail centers. Our results suggest that removal of barriers to inter-state trade in food[12] and monitoring of long-distance freight will aid in post-lockdown economic recovery. The rest of the paper is organized as follows. We describe the context in Section 2 and the data in Section 3. The empirical strategy is presented in Section 4. The main findings are discussed in Section 5, while Section 6 provides robustness checks. Section 7 gathers concluding remarks.

2 Background

The first lockdown in India was announced on March 24, 2020 and came into force from the midnight of March 25, 2020, until April 14, 2020. The lockdown was further extended multiple times until May 31, 2020, with staggered relaxations post-April 20, 2020. While the later lockdowns were anticipated, the geographical coverage of the first lockdown as well as the timing came as a surprise and was unanticipated. India closed down most economic activities across all regions at the same time, while the COVID-19 cases were present only in a few areas. In fact, the number of confirmed COVID-19 cases was around 500 among India's 1.3 billion population, when the first lockdown was implemented.

The lockdown in India was also one of the most stringent. Figure 1 compares the mean stringency of economic lockdown and COVID-19 infections across countries, based on the data from OxCGRT (Hale *et al.* (2020)). It shows that the mean stringency enforced by India was one of the highest relative to its number of COVID-19 cases (high mean stringency index implies more severe lockdown).[13] India gets a high value on the stringency index because it curtailed most economic activities, except those deemed essential like food and medicine.

[12] The government of India recently passed an ordinance to allow free trade in agricultural commodities, allowing farmers to sell their crops to anyone. Report: The Print.

[13] Balajee *et al.* (2020) show that India's stringency measures were the harshest for its given number of COVID-19 cases in the early phase of lockdown.

The state governments also enforced border controls, which led to restricted movement of goods. The decline in overall freight services could have impacted even the transport of essential goods.

In such a situation, the lack of adequate warehousing facilities in India would have worsened the food supply situation, especially for perishables. According to the Central Institute of Post-Harvest Engineering and Technology (CIPHET), the inadequacy of warehousing facilities in India leads to an annual wastage of 16% in vegetables' and fruits' produce value.[14] The food supply chains in India are long as they operate along the rural-urban geography. These are dominated by private players since 95% of all purchased food is sold by the private sector (Reardon & Minten (2011)). Inadequate warehousing is then likely to lead to greater spoilage if supplies fail to reach the urban markets.

Lastly, we discuss the role of online market in India. The landscape of food supply chains has been undergoing a rapid change in India, with an increase in modern retail sales (Reardon & Minten (2011)). The share of online grocery retail in India has also been increasing at a fast pace. While it constitutes a small proportion of the total urban and rural grocery sales market in India, it has witnessed high growth over the recent years (106% growth rate in 2019-20).[15] Its share is also likely to be much higher for the cities in our study. Additionally, given similar intermediate feeder supply chains, the online and the offline markets are interlinked. Past data shows that prices in offline and online data co-move and the latter can be used to track inflation (Figure A.1).[16] Thus, reduction in supplies is likely to hit both the online and the offline retailers. The effect on online retailers can be smaller due to greater resilience in their supply chains. Hence any evidence of disruption in online data points at a bigger crises in the retail sector.

[14]India has a cold storage capacity of 35 MT (Ministry of Food Processing Industries) across 7600 cold storage facilities, but 75% of storage is for potatoes. Also, most cold storage facilities are usually built in the regions where these crops are cultivated (e.g., Uttar Pradesh for potato and Maharashtra for onions have some of the largest capacities in these crops). Source: CIPHET.

[15]See: RedSeer report.

[16]Banerjee *et al.* (2018) use it to predict the state-level food inflation using data from one city.

3 Data

We collect *online data* on product availability and prices from one of the biggest online grocery retailers in India. This online grocery delivery firm holds 70% of the market share. It is important to note that unlike big retailers, like Amazon, which sells all types of products and mainly provides a platform to small retailers, this retailer specializes in grocery delivery and has its own supply chain, akin to big brick and mortar stores. We use daily data on products available for sale from March 1, 2020- April 13, 2020, which captures information on the product name, sale price, and discount offered, for three cities- Delhi, Chennai, and Kolkata.[17] We include four categories of food products in our analyses: vegetables and fruits, edible oils, cereals, and pulses. These four categories together comprise 25% value of the urban consumer basket and 65% value of the total food basket in urban India.[18]

Within the category of vegetables and fruits, we restrict our analyses to 22 major commodities. Each of these commodities contributes at least 0.1% value of consumer basket and together constitute 85% of the vegetables and fruits basket in India.[19] In the online data, multiple products can lie within a commodity, e.g., *cabbage* may be of two types - green cabbage and red cabbage. In our analyses, green and red cabbage will be products that are part of the commodity named *cabbage*. Most commodities have one to seven products (Figure C.1 gives frequency distribution). Within the categories of edible oils, cereals, and pulses, we use all available products. Table 1, Panel (a) shows the mean daily product availability (column (2)) and total products (column (6)) for each product category during the entire period. Table 1, Panel (b), reports the mean product availability in the period before and after the lockdown. It shows that the mean availability for vegetables and fruits and edible

[17] We drop the day just after Holi (March 11) since the wholesale markets were shut on Holi affecting retail sales on the next day and the day of first public curfew in India (March 22). Thus, the number of days in the pre-lockdown period in the data is 22. The number of days in the post lockdown period is 18, after excluding March 29 and March 30, the dates for which data could not be scraped.

[18] These proportions are based on the commodity weights in the Consumer Price Index for India (2013).

[19] Figure C.1 shows the product distribution for the 18 commodities (out of the 22 commodities) present in the online data. Chilies, lemon, ginger, and garlic also contribute more than 0.1% of the CPI basket but are dropped from our analyses due to insufficient online availability in the pre-lockdown period.

oils falls post the lockdown but not for cereals and pulses.

In addition to the online retail data, we also use data on commodity quantity arrivals for vegetables and fruits in the primary agricultural markets, called *Mandis*.[20] In India, *Mandis* are the markets where farmers sell their produce to the intermediaries, and can be used to gauge farm-gate arrivals. Given the nature of the products sold in the *Mandis*, our analysis is restricted to fruits and vegetables. We use daily data on quantity arrivals at the commodity level in the *Mandis* from March 1-April 13, 2020. This is done for two of the three cities included in our main analyses - Delhi and Kolkata - since the data for the third city, Chennai has not been updated for recent months. The data is aggregated across all *Mandis* in each city. There are five primary *Mandis* in Delhi and three in Kolkata. For comparability, we keep the same set of 22 commodities as in our main analyses using the online retail data.[21] In the case of prices, *Mandi* data is available only for Kolkata and that too for a limited number of commodities.

Unlike the online data, we do not observe the exact product within a commodity in *Mandi* data. Hence, our analysis is restricted at the commodity level. Table 1, Panel (c), reports the mean inverse hyperbolic sine transformation of quantity arrivals[22] in the period before and after the lockdown. This transformation is defined at zero and the difference between the two means gives the percentage change in arrival quantities during the first lockdown in comparison to the pre-lockdown period. The difference between the two means shows that the quantity arrivals for vegetables and fruits falls by 22% post the lockdown.

[20] *Mandis* are also referred as Agricultural Produce Market Committees. See Chatterjee (2019), Tomar & Narayanan (2020) and Banerji & Meenakshi (2004) for details about the organization of agricultural trade in India and the role of *Mandis*. The data for quantity arrivals for various commodities is available at `http://agmarknet.dac.gov.in`.

[21] The data includes the 18 commodities in our main analysis and four more - chillies, lemon, ginger and garlic - which were excluded from the online availability analyses due to insufficient observations. We drop the day of Holi (March 10) since the *Mandis* were shut that day and the day of first public curfew in India (March 22). The final set includes 22 commodities whose data was available for 42 days in each city=924 observations.

[22] We use this transformation to account for the possibility of zero arrivals on some dates for certain commodities. The interpretation of the estimates obtained using the inverse hyperbolic sine transformation is the same as those obtained using a natural logarithm transformation of the dependent variable, with the advantage of being defined at zero (Burbidge *et al.* (1988)).

We supplement the above datasets with distance to the manufacturing plant/production zone. We hand-collect the data on the nearest manufacturing plant for different edible oil brands present in each city (we can map 93 percent of the total products under edible oils). We are unable to collect this data for cereals and pulses, as a significant number of products are sold under retailers' own brand name, and the plant information is not available in the public domain. For vegetables and fruits, individual products cannot be mapped to a manufacturing plant. Instead, we use state-wise aggregate horticulture production from the Ministry of Agriculture for the most recent year 2017-18 to construct a production-weighted distance index.[23] Finally, we use Google API to calculate the road distance between our cities and actual plant location, in the case of edible oils, and state capitals, in the case of vegetables and fruits.

4 Empirical Strategy

We use an event study design to evaluate the impact of the first lockdown on online product availability and prices in India. The first shutdown started on March 25 (announced on March 24 at 8:00 pm IST). We restrict our analyses to a small time period around the event and use daily data from March 1, 2020 to April 13, 2020. In our baseline specification, we estimate the impact of the lockdown on online product availability and prices using the following equation:[24]

$$y_{jic,t} = \beta_0 + \beta_1 * Lockdown_t + \delta_{jic} + \delta_{dow,c} + \epsilon_{jic,t} \tag{1}$$

where $y_{jic,t} \in \{\mathrm{D}_{jic,t}, ln(P_{jic,t})\}$ is a dependent variable. $D_{jic,t}$ is a dummy equal to one, if product j of commodity i is available in city c on date t, else it is zero. Similarly, $ln(P_{jic,t})$

[23] Horticultural Statistics at a Glance, 2018. Source: Ministry of Agriculture & Farmers' Welfare

[24] All products which were available for less than ten days in the pre-lockdown period were dropped from the analyses since these are likely to be the ones with larger variance in availability. We check the robustness of all the results to incorporating all products and find that that the conclusions do not change.

is the log price of product j of commodity i in city c on date t. In the case of $D_{jic,t}$, equation 1 represents a linear probability model, whereas it represents a linear regression model for $ln(P_{jic,t})$. Our primary variable of interest is the dummy variable $Lockdown_t$, which is equal to one if India was under COVID-19 induced national lockdown on date t, else it is zero. Thus, $Lockdown_t = 1$ for t after March 24, 2020. We also control for the time-invariant product, commodity, and city heterogeneity through the fixed effect terms δ_{jic}, which captures the average difference in product availability across cities. Differential availability and prices on different days of the week in the three cities are captured through the fixed effects term $\delta_{dow,c}$. The standard errors are clustered at the product level and regressions are weighted to give equal representation to each city.

If the lockdown reduces product availability, β_1 should be negative for $D_{jic,t}$. Here, non-availability indicates that the product went out of stock on that day. In case of log prices, $ln(P_{jic,t})$, a positive β_1 implies that the prices went up during the lockdown period. The above equation cannot provide a reason behind the change in prices. However, it helps gauge the impact on the prices in equilibrium. For the above framework to work and give an unbiased estimate of β_1, we require that the lockdown was unanticipated. While there were media reports on the possibility of an economic shutdown, but the exact date and stringency measures came as a surprise. Furthermore, we include only twenty days after the first lockdown in our analysis as the later announced extensions of the lockdown were anticipated. Restricting our sample to a narrow window also allows us to reduce seasonality concerns.

We estimate equation 1 separately for the four categories of products as they differ on perishability and can witness differential impact due to lockdown. First, non-perishables are more likely to be stockpiled by the retailer as well as consumers. Second, the non-perishables can come back in circulation when the supply chains are partially restored, and products can be delivered, albeit with a delay.

Lastly, we estimate the impact of the lockdown on quantity of commodity arrivals in

Mandis before and after the first national lockdown using a similar specification:

$$Q_{ic,t} = \beta_0 + \beta_1 * Lockdown_t + \delta_{ic} + \delta_{dow,c} + \epsilon_{ic,t} \tag{2}$$

where $Q_{ic,t}$ is the inverse hyperbolic sine transformation (Burbidge *et al.* (1988)) of quantity arrivals (in tonnes) of commodity i in city c on date t. Unlike equation 1, here we control for unobserved heterogeneity at the commodity-city level through the term δ_{ic}. A negative sign on β_1 shows a fall in quantity arrivals of commodities after the lockdown in the primary *Mandis* and is interpreted as a percentage change, given the transformation.

5 Results

In this section, we provide our main set of results on product availability and prices.

5.1 Fall in Average Product Availability in Retail Data

Table 2 shows the estimation results based on equation 1 for online product availability in Panel (a). Each column reports the results separately for each category of products. We find that the probability of product availability for vegetables and fruits (column (1)) post lockdown falls by 0.063, which is around 8% of their average pre-lockdown availability. The columns (2)-(4) report results for the non-perishable product categories. We find that the availability of edible oils falls significantly by 14%. However, cereals and pulses do not show any fall in the overall availability of products. In Section 5, we show that there is a fall in availability of some products within these categories as well, but there is no aggregate impact on availability.

The above results show that the average availability falls sharply for vegetables and fruits and edible oils during the lockdown, but did it lead to an increase in their prices? To estimate the effect of the lockdown on online prices, we estimate Equation 1 with the log price of the product as our dependent variable (for days the product was available). These results are reported in Panel (b) of Table 2. We find that the prices for vegetables and fruits went up very marginally by around 0.6% (column (1)). For edible oils, we find that their prices fell marginally by 0.8%. On the other hand, for cereals and pulses, we find an average increase of 2% in prices.[25] Overall, the online price increase is low and not commensurate with the fall in availability. This evidence is consistent with previous studies that find little impact of disasters on product prices (Gagnon & Lopez-Salido (2020) and Cavallo *et al.* (2014)). In our case, it can happen for two reasons. The online sellers can have reputation concerns. Also, their prices are easily monitored.[26]

The above results raise the question about what led to a fall in the availability of vegetables and fruits and edible oils. Change in average demand over this period is unlikely to kick in for online retailers as they generally cater to the middle to upper-income segments in India. Also, a reduction in demand can result in a lower stocking up of a product by a retailer, but it is less likely to cause a complete stock-out. We now test if supply chain disruptions can explain this observed fall in product availability.

5.2 Supply Chain Disruption: Distance to Production Matters

We hypothesize that supply chain disruptions during the lockdown are likely to be more severe for products that travel long distances to reach the retail markets. It can happen due to increased border control by states as well as a fall in freight services during the lockdown. We test for these disruptions for vegetables and fruits and edible oils by calculating distances from production zones for the former and from the nearest manufacturing unit for the latter. For each edible oil sold in our cities, we find the nearest manufacturing unit for a given product-city combination. We then calculate the road distance (in kilometers) from the

[25] We also estimate the effect of the lockdown on retail prices using the data collected by the Department of Consumer Affairs (DCA). The details of the data and the estimation are available in Appendix B. We find broadly similar results which are reported in Table B.1, except for restricted set of vegetables and fruits (potato, onion, and tomato). Narayanan & Saha (2020) also look at changes in food prices in India during the lockdown using commodity level price data collected by the government agencies. However, they do not look at changes in the availability of goods.

[26] Government of India had directed the states to ensure that retailers do not increase prices of essential commodities during the lockdown (The Economic Times Report).

nearest manufacturing unit to each city.

In the case of edible oils, the dependent variable in the regression is whether a product is available on a particular day. The explanatory variables include an indicator for the lockdown period and its interaction with inverse distance to the nearest manufacturing unit. The results are reported in column (1) of Table 3. The coefficient on the interaction term is negative and significant. It shows that as distance decreases, there is an exponential increase in the availability of a given edible oil product and that there is no fall in availability of edible oils which are manufactured within the city.

We undertake a similar analysis for fruits and vegetables but at the commodity level. To measure how near a city is to the production zone of a commodity, we combine information on state-level production (available for 19 out of 22 commodities) with the road distance for each city from each state of India.[27] We construct a $Near\ Index_{ic}$ for each commodity-city pair. The index is calculated by weighting the inverse road distance of each state capital, s, from city c, by the production contribution of that state in commodity i:

$$Near\ Index_{ic} = \sum_{s=1}^{S} \frac{1}{d_{cs}} Production_{is}$$

where d_{cs} is the distance between city c and state s. $Production_{is}$ is the proportion of production of commodity i from state s, and sums to one across all states.[28] Our measure is similar to the one used by McArthur & McCord (2017) who use an inverse cost-distance measure across countries for capturing access to fertilizers. Finally, we categorize the commodity as having a production center near to the city (*Near Production=1*) if the *Near Index* is above the median value for all commodities in a given city, else it is zero.

Since the information on distance to production zones is available for vegetables and fruits only at the commodity level, we use mean daily product availability for each commodity as

[27] There exists large domestic trade in agricultural commodities in India.

[28] Since our distance measures are within India, we assume that per kilometer cost of transport is the same across cities for each commodity and hence is a scaling factor which can be omitted.

our dependent variable.[29] The explanatory variables include an indicator for the lockdown period and its interaction with the *Near Production* zone indicator. Our identification here comes from a between commodity comparison. The results for this specification are shown in Table 3, column (2). We again find that the mean availability falls during the lockdown, as the coefficient on lockdown is negative. However, the coefficient on the interaction term is positive and significant. It shows that the fall in mean product availability for a commodity is lower (almost by half) if it is produced relatively near the city. The above results show that the products which travel farther were more likely to go out of stock with the online retailer. Next, we test if quantity arrivals for commodities at the farm-gate also witness a similar fall.

5.3 Fall in Quantity Arrivals in *Mandis*

Table 4, column (1) reports the estimation results for the *Mandi* arrivals and shows that the quantity arrivals for vegetables and fruits fall by 20 percent in these cities. As expected, the percentage fall in quantities of arrivals at the farm-gate is larger than the increase in product stock-outs at the retail level. The latter is an extreme event and occurs when zero quantity of a product is available. Thus, the product stock-outs in online retail captures only the extreme disruption in food supply chains.[30]

Next, we estimate if the fall in quantity arrivals at the farm-gate, i.e. *Mandis*, also varies by the distance to their production zones. The results presented in column (2) of Table 4 show that quantity arrivals in *Mandis* fall by 42% post the lockdown for commodities which are produced farther. However, there is no fall in the arrivals for commodities that are produced near the retail centers. The coefficient on the interaction term is positive and significant and nullifies the negative impact due to lockdown on commodities produced

[29] For example, our data has a measure of production of cabbage in each state and not for each product within cabbage. If one out of five types of cabbage is available on a given day, the dependent variable gets a value equal to 0.2.

[30] We also examine the price data for the limited set of commodities in *Mandis* from Kolkata and do not find any increase in farm-gate prices during the first lockdown.

near the cities. The results on distance are again stronger in *Mandi* data as the online data captures the mean availability on the extensive margin, an extreme fall in availability. Overall, our results show that long distance freight disruptions are behind the observed fall in commodity supplies that eventually lead to product stock-outs at the retail level.

6 Robustness

In this section, we present robustness checks for our main results.

6.1 No Pre-trends in Availability and Persistence in Fall

Our main results show that products like vegetables and fruits and edible oils are more likely to go out of stock. However, the lack of cold storage facilities and seasonal availability of certain commodities, more likely for vegetables and fruits, can also lead to a change in product availability over time. Since we restrict our analyses to a narrow time window before and after the lockdown, it partially alleviates this concern. Nevertheless, we estimate the change in the week-wise availability of products taking the week of March 1-7 (W1) as the baseline. Unlike our main specification, we now allow for a longer time series to evaluate if the product availability reverted to its level in the pre-lockdown period.

Figure 2, Panel (a), plots the weekly coefficients for vegetables and fruits using online data. The period between the red and blue lines corresponds to the first lockdown. We find that product availability sharply reduces after the lockdown with no pre-trends before the lockdown. Panel (b) plots the weekly coefficients for vegetables and fruits with *Mandi* data. We again find that the fall begins only post the lockdown. Notably, the fall in *Mandi* arrivals occurs a week before the product stock-outs happen in the online retail market. This clearly hints at disrupted supplies to the city, leading to product stock-outs. Figure 3, Panel (a) for edible oils also shows that the product availability for oils falls only after the lockdown, and there are no pre-existing negative trends as the coefficients for week 2 and week 3 are not statistically different from those in week 1.

We now examine the persistence in the effects on product availability, and arrivals post the first lockdown. Figure 2 (Panel (a)) for online retail shows that the availability of vegetables and fruits does not improve even after week six (end of the first lockdown) and continues to remain at a lower level. For *Mandi* data, in Panel (b), we find that the percentage fall in arrival quantities reduces towards the end of the first lockdown, but the gains are quickly reversed thereafter. These results for perishables show that their supply chains continue to remain disrupted. On the other hand, the availability of edible oils recovers after week six (Figure 3, Panel (a)). A delay in transportation does not lead to spoilage of non-perishables like edible oil, allowing for their revival in the later period. The recovery in the availability of edible oils also shows that a fall in demand alone cannot explain our results. Any fall in demand should have only increased over time as incomes fell due to the lockdown.[31] Next, we rule out that no such trends existed in 2019.

6.2 No Seasonality in Availability

We implement a placebo test using data from 2019 to check for the impact of seasonality on availability. We consider the period from March 1-April 13, 2019, with a placebo lockdown on March 25.[32] The weekly coefficients on vegetables and fruits are plotted in Figure 4. Panel (a) plots the coefficients for the online retail data and panel (b) plots it for the *Mandi* data. It can be clearly seen that the seasonality patterns in 2019 do not mimic the patterns in 2020, for the same period. It thus eliminates seasonality as the main reason behind our results on vegetables and fruits. Similar results follow when we test for seasonality in the availability of edible oils in online data. Panel (b) of Figure 3 plots the coefficients for edible oils availability in 2019, which shows no change in availability over time.

[31] Long term price changes can reflect changes in demand and supply. For example, general demand for food products can reduce as incomes fall due to economic contraction as lockdowns are extended.

[32] For the online retailer, the data for 2019 is only available for the city of Delhi. The data scraping during this period could not be done for Kolkata and Chennai till mid-April 2019 due to structural changes to the retailer's website.

6.3 Heterogeneity by Initial Listing

Lastly, we check for heterogeneity in online availability as a function of the initial listing of products. For vegetables and fruits, we classify a product j within commodity i and city c as *high listing* if its pre-lockdown availability is above the median availability for products within i and city c, and *low listing* otherwise.[33] For edible oils, pulses, and cereals, *high listing* is defined within each category-city pair. The supply chains for *high listing* products are likely to be more resilient as the retailer can have a stronger relationship with the trader or supplier of these products. Also, the retailer is likely to have larger stocks of *high listing* products, especially the non-perishables. In both cases, we expect that the *low listing* products will suffer a larger decline in availability during the lockdown as the retailer finds it difficult to procure them when stocks run dry.[34]

To test this hypothesis, we modify equation 1 to include an interaction term of the lockdown period with the *high listing* product indicator. We report the results for this regression in Table 5. The results show that across different types of goods, perishables and semi-perishables, and non-perishables, the availability of the *high listing* products reduced less during the lockdown. The coefficient on the lockdown indicator is negative, while on the interaction term it is positive and significant for all categories. This table also explains why we saw no impact on aggregate availability of cereals and pulses in Table 2. The greater availability of *high listing* products under cereals and pulses nullified the negative impact on availability due to stock-out of *low listing* products.

However, could the increased availability of *high listing* products reflect an increased demand for *high listing* products as consumers would want to stock them up during the lockdown. The finding that *high listing* products show a lower fall for both perishables/semi-perishables (fruits and vegetables) and non-perishables (oils, cereals, pulses) negates this

[33] For a few commodities, all products were available on all days before the lockdown, in that case all products are coded as *high listing*.

[34] The *low* and *high listing* products have an average 15-20 percent difference in availability in the pre-lockdown period. Our classification thus captures only a relative strength of the retailer-supplier relationship. Even the *low listing* products in our sample have around 70 percent availability in the pre-period.

channel since only non-perishables can be stockpiled.[35] All the above findings then suggest stronger supply chains for *high listing* products, leading to their greater availability during the lockdown.[36]

7 Conclusion

This paper quantifies the impact of economic lockdowns to deal with COVID-19 pandemic on food availability in a developing country setting using data from online retail and primary agricultural markets. We find that online product availability fell by 10 percent on average, but there was little impact on online prices. We show that supply chains during COVID-19 are more fragile for products that travel long distances before reaching their final point of sale. Our work highlights how online data can be used in conjunction with other data-sets for real-time policymaking. This is especially relevant during COVID-19 when the official data collection itself has suffered due to the pandemic. However, since our data pertains to urban households that use online shopping, a few caveats are in order. First, we use data from a large online retailer that can have more resilient supply chains than smaller retailers. Second, we look at online product stock-outs. Therefore, our estimate is likely to be a lower bound on the overall fall in quantity available. This bears out in the agricultural market arrivals data analyses, which shows a larger fall in quantity arrivals. Third, the impact can be very different on rural households. Our results suggest that disrupted supply chains can lead to income loss for farmers, especially those located farther from retail centers, who are unable to bring their products to the cities.

[35] We find no variation in the availability of perishables/semi-perishables post the lockdown along any of the other dimensions like perishability, cpi weight, initial price (Table C.1).

[36] If an increase in the relative demand for *high listing* products was responsible for the change in product availability, then the prices of *high listing* products relative to *low listing* products should have increased more post the lockdown. The results reported in Table C.2 show that for none of the goods there was an increase in relative price for the *high listing* products.

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Table 1: Summary Statistics

Panel (a): Online Product Availability

	Observations (1)	Mean (2)	Std. Dev. (3)	Min (4)	Max (5)	Varieties (6)
Veggies & Fruits	9800	0.81	0.39	0	1	164
Edible Oils	6480	0.69	0.46	0	1	135
Cereals	18320	0.79	0.40	0	1	351
Pulses	8560	0.83	0.37	0	1	139

Panel (b): Online Product Availability Before and After Lockdown

	Pre-Lockdown			Post-Lockdown		
	Observations (1)	Mean (2)	Std. Dev. (3)	Observations (4)	Mean (5)	Std. Dev. (6)
Veggies & Fruits	5390	0.84	0.37	4410	0.78	0.42
Edible Oils	3564	0.72	0.45	2916	0.65	0.48
Cereals	10076	0.79	0.41	8244	0.80	0.40
Pulses	4708	0.81	0.39	3852	0.86	0.35

Panel (c): Mandi log(Arrivals): Before and After Lockdown

	Pre-Lockdown			Post-Lockdown		
	Observations (1)	Mean (2)	Std. Dev. (3)	Observations (4)	Mean (5)	Std. Dev. (6)
Veggies & Fruits	968	3.29	2.81	880	3.07	2.63

Notes: Panel (a) shows the mean product availability by category in our data (all cities) for March 1, 2020-April 13, 2020. Panel (b) shows the mean product availability by category before and after the lockdown in our data (all cities). Panel (c) shows the mean log of arrivals (in tonnes) in *Mandis* across the cities. The log value is arrived at by taking an Inverse Hyperbolic Sine Transformation (IHST) of the actual arrivals which takes care of zeroes and the difference can be interpreted in terms of percentage change (as in a log transformation). The pre-lockdown period is March 1, 2020-March 24, 2020 and post-lockdown period is March 25, 2020-April 13, 2020. The number of days in the pre-lockdown period are 22, after excluding March 11 (day after Holi) and March 22 (national curfew). The number of days in the post lockdown period are 18 for online data, after excluding March 29 and March 30 (the data was not scraped for these two dates) and 20 for *Mandi* data.

Table 2: Impact of Lockdown on Online Product Availability and Price

	Veggies & Fruits (1)	Edible Oils (2)	Cereals (3)	Pulses (4)
Panel (a): Availability				
Lockdown	-0.063***	-0.103***	-0.000	0.039***
	(0.008)	(0.016)	(0.008)	(0.009)
R-sq	0.204	0.228	0.253	0.241
Observations	9800	6480	18320	8560
Panel (b): Prices				
Lockdown	0.006**	-0.008**	0.024***	0.023***
	(0.003)	(0.004)	(0.003)	(0.005)
R-Sq	0.965	0.955	0.980	0.969
Observations	7928	4472	14538	7134
City×Product FE	Y	Y	Y	Y
City×Day of Week FE	Y	Y	Y	Y

Notes: The table gives the impact of lockdown on online product availability and prices. In Panel (a), the dependent variable is whether or not a product is available for a given category in each column. The estimates are based on a LPM model and give the impact of lockdown on probability of product availability. In Panel (b), the dependent variable is log (Price) of a product. The variable *Lockdown* equals one for March 25, 2020-April 13, 2020. All regressions are weighted to give equal representation to each city. Clustered standard errors (at product level) in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Table 3: Impact of Lockdown on Online Product Availability (Heterogeneity by Distance to Production)

	Edible Oils	Veggies & Fruits
	Online Data	Online Data
Dependent variable	*Availability*	*Mean Availability*
	(1)	(2)
Lockdown	-0.109***	-0.082***
	(0.016)	(0.015)
Lockdown × Inverse Distance	0.103**	
	(0.000)	
Lockdown × Near Production		0.040*
		(0.021)
Estimate		-0.041
P-Value		0.008
R-sq	0.232	0.188
Observations	6040	1760
City × Product FE	Y	
City × Day of Week FE	Y	Y
City × Commodity FE		Y

Notes: The dependent variable is whether or not a product is available for edible oils (column 1). The dependent variable is the fraction of products available for sale on a day for a given commodity under vegetables and fruits (column 2). The variable *Lockdown* equals one for March 25, 2020-April 13, 2020. The distance in column (1) is measured in kilometers. The *Near Production* variable is defined in Section 5.2 and is available for 16 out of 18 commodities. Regressions are weighted to give equal representation to each city. Clustered standard errors (at product level) in parentheses for edible oils. Robust standard errors in parentheses for vegetables and fruits since the number of commodities are small (18). *** p<0.01, ** p<0.05, * p<0.1.

Table 4: Impact of Lockdown on Commodity Arrivals in *Mandis* (Vegetables and Fruits)

	Quantity Arrivals	
	(1)	(2)
Lockdown	-0.201***	-0.421***
	(0.055)	(0.088)
Lockdown × Near Production		0.418***
		(0.122)
R-sq	0.819	0.803
Observations	1848	1596
Estimate		-0.003
P-Value		0.972
City×Commodity FE	Y	Y
City×Day of Week FE	Y	Y

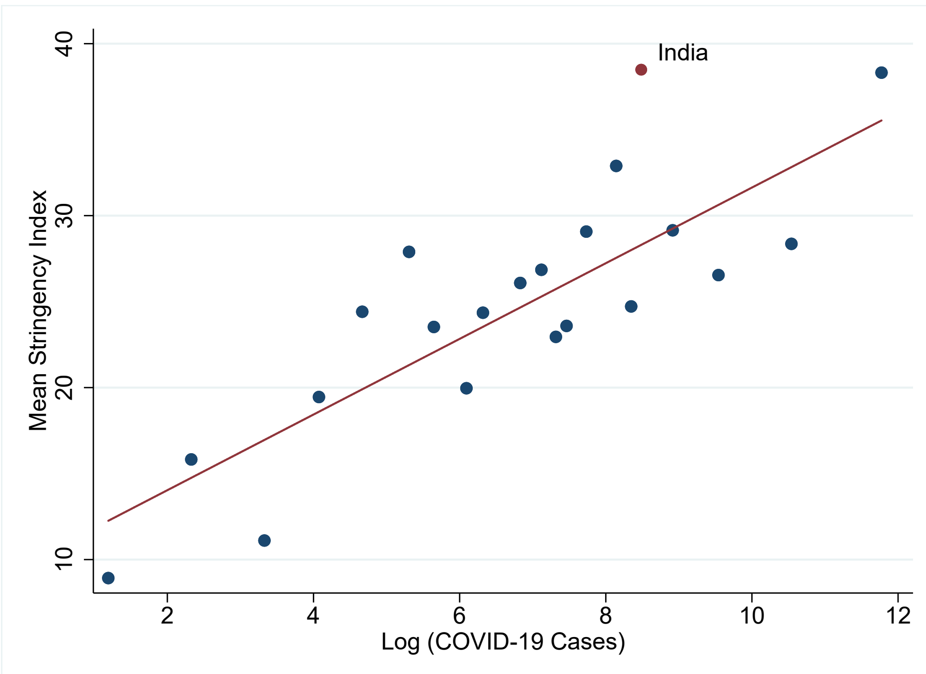
Notes: The dependent variable is an inverse hyperbolic sine transformation of quantity arrivals (in tonnes) on a day for a given commodity across all *Mandis* in a city. The variable *Lockdown* equals one for March 25, 2020-April 13, 2020. The *Near Production* variable is defined in Section 5.2 and is available for 19 out of 22 commodities. *Mandi* arrivals is available only for two cities (Delhi and Kolkata) since data for Chennai was unavailable for this period. In *Mandi* data each city has equal observations, since each commodity is observed for each city, hence the results are unweighted. Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table 5: Impact of Lockdown on Online Product Availability (Heterogeneity by Initial Listing)

	Veggies & Fruits (1)	Edible Oils (2)	Cereals (3)	Pulses (4)
Lockdown	-0.112***	-0.189***	-0.062***	-0.000
	(0.011)	(0.025)	(0.012)	(0.016)
Lockdown×High Listing	0.106***	0.175***	0.141***	0.074***
	(0.014)	(0.033)	(0.013)	(0.017)
Estimate	-0.006	-0.015	0.079	0.074
P-Value	0.469	0.482	0.000	0.000
R-sq	0.207	0.237	0.260	0.243
Observations	9640	6480	18320	8560
Mean Availability (Low-Listing)	0.756	0.638	0.697	0.695
Mean Availability (High-Listing)	0.937	0.813	0.912	0.917
City×Product FE	Y	Y	Y	Y
City×Day of Week FE	Y	Y	Y	Y

Notes: The dependent variable is whether or not a product is available on a day. For vegetables and fruits, *High listing* refers to a higher than median percentage days availability in the pre-lockdown period for a product within a given commodity-city pair. A few commodities having only single products in a city are dropped from the analyses leading to smaller number of observations than the base specification. For edible oils, cereals and pulses, *High listing* refers to a higher than median percentage days availability in the pre-lockdown period for a product within a given category-city pair. The variable *Lockdown* equals one for March 25, 2020-April 13, 2020. The regressions are weighted to give equal representation to each city. Clustered standard errors (at product level) in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

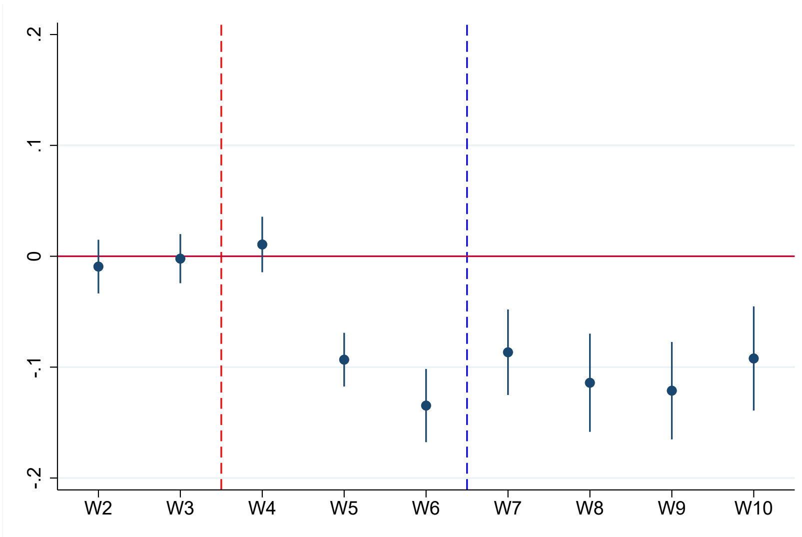
Figure 1: Mean Stringency vs Log (COVID-19 Cases)



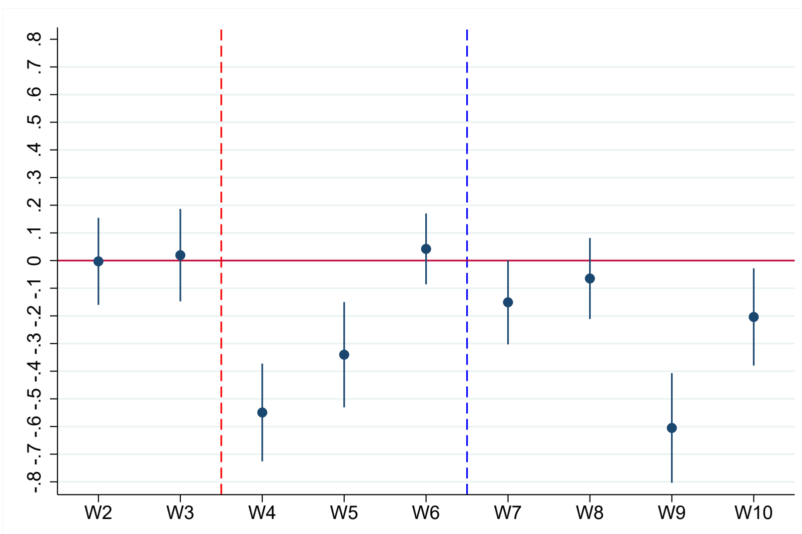
Notes: The figure gives bin-scatter based on data till April 16, 2020. The x-axis is based on log (COVID-19 Cases), and the y-axis corresponds to Mean Stringency Index for 106 countries. The figure shows India as an outlier as it's mean stringency is much higher relative to countries with a similar number of confirmed cases. Data Source: OxCGRT.

Figure 2: Pre-Trends and Persistence in Vegetables and Fruits (2020)

(a) Product Availability in Online data



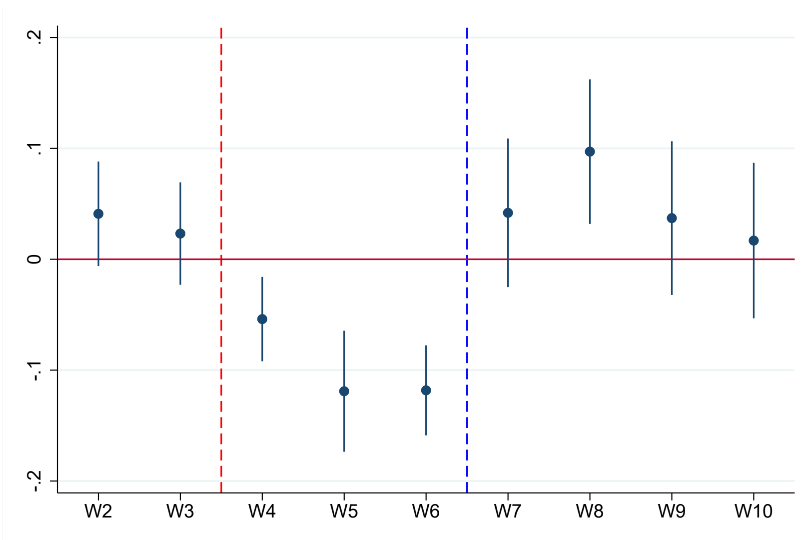
(b) Quantity Arrivals in *Mandis*



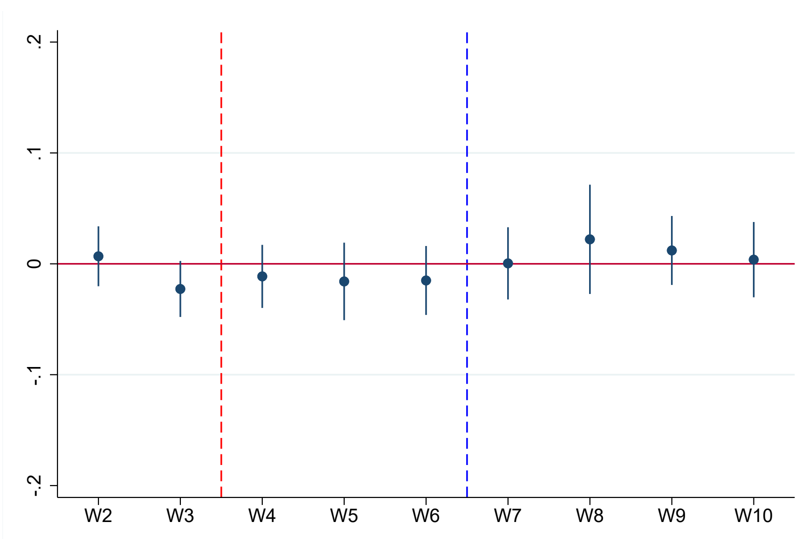
Notes: The figures plot the weekly coefficients and their 95% confidence intervals. In Panel (a), the dependent variable is whether or not the product is available on a day on the website. In Panel (b), the dependent variable is an inverse hyperbolic sine transformation of quantity arrivals in *Mandis* (in tonnes) for a commodity. The red (blue) dashed line is the week of the first lockdown (end of first lockdown). Sundays are removed from the weekly analyses since product availability shows large fluctuations on Sundays due to *Mandi* closures. W1 = March 1-7, W2 = March 8-14, W3 = March 15-21, W4 = March 22-28, W5=March 29-April 4, W6=April 5-11, W7=April 12-18, W8=April 19-25, W9=April 26- May 2, W10=May 3-10. The regressions are weighted to give equal representation to each city and 95% confidence intervals are plotted using clustered standard errors (at product level) for online data. 95% confidence intervals are plotted using robust standard errors for *Mandi* data.

Figure 3: Persistence and Seasonality for Edible Oils

(a) Persistence: Edible Oils (2020)



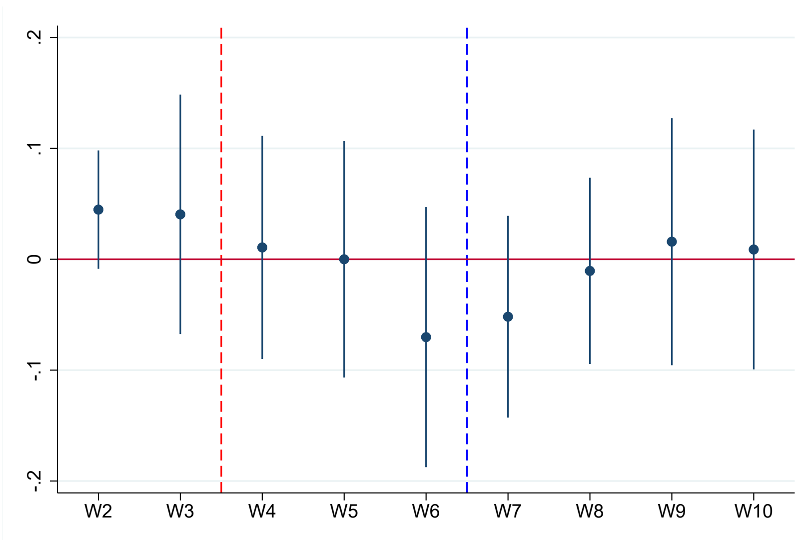
(b) Seasonality: Edible Oils (2019)



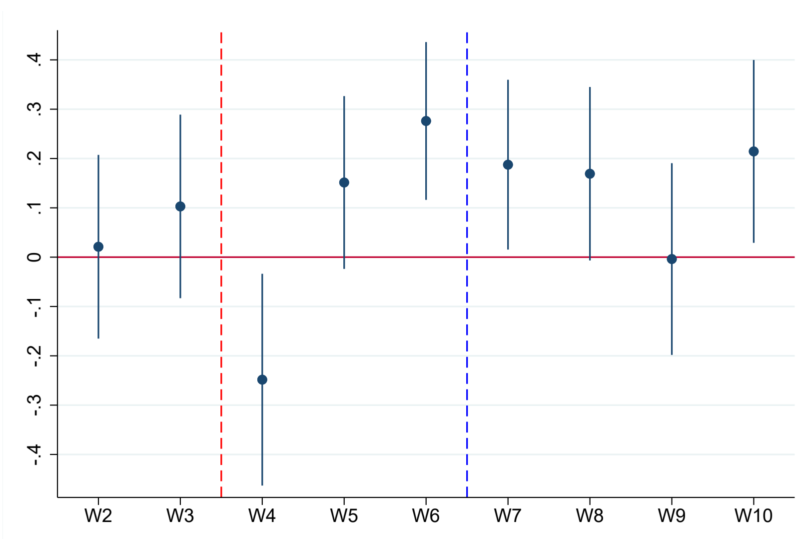
Notes: The figures plot the weekly coefficients and their 95% confidence intervals. In both panels, the dependent variable is whether or not the product is available on a day on the website.. The above graphs plot the weekly effects for the year 2020 (Panel (a)) and the year 2019 (Panel (b)) using the same set of dates (March 1-May 10). The red (blue) dashed line is the week of the first lockdown (end of first lockdown). We draw red and blue line corresponding to the same weeks in 2019, in Panel (b). Sundays are removed from the weekly analyses since product availability shows large fluctuations on Sundays due to Mandi closures. W1 = March 1-7, W2 = March 8-14, W3 = March 15-21, W4 = March 22-28, W5=March 29-April 4, W6=April 5-11, W7=April 12-18, W8=April 19-25, W9=April 26- May 2, W10=May 3-10. The regressions are weighted to give equal representation to each city and 95% confidence intervals are plotted using clustered standard errors (at product level) for online data. In Panel (a) data is available for all three cities, while in Panel (b), it comes from Delhi. Clustered standard errors (at product level).

Figure 4: Seasonality in Vegetables and Fruits (2019)

(a) Product Availability in Online data



(b) Quantity Arrivals in *Mandis*



Notes: The figures plot the weekly coefficients and their 95% confidence intervals. In Panel (a), the dependent variable is whether or not a product is available on a day in Delhi. In Panel (b), the dependent variable is an inverse hyperbolic sine transformation of quantity arrivals in *Mandis* (in tonnes) for a commodity. The above graphs plot the weekly effects for the year 2019 using the same set of dates as that in our main analyses but for the year 2019. The red line is the week in 2019 corresponding to the first lockdown week in 2020. The blue dashed line is the week in 2019 corresponding to when the first lockdown ends in 2020. Sundays are removed from the weekly analyses since product availability shows large fluctuations on Sundays due to Mandi closures. W1 = March 1-7, W2 = March 8-14, W3 = March 15-21, W4 = March 22-28, W5=March 29-April 4, W6=April 5-11, W7=April 12-18, W8=April 19-25, W9=April 26- May 2, W10=May 3-10. The regressions are weighted to give equal representation to each city and 95% confidence intervals are plotted using clustered standard errors (at product level) for online data. 95% confidence intervals are plotted using robust standard errors for *Mandi* data.

Online Appendix

A Online Data

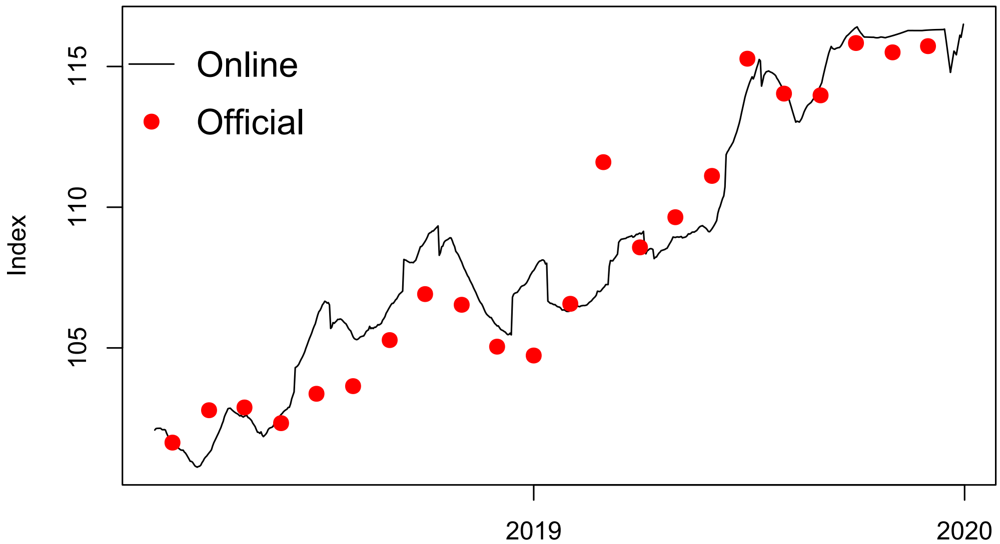
In this section, we show that our scraped online prices capture the general price trends in urban India very well. We construct an online price index using the official weight of commodities in the Consumer Price Index (CPI) basket. This is shown in Figure A.1.[1] The index covers forty-two percent of the urban CPI basket (thirty-six percent food and six percent fuel). The index uses the same weights as those in the CPI basket to arrive at the final index price. In Figure A.1, the online index is reported from January 1, 2018 - December 31, 2019 by black line. The red dots correspond to the official urban price index value reported by the Ministry of Consumer Affairs.[2] We can see that the online price index tracks the urban prices in India well. Furthermore, it is also able to track the changes in the direction of prices at the peaks and troughs of the cycle. Overall, it shows that the online market is not disconnected from the offline retail market for the food commodities used in our paper.

We also report the price stickiness for the set of products used in our main analysis in Table A.1. The prices are least sticky for fruits and vegetables and change on an average every 9.1 days. Also, when the prices change, the absolute size of median change is around 14.2 percent. It goes in line with high volatility in food price inflation in India. The other non-perishable products are more sticky and take longer to change and the median absolute size of change is also lower. The stickiness for food products is lower and has been reported in earlier work by Cavallo (2018).

[1]The price index construction is an ongoing project and is part of the economic activity index initiative at the Indian School of Business. The author, Shekhar Tomar, is one of the members managing this initiative and is working on releasing the index as well as sharing the methodology behind it. Shekhar Tomar also thanks CAFRAL for its help in the collection of data for the initial one-year of the project.

[2]The official statistics report commodity-wise index, and we have reconstructed the aggregate official index corresponding to the commodities in our basket.

Figure A.1: Online vs Official Price Index



Notes: The figure gives a comparison of online vs official price index (urban) for a subset of commodities in the official CPI basket of India. The online index is constructed based on food and fuel items and has a weight of around forty-two percent in the urban CPI basket.

Table A.1: Price Stickiness in Online Data

	Veggies & Fruits (1)	Cereals (2)	Pulses (3)	Edible Oils (4)
Average Days for Change	9.1	25.0	15.6	25.8
Median (Absolute) Size Change (%)	14.2	7.4	6.4	4.9

Notes: The above statistics are based on prices data from 2019 for the three cities and the same set of products used in the main analysis. The Average Days for Change gives the average number of days it takes for price to update at the product level. The Median (Absolute) Size Change (%) is the median over absolute size of price change, when the change happens. We drop the missing values in our computation.

B Offline Data for Prices

In this section, we estimate the impact of the lockdown on prices using offline retail price data. This data is collected by the Department of Consumer Affairs (DCA) for 22 essential commodities across major cities of India. We use the data for the three cities included in our analyses. We divide the 22 commodities into four subsets that correspond to the main categories in our paper. The vegetables and fruits include potato, onion and tomato (POT). The DCA data thus covers very few commodities under vegetables and fruits. The edible oils include mustard oil, sunflower oil, soyabean oil, palm oil, groundnut oil, and butter. The pulses include all the major pulses (gram, masoor, moong, tur and urad), while cereals include rice and wheat.

As in the baseline specification, we restrict our sample to the same dates before and after the lockdown. Finally, it is important to mention that the prices collected by DCA are at the commodity level and do not allow one to control for product level heterogeneity. We thus use a modified form of the estimation equation as given below:

$$ln(P_{ic,t}) = \beta_0 + \beta_1 * Lockdown_t + \delta_{ic} + \delta_{dow,c} + \varepsilon_{ic,t}$$

where $ln(P_{ic,t})$ is the log price of commodity i in city c on date t. The indicator variable $Lockdown_t$, is equal to one if India was under the national lockdown on date t, else it is zero. We also control for non time-varying heterogeneity at the commodity-city level through the fixed effects δ_{ic}. Table B.1 report the estimates. The results show that the lockdown led to a small increase in prices (less than 6 percent) for all commodities except for POT. The magnitude of the increase in DCA retail prices is similar to the online change in price for cereals and pulses. Since, the exact product of the commodity sold is not provided in the DCA data, one cannot know if the change in price is due to a change in the product mix. This could lead to some divergence in price trends across online and offline datasets.

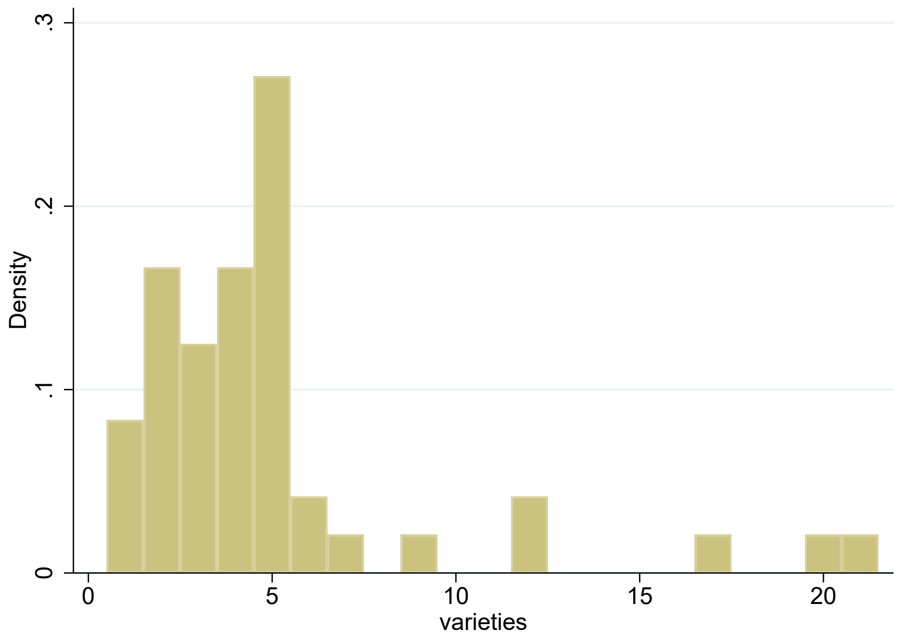
Table B.1: Impact of Lockdown on Retail Prices (Offline)

	Veggies & Fruits (POT)	Edible Oils	Cereals	Pulses
	(1)	(2)	(3)	(4)
Lockdown	0.160***	0.026***	0.026***	0.054***
	(0.012)	(0.003)	(0.003)	(0.003)
R-Sq	0.833	0.975	0.984	0.964
Observations	390	687	345	645
City×Commodity FE	Y	Y	Y	Y
City×Day of Week FE	Y	Y	Y	Y

Notes: The dependent variable is log price of the product. POT includes Potato, Onion and Tomato. Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

C Figures and Tables

Figure C.1: Frequency Distribution of Products within Commodities (Vegetables and Fruits)



Notes: The data for pre-lockdown period is used to calculate the number of products of each commodity being sold across cities. The 18 commodities include potato, onion, tomato, banana, apple, spinach/other leafy, brinjal, mango, groundnut, ocra, coconut, cauliflower, gourd, cabbage, grapes, beans, citrus fruits and peas. Four commodities - chillies, lemon, ginger and garlic - are excluded from the online availability analyses due to insufficient observations.

Table C.1: Impact of Lockdown on Online Product Availability of Vegetables and Fruits (Heterogeneity by Other Characteristics)

	(1)	(2)	(3)	(4)
X=	Perishability	CPI Weight	POT	High Price
Lockdown	-0.059***	-0.076***	-0.063***	-0.065***
	(0.018)	(0.016)	(0.008)	(0.013)
Lockdown×X	-0.004	0.254	0.002	0.011
	(0.020)	(0.239)	(0.020)	(0.020)
R-sq	0.204	0.204	0.204	0.205
Observations	9800	9800	9800	6560
Mean Availability Pre-Lockdown	0.837	0.837	0.837	0.849
City×Product FE	Y	Y	Y	Y
City×Day of Week FE	Y	Y	Y	Y

Notes: The dependent variable is whether or not a product is available on a day. POT refers to potato, onion and tomato. High price refers to a higher than median price (price per kg) in the pre-lockdown period for a product within a given commodity (for vegetables and fruits) and within all the products in the overall category for edible oils, cereals and pulses. Products measured in numbers (e.g number of apples) are dropped due to non-comparability of price with other products leading to a smaller number of products in the last column. The regressions are weighted to give equal representation to each city. Clustered standard errors (at product level) in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table C.2: Effect of Lockdown on Online Prices (Heterogeneity by Initial Listing)

	Veggies & Fruits (1)	Edible Oils (2)	Cereals (3)	Pulses (4)
Lockdown	0.004	0.005	0.027***	0.020**
	(0.004)	(0.005)	(0.005)	(0.008)
Lockdown×High Listing	0.004	-0.022***	-0.007	0.006
	(0.005)	(0.006)	(0.006)	(0.009)
Estimate	0.008	-0.017	0.020	0.026
P-Value	0.044	0.001	0.000	0.000
R-sq	0.972	0.991	0.987	0.969
Observations	7804	4472	14538	7134
City×Product FE	Y	Y	Y	Y
City×Day of Week FE	Y	Y	Y	Y

Notes: The dependent variable is log price of the product. *High Listing* refers to a higher than median percentage days availability in the pre-lockdown period for a product within a given commodity-city pair. A few products having only single products in a city are dropped from the analyses leading to smaller number of observations that the base specification. The regressions are weighted to give equal representation to each city. Clustered standard errors (at product level) in parentheses. *** p<0.01, ** p<0.05, * p<0.1.