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Abstract

We document the impact of India's COVID-19 lockdown on the food supply chain. Food arrivals in wholesale markets dropped by 62% in the three weeks following the lockdown and wholesale prices rose by 8%. Six weeks after the lockdown began, volumes and prices had fully recovered. The initial food supply shock was highly correlated with early incidence of COVID-19. We provide evidence that this correlation is due more to state-level lockdown policy variation than local responses of those in the food supply chain. Finally, during the recovery phase, the correlation between the food supply disruption and COVID-19 exposure disappeared, suggesting uniform recovery.

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1 Introduction

Since the COVID-19 pandemic began, one concern has been that lockdowns might be especially damaging in the poorest countries – in these places lockdowns may reduce the spread of coronavirus, but only by simultaneously leaving poor families without cash to spend, and without food to eat. In this paper, we shed light on a particular aspect of this concern: can food supply chains themselves remain functional in the face of a national lockdown, and a growing burden of coronavirus cases? We address this question by documenting the breakdown and subsequent recovery of India's food supply chain during the first three months of India's national lockdown.

On March 24, 2020, India announced a strict lockdown for 21 days in response to a surge in COVID-19 cases. According to the World Bank, India's lockdown was the largest implemented by any country.[1] The lockdown was extended in three additional phases of 14 days each, with each phase accompanied by relaxations in lockdown rules. Following these three additional phases, the central government announced a staggered lifting of the lockdown. Using web-scraped daily data on wholesale volumes and prices for 271 food varieties traded at 1804 agricultural markets in 24 states of India, we document trends in the supply and prices of food during these phases. Specifically, we estimate the size of the initial shock to food supply and wholesale prices following the lockdown announcement, the extent of the recovery, and the correlation of the shock and the recovery with the spread of the virus.

We describe four findings. First, food arrivals in wholesale markets dropped by 62% in the three weeks following the lockdown, but subsequently recovered, reaching similar levels to those in 2019 as soon as three weeks later. Second, we estimate dynamic effects of the lockdown on wholesale prices that are similar to the effects on volumes. In particular, while wholesale prices initially increased by 8%, they quickly returned to a downward trend. Third, the initial state-level food supply shock was highly correlated with exposure to COVID-19 – states with more COVID-19 suffered larger drops to food arrivals after the lockdown relative to previous years – but this correlation disappeared during the recovery phase, suggesting that food supply volumes recovered irrespective of the incidence of the virus spread. Fourth and finally, we use within-state variation to unpack the correlation between COVID-19 exposure and the initial supply shock. We find evidence that the correlation is driven by state-level policies, rather than local responses of those in the food supply chain. In particular, districts exposed to COVID-19 *did not* have larger food supply disruptions than less-exposed districts belonging to the same state.

This study contributes to the growing literature on the impact of the COVID-19 shock on the economy

[1] See https://www.worldbank.org/en/news/press-release/2020/05/15/world-bank-support-protect-poorest-india-coronavirus. The Oxford COVID-19 Government Response Tracker (https://covidtracker.bsg.ox.ac.uk) also shows that the initial lockdown in India was one of the strictest.

in general and the food sector in particular. Closest to this paper, in contemporaneous work Rawal and Verma (2020) use the same data source to study the evolution of volumes and prices during the first three weeks of the lockdown. Their results parallel part of the first of our four findings. Our remaining findings go further by linking impacts to across-state and within-state variation in COVID-19 incidence. In addition, we substantially broaden the sample to cover more food varieties and a longer time frame. Other work finds that prices in urban food markets rose 3% in the 28 days post-lockdown (Narayanan and Saha 2020), that supply to a major online retailer fell by 10% (Mahajan and Tomar 2020), and more generally, reports on the food security risks faced in India as a result of COVID-19 (Reardon et al. 2020; Ray and Subramanian 2020). Outside of food supply chain concerns, Jain and Dupas (2020) document the impact of the lockdown on India's non-COVID-19 health outcomes and Ravindran and Shah (2020) examine the impact of the Indian lockdown on rates of domestic abuse. More broadly, our work connects to the literature examining the consequences of policy responses to COVID-19 in the developing world (see e.g. Banerjee et al. (2020a) and Ajzenman et al. (2020) on the impacts of public health messaging, and Banerjee et al. (2020b) and Londono-Velez and Querebin (2020) on the impacts of emergency cash assistance).

Our work also connects to the more general global debate on whether economic responses to COVID-19 are more policy-driven or more related to individual assessments of risk. This debate informs central questions: does lifting a lockdown cause economic activity to increase? Or will people stay at home regardless of the official lockdown policy in the hope of mitigating personal and social risks? Coibion et al. (2020) estimate that lockdowns account for close to 60% of the decline in the employment to population ratio in the US. Our results suggest that the shock to food supply in India was driven more by lockdown policies, which varied in stringency across states, than by local responses to COVID-19 risk, which also varied dramatically within each state.

The rest of this paper is organized as follows. In the next section, we give an overview of the COVID-19 situation in India, the policy response of both the central and state governments, and the labor supply response of individuals. Thereafter, we describe our data sources. We then present our four empirical findings. Finally, we give concluding observations.

2 Background and Data

2.1 COVID-19 in India

The COVID-19 virus spread rapidly across the globe in the early months of 2020 forcing the World Health Organisation to declare it a pandemic by early-March. India reported its first case on January

30, 2020, though the initial spread remained contained, with only 500 cases reported by March 23.[2] Despite the low reported caseload, India responded to the rapid global spread of the virus by announcing a nationwide lockdown on March 24.

As the virus began to spread rapidly within the country, the lockdown was extended on April 14 until May 3. The intensity of the lockdown was, however, eased partially. Areas with large COVID-19 outbreaks were designated as hotspots, and within hotspots, containment zones were demarcated where the intensity of virus spread was the highest. Strict lockdowns were implemented in hotspots while non-hotspot areas were allowed to open up necessary activities from April 20. The lockdown was further extended by two-week periods beginning May 3 and May 17, along with more relaxations in non-hotspot areas. Apart from the containment zones, the government started opening up the country from June 1. The virus, however, continued to spread, and by June 30 India had the fourth highest number of positive cases reported (over 585 thousand)[3] with over 17,000 deaths. In terms of cases per capita, however, India had a relatively low rate, with 0.4 confirmed cases per thousand population as compared with 7.8 per thousand in the US (the country with the highest number of confirmed cases as of June 30).[4]

The distribution of confirmed cases was very uneven, with more than half of the confirmed cases reported in six major cities: Mumbai, Delhi, Ahmedabad, Chennai, Pune, and Kolkata. As a result, the response of state-level governments to COVID-19 has varied, with some states, e.g. Punjab and Telangana, extending the lockdown until June 30th. In order to understand whether such state-level variation in policies mattered for food supply chains, our analysis explores differential impacts across states.

One of the major responses of individuals to government measures has been the large exodus of migrant laborers from urban centers to rural areas in response to the lockdown. Nearly half of the total population in urban India are migrants (Bhagat et al. 2020). Faced with a situation of unemployment, many migrant laborers returned to their native place with the initial estimates putting the number of people returning to their home states at 6.7 million for just six states.[5] This dramatically diminished available labor for the food supply chain, often leaving wholesale markets and traders with insufficient workers, especially in the initial days of the lockdown. Since most of the supply chain in India is informal in nature and labor intensive, the repercussions of such a labor shortage can be substantial. Our analysis of the food supply chain is set in this background.

[2] See https://coronavirus.jhu.edu/map.html.

[3] https://www.mohfw.gov.in/# accessed on August 30, 2020.

[4] https://ourworldindata.org/grapher/total-confirmed-cases-of-covid-19-per-million-people?time=2020-01-30..&country=∼IND accessed on August 31, 2020.

[5] Bihar, Uttar Pradesh, Rajasthan, Madhya Pradesh, Odisha, and Jharkhand (from https://indianexpress.com/article/india/coronavirus-lockdown-67-lakh-migrants-return-to-116-dists-in-6-states-6453084/ accessed on June 22, 2020).

2.2 Data

Our main source of data is the online database set up by the central government's Ministry of Agriculture. As part of an initiative to enhance transparency and improve price discovery, the Ministry of Agriculture created a network of mandis (local agricultural markets) by connecting them through an integrated scheme for agricultural marketing. The volume of arrivals of each food variety, along with price information (maximum, minimum, and modal traded price), are reported by each mandi to the Agricultural Marketing Network which is consolidated and uploaded to its portal, agmarknet.gov.in, on a daily basis. The data covers 307 food varieties (e.g. coconut, beans, tomato), with each variety belonging to one of 15 broad food groups.[6]

Our initial dataset includes all varieties reported to the Agmarknet portal during January 1 to June 30 of 2018, 2019, and 2020. To enable aggregation of volumes across varieties, we include only those products that are measured in tonnes, meaning we exclude those measured in numbers. This excludes 31 of the 307 varieties, which together constitute only 4.1% of the total number of mandi-variety-day-level observations. For our analysis of wholesale prices we use the modal price, which better reflects the general price level than the minimum or maximum price. Though 2905 markets have reported data to Agmarknet at some point during January to June of 2018 to 2020, the number of markets reporting at any one time has varied year-to-year (Figure A1). To get closer to a balanced panel, we restrict our sample only to those mandis that reported at least once during the month of March 2020. Our final dataset consists of 271 varieties traded at 1804 markets in 24 states of India. This data captures a substantial share of total food in India, though it does not capture food that is traded outside of the mandi supply chain network (e.g. through the direct selling of produce by farmers to customers).

3 The Lockdown and the Response of India's Food Supply Chain

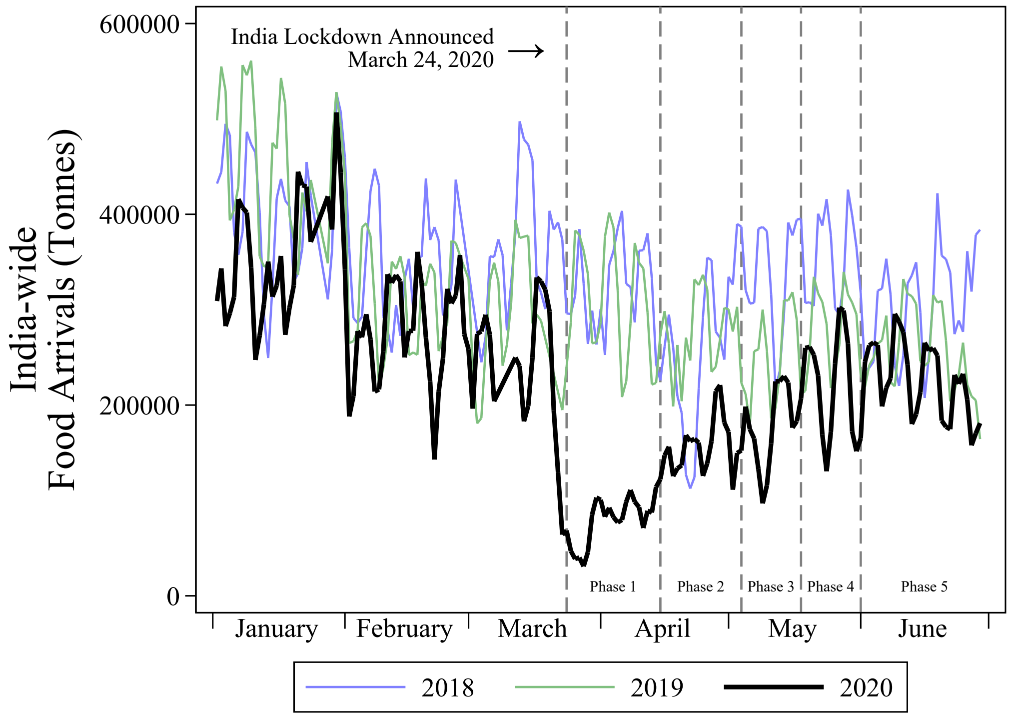
3.1 Food Arrivals Fell Immediately But Subsequently Recovered

Among the sample of mandis that reported at least once in March 2020, aggregate food arrivals were similarly volatile prior to March 24 in 2018 and 2019 as compared with 2020 (Figure 1).[7] Following March 24, 2020, arrivals dropped dramatically as compared with levels in 2018 and 2019, and gradually

[6] The food groups are: Cereals, Spices, Fibre Crops, Oil Seeds, Fruits, Pulses, Forest Products, Other, Vegetables, Dry Fruits, Drug and Narcotics, Oils and Fats, Live Stock and Poultry and Fisheries, Beverages, and Flowers.

[7] We exclude wheat in our aggregate measure of food arrivals as wheat volumes are driven by central government grain procurement policy for most of the wheat-producing states. As of May 25, 2020 total wheat procurement in the country exceeded the level of the previous year (https://pib.gov.in/PressReleasePage.aspx?PRID=1626703). Our findings are similar when we include wheat (Figure A2), though with wheat arrivals considerably increasing the total tonnes of arrivals.

Figure 1: The Lockdown Caused Wholesale Volumes to Plummet



Notes: The y-axis variable is a three-day moving average of aggregate tonnes of food arrivals, excluding wheat, to the 1804 mandis that reported data to Agmarknet at least once in March 2020. The data covers January 1 to June 30, 2018 to 2020, with the exception of the national holidays of Republic Day (January 26) and Holi (March 1-2 2018, March 20-21 2019, March 9-10 2020). Source: agmarknet.gov.in.

recovered from Phase 2 of the lockdown onwards. This core pattern is similar for each of six major food groups (Figure A3), suggesting that the recovery was not driven by product-specific government procurement.

To quantify the aggregate patterns in Figure 1 we use variants of the following difference-in-differences specification:

$$ln\left(\text{Volume}\right)_{yd} = \alpha_y + \alpha_d + \sum_{t=1}^{5} \beta_t \text{Phase}^t_{yd} + \varepsilon_{yd} \tag{1}$$

where $ln\left(\text{Volume}\right)_{yd}$ is the log of the total volume of food arrivals in tonnes, excluding wheat, on calendar date d (e.g. January 1) during year y (either 2019 or 2020). α_y and α_d are year and calendar date fixed effects, respectively, making this a difference-in-differences design where we are comparing the volume change before and after the lockdown began in 2020 with the volume change before and after March 24 in 2019. We include only data from March 1 to June 30 in these regressions, making the "before" period

March 1 to 24. To estimate separate effects for each phase of the lockdown, we include a set of dummy variables for the five phases. Phase^1_{yd} is a dummy variable equal to one for the period March 25, 2020 to April 14, 2020, and equal to zero otherwise. The remaining dummies are switched on for April 15 to May 3 (Phase^2_{yd}), May 4 to May 17 (Phase^3_{yd}), May 18 to May 31 (Phase^4_{yd}), and June 1 to June 30 (Phase^5_{yd}), with all of these dates in 2020 only. For specifications at the day-level, we use robust standard errors, while for specifications at the mandi-day-level, we cluster standard errors at the mandi-level.

Phase 1 of the lockdown reduced nationwide food arrivals by 62%[8] (column 1, Table 1), with a similar estimated drop of 60% when we also include data from 2018 in the "control group" (column 2). Volumes subsequently recovered – the Phase 2 fall is only 13% (column 1), while each of the coefficients for Phase 3 to 5 are actually positive, though not significant, in both columns 1 and 2. These regression results show that aggregate volumes fully returned to normal levels by early-May, and even somewhat exceeded normal levels by June.

The large volume reduction during Phase 1 could reflect two margins: mandis closing completely (the extensive margin) or mandis remaining open but at lower capacity (the intensive margin). We find evidence for both margins. The number of functional mandis fell by 39 to 42% during Phase 1 (columns 3 and 4, Table 1, and visualised in Figure 2), showing that the extensive margin drove some of the volume reduction.[9] These extensive margin effects are potentially more damaging than intensive margin effects – extreme food insecurity is presumably less likely if all markets remaining functioning, though at lower capacity, than if markets in some locations shutdown completely, with other locations functioning at normal levels.

To isolate intensive margin effects, we aggregate food arrivals to the mandi-day-level, and re-run the difference-in-differences specification with mandi fixed effects. Given that the outcome is the natural logarithm of arrivals, any non-functional mandi-days are dropped from the regression. As a result, the coefficients can be interpreted as the effects on mandi-level volumes conditional on the mandi remaining open. When considering only the intensive margin, volumes fell by 36 to 38% during Phase 1 (columns 5 and 6, Table 1), with a similar pattern of recovery, including significantly higher volumes than normal during Phases 3 to 5.

[8]The Phase t volume fall in % is estimated as $100 \times \left(1 - e^{\beta_t}\right)$.

[9]One important assumption we make here is that effects on the number of functioning mandis are given by our estimated effects on the number of *reporting* mandis. If the reporting itself (holding constant whether the mandi was functioning) was negatively impacted by the lockdown, we would overestimate the fall in functionality that followed the lockdown. We think our assumption is reasonable given two pieces of evidence that non-reporting mandis are likely non-functioning. First, other experts (e.g. Rawal and Verma 2020) and Government of India officials themselves report the number of functional mandis as the number of mandis reporting data to Agmarknet. Second, the Ministry of Agriculture states that mandis that are part of the Agmarknet scheme are fully computerized and the dataflow is nearly automatic, suggesting that reporting is straightforward conditional on having data to report.

Table 1: The Lockdown's Impact on Food Arrivals

	ln(Food Arrivals)		ln(Functioning Mandis)		ln(Food Arrivals)	
	(1)	(2)	(3)	(4)	(5)	(6)
Phase 1 (Mar 25-Apr 14)	-0.96***	-0.92***	-0.54***	-0.50***	-0.48***	-0.44***
	(0.28)	(0.23)	(0.15)	(0.12)	(0.04)	(0.04)
Phase 2 (Apr 15-May 3)	-0.14	-0.01	-0.10	-0.04	-0.12***	-0.06*
	(0.26)	(0.23)	(0.14)	(0.14)	(0.03)	(0.03)
Phase 3 (May 4-May 17)	0.07	-0.02	-0.12	-0.14	0.13***	0.12***
	(0.31)	(0.26)	(0.19)	(0.17)	(0.04)	(0.03)
Phase 4 (May 18-May 31)	0.20	0.12	-0.10	-0.11	0.24***	0.24***
	(0.32)	(0.26)	(0.19)	(0.17)	(0.04)	(0.03)
Phase 5 (Jun 1-Jun 30)	0.37	0.33	0.07	0.08	0.24***	0.31***
	(0.25)	(0.21)	(0.14)	(0.12)	(0.04)	(0.03)
Observations	240	360	240	360	252626	377749
Sample Period	2019-20	2018-20	2019-20	2018-20	2019-20	2018-20
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Date Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Mandi Fixed Effects	No	No	No	No	Yes	Yes

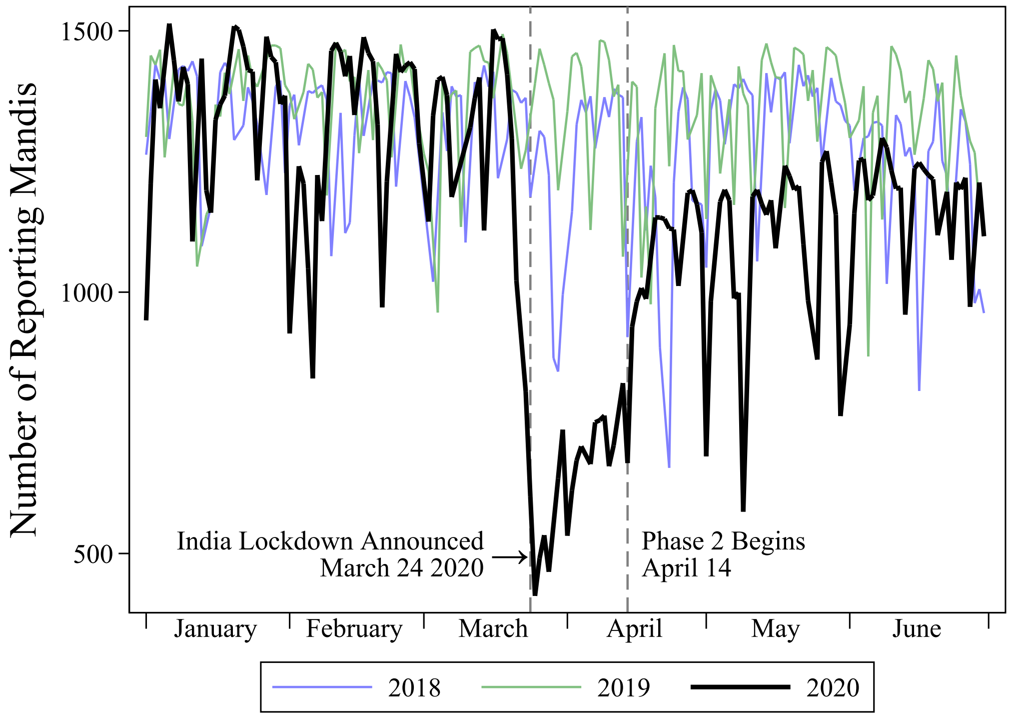
Notes: The unit of observation is a day in columns 1 to 4, and a mandi-day in columns 5 and 6. The regressions include data from March 1 to June 30 for each year (either 2019-2020 or 2018-2020), with the exception of national holidays (Republic Day and Holi). Robust standard errors in columns 1 to 4, standard errors clustered at mandi-level in columns 5 and 6. The outcome for columns 1 and 2 is the natural logarithm of the tonnes of non-wheat nationwide food arrivals to mandis that reported at least once in March 2020. The outcome for columns 3 and 4 is the natural logarithm of the number of functional (i.e. reporting) mandis among the sample relevant for columns 1 and 2. The outcome for columns 5 and 6 is same as that for columns 1 and 2, though measured at the mandi-day-level. *** p<0.01, ** p<0.05, * p<0.1.

To understand what drove the initial volume shock we draw on a set of qualitative interviews with wholesale traders in Delhi, and collated information from publicly available sources.

A sudden fall in the volume of arrivals could be due to a fall in demand or issues pertaining to the supply chain. Supply-side issues appear to have been important contributors. First, uncertainty about the rules on inter-state travel made it cumbersome to transport produce across state borders. Border closures, extra layers of inspection and documentation requirements, and a lack of clarity on the rules regarding the transport of agricultural produce created uncertainty for truck drivers.[10] Inability to find paid work to transport produce added to these frictions. Secondly, at the market level, a sharp fall in the supply of labor, driven by the exodus of migrant laborers from urban areas to their native places, reduced the pace

[10] See https://thewire.in/economy/covid-19-border-lockdown-how-precariously-placed-are-our-food-supply-chains.

Figure 2: The Number of Functioning Mandis Plummeted and Then Recovered



Notes: The y-axis variable is the number of mandis that reported any data to Agmarknet on each date, among the 1804 mandis that reported data to Agmarknet at least once in March 2020. The data covers January 1 to June 30, 2018 to 2020, with the exception of the national holidays of Republic Day (January 26), Holi (March 1-2 2018, March 20-21 2019, March 9-10 2020), and Sundays, to make the trends clearer (far fewer mandis report on Sundays). Source: agmarknet.gov.in.

at which trucks could be loaded and unloaded. A shortage of ancillary workers, e.g. book keepers, also impacted the daily functioning of the markets.[11]

Constraints faced at the last mile of the supply chain by retail vendors also played a part in reducing transaction volumes. Rules on social distancing made many retail markets non-functional in urban areas, and retail vendors had to resort to alternative business models – e.g. selling in multiple neighborhoods in the same day – which increased effort costs and reduced volumes. Many other retail vendors decided not to operate at all.

The recovery of wholesale volumes since mid-April 2020 is significant given these supply-side vulnerabilities. After the initial hiatus, inter-state movement of agricultural goods recovered as policies to ease restrictions on the cross-state movement of agricultural goods were put in place.[12] The central

[11] See https://www.hindustantimes.com/delhi-news/traders-of-perishables-faced-with-stock-shortage-transport-problems/story-QE5HAldeot02VMgvNo7NSM.html.

[12] See https://pib.gov.in/PressReleseDetail.aspx?PMO=3&PRID=1608009 accessed on July 20, 2020.

government issued directives to free the inter-state movement of vehicles carrying essential commodities and worked in coordination with State Agricultural Marketing Boards to ensure the smooth movement of agricultural goods across state borders.[13] In addition, wholesale markets adapted by resuming operations with physical distancing and other measures to limit the spread of the virus. For example, in Asia's largest wholesale fruit and vegetable market in Delhi, Azadpur mandi, traders with odd- and even-numbered sheds ran business on alternate days, vegetables and fruits were sold at separate times, and limits on the number of trucks that could be operated by each individual trader were introduced.[14]

3.2 Wholesale Prices Increased and Then Returned to a Downward Trend

A return to pre-lockdown food volumes may still be consistent with a threat to food security if prices are higher. To explore this, we use an event study approach to compare the evolution of wholesale prices in 2020 with 2018 and 2019. We estimate the following specification separately for each of the three years:

$$ln\left(\text{Modal Price}_{smfd}\right) = \alpha_{smf} + \sum_{t=-11}^{-1} \beta_t^{\text{pre}} \text{Week}_d^t + \sum_{t=1}^{14} \beta_t^{\text{post}} \text{Week}_d^t + \varepsilon_{smfd} \qquad (2)$$

where $ln\left(\text{Modal Price}_{ycid}\right)$ is the natural logarithm of the modal price of food variety f in mandi m in state s on calendar date d. α_{smf} are state-by-mandi-by-food variety fixed effects. Week_d^t is a dummy variable equal to one if date d belongs to the t^{th} week after March 24 – for example, Week_d^1 is equal to one for March 25 to 31, while the first and last weeks are January 1 to 7 (Week_d^{-11}) and June 24 to 30 (Week_d^{14}), respectively. The omitted category is Week_d^0, covering March 18 to 24. From this specification we estimate pre-lockdown trends in prices (β_t^{pre}) and post-lockdown trends (β_t^{post}), holding constant the food variety and location, and implicitly conditioning on availability of the variety.[15] We can then compare these estimated trends with the trends estimated for 2018 and 2019.

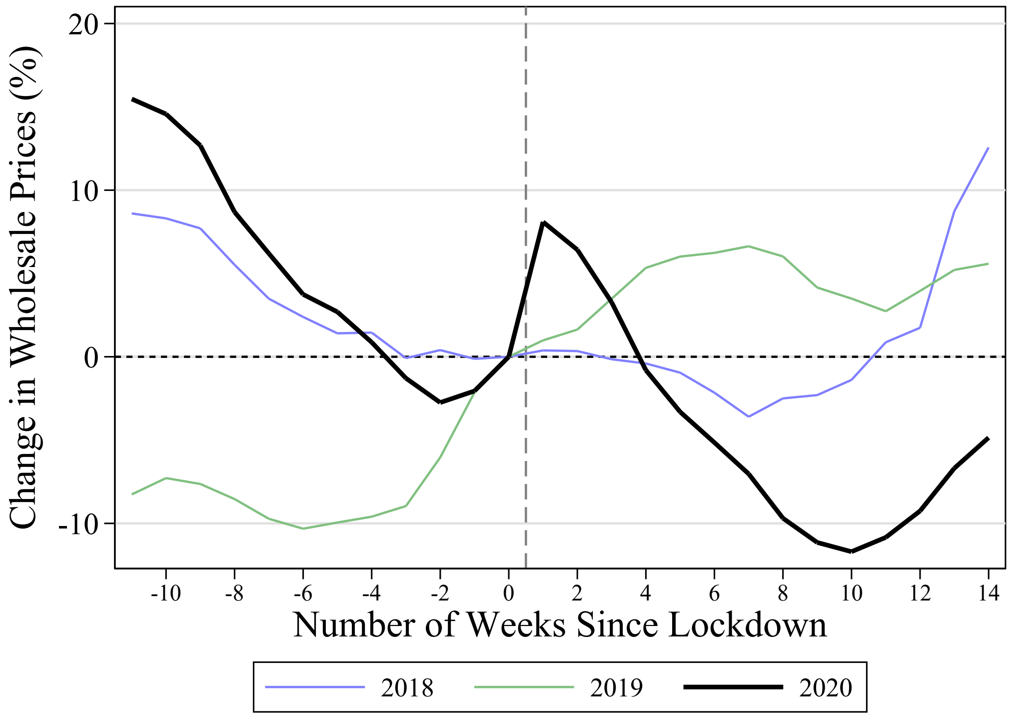
Wholesale prices did not change noticeably around March 25 in 2018 or 2019, while in 2020 prices jumped sharply by 8% (Figure 3). The increase suggests that the sudden fall in supply was not matched by a commensurate fall in demand. This price spike was however short-lived – four weeks after the lockdown began, price levels were similar to those immediately prior to the lockdown. Following this, wholesale prices returned to a downward trend, such that prices were 5 to 10% lower than pre-lockdown

[13] See https://pib.gov.in/PressReleseDetailm.aspx?PRID=1616771 accessed on July 20, 2020.

[14] See https://economictimes.indiatimes.com/news/politics-and-nation/covid-19-odd-even-rules-for-sale-of-vegetables-at-azadpur-mandi-from-monday/articleshow/75107337.cms accessed on July 20, 2020.

[15] One caveat is that during the lockdown, due to the non-functionality of many markets (Figure A1), sometimes food was not available at all, making the prices of some food varieties effectively infinite. This means that our analysis here understates the effective lockdown-induced increase in wholesale prices, given that we study only the effects on prices conditional on availability.

Figure 3: After an Initial Increase in Wholesale Prices, Prices Returned to Trend



Notes: The Figure plots the percentage change in wholesale prices implied by the year-by-year estimates from equation 2. Specifically, the pre-lockdown y-axis variable is $100 \times \left(e^{\hat{\beta_t^{pre}}} - 1\right)$ for $t \in \{-11, -10, ..., -2, -1\}$, while the post-lockdown variable is $100 \times \left(e^{\hat{\beta_t^{post}}} - 1\right)$ for $t \in \{1, 2, ..., 13, 14\}$. The sample comprises only those mandis that reported data at least once in March 2020.

levels toward the end of Phase 5.[16] In short, prices were affected similarly to volumes (Figure 1) – an initial shock during Phase 1 followed by a return to normality during the subsequent lockdown phases.[17]

While our analysis considers wholesale prices, evidence for urban areas from Narayanan and Saha (2020) suggests that our findings may also hold for retail prices – they find that the retail price mark up over wholesale prices remained fairly constant during the lockdown period.

[16]One possible explanation for the lower price level by Phase 5, other than that of a return to trend, could be that while supply rebounded, demand remained low, placing downward pressure on prices.

[17]The pattern of rising and then falling wholesale prices holds for most of the major commodity groups (Figure A4), with the exception of spices, which did not see a lockdown-induced price increase at all. One possible explanation is that the non-perishability and relative non-necessity of spices meant that demand was more elastic than it was for other commodity groups and therefore a supply disruption did not lead to major changes in prices.

3.3 State-Level Food Supply Disruptions Versus Coronavirus Spread

An important question is whether the supply chain disruption was driven more by state-level lockdown policies or by local behavioral responses. If the latter, continued virus transmission would disrupt supply chains even in the absence of state-mandated lockdowns. We approach this question in two main steps. First, we correlate the evolution of food arrivals at the state-level with the state-level coronavirus caseload. We will show that the initial disruption was highly positively correlated with coronavirus at the state-level. Second, we use *within*-state variation to unpack the correlation, and find the correlation between district-level COVID-19 incidence and food supply disruption breaks down, indicating that the relationship is not driven by local responses to COVID-19 exposure. We conclude that the strong correlation between state-level COVID-19 exposure and the initial supply shock is likely due to the fact that states with more COVID-19 introduced more stringent lockdown policies.

For the first step, we estimate the size of the volume shock for each state, separately for the first phase of the lockdown versus the subsequent four phases of the lockdown. This way we broadly split the post-lockdown period into the "shock" phase and the "recovery" phase (as is clear in Figure 1). We use the following specification for each state s:

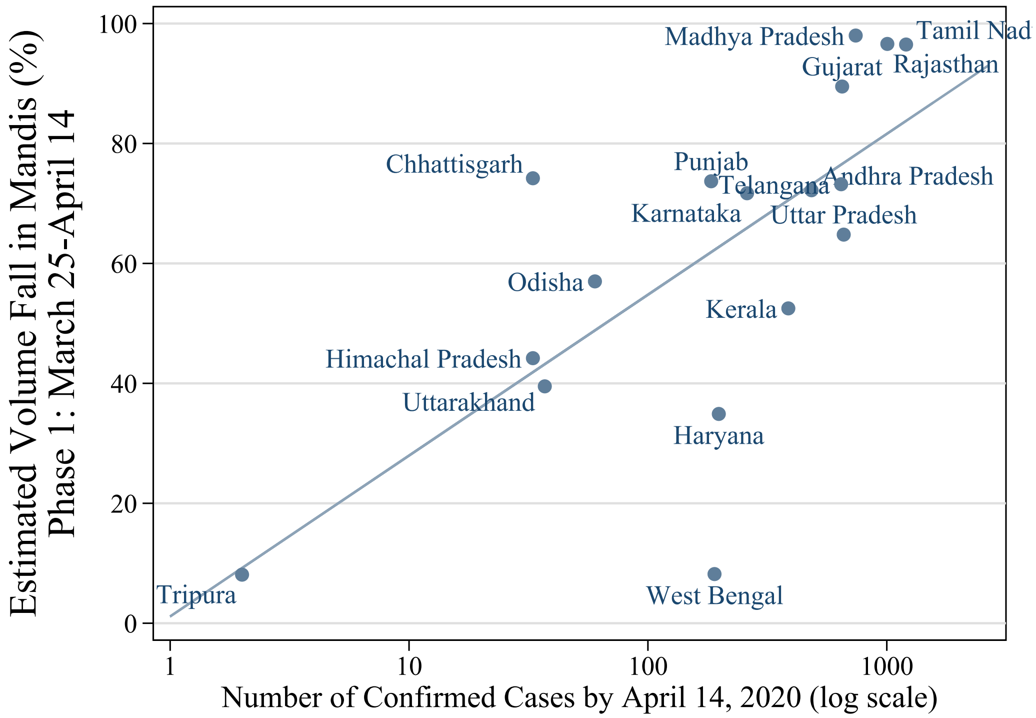
$$ln\,(\text{Volume})^s_{yd} = \alpha^s_y + \alpha^s_d + \gamma^s \text{Phase}^1_{yd} + \theta^s \text{Phase}^{2-5}_{yd} + \varepsilon^s_{yd} \tag{3}$$

which differs from equation 1 in two ways. First, the s super-scripts indicate that this regression is run state-by-state for state-specific coefficients. Second, we replace the dummy variables for each of the Phases 2 to 5 with Phase^{2-5}_{yd}, a dummy variable equal to one for the entire post-Phase 1 period (April 15 to June 30). Importantly, the outcome is now the natural logarithm of *state*-level food arrivals on a particular day, rather than that of nationwide food arrivals. We again use data only from March 1 to June 30, in 2019 and 2020, and estimate effects for 17 states with consistent data[18] – those with at least 10 mandis on average reporting daily data during each of the months from March to June in 2019, and from January to March in 2020. These 17 states cover 885 million people, or 73% of India's population as of the 2011 census.

The Phase 1 volume fall at the state-level ($100\times\left(1-e^{\hat{\gamma}^s}\right)$) is strongly positively correlated with the number of confirmed cases of coronavirus as of the end of Phase 1 ($r = 0.72$, $p = 0.001$, Figure 4). In fact, the number of confirmed cases of coronavirus alone explains the majority of the variation in the state-level volume shocks ($R^2 = 52\%$). While the lockdown was national, the impact on essential food supply was more severe in regions which had a higher incidence of the virus.

[18] These states are Andhra Pradesh, Chattisgarh, Gujarat, Haryana, Himachal Pradesh, Karnataka, Kerala, Madhya Pradesh, Odisha, Punjab, Rajasthan, Tamil Nadu, Telangana, Tripura, Uttar Pradesh, Uttrakhand, and West Bengal.

Figure 4: States With More Coronavirus Cases Had Bigger Supply Chain Disruptions During Phase 1



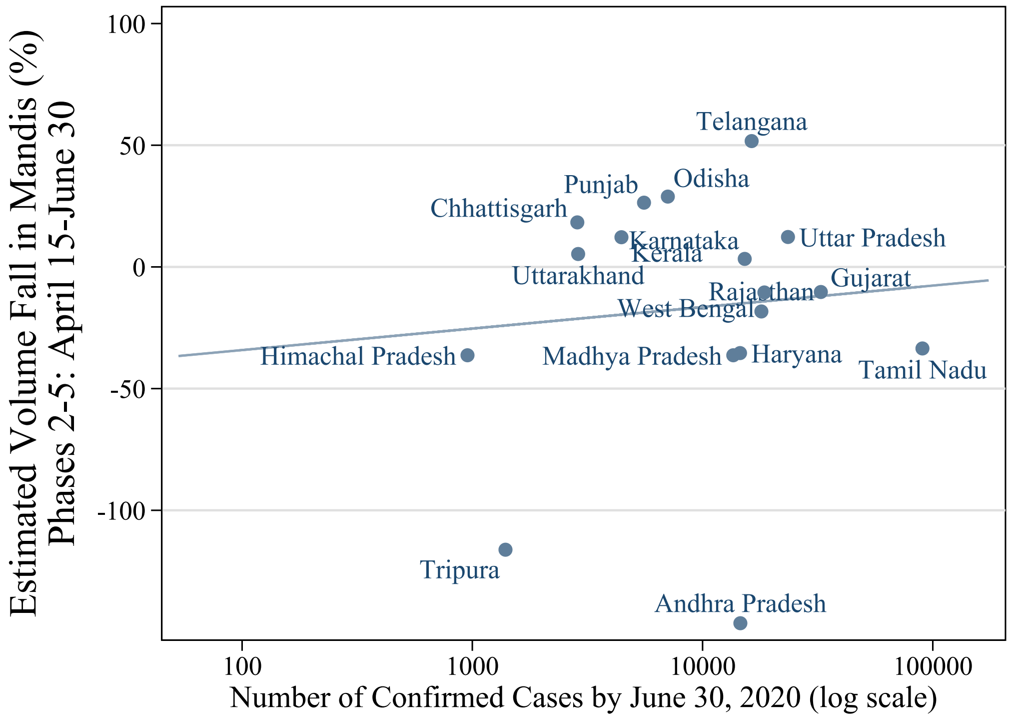
Notes: The y-axis is the estimated Phase 1 volume fall for each of 17 states, where the estimate is $100 \times \left(1 - e^{\hat{\gamma}^s}\right)$ using estimated coefficients from equation 3. The x-axis is the number of confirmed cases of coronavirus by the end of Phase 1 (April 14), from api.covid19india.org.

The picture that emerges in the period starting in Phase 2 is, however, quite different. The state-level volume fall during Phases 2 to 5 is uncorrelated with the coronavirus caseload as of the end of Phase 5 ($r = -0.05$, $p = 0.85$, Figure 5). This shows that the nationwide supply recovery visualized in Figure 1 does not mask heterogeneity across states with more versus less coronavirus – in essence, volumes recovered regardless of the spread of coronavirus.

3.4 Is the Supply Disruption-COVID-19 Relationship Due to State-Level Policies or Local Responses?

There are two main factors that would lead to a correlation between the initial food supply disruption and the state-level incidence of coronavirus. First, states with more coronavirus introduced stricter lock-down policies with greater efforts at enforcement. These policies could have disrupted the supply chain. Second, even holding state-level policies constant, people could voluntarily change their behavior in re-

Figure 5: Volume Shocks Were Not Correlated With Coronavirus Cases After Phase 1



Notes: The y-axis is the estimated Phase 2-5 volume fall for each of 17 states, where the estimate is $100 \times \left(1 - e^{\hat{\theta}^s}\right)$ using estimated coefficients from equation 3. The x-axis is the number of confirmed cases of coronavirus by the end of Phase 5 (June 30), from api.covid19india.org.

sponse to a high local incidence of coronavirus. For example, they might withdraw their labor supply, affecting the functioning of labor-intensive wholesale markets. Distinguishing between the two factors matters – if voluntary individual responses are most important, the lifting of lockdown policies would not reliably restore the functioning of food supply chains.

We look at this question by examining within-state variation in food supply and COVID-19 intensity. If state-level policy variation alone is responsible for the correlation between COVID-19 intensity and the disruption of the food supply, then the relationship should break down in a within-state analysis. However, if the disruption is driven by voluntary behavioral responses or local policy variation, then the correlation should persist even using within-state variation. In what follows we demonstrate that the correlation breaks down at the within-state level and is therefore most likely due to state-level policy variation.

Specifically, we use district-level data to estimate the evolution of food supply in districts with more versus less coronavirus exposure. Our core triple-difference specification estimates the additional effects of the lockdown on volumes in high-exposure districts relative to low-exposure districts:

$$\begin{aligned} ln\left(1+\text{Volume}_{xyd}\right) = {} & \alpha_{xd}+\alpha_{xy}+\alpha_{dy} \\ & +\phi_1\left(ln\left(1+\text{COVID-19 Cases}_x\right)\times \text{Phase}^1_{yd}\right) \\ & +\phi_2\left(ln\left(1+\text{COVID-19 Cases}_x\right)\times \text{Phase}^{2-5}_{yd}\right)+\varepsilon_{xyd} \end{aligned} \tag{4}$$

where Volume_{xyd} is the total quantity of non-wheat food arrivals in tonnes to district x during year y on calendar date d. Here we take the natural logarithm of one plus Volume_{xyd} given that 18% of our analysis sample observations at the district-day-level are zero-valued. As is standard with triple-difference specifications, we include all possible two-way interactions: α_{xd} are district-by-calendar date fixed effects, α_{xy} are district-by-year fixed effects, and α_{dy} are date fixed effects.[19] COVID-19 Cases_x is the number of confirmed coronavirus cases in district x by the end of Phase 1 (April 14, 2020). Given that 166 of our 399 analysis sample districts had zero cases of COVID-19 by April 14, we add one to this variable before taking the logarithm, paralleling the x-axis in Figure 4. Phase^1_{yd} and Phase^{2-5}_{yd} are as defined earlier. We cluster standard errors at the district-level. $\hat{\phi}_1$ is our estimate of the *additional* effect of Phase 1 of the lockdown on volumes in COVID-19 affected districts relative to unaffected districts, while $\hat{\phi}_2$ is the estimate for Phases 2 to 5.

We estimate three variants of this specification. First, we replace $ln\left(1+\text{COVID-19 Cases}_x\right)$ with $ln\left(1+\text{COVID-19 Cases}_s\right)$ where s denotes the state that district d belongs to. This initial specification aims to replicate the strong positive correlation in Figure 4 – showing that districts that belong to states with more COVID-19 suffered a larger supply shock during Phase 1. In the second variant we estimate equation 4 itself. In doing so, we test whether districts with more COVID-19 themselves suffered a larger supply shock. In the third variant, we add state-date fixed effects (α_{sdy}), fully absorbing any time-varying state-level policy (or even non-policy) variation. This specification allows us to estimate the different effects of the pandemic on affected versus unaffected districts while only making comparisons within the same state.[20]

Before turning to the three specifications described, we first replicate the negative effects of the lockdown on supply (e.g. as in column 1, Table 1) using the district-day-level data.[21] Consistent with our earlier results, food arrivals to districts dropped by 81% during Phase 1 of the lockdown (column 1, Table

[19] Equivalent to calendar date-by-year fixed effects.

[20] In support of the key assumption for a triple-difference specification, pre-trends are relatively parallel for each of these three variants of our core specification (Table A1), with the one marginally significant pre-trend in column 3 unable to explain our results.

[21] Note that our district-level estimates need not coincide with our India-level estimates given that our district-level regressions are unweighted.

2, compared with a 62% drop in column 1, Table 1), and recovered fully during Phases 2 to 5.

The Phase 1 disruption was larger in COVID-19-affected states ($p < 0.01$, column 2, Table 2), consistent with the strong positive correlation between caseload and state-level supply shocks in Figure 4. Specifically, the point estimates imply that a doubling of state-level cases by April 14 is associated with a negative supply shock that is 29% larger.

Strikingly, the correlation between COVID-19 exposure and supply disruption disappears when we instead define exposure at the district-level (column 3, Table 2), and remains small and not statistically significant when we exploit only within-state variation (column 4). These results suggest that the strong relationship between supply disruptions and COVID-19 exposure is not driven by local reactions – for example, the withdrawal of labor due to local fears of catching coronavirus. Instead, the pattern of results is most consistent with supply disruptions being driven by state-led reactions, with states with more COVID-19 reacting more aggressively.[22]

[22] Phase 2 to 5 district-level supply disruptions are also not mediated by COVID-19 exposure (columns 3 and 4, Table 2). These Phase 2 to 5 results are similar if we instead define COVID-19 exposure as of the end of Phase 5, i.e. June 30, paralleling Figure 5 (Table A2).

Table 2: District-Level Supply Disruptions by COVID-19 Exposure

	ln(1 + Food Arrivals in Tonnes to District)			
	(1)	(2)	(3)	(4)
Phase 1 (Mar 25-Apr 14)	-1.66***			
	(0.08)			
Phases 2-5 (Apr 15-Jun 30)	0.12**			
	(0.06)			
ln(1+COVID-19 Cases in State) × Phase 1		-0.34***		
		(0.04)		
ln(1+COVID-19 Cases in State) × Phases 2-5		0.05**		
		(0.02)		
ln(1+COVID-19 Cases in District) × Phase 1			-0.02	0.01
			(0.06)	(0.05)
ln(1+COVID-19 Cases in District) × Phases 2-5			-0.01	-0.04
			(0.05)	(0.06)
Observations	94164	94164	94164	93928
Number of Districts	399	399	399	398
District-Calendar Date Fixed Effects	Yes	Yes	Yes	Yes
District-Year Fixed Effects	Yes	Yes	Yes	Yes
Date Fixed Effects	No	Yes	Yes	No
State-Date Fixed Effects	No	No	No	Yes

Notes: The unit of observation is a district-day. The regressions include data from March 1 to June 30 for 2019-2020, with the exception of national holidays (Republic Day and Holi). Standard errors are clustered at the district-level. The outcome is the natural logarithm of one plus the number of tonnes of non-wheat food arrivals to mandis in the districts that reported at least once in March 2020. COVID-19 Cases in State/District are as of April 14, 2020. *** p<0.01, ** p<0.05, * p<0.1.

4 Conclusion

This paper documents how India's food supply chain responded following the national lockdown. Aggregate volumes dropped by 62% during the first few weeks of the lockdown, but subsequently fully recovered. Similarly, wholesale prices rose by 8% initially, but then returned to a downward trend. Exploiting regional variation, we also show that the initial volume shock was closely correlated with local exposure to COVID-19, and we demonstrate that this was more likely driven by state-level policy variation than by voluntary responses of those within the food supply chain. These facts provide some comfort with regard to the concerns of food security in large emerging economies like India's in the wake of the pandemic.

Policy makers around the world, and especially in the developing world, face an important tradeoff in reacting to a pandemic. The more stringent their initial lockdown the less the pandemic can spread, but also the worse is the potential damage to the economy's most critical functions. That India's food supply chain began recovering immediately following the strictest phase of the lockdown was not a forgone conclusion. Shutting the country down for three weeks – and then beginning a staggered reopening – could have introduced a coordination breakdown along the many components of the supply chain, hampering its recovery even far after the lockdown was lifted. Though it is only a single case study, the fact that India's food supply chain recovered so quickly and completely suggests that strict lockdown measures at the onset of pandemics need not cause long-term economic damage.

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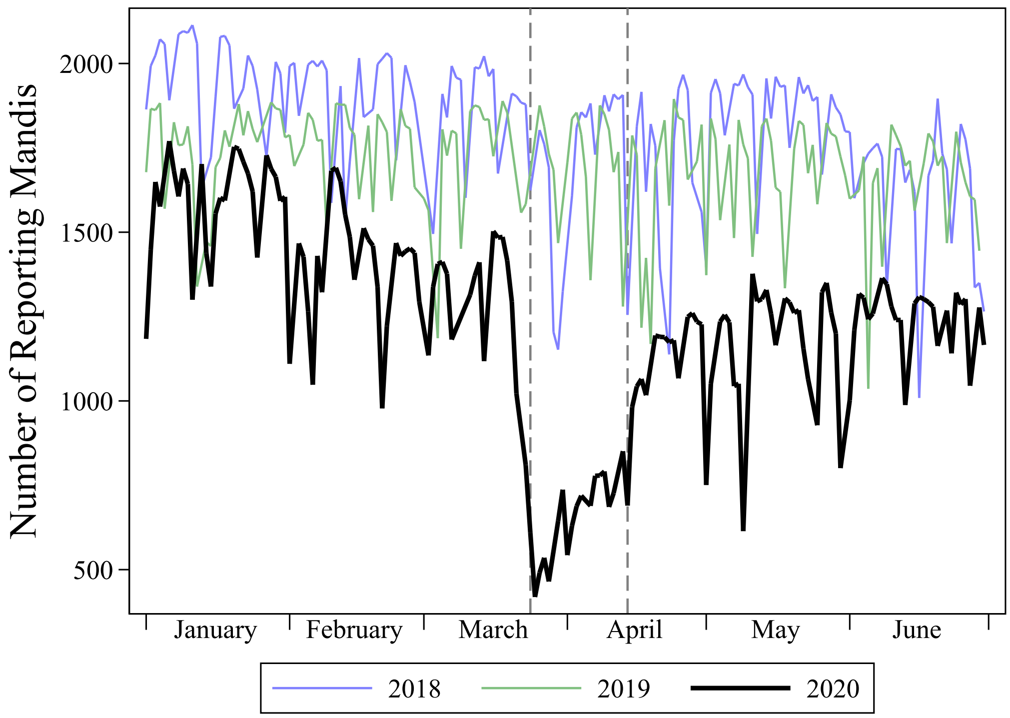
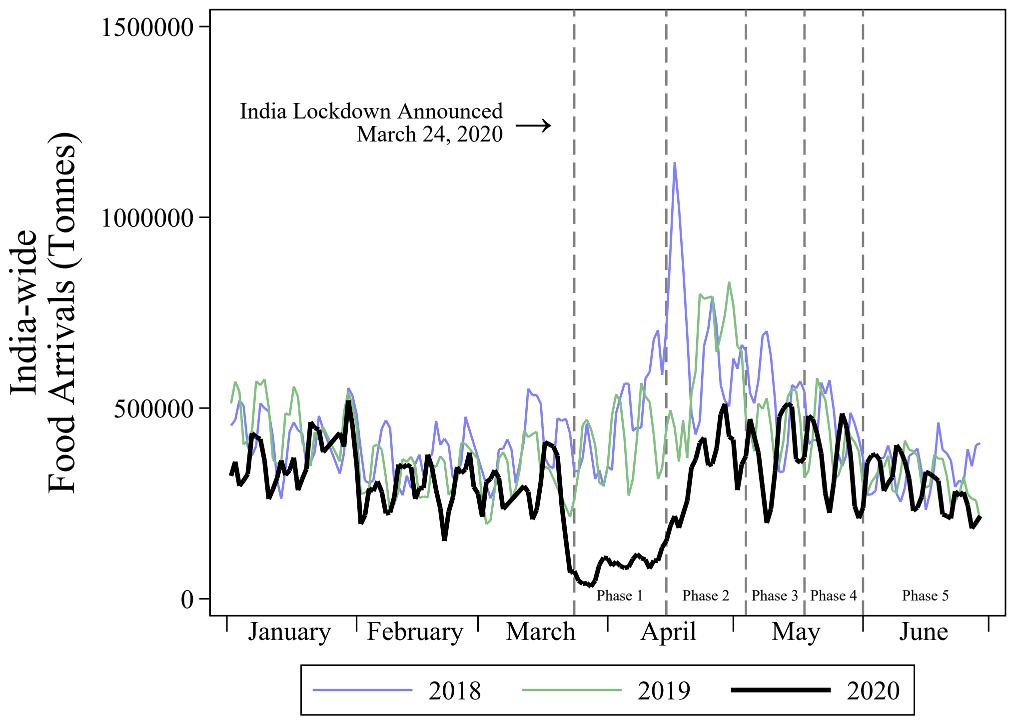
A Appendix [For Online Publication]

Figure A1: Reporting Mandis From 2018 to 2020



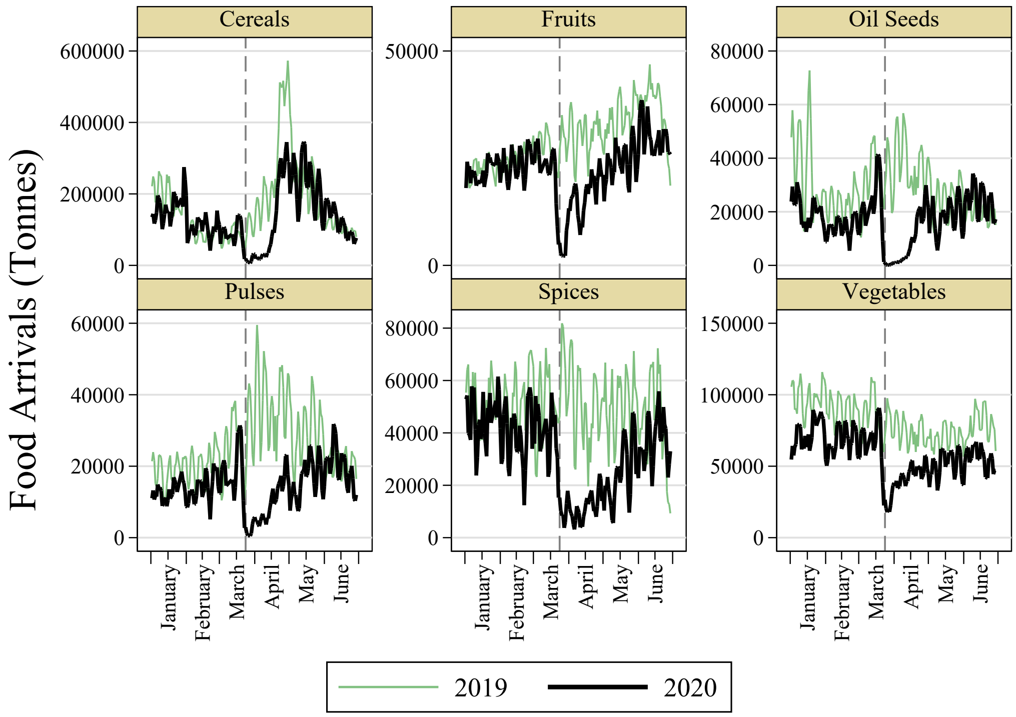
Notes: The y-axis variable is the total number of mandis that reported any data to Agmarknet on each date. The data covers January 1 to June 30, 2018 to 2020, with the exception of the national holidays of Republic Day (January 26), Holi (March 1-2 2018, March 20-21 2019, March 9-10 2020), and Sundays, to make the trends clearer (far fewer mandis report on Sundays). Source: agmarknet.gov.in.

Figure A2: Food Arrivals Including All Commodities



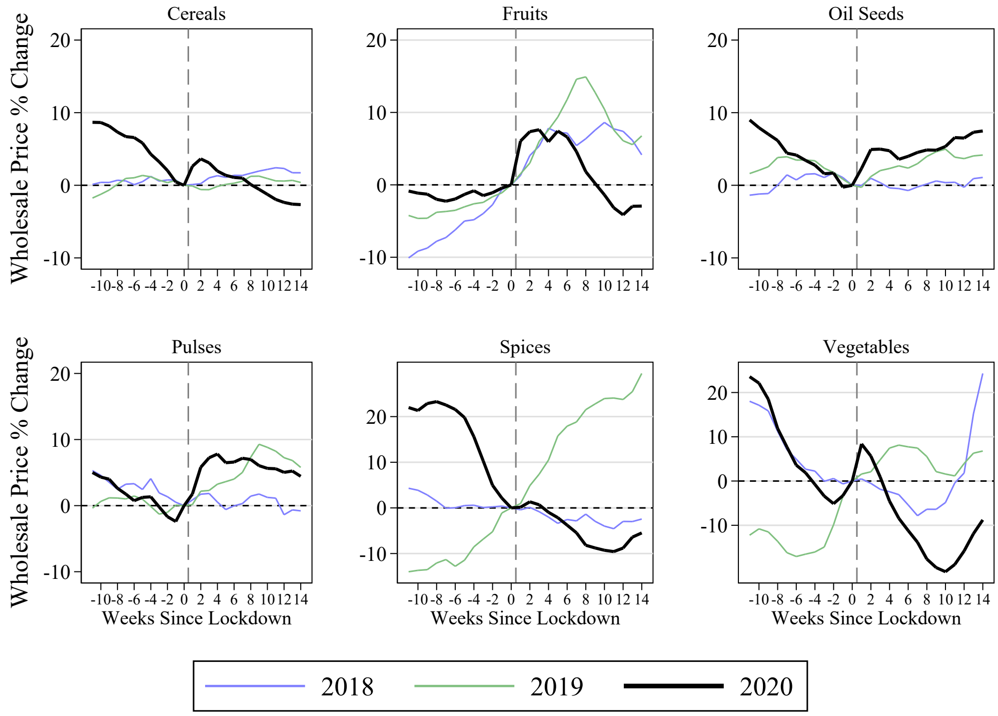
Notes: The y-axis variable is a three-day moving average of aggregate tonnes of food arrivals to the 1804 mandis that reported data to Agmarknet at least once in March 2020. The data covers January 1 to June 30, 2018 to 2020, with the exception of the national holidays of Republic Day (January 26) and Holi (March 1-2 2018, March 20-21 2019, March 9-10 2020). Source: agmarknet.gov.in.

Figure A3: The Lockdown's Impact by Food Group



Notes: The y-axis variable is a three-day moving average of aggregate tonnes of food arrivals, separately for each of six major product groups, to the 1804 mandis that reported data to Agmarknet at least once in March 2020. The data covers January 1 to June 30, 2018 to 2020, with the exception of the national holidays of Republic Day (January 26) and Holi (March 1-2 2018, March 20-21 2019, March 9-10 2020). Source: agmarknet.gov.in.

Figure A4: Wholesale Prices Evolved Similarly for Most Commodity Groups



Notes: The Figure plots the percentage change in wholesale prices implied by the year-by-year estimates from equation 2, separately for six major commodity groups. Specifically, the pre-lockdown y-axis variable is $100 \times \left(e^{\hat{\beta_t^{pre}}} - 1\right)$ for $t \in \{-11, -10, ..., -2, -1\}$, while the post-lockdown variable is $100 \times \left(e^{\hat{\beta_t^{post}}} - 1\right)$ for $t \in \{1, 2, ..., 13, 14\}$. The sample comprises only those mandis that reported data at least once in March 2020. Source: agmarknet.gov.in.

Table A1: Pre-Trends Check for District-Level Analysis

	ln(1 + Food Arrivals to District)		
	(1)	(2)	(3)
ln(1+COVID-19 Cases in State) $\times$ March 1-24 2020	-0.03		
	(0.02)		
ln(1+COVID-19 Cases in District) $\times$ March 1-24 2020		-0.02	-0.05*
		(0.03)	(0.03)
Observations	38304	38304	38208
Number of Districts	399	399	398
District-Calendar Date Fixed Effects	Yes	Yes	Yes
District-Year Fixed Effects	Yes	Yes	Yes
Date Fixed Effects	Yes	Yes	No
State-Date Fixed Effects	No	No	Yes

Notes: The unit of observation is a district-day. The regressions include data from February 1 to March 24 for 2019-2020, with the exception of national holidays (Republic Day and Holi). Standard errors are clustered at the district-level. The outcome is the natural logarithm of one plus the number of tonnes of non-wheat food arrivals to mandis in the districts that reported at least once in March 2020. COVID-19 Cases in State/District are as of April 14, 2020. *** p<0.01, ** p<0.05, * p<0.1.

Table A2: District-Level Supply Disruptions by COVID-19 Exposure as of June 30, 2020

	ln(1 + Food Arrivals in Tonnes to District)			
	(1)	(2)	(3)	(4)
Phase 1 (Mar 25-Apr 14)	-1.66***			
	(0.08)			
Phases 2-5 (Apr 15-Jun 30)	0.12**			
	(0.06)			
ln(1+COVID-19 Cases in State) × Phase 1		-0.28***		
		(0.06)		
ln(1+COVID-19 Cases in State) × Phases 2-5		0.03		
		(0.04)		
ln(1+COVID-19 Cases in District) × Phase 1			0.10*	-0.00
			(0.06)	(0.05)
ln(1+COVID-19 Cases in District) × Phases 2-5			-0.04	-0.07
			(0.04)	(0.06)
Observations	94164	94164	94164	93928
Number of Districts	399	399	399	398
District-Calendar Date Fixed Effects	Yes	Yes	Yes	Yes
District-Year Fixed Effects	Yes	Yes	Yes	Yes
Date Fixed Effects	No	Yes	Yes	No
State-Date Fixed Effects	No	No	No	Yes

Notes: The unit of observation is a district-day. The regressions include data from March 1 to June 30 for 2019-2020, with the exception of national holidays (Republic Day and Holi). Standard errors are clustered at the district-level. The outcome is the natural logarithm of one plus the number of tonnes of non-wheat food arrivals to mandis in the districts that reported at least once in March 2020. COVID-19 Cases in State/District are as of June 30, 2020. *** p<0.01, ** p<0.05, * p<0.1.