Food Policy 105 (2021) 102162

Contents lists available at ScienceDirect

Food Policy

journal homepage: www.elsevier.com/locate/jfpo

India's food supply chain during the pandemic

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ARTICLE INFO

Keywords:
COVID-19
India
Food supply chain

ABSTRACT

We document the impact of India's COVID-19 lockdown on the food supply chain. Food arrivals in wholesale markets dropped by 69% 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.

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 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 (Karaban and Mozumder, 2020).[3] 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 69% in the three weeks following the lockdown, but subsequently recovered, reaching similar levels to those in 2019 by early-May. 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 more exposed to COVID-19 *did not* have larger food supply disruptions than less-exposed districts belonging to the same state. In addition, using state-level declines in mobility as a proxy for policy responses to the pandemic, we demonstrate a strong positive relationship between state-level declines in mobility and the severity of the food supply shock.

This study contributes to the growing literature on the impact of the COVID-19 shock on the food sector in the developing world (Abay et al., 2020; Adjognon et al., 2020; Aggarwal et al., 2020; Ceballos et al., 2020; Kansiime et al., 2021; Mahmud and Riley, 2021; Hirvonen et al.,

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[2] We are grateful for excellent field assistance from Simranjeet Dhir and Toshan Majumdar, research assistance from Pulkit Aggarwal, and financial support from Private Enterprise Development in Low-Income Countries (PEDL), UK. The analysis and opinions expressed in this piece are solely those of the authors.

[3] 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.

https://doi.org/10.1016/j.foodpol.2021.102162
Received 23 December 2020; Received in revised form 3 September 2021; Accepted 6 September 2021
Available online 16 November 2021

2021). Closest to this paper are the contemporaneous studies of Rawal and Verma (2020) and Varshney et al. (2020). These studies use the same principal data source to study the evolution of food volumes and prices in India during the lockdown. We complement their analyzes by extending the sample to cover more food varieties, and more states. This allows us to explore richer patterns between COVID-19 exposure and the health of the food supply chain. In particular, by exploiting both within-state and between-state variation in COVID-19 incidence we attribute the food supply shock largely to state-level policies rather than the voluntary behavioral response of market participants. We also demonstrate that the impacts on the food supply chain are similar in urban versus rural districts, and establish a relationship between state-level mobility patterns and the food supply shock.

Other work in India finds that prices in urban food markets rose 3% in the 28 days post-lockdown (Narayanan and Saha, 2021), that supply to a major online retailer fell by 10% (Mahajan and Tomar, 2021), and more generally, reports on the food security risks faced in India as a result of COVID-19 (Ceballos et al., 2020; Reardon et al., 2020; Ray and Subramanian, 2020; Kesar et al., 2021). 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., 2021 on the impacts of public health messaging, and Banerjee et al., 2020b and Londoño-Vélez and Querubin, 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 voluntary individual responses. 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 Organization 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.[4] Despite the low reported caseload, India responded to the rapid global spread of the virus by announcing a nationwide lockdown on March 24. In an effort to preserve the functioning of the food supply chain, most of the agricultural sector and food markets were exempted from the lockdown. Nevertheless, frictions in inter-state travel and labor shortages posed significant obstacles for the food supply chain.

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 585,000) with over 17,000 deaths.[5] In terms of cases per capita, however, India had a relatively low rate of confirmed cases, with 0.4 per one thousand population as compared with 7.8 per one thousand in the US (the country with the highest number of confirmed cases as of June 30).[6]

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, and many beginning their lockdown several days prior to the national lockdown. State-level policies varied on other dimensions as well. For instance, in Delhi, mandis (local agricultural markets) were restricted to operate at half capacity, with vendors operating on alternate days (Press Trust of India, 2020). The government of Tamil Nadu placed restrictions on the timings at which trucks could unload deliveries in mandis (The New Indian Express, 2020). And the government of Maharashtra enforced mandi closures in response to pandemic surges (Srivastava, 2020).[7]

One of the major responses to the government measures was a large exodus of migrant laborers from urban centers to rural areas. 40% of India-born men in urban India live in a place different to their birthplace (versus 14% in rural India, Census 2011). Because opportunities to work were scarce, many migrant laborers returned to their locations of origin at the onset of the lockdown. Estimates place this exodus at about 6.7 million people by June 2020 across just the six states of Bihar, Uttar Pradesh, Rajasthan, Madhya Pradesh, Odisha, and Jharkhand (Mathew, 2020), and 11.4 million people by February 2021 across all states.[8] This reduced available labor for the food supply chain, often leaving wholesale markets and traders with insufficient workers, especially in the initial days of the lockdown.[9] Since most of the supply chain in India is informal 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.

2.2. 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

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

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

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

[7] For a more thorough discussion of state-level policy variation, see Narayanan and Saha (2020).

[8] This data was provided by Shri. Santhosh Kumar Gangwar, Minister of State for Labor and Employment in Indian parliament on February 8, 2021 as an answer to Lok Sabha unstarred question No. 1056.

[9] In principle, laborers who returned to their native villages could supply labor in their nearby mandis, reducing the labor supply shock to rural mandis. But frictions due to the lockdown may have made it difficult to establish relationships in new markets. Indeed, in Section 3.1 we find that the food supply shock was similarly severe in rural and urban districts.

transparency and improve price discovery, the Ministry of Agriculture created a network of mandis 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), is 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 varieties (e.g. coconut, beans, tomato), with each variety belonging to one of 15 broad categories.[10]

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. While all 15 broad categories remain represented, this sample restriction excludes 31 of the 307 varieties. Nevertheless, these 31 varieties 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 products measured in tonnes 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 arrivals in tonnes at least once during the month of March 2020. This sample restriction leads us to drop a handful of large states, including Bihar and Maharashtra (Table A1). Our final dataset consists of 271 varieties traded at 1804 markets in 24 states of India.

Despite our sample restrictions, our geographic coverage is representative of India as a whole. Districts with mandis ever reporting data to the Agmarknet portal are remarkably similar on average observables to Indian districts overall (columns 2 and 3, Table A2) – most notably, the 640 Indian districts have a rural share of households of 73% on average, and so do the 508 districts represented by mandis on Agmarknet. More importantly, the 391 districts represented by our 1804 analysis sample mandis are also similar. Only two exceptions stand out. First, our analysis sample districts are on average slightly more populous than Indian districts overall (2.1 versus 1.9 million people). Second, our analysis sample districts have a lower share of Scheduled Tribes (13 versus 18%). Given that even these two differences are small, our results likely generalize to agricultural markets nationwide.

Importantly, we note that a key limitation of our dataset is that 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). Nevertheless, a significant fraction of India's food supply appears to be traded at the 1804 markets that comprise our analysis sample. For the 18 varieties (among cereals, oil seeds, and commercial crops) for which we have compiled production data, our analysis sample markets covered an average of 25% of nationwide production during 2019/20 (Figure A2). Furthermore, this number is a lower bound on sales coverage, given that not all production is marketed – for example, the marketed surplus ratio (the ratio of marketed output to total output) was 74% for wheat and 84% for rice in 2014/15, the most recent year with data available (Government of India 2019). An overall marketable surplus of 80% would suggest that our mandis cover 31% of India's agricultural sales.

To link supply shocks with variation in COVID-19 exposure, we use data from api.covid19india.org on the number of confirmed cases of coronavirus at the state- and district-level as of April 14, 2020 (the end of Phase 1 of the lockdown) and as of June 30, 2020 (the end of Phase 5). covid19india.org aggregates COVID-19 numbers in real-time across state bulletins, official handles (e.g. Chief Ministers, Health Ministers) and press reports, and uses a team of volunteers to validate the data. We note that *confirmed cases* differ from the true case count given underreporting and insufficient testing.[11] Nevertheless the relationship between confirmed cases and the health of the food supply chain is informative given that confirmed cases are likely an important input into policy decisions. We return to this point in Section 3.3.

Finally, to link supply shocks with declines in mobility we use Google mobility data.[12] Google infers mobility from users of its applications who allow it to track their location. The data reports aggregate mobility patterns without revealing the travel data of individual users.

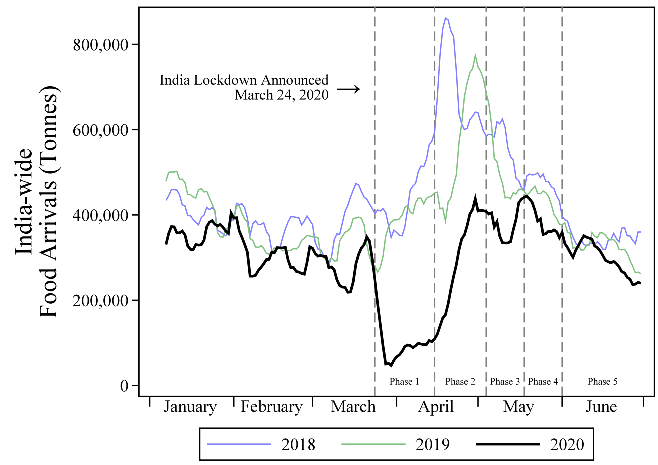

Fig. 1. The lockdown caused wholesale volumes to plummet. *Notes:* The y-axis variable is a seven-day moving average of aggregate tonnes of food arrivals to the 1804 mandis that reported arrivals in tonnes to Agmarknet at least once in March 2020. The data covers January 1 to June 30, 2018 to 2020. Given that the variable is a seven-day moving average, the first data point shown is January 7 (the average arrivals for January 1 to 7).
Source: agmarknet.gov.in.

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 similar prior to March 24 in 2018 and 2019 as compared with 2020 (Fig. 1).[13,14] Following the lockdown on March 24, 2020, arrivals dropped dramatically as compared with levels in 2018 and 2019, and gradually recovered from Phase 2 of the lockdown onwards. This core pattern is similar for each of six major food groups (Figure A5), suggesting that the recovery was not driven by product-specific government procurement.

[10] The categories are: Cereals, Spices, Fiber 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. Except where explicitly mentioned, all groups are included in our analysis.

[11] Related, Anand et al. (2021) estimates that the true number of deaths from COVID-19 in India exceeds the confirmed deaths by an order of magnitude.

[12] From https://www.google.com/covid19/mobility/

[13] Wheat accounts for 30.7% of total food volume in our data, and exhibits considerable volatility from year to year (see Figure A3). To confirm that wheat does not drive our results, we replicate all the main tables and figures involving total food volumes in Appendix B, excluding wheat. None of our core results are affected by the exclusion of wheat. We do not replicate our analysis of price trends without wheat, as these analyses are at the product-day level, so wheat does not have an outsized influence.

[14] We plot the seven-day moving average to smooth weekly fluctuations in arrivals, given notable dips on Sundays (Figure A4).

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

$$ln(\text{Volume})_{yd} = \alpha_y + \alpha_d + \sum_{t=1}^{5} \beta_t \text{Phase}^t_{yd} + \epsilon_{yd} \quad (1)$$

where $ln(\text{Volume})_{yd}$ is the log of the total volume of food arrivals in tonnes 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-difference 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.[15] 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 69%[16] (column 1, Table 1), with a nearly identical estimated drop when we also include data from 2018 in the "control group" (column 2). Volumes subsequently recovered – the Phase 2 fall is only 20% (column 1), while each of the coefficients for Phase 3 to 5 are actually positive, though not significant, in both columns 1 and 2 (with the exception of Phase 5 in column 2, significant at the 10% level). 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 visualized in Fig. 2), showing that the extensive margin drove some of the volume reduction.[17] 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.

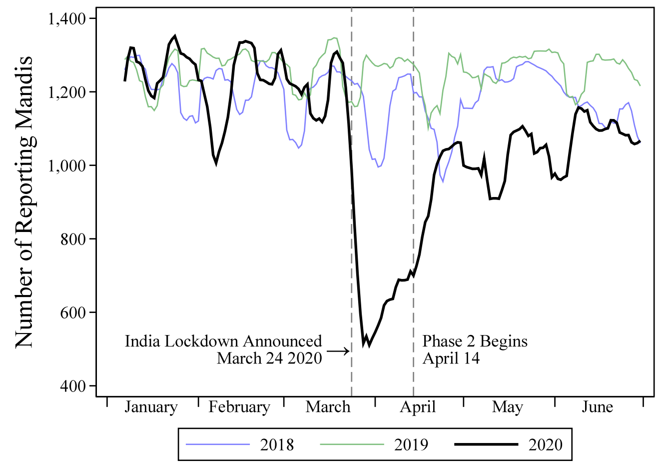

Fig. 2. The number of functioning mandis plummeted and then recovered. *Notes:* The *y*-axis variable is a seven-day moving average of the number of mandis that reported any data to Agmarknet on each date, among the 1804 mandis that reported arrivals in tonnes to Agmarknet at least once in March 2020. The data covers January 1 to June 30, 2018 to 2020. Given that the variable is a seven-day moving average, the first data point shown is January 7 (the average number of reporting mandis for January 1 to 7).
Source: agmarknet.gov.in.

To isolate intensive margin effects, we aggregate food arrivals to the mandi-day-level, and re-run the difference-in-difference 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 44% 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.

While we see effects at both the extensive and intensive margins, we might expect effects to vary spatially. Given that high population density facilitates the transmission of COVID-19, one hypothesis would be that the volume shock is more severe at mandis in more urban districts. In fact, the phase-wise patterns of shock and recovery are similar in urban and rural districts (Fig. 3). If anything, we estimate a slightly larger Phase 1 volume shock in the more *rural* districts, though we cannot reject that the Phase 1 effects are equivalent in rural and urban districts at conventional levels (Table A3). These results suggest that local COVID-19 risk, which is higher in urban areas, may not be a key driver behind supply disruptions – a theme we return to more systematically in Section 3.3.

Drivers of the Volume Shock. To understand what drove the initial volume shock we draw on a set of qualitative interviews with wholesale traders in Delhi, and 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 (Hussain, 2020). 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 at which trucks could be loaded and unloaded. A shortage of ancillary workers,

[15] With only data for 2020 we could estimate a pre-post (or before–after) specification, in which we compare volumes before and after March 24, 2020. The key drawback with such a specification is that changes after March might reflect seasonality in volumes, rather than the causal effect of the lockdown and associated COVID-19 shocks. By including the 2019 data, we "difference out" this seasonality (formally by including calendar date fixed effects), making our estimates difference-in-difference estimates. These estimates essentially ask how much bigger the volume drop was after March 2020 when compared with that after March 2019, and attribute this difference to the effects of the pandemic. Put another way, we implicitly estimate the counterfactual volumes (in the absence of the pandemic) after March 24, 2020 to be those implied by applying the seasonality in 2019 to the levels of volumes at the start of 2020.

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

[17] 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)	−1.17***	−1.18***	−0.54***	−0.51***	−0.58***	−0.59***
	(0.30)	(0.24)	(0.14)	(0.12)	(0.04)	(0.04)
Phase 2 (Apr 15–May 3)	−0.22	−0.20	−0.07	−0.02	−0.17***	−0.16***
	(0.26)	(0.23)	(0.14)	(0.13)	(0.04)	(0.04)
Phase 3 (May 4–May 17)	0.17	0.16	−0.12	−0.13	0.18***	0.21***
	(0.32)	(0.28)	(0.19)	(0.17)	(0.04)	(0.04)
Phase 4 (May 18–May 31)	0.30	0.29	−0.10	−0.11	0.27***	0.31***
	(0.33)	(0.28)	(0.19)	(0.16)	(0.04)	(0.04)
Phase 5 (Jun 1–Jun 30)	0.40	0.40*	0.06	0.08	0.21***	0.31***
	(0.26)	(0.22)	(0.14)	(0.12)	(0.04)	(0.03)
Observations	240	360	240	360	260 181	388 382
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 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. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

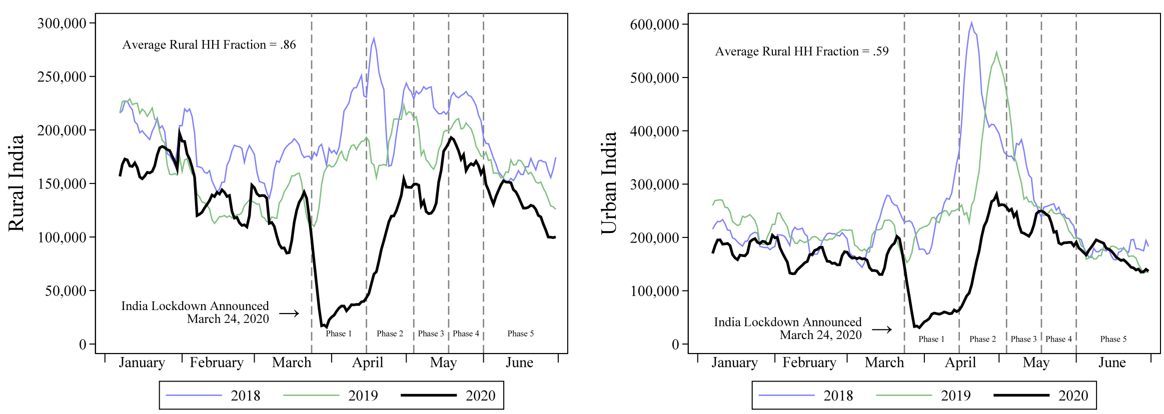

Fig. 3. Food arrivals to urban vs. rural India. *Notes:* The *y*-axis variable is a seven-day moving average of aggregate tonnes of food arrivals to the 1804 mandis that reported arrivals in tonnes to Agmarknet at least once in March 2020. Rural India includes any mandis residing in a district with an above-median share of rural households in the 2011 Census, with Urban India including all other mandis. The data covers January 1 to June 30, 2018 to 2020. Given that the variable is a seven-day moving average, the first data point shown is January 7 (the average arrivals for January 1 to 7).
Source: agmarknet.gov.in.

e.g. book keepers, also impacted the daily functioning of the markets (Mishra and Pillai, 2020).

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.[18] The central 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.[19] 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 (Press Trust of India, 2020).

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. This year-by-year event study approach differs from the analysis in Table 1 in that we do not explicitly estimate a difference-in-difference effect of the pandemic. We change the

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

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

approach when considering prices because the strong autocorrelation in prices makes the parallel trends assumption unreasonable. As a result, our analysis of prices is more descriptive in nature than our analysis of volumes.

We estimate the following specification separately for each of the three years:

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

where $ln\left(\text{Modal Price}_{smfd}\right)$ 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 tth 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.[20] 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% (Fig. 4). 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 levels toward the end of Phase 5.[21] In short, prices were affected similarly to volumes (Fig. 1) – an initial shock during Phase 1 followed by a return to normality during the subsequent lockdown phases.[22]

While our analysis considers wholesale prices, evidence for urban areas from Narayanan and Saha (2021) suggests that our findings may also hold for retail prices – they find that the retail price markup over wholesale prices remained fairly constant during the lockdown period.

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 is neither economically nor statistically significant, indicating that the relationship is not driven by local responses to COVID-19 exposure. Finally, utilizing the decline in state-level mobility as a proxy for state-level policy, we show a strong positive relationship between decline in mobility and the food supply disruption. We conclude that state-level policy responses are more likely responsible for the food supply shock rather than voluntary individual responses.

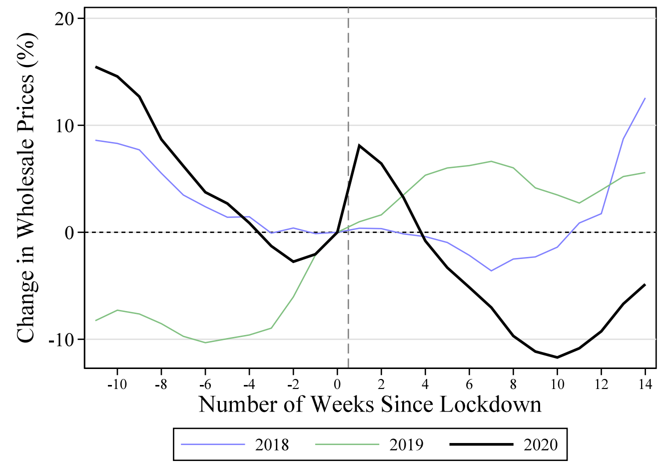

Fig. 4. After an initial increase in wholesale prices, prices returned to trend. *Notes:* The figure plots the percentage change in wholesale prices implied by the year-by-year estimates from Eq. (2). Specifically, the pre-lockdown y-axis variable is $100\times\left(e^{\beta_t^{\text{pre}}}-1\right)$ for $t\in\{-11,-10,\ldots,-2,-1\}$, while the post-lockdown variable is $100\times\left(e^{\beta_t^{\text{post}}}-1\right)$ for $t\in\{1,2,\ldots,13,14\}$. The sample comprises only those mandis that reported data at least once in March 2020.

It is important to note that the confirmed COVID-19 case counts differ from the true COVID-19 case counts due to underreporting and insufficient testing, and that the extent of undercounting may differ by state. Nevertheless, confirmed COVID-19 case counts represent the best information about the severity of the pandemic available to policymakers and market participants. Thus the analysis to follow can be viewed as investigating the relationship between (potentially mistaken) views about the severity of the pandemic and the health of the food supply chain.[23]

To analyze the relationship between food supply and confirmed COVID-19 cases at the state level, we first 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 Fig. 1 and Table 1). We use the following specification for each state s:

$$ln\left(\text{Volume}\right)_{yd}^{s} = \alpha_y^s + \alpha_d^s + \gamma^s\text{Phase}_{yd}^{1} + \theta^s\text{Phase}_{yd}^{2-5} + \epsilon_{yd}^{s} \quad (3)$$

which differs from Eq. (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_{yd}^{2-5}, 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 – those with at least 10 mandis on average

[20] One caveat is that with non-functional markets (Figure A1), sometimes food was not available at all during the lockdown, 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.

[21] 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.

[22] The pattern of rising wholesale prices at the onset of the lockdown holds for most of the major commodity groups (Figure A6), 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. However, we do not find strong evidence for heterogeneity in the lockdown-induced price increase by perishability overall (Figure A7). While the 2020 wholesale price trends for (manually-classified) perishables are more volatile than those for non-perishables, both product categories see a similar short-term spike in prices after the lockdown.

[23] For a discussion of related issues, see Abay et al. (2021).

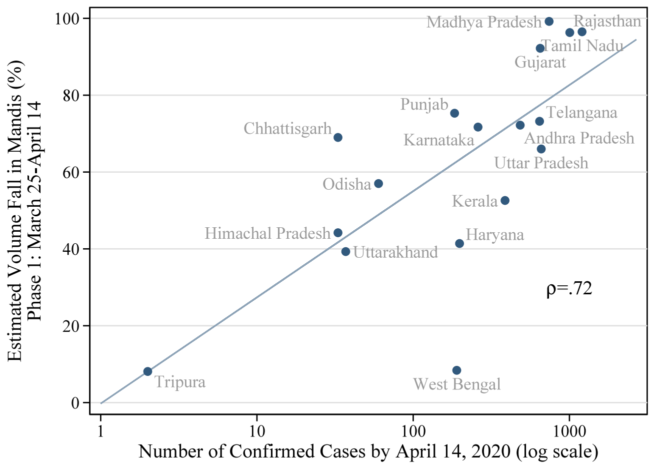

Fig. 5. States with more coronavirus cases had bigger supply chain disruptions during phase 1. *Notes:* The y-axis is the estimated Phase 1 volume fall for each of 17 states, where the estimate is $100\times\left(1-e^{\hat{\gamma}^s}\right)$ using estimated coefficients from Eq. (3). The x-axis is the number of confirmed cases of coronavirus by the end of Phase 1 (April 14), from api.covid19india.org. ρ is Pearson's correlation coefficient between the estimated Phase 1 volume fall and the natural logarithm of the number of confirmed cases by April 14, 2020.

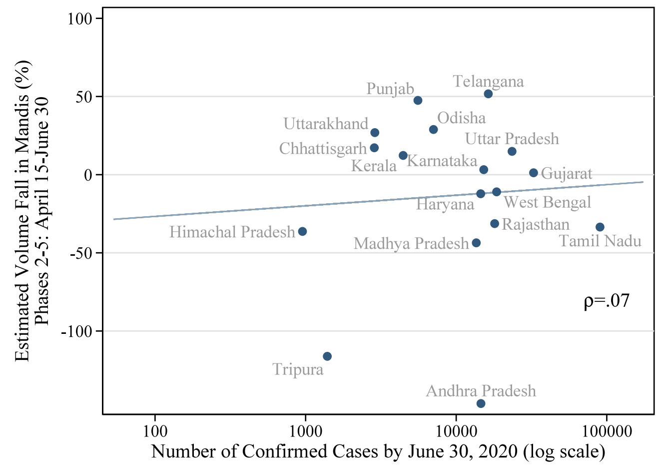

Fig. 6. Volume shocks were not correlated with coronavirus cases after phase 1. *Notes:* The y-axis is the estimated Phase 2–5 volume fall for each of 17 states, where the estimate is $100\times\left(1-e^{\hat{\theta}^s}\right)$ using estimated coefficients from Eq. (3). The x-axis is the number of confirmed cases of coronavirus by the end of Phase 5 (June 30), from api.covid19india.org. ρ is Pearson's correlation coefficient between the estimated Phase 2–5 volume fall and the natural logarithm of the number of confirmed cases by June 30, 2020.

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.[24]

The Phase 1 volume fall at the state-level ($100\times\left(1-e^{\hat{\gamma}^s}\right)$) is strongly positively correlated with the log number of confirmed cases of coronavirus as of the end of Phase 1 ($\rho = 0.72$, $p = 0.001$, Fig. 5). In fact, the log number of confirmed cases of coronavirus alone explains over half 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.

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 ($\rho = 0.07$, $p = 0.8$, Fig. 6). This shows that the nationwide supply recovery visualized in Fig. 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 lockdown policies with greater efforts at enforcement. These policies could have disrupted the supply chain.[25] Second, even holding state-level policies constant, people could voluntarily change their behavior in response to a high local incidence of coronavirus. For example, rather than being deterred by state-level policies, people might voluntarily restrict their labor supply out of fear of contracting the disease. 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 disappear in a within-state analysis. However, if the disruption is driven by voluntary behavioral responses, then the correlation should persist even using within-state variation. In what follows we demonstrate that there is no economically or statistically significant correlation between the food supply shock and COVID-19 intensity at the within-state level and therefore the food supply shocks are most likely due to state-level policy variation.[26] At the close of this section we provide a more direct form of evidence that state-level policy is responsible for the food supply shock. Namely, we demonstrate that declines in mobility, measured using Google mobility data, are strongly correlated with food supply shocks at the state level.

We begin with our analysis of district-level data to estimate the evolution of food supply in districts with more versus less coronavirus exposure. Earlier, we used a difference-in-difference specification (Eq. (1)) to estimate the effect of the lockdown as the additional fall in volumes post-March 24 in 2020 relative to 2019. Now we test whether this difference-in-difference effect is larger in districts with more exposure to COVID-19. This amounts to a triple-difference approach, in which the triple interaction term is between (i) post-March 24, (ii) the year 2020, and (iii) confirmed COVID-19 cases at the district-level. More formally, we estimate:

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

[24] These 17 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. The seven states (or union territories) that are dropped relative to our previous 24-state analyzes are: Goa, Jammu and Kashmir, Jharkhand, Meghalaya, Nagaland, NCT of Delhi, and Pondicherry (Table A1).

[25] While we do not directly observe state-level lockdowns in our data, we utilize declines in state-level mobility, measured via Google mobility data, to proxy for state-level lockdowns. Figure A8 demonstrates a strong relationship between state-level COVID-19 incidence and mobility reductions as of April 14 (Phase 1 of the national lockdown).

[26] We note that policy can vary at the district-level as well. Nevertheless, the fact that we find no evidence of a relationship between district-level COVID-19 incidence and the food supply shock indicates that neither district-level policy nor voluntary individual withdrawal of labor supply are responsible for the shocks.

$$+\ \phi_2 \left(arcsinh \left(\text{COVID-19 Cases}_x \right) \times \text{Phase}^{2-5}_{yd} \right) + \epsilon_{xyd}$$

where Volume_{xyd} is the total quantity of food arrivals in tonnes to district x during year y on calendar date d. Here we take the inverse hyperbolic sine, rather than the natural logarithm, of 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.[27] These two-way interactions fully absorb the overall difference-in-difference effect of the lockdown, meaning our focus in this specification is only on estimating the *differential* effect of the lockdown in high- versus low-exposure districts.

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 confirmed cases of COVID-19 by April 14, we again take the inverse hyperbolic sine of this variable. 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. Given the inverse hyperbolic sine transformations on the left- and right-hand-side, these coefficients can be interpreted as elasticities for large enough values of Volume and COVID-19 Cases (Bellemare and Wichman, 2020).

We estimate three variants of this specification. First, we replace $arcsinh \left(\text{COVID-19 Cases}_x \right)$ with $arcsinh \left(\text{COVID-19 Cases}_s \right)$ where s denotes the state that district d belongs to. This initial specification aims to replicate the strong positive correlation in Fig. 5 – 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 Eq. (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.[28]

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.[29] Consistent with our earlier results, food arrivals to districts dropped by 86% during Phase 1 of the lockdown (column 1, Table 2, compared with a 69% 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 Fig. 5. Specifically, the point estimates imply that a doubling of state-level cases by April 14 is associated with a negative supply shock that is 33% 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.[30]

We note that, much as in the case of state-level confirmed COVID-19 cases, district-level COVID-19 cases are very likely to be measured with error, and this error may vary systematically across districts. For instance, some districts may not have testing facilities, and people may cross district boundaries to get tested. As in the case of state-level confirmed COVID-19 cases, if people utilize district-level confirmed COVID-19 case statistics to inform their decisions, then our analysis demonstrates that voluntary responses to perceived COVID-19 intensity are not a significant contributor to the food supply shock. However, people may have also used other sources of information about the pandemic's intensity, which were only imperfectly correlated with confirmed cases. In this event the lack of district-level correlation between confirmed cases and the food supply shock may in part be due to our imprecise measurement of perceived COVID-19 intensity at the district level.

To provide more direct evidence that state-level policy is a primary driver of the food supply shock, we turn to Google mobility data. In the absence of a comprehensive list of state-level policy responses to the pandemic, declines in mobility may be a good proxy for policy responses. Namely, states with more stringent lockdowns should see a larger decline in mobility. In Figure A9 we replicate the analysis of Fig. 5, but rather than confirmed COVID-19 cases, the x-axis measures the decline in state-level mobility during Phase 1 of the lockdown. Indeed, there is a strong positive correlation ($\rho = 0.54$, $p = 0.03$) between declines in state-level mobility and the food supply shock. Table A4 confirms this conclusion in a regression framework. Every 1% decrease in mobility at the state-level corresponds to a 2.6% decrease in food volumes ($p < 0.01$), though this relationship disappears once controlling for COVID-19 intensity. Echoing Fig. 6, the unconditional relationship also disappears in Phases 2–5 ($\rho = 0.15$, $p = 0.56$, Figure A10).

4. Conclusion

This paper documents how India's food supply chain responded following the national lockdown. Aggregate volumes dropped by 69% 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.

Policymakers 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.

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

[28] In support of the key assumption for a triple-difference specification, pre-trends are parallel for each of these three variants of our core specification (Table A5).

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

[30] 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 Fig. 6 (Table A6).

Table 2
District-level supply disruptions by COVID-19 exposure.

	arcsinh(Food Arrivals in Tonnes to District)			
	(1)	(2)	(3)	(4)
Phase 1 (Mar 25–Apr 14)	−1.963***			
	(0.100)			
Phases 2–5 (Apr 15–Jun 30)	0.148**			
	(0.063)			
arcsinh(COVID-19 Cases in State) × Phase 1		−0.404***		
		(0.046)		
arcsinh(COVID-19 Cases in State) × Phases 2–5		0.055**		
		(0.025)		
arcsinh(COVID-19 Cases in District) × Phase 1			−0.004	0.017
			(0.061)	(0.047)
arcsinh(COVID-19 Cases in District) × Phases 2–5			0.044	0.043
			(0.042)	(0.046)
Observations	94 164	94 164	94 164	93 928
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 inverse hyperbolic sine (arcsinh) of the number of tonnes of 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. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Appendix A. Supplementary data

Supplementary material related to this article can be found online at https://doi.org/10.1016/j.foodpol.2021.102162.

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