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Food supply chains and resilience to shocks: Evidence from India's COVID-19 lockdown

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Abstract

We study the disruption of food supply to households and reduced farm-to-market arrivals in India's food supply chain during the COVID-19 lockdown. We focus on the relationship between logistics quality (and performance) and the intensity of disruptions across India's states. We find four policy-relevant findings: (1) Food consumption expenditure was higher in states with better logistics quality; (2) These states recovered more quickly from farm-to-market disruptions with higher agricultural market arrivals in the later phases of the lockdown; (3) Rural food supply chains turned out to be as vulnerable as urban ones; and (4) Expenditure on cereals and pulses faced large reductions.

KEYWORDS

agricultural markets, covid-19, food supply chains, India, state policy

JEL CLASSIFICATION

Q10, Q13, Q18

The COVID-19 pandemic and the government responses to curb the spread of disease provided a unique opportunity to understand the effects of shocks, such as lockdowns on the economy (Beyer et al., 2020; Cariappa et al., 2021; Deshpande, 2020b; Gupta & Kishore, 2022; Reardon et al., 2020). The negative effects on access to food have been particularly concerning during the lockdown across the world. One pathway through which lockdowns affect food access is the disruption of food supply chains (Choi, 2020; Ivanov, 2020). The other pathways are through price (Matz et al., 2015) and income shocks (Leete & Bania, 2010). Research so far has shown that stringent measures to curb COVID-19 disrupted supply chains for vegetables, fruits, and food grains and increased undernourishment (Ivanov & Dolgui, 2020; Khan et al., 2021). Understanding these effects becomes vital as lockdown-induced shocks can decrease the share of nutrient-rich foods in diets, making the poor vulnerable to disease (Short et al., 2018). Household responses to price and income shocks have been studied in many contexts. Coping with these shocks requires household-level resilience as well as resilient supply chains. While the literature on resilient supply chains and supply chain disruption is expanding, the impact of supply chain logistics quality on disruptions remains underexplored.

According to Reardon et al. (2022), investment in the "blood" and "bones" of food systems is essential for building resilience. "Bones" refer to roads, infrastructure, and wholesale markets. "Blood" refers to logistics services and the regulatory environment. We utilize the "Logistics Ease Across Different States" or LEADS index as a proxy for the "blood" and "bones" of food supply chains. While ours is the first paper to use logistics quality and performance to analyze domestic supply chain disruption in India, it is widely used in the international trade literature. For instance, Song and Lee (2022) show that improvements in logistics performance reduce trade costs and increase international trade volumes. Chu (2012) and Navickas et al. (2011) show how investing in logistics helps underdeveloped and developing countries foster growth. Studies have linked logistics performance to not only growth or volume of trade but also the resilience of trade (Mena et al., 2022).

In this paper, we study the effects of the Government of India imposed lockdown that began on March 24, 2020.[1] We study two kinds of supply chain disruptions caused by the lockdown. First, we look at disruptions that may have led to food inaccessibility for consumers, and second, we look at disruptions that led to reduced farm-to-market volume arrivals at mandis (wholesale agricultural marketplaces[2]). We provide estimates of the effects of logistics quality using a difference-in-differences (DiD) design. We follow two approaches.

The first approach analyzes household food supply disruptions. We use monthly household panel data for foods and food groups (cereals, pulses, dairy, fruits, vegetables, meat and fish, and eggs). We compare the lockdown period of the first wave of COVID-19 in April–June 2020 with January–March 2020, with the control group being the same households in the corresponding months in 2019, a period of relative normalcy. Our measure of disruption is the fall in expenditure on food, which occurs even after controlling for income and prices, which may imply that expenditure is lower due to changes in food access. To be sure, we do not directly observe the availability of food in retail markets for consumers during these months. However, we believe that sudden changes in preferences between food (essential goods) and non-food commodities may not be driving these results. We find it unlikely that people would prefer to consume less food in the lockdown months if it were accessible in the market (given that we control for price and income). In addition, we also look at rural/urban differences in supply chain disruptions during the same periods.

Our second approach is an analysis of wholesale agricultural market arrivals. We follow Lowe et al. (2021) and compare mandi arrival volumes in five phases of the lockdown in 2020 (Phase 1: 25 March–14 April, Phase 2: 15 April–3 May, Phase 3: 4–17 May, Phase 4: 18–31 May, and Phase 5: 1–30 June) with the period just prior to the lockdown (1–24 March). The control group is the same mandis during the corresponding periods in 2019. In both approaches, we use the LEADS index put out by the Ministry of Commerce and Industry, Government of India. This allows us to analyze state-wise differences in logistics quality.

We find that the lockdown caused a household food supply disruption, as measured by the 14% reduction in all-India food consumption expenditure. States with a one-point higher

LEADS index saw a less intense household food supply disruption, as evidenced by 11% higher food consumption expenditure. In the wholesale market analysis, we find that the total daily food arrivals in mandis fell across states in the first three phases of the lockdown, irrespective of LEADS index scores. In the last two phases of the lockdown, states with a one-point higher LEADS index score experienced 45% to 46% higher mandi arrivals. Better logistics appear to improve resilience to unforeseen supply shocks and enable quicker recovery from disruption. Our findings provide fresh evidence in support of developing supply chains to ensure food security.

In the analysis of urban and rural supply chains, we find a negligible difference in the magnitude of household food supply disruption. Urban supply chains were considered longer and more vulnerable to disruptions (Reardon et al., 2014) since nearly all food is produced in rural India. Our results are not in line with this view and are more in line with recent work that finds small-town India to be more vulnerable to price shocks during the COVID-19 lockdown (Narayanan & Saha, 2021). Our results have potentially significant implications for rural food supply chain development.

LITERATURE

A few studies focus on food supply chain disruptions due to the COVID-19 lockdown shock. Reardon et al. (2020) discuss India's food security risk due to COVID-19, which is heightened by its overwhelmingly private-sector food supply chains. Aday and Aday (2020) show that lengthy supply chains caused by centralized manufacturing were one of the factors for supply chain disruption during COVID-19. Mahajan and Tomar (2021) use datasets from online grocery retailers to conclude that supply chain disruption is the main driver for the decline in availability of vegetables, fruits, and edible oils and that more distant food supply chains were hit the hardest.

Lowe et al. (2021) find decreases in arrivals in the mandis following the lockdown and increases in wholesale prices. They show that the initial food supply shock correlates with the onset of COVID-19, and that this disruption disappears during the recovery phase. They find that states with more COVID-19 cases experienced a greater fall in food arrivals in mandis after the lockdown as compared to previous years. However, they study only farm-to-market disruptions. They also show a similar impact of disruption in the urban and rural supply chains for mandi arrival volumes (for rural impact, see Rawal et al., 2020).

Narayanan and Saha (2021) in their paper assessed the effect of the 2020 pan-India lockdown on urban food markets through their analysis of retail and wholesale prices of major food items. They found frictions in the supply chain, as inferred from the increase in spatial dispersion and the price wedge between wholesale and retail prices. They found that the increase in price was more pronounced in smaller cities (see also Ramakumar, 2020). Findings from the study by Erokhin and Gao (2020) showed that in developing countries, both food security and food supply chain stability have been adversely affected due to this pandemic (see also Ceballos et al., 2021).

According to Naja and Hamadeh (2020), transportation and distribution disruptions due to pandemics have increased vulnerability in terms of food accessibility and availability at the community level. Ceballos et al. (2020) showed how farmers in one state faced more disruption due to a reduction in food available in the markets, whereas in other states, farmers benefited because of an increase in the local food supply. According to Chenarides et al. (2021), the lack of resilient food supply chains was evident from stories of food shortages. Kumar et al. (2021), through a telephonic survey during the lockdown period in 57 districts of Uttar Pradesh, analyzed factors that were responsible for the disruption of agricultural systems (for a pan-India analysis, see Jaacks et al., 2021). One of the factors identified is the sudden halt of large-scale procurement operations by the Indian Government and the closure of agricultural mandis in many states. Hirvonen et al. (2021) find no change in fruit consumption, so they indirectly conclude that the value chains of perishable foods continue to function without disruptions.

Our study speaks to this literature and relies on food expenditure data for household food supply disruptions, and mandi volume arrivals data for farm-to-market disruptions. Our main departure from the existing literature is the analysis of state-wise variations in supply chain characteristics, which no study has examined so far. For instance, apart from our analysis of household food supply disruptions, we extend the analysis of mandi-level food arrival disruptions by Lowe et al. (2021) by looking at how state-wise variation in logistics quality and performance matters in understanding farm-to-market disruptions. We make three contributions to the literature: (1) Ours is the first study that provides evidence for household food supply chain disruptions due to the COVID-19 lockdown. (2) We evaluate differences in supply chain characteristics of India's states (as measured by the LEADS index) to explain state-wise variations in household and farm-to-market food supply chain disruptions. (3) Our empirical analysis identifies specific supply chain characteristics that are needed to build resilient supply chains. In addition to the above three contributions, we also provide evidence for differences in rural and urban household food supply chain disruptions and variations in the extent of these disruptions for different food groups. Our study has important policy implications, as it not only documents the vulnerabilities of food supply chains across states in a developing country context, but also informs policymakers about which supply chain characteristics to focus on and strengthen.

The next section describes the data we use and our key variables of interest, followed by a section describing our methodology and specification, followed by results, discussion, robustness checks, and conclusions.

DATA AND VARIABLES

We use two principal sources of data: The Consumer Pyramids database by the Centre for Monitoring Indian Economy (CMIE) and Agmarknet data provided by the Directorate of Marketing & Inspection (DMI), Ministry of Agriculture and Farmers Welfare, Government of India (https://agmarknet.gov.in/). We supplement this with other sources for specific variables (Table A2).

For the analysis of household food supply disruptions, we use household monthly consumption and expenditure panel data from the CMIE. We use data from January to June for 2019 and 2020, covering 1,68,241 households with a response rate varying from 83% in January 2020 to 59% in June 2020. This dataset includes details of monthly consumption expenditures on food and non-food items. Data is available separately for 39 food items like cereals, pulses, vegetables, fruits, milk, processed food, and so forth, and 110 non-food items like power and fuel, medicine, education, the Internet, and so forth. For our analysis, we define five categories: cereals (includes processed cereals), pulses, dairy, fruits, vegetables, meat and fish, and egg. CMIE does not provide price and quantity data. We use an alternative government source for price information. The nominal prices of food and its subgroups were deflated using the appropriate Consumer Food Price Index (CFPI)[3] at the all-India level (for rural and urban regions separately), made available by the Central Statistics Office. We acknowledge that CMIE households may be picking up spatial variations in prices. This is a limitation, as price data with appropriate food group indices was not collected during the lockdown months at the state level.[4]

CMIE data has been criticized for not being representative of India, especially of the poorest. This is mainly because of the choice of sampling at the village level, where sampling was conducted beginning at the village main street (Dreze & Somanchi, 2021). This potentially misses out on the poorest rural respondents, who tend to reside away from the main street. Further, some key variables in the CMIE do not match estimates from other surveys like the National Family Health Survey (Dreze & Somanchi, 2021). We are aware of these issues and acknowledge that our findings must be viewed in light of these larger concerns with the CMIE.[5] We also find comparable results using farm-to-market data from the same period. Under the circumstances, we feel our findings do capture the effects of the COVID-19 lockdown on food supply chains.

To analyze farm-to-market supply chain disruptions, we use daily data of agricultural commodities volume arrivals at the Agricultural Produce Market Committee (APMC) mandis.[6] The total market arrivals volume is recorded daily along with the price per quintal (maximum, minimum, and modal price) at each market. The volume arrivals data for each crop is in quintals and is available for both perishables like fruits and vegetables and non-perishables like cereals and pulses. The analysis for state-wise variation in arrivals at mandis is done for 22 states and excludes North East India's hilly states like Tripura, Sikkim, Arunachal Pradesh, Meghalaya, Manipur, Mizoram, and Nagaland. It also excludes Chandigarh, Delhi, Puducherry, Dadra and Nagar Haveli, and Daman and Diu.

We use the LEADS index to distinguish logistics quality and performance across states. LEADS was first released by the Department of Commerce, Ministry of Commerce and Industry, Government of India, in 2018. The LEADS index captures the perception of users (like domestic traders, transport, and terminal operators) and logistic service providers about indicators of logistic efficiency identified through an in-depth literature review of composite indices. It then provides a ranking of states based on a composite index comprising a variety of indicators that capture logistics infrastructure (availability and quality of roads, rail, airports, ports, warehouses, and cold storage), services (timeliness of cargo delivery, quality of handling, affordability, security), and regulations (de jure laws and rules).[7] We use the LEADS index for 2019. The department did not produce the 2020 report. The LEADS index is based on nine sub-indices[8] that capture specific aspects of logistics quality and performance. Refer to Table A3 for the values of LEADS and sub-indices for 2019. We use the LEADS index in both household and farm-to-market analyses to distinguish between states by the quality and performance of their logistics infrastructure and services.

We believe that LEADS is a reasonable proxy for differences in food supply chain logistics quality between states. Food supply logistics are related to the overall quality of supply chain logistics. The important aspects of the food supply chain that LEADS directly measures are warehouse capacity owned by Food Corporation of India, and number and capacity of cold storage facilities. In addition, the road and rail network quality available to farmers and other transportation issues like ease of track and trace, bear similarity with logistics of non-agricultural commodities. Even as food is only one of the many commodities being transported, the index gives a fair approximation of differences across states.To control for the stringency of lockdown across states, we use the number of COVID cases as a proxy, which we sourced from https://data.covid19india.org/.

METHODOLOGY

The COVID-19 lockdown in India was nationwide. Such a situation is challenging to study accurately because of the lack of a contemporaneous control group. To address this problem, we define control and treatment groups temporally as used by Çakır et al. (2021) and Aggarwal and Narayanan (2022). Thus, we use a DiD design where the control group is the same set of households in the past. We compare households in January–June 2020 to themselves in January–June 2019. Further, we also employ variations along two axes: rural/urban locations (that differ in lockdown intensity and length of supply chain) and the state-wise LEADS index score (that captures variation in logistics quality and performance). We utilize a triple difference design like other studies (Aggarwal & Narayanan, 2022)[9] to understand the effects of the above two variations. We verify that parallel trends are reasonable and present the relevant evidence to justify using a DiD design (see Figure A1). The temporal dimension for triple DiD is used for analyses of farm-to-market supply chain disruption, where daily food arrival volumes at mandis in March–June 2020 is compared to arrivals in March–June 2019 (with 1–24 March as pre-treatment period).

The following are the specifications we estimate:

$$\mathrm{Y}_{\mathrm{it}} = \alpha + \xi_1 Treat + \xi_2 Post_t + \xi_3 (Post \times Treat)_{it} + Z_{it} + P_{crt} + C_{st} + \epsilon_{it} \tag{1}$$

$$\begin{aligned}\mathrm{Y}_{\mathrm{it}} = \alpha &+ \beta_1 Treat + \beta_2 Post_t + \beta_3 (Post \times Treat)_t + \beta_4 LEADS_s + \beta_5 (Post \times LEADS)_{st} \\ &+ \beta_6 (Treat \times LEADS)_s + \beta_7 (LEADS \times Post \times Treat)_{st} + Z_{it} + P_{crt} + C_{st} + \epsilon_{ist}\end{aligned} \tag{2}$$

$$\begin{aligned}\mathrm{Y}_{\mathrm{it}} = \alpha &+ \gamma_1 Treat + \gamma_2 Post_t + \gamma_3 (Post \times Treat)_t + \gamma_4 Urban_i + \gamma_5 (Post \times Urban)_{it} \\ &+ \gamma_6 (Treat \times Urban)_i + \gamma_7 (Urban \times Post \times Treat)_{it} + Z_{it} + P_{crt} + \epsilon_{it}\end{aligned} \tag{3}$$

$$\begin{aligned}Q_{md} = \alpha &+ \zeta_1 Treat + \zeta_2 Phase_d + \zeta_3 (Phase \times Treat)_d + \zeta_4 LEADS_m + \zeta_5 (Phase \times LEADS)_{md} \\ &+ \zeta_6 (Treat \times LEADS)_m + \zeta_7 (LEADS \times Phase \times Treat)_{md} + W_{md} + \epsilon_{md}\end{aligned} \tag{4}$$

In the first, second, and third specifications, Y_{it} is the mean household monthly expenditure on total food for the i^{th} household for all states and for the t^{th} month.[10] For households in 2020, $Treat = 1$, that is, treatment group, and $Treat = 0$ for households in 2019, that is, control group. For April, May, and June $Post_t = 1$ and $Post_t = 0$ for January, February, and March. $(Post \times Treat)_t$ is the DiD term, and this is the coefficient of interest. In the second equation, we execute a triple difference by interacting $Post_t$ *and Treat* with $LEADS_i$. The coefficient on β_7 is the triple difference estimate, which helps understand the difference in supply chain disruptions due to logistics quality. The control variables are represented by Z_{it} which refers to all controls such as log of total income, time-fixed effects, and household-specific characteristics like income, occupation, region, gender, education, household size, and age group. ϵ_{it} is the error term. We have also controlled for log of prices of food ($\mathrm{P}_{\mathrm{crt}}$) which is available for all food groups in rural and urban regions separately. C_{st} is another control for the log of COVID cases for each state and month. For a detailed description of variables, refer to Table A2.

In the third equation, we execute a triple difference by interacting $Post_t$ *and Treat* with $Urban_i$. The coefficient on γ_7 is the triple difference estimate, which helps understand the difference in supply chain disruptions between rural and urban regions. In the first two specifications, the same design is applied to food-groups (i.e., cereals, pulses, fruits, vegetables, dairy, meat and fish, and egg). In the regressions using CMIE data, we have included the appropriate survey weights that account for survey non-response.[11] All our summary statistics and regressions account for survey weights with non-response adjustment.

In specification four, we broadly follow Lowe et al. (2021). Q_{md} is the total daily volume of arrivals at APMC mandis in all states for the m^{th} mandi on the d^{th} day. Treatment and control groups are the same as in the earlier specification, that is, treated mandis are those in 2020, and control mandis are those in 2019. Here the post period is divided into five phases and is each coded 1 for the respective dates: Phase 1 (25 March–14 April), Phase 2 (15 April–3 May), Phase 3 (4 May–17 May), Phase 4 (18 May–31 May), and Phase 5 (1 June–30 June). The pre-period for each phase is March 1–24 and is coded 0. W_{md} is a set of control variables, including "mandiclose" and COVID cases. "Mandiclose" is a dummy variable and equals 0 if, for any day, the total food arrivals at an APMC mandi were zero. This is done to control for the effect of the decrease in arrivals due to the closure of APMC mandis (see Lowe et al., 2021). Do note that we do not separately account for state-wise variations in APMC regulations in Model 4. APMC regulation is not a part of the LEADS index. The first specification is a fixed effects model, where we are interested in the extent of the supply chain disruption. The rest of the specifications are random effects models, where we are interested in supply chain characteristics that are assumed to be time-invariant during the study period.

RESULTS

Summary statistics show preliminary evidence about the effects of the lockdown (see Table 1) and the state-wise variations in mean food consumption expenditure (see Figure 1 and Table A4). Table 2 shows some of our key results. We find a 14% decline in food consumption expenditure due to the lockdown after controlling for changes in price and income. All food groups saw declines, especially eggs, meat, fish,[12] and cereals. Pulses saw a 21% decline in food consumption expenditure, while cereals saw a 30% decline. Thus, we infer that there are severe household supply chain disruptions for food and food groups, and this has perhaps led to reduced accessibility of food.

State-wise household food disruptions

Table 3 shows that states with a one-point higher LEADS index score saw 11% higher food consumption expenditure, which implies less disruption in states with better logistics quality. The differences in disruption were considerable for eggs, meat and fish, dairy, and cereals. Pulses, fruits, and vegetables showed no large differences by supply chain characteristics. In this specification, we have controlled for income, COVID-19 cases, rural/urban regions, commodity prices, seasonality, and household controls. The results indicate that household food supply disruptions were due to the lockdown, and the quality and performance of logistics played an important role in mitigating the effects of the disruption.

Urban and rural differences

Table A5 shows the change in consumption expenditure for urban regions as compared to rural regions after controlling for price, income, and household controls. The coefficient of Treat * Urban * Post shows that overall food expenditure changes were the same in urban and rural regions. By food groups, the rural/urban difference is not significant for pulses, fruits,

TABLE 1 Summary statistics in difference-in-differences framework (monthly household consumption expenditure in rupees).

	Control group				Treatment group					
	Baseline		Difference		Baseline		Difference		Difference-in-differences	
	1	2	3	4	5	6	7	8	9	10
Food groups	**N**	**Mean/SE**	**N**	**Coef/SE**	**N**	**Mean/SE**	**N**	**Coef/SE**	**N**	**Coef/SE**
Food (Rs)	441,904	4,961.85	885,051	100.32***	232,445	4,874.39	493,848	−578.34***	1,378,899	−678.66***
		3.84		5.83		7.44		9.66		11.28
Cereals (Rs)	441,904	1,014.67	885,051	51.88***	232,445	948.27	493,848	−70.12***	1,378,899	−122.00***
		1.01		2.17		4.49		5.49		5.9
Pulses (Rs)	441,904	239.83	885,051	−0.97***	232,445	237.82	493,848	−22.85***	1,378,899	−21.89***
		0.25		0.36		0.42		0.56		0.66
Fruits (Rs)	441,904	119.17	885,051	10.22***	232,445	121.42	493,848	−25.99***	1,378,899	−36.21***
		0.2		0.31		0.44		0.63		0.7
Dairy (Rs)	441,904	811.5	885,051	3.00*	232,445	854.21	493,848	−35.18***	1,378,899	−38.18***
		1.21		1.74		2.06		2.81		3.31
Meat/Fish (Rs)	441,904	467.9	885,051	5.54***	232,445	438.83	493,848	−133.58***	1,378,899	−139.12***
		0.94		1.36		1.41		1.95		2.38
Vegetables (Rs)	441,904	670.53	885,051	−7.89***	232,445	642.41	493,848	−43.69***	1,378,899	−35.79***
		0.77		1.1		1.14		1.54		1.89
Total income (Rs)	441,904	20,292.63	885,051	1025.74***	232,445	19,111.59	493,848	−4,979.65***	1,378,899	−6,005.39***
		44.04		64.91		60.18		85.38		107.25
Total expenditure (Rs)	441,904	11,957.89	885,051	129.06***	232,445	11,011.18	493,848	−3,136.18***	1,378,899	−3,265.24***
		16.09		25.31		26.27		29.72		39.03
Household size (No.)	441,904	4.04	885,051	−0.05***	232,445	3.95	493,848	0.00	1,378,899	0.05***
		0		0		0		0.01		0.01

Note: The control group comprises panel households during January to June 2019. The treatment group comprises the same households during the corresponding months of 2020. The baseline values are initial/pre-treatment means. The difference in column 4 is the first difference, that is, the difference in the control group before and after the treatment time (March 2019). Column 8 shows the difference in treatment group before and after the lockdown (March 2020). Column 10 is the difference-in-differences coefficient. Note that this table is showing a difference-in-differences raw estimate. We eventually go on to estimate a triple difference estimator which analyzes the role of supply chain characteristics using the LEADS index. Data is sourced from CMIE and is weighted with survey weights that have been adjusted for survey non-response.

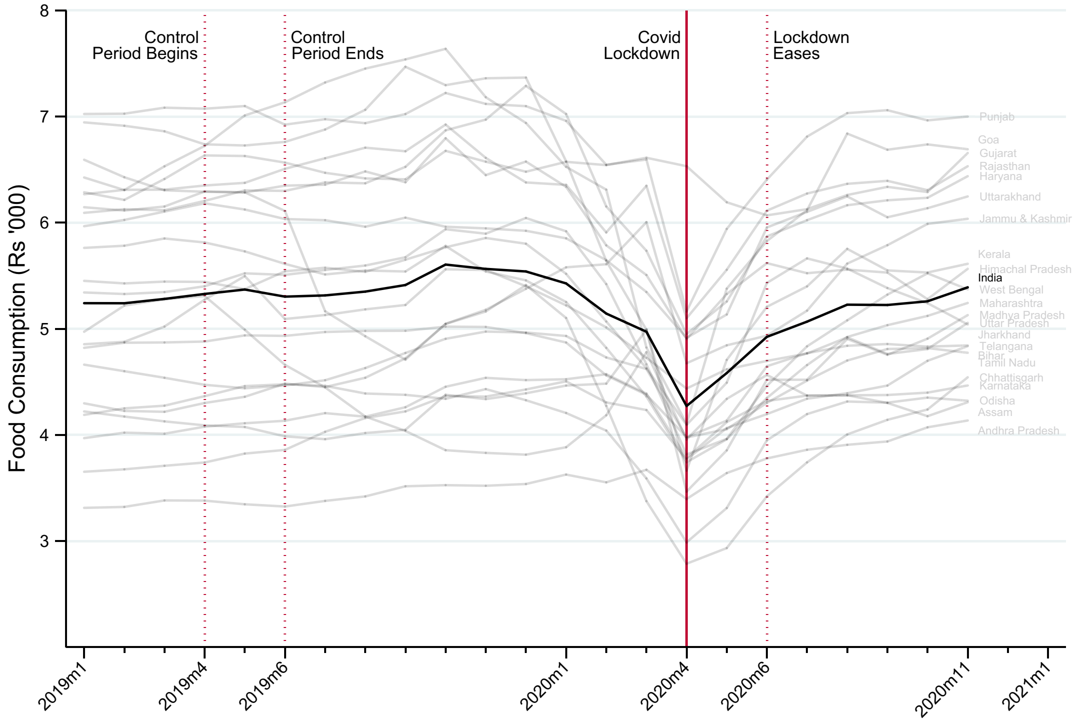

FIGURE 1 The effect of the Covid-19 lockdown varied across states. Some saw large negative effects, while some recovered faster than others. Here monthly household food consumption expenditure is presented to illustrate the variation in shock-related effects.

vegetables, dairy, and meat and-fish. This is not in line with literature that views urban supply chains for food as longer and more vulnerable to disruptions (Mahajan & Tomar, 2021). By food groups, cereals saw a 10% greater disruption in rural regions as compared to urban regions.

State-wise farm-to-market disruptions

Table 4 shows the LEADS index and sub-indices in the first column and the triple difference coefficient from the third specification, that is, β_7 in the rest of the columns for different phases of the lockdown (see Table A1 for summary statistics). While an earlier study (Lowe et al., 2021) showed that states with the most COVID-19 cases experienced higher disruption, our study shows that there exists no significant difference in disruption across states during the initial phase of the lockdown (i.e., until May 17,2020). This means that all states, irrespective of their LEADS index score, saw the same levels of disruption in phases 1 to 3. However, in phases 4 and 5, the states with better supply chains in terms of a higher ranking in the LEADS index recovered faster than states with lower LEADS scores. States with a one-point higher LEADS index score, saw 45% higher arrivals in Phase 4 and 46% higher arrivals in Phase 5. This implies that supply chain characteristics mattered in determining which states recovered quickly from the lockdown. States with better LEADS index scores, and by implication, better logistics quality, showed greater arrivals as compared with states with lower LEADS scores in phases 4 and

TABLE 2 Estimates of household food supply chain disruption during the lockdown

VARIABLES	(1) Food	(2) Pulses	(3) Cereals	(4) Fruits	(5) Vegetables	(6) Egg	(7) Meat-Fish	(8) Dairy
Treat * Post	−0.14*** (0.02)	−0.21*** (0.05)	−0.30*** (0.07)	−0.25** (0.12)	−0.06** (0.03)	−0.61*** (0.10)	−1.51*** (0.18)	−0.07 (0.08)
Treat	−0.06* (0.03)	−0.06 (0.06)	−0.02 (0.05)	0.12 (0.10)	−0.02 (0.03)	−0.25*** (0.07)	−0.91*** (0.18)	−0.04 (0.05)
Post	−0.00 (0.01)	−0.01 (0.02)	0.03 (0.02)	0.59*** (0.10)	−0.01 (0.02)	0.04 (0.03)	−0.36*** (0.12)	−0.04* (0.02)
Income	0.03*** (0.00)	0.02*** (0.00)	0.05*** (0.01)	0.09*** (0.01)	0.01*** (0.00)	0.05*** (0.01)	0.10*** (0.01)	0.05*** (0.01)
Covid-Case	0.01 (0.00)	0.01 (0.01)	0.02*** (0.01)	-0.07*** (0.01)	0.00 (0.00)	0.02* (0.01)	0.14*** (0.03)	0.00 (0.01)
Constant	7.65*** (0.32)	4.97*** (0.28)	8.46*** (1.02)	8.26*** (1.13)	6.22*** (0.09)	1.85*** (0.54)	-3.57** (1.57)	5.65*** (0.51)
Observations	1,378,417	1,378,417	1,378,417	1,378,417	1,378,417	1,378,417	1,378,417	1,378,417
R-squared	0.71	0.40	0.41	0.47	0.59	0.71	0.75	0.66
Price controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Weights for non-response	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Robust SE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Household fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
District fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Note: Robust standard errors in parentheses. The topmost row indicates the dependent variable, log of monthly expenditure of households on food (1) and sub food groups like pulses (2) and cereals (3) in rupees (Rs). The monthly household food consumption expenditure panel data is sourced from the Consumer Pyramids database by CMIE. Treat * Post is the interaction of treatment (2020) with post (April, May, June) that is, the main DID estimator. This model controls for both households fixed effects and time fixed effects with robust standard error estimation. To account for the high rate of attrition or non-response during lockdown, we run a weighted regression with survey weights adjusted for non-response.

***$p < 0.01$; **$p < 0.05$; *$p < 0.1$.

TABLE 3 Estimates of differences in food supply chain disruptions by logistics quality during the lockdown

VARIABLES	(1) Food	(2) Pulses	(3) Cereals	(4) Fruits	(5) Vegetables	(6) Egg	(7) Meat-Fish	(8) Dairy
$\beta_7(LEADS \times Post \times Treat)_{st}$	0.11** (0.05)	0.04 (0.10)	0.27* (0.14)	0.03 (0.35)	0.09 (0.08)	0.56** (0.26)	1.04*** (0.37)	0.45** (0.21)
Income	0.04*** (0.00)	0.02*** (0.00)	0.05*** (0.01)	0.14*** (0.01)	0.02*** (0.00)	0.07*** (0.01)	0.14*** (0.01)	0.09*** (0.01)
Covid-Case	0.00 (0.00)	-0.01 (0.02)	0.00 (0.01)	−0.09*** (0.02)	−0.00 (0.01)	−0.04* (0.02)	−0.13** (0.05)	0.03 (0.02)
Constant	7.01*** (0.39)	2.95*** (0.56)	9.03*** (1.17)	5.99*** (1.45)	4.65*** (0.36)	7.97*** (1.43)	15.58*** (2.85)	1.12 (1.09)
Observations	1,378,899	1,378,899	1,378,899	1,378,899	1,378,899	1,378,899	1,378,899	1,378,899
R-squared	0.36	0.05	0.10	0.13	0.12	0.11	0.13	0.13
Price controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Weights for non-response	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Robust SE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Random effects model	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Household controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Note: Robust standard errors in parentheses. In the above table, the topmost row is the dependent variable which is log of monthly expenditure of households on food (1) and sub food groups like pulses (2) and cereals (3). Expenditure data is sourced from CMIE (Consumer Pyramids). Treat * Post * LEADS is the interaction of Treatment (2020) with post (April, May, June) and LEADS (logistics quality score of states) that is, the main triple DID estimator. This is a random effects model which controls for time fixed effects with robust standard error estimation. The household controls that have been used in above regression are (occupation, region, gender, education, household size and age). To account for high rate of attrition or non-response during lockdown, we run a weighted regression with weights added for non-response.

***$p < 0.01$; **$p < 0.05$; *$p < 0.1$.

TABLE 4 Triple DID coefficient of log(food) (volume of daily mandi arrivals[Quintals]) Treat * Post * LEADS with March1-25 as base (& sub-indices) in all five phases of the lockdown

LEADS and Sub-Indices	Phase1	Phase2	Phase3	Phase4	Phase5
LEADS	0.237 (0.208)	−0.129 (0.190)	0.117 (0.202)	0.450** (0.198)	0.466*** (0.178)
Availability of logistics infrastructure (leads_ali)	0.202 (0.170)	−0.141 (0.142)	0.0291 (0.159)	0.262* (0.156)	0.310** (0.137)
Quality of logistics infrastructure (leads_qli)	0.429** (0.178)	−0.176 (0.144)	−0.141 (0.160)	0.170 (0.159)	0.180 (0.136)
Quality of logistics service provided by service providers (leads_qlspsp)	−0.148 (0.193)	−0.00591 (0.177)	0.278 (0.185)	0.495*** (0.179)	0.549*** (0.161)
Ease of arranging logistics at competitive Rates (leads_ealcr)	−0.170 (0.230)	−0.0418 (0.189)	0.214 (0.192)	0.371* (0.202)	0.215 (0.174)
Timeliness of cargo delivery (leads_tcd)	0.270 (0.209)	−0.127 (0.192)	0.0976 (0.217)	0.489** (0.219)	0.638*** (0.187)
Ease of track and trace (leads_ett)	−0.268 (0.177)	−0.432** (0.168)	−0.184 (0.191)	0.0746 (0.187)	0.190 (0.194)
Safety/security of cargo movement (leads_sscm)	0.905*** (0.186)	−0.0542 (0.191)	−0.0724 (0.207)	0.327* (0.198)	0.219 (0.188)
State facilitation and coordination (leads_sfc)	0.128 (0.235)	0.111 (0.189)	0.643*** (0.207)	0.747*** (0.198)	0.639*** (0.180)
Efficiency of regulatory processes (leads_erp)	0.660*** (0.241)	0.106 (0.216)	0.216 (0.220)	0.614*** (0.216)	0.579*** (0.195)

Note: Robust standard errors in parentheses (clustered at district level). Phase 1 (Mar 25–Apr 14), Phase 2 (Apr 15–May 3), Phase 3 (May 4–May 17), Phase 4 (May 18–May 31), and Phase 5 (Jun 1–Jun 30). The sub-indices are logistics quality indicators from LEADS 2019 index. While the explanatory variable that is, volume arrivals is measured in quintals, the dependent variable are scores obtained through PCA (footnote 5). Thus, these coefficients reflect that on an average there were smaller decreases in the daily volume arrivals (in quintals) in phase 4 and 5 of the covid-19 lockdown for states with higher scores in indicators like "state facilitation and coordination" or "efficiency of regulatory process".
***$p < 0.01$; **$p < 0.05$; *$p < 0.1$.

5. A further sub-index analysis reveals that in phases 4 and 5, coefficients of "Quality of Logistics Service Provided by Service Providers," "Efficiency of Regulatory Processes," "State Facilitation and Coordination," "Timeliness of Cargo Delivery," and "Availability of Logistics Infrastructure" were positive and significant. It shows that these sub-indices are important for a resilient supply chain.

To be sure, the agricultural wholesale markets data does not account for all farm-to-market supply in India. A large proportion of food is traded outside these mandis. This is a limitation, and our results must be viewed with this in mind. The decline we find in agricultural wholesale markets, we believe, still captures some part of what happened during the food supply chain disruption during the COVID-19 lockdown.

DISCUSSION OF RESULTS

In this section, we discuss the quality of our results, our contributions to the literature, and their policy implications. First, the COVID-19-induced lockdown affected the food supply across India. Second, there was considerable heterogeneity across states in food consumption expenditures and farm-to-market arrivals, which we argue, is due to differences in supply chain characteristics. Apart from these, we also discuss what our results tell us about food-group-wise variations in supply chain disruptions and the role of supply chain characteristics.

Food supply chains

Our first finding raises concerns about the quality and performance of logistics in India. The lockdown disrupted the food supply in important ways, reducing consumption and expenditure substantially. Here we find that consumption expenditure fell, irrespective of the financial means to purchase food. Our key result is the 14% decline in food consumption expenditure caused by the lockdown (see Table 2). Other studies have approached supply chain disruptions differently. They analyze various indicators of food supply disruptions. For instance, Mahajan and Tomar (2021) found that agricultural produce that was produced further from the point of final sale was more adversely affected by the lockdown. Another study looks at the reduction in food-carrying trucks operating during the lockdown (Iyer, 2020), while others look at shortages in labor for harvesting or loading/unloading cargo (Gupta, 2020; Kumar et al., 2021; Mukhra et al., 2020; Singh et al., 2020), and one other looks at reduced arrivals at agricultural mandis (Lowe et al., 2021).

Quality and performance of logistics

Our second finding explores the question of logistics quality and performance. We utilize the variation in supply chain characteristics across India's states (measured by the LEADS index) to understand why different states performed differently. Here, our design allows us to utilize the prior differences in logistics characteristics between states to understand their importance. We find no literature that utilizes this variation in the context of supply chain disruptions during COVID-19 in India. There are two aspects to our results that leverage the LEADS index to understand why some states do better than others. The first comes from the food consumption expenditure results, where we find that households in states with better quality logistics had

11% more food consumption expenditure than households in states with poorer quality logistics (Table 3). The second result has to do with farm-to-market volume arrivals and their variation by LEADs index scores of different states (see Table 4). This particular result builds on the methods used by Lowe et al. (2021). One of their findings is that state-specific lockdown policies may explain the decline in volume arrivals and the subsequent recovery. We approach this explanation differently to argue that while all states may have recovered in the later phases of the lockdown (like Lowe et al., 2021 find), the recovery was not uniform and is explained by the quality of their supply chain infrastructure, service provision, and government processes.

Expenditure on food groups

Results show a decline in consumption expenditure on fruits and vegetables during the lockdown due to the supply chain disruption (Table 2). Perishable foods like vegetables and fruits have the highest number of nutrients per calorie (Beal et al., 2017). Their reduced share in diets is likely to have adverse nutritional implications. As per the Indian Council of Medical Research (ICMR), Indians consume more than the daily recommended levels of carbohydrates, fewer proteins, and fewer fruits and vegetables. There is both a lack of adequacy and diversity in dietary intake from vegetables, fruits, pulses, dairy, that is, the non-cereal food groups. The regression results also show a decline in expenditure on pulses, possibly indicating inaccessibility during lockdown months.

Rural–urban supply chains

The results in Table A5 show that there is no significant difference in household food supply chain disruption between rural and urban regions, as both experience similar declines in food consumption expenditure during the lockdown. While the literature acknowledges that rural–urban supply chains are long and more vulnerable to shocks (Reardon et al., 2020), rural food supply chains and their importance are underemphasized.

Rural areas are increasingly specializing in specific kinds of crops, making them reliant on supply chains for their otherwise mixed consumption needs. For instance, large tracts of rural India produce primarily cotton or sugarcane. Farmers in such regions also have diverse consumption needs, which are met through supply chains. Gupta et al. (2022) gave us some sense of how rural supply chains were affected by the pandemic. They found that four fifths of the total rural households surveyed showed a perceived decline in the food availability in markets during the COVID-19 lockdown (Gupta et al., 2022). Narayanan and Saha (2021) find higher vulnerability to price shocks during the COVID-19 lockdown in small-town India relative to larger cities. Even though they did not analyze rural prices, their results do speak to ours. Our results are also in line with the farm-to-market analysis of food supply chains by Lowe et al. (2021), who find no significant difference between rural and urban markets during COVID-19 lockdown.

Supply chain characteristics

The LEADS index allows us to get a sense of which aspects of the supply chain mattered during the disruption and recovery. From our results, we can say that states with better state facilitation and coordination, quality of service providers, timeliness of cargo, and availability of infrastructure recovered faster from the lockdown than states that had lower LEADS sub-index scores (Table 4). One interesting aspect of the sub-index results is that the availability of infrastructure matters, indicating that there remains a disparity in the availability of infrastructure among states. The quality of infrastructure did not seem to matter for state-wise variation. State facilitation and coordination is a relatively broad category, including law and order, the existence of unions, and labor law. This too mattered for better arrivals in the later phases of the lockdown.

ROBUSTNESS

Parallel trend assumption

To verify the parallel trend assumption, we show a raw parallel trend (Figure A1) and modify the main specification (Equation 2) to derive monthly coefficients to make a coefficient plot (Figure A2). The plot shows that pre-period differences between higher-ranked LEADS states and lower-ranked LEADS states were insignificant before the COVID-19 lockdown. This shows that the parallel trend assumption holds. The higher-ranked LEADS states had higher consumption expenditures after the March 2020 COVID-19 lockdown. These coefficients are derived from a fully specified equation with all controls and weights included. The detailed specification is provided in the Appendix A.

Lowest quartile does not drive our result

We dropped households belonging to the lower quartile (of total expenditure) and regressed log(food) using the first three specifications in the methodology section. This is done because CMIE does not differentiate between consumption through the Public Distribution System (PDS) and the open market. PDS access is typically targeted at the poorest in most states in India, and this would likely be the case with the bottom quartile. PDS prices will account for only a small proportion of food expenditure but will not reflect the actual quantities consumed. This could mean that while consumption and expenditure fell, it does not rule out a switching/reliance on PDS during the crisis. To check if this drives the results, we drop the bottom quartile in the sample to see if our results hold. If they do, this confirms that private food supply chains were indeed affected, intake most certainly fell, and it was not the effect of a switching/reliance on PDS. It can be seen from model (a) in Table A6 that all the major results hold as the signs of the coefficient of interest are the same and significant. Model 1 shows a significant decline in food expenditure (main model without dropping the lower income quartile showed a 14% decline). Thus, even after dropping households belonging to the low expenditure quartile, we still find negative significant values for changes in food consumption expenditure, confirming household food supply chain disruptions due to the lockdown. Similarly, we obtain the same results for Model 2 (a, b, c) with regressions run for 25%, 50%, and 75% ranges of total expenditure to see heterogeneity across quartiles.

Hilly states do not drive the results.

The third robustness check is done to evaluate the influence of hilly states in the sample. Hilly terrain economies are often heavily dependent on supplies from the plains. Difficult terrain entails requirements for high-quality infrastructure (roads, railways, etc.) and logistics services. The household food supply disruptions during any crisis would tend to be much higher in hilly states than in the plains. Thus, our results could be driven by large-scale disruption only in hilly regions, that is, it could be the case that lockdown has adversely affected supply chains in hilly regions with negligible effect in non-hilly states. To rule out this possibility, states, such as Arunachal Pradesh, Assam, Himachal Pradesh, Jammu & Kashmir, Manipur, Meghalaya, Mizoram, Nagaland, Sikkim, Tripura, and Uttarakhand are dropped. The first specification in the methodology section is rerun with log(food) as the dependent variable. We observe from model (b) in Table A6 that all results hold. While in the main results for specification 1, we estimated a decline of 14% in food consumption expenditure during lockdown months, for non-hilly states we still estimate a high decline of 17%, thus confirming that supply chain disruption was indeed pan-India.

Results not affected by interstate trade

Mandi arrivals in a state may reflect disruptions elsewhere as commodity flows transcend state boundaries. Thus, to account for interstate border flows, we do a robustness check by rerunning the regression with a dummy "border district" as a control variable. The "border district" dummy is 1 for all districts whose administrative boundaries coincide with the administrative boundaries of a neighboring state. Thus, the dummy assumes a value of zero for all the districts not lying within the borders of states. Even after controlling interstate trade, our results continue to hold. Without controlling for the border dummy, the coefficient for the triple interaction term ($\zeta_7(LEADS \times Phase \times Treat)_{md}$) is 0.46 in Phase 5 and after controlling for the border dummy, the coefficient value increases to 0.50 (Table A7).

Additional robustness

We introduce a state-month fixed-effect as an additional control variable in Model 2 to account for the policies of states in different months and other state-specific characteristics in each month (like prices). The results continue to hold (Tables A8 and A9). Thus, the results are robust after accounting for all factors like the influence of lower income quartiles, hilly states, state-month interaction, and interstate trade (border districts dummy).

CONCLUSION

The stringent lockdown in response to the COVID-19 pandemic in India disrupted food supply chains, just as lockdowns did to different degrees across the world. To analyze India's lockdown, we focus on two supply disruptions: (i) for end-consumers, and (ii) farm-to-market supply chains. We find that household food supply chain disruptions are larger for states with relatively underdeveloped logistics; that is, states with a one-point higher LEADS index score had 11% higher food consumption expenditure. In addition, all states saw large declines in arrivals at mandis, but states with better logistics recovered faster (over 45% higher in the later phases of the lockdown). Both findings imply that the development of logistics quality and performance is important for resilience to shocks.

Our findings suggest that the LEADS index, a multidimensional index of supply-chain-related infrastructure and services, captures some of the differences between states' ability to cope with supply disruptions. Supply chain logistics development entails both public investment in infrastructure and well-framed state policy, as well as private-sector involvement in infrastructure and service provisioning. Our study is the first to evaluate how variations in logistics quality mattered in the COVID-19-induced lockdown. We provide estimates using a very large panel of households, covering all major states in India. We also extend the work of Lowe et al. (2021) to argue that logistics quality and performance matter in farm-to-market supply chains.

Our study does not account for the intra-state variations in logistics quality, but gives a good sense of how it matters in times of exigency. More importantly, it indicates which supply chain characteristics are required for building a resilient supply chain. Our results show that supply chain development is important for food security. They matter in two ways: first, to mitigate the effects of unexpected supply chain shocks, and second, to facilitate quicker recoveries. Governments must focus on three aspects of supply chains: One, physical infrastructure must be developed, such as warehouses, cold storage, and road and rail connectivity, which are all within the purview of the state. Two, the state must create conditions to improve private sector logistics service provisioning. Three, state regulatory processes must be more transparent; better systems for quicker approvals must be put in place; and processes must be more responsive to supply chain requirements.

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ENDNOTES

[1] Initially the lockdown was declared for 21 days, but was extended from time to time (https://www.mha.gov.in/sites/default/files/PR_StatesUTscannotdiluterestrictionsimposedinMHAguidelines_18052020_0.pdf).

[2] Mandis are wholesale agricultural marketplaces governed by the Agricultural Product Market Committee (APMC).

[3] The CFPI data is available from the Ministry of Statistics and Programme Implementation (MOSPI) for different months with the base year 2012 = 100

[4] Alternative sources of price data we explored do not provide complete data with the appropriate food group classifications we require for our analysis. We believe that state-time interactions will pick up some of these variations in prices across states, even if in an incomplete manner. We have now included results with state-time interactions (included in Tables A8 and A9).

[5] However, in the absence of high frequency household consumption data, any analysis of the COVID-19 lockdown and its effects would entail an engagement with CMIE panel survey data. This is the reason many others have also relied on this data to get some sense of what happened during and after the lockdown (Beyer et al., 2020; Deshpande, 2020a; Gupta & Kishore, 2022; Wadhwa, 2020).

[6] Though the data is available for public use at https://agmarknet.gov.in/, we received it from the authors of Lowe et al. (2021). They had scraped the website and cleaned the data for their paper, and generously shared their dataset and code with us. We acknowledge and thank Matt Lowe, G V Nadhanael and Benjamin N. Roth.

[7] Construction of LEADS index: All categories of stakeholders across all states and UTs are adequately represented by using stratified random sampling technique. Standard 5-point Likert scale is used for conducting

surveys on perception of identified indicators. The data is collected and imputed for missing values, after which it is normalized using Z-score standardization. This is done for reasons like accounting for biases with respect to geographical characteristics or respondent profile. For instance, for the indicator, "Availability of Logistics Infrastructure", the normalizing parameters are population, Gross State Value Added (GSVA) (in rupees lakh), total geographical area (in '000 hectares), total forest cover (in '000 hectares), total hilly area (in '000 hectares), total production of Horticulture and plantation crops (in '000 MT), total production of food grains (in '000 MT). Principal Component Analysis (PCA) is used for getting indicator weights and weighted average of these scores helped in arriving at the composite LEADS score. The indicator weights are the sub-indices LEADS score (no units) and the states have been ranked on the basis of composite LEADS score.

[8] See Box 6, page 15, LEADS Report 2019 (https://commerce.gov.in/wpcontent/uploads/2020/08/MOC_637051086790146385_LEAD_Report-2.pdf)

[9] The triple difference design to examine the impact of shocks has also been used in previous studies like that by Aggarwal and Narayanan (2022), whereby they find impact of demonetization on domestic agricultural trade in India's regulated markets.

[10] While one could have used per capita expenditure, we use household monthly expenditure as the outcome variable and control for any changes in household size that might affect our results.

[11] The survey weights provided in the data are population in strata divided by sample in strata. The adjustment factor for non-response is the ratio of proposed sample in strata divided by actual sample surveyed. We multiple the survey weights with the non-response adjustment factor to derive the final weights we use for the analysis. These weights are essentially population in strata divided by actual sample surveyed in strata. These weights explicitly address non-response.

[12] The decline in meat, fish and eggs was potentially also caused by misinformation regarding the transmission of COVID-19. There were rumors circulating regarding the transmission of the virus via meat, egg, and fish (Dev, 2020) and misinformation regarding poultry being carriers of COVID-19. The fear of getting infected could have led to a severe reduction in consumption, and it may not be strictly due to supply chain disruptions.

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APPENDIX A

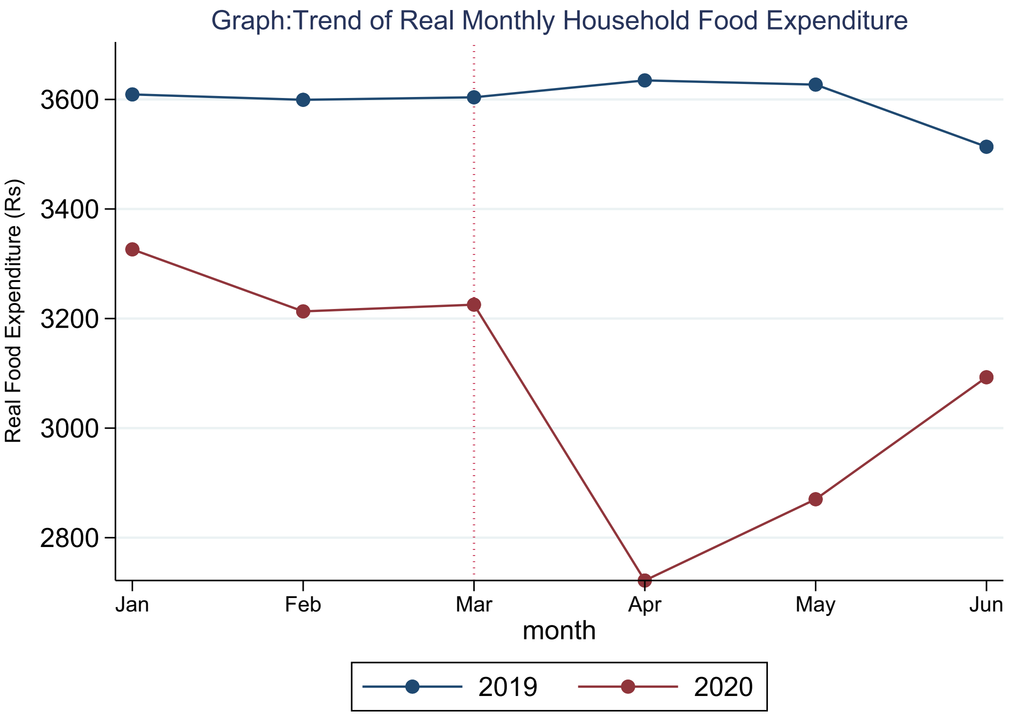

FIGURE A1 This is a raw parallel trend line of real mean household food consumption expenditure using survey weights adjusted for non-response. The line for 2020 deviates from the trend path for the same months represented by the values for 2019.

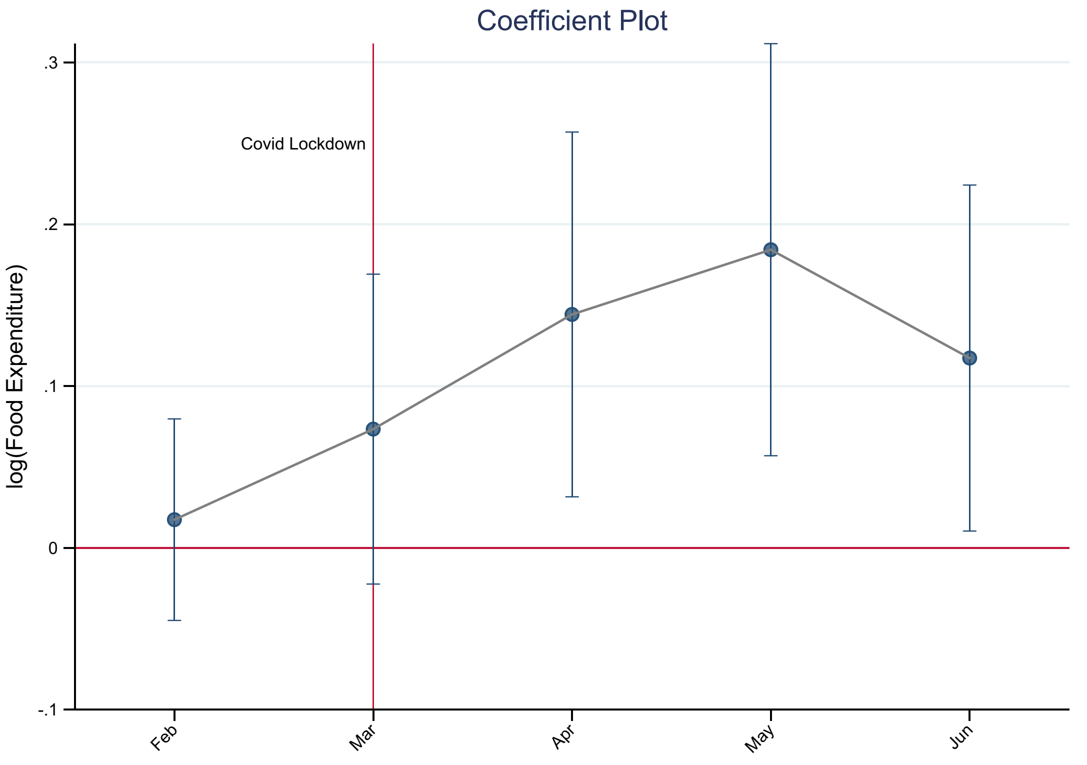

FIGURE A2 The coefficients obtained from the main estimation are plotted at a confidence interval of 90%. The base month for the coefficient plot is January.

TABLE A1 Description of variables.

Variable	Source	Description
Food	CMIE (Consumption Pyramids$_{dx}$)	This variable refers to the log of monthly household food consumption expenditure (Rs) for both rural and urban regions and all states covered in the analysis.
Pulses, Cereals, Fruits, Vegetables, Egg, Meat-Fish, Dairy	CMIE (Consumption Pyramids$_{dx}$)	These variables refer to the log of monthly household food consumption expenditure (Rs) of that food group. For instance, pulses refers to the log of monthly household expenditure on pulses.
Food (Arrivals)	https://agmarknet.gov.in/	This variable refers to the log of volume of daily arrivals of different crops in agricultural wholesale markets (APMCs). The volume for each crop is measured in quintals.
Mandiclose	https://agmarknet.gov.in/	"Mandiclose" is a dummy variable which equals 0 if for any day, the total food arrivals at an APMC mandi was zero. Otherwise, coded 1.
Income	CMIE (Income Pyramids$_{dx}$)	This variable reflects the log(income)
Price	Consumer Food Price Index (CFPI)	This variable is the consumer food price index which has been used separately for each food group and for rural and urban regions separately.
Real food expenditure	Generated by authors	The nominal prices of food and its subgroups were deflated using the appropriate Consumer Food Price Index (CFPI). Real Food Expenditure variable refers to log of the deflated expenditure
Covid-Cases	https://data.covid19india.org/.	This variable refers to the log of COVID-19 cases used as a proxy to control for the stringency of lockdown across states
Post	Generated by authors	$Post_t = 1$ for months April, May, and June and $Post_t = 0$ for January, February, and March. Post period is divided into 5 phases.
Phase1	Generated by authors	Phase 1 is a dummy variable which is 1 for dates: March 25–April 14, otherwise 0.
Phase2	Generated by authors	Phase 2 is a dummy variable which is 1 for dates: April 15–May 3, otherwise 0.
Phase3	Generated by authors	Phase 3 is a dummy variable which is 1 for dates: May 4–May 17, otherwise 0.
Phase4	Generated by authors	Phase 4 is a dummy variable which is 1 for dates: May 18–May 31, otherwise 0.
Phase5	Generated by authors	Phase 5 is a dummy variable which is 1 for dates: June 1–June 30, otherwise 0.

(Continues)

TABLE A1 (Continued)

Variable	Source	Description
Treat	Generated by authors	Treat = 1, if the year is 2020 (treatment group) and Treat = 0 if the year is 2019 (control group).
Urban	CMIE (Consumption Pyramids$_{dx}$)	Urban is a dummy variable which is 1 for households in urban regions, otherwise 0.
Border_District	Generated by authors	It is a dummy variable which is equal to one if any of the district's administrative borders coincide with the neighboring state's administrative borders
Household controls • Occupation • Education • Age • Gender • Household size	CMIE (Consumption Pyramids$_{dx}$)	The occupation, education, age and gender of a household is based on the distribution of members of a household by their occupation, education, age, and gender respectively. The size group of a household is based on the number of members in a household.
LEADS	LEADS Index (2019)	LEADS is an index which refers to "Logistics Ease Across Different States". This index was put out by the Ministry of Commerce and Industry, Government of India. "The composite indicator would reflect relative performance "across" these units (states and UTs) rather than performance "of" these units themselves"

Note: For details regarding construction of the LEADS Index, refer to "Exhibit 48: Construct of the LEADS Index". For data points of sub-indicators and their normalization, refer to "Exhibit 56: Sub-indicators for objective assessment of logistics ease" in LEADS index (2019) report (https://commerce.gov.in/wpcontent/uploads/2020/08/MOC_637051086790146385_LEAD_Report-2.pdf).

TABLE A2 Index value state wise of LEADS and sub-indices.

State	LEADS	LEADS sub-indices score								
		leads_ali	leads_qli	leads_qlspsp	leads_ealcr	leads_tcd	leads_ett	leads_sscm	leads_sfc	leads_erp
Andhra Pradesh	3.42	3.59	3.5	3.51	3.37	3.54	3.37	3.52	3.14	3.27
Assam	3	3	3	3.11	2.72	2.98	3.11	3.31	2.85	2.92
Bihar	2.85	2.87	2.89	2.96	2.91	2.89	2.93	2.96	2.49	2.75
Chattisgarh	3.01	3.08	2.97	3.08	3.25	3.03	2.79	3.12	2.87	2.94
Goa	2.78	2.76	2.61	2.79	2.73	2.89	2.87	3.13	2.49	2.81
Gujarat	3.62	3.92	3.8	3.8	3.45	3.7	3.53	3.57	3.31	3.41
Haryana	3.37	3.62	3.53	3.44	3.16	3.45	3.46	3.46	3.1	3.09
Himachal Pradesh	2.72	2.69	2.52	2.71	2.17	3	2.6	3.31	2.45	3.06
Jammu And Kashmir	2.87	3.09	2.97	3.06	2.56	2.76	2.68	3.09	2.71	2.82
Jharkhand	2.88	2.93	2.8	3	3.1	3.1	2.96	3.13	2.39	2.57
Karnataka	3.37	3.51	3.44	3.49	3.29	3.42	3.51	3.5	2.98	3.15
Kerala	3.16	3.18	3.27	3.29	2.92	3.27	3.27	3.47	2.78	2.99
Madhya Pradesh	3.21	3.3	3.13	3.45	3.23	3.23	3.3	3.19	3.03	2.98
Maharashtra	3.42	3.64	3.51	3.66	3.21	3.5	3.48	3.47	3.11	3.2
Odisha	3.18	3.36	3.2	3.23	3.04	3.3	3.33	3.21	2.93	3.03
Punjab	3.46	3.64	3.65	3.58	3.29	3.35	3.5	3.7	3.15	3.27
Rajasthan	3.16	3.33	3.2	3.32	2.99	3.34	3.32	3.18	2.78	2.94
Tamil Nadu	3.4	3.63	3.52	3.53	3.3	3.48	3.45	3.48	3.05	3.18
Telangana	3.22	3.34	3.29	3.27	3	3.43	3.13	3.35	2.96	3.18
Uttar Pradesh	3.08	3.22	3.17	3.17	3.13	3.17	3.2	3.08	2.74	2.87
Uttrakhand	2.85	2.78	3	3.08	2.84	3.14	2.78	3.13	2.35	2.56
West Bengal	2.99	3.15	3	3.12	2.95	2.93	3.11	3.17	2.72	2.79

Note: Availability of logistics infrastructure (leads_ali), quality of logistics infrastructure (leads_qli), quality of logistics service provided by service providers (leads_qlspsp), ease of arranging logistics at competitive rates (leads_ealcr), timeliness of cargo delivery (leads_tcd), ease of track and trace (leads_ett), safety/security of cargo movement (leads_sscm), state facilitation and coordination (leads_sfc), and efficiency of regulatory processes (leads_erp).

TABLE A3 State-wise variations in food expenditure before and during lockdown compared to corresponding months in 2019.

		Household consumption expenditure on food (₹)			
STATE	**LEADS index**	**Jan–Mar 2019**	**Jan–Mar 2020**	**Apr–Jun 2019**	**Apr–Jun 2020**
Gujarat	3.62	6305.4	6574.3	6609.6	6242.6
Punjab	3.46	7045.2	6713.3	7031.8	5901.4
Chandigarh	3.45	7499	6829.6	6657.9	5618.3
Andhra Pradesh	3.42	3339.6	3617.8	3351	3627.7
Maharashtra	3.42	5799.4	4874.1	5718.4	4051.8
Tamil Nadu	3.4	4600.5	4791.6	4459.8	4139.4
Haryana	3.37	6113.3	6334.2	6275.3	5406.5
Karnataka	3.37	4005	4507.3	4108	4111.4
Delhi	3.36	8465.3	9431.5	9000.2	6964
Puducherry	3.28	4434.1	5509.1	4532.5	4580.1
Telangana	3.22	3679.9	4364.8	3805.8	4034.5
Madhya Pradesh	3.21	4174.7	4644	4050.7	3991.8
Odisha	3.18	4238.7	3984.3	4433.6	3439.3
Kerala	3.16	6907.2	5817.1	6742.5	4585.2
Rajasthan	3.16	6296.7	6214.3	6411.6	5629.3
Uttar Pradesh	3.08	4918.1	4999.4	5288.4	4597.6
Chhattisgarh	3.01	4247	4409.6	4381.2	3088.2
Assam	3	5157.3	4232.1	4983.9	4331.7
West Bengal	2.99	5340.2	5441.4	5478	4104.5
Tripura	2.95	6540.8	4931.7	6232.7	4602.1
Sikkim	2.9	5718.3	6227	5861	5747.5
Jharkhand	2.88	5441.8	5104.1	5453.5	4739.7
Jammu & Kashmir	2.87	6442.8	5698.1	6244	4831.3

TABLE A3 (Continued)

STATE	LEADS index	Household consumption expenditure on food (₹)			
		Jan–Mar 2019	Jan–Mar 2020	Apr–Jun 2019	Apr–Jun 2020
Bihar	2.85	4854.3	4618.7	4917.7	4290.7
Uttarakhand	2.85	6031.8	5634	6114.7	5363.7
Goa	2.78	6421	6033.2	6961.6	5257.3
Himachal Pradesh	2.72	6137.8	5882.3	6309.5	5304.5
Meghalaya	2.56	8523	7878.3	9007.6	7012.8

TABLE A4 Estimates of differences in food supply chain disruption between rural and urban regions during the lockdown.

VARIABLES	(1) Food	(2) Pulses	(3) Cereals	(4) Fruits	(5) Vegetables	(6) Egg	(7) Meat-fish	(8) Dairy
Treatment * Urban * Post	−0.02 (0.02)	−0.03 (0.04)	0.10* (0.05)	0.05 (0.12)	0.03 (0.04)	0.33*** (0.09)	0.13 (0.13)	0.03 (0.06)
Income	0.04*** (0.00)	0.02*** (0.00)	0.05*** (0.01)	0.14*** (0.01)	0.02*** (0.00)	0.08*** (0.01)	0.14*** (0.01)	0.09*** (0.01)
Constant	7.39*** (0.14)	4.56*** (0.13)	9.08*** (0.85)	7.58*** (1.51)	5.85*** (0.06)	0.17 (0.40)	2.82*** (0.54)	5.02*** (0.28)
Observations	1,378,899	1,378,899	1,378,899	1,378,899	1,378,899	1,378,899	1,378,899	1,378,899
R-squared	0.36	0.04	0.10	0.12	0.11	0.09	0.12	0.11
Price controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Weights for non-response	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Robust SE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Random effects model	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Household controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Note: Robust standard errors in parentheses. In the above table, the topmost row is the dependent variable which is log of monthly expenditure of households on food (1) and sub food groups like pulses (2) and cereals (3). Expenditure data is sourced from CMIE (Consumer Pyramids). Treat * Post * Urban is the interaction of Treatment (2020) with post (April, May, June) and Urban (households in urban regions vs those in rural regions) that is, the main triple DID estimator. This is a random effects model which controls for timefixed effects with robust standard error estimation. The household controls that have been used in above regression are occupation, region, gender, education, household size and age. To account for high rate of attrition or non-response during the lockdown, we run a weighted regression with weights added for non-response.

***$p < 0.01$; **$p < 0.05$; *$p < 0.1$.

TABLE A5 Summary statistics in difference-in-differences framework (volume of food in markets in quintals).

	Control group				Treatment group					
	Baseline		Difference		Baseline		Difference		Difference-in-differences	
	1	2	3	4	5	6	7	8	9	10
All foods	N	Mean/SE	N	Coef/SE	N	Mean/SE	N	Coef/SE	N	Coef/SE
Phase 1	1119531	440.29	1152843	−62.04**	292232	395.57	305517	−161.21***	1458360	−99.17*
		4.85		28.23		9.33		44.22		52.95
Phase 2	1122830	432.18	1152843	242.48***	285648	384.95	305517	55.45	1458360	−187.04***
		4.82		29.7		9.52		36.57		47.46
Phase 3	1130857	437.21	1152843	67.39*	290448	385.68	305517	58.39	1458360	-9.00
		4.72		34.57		9.44		41.65		54.52
Phase 4	1130645	438.99	1152843	−25.94	290325	387.31	305517	25.12	1458360	51.06
		4.79		34.41		9.45		41.49		54.29
Phase 5	1107601	442.06	1152843	−90.83***	270785	395.07	305517	−57.27**	1458360	33.56
		4.87		24.35		10.06		28.41		37.68

Note: The Control Group comprises panel mandis during 2019. The Treatment Group comprises the same mandis during the corresponding months of 2020. The Baseline values are initial/pre-treatment means. The Difference in column 4 is the first difference, that is, the difference in the control group before and after the treatment time (March 2019). Column 8 shows the difference in treatment group before and after the lockdown (March 2020). Column 10 is the difference-in-differences coefficient. Phase 1 (March 25–April 14), Phase 2 (April 15–May 3), Phase 3 (May 4–May 17), Phase 4 (May 18–May 31), and Phase 5 (June 1–June 30). Note that this table is showing a difference-in-differences raw estimate. We eventually go on to estimate a triple difference estimator which analyzes the role of supply chain characteristics using the LEADS index. Data is sourced from Agmarknet.

TABLE A6 Robustness of main results for Model 1 by removing (a) lower expenditure quartile, and (b) hilly states and Model 2 for all expenditure quartiles, that is, (a) 1st quartile, (b) 2nd quartile and (c) 3rd quartile. Dependent Variable: log(Food).

Model 1	(a)	(b)	Model 2	(a)	(b)	(c)
Treat *Post	−0.04* (0.02)	−0.17*** (0.03)	Treat * Post	−0.17*** (0.02)	−0.15*** (0.04)	−0.13** (0.06)
Observations	1,022,348	1,298,237	Observations	1,378,899	1,378,899	1,378,899

Note: Robust standard errors in parentheses. For model 1, we have used similar specifications as used in Table 2. The dependent variable is log of monthly expenditure of households on food (Rs). Treat * Post is the interaction of Treatment (2020) with post (April, May, June) that is, the main DID estimator. This model controls for both household fixed effect and time fixed effects with robust standard error estimation. To account for high rate of attrition or non-response during lockdown, we run a weighted regression with survey weights adjusted for non-response. For model 2, we are running regression to understand the heterogeneity across all total expenditure quartiles.

***$p < 0.01$; **$p < 0.05$; *$p < 0.1$.

TABLE A7 Robustness of Main results for Model 4 after introducing dummy for border districts.

Dependent variable: Log(food) (volume of daily mandi arrivals[quintals])					
	(phase1)	**(phase2)**	**(phase3)**	**(phase4)**	**(phase5)**
$\zeta_7(LEADS \times Phase \times Treat)_{md}$	−0.332 (0.370)	−0.441 (0.305)	0.230 (0.292)	0.459 (0.288)	0.507** (0.252)
Constant	5.169*** (1.055)	5.023*** (1.052)	5.057*** (1.053)	5.085*** (1.056)	5.083*** (1.053)
Observations	109,433	112,860	100,033	100,368	142,952
R-squared	0.113	0.113	0.110	0.116	0.116

Note: Robust standard errors in parentheses (clustered at district level). Phase 1 (Mar 25–Apr 14), Phase 2 (Apr 15–May 3), Phase 3 (May 4–May 17), Phase 4 (May 18–May 31), and Phase 5 (Jun 1–Jun 30).
***$p < 0.01$; **$p < 0.05$; *$p < 0.1$.

TABLE A8 Robustness of main results for Model 1 by introducing state * month interaction

VARIABLES	(1) Food	(2) Pulses	(3) Cereals	(4) Fruits	(5) Vegetables
$\xi_3(Post \times Treat)_{it}$	−0.16*** (0.03)	−0.22*** (0.06)	−0.30*** (0.07)	−0.20* (0.12)	−0.10*** (0.03)
Observations	1,378,417	1,378,417	1,378,417	1,378,417	1,378,417
R-squared	0.72	0.40	0.44	0.48	0.60

Note: Robust standard errors in parentheses. The topmost row indicates the dependent variable, the log of monthly expenditure of households on food (1) and sub-food groups like pulses (2) and cereals (3) in rupees (Rs). We have controlled for prices, weights for non-response, robust standard error, household fixed effects, district fixed effects, time fixed effects, and interaction of state and month.

***$p < 0.01$; **$p < 0.05$; *$p < 0.1$.

TABLE A9 Robustness of main results for Model 2 by introducing state * month interaction.

VARIABLES	(1) Food	(2) Pulses	(3) Cereals	(4) Fruits	(5) Vegetables
$\beta_7(LEADS \times Post \times Treat)_{st}$	0.12** (0.05)	−0.04 (0.10)	0.26* (0.14)	0.03 (0.35)	0.08 (0.07)
Constant	7.79*** (0.39)	5.82*** (0.50)	9.37*** (1.11)	7.95*** (1.26)	5.96*** (0.09)
Observations	1,378,899	1,378,899	1,378,899	1,378,899	1,378,899
R-squared	0.49	0.12	0.20	0.18	0.33

Note: Robust standard errors in parentheses. The topmost row indicates the dependent variable, log of monthly expenditure of households on food (1) and sub food groups like pulses (2) and cereals (3) in rupees (Rs). This is a random effects model in which we have controlled for prices, weights for non-response, robust standard error, household controls, time fixed effects along with interaction of state and month.

***p<0.01; **p<0.05; *p<0.1.

Specification of the coefficient plot

$$
\begin{aligned}
Y_{it} = {} & \alpha + \beta_1 Treat + \sum\nolimits_{t=1}^{6} \eta_t Month_t + \sum\nolimits_{t=1}^{6} \gamma_t (Month \times Treat)_t + \beta_2 LEADS_{it} \\
& + \sum\nolimits_{t=1}^{6} \theta_t (Month \times LEADS)_{st} + \beta_3 (Treat \times LEADS)_s + \sum\nolimits_{t=1}^{6} \delta_t (LEADS \times Month \times Treat)_{st} \\
& + Z_{it} + \epsilon_{it}
\end{aligned}
$$

NOTE: The standard specification explained previously has been modified to estimate month-wise triple difference estimates to see how the coefficient is behaving over different months. The regression would yield five coefficients of interest, with one time period being taken as the comparative base level.