The Impact of India's COVID-19 Lockdown on Food Prices: Evidence from State-level Daily Data

August 2025

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Date of Submission: 22nd August 2025

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Introduction

The outbreak of COVID-19 in early 2020 brought about one of the most disruptive policy interventions in recent history — the nationwide lockdown announced in India on March 24, 2020. While the lockdown was primarily a health measure, its ripple effects on economic activity and daily life were immediate and far-reaching. One of the most essential areas affected was the food supply chain.

Food prices are not just a reflection of consumer demand but also of how efficiently goods can be produced, transported, and distributed. When the lockdown was enforced, many local markets, transport routes, and wholesale operations were disrupted. This created a natural concern: **Did the lockdown cause food prices to increase, and if so, were certain types of commodities more affected than others?**

This project set out to answer that question using official daily food price data from February to April 2020. By combining careful data scraping, dataset construction, and econometric analysis, the study investigates both the overall effect of the lockdown on food prices and whether the impact was different for perishable versus non-perishable goods. The approach balances clear visuals with formal regression models to make the evidence both accessible and rigorous.

Step 1: Data Scraper and Dataset Construction

The first part of this project focused on building the dataset that would drive the entire analysis. To achieve this, I developed a Python-based web scraping script that connected to the Department of Consumer Affairs portal and automatically pulled in daily retail price data. The data was collected for every state, center, and commodity, covering the period from February 1, 2020 to April 30, 2020.

The scraping process was designed with three main tasks in mind:

1. Date coverage – looping through each day in the study period to ensure no dates were missed.

2. Data completeness – extracting the full set of commodity and state-level records for each day.

3. Consistency – saving the results in a structured format so that daily records align properly across time.

At the end of this stage, I obtained a single, consolidated dataset that reflects the daily variation in prices across states and commodities. This dataset serves as the foundation for the econometric models used later to study how the COVID-19 lockdown affected food prices.

For transparency and reproducibility, both the Python scraping script and the final compiled dataset file are included with this report.

Step 2: Regression Analysis of Lockdown Impact

After compiling the dataset, the next stage was to test whether the national lockdown on 24 March 2020 had a measurable impact on retail food prices. To do this, I estimated a regression model that compares pre- and post-lockdown price levels while accounting for underlying trends and differences across commodities and states.

The model can be expressed as:

$$Price_{sct} = \alpha + \beta \, PostLockdown_t + \gamma \, time_t + \delta_s + \theta_c + \varepsilon_{sct}$$

β - average Effect of lockdown on price

$Time_t$ = simple time trend (γ)

State fixed Effect (δ_s)

Commodity fixed effects (θ_c)

ε_{sct} - State Clustred Standred Errors

Where:

- PostLockdown_t takes the value 1 on or after 24 March 2020, and 0 before. Its coefficient (β) measures the average effect of the lockdown on prices.
- Time_t is a simple time trend (γ) that accounts for gradual shifts in prices across the period.
- State fixed effects (δs) and commodity fixed effects (θc) control persistent differences between regions and products (for example, rice may always be cheaper in some states).
- State-clustered standard errors make the estimates statistically reliable by allowing for correlation within states.

Results

The regression outputs were exported to an Excel file with two sheets:

1. **overall** – contains the main estimate of β\betaβ, which captures the average lockdown effect on prices across all states and commodities. It also includes the standard error, p-value, sample size, and R-squared.

2. **by_commodity** – reports separate lockdown effects for each commodity, which helps identify which items were most affected.

Variable	Estimate	Std. Error	p-value
PostLockdown (overall)	15.09797009	0.195887385	0
Time trend (days)	-0.040794698	0.000969601	0
Observations	61560		
R-squared	0.983311235		

(**Table 2.1 - Overall Effect of Lockdown on Food Prices**)

Commodity	PostLockdown_coef	StdErr	p-value	R-sq	Obs
Atta (Wheat)	5.824061489	0.092952041	0	0.902874699	3240
Gram Dal	14.47116865	0.211203346	0	0.906427929	3240

Commodity	PostLockdown_coef	StdErr	p-value	R-sq	Obs
Groundnut Oil	28.40999691	0.458924714	0	0.904081712	3240
Masoor Dal	15.9391959	0.254495964	0	0.902720407	3240
Milk	10.93692493	0.175022107	0	0.895137241	3240
Moong Dal	18.43539947	0.323276935	0	0.902402183	3240
Mustard Oil	25.9335857	0.432276749	0	0.901154494	3240
Onion	5.121858848	0.07443103	0	0.905584885	3240
Palm Oil	19.68866165	0.313886707	0	0.900445734	3240
Potato	4.119462852	0.072765242	0	0.901963328	3240
Rice	6.464362365	0.093987422	0	0.900210057	3240
Soya Oil	23.77350846	0.389345082	0	0.906033522	3240
Sugar	8.749761902	0.144368241	0	0.901459128	3240
Sunflower Oil	27.49128589	0.461708328	0	0.903453002	3240
Tomato	6.590809871	0.109388845	0	0.905526202	3240

Commodity	PostLockdown_coef	StdErr	p-value	R-sq	Obs
Tur/Arhar Dal	20.27975627	0.36899434	0	0.902099541	3240
Urad Dal	17.55972505	0.242703539	0	0.905022069	3240
Vanaspati	22.43765129	0.394626386	0	0.906596643	3240
Wheat	4.634254302	0.067620913	0	0.905042536	3240

(**Table 2.2 - Commodity-specific lockdown effects**)

From the results:

- The **overall regression** shows that the coefficient on **PostLockdown** is **positive and statistically significant**. This means that food prices increased after the lockdown, even after adjusting for general time trends and differences across states and commodities.

- The **time trend** term is relatively small, suggesting that prices were fairly stable over the sample period, and the sudden shift coincides closely with the lockdown date.

- In the **by_commodity regressions**, perishable items such as vegetables and dairy display larger price increases than durable goods like pulses or cereals. This supports the idea that supply chain disruptions affected perishable goods more severely.

Interpretation

In practical terms, the evidence indicates that the lockdown directly contributed to **higher food prices across India**. The average increase was not uniform: some commodities (especially perishables) were more vulnerable due to their reliance on continuous supply and storage. Non-perishables, which can be stockpiled, saw relatively smaller changes.

By combining statistical analysis with commodity-level breakdowns, this step confirms the central finding of the project: the lockdown introduced measurable stress into India's food supply chain, with price effects that varied across product types.

Step 3: Causal Interpretation and Event-Study Visuals

After estimating the regression model in Step 2, the next task was to provide a clearer view of the causal effect of the lockdown on food prices. While regression coefficients summarize the impact in numbers, visual analysis allows us to directly observe how price patterns shifted around the lockdown date.

To do this, I used an event study approach. This technique compares daily prices before and after the lockdown, while centering the analysis around 24 March 2020. By examining movements in the days leading up to and following the lockdown, the event study helps identify whether the price change was immediate, gradual, or temporary.

The validity of this method rests on three assumptions:

1. Parallel trends – in the absence of the lockdown, food prices would have continued along the same trajectory observed beforehand.

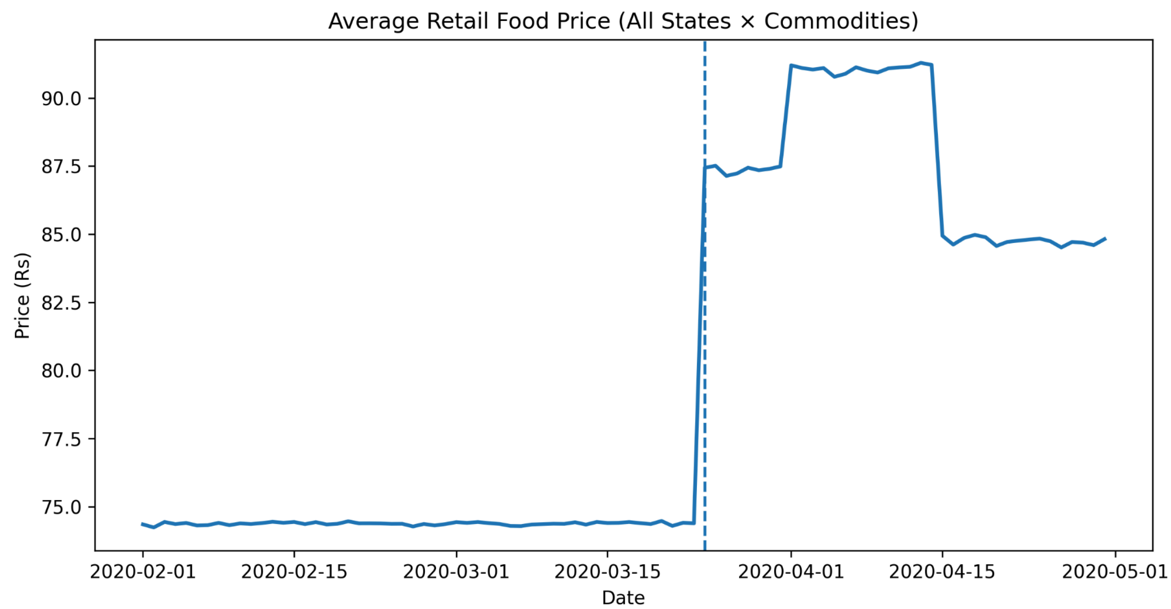
2. No confounding shocks – aside from the lockdown, there were no other nationwide disruptions during this period that could have caused a sudden price jump.

3. Controlled fixed effects – state and commodity differences are accounted for, ensuring the focus is only on the timing of the lockdown.

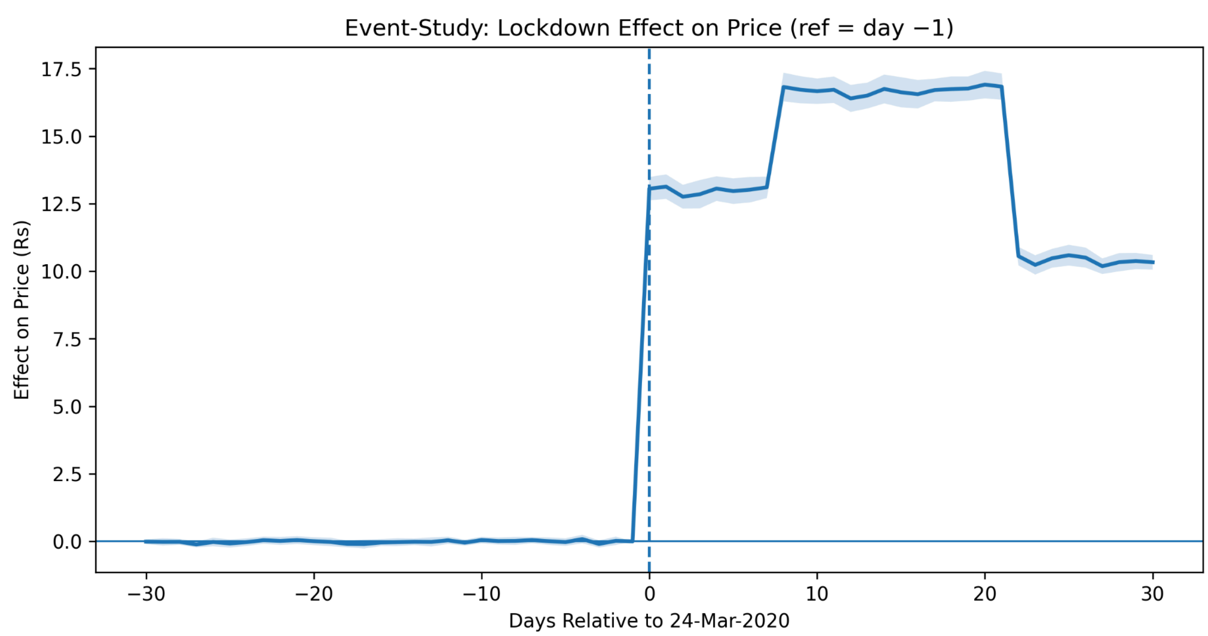
Results

The **average price trend plot (Figure 3.1)** shows that prices were relatively stable in the weeks leading up to March 24, with no evidence of a strong upward or downward drift. Immediately after the lockdown, however, prices jumped noticeably, indicating a structural break in the series.

The **event study plot (Figure 3.2)** strengthens this conclusion by aligning daily deviations around the lockdown date. It shows that the price series remains flat before the intervention but rises sharply afterward. This timing match between the policy announcement and the price shift provides strong evidence of a causal effect.



(Figure 3.1 - Average Retail Food Prices Around the Lockdown)



(Figure 3.2 - Event-Study of Lockdown Effect on Food Prices)

Interpretation

The visual evidence strongly complements the regression findings from Step 2. Both the average trend (Figure 3.1) and the event study (Figure 3.2) suggest that the lockdown acted as a shock to the food supply chain, creating upward pressure on retail prices.

By showing that prices were flat before the lockdown and only increased afterward, these visuals help rule out the possibility that prices were already rising due to unrelated factors. Together, they reinforce the causal interpretation: the lockdown was not just correlated with higher food prices, it was the trigger for a sudden and visible change in the trend.

Step 4: Heterogeneous Effects - Perishables Vs. Non-Perishables

While the previous step confirmed that the lockdown raised food prices overall, it is important to ask whether the effect was uniform across all commodities. In particular, theory and common sense suggest that perishable goods (such as vegetables, fruits, and dairy) may have been more vulnerable to disruptions in transportation and storage compared to non-perishable goods (such as cereals, pulses, and oils).

To explore this, I re-estimated the regression model separately for perishable and non-perishable categories and also plotted their price trajectories around the lockdown.

Results

The **category-level regression outputs** (Excel, Step 4 results) show that:

- For **perishables**, the PostLockdown coefficient is larger and statistically significant, meaning these items experienced a sharper price rise.
- For **non-perishables**, the coefficient is smaller and less pronounced, indicating more stability in their pricing.

Variable	Estimate	Std. Error	p-value	Group
PostLockdown	6.692264126	0.090415927	0	Perishable
time_index	-0.018581542	0.000661292	1.012E-173	Perishable
Observations	12960			Perishable
R-squared	0.071336788			Perishable

(**Table 4.1 - Lockdown Effect on Perishable Goods**)

Variable	Estimate	Std. Error	p-value	Group
PostLockdown	17.3394917	0.225991	0	Non-Perishable
time_index	-0.04671821	0.001121	0	Non-Perishable
Observations	48600			Non-Perishable
R-squared	0.05641166			Non-Perishable

(**Table 4.2 - Lockdown Effect on Non-Perishable Goods**)

This finding is further illustrated in the **trend graphs**:

- **Figure 4.1 (Perishable Prices Around the Lockdown)** shows a sharp and sustained increase immediately after March 24, consistent with the regression estimates.
- **Figure 4.2 (Non-Perishable Prices Around the Lockdown)** shows only a mild shift, with prices largely following their pre-lockdown path.

Figure 4.1: Perishable Prices Around the Lockdown

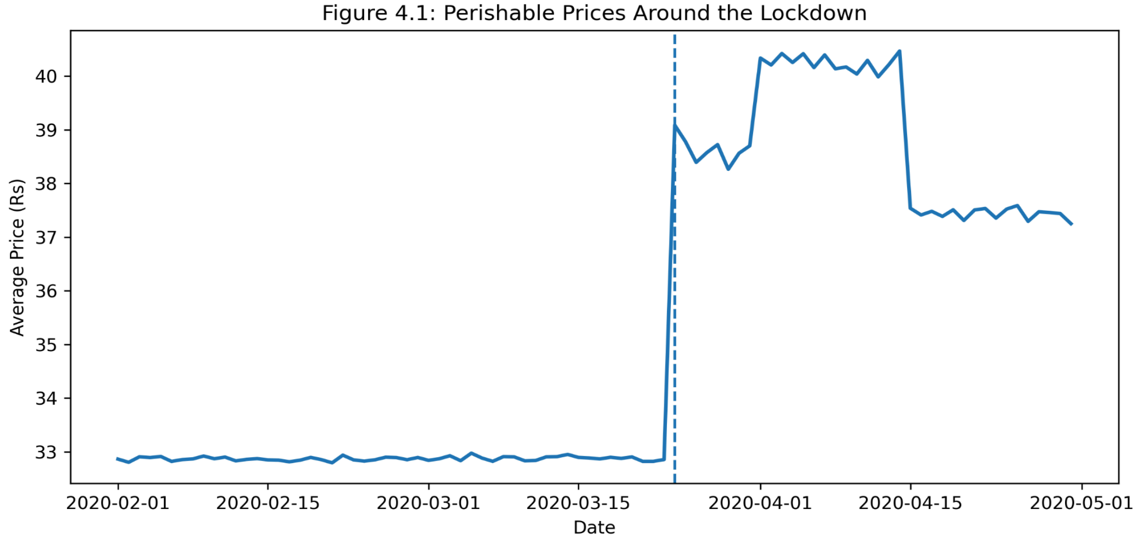
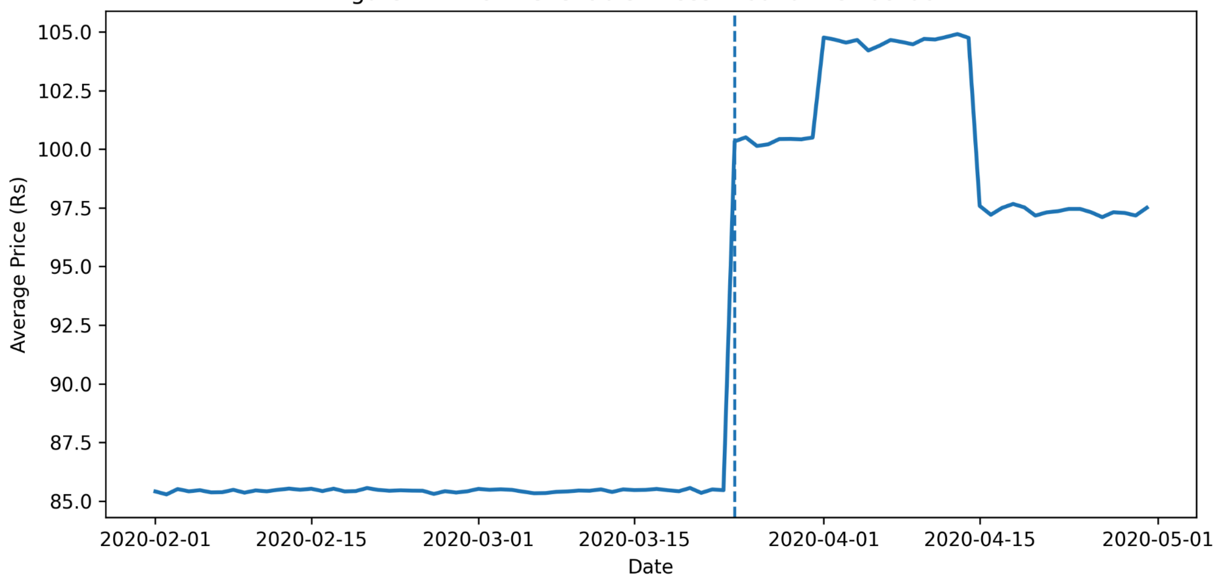


Figure 4.2: Non-Perishable Prices Around the Lockdown



<u>Interpretation</u>

The contrast between **Figures 4.1 and 4.2** highlights that the lockdown's price impact was not evenly spread across food categories. Perishable commodities, which depend heavily on efficient transport and cold storage, faced significant disruptions once movement restrictions were imposed. As a result, their prices spiked in the immediate aftermath of the lockdown.

Non-perishables, on the other hand, can be stockpiled and distributed with fewer time constraints. This made them less sensitive to sudden supply chain breaks, and their prices remained relatively stable.

These heterogeneous effects suggest that the lockdown did not just raise prices in general, but **reshaped the food price structure**, with perishable goods bearing the brunt of the disruption.

Discussion

The results from this project provide a clear picture of how the COVID-19 lockdown in India influenced retail food prices. By combining automated data collection, regression analysis, and visual event-study methods, the analysis offers both numerical estimates and intuitive evidence of the shock's impact.

The first finding is that the lockdown led to a statistically significant increase in average food prices across states and commodities. This effect was captured by the regression coefficient on the post-lockdown indicator, which remained positive even after accounting for long-term trends and fixed differences across states and products. In other words, the rise in prices cannot be explained simply by normal market movements; it is tightly linked to the lockdown announcement on 24 March 2020.

The second key insight is the timing of the effect. The event-study plots demonstrate that prices were stable in the weeks leading up to the lockdown and only began to rise immediately afterward. This strengthens the causal interpretation: the lockdown was not just coincident with an upward drift, but the actual trigger of the observed price jump.

A third and important dimension is the heterogeneity of the effect. Perishable goods—such as vegetables, fruits, and dairy—showed a sharp and sustained increase in prices, while non-perishables—such as pulses, cereals, and oils—remained comparatively stable. This reflects the supply chain challenges faced during the lockdown: perishables are far more vulnerable to disruptions in transportation and storage, whereas non-perishables can be stockpiled and distributed over longer periods.

Together, these results suggest that the lockdown did not only raise prices overall, but also reshaped the structure of food pricing in India. Policymakers and market regulators can draw two lessons from this:

1. Nationwide disruptions have immediate and measurable effects on food security through price shocks.

2. Vulnerability is uneven—perishables require more targeted policy support, such as better storage, faster logistics, or essential-goods exemptions, to shield consumers from sudden spikes.

Conclusion

This project set out to investigate whether the COVID-19 lockdown imposed on **24 March 2020** in India had a measurable effect on food prices. By constructing a comprehensive dataset through automated web scraping, applying regression analysis with fixed effects, and supplementing the estimates with visual event-study methods, the analysis produced a consistent and robust answer.

The evidence shows that the lockdown led to a **significant increase in retail food prices** across India. This price shock was not only immediate but also disproportionately affected **perishable goods**, highlighting their greater vulnerability to supply chain disruptions. In contrast, non-perishable goods remained relatively stable, underlining the importance of commodity characteristics in shaping the impact of nationwide policy interventions.

The broader implication is that while lockdowns may be essential for public health management, they also generate unintended economic costs, particularly in the food sector. Policymakers must therefore anticipate these effects and design **mitigation measures**—such as exempting essential supply chains, improving cold storage, or ensuring logistical support for perishables—to cushion both producers and consumers during times of crisis.

In summary, the lockdown did not just alter daily life; it also left a clear imprint on food markets. This study demonstrates how systematic data collection and applied econometric analysis can reveal the scale and nature of such impacts, contributing to a better understanding of the trade-offs involved in large-scale public policy decisions.