

Commodity Price Shocks, Air Pollution, and Labour Markets in India: Evidence from State-Month Variation

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ABSTRACT

Geopolitical conflicts can generate commodity-price shocks that may affect household fuel choices, air pollution and labour-market outcomes. This paper examines this potential transmission mechanism in India using a state-month panel covering 36 states and union territories from January 2025 to June 2026. Fixed-effects regressions relate state-level LPG and oils-and-fats prices to ambient PM2.5, and PM2.5 to aggregate labour-market outcomes. The results provide little evidence of a systematic relationship between price levels and PM2.5. Oils-and-fats inflation is positively associated with PM2.5 in one specification, but the relationship is not robust, while LPG inflation is insignificant given limited state-specific price variation. PM2.5 is also not systematically associated with labour-market outcomes. Overall, the findings provide limited evidence for the proposed transmission mechanism at the state-month level.

Keywords: Geopolitical shocks; Commodity prices; LPG; PM2.5; Air pollution; Labour markets; India

JEL Code: Q43; Q53; E31; J21

1. Introduction

Household energy is critical to wellbeing in low-income countries. Choices of cooking, heating and lighting fuels shape health, time allocation, women's labour-force participation and local air pollution. Governments across South Asia, Sub-Saharan Africa and Latin America have therefore invested heavily in shifting households from traditional biomass towards cleaner fuels. Yet this transition remains incomplete. Even after acquiring access to a cleaner fuel, low-income households often do not abandon their traditional energy sources entirely. Instead, they engage in fuel stacking, using clean and polluting fuels simultaneously.

The extent to which households rely on each fuel is likely to depend on their relative prices. As the cost of clean fuel increases, individuals are more likely to substitute towards firewood, dung cakes and crop residue. These decisions have impacts not only on individual household members but also on air quality, productivity and labour supply. India, the largest country in which households have experienced this phenomenon.¹ While the number of LPG connections in India increased from approximately 140 million in 2014 to over 330 million by 2024 due to the Pradhan Mantri Ujjwala Yojana (PMUY), nearly one-third of households in India—and almost half of rural households—still use biomass as their primary cooking fuel.

This relationship is especially consequential in the Indian context. India is one of the largest importers of crude oil and edible oil globally, making the prices of LPG and cooking oil highly sensitive to global commodity prices. For example, during the Russia-Ukraine war in 2022,² global vegetable oil prices spiked to record levels due to significant reductions in Black Sea sunflower oil exports. India imports nearly all of its sunflower oil from Russia and Ukraine, and thus bore the brunt of this increase.³ Consequently, in 2022, sunflower oil prices in major Indian cities increased by 25–35 percent.⁴ Additionally, there were two increases in the prices of domestic LPG cylinders in 2022, resulting in a 14.2 kg cylinder refill in Delhi being sold for over ₹1000 for the first time.

The conflict motivating this paper has reproduced a similar outcome within its sample window as well. Once the US-Israel-Iran war broke out on 28 February 2026, with the closing of the Strait of Hormuz, through which about a fifth of the world's seaborne oil and liquefied natural gas flowed, Brent crude shot up from around US\$75 to over US\$100 a barrel within a few days.⁵ In India, the oil marketing companies hiked the cylinder price by ₹60 on 7 March 2026, saying

¹ Ministry of Petroleum and Natural Gas: total active domestic LPG consumers rose from 14.52 crore in April 2014 to 32.94 crore by March 2025, including 10.33 crore connections under the PMUY (Lok Sabha reply, March 2025). On biomass reliance, the International Institute for Sustainable Development (India's Clean Cooking Shift, February 2026) estimates that 37 per cent of households nationally and 51 per cent of rural households depend primarily on polluting cooking fuels; NFHS-5 (2019-21) reported 40.6 and 56.1 per cent respectively.

² (on "global vegetable oil prices spiked to record levels"): The FAO Vegetable Oil Price Index reached its all-time high of 251.8 points in March 2022, immediately following the invasion (FAO Food Price Index database).

³ Before the war India sourced approximately 70 per cent of its imported sunflower oil from Ukraine and 20 per cent from Russia (ICRA, Indian Edible Oil Industry, March 2022). Retail price data from the Department of Consumer Affairs Price Monitoring Division show all-India average sunflower oil prices rising from about ₹150 per litre in late 2021 to ₹185-190 by mid-2022.

⁴ Oil marketing company price notifications: increases of ₹50 (22 March 2022), ₹50 (7 May 2022), ₹3.50 (19 May 2022, taking the Delhi price to ₹1,003) and ₹50 (6 July 2022, to ₹1,053).

⁵ The conflict began on 28 February 2026 with US and Israeli strikes on Iran; Iran responded by closing the Strait of Hormuz, which previously carried about 20 per cent of global seaborne oil and LNG trade (Congressional Research Service, The Strait of Hormuz, August 2026). Brent rose from approximately US\$75 to above US\$100 a barrel within days, peaking near US\$120.

there had been “disruption in global energy market[s] due to the current situation”. Another hike of ₹29 followed in June 2026.⁶

Large increases in the price of LPG and sunflower oil create incentives to substitute towards biomass, especially for poorer and rural households. At the aggregate level, this substitution may lead to higher ambient PM_{2.5} concentrations, exacerbating air pollution in the Indo-Gangetic plain, where ambient PM_{2.5} already exceeds the National Ambient Air Quality Standard by a factor of two or more.⁷ This higher ambient pollution may also affect labour markets, leading to lower productivity in industries with high outdoor exposure and a decline in labour supply on the extensive and time-use margins, affecting the informal and casual labour force.

This paper attempts to estimate the reduced-form effect of retail LPG and edible-oil prices on ambient PM_{2.5} in India, and the subsequent effect of ambient PM_{2.5} on wages, employment status and sector reported in the Periodic Labour Force Survey (PLFS). Identification relies on continuous monthly variation in state-level retail prices, with state and time fixed effects controlling for unobserved state-level and time-level heterogeneity. Contributions to the existing literature are threefold. First, the paper estimates the entire chain from domestic prices to labour market outcomes, whereas previous work has looked at each step in isolation. Second, the PLFS micro-data allows examination of how the outcome varies by employment status and industry sector, which allows us to look at the distributional implications of this price change, something that studies based on aggregate data cannot do. Third, by relying on continuous variation in prices rather than a discrete shock, this paper’s estimates are less sensitive to unobserved confounders, making them informative for recurring commodity market shocks.

The rest of the paper is organised as follows. Section 2 discusses and reviews related literature. Section 3 describes the data and methodology. Section 4 presents the empirical strategy and reports the results. Section 5 presents the findings and their limitations. Finally, Section 6 concludes.

2. Literature Review

The empirical question that motivates this paper sits at the intersection of three strands of literature: the transmission of geopolitical shocks to retail prices in developing economies, particularly for fuel and edible oils; the response of household cooking-fuel choices to changes in

⁶ Price notifications of ₹60 per 14.2 kg cylinder effective 7 March 2026 and ₹29 effective 7 June 2026, taking the Delhi price from ₹853 to ₹942 over the period; the Ministry of Petroleum and Natural Gas reported per-cylinder under-recoveries of roughly ₹700 during the episode.

⁷ The annual National Ambient Air Quality Standard for PM_{2.5} is 40 µg/m³ (Central Pollution Control Board). CREA's Tracing the Hazy Air 2025 reports 2024 annual average PM_{2.5} of 105 µg/m³ in Delhi and above 90 µg/m³ in other Indo-Gangetic plain cities, two to three times the standard.

clean-fuel prices and its implications for ambient air quality; and the effects of particulate pollution on output, productivity and labour supply. This section reviews each strand and identifies the gap that the present paper addresses.

2.1 Geopolitical risk, commodity prices, and developing-economy pass-through

The connection between negative geopolitical developments and global oil prices is a longstanding topic of interest to macroeconomics. However, until relatively recently, there did not exist a long-run, consistently measured proxy for geopolitical risk in the empirical literature. This gap has been filled by Caldara & Iacoviello (2022), who constructed the Geopolitical Risk (GPR) Index using automated text search of the archived digital records of major newspapers from 1900 to the present day. The measure was constructed based on a set of historical events, whose chronology served as a validation mechanism for the text search. In vector autoregressions in which the index was included and exogenous innovations to the index propagated through to oil prices, industrial production, employment and equity returns, the authors found that a positive one-standard-deviation shock to the index raised the real price of oil, and lowered industrial production and private employment, both in a statistically and economically significant manner. They also decomposed the index into geopolitical threats and geopolitical acts, finding that threats affected forward-looking financial and commodity market variables, while acts had more enduring effects on real activity. The implication of this strand of literature for the present paper is that repeated geopolitical shocks (such as the Russia–Ukraine war and the 2026 Middle Eastern conflict that serve as our motivating case studies) can be expected to raise global oil prices, rather than being isolated incidents.

The second strand of literature relevant to the present paper concerns the question of whether, and to what extent, these global price increases are passed through to domestic prices in developing economies. Arndt et al. (2023) answer this question by employing a range of country-level computable general equilibrium models, representing nineteen developing economies from Africa, Asia and Latin America. They examine the transmission of world price increases for energy, food and fertilisers during the first half of 2022 to domestic prices, real household income, poverty rates and calorie consumption in these economies. They estimated that the shock to commodity prices triggered by the Ukraine war pushed an additional 27.2 million people into poverty, and 22.3 million people into hunger, across the countries under study. The rise in fuel and fertiliser prices was found to be the largest channel for the welfare losses associated with the shock, followed by food prices, which affected the quality of diets. Among the commodity categories, refined fuels and edible oils were seen to have the highest rates and speed of pass-through from world to domestic prices, reflecting their heavy reliance on imports and lack of short-term substitutes.

Given the high level of import dependence for crude oil and edible oils in India (roughly 88% and 57% respectively), it is reasonable to expect that geopolitical shocks that reach the country via international commodity markets will result in a measurable increase in domestic retail prices for LPG cylinders and cooking oils.

2.2 Clean-fuel demand and household fuel substitution

The price-elasticity of household demand for clean cooking fuel defines whether the variation in retail prices will lead to any change in behaviour. In a randomised controlled experiment, Jeuland et al. (2023) provide direct evidence of whether such a behavioural response is likely to occur. The sample for their experiment was 580 low-income households from rural Tamil Nadu, India. The households were randomly assigned to a control group that was provided with the existing government subsidy and to three treatment groups that received coupons for a US\$1.7, US\$3.4, or US\$5.1 discount for every cylinder refill. LPG purchases increased significantly and monotonically with the size of the coupon value. The average LPG consumption in a month rose from 4.7 kg to 9.5 kg in the control group and the highest-subsidy group, respectively. Based on these figures, the authors estimate that the price-elasticity of LPG demand is approximately negative. Two other aspects of their results deserve mention. The first is that in the largest subsidy group, there was no significant decline in self-reported hours spent collecting firewood, suggesting that the practice of fuel stacking continues despite substantial reductions in the price of LPG. Second, the price elasticity is calculated for the very same population – poor rural households – that the Pradhan Mantri Ujjwala Yojana targets and that is most likely to be exposed to household energy price shocks. For the present paper, this implies that the demand response on the substitution margin is sufficient to observe measurable differences in fuel use based on the varying exposure to shocks in LPG and edible oil prices.

Once fuel substitution occurs, the question is whether it will result in any measurable difference in ambient air quality. Chowdhury et al. (2019) examine this issue empirically by using satellite-based estimates of ambient PM_{2.5} that are aggregated at the district level. They combine this with information on household-level use of solid fuels for cooking, space heating, water heating and lighting from the National Family Health Survey. Then they consider various counterfactual scenarios in which different sets of household emissions are completely removed. They then estimate what the change in population-weighted ambient PM_{2.5} would be if household emissions are completely eliminated. According to their analysis, eliminating all emissions from cooking with biomass alone would reduce India's national population-weighted ambient PM_{2.5} by around 17.5 per cent. If emissions from cooking, space and water heating, and lighting are eliminated, then the national average will fall from about 55.1 µg/m³ to 38 µg/m³, which is below the National Ambient Air Quality Standard of 40 µg/m³, and 103 new districts (which accounts for 187 million people) would meet the standard. This suggests that a reduction in the use of

solid fuels can result in a significant drop in ambient air pollution. Conversely, if LPG and cooking oil prices rise, leading to a shift in the use of fuels, this should increase ambient PM2.5 at the district and state level, not just indoors. This means that the present paper will also observe an impact on the outcome variable of interest (ambient pollution) if the treatment variable (energy prices) varies.

2.3 Ambient pollution and labour-market outcomes

The final stage of the causal mechanism concerns the relationship between ambient PM2.5 and labour-market outcomes. The literature has some macro evidence on this topic. Behrer et al. (2023) construct a panel of real GDP for 550 Indian districts from 1998 to 2020 and estimate the causal effect of ambient PM2.5 on the annual rate of growth of district GDP. One challenge is that economic activity can influence ambient pollution levels. For instance, increased economic activity may drive up pollution because of increased traffic and electricity generation. So there is a potential problem of endogeneity or reverse causality. To deal with this issue, the authors instrument for PM2.5 using thermal inversions, which are derived from NASA MERRA reanalysis temperature data. Thermal inversions trap pollutants near the ground and do not respond to any changes in local economic activity. The estimates indicate that a 1 $\mu\text{g}/\text{m}^3$ increase in PM2.5 decreases district GDP growth by about 0.7 percentage points. While the contemporaneous effect is somewhat offset in subsequent years, the long-run effect is not zero, suggesting that the reduction in GDP is not purely due to a short-term delay in economic activity. Interestingly, the estimated impact is similar to those found in studies conducted in Europe even though ambient pollution levels in India are about five times higher, which the authors argue is evidence of partial adaptation at high exposure.

The micro-level evidence is discussed in Adhvaryu et al. (2022). They link hourly production data for each worker to hourly PM2.5 at a large garment factory in Bangalore. The key identification strategy relies on variation in hourly PM2.5 at each production line within an hour, after controlling for worker fixed-effects, production line fixed-effects, date fixed-effects and hour-of-day fixed-effects. The results suggest that a 10 $\mu\text{g}/\text{m}^3$ increase in PM2.5 decreases hourly worker efficiency by more than 0.3 percentage points. Given that the workers in the plant are paid on the basis of hourly output, a decrease in hourly efficiency will result in a proportionate drop in hourly wages. This provides a theoretical micro-foundation for the possibility that changes in PM2.5 affect the dependent variable of hourly wages in the PLFS.

Jafarov et al. (2023) analyse the effects of ambient pollution on labour supply. They merge data from the 2019 Time Use Survey with district-level estimates of ambient PM2.5 from satellite observations. The authors use the change in local wind direction to instrument for PM2.5 and find that higher pollution levels significantly decrease time spent in market work. These results

are concentrated among the self-employed and casual labour categories, both of which are crucial segments of the Indian labour force. In contrast, the effects for salaried workers are lower and statistically imprecise, since many of them work inside closed environments. Taken together, Behrer et al. (2023) for district-level GDP, Adhvaryu et al. (2022) for hourly productivity and hourly wages, and Jafarov et al. (2023) for the labour supply margin offer a comprehensive framework linking the changes in ambient PM2.5 (predicted by Chowdhury et al. (2019)) to the labour market outcomes.

These studies correspond to separate links along the causal chain that underlies the motivation for this paper. The current paper interacts with these literatures in three ways. First, it tests the entire route from domestic retail prices to labour-market outcomes in a single state-month panel dataset, while existing papers look at fragments of this route using different datasets, methodologies and settings. Second, it investigates whether mechanisms that have been established at the household and worker level can be observed in aggregate state-month data, the level at which Indian labour and air quality outcomes are typically reported; this question is explored in Section 4, and its answer depends on how much identifying price variation remains in India's administered LPG pricing regime and at what margin Indian labour statistics are reported. Finally, the paper takes advantage of the fact that state-level retail prices vary each month continuously, instead of focusing on a one-off policy intervention or geopolitical event; this allows the results to speak to repeated shocks to commodity markets, of which the 2026 West Asia conflict that plays out during the sample period and the 2022 Russia-Ukraine war prior to it are the most recent examples.

3. Data and Methodology

To empirically test the transmission of household energy price shocks via fuel substitution onto air quality and labour outcomes, a state-monthly panel dataset covering all 36 Indian states and union territories over the period January 2025 to June 2026 was assembled. The dataset is constructed from secondary, publicly available sources, integrating data on household energy prices, air quality, and labour force characteristics along with controls for weather conditions and other state-level characteristics.

The dataset features two sets of dependent variables, one for each step in the proposed causal chain. First, the outcome is the state-monthly weighted mean of PM2.5 (henceforth PM2.5). This is derived from monthly snapshots of air quality reported by the Centre for Research on Energy and Clean Air (CREA)⁸ which gives the number of monitored cities in each state falling in five

⁸ Centre for Research on Energy and Clean Air (CREA), India monthly ambient air quality snapshots ("Distribution of cities by PM2.5 air quality index based on monthly average PM2.5 concentrations"), 2025-2026 editions, compiled from Central Pollution Control Board CAAQMS data; accessed July-August 2026.

bands of the air quality index calculated using monthly average concentrations of PM_{2.5}. These PM_{2.5} readings are taken from the Continuous Ambient Air Quality Monitoring Stations maintained by the Central Pollution Control Board (CPCB).

For each state-month, the number of monitored cities in each PM_{2.5} concentration band is used to construct an estimated state-level mean. The midpoint of each concentration band is assigned as the representative PM_{2.5} concentration for cities in that band, and these midpoints are weighted by the share of monitored cities falling in each band (Table 1). This procedure implicitly assigns equal weight to each monitored city and assumes that the midpoint provides a reasonable approximation to the average PM_{2.5} concentration of cities within each band. PM_{2.5} averages 40.30 µg/m³ (SD = 26.24), slightly over India's National Ambient Air Quality Standard of 40 µg/m³, ranging from 15 to 185.5 µg/m³ and exhibiting strong seasonal and geographic variation.

In the second stage, the outcomes are eight labour-force indicators sourced from the Periodic Labour Force Survey (PLFS) unit-level data for calendar year 2025: the worker population ratio, the labour force participation rate (LFPR) disaggregated by sex and by age group, the unemployment rate, and average weekly hours worked.⁹ The LFPR averages 60.92 per cent (SD = 8.92). The unemployment rate averages 4.62 per cent (SD = 2.94) but ranges up to 20.36 per cent at its peak, showing large disparities in labour market slack across states (Table 2A).

Table 1: Air Quality Index Categories Used to Construct the PM_{2.5} Weighted Mean

AQI Category	PM _{2.5} Range (µg/m ³)	Representative PM _{2.5} value (µg/m ³)
Good	0–30	15.0
Satisfactory	31–60	45.5
Moderate	61–90	75.5
Poor	91–120	105.5
Very Poor	121–250	185.5

⁹ Ministry of Statistics and Programme Implementation, January to December 2025. The redesigned PLFS has published monthly state-level estimates since January 2025; comparable monthly estimates for 2026 were not available at the time of writing, so the labour outcomes are observed for the twelve months of 2025 (see Section 4, Model 3)

The main independent variables are state-monthly consumer price indices for oils and fats and for LPG, along with their month-on-month inflation rates. These series come from MoSPI's e-Sankhyiki portal, with a base of 2024 = 100 and the index covering both rural and urban sectors. The oils and fats index comes at the class level (COICOP 01.1.5), while LPG is measured at the item level (COICOP 04.5.2.2.1.01), the most granular disaggregation available from MoSPI. The oils and fats index averages 117.18 (SD = 10.91), significantly above the base of 2024 and ranging up to 191.85 at its peak. The LPG index averages 102.19 (SD = 3.05, range = 96.12 to 111.11), with a much narrower range, consistent with LPG's administered nature and suggesting that most of the variation in LPG prices stems from the timing of price revisions at the national level rather than cross-state differences. The month-on-month inflation rate for oils and fats averages 0.66 per cent (SD = 1.40), and for LPG, 0.48 per cent (SD = 1.41) (Table 2B).

To ensure that the association between household energy prices and environmental and labour outcomes is not driven by confounding factors, controls for rainfall, per capita NSDP, urbanisation, literacy, and per capita social sector expenditure were included. These were chosen to capture weather conditions influencing air pollution dispersal, state income, structural factors such as rural-urban mix, human capital endowment, and state spending power. Rainfall comes from IMD's subdivision rainfall maps, with each state mapped to its primary meteorological subdivision; the remaining controls come from RBI's Handbook of Statistics on Indian States, RBI's State Finances, and NPC's 2020 projections. Table 2C shows summary statistics for the controls.

Table 2A: Summary Statistics for Dependent Variables

Variable	Obs	Mean	Std. Dev.	Min	Max
PM2.5 Weighted Mean ($\mu\text{g}/\text{m}^3$)	648	40.30	26.24	15.00	185.50
Worker Population Ratio	432	58.51	8.70	19.22	85.53
Labour Force Participation Rate	432	61.06	8.79	21.39	85.69
LFPR (Male)	432	78.14	5.95	49.69	97.23

Variable	Obs	Mean	Std. Dev.	Min	Max
LFPR (Female)	432	43.96	14.50	10.05	81.18
Unemployment Rate	432	4.63	3.01	0.00	20.36
Youth LFPR	432	47.37	11.12	9.36	81.96
Prime-age LFPR	432	76.93	9.75	28.27	97.24
Average Weekly Hours	432	39.84	5.99	20.55	68.27

Note: Labour indicators are observed for calendar year 2025 (36 states $\times$ 12 months = 432); see Section 4, Model 3.

Table 2B: Summary Statistics for Independent Variables

Variable	Obs	Mean	Std. Dev.	Min	Max
CPI: Oils and Fats (2024=100)	612	117.18	10.91	101.04	191.85
CPI: Oils and Fats, MoM Inflation (%)	576	0.66	1.40	-4.11	12.08
CPI: LPG (2024=100)	612	102.19	3.05	96.12	111.11
CPI: LPG, MoM Inflation (%)	576	0.48	1.41	-3.15	6.89

Table 2C: Summary Statistics for Control Variables

Variable	Obs	Mean	Std. Dev.	Min	Max
Rainfall, Actual (mm)	648	109.86	149.80	0.00	1014.50
Per Capita NSDP, Constant Prices (₹)	594	146,389.10	75,167.04	36,342	357,611
Urbanisation Rate, Projected 2025 (%)	648	45.65	24.16	10.36	100.00
Literacy Rate, Census 2011 (%)	594	77.69	8.58	61.80	94.00
Social Sector Expenditure per Capita (₹)	522	33,593.15	20,178.70	12,837.67	95,108.02

4. Empirical Specification and Analysis

This section reports the results. Models 1 and 2 examine whether household energy prices are related to ambient PM2.5. Model 3 examines whether PM2.5 is related to labour market outcomes. All models are run on the state-month panel described in Section 3 with fixed-effects regression. State fixed effects absorb differences in permanent characteristics between states; month fixed effects absorb seasonality and any shocks that affect all states equally; standard errors are clustered at the state level. The state-level controls (per capita NSDP, urbanisation rate, literacy rate and social sector expenditure) do not vary over the 18-month window, so the state fixed effects will automatically absorb them. The only control that appears directly in the regressions, therefore, is rainfall.

Model 1: Retail Price Levels and Ambient PM2.5

To test whether the level of household energy prices is associated with air pollution, we regress state-level PM2.5 on the consumer price indices for LPG and for oils and fats. These are the two

retail prices through which the conceptual framework predicts substitution towards biomass. The dependent variable is the monthly state-level PM2.5 measure constructed in Section 3.

The regression equation is specified as follows:

$$Pollution_{st} = \alpha + \beta_1 LPGPrice_{st} + \beta_2 FoodOilPrice_{st} + \gamma'X_{st} + \mu_s + \lambda_t + \varepsilon_{st}$$

Here, $Pollution_{st}$ is ambient PM2.5 in state s and month t ; $LPGPrice_{st}$ and $FoodOilPrice_{st}$ are the state CPI series for LPG and for oils and fats; X_{st} contains rainfall; μ_s and λ_t are state and month fixed effects; and ε_{st} is the error term.

Table 3: Retail Price Levels and Ambient PM2.5

	FE (Without Controls)	FE (With Controls)
CPI: LPG	-0.947 (0.697)	-0.890 (0.711)
CPI: Oils and Fats	0.063 (0.127)	0.025 (0.158)
Rainfall (mm)		-0.027 (0.020)
_cons	148.23** (68.54)	141.74* (69.79)
No. of Observations	507	450
No. of States	32	28
R-Squared (within)	0.504	0.526

Notes: Standard errors clustered at the state level in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. All specifications include state and month fixed effects. The control variables include rainfall; per capita NSDP, urbanisation rate, literacy rate and social sector expenditure are absorbed by the state fixed effects.

The results provide little evidence of a systematic relationship between commodity price levels and ambient PM2.5. Neither LPG nor oils and fats is statistically significant in either specification. The LPG coefficient is negative (−0.947 without controls and −0.890 with controls), opposite to the direction predicted by the fuel-substitution mechanism, but it is statistically indistinguishable from zero. The oils-and-fats coefficient is small and close to zero in both specifications. The inclusion of rainfall does not materially alter the price coefficients. Since state and month fixed effects absorb persistent differences across states and common monthly movements, the estimates are identified from state-specific deviations in prices within a given month, rather than from differences in average prices across states or nationwide price increases. Thus, the level specification does not provide evidence that higher household

commodity prices are associated with higher PM2.5, motivating the next specification based on monthly price changes, which may better capture short-run household responses to price shocks.

Model 2: Month-on-Month Price Inflation and Ambient PM2.5

The second model replaces price levels with month-on-month inflation. Short-run changes in prices may be more relevant for household responses than price levels, as households directly observe changes in the cost of refilling an LPG cylinder or purchasing cooking oil.

The regression equation is specified as follows:

$$Pollution_{st} = \alpha + \beta_1 \Delta LPGPrice_{st} + \beta_2 \Delta FoodOilPrice_{st} + \gamma'X_{st} + \mu_s + \lambda_t + \varepsilon_{st}$$

Here, $\Delta LPGPrice_{st}$ and $\Delta FoodOilPrice_{st}$ are month-on-month inflation (in per cent) in the two indices; all other terms are as in Model 1.

Table 4: Month-on-Month Price Inflation and Ambient PM2.5

	FE (Without Controls)	FE (With Controls)
CPI: LPG, MoM inflation	-2.155 (1.331)	-1.433 (1.169)
CPI: Oils and Fats, MoM inflation	0.591 (0.389)	1.155** (0.518)
Rainfall (mm)		-0.037* (0.020)
_cons	51.97*** (2.34)	49.51*** (2.32)
No. of Observations	476	422
No. of States	32	28
R-Squared (within)	0.503	0.526

Notes: Standard errors clustered at the state level in parentheses. *** p < 0.01, ** p < 0.05, * p < 0.1. All specifications include state and month fixed effects. The control variables include rainfall; per capita NSDP, urbanisation rate, literacy rate and social sector expenditure are absorbed by the state fixed effects.

LPG inflation remains statistically insignificant. The only significant price coefficient is that on oils and fats inflation in the controlled specification. Its coefficient of 1.155 (p = 0.034) implies that a one-percentage-point increase in monthly edible-oil inflation is associated with approximately 1.2 $\mu\text{g}/\text{m}^3$ higher PM2.5. However, this result should be interpreted cautiously.

One reason for the difference across the two price measures is the amount of state-specific variation remaining after the fixed effects. LPG prices move closely together across states, with an average cross-state correlation of 0.875 for monthly inflation, and state and month fixed

effects remove 82.8 per cent of its total variation. Oil and fats prices exhibit substantially more state-specific variation: their average cross-state correlation is 0.192, and only 18 per cent of the variation in monthly inflation is removed by the fixed effects.

Table 5: Identifying Variation in the Price Variables

	Total SD	SD after fixed effects	Share of variance removed	Cross-state correlation
CPI: LPG (level)	3.05	1.11	86.7%	0.890
CPI: Oils and Fats (level)	10.91	4.31	84.3%	0.751
CPI: LPG, MoM inflation	1.41	0.59	82.8%	0.875
CPI: Oils and Fats, MoM inflation	1.40	1.26	18.0%	0.192

Notes: SD after fixed effects is the standard deviation remaining after removing state and month fixed effects. Cross-state correlation is the average pairwise correlation between state-level series over the sample window.

This limited variation makes it difficult to identify an association between LPG inflation and PM2.5. The insignificant LPG coefficient therefore cannot by itself be interpreted as evidence against fuel substitution; rather, the administered nature of domestic LPG pricing leaves relatively little state-specific price variation from which to estimate such a relationship. The same issue helps explain why oils and fats prices are insignificant in the levels specification: although their monthly changes retain substantial variation, their price levels are largely absorbed by the fixed effects.

The positive association between oils and fats inflation and PM2.5 is also not robust enough to establish the proposed mechanism. First, it is significant only in the controlled specification, while the estimate in the larger sample is 0.780 ($p = 0.156$). Second, any effect would operate indirectly: higher cooking-oil prices could place pressure on household budgets and potentially affect expenditure on cleaner cooking fuels. Finally, oil prices may also capture seasonal agricultural conditions, particularly in northern states where oilseed harvesting and crop-residue burning occur around the same period. The estimated relationship may therefore reflect factors other than household fuel substitution. We therefore treat this result as suggestive evidence of a possible price–pollution relationship rather than as robust evidence of the proposed mechanism.

Model 3: Ambient PM2.5 and Labour Market Outcomes

The third model relates labour-market outcomes from the Periodic Labour Force Survey (PLFS) to ambient PM2.5. Monthly PLFS estimates are available only for calendar year 2025, so the

analysis is restricted to January–December 2025. Month fixed effects are included to account for common seasonal patterns in both pollution and labour-market outcomes.

The regression equation is specified as follows:

$$Y_{st} = \alpha + \beta_3 \text{Pollution}_{st} + \gamma'X_{st} + \mu_s + \lambda_t + \varepsilon_{st}$$

Here, Y_{st} is one of eight PLFS outcomes for state s and month t : the labour force participation rate (LFPR), the worker population ratio (WPR), the unemployment rate, male and female LFPR, youth and prime-age LFPR, and average weekly hours worked. Each outcome is estimated without controls and with rainfall.

Table 6: Ambient PM2.5 and PLFS Labour Market Outcomes, 2025

Dependent variable	FE (Without Controls)	FE (With Controls)	R-Sq. (within)
LFPR (%)	0.001 (0.014)	0.001 (0.014)	0.085
WPR (%)	0.007 (0.014)	0.007 (0.014)	0.079
Unemployment rate (%)	-0.014** (0.006)	-0.014** (0.006)	0.048
LFPR, male (%)	0.019 (0.018)	0.019 (0.017)	0.055
LFPR, female (%)	-0.009 (0.023)	-0.011 (0.024)	0.081
LFPR, youth (%)	0.023 (0.024)	0.023 (0.024)	0.045
LFPR, prime age (%)	-0.006 (0.014)	-0.007 (0.014)	0.081
Average weekly hours	0.009 (0.006)	0.009 (0.006)	0.077
No. of Observations	358	358	
No. of States	32	32	

Notes: Each row reports the PM2.5 coefficient from a separate fixed-effects regression of the named outcome on ambient PM2.5, January to December 2025. Standard errors clustered at the state level in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. All specifications include state and month fixed effects; the controlled specification adds rainfall. R-squared (within) refers to the uncontrolled specification.

Of the eight labour-market outcomes, only unemployment is statistically significantly associated with PM2.5. The coefficients on LFPR, WPR, male and female LFPR, youth and prime-age LFPR, and weekly hours are all statistically indistinguishable from zero. The estimates are also relatively small in magnitude. For example, the LFPR coefficient implies an association of only 0.01 percentage points per 10 $\mu\text{g}/\text{m}^3$ increase in PM2.5, while the coefficient for weekly hours implies approximately 0.09 minutes per week. These aggregate estimates therefore do not indicate economically large relationships between monthly state-level pollution and labour-market outcomes.

The unemployment rate is the only exception, with a negative and statistically significant coefficient of -0.014 ($p = 0.016$). This implies that a 10 $\mu\text{g}/\text{m}^3$ increase in PM2.5 is associated with approximately a 0.14 percentage-point lower unemployment rate, conditional on state and month fixed effects. This should not be interpreted as evidence that higher pollution improves labour-market conditions. A more plausible explanation is reverse causality: periods of stronger economic activity may simultaneously generate greater pollution and lower unemployment. The negative coefficient could therefore capture the relationship between economic activity and both variables rather than an effect of pollution on unemployment.

These findings also differ in scale from the mechanisms identified in the existing literature. Studies using plant-level or individual time-use data find effects of pollution on worker productivity and time allocation, whereas the present analysis uses monthly state-level aggregates. Such effects may therefore be too small or heterogeneous to appear in aggregate participation, employment, or hours measures.

5. Conclusion

This paper examined a potential mechanism through which geopolitical commodity-price shocks may affect economic conditions in India: changes in household commodity prices may alter fuel-use decisions, affect ambient air pollution, and ultimately influence labour-market outcomes. The analysis does not estimate the causal effect of the Russia–Ukraine war or the 2026 West Asia conflict themselves. Rather, these conflicts provide the motivating context for examining whether the subsequent links in this transmission mechanism are observable in Indian state-month data.

The empirical evidence is limited. We find no systematic association between the **levels** of LPG or oils-and-fats prices and ambient PM2.5. When the analysis instead considers monthly price changes, LPG inflation remains insignificant, while oils-and-fats inflation is positively associated with PM2.5 in the specification including rainfall. However, this relationship is not robust to the larger sample and may also capture state-specific agricultural conditions. The limited identifying

variation in LPG prices is particularly important: because domestic LPG prices move closely across states, state and month fixed effects remove most of the variation available for estimation. The absence of a significant LPG coefficient therefore cannot be taken as evidence that households do not respond to clean-fuel prices.

The second stage similarly provides little evidence that monthly state-level PM2.5 is systematically associated with aggregate labour-market outcomes. Across eight outcomes, only unemployment is statistically significant, with higher PM2.5 associated with lower unemployment. Given the sign of this relationship, reverse causality provides a more plausible interpretation than a beneficial effect of pollution: stronger economic activity may simultaneously generate greater pollution and lower unemployment. Moreover, the effects documented in previous studies at the plant and individual levels may not translate into detectable changes in aggregate monthly labour-market indicators.

Taken together, the results do not provide strong evidence for the complete proposed transmission mechanism in the available data. This should not be interpreted as evidence that the underlying household or worker-level mechanisms are absent. Rather, the analysis illustrates the difficulty of tracing a micro-level mechanism through aggregate state-month data when the key price variable has limited identifying variation and when pollution itself is endogenous to economic activity. Future work could address these limitations using household-level fuel-use data, more granular pollution measures, or exogenous variation in commodity prices and ambient pollution. Such approaches would allow the mechanisms identified in the existing micro-level literature to be tested more directly and would provide a stronger basis for assessing how geopolitical commodity shocks propagate to household welfare and labour-market outcomes.

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