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Digvijay S. Negi, Ashoka University

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State Mediated Trade, Distortions and Air Pollution

Digvijay S Negi*

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Abstract

Can government imposed market integration and resultant specialization contribute to a large-scale negative environmental externality? I compare agricultural fire activity and air pollution levels in districts where the government interferes in the local grain markets with districts without such interference to establish a robust link between food prices and air pollution in India. This link comes about due to higher prices leading to increased agricultural fire activity in districts where the government procures foodgrains from the local markets. Estimates suggest a 21 percent increase in morbidity and a 19 percent increase in out of pocket medical expenditure associated with procurement led air pollution. The mortality cost of resultant pollution is USD 1 billion larger than gains to producers from higher prices.

Keywords: fires, air pollution, price floor, distortion, India
JEL codes: F14, Q11, Q52, Q53

*Associate Professor, Ashoka University, Rajiv Gandhi Education City, Sonepat, Haryana, India. Email: digvijay.negi@ashoka.edu.in

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1 Introduction

Trade frictions can explain why some regions are less specialized, have low productivity, and exhibit misallocation (Adamopoulos, 2011; Atkin and Khandelwal, 2020; Restuccia and Rogerson, 2017). With free trade and economic integration, there are gains from specialization as agents respond to global price signals rather than local needs, but such gains may not be equally distributed (Sotelo, 2020; Topalova, 2007). But what about trade which is mediated by the state? Given the importance of agriculture and the vested interests of several different interest groups, agricultural trade is also often intermediated by governments in developing countries (Atkin and Khandelwal, 2020). While such intermediation may be in the form of creating infrastructure and improving access to markets, in the case of India, it takes the extreme form of the federal government being the largest buyer and mover of grains across the country.

Democratically elected governments are generally trying to maintain the difficult balance between maximizing the producer and the consumer surpluses while maintaining their own revenues. The objective function of the government, therefore, is far more complex than a simple profit-maximizing intermediary, and the multiplicity of objectives governments try to achieve with commodity market interventions can lead to welfare losses and sub-optimal outcomes (Anderson et al., 2013; Gerrard and Roe, 1983; Giordani et al., 2016). Such interventions are also susceptible to political pressures and interest group politics (De Gorter and Swinnen, 1995). While government support is one fact, another reality is that *modern* agriculture is a significant polluter and contributor to global emissions (Mamun et al., 2021). Agricultural support policies are known to distort global and domestic market incentives, but can they also lead to large-scale negative environmental externalities?

In this paper, in the context of foodgrain cultivation and marketing, I establish the role price support and government interference in local grain markets play in linking food prices with agricultural fires and air pollution across India. I also highlight the distributional consequences of such a policy, where gains to food producers come from higher prices, but additional and previously unaccounted costs arise due to higher air pollution.

Air pollution is emerging as a major problem in India. Though higher levels of air pollution in a developing economy experiencing rapid economic growth is understandable, most Indian urban centers recurringly feature as the most polluted cities in the world (Greenstone and Fan, 2019). It is well known that seasonal crop residue burning plays an important role in air pollution across Northern India (Cusworth et al., 2018; Jethva et al., 2019; Liu et al., 2020). Rice farmers, in a hurry to prepare their fields to plant the next crop, set ablaze leftover rice stubble standing in their fields (Shyamsundar et al., 2019; Singh et al., 2023). These fires burn at such scale and intensity that satellites are able to capture them from outer space.[1] The region is densely populated and is home to more than 400 million people who are directly exposed to toxic gases and high levels of particulate matter released from burnt crop residue. While the decision to burn leftover crop residue may be rational from a farmer's perspective, the health costs of resultant air pollution can be significant (Lan et al., 2022; Singh et al., 2021). A large body of literature now shows that exposure to pollutants released from biomass burning has severe implications for human health, adding to the disease burden and stressing limited resources and healthcare infrastructure available in the region (Cusworth et al., 2018; Jayachandran, 2009; Lan et al., 2022; Pullabhotla and Souza, 2022; Sarkar et al., 2018).

Indian agriculture offers a unique setting to study the link between food prices and air pollution as there are large variations in the degree of agricultural specialization, intensification, supporting infrastructure, access to local and global agricultural markets, and government interference in these markets. While agriculture in the Northern part of the country is highly specialized, other regions have a more diversified crop portfolio (Birthal et al., 2014). Agricultural specialization and intensification started with the Green Revolution in the late 1960s when modern High-Yielding Varieties (HYV) of rice and wheat were introduced in India. Northern states of Punjab and Haryana were the first to adopt these varieties and are now the top producers of foodgrains in the country (Munshi, 2004; Pingali et al., 2019). The adoption of HYVs was incentivized by input subsidies and assured prices (Pingali et al., 2019). Northern states, due to reasonably good irrigation infrastructure had a first-mover advantage in adopting these

[1] See https://earthobservatory.nasa.gov/images/91185/crop-fires-in-northern-india.

new varieties (Rud, 2012). With support from the government, these regions specialized in the production of rice and wheat. Though HYV adoption is now universal and India is a food surplus nation, the policy of assured prices and grain procurement remains.

A unique feature of the Indian agricultural marketing structure is that the federal government is the largest buyer of staple foodgrains like rice and wheat and commits to buying all the surplus at pre-announced fixed price floors called the *Minimum Support Prices* (MSP) (Krishnaswamy, 2018; Saini and Gulati, 2016). This leads to forced integration in regions where the government actively procures foodgrains and provides unique spatial variation in market integration. I exploit this variation in my empirical framework. I follow the basic intuition in Allen and Atkin (2022) to conceptualize market integration and establish the price mechanism. Using a general equilibrium trade model, which generalizes ideas in Newbery and Stiglitz (1984), Allen and Atkin (2022) show that equilibrium prices can be expressed as a function of the local productivity and the central market price. Using these ideas, I first show that in the absence of government interference in the local grain markets, local prices endogenously respond to local supply shocks.[2] Government procurement operations, however, delink local prices from local supply conditions and link them with national minimum support prices. Procurement breaks the local equilibrium demand-supply relationship and makes local prices exogenously respond to changes in MSP.

I then use a difference-in-differences strategy to compare agricultural fire activity and air pollution levels in districts where the government interferes in the local grain markets with districts without such interference, before and after the surge in global and domestic minimum support prices. I find that districts with government procurement of rice and wheat had higher fire activity and air pollution levels after the increase in minimum support prices than districts without government procurement operations. In terms of mechanisms, I observe higher prices leading to specialization and higher rice production in districts with government interference. I

[2] Allen and Atkin (2022) also focus on the Indian agricultural marketing structure but abstract away from distortion in the form of government procurement of foodgrains and only focus on gains from trade and market integration.

do find evidence of electoral cycles influencing the link between support prices and pollution, but my baseline DID estimates remain robust to such influence. My estimates are also robust to controlling for spillover effects and several concurrent government welfare programs.

I also quantify morbidity and short-run health costs associated with procurement-led air pollution. I observe a 2 percentage point higher likelihood of illness in procurement districts after the price increase. This is primarily attributable to respiratory diseases like asthma and tuberculosis, heart diseases, and other illnesses. The estimate for respiratory illnesses is 36 percent of the average incidence of respiratory illnesses in the sample; for heart diseases, the estimate is larger. Estimates suggest a 19 percent increase in the average per-person out-of-pocket medical expenditure. For procurement districts, the overall associated increase in out-of-pocket medical expenditure comes out to be USD 29 million. This estimate increases to USD 63 for persons aged 30 years and above.

This paper contributes to the literature on gains from trade and market integration (Allen and Atkin, 2022; Donaldson, 2015; Donaldson and Hornbeck, 2016; Topalova, 2007). I contribute to this literature by looking at India's food price and grain procurement policy as a unique case of government imposed market integration. I also illustrate an additional channel of redistribution, i.e., gains from high price passthrough to net producing regions but losses due to pollution externality and associated mortality costs. With higher support prices post-2006, back-of-the-envelope calculations suggest that districts with government procurement experienced a net loss of USD 1 billion. Gains were primarily experienced in the surplus grain-producing districts at the cost of higher pollution-based mortality in the rest of the region.

This paper also contributes to the literature on the unintended consequences of subsidies and support to the agricultural sector. Agricultural support policies have been know to distort market incentives (Anderson et al., 2013; Narayanan and Tomar, 2023). However, such distortions can also have environmental costs (Laborde et al., 2021; Mamun et al., 2021). Evidence shows that subsidies on electricity, fertilizer, irrigation, and agro-chemicals have serious environmental and health consequences (Abman et al., 2023; Badiani-Magnusson and Jessoe, 2018; Brainerd and Menon, 2014; Lai, 2017; Mishra et al., 2018). While subsidies on fertilizer and electricity may indirectly lead to greater emissions, agricultural residue burning directly contributes to air pollution and greenhouse gas emissions. I add to this literature by establishing a previously unexplored consequence of price supports and grain procurement policies, i.e., agricultural waste burning and air pollution.

Finally, this paper also connects with research on the environmental consequences of agricultural production and intensification (Balboni et al., 2023; Carreira et al., 2024; Cisneros et al., 2021; Gatto et al., 2017; Hargrave and Kis-Katos, 2013). A strand of the literature has looked at the role of commodity prices in agricultural intensification, land use changes, and deforestation (Assunção et al., 2015; Barrett, 1999; Berman et al., 2023; Carrillo et al., 2019; Da Mata and Dotta, 2021; Harding et al., 2021; Lundberg and Abman, 2022). I add to this literature by exploring the link between food prices, agricultural fires and air pollution. I also highlight the role of policy-based distortions in generating this outcome. The last two decades have seen major spikes in global food prices (Glauber et al., 2022; Kalkuhl et al., 2016). While food prices in India are heavily regulated, rising global prices have also led to upward revisions in domestic price floor for staple food grains (Saini and Gulati, 2016). The question of how staple food prices influence agricultural intensification and environmental degradation remains more relevant than ever, given that trade disruptions due to wars, conflicts, and geopolitical instability have again put upward pressure on global food prices (Glauber and Laborde, 2022).

2 Background

Rice production is done by a large number of small atomistic farm households. Though a larger number of small farmers sell produce locally, the Indian government is the largest buyer of foodgrains (Chand, 2005; Ganesh-Kumar et al., 2007; Ganga et al., 2012; Saini and Gulati, 2016). Grain purchases by government agencies are done at fixed prices which are announced at the beginning of the agricultural season before planting operations (Krishnaswamy, 2018). The idea of announcing support prices at the beginning of the season is to influence farmers' acreage allocation and production decisions (Basu, 2011). Though procurement happens for both rice and wheat, it happens more intensely for rice than any other grain (Chatterjee and Kapur, 2017). Rice is grown all across India, but procurement does not happen uniformly across the country. Government interference in local markets and grain procurement operations are strongly correlated with the adoption and spread of Green Revolution technologies (Ganesh-Kumar et al., 2007). It also correlates with agro-ecologically suitable surplus producing regions or regions with relatively better developed agricultural market infrastructure (Chatterjee and Kapur, 2017). My empirics pay special attention to testing the sensitivity of results to drivers of spatial heterogeneity in grain procurement operations.

The roots of the current foodgrain procurement policy go as far back as the Great Bengal Famine of 1943 which led the colonial British government to establish the Food Department (Ganesh-Kumar et al., 2007; Saini and Kozicka, 2014). The British realized that the free market was unable to prevent periodic food price surges and frequent food crises. The department, therefore, was tasked with procuring grains from surplus regions, regulating prices, and maintaining stocks, and storage. The post-independence Indian government continued with the policy and intensified its control over food trade and agricultural markets (Saini and Kozicka, 2014). The government enacted the Essential Commodities Act in 1955, essentially giving itself the monopoly power over grain trade. While the initial rationale for the policy was to prevent severe food shortages and speculation in grain markets, the Green Revolution and the introduction of High Yielding Varieties (HYV) of rice and wheat during the late 1960s introduced another dimension to the policy (Ganesh-Kumar et al., 2007). Assured prices and open-ended procurement were also used to provide a stable and favorable environment for farmers to adopt new technologies.

India achieved self-sufficiency in food production due to the introduction of HYVs and the successful implementation of the procurement policies. Since then, grain stocks with the government have grown steadily. Though the volumes have grown, the geography of procurement remains more or less stable (Saini and Kozicka, 2014). Government agencies like the Food Corporation of India (FCI) operate with the sole purpose of buying excess grains from local agricultural markets at fixed prices (Ganesh-Kumar et al., 2007). On average, these agencies procure almost one-third of the total rice production in the country with the purchase volumes varying across states. Few states, like Punjab, Haryana, and Andhra Pradesh, sell a large share of the total rice production to the government. For example, half of the rice and wheat produced in Haryana and two-thirds in Punjab is procured by the government. Given the large volumes purchased by the government every year, the FCI also ships a large volume of grains across states both to national grain stocking facilities and to distribute it to the poor through the Public Distribution System (PDS) of India.[3] This implies that the price dispersion would largely be influenced by government procurement and shipping operations across the country. Given this structure, the transmission of domestic minimum support prices to agricultural market prices would depend upon the degree of government procurement operations (Chatterjee and Kapur, 2017).

The Commission for Agricultural Costs and Prices (CACP), responsible for setting up support prices for rice every agricultural season, considers the production cost but explicitly reports that to be just one factor in determining the MSP. This implies that there is ambiguity in setting the MSP. This also means that, from the perspective of foodgrain farmers in the country, the MSP is exogenous and is taken as given. While the rationale for MSP is to assure farmers a remunerative price and set a price floor, it has essentially protected domestic consumers at the cost of producers (Saini and Gulati, 2016). As Saini and Gulati (2016) note, Indian Minimum Support Prices have broadly followed the trends in global rice prices. Since the support prices are honored by buying excess grains, the procurement of rice has also been increasing over time. Even with frequent foodgrain export bans in periods of high global price variability, rice exports have been an important mechanism through which the government has managed excessive stocks of foodgrains (Chatterjee and Kapur, 2017; Gulati and Dutta, 2010).

While the federal government announces MSPs for rice and wheat in the beginning of every agricultural season, the state governments are also known to announce *bonuses* on

[3]Based on official government data, in 2012-13, the FCI shipped 66%, 47% and 56% of the total rice production from Punjab, Haryana and Andhra Pradesh across India.

the national MSP.[4] These bonuses are often influenced by interest-group politics (Ganguly and Gulati, 2013; Krishnamurthy, 2012). Political contenders and the incumbent are known to be more accommodating of farmers' demands to increase government support prices in years of state elections (Krishnamurthy, 2012). Farm support, including better prices, is a major issue on which state elections are contested and won in the foodgrain cultivating states of India.

Evidence suggests that recent efforts to build new rural road infrastructure have accentuated the problem of biomass burning by inducing farm labor exits and making farm labor expensive (Garg et al., 2023). Garg et al. (2023) show that the large-scale rural road construction under the Pradhan Mantri Gram Sadak Yojana (PMGSY) increased agricultural fires and particulate emissions in the rice harvest season in India.[5] Arriving at similar conclusions but in the context of a social welfare program, the Mahatma Gandhi National Rural Employment Guarantee Act (MGNREGA), Behrer (2023) shows that MGNREGA made labor expensive and induced rice farmers to mechanize harvesting operations.[6] This, Behrer (2023) points out, had the unintended effect of increased fire activity and air pollution. The key argument in these studies is that expensive labor and the unaffordability of manual rice harvesting have led farmers to resort to burning as a labor-saving but polluting land preparation technology (Behrer, 2023; Garg et al., 2023; Liu et al., 2021). While the programs in question are pan-India, the practice of agricultural residue burning is most prevalent in Northern India, where the government is the largest buyer of food grains. I take these findings as given but focus on an additional channel, i.e., assured prices and interference in staple grain markets. In that respect, this paper's findings

[4] There are two main agricultural seasons in India, *Kharif* or monsoon season and *Rabi* or winter season.

[5] The Pradhan Mantri Gram Sadak Yojana (PMGSY, the Prime Minister's Village Road Construction scheme) was started in early 2000s to provide rural all-weather roads to unconnected villages across India. PMGSY rollout followed a population-based rule (Asher and Novosad, 2020). Villages with a household population greater than 1,000 were to be connected first, followed by villages with a population greater than 500, and only then villages with a population smaller than 500.

[6] The Mahatma Gandhi National Rural Employment Guarantee Act (MGNREGA) is India's large-scale anti-poverty rural workfare program. It was introduced in 2005 and provides 100 days per year of voluntary employment at minimum wages to individuals in the working age group. The MGNREGA is mostly operational in rural areas and provides unskilled labor employment on local public work projects.

complement those of Garg et al. (2023) and Behrer (2023).

3 Data and Summary Statistics

3.1 Data

I use several novel data sources to compile my main datasets. The data sources vary in terms of the type and level of aggregation. I compile district-level panels using these different sources. Based on common time dimensions across different data sources and after removing years with missing or outlying observations, I retain the fifteen years from 2002 to 2016 in the final datasets.

3.1.1 Pollution and Fire Events Data

I consider PM 2.5 levels as my main pollution outcome variable. Data for ground level fine particulate matter or PM 2.5 concentration is available in a gridded format from Van Donkelaar et al. (2021) Atmospheric Composition Analysis Group. These high-resolution 0.01°× 0.01°global monthly grids are modeled from NASA's satellite based Aerosol Optical Depth (AOD) measurements and are calibrated to actual ground based PM 2.5 measurements. The PM 2.5 grids start from 1998 all the way through 2021. I use these grids and district geographic boundaries from the 2012 census of India to generate a district-level panel of average monthly PM 2.5 levels from 1998 to 2021. To link PM 2.5 levels with fire activity, I use the time and geocoded active biomass fire data from NASA's Fire Information for Resource Management System (FIRMS) available from 2000 to 2022 (NASA, 2023). The FIRMS data identifies thermal anomalies or active fire within a 1 km pixel from satellite measurements based on the Moderate Resolution Imaging Spectroradiometer (MODIS) Fire and Thermal Anomalies algorithm (Giglio et al., 2015). This data is available at a daily frequency and provides pixel-level information on fire events by the type of fire event. The type is coded as vegetation fire, active volcano, other static land sources, or offshore. The data also provides the confidence level of the identified fire event which ranges from 0 to 100%. I only consider vegetation-based fire events and drop all pixels with a confidence level recorded as zero. I use district boundaries and pixel level and datewise geocoded fire events to calculate the district-level monthly count of fire events for the entire time period.

3.1.2 Agricultural and Price Data

Data on district-level agricultural variables like crop-wise cultivated area and production, area under irrigation, fertilizer use, and farm harvest prices comes from the International Crop Research Institute for Semi-Arid Tropics and Tata Cornell Institute's (ICRISAT-TCI) District Level Data for India (ICRISAT-TCI, 2023). This database has been compiled from official government sources and ranges from 1990 to 2017. The ICRISAT-TCI database also provides data on important infrastructure variables like the district level total road length and number of banks.

I use natural endowment based potential yields from the Food and Agriculture Organization's Global Agro-Ecological Zones (FAO-GAEZ) database to proxy for suitable and surplus producing districts. These estimates are based on agronomic crop models that predict potential crop yields based on natural endowments and local weather conditions. I use potential yield measures for irrigated and modern input use scenarios to reflect the potential crop suitability post adoption of green revolution technologies and inputs in India.

I also collect data on the location of agricultural markets across India from various government sources.[7] I geocode these markets based on their location and addresses. I use these geocoded agricultural markets data to construct a within state measure of market access.

I extract data on government announced Minimum Support Prices (MSP) from publications of the Ministry of Agriculture, Government of India. I also collect local agricultural

[7]The data on agricultural markets correspond to the year 2004.

market price data from the Center for Economic Data and Analysis (CEDA) portal (CEDA, 2023). The CEDA portal contains data on prices and arrivals of major agricultural commodities from around 2700 agricultural markets all across the country. I deflate prices using the national income deflator calculated from the National Accounts Statistics compiled by the Ministry of Statistics and Program Implementation, Government of India.

3.1.3 Weather, Nightlight and Elections Data

I calculate the district-level average rainfall, temperature, pressure, and wind components from the ERA5 gridded global climate and weather dataset (Muñoz Sabater et al., 2021).[8] The ERA5 climate data comes in 0.25°× 0.25°resolution grids from 1940 to present. I extract average district-level nightlight intensity from the Socioeconomic High-resolution Rural-Urban Geographic Platform for India (SHRUG) to proxy for economic activity (Asher et al., 2021). I also collect state legislative election timing data from the Election Commission of India.[9]

3.1.4 Survey Data

Administrative data on rice and wheat procured by government agencies at the district level in not available. I use the National Sample Survey Organization's Situation Assessment Survey (SAS) of agricultural households conducted in 2013 to identify districts with government grain procurement operations. The SAS is a nationally representative large-scale cross-sectional survey that records detailed information on farm households' cultivation and sales activities. The survey records farmers' awareness about government-administered Minimum Support Prices and whether they sold foodgrains to government agencies.[10] It also records the quantities sold to different agencies. I aggregate this information at the district level to estimate the proportion

[8]see https://cds.climate.copernicus.eu.

[9]State legislative assembly elections are roughly held after every five years, though I do observe early elections in some states.

[10]This information is based on the recall period of agricultural year 2012-2013.

of farm households aware of the MSP and the proportion of rice and wheat sold to government agencies.

I also explore whether higher prices are correlated with higher cost of rice and wheat cultivation at the farm level. I extract cost of cultivation data from cost of cultivation surveys conducted by the Ministry of Agriculture, Government of India. These are large scale rotated panel surveys that collect detailed input cost data for all cultivated plots of the sampled farm households. Same farm households are surveyed in a three year block period. The district identifiers for these surveys are only available from 2005 onwards. I am able to identify districts in these surveys starting from 2005 to 2012.

I use the Indian Human Development Surveys (IHDS) dataset to quantify the morbidity costs of procurement-led air pollution (Desai et al., 2008). The IHDS are nationally representative household-level panel surveys that were jointly administered by the National Council of Applied Economic Research (NCAER) India, the University of Maryland, Indiana University, and the University of Michigan. Two rounds of the IHDS are publicly available. The first round was conducted in 2004-05 on more than 40,000 households and covered both urban and rural regions in all states of India. The second round was conducted in 2011-12. The most important aspect of these surveys is that 85% of the same households could be reinterviewed in 2011-12, making it the only large-scale and pan-India household-level panel data. I treat the first IHDS survey as the baseline and the second survey as the endline. The IHDS also provides district identifiers so data on grain procurement can be readily linked.

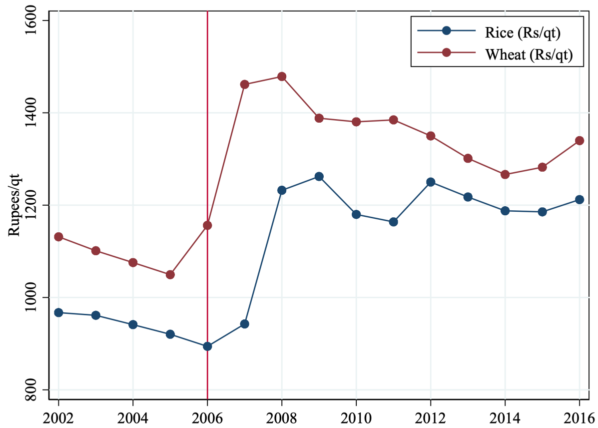
The IHDS collected information on household and individual-level data on a wide variety of indicators ranging from household income, expenditure, assets, employment, and different indicators of human development. These surveys also had a dedicated health module that collected detailed information on the health status and morbidity of individuals in the household. The module also recorded self reported total medical expenditure on treatment.

For gains and mortality-based costs calculations, I use the 61st and 68th rounds of the National Sample Survey Organization's (NSSO) Consumption and Expenditure surveys and total and activity-wise worker population from the 2001 Census of India. I also extract state-level death rates for 2005 from the publications of the Registrar General of India.

3.2 Summary Statistics

Figure 1: Trends in Global and Domestic Food Prices

(a) Global Prices



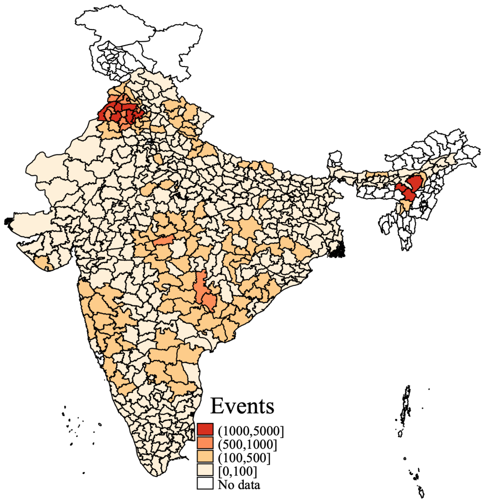
(b) Minimum Support Prices

Note: I consider the price of Thai 5% broken rice and US Hard Red Wheat as global rice and wheat prices. Global rice and wheat price time series is from the World Bank's commodity price database. Global prices are converted to rupees using exchange rate. Minimum Support Prices are the Government administered price floors announced in the beginning of the rice and wheat planting season. Data sourced from the Ministry of Agriculture, Government of India. All prices are in real terms and deflated by the national income deflator.

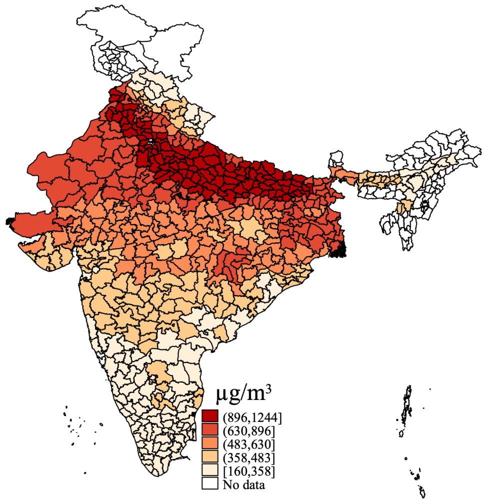
As can be observed from the dramatic movements in global rice prices (Figure 1 Panel (a)), the last two decades have seen much upheaval in global food markets (Negi, 2022). The first surge in global prices was observed during 2007-2008, and the second one around

2011-2012. Figure 1 Panel (b) plots the trends in Minimum Support Prices for rice and wheat in real terms. The MSP for both rice and wheat were on a slight downward trend before 2006 but surged around 2007. While wheat MSP seems to have gone on a downward trajectory after the initial surge in 2007, rice MSP stabilized at the new higher level. As global rice and wheat prices rose around 2007-2008, domestic MSPs were also increased to maintain parity between global and domestic prices (Saini and Gulati, 2016).

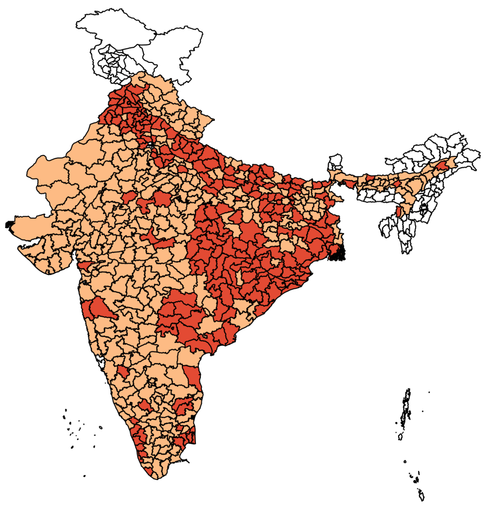
Figure 2: Spatial Distribution of Fires, Air Pollution and Grain Procurement



(a) Annual Fire Events



(b) Annual PM 2.5 Levels



(c) Government Procurement

Note: Averages for total PM 2.5 levels and fire events from 2002 to 2016 (Figures (a) and (b)). Identification of districts with government procurement is based on agricultural year 2012-2013 (Figure (c)).

Figure 2 panels (a) and (b) show the spatial distribution of average annual PM 2.5 levels and fire events for the 15-year period from 2002 to 2016. The highest levels of PM 2.5 are observed in the Northern belt covering the rice and wheat cultivating states of Punjab, Haryana, and Uttar Pradesh. Fire activity seems more concentrated in the North-West and South-East parts of the country. Finally, panel (c) shows districts with government grain procurement operations.

Fire activity seasonally peaks in the winter months of October and November, though it is also higher in the summer months of March, April, and May (Appendix Figure A1a). The increase in winter fire activity is matched by an increase in PM 2.5 levels during these months (Appendix Figure A1b). The important thing to note is that the increase in fire activity and PM 2.5 levels observed during winter months is higher for districts with procurement and overlaps with the rice harvesting season. Weather conditions also support the fire-air pollution link as average wind speeds are the lowest in winter months (Appendix Figure A1c). This, combined with low rainfall in the winter months in Northern India implies that pollutants from fires remain suspended in the atmosphere for longer durations. Based on the observed seasonal patterns and the rice harvest window, I will only focus on total fire events and PM 2.5 levels for the winter months of October, November, and December for the rest of my analysis. Appendix Table A1 presents the summary statistics of key variables by treated and control districts.

4 Empirical Framework

I start by studying the relationship between local supply and prices using the following specification:[11]

$$\begin{aligned}\ln p_{ist} = \delta_1 \mathbf{Drought}_{ist} + \lambda_1 \mathbf{PROC}_i \times \mathbf{Drought}_{ist} \\ + \eta_1 \mathbf{PROC}_i \times \ln \mathbf{MSP}_t + \mathbf{X}_{ist}\beta_1 + \alpha_{1i} + \mu_{1t} + \epsilon_{1ist}\end{aligned} \tag{1}$$

where p_{ist} is the average farm harvest price for district i in state s at year t. **Drought** is

[11] See Appendix B for the Allen and Atkin (2022) framework and the implied relationship between local and central market price.

a dummy variable that indicates years of rainfall shortfall. I code a year as a drought year if the total annual rainfall is below one standard deviation of the district normal. **PROC** is a dummy variable which is one if the government procures rice and wheat from the district. **MSP** is the minimum support price. Vector **X** includes important weather-related control variables like rainfall, temperature, pressure, and wind speed. I also include average district-level nightlight intensity, road length, and number of banks as control variables in vector **X** to control for changes in economic activity and complementary infrastructure.

The coefficient, η_1, captures the differential passthrough elasticity of MSP to local prices. In autarky, local price and supply will have an inverse relationship, implying $\hat{\delta}_1 > 0$. I hypothesize that local prices in procurement districts should have a lower sensitivity to supply shocks and should align with the MSP. This implies that $\hat{\lambda}_1 < 0$ and $\hat{\eta}_1 > 0$.

Consider the following difference-in-differences specification to study the link between support prices, procurement, and the main outcome variables:

$$\ln y_{ist} = \theta_2 \mathbf{PROC}_i \times \mathbf{POST}_t + \mathbf{X}_{ist}\beta_2 + \alpha_{2i} + \mu_{2t} + \epsilon_{2ist} \tag{2}$$

where y_{ist} is the outcome variable for district i, in state s at year t. **PROC** indicates districts with government procurement and **POST** equals one from 2006 onwards to differentiate the higher MSP regime. The coefficient, θ_2, captures the difference in the outcomes for districts with and without government procurement, before and after the increase in MSP. I will estimate Equation (2) on pollution outcomes as well as agricultural variables. Apart from baseline differences in market access and procurement, changes in cropping patterns can also happen due to improvements in banking and road infrastructure. Such improvements could also be correlated with prices. Therefore, controls for improvement in formal banking and roads will be critical when I use Equation (2) to study changes in crop acreage and land use.

With higher procurement prices, farmers from neighboring districts can sell produce in districts with government procurement operations. This implies that higher MSP can also lead to increased fire activity and higher pollution in neighboring control districts. Such spillovers, however, will be bounded by transportation costs. Even in the absence of such spillovers, winds can spread price induced higher pollution levels from treated districts to the neighboring control districts. With spillovers, the estimate of θ_2 will be biased. I use the approach in Butts (2021, 2023) to control for spillovers in a DID specification. The method can semi-parametrically estimate the spillover effects and correct the bias in my estimates (Butts, 2021, 2023). Consider the following variant of Equation (2):

$$\begin{aligned}\ln y_{ist} = {} & \theta_3 \mathbf{PROC}_i \times \mathbf{POST}_t + \sum_{j \in Dist} d_{3j} Ring_{ij} \times \mathbf{POST}_t \\ & + \mathbf{X}_{ist}\beta_3 + \alpha_{3i} + \mu_{3t} + \epsilon_{3ist}\end{aligned} \tag{3}$$

where I include indicators for control districts lying in concentric distance based rings around the treated district interacted with the **POST** dummy. The distance intervals are $Dist = \{(0, 50], (50, 100], (100, 150], (150, 200], (200, 250]\}$ and $Ring_{ij}$ is an indicator for a control district lying within the $d \in Dist$ distance interval away from a treated district. The coefficients d_{3j} capture the average spillover effect on control districts for each distance bin. Butts (2021) shows that under the assumption of spillovers limited to 250 kilometers, Equation (3) gives the unbiased estimate of the treatment effect. If fire activity and pollution in neighboring control districts also positively respond to higher MSP then $\hat{\theta}_2$ will have a downward bias and $\hat{\theta}_3 \geq \hat{\theta}_2$. Spillovers also mean that the errors in Equation (3) would be spatially correlated. I account for such spatial correlation by estimating Conley (1999) standard errors with a distance cutoff of 250 kilometers.

Although farmers cannot directly influence global prices, India being a large producer and exporter of rice, actions of the Indian government can influence global prices (Gouel, 2014; Negi, 2022). Given that a large proportion of procured foodgrain comes from surplus producing regions in the country, farmer lobby in these regions can also influence government decisions regarding agricultural price policy. To test whether my estimates are driven by politically motivated endogenous MSP changes and bonuses, I exploit the state legislative election cycles.

If farmers in Northern India have any power to influence agricultural price policy, then it should be the highest during election years. Consider the following specification to test whether state election cycles influence the relationship between prices, fires and air pollution:

$$\begin{aligned}\ln y_{ist} = {} & \theta_4 \mathbf{PROC}_i \times \mathbf{POST}_t + \omega_4 \mathbf{ELECTION}_{st} \\ & + \phi_4 \mathbf{ELECTION}_{st} \times \mathbf{PROC}_i + \tau_4 \mathbf{ELECTION}_{st} \times \mathbf{POST}_t \\ & + \gamma_4 \mathbf{ELECTION}_{st} \times \mathbf{PROC}_i \times \mathbf{POST}_t \\ & + \mathbf{X}_{ist}\beta_4 + \alpha_{4i} + \mu_{4t} + \epsilon_{4ist}\end{aligned} \tag{4}$$

where **ELECTION** is an indicator variable for years of state legislative elections. The coefficient γ_4 captures the differential effect of higher MSP on districts with government procurement in years of state elections. If the DID estimate in Equation (2) is confounded by an endogenous change in MSP due to electoral cycles and the influence of interest groups in districts with government procurement, then $\hat{\gamma}_4$ should be positive, and $\hat{\theta}_4$ should be lower in magnitude compared to $\hat{\theta}_2$. I cluster standard errors at the district level across all specifications.

5 Results

5.1 Prices Floor, Procurement and Market Integration

Table 1 shows how the policy of grain procurement and assured prices influence the relationship between local prices and supply shocks. In autarky, one would expect local prices and supply shocks to have an inverse relationship. This is what I observe in the first row of Table 1. Local farm prices are higher in periods of droughts. Districts with procurement, however, show a reduced price sensitivity to local supply shocks and a greater alignment with the national minimum support price. In the absence of government interference in the local grain markets, local prices endogenously respond to local supply shocks. Government procurement operations, however, delink local prices from local supply conditions and link them with national minimum

Table 1: Procurement, Farm Harvest Prices and Supply Shocks

	(1) Rice	(2) Wheat	(3) Both
Drought	0.023^{***}	0.033^{***}	0.033^{***}
	(0.009)	(0.008)	(0.007)
PROC × Drought	-0.032^{***}	-0.019^{**}	-0.032^{***}
	(0.011)	(0.009)	(0.009)
PROC × Ln(MSP)	0.075	0.007	0.102^{**}
	(0.063)	(0.039)	(0.040)
Observations	4752	4714	9493
Mean of Dep. Variable	7.00	7.21	7.10

Notes: Dependent variable is the log of district average rice and wheat prices received at the farmgate. PROC is a dummy variable indicating district with government procurement of rice and wheat and MSP is Minimum Support Price. All regressions include district and year fixed effects. Drought is a dummy variable which equals one if district rainfall falls below 1 SD of the long term average rainfall, otherwise zero. Control variables include road length in kilometers, number of bank branches, average nightlight intensity, wind speed, rainfall, temperature and pressure. Prices are in rupees per quintals and deflated by the state GDP deflator. District clustered standard errors in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

support prices. Procurement at a fixed price floor breaks the local equilibrium demand-supply relationship and makes local prices exogenously respond to changes in MSP.

Table 2: Support Price, Procurement and Local Prices

	(1) Rice	(2) Wheat	(3) Paddy/Wheat	(4) Maize	(5) Sugarcane	(6) Cotton
A. Agricultural Market Price						
PROC × POST	0.043^{***}	-0.020^{**}	0.076^{**}	-0.027^{*}	0.009	0.055
	(0.016)	(0.009)	(0.038)	(0.014)	(0.020)	(0.036)
Observations	168198	125455	11487	78156	5679	45154
Mean of Dep. Variable	7.06	7.23	-0.11	6.97	7.97	8.19
B. Farm Harvest Price						
PROC × POST	0.039^{**}	-0.008	0.065^{***}	-0.030^{*}	-0.037	0.023
	(0.017)	(0.010)	(0.025)	(0.016)	(0.028)	(0.026)
Observations	4763	4724	3056	4601	2471	1868
Mean of Dep. Variable	7.00	7.21	-0.22	6.95	7.80	8.24

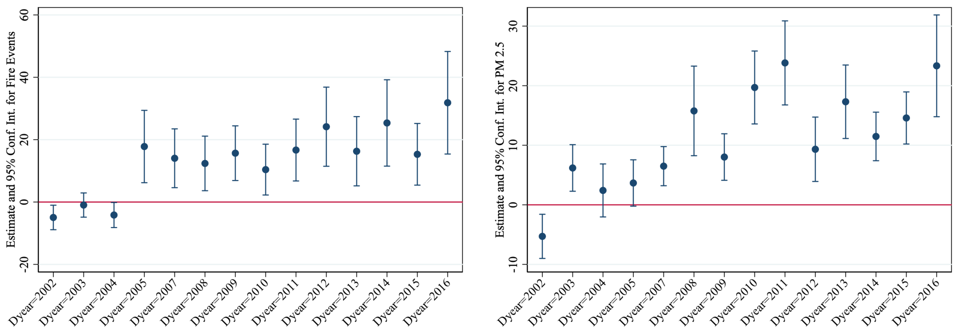
Notes: (A) Dependent variables are logs of monthly prices prevailing in local agricultural markets. (B) Dependent variables are logs of average district level prices received at the farmgate. Both prices are in rupees per quintal and are deflated by the state GDP deflator. All regressions include district and year fixed effects. Regressions with market prices additionally include market fixed effects and dummies for variety and month. PROC is a dummy variable indicating district with government procurement of rice and wheat and POST is a dummy variable which equals one after 2006. Control variables include road length in kilometers, number of bank branches, average nightlight intensity, wind speed, rainfall, temperature and pressure. Standard errors are clustered at the district level. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 2 presents DID estimates with market prices in panel A and farm harvest prices in panel B. I observe that, on average, there was a 4 percent increase in both market price and farm harvest price for rice in districts with procurement after 2006. While the MSP for both rice and wheat increased post-2006, relative to wheat, rice price shows a 6 to 7 percent increase post-2006 (Column (3)). The greater influence of MSP on local rice prices is consistent with the existing evidence on food price transmission in India (Acharya et al., 2012; Morales et al., 2021). These findings are also consistent with the fact that rice procurement is more widespread and happens more intensely than any other grain (Sharma, 2016). Higher rice and wheat MSP do not translate into higher farm prices for maize, sugarcane, and cotton. In the next section, I show that the delinking of local prices from local supply in procurement districts and higher MSPs post-2006 led to a supply response in the form of specialization and greater rice production.

5.2 Procurement, Fires and Air Pollution

I first test for pre-trends in my outcome variables. Figure 3 presents the yearwise estimated coefficients for the treatment dummy using Equation 2. I also test the robustness of my estimates to pretrends using the Rambachan and Roth (2023) approach. Rambachan and Roth (2023) show that the parameter of interest can be partially identified based on certain restrictions on post-treatment differences in trends based on the pre-treatment differences.

Figure 3: Event Plots for Fire Events and Air Pollution



(a) Fire Events **(b) PM 2.5 Levels**

Note: Figure plots the difference in outcome between the treated and control districts over years with 95% confidence intervals. Estimated from regressions with distirct fixed effects, year fixed effects and full set of control variables. Control variables include road length in kilometers, number of bank branches, average nightlight intensity, wind speed, rainfall, temperature and pressure. The base year is 2006. Total fire events and PM 2.5 levels for October, November and December.

Figure A2 shows the robust confidence intervals based on the Rambachan and Roth (2023) method. These confidence intervals are estimated for different values of $\bar{M}$, i.e., the magnitude of pre-treatment differences that continues post-treatment. For example, with $\bar{M} = 1$, I assume the post-treatment parallel trends violation to be no larger than the maximal pre-treatment violation of parallel trends. Likewise, for $\bar{M} = 2$, I assume that the post-treatment violations of parallel trends can be no more than twice as large as the maximal pre-treatment violation. For fires, I find that the confidence intervals do not contain a zero till $\bar{M} = 1.5$. However, the estimate for PM 2.5 seems more sensitive to the violation of parallel trends.

Table 3 presents the estimates from Equation (2) with district total fire events and total PM 2.5 levels for October, November, and December. Starting with specifications without controls, I observe a positive and statistically significant DID coefficient for both fire events and PM 2.5 levels (Columns (1) and (5)).

Table 3: Prices, Procurement, Fires and Air Pollution

	(1) Fires	(2) Fires	(3) Fires	(4) Fires	(5) PM 2.5	(6) PM 2.5	(7) PM 2.5	(8) PM 2.5
PROC × POST	15.17***	17.01***	15.02***	14.64***	14.37***	11.08***	14.53***	11.79***
	(4.02)	(4.62)	(3.99)	(4.07)	(1.77)	(1.70)	(1.76)	(1.61)
SUIT × POST		-3.77**				6.76***		
		(1.84)				(0.74)		
MA × POST			86.16*				-90.25***	
			(47.34)				(34.90)	
Windspeed in $\frac{mtr}{sec}$ (Oct-Dec)				4.88				-31.34***
				(3.98)				(2.31)
Temperature in Kelvin (Oct-Dec)				-1.21**				0.17
				(0.49)				(0.43)
Surface pressure in Pascal (Oct-Dec)				-0.02				-0.14***
				(0.01)				(0.01)
Rainfall in meters (Oct-Dec)				-65.78***				-120.38***
				(19.37)				(17.96)
Nightlight intensity				-1.09**				0.66***
				(0.51)				(0.25)
Road length (Km)				-0.00				-0.00***
				(0.00)				(0.00)
Bank branches (No)				0.00				0.01***
				(0.01)				(0.00)
Observations	8040	8040	8040	7750	8040	8040	8040	7750
Mean of Dep. Variable	35.09	35.09	35.09	35.12	200.20	200.20	200.20	200.05

Notes: All regressions include district and year fixed effects. PROC is a dummy variable indicating district with government procurement of rice and wheat and POST is a dummy variable which equals one after 2006. SUIT is the district level average suitability for rice and wheat cultivation under irrigation, modern technology and high input use. The suitability estimates come from the FAO-GAEZ database and are based on agronomic crop models which predict potential crop yields based on natural conditions. I use suitability measures for irrigated and high modern input use scenario to reflect the suitability post adoption of green revolution technologies in India. MA denotes district level within state market access at the baseline. Standard errors are clustered at the district level. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Government procurement can be correlated with regions suitable for grain cultivation. To see the influence of procurement from agroecologically suitable surplus-producing regions, I introduce an interaction of district-level suitability for rice and wheat cultivation and POST dummy in my baseline specification (Columns (2) and (6)). Likewise, government procurement can also be correlated with access to agricultural markets within the state.[12] To see the influence of differences in market access, I introduce an interaction of district-level agricultural market access and POST dummy in my baseline specification (Columns (3) and (7)).[13]. The DID estimates are robust to differential trends based on market access and suitability for cereal cultivation.

My estimates are also robust to the inclusion of weather controls, economic growth, and infrastructure improvements (Columns (4) and (8)). In terms of magnitude, I observe that districts with procurement witnessed a 43% (15 additional fires) increase in fire events and a 6% increase in PM 2.5 levels (12 $\frac{\mu g}{m^2}$) post-2006.[14]

5.3 Spillovers

Table 4 presents the DID estimates with controls for spillover effects. I present specifications with and without weather controls. For fire events, I do not find evidence of spillovers as the coefficients on the indicators for concentric distance-based rings interacted with the POST dummy are small in magnitude and statistically insignificant. This rules out the possibility of farmers in the neighboring control districts responding to higher MSP by greater burning. For PM 2.5, I do find evidence of spillovers as the control districts lying in the 0 to 50 kilometer radius

[12]Due to various government regulations on grain movement and trade across states, majority of the grain produced is sold within the state (Ganesh-Kumar et al., 2007).

[13]Following Donaldson and Hornbeck (2016), I construct a theoretically consistent measure of within state agricultural market access. Trade costs within a state will depend upon the cost of transporting grains from the farm to the market. To capture such trade friction within a state, I construct market access as $\mathrm{MA}_{is0} = \sum_{j \in J} \frac{1}{d_{ij0}}$, where d_{ij0} denotes the linear distance between a location (district) i's centroid and the geographic location of all regulated agricultural markets $j \in J$ within the state at the baseline. The market location data corresponds to the year 2004. A larger number of well-dispersed agricultural markets will reduce transportation costs and increase the spatial competition between traders, leading to greater alignment between local and terminal market prices (Allen and Atkin, 2022; Donaldson and Hornbeck, 2016).

[14]These estimates are based on overall average fire events and PM 2.5 levels. With treatment group means, the estimates are a 25% increase in fire events and a 5% increase in PM 2.5 levels.

Table 4: Prices, Procurement and Spillovers

	(1) Fires	(2) Fires	(3) PM 2.5	(4) PM 2.5
PROC × POST	15.73**	15.05**	22.16***	17.93***
	(7.18)	(7.56)	(4.52)	(4.09)
Ring (0-50 Km) × POST	-2.20	-2.87	25.07***	19.81***
	(2.34)	(3.81)	(5.63)	(5.02)
Ring (50-100 Km) × POST	2.04	2.09	6.85*	4.48
	(2.51)	(3.41)	(4.04)	(3.92)
Ring (100-150 Km) × POST	0.31	-0.03	1.32	1.48
	(1.99)	(3.06)	(3.93)	(3.92)
Ring (150-200 Km) × POST	1.28	1.85	-0.79	1.45
	(1.88)	(2.43)	(3.23)	(3.33)
Ring (200-250 Km) × POST	0.17	0.11	0.30	0.38
	(1.16)	(1.70)	(2.79)	(2.96)
Controls	No	Yes	No	Yes
Observations	8040	7752	8040	7752
Mean of Dep. Variable	35.09	35.09	200.20	200.20

Notes: All regressions include district and year fixed effects. PROC is a dummy variable indicating district with government procurement of rice and wheat and POST is a dummy variable which equals one after 2006. Control variables include road length in kilometers, number of bank branches, average nightlight intensity, wind speed, rainfall, temperature and pressure. Conley standard errors with a correlation cutoff of 250 kilometers following Conley (1999). ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

of the treated district also show higher PM 2.5 levels post-2006. Both the DID estimate and the spillover effect go down in magnitude when I include weather controls but remain relatively large and statistically significant (Columns (3) and (4)). These results imply that though fire activity in neighboring districts does not respond to higher MSP, pollution levels do, possibly because winds spread higher particulate matter from the treated districts to the neighboring control districts. Controlling for such spillovers in PM 2.5 levels, however, increases the effect size as the DID estimate in specification (4) is higher in magnitude than the comparable specification (8) in Table 3.

5.4 Election Cycles

In this section, I explore whether my results can be explained by electoral cycles. Specifications (1) and (3) of Table 5 present the DID estimates including interactions with state election cycles. In Specifications (2) and (4), I additionally include interactions with an indicator for the timing of national elections.[15] State elections by themselves seem to be uncorrelated with fire

[15]National elections were held three times between 2002 and 2016. The years of national general elections are 2004, 2009, and 2014.

Table 5: **Prices, Procurement and Election Cycles**

	(1) Fires	(2) Fire	(3) PM 2.5	(4) PM 2.5
PROC × POST	12.81***	7.89**	12.27***	12.85***
	(4.03)	(3.59)	(1.61)	(1.66)
ELECTION	0.78	0.14	-6.75***	-9.88***
	(0.72)	(0.94)	(1.22)	(1.92)
PROC × ELECTION	-6.02*	-12.09**	2.15	1.43
	(3.14)	(4.96)	(1.88)	(2.68)
POST × ELECTION	-0.95	-0.79	1.47	2.48
	(1.16)	(1.57)	(1.31)	(1.90)
PROC × POST × ELECTION	8.85*	18.13**	-4.03**	-3.70
	(4.80)	(7.46)	(1.95)	(2.69)
PROC × NELECTION		-13.57***		-0.75
		(5.10)		(1.53)
PROC × POST × NELECTION		21.58***		-4.25
		(6.87)		(2.64)
ELECTION × NELECTION		0.95		10.51***
		(2.52)		(2.89)
PROC × ELECTION × NELECTION		28.84***		8.01**
		(9.91)		(4.01)
POST × ELECTION × NELECTION		1.95		-1.02
		(2.83)		(3.28)
PROC × POST × ELECTION × NELECTION		-44.48***		-5.35
		(14.27)		(4.60)
Observations	7750	7750	7750	7750
Mean of Dep. Variable	35.12	35.12	200.05	200.05

Notes: All regressions include district and year fixed effects. PROC is a dummy variable indicating district with government procurement of rice and wheat and POST is a dummy variable which equals one after 2006. ELECTION is an indicator for timing of state legislative elections. NELECTION is an indicator for years of national general elections. Control variables include road length in kilometers, number of bank branches, average nightlight intensity, wind speed, rainfall, temperature and pressure. Standard errors are clustered at the district level. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

events and are negatively correlated with air pollution levels. I do find evidence of higher fire activity in treated districts post-2006 in years of state as well as national elections (coefficient estimates on PROC×POST×ELECTION and PROC×POST×NELECTION). However, the DID estimates for fire events and PM 2.5 levels remain positive and statistically significant across these specifications.

While election cycles can influence the link between prices and agricultural fires, the local ruling party's affiliations with the central government can influence national budget allocations and transfers to politically important and favorable states. I also estimate variants of Equation (4) including interactions with the timing of national elections and an indicator for the same ruling party at the national and state levels.[16] Findings from these regression are qualitatively similar to what I observe in Table 5.

[16]These estimates are not reported but are available with the author.

6 Mechanisms

6.1 Specialization

To understand the possible mechanisms behind the results in the previous sections, I first examine the correlation between agricultural fires and area under and production of different crops. Appendix Table A2 shows that fires positively correlate with only rice area and production (Columns 1 and 8). These estimates are consistent with the evidence that agricultural fires in the winter months are primarily due to the burning of rice crop residue.

Table 6: Support Prices, Procurement and Specialization

	(1) Rice	(2) Wheat	(3) Coarse cereals	(4) Pulses	(5) Oilseeds	(6) Sugarcane	(7) Cotton	(8) DIV
A. Area								
PROC × POST	0.13***	-0.00	-0.02	0.00	0.00	-0.09***	-0.07**	
	(0.03)	(0.02)	(0.03)	(0.04)	(0.04)	(0.03)	(0.04) 7	
Observations	7731	7669	7738	7732	6550	7605	6944	
Mean of Dep. Variable	3.46	2.76	2.66	2.77	2.93	1.05	1.09	
B. Production								
PROC × POST	0.20***	0.06**	-0.02	0.01	0.08*	-0.10**	-0.13***	
	(0.04)	(0.03)	(0.05)	(0.04)	(0.05)	(0.05)	(0.03)	
Observations	7731	7638	7738	7734	6257	7608	6945	
Mean of Dep. Variable	3.99	3.31	3.01	2.43	2.78	1.89	0.76	
C. Proportion of cropped area								
PROC × POST	0.008	0.003	0.006	0.000	0.005*	-0.003*	-0.009***	-0.013**
	(0.005)	(0.004)	(0.005)	(0.006)	(0.003)	(0.002)	(0.003)	(0.005)
Observations	7794	7794	7794	7794	7794	7794	7794	7794
Mean of Dep. Variable	0.36	0.20	0.16	0.15	0.06	0.03	0.04	0.58

Notes: Dependent variables in panel A and B are in logs. Area under crops is in 1000 hectares and production is in 1000 tonnes. Dependent variable in the last column is the crop diversification index based on proportion of area under different crops. All regressions include district and year fixed effects. PROC is a dummy variable indicating district with government procurement of rice and wheat and POST is a dummy variable which equals one after 2006. Control variables include road length in kilometers, number of bank branches, average nightlight intensity, wind speed, rainfall, temperature and pressure. Standard errors are clustered at the district level. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 6 presents the estimates of Equation (2) with crop-wise area and production as the dependent variables. I observe an increase in the area under rice in districts with procurement post-2006 (Panel A). I also observe an increase in rice and wheat production in procurement districts post-2006, though the magnitude of increase in rice production is more than three times that of wheat (Panel B). This increase in rice area and production has happened at the cost of cash crops like sugarcane and cotton.

To see whether higher support prices lead to specialization, I also present estimates of Equation (2) with the proportion of total cropped area under different crops in Table 6 Panel

C. I observe that districts with procurement showed lower acreage allocation to sugarcane and cotton post-2006 (Columns 6 and 7). Finally, the last column of Table 6 shows that a higher MSP led to lower crop diversification in districts with grain procurement.[17] Note that such specialization can happen on account of both remunerative prices in procurement districts or because a fixed price floor reduces exposure to market price risk.

6.2 Inputs and Cost of Cultivation

I next explore whether specialization induced land use changes and intensification (Appendix Table A3). I do not find evidence of higher MSP leading to changes in land use, fertilizer use, and greater area under irrigation. I also test and find no evidence of higher MSPs leading to higher agricultural wages.

While the previous estimates were based on district-level aggregates, the picture could be different at the farm level. I also investigate whether procurement and higher MSPs led to higher input usage and higher cost of cultivation for rice and wheat at the plot level using unit-level cost of cultivation data (Appendix Table A4). I do find evidence of higher machine use in rice cultivation in procurement districts post-2006 (Column 2). I also find evidence of higher labor, machine and total cost in wheat cultivation in procurement districts post-2006. Column 4 of Appendix Table A4 however shows no differential change in the total per-hectare cost of rice cultivation in procurement and no-procurement districts.

7 Health Implications

While previous sections link pollution with changes in price floor and the procurement policy, what could be the resultant health implicaitons of this policy? In this section I focus on quantifying the morbidity costs of residue burning and air pollution. I also highilight the

[17] The dependent variable in the last column is a Simpson Diversity Index (SDI) for crop shares where higher values of the index imply greater diversification.

tradeoff in terms of gains to producers but losses due to additional mortality.

7.1 Morbidity and Medical Expenditures

I first quantify the likelihood of associated morbidity and medical expenditure using individual-level data from the IHDS. Table 7 presents the estimates for different illnesses and the total out-of-pocket medical expenditures. In general, I observe a 2 percentage point higher likelihood of illness in procurement districts after the price increase. This is primarily attributable to respiratory diseases like asthma and tuberculosis, heart diseases, and other illnesses. While the coefficient estimates may look small, they are economically significant. For example, for overall illness, the coefficient estimate is 21 percent of the mean; for respiratory diseases, it's 36 percent of the average incidence of such diseases in the sample; and for heart diseases, it's larger. The out-of-pocket medical expenditure on treating these illnesses is also higher by INR 122 per person (around USD 3 per person). This turns out to be a 19 percent increase in the average per-person out-of-pocket medical expenditure.

Table 7: Prices, Procurement, and Morbidity

	(1) Illness	(2) Eye	(3) Respiratory	(4) Heart	(5) Diabetes	(6) Viral	(7) Cancer	(8) Brain	(9) Other	(10) Expense
PROC × POST	0.018***	0.000	0.004***	0.003***	0.003*	-0.000	0.000	0.000	0.009**	121.944**
	(0.006)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.000)	(0.001)	(0.004)	(56.601)
Observations	370894	370891	370894	370891	370891	370894	370891	370894	370891	370894
Mean of Dep. Variable	0.084	0.009	0.011	0.006	0.012	0.002	0.001	0.007	0.031	656.020

Notes: Dependent variables in specifications (1) to (8) are dummies for an individual suffering from the mentioned diseases. The dependent variable in specification (9) is the total medical expenditure incurred to treat the illness. Medical expenditure is in real terms and is deflated by state-specific consumer price index. All regressions include household and year-fixed effects. PROC is a dummy variable indicating a district with government procurement of rice and wheat, and POST is a dummy variable that equals one after 2006. Individual and household controls include age, gender, literacy, and household size. District control variables include road length in kilometers, number of bank branches, average nightlight intensity, wind speed, rainfall, temperature, and pressure. Standard errors are clustered at the district level. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Based on estimates from Table 7, the total out-of-pocket medical expenditure associated with the increase in MSP and procurement-driven air pollution comes out to be USD 29 million. This estimate increases to USD 63 million if I limit the sample to persons aged 30 years and above.[18]

[18] These estimates may also capture additional illnesses and associated health costs due to increased agrochemical and pesticide use after the price increase.

7.2 Gains and Mortality Costs

It would be wrong to assume that farmers didn't gain from high prices. In this section, I focus on calculating the income gains and costs of pollution-based mortality for districts with grain procurement. While doing these simple back-of-the-envelop calculations, I only focus on the gains and costs due to the price surge between 2005 and 2012.[19] I do these calculations at the district level to capture the heterogeneity and the distributional aspects of resultant gains or losses.

To quantify the gains, I use district-level average consumption expenditure estimates from the 61th (2004-2005) round of the NSS Consumption and Expenditure Surveys (CES).[20] I borrow elasticity estimates from a study which estimates the domestic income/consumption elasticity of global food prices.[21] Negi (2022) shows that the global food price surge between 2005 and 2012 led to income gains for net foodgrain producers which varied based on the acreage allocated to rice and wheat cultivation. It also shows that net consumers incurred no welfare losses due to the availability of subsidized foodgrains from the Public Distribution System (PDS) of India. These estimates, therefore, also account for the consumption insurance from redistribution of procured foodgrains to the poor through the PDS (Gadenne et al., 2021).

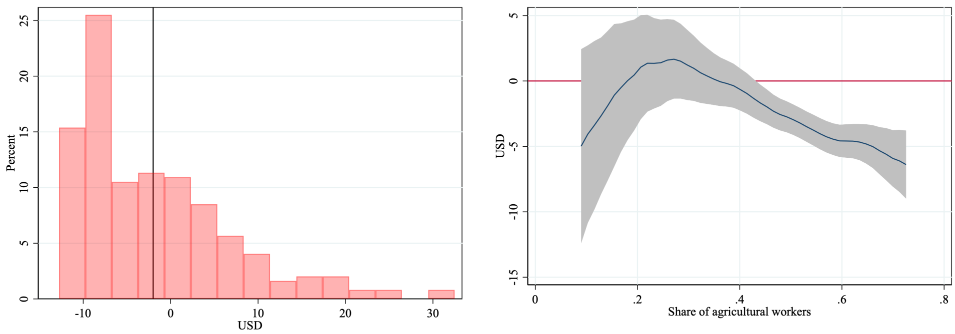
[19]The second-order effects of fixed-price floors are complex. On the one hand, assured prices will have welfare gains due to reduced market price risk; there can also be a welfare loss due to delinking of local prices with local supply conditions and the reduction in implicit insurance provided by the inverse price-productivity relationship Allen and Atkin (2022); Newbery and Stiglitz (1984). These second-order welfare effects are beyond the scope of the simple back-of-the-envelope calculations done here. Likewise, the comprehensive assessment of health costs associated with long-term exposure is also complicated. Illness due to long-term exposure can reduce labor productivity and income (Azomahou et al., 2016).

[20]I calculate gains based on per capita consumption expenditure for two reasons. One, the elasticity estimates are based on consumption expenditure, and two, district-level income estimates are not available for the time period.

[21]These estimates are based on a reduced form empirical specification which exploits the surge in global food prices and variation based on the degree of specialization in foodgrain cultivation to estimate elasticities. The advantage is that the estimation procedure does not impose any structure on the relationship between price change and household welfare.

To quantify pollution-based losses, I focus on the associated costs of additional mortality due to PM 2.5 exposure.[22] I only focus on the increase in average monthly PM 2.5 levels during the three months of October, November, and December. I use my DID estimates and the Relative Risk (RR) of death from PM 2.5 exposure from de Bont et al. (2024) to estimate the district-level additional deaths in procurement districts due to higher prices post-2006. I use the Value of Statistical Life (VSL) estimates for India from Viscusi and Masterman (2017) to quantify the monetary cost of excess mortality due to higher PM 2.5 levels. The exact procedure for these calculations is detailed in Appendix C.

Figure 4: Distribution of Per Capita Net Gains



(a) Distribution of Net Gains **(b) Net Gains and Farm Workers**

Note: Figure (a) plots the distribution of per capita net gains for procurement districts. Vertical line indicates the mean. Figure (b) plots the non-parametrically estimated relationship between net gains per capita and proportion of agricultural workers in the district. Agricultural workers include both land-owning cultivators and landless laborers.

In districts with government procurement, my estimates suggest an overall income gain of USD 4.5 billion due to higher prices and a mortality cost of USD 5.6 billion due to resultant pollution.[23] On average, districts with government procurement experienced a net loss of around USD 1 billion. In per capita terms, the net loss turns out to be USD 2 per person per year. These are aggregate estimates and hide the distributional aspect of these losses. Figure 4a,

[22]These estimates are most likely an underestimate of the actual health costs as I do not consider other toxic compounds like nitrogen oxides, ammonia, and sulfur dioxide, which are also released from biomass burning.

[23]Lan et al. (2022) estimate India's annual monetized mortality cost of crop residue burning to be 23 billion USD. They also find that the Northern states of Punjab, Haryana, and Uttar Pradesh, which are also the states where the government procures grains from the market, contribute 67–90% to the overall mortality. Evidence also shows that the monetary gains from rice cultivation are substancially less than the mortality cost of air pollution (Jack et al., 2023).

which presents the distribution of net gains per capita, shows that some districts also experienced net losses. Positive net gains were primarily experienced in the surplus grain-producing states of Punjab and Haryana but at the cost of rest of the region. Finally, Figure 4b shows a negative association between proportion of farm workers and net gains implying that regions with greater employment in agriculture also experienced net losses.[24]

8 Robustness Tests

I briefly discuss an issue related to how I define the treatment districts. I identify districts with government procurement operations based on the sample of farmers reporting selling grains to government agencies rather than actual administrative data. Although NSS surveys are large-scale and representative of administrative regions, there is a possibility of under or no reporting of sales to the government. This could either be because farmers do not want to report that they benefit from the policy or because they do not directly sell but rely on intermediaries to sell to government agencies. The implication is that some treated districts can be in the control group. This should lead to an underestimation of the true effect. If this problem is substantial enough then it should also be reflected in the spillover effects regressions. However, as observed in Table 4, I find no evidence of neighboring control districts showing higher fire activity post-2006, alleviating such concerns.

Evidence suggests that the Preservation of Subsoil Water Act passed in 2009 increased agricultural fires in the northern states of Punjab and Haryana (Agarwala et al., 2022; Kant et al., 2022). Districts of Punjab and Haryana are also part of my treatment group; hence, these policy changes can also partially contribute to the DID estimates. Appendix Table A5 presents estimates while limiting the sample till 2009 (Columns (1) and (2)) and excluding the two states (Columns (3) and (4)) to check whether policy changes in Punjab and Haryana drive the results. By excluding these surplus foodgrain producing states, I can also test whether my results are driven by endogenous price changes influenced by farmer lobby in these states. I still

[24]Farm workers include both land-owning cultivators and landless laborers.

find a positive effect of the MSP increase on procurement districts. However, these estimates seem smaller in magnitude. To see whether these estimates are statistically indistinguishable from the benchmark estimates in Table 3, I conduct tests of the equality of coefficients across specifications. Based on these tests, I am not able to reject the null that the DID estimate for fire events in specification (4) of Table 3 is statistically different from the one with sample limited to year 2009. Likewise, I am not able to reject the null of equality of DID coefficients in specifications (1) and (3) in Appendix Table A5.

I also test whether my estimates are driven by large-scale rural road construction under the PMGSY. To investigate whether new roads are driving my results, I add the district-level population covered under new roads as a control variable in my regressions. Likewise, my estimates could also be confounded by the launch of MGNREGA. I include a dummy variable indicating the district-wise rollout of MGNREGA as a control variable. Appendix Table A6 shows that the DID estimates are robust to inclusion of PMGSY road expansion and MGNREGA rollout.

Another critical policy change during the period was the change in Reserve Bank of India's (RBI) bank branch licensing policy. The RBI allowed banks to propose annual bank branch expansion plans in line with each respective bank's medium-term goals and strategy. Commercial banks were incentivized to establish new bank branches in inadequately served regions. This policy led to a significant bank-branch expansion in rural areas. While availability of banks and formal credit can also confound my estimates, I do not find evidence of that being the case (Appendix Table A6).

Historically, federal government agencies have procured grains in India, but recently, some states have also switched to the Decentralized Procurement Scheme (DCP). Under the DCP, state governments take responsibility for procuring food grains locally. The DCP was introduced to improve efficiency in grain procurement operations, reduce transaction costs, encourage procurement in other states, and extend the outreach of the MSP. The staggered adoption of the DCP scheme can confound by estimates as the effects I capture can be driven by the adoption of the scheme. To test for the influence of the DCP scheme on my estimates, I include an indicator for DCP adoption as an additional control in my regression specifications. Appendix Table A6 shows that my estimates are robust to the inclusion of DCP adoption across states.

The main analysis completely ignores the distribution side of the grain procurement policy. The procured foodgrain is distributed to food deficit districts under the Public Distribution System of India. This grain is distributed to the poor at highly subsidized prices. To test how distribution influences my main results, I introduce an additional interaction of rice and wheat distributed under the PDS as a proportion of total production and the post dummy. Appendix Table A7 shows that the main results are robust to including differential trends based on grain distribution via the PDS. While the PDS is the flip side of the grain procurement policy, it does not change the main narrative of this study.

Finally, I also present estimates from alternative specifications with the interaction of continuous procurement proportion and the log of MSP (Appendix Table A8). I also present estimates from specifications where I replace the proportion of rice and wheat sold to government agencies with the proportion of farmers aware of the MSP.[25] Estimates from these specifications are consistent with my main results.

9 Conclusion

In this paper, I uncover a robust relationship between support prices and air pollution in India. I establish that this link comes about due to higher support prices leading to increased agricultural fire activity in districts with grain procurement. I observe that market distortion in the form of a price floor supported by government procurement of surplus rice and wheat delinks local prices from local supply shocks and links them with MSP movements. Though the MSP does achieve the objectives of stabilizing local market prices and reducing market price risk, that

[25] Awarness about MSP and sales to government agencies have a positive and statistically significant correlation coefficient of 0.64.

comes at the cost of more agricultural fires and air pollution. Even with the MSP, profitability in rice cultivation remains low (Liu et al., 2021). To maximize returns from farming, farmers in the cereal belt of India follow the rice-wheat cropping system where wheat is supposed to be sown right after rice harvest. Given that rice-wheat farmers in Northern India mainly depend on government agencies as the primary buyers of their output, farmers find residue burning to be the most cost-effective way of land preparation (Liu et al., 2021).

The finding that the price-fire-air pollution link is driven by districts where the government is the largest buyer of foodgrains is telling of the agricultural policy supported cultivation system practiced in India. Given the distorted nature of Indian agricultural markets, where the government procures surplus production at fixed price floors, upward movements in rice prices are matched with greater rice procurement. While the government procured rice is distributed to the poor as in-kind transfers through the Public Distribution System of India, this foodgrain has also found its way into the export markets in recent decades to the extent that India has now risen as the largest exporter of rice globally. This is ironic given that farmers in Northern India produce this rice with a slew of input subsidies and with immense environmental costs to the region. These findings hint towards the cost of policies supporting agriculture without factoring in the social costs of such decisions.

The policy response to residue burning has mostly been in the form of bans and fines on such activities. Such policies, however, are poorly implemented and have been ineffective in curbing crop residue burning (Sekhri et al., 2023). An immediate short-run solution may probably lie in introducing new planting technologies that do not require residue burning or in creating markets for byproducts and crop residue. Evidence also suggests some success in financially incentivizing farmers not to burn crop residue (Jack et al., 2022). The idea is that cash incentives increase the private costs of burning yet are less distortionary and do not make farmers worse off compared to bans and fines (Jack et al., 2022). Longer-run solutions would probably demand a rethinking of current agricultural policies.

References

Abman, R., Edwards, E. C., and Hernandez-Cortes, D. (2023). Water, dust, and environmental justice: The case of agricultural water diversions. *American Journal of Agricultural Economics*.

Acharya, S., Chand, R., Birthal, P., Kumar, S., and Negi, D. S. (2012). Market integration and price transmission in india: A case of rice and wheat with special reference to the world food crisis of 2007/08. *Rome: Food and Agriculture Organization*, pages 447–456.

Adamopoulos, T. (2011). Transportation costs, agricultural productivity, and cross-country income differences. *International Economic Review*, 52(2):489–521.

Agarwala, M., Bhattacharjee, S., and Dasgupta, A. (2022). Unintended consequences of indian groundwater preservation law on crop residue burning. *Economics Letters*, 214:110446.

Allen, T. and Atkin, D. (2022). Volatility and the gains from trade. *Econometrica*, 90(5):2053–2092.

Anderson, K., Rausser, G., and Swinnen, J. (2013). Political economy of public policies: insights from distortions to agricultural and food markets. *Journal of Economic Literature*, 51(2):423–477.

Antras, P. and Costinot, A. (2011). Intermediated trade. *The Quarterly Journal of Economics*, 126(3):1319–1374.

Asher, S., Lunt, T., Matsuura, R., and Novosad, P. (2021). Development research at high geographic resolution: an analysis of night-lights, firms, and poverty in India using the shrug open data platform. *The World Bank Economic Review*, 35(4).

Asher, S. and Novosad, P. (2020). Rural roads and local economic development. *American Economic Review*, 110(3):797–823.

Assunção, J., Gandour, C., and Rocha, R. (2015). Deforestation slowdown in the Brazilian Amazon: Prices or policies? *Environment and Development Economics*, 20(6):697–722.

Atkin, D. and Khandelwal, A. K. (2020). How distortions alter the impacts of international trade in developing countries. *Annual Review of Economics*, 12:213–238.

Azomahou, T. T., Boucekkine, R., and Diene, B. (2016). Hiv/aids and development: a reappraisal of the productivity and factor accumulation effects. *American Economic Review*, 106(5):472–477.

Badiani-Magnusson, R. and Jessoe, K. (2018). Electricity prices, groundwater, and agriculture: the environmental and agricultural impacts of electricity subsidies in india. In *Agricultural Productivity and Producer Behavior*, pages 157–183. University of Chicago Press.

Balboni, C., Berman, A., Burgess, R., and Olken, B. A. (2023). The economics of tropical deforestation. *Annual Review of Economics*, 15:723–754.

Barrett, C. B. (1999). Stochastic food prices and slash-and-burn agriculture. *Environment and Development Economics*, 4(2):161–176.

Basu, K. (2011). India's foodgrains policy: An economic theory perspective. *Economic and Political Weekly*, pages 37–45.

Behrer, A. P. (2023). Man or machine? environmental consequences of wage driven mechanization in indian agriculture. *World Bank Policy Research Working Paper 10376*.

Berman, N., Couttenier, M., Leblois, A., and Soubeyran, R. (2023). Crop prices and deforestation in the tropics. *Journal of Environmental Economics and Management*, 119:102819.

Birthal, P. S., Joshi, P. K., Negi, D. S., and Agarwal, S. (2014). *Changing sources of growth in Indian agriculture: Implications for regional priorities for accelerating agricultural growth*, volume 1325. Intl Food Policy Res Inst.

Brainerd, E. and Menon, N. (2014). Seasonal effects of water quality: The hidden costs of the green revolution to infant and child health in India. *Journal of Development Economics*, 107:49–64.

Butts, K. (2021). Difference-in-differences estimation with spatial spillovers. *arXiv preprint arXiv:2105.03737*.

Butts, K. (2023). Jue insight: Difference-in-differences with geocoded microdata. *Journal of Urban Economics*, 133:103493.

Carreira, I., Costa, F., and Pessoa, J. P. (2024). The deforestation effects of trade and agricultural productivity in brazil. *Journal of Development Economics*, 167:103217.

Carrillo, B., Branco, D. K., Trujillo, J. C., and Lima, J. E. (2019). The externalities of a deforestation control policy in infant health: Evidence from Brazil. *Economic Development and Cultural Change*, 67(2):369–400.

CEDA (2023). Centre for Economic Data and Analysis (CEDA). https://ceda.ashoka.edu.in/data-portal-landing-page/.

Chand, R. (2005). Whither India's food policy? From food security to food deprivation. *Economic and Political Weekly*, pages 1055–1062.

Chatterjee, S. and Kapur, D. (2017). Six puzzles in Indian agriculture. In *India Policy Forum*, volume 13, pages 185–229. National Council of Applied Economic Research.

Cisneros, E., Kis-Katos, K., and Nuryartono, N. (2021). Palm oil and the politics of deforestation in indonesia. *Journal of Environmental Economics and Management*, 108:102453.

Conley, T. G. (1999). Gmm estimation with cross sectional dependence. *Journal of Econometrics*, 92(1):1–45.

Cusworth, D. H., Mickley, L. J., Sulprizio, M. P., Liu, T., Marlier, M. E., DeFries, R. S., Guttikunda, S. K., and Gupta, P. (2018). Quantifying the influence of agricultural fires in northwest India on urban air pollution in Delhi, India. *Environmental Research Letters*, 13(4):044018.

Da Mata, D. and Dotta, M. (2021). Commodity booms and the environment. *Available at SSRN 3900793*.

de Bont, J., Krishna, B., Stafoggia, M., Banerjee, T., Dholakia, H., Garg, A., Ingole, V., Jaganathan, S., Kloog, I., Lane, K., et al. (2024). Ambient air pollution and daily mortality in ten cities of india: a causal modelling study. *The Lancet Planetary Health*, 8(7):e433–e440.

De Gorter, H. and Swinnen, J. (1995). The political economy and institutional determinants of public policy in agriculture.

Desai, S., Dubey, A., Joshi, B., Sen, M., Shariff, A., and Vanneman, R. (2008). India human development survey. *College Park, Maryland: University of Maryland*.

Donaldson, D. (2015). The gains from market integration. *Annual Review of Economics*, 7(1):619–647.

Donaldson, D. and Hornbeck, R. (2016). Railroads and american economic growth: A "market access" approach. *The Quarterly Journal of Economics*, 131(2):799–858.

Gadenne, L., Norris, S., Singhal, M., and Sukhtankar, S. (2021). In-kind transfers as insurance. Technical report, National Bureau of Economic Research.

Ganesh-Kumar, A., Gulati, A., and Cummings, J. R. (2007). Foodgrains policy and management in india.

Ganga, S., Neelmani, G., Pullabhotla, H., Ganesh-Kumar, A., Ashok, G., et al. (2012). A review of input and output policies for cereals production in india. *IFPRI-Discussion Papers*, (1159).

Ganguly, K. and Gulati, A. (2013). The political economy of food price policy in India. *Food Price Policy in an Era of Market Instability*, page 339.

Garg, T., Jagnani, M., and Pullabhotla, H. (2023). Rural roads, farm labor exits, and crop fires. *American Economic Journal: Economic Policy*.

Gatto, M., Wollni, M., Asnawi, R., and Qaim, M. (2017). Oil palm boom, contract farming, and rural economic development: Village-level evidence from indonesia. *World Development*, 95:127–140.

Gerrard, C. D. and Roe, T. (1983). Government intervention in food grain markets: An econometric study of tanzania. *Journal of Development Economics*, 13(1-2):109–132.

Giglio, L., Schroeder, W., Hall, J. V., and Justice, C. O. (2015). Modis collection 6 active fire product user's guide revision a. *Department of Geographical Sciences. University of Maryland*, 9.

Giordani, P. E., Rocha, N., and Ruta, M. (2016). Food prices and the multiplier effect of trade policy. *Journal of International Economics*, 101:102–122.

Glauber, J., Hernández, M., Laborde, D., Martin, W., Rice, B., and Vos, R. (2022). No end in sight yet for the global food price crisis. *International Food Policy Research Institute*, 27.

Glauber, J. W. and Laborde, D. (2022). How Russia's invasion of Ukraine is affecting global agricultural markets.

Gouel, C. (2014). Food price volatility and domestic stabilization policies in developing countries. In *The Economics of Food Price Volatility*, pages 261–306. University of Chicago Press.

Greenstone, M. and Fan, Q. C. (2019). India's 'war against pollution': An opportunity for longer lives.

Gulati, A. and Dutta, M. (2010). Rice policies in India in the context of the global rice price spike. In *The Rice Crisis: Markets, Policies and Food Security*, pages 273–95. Earthscan and FAO London.

Harding, T., Herzberg, J., and Kuralbayeva, K. (2021). Commodity prices and robust environmental regulation: Evidence from deforestation in brazil. *Journal of Environmental Economics and Management*, 108:102452.

Hargrave, J. and Kis-Katos, K. (2013). Economic causes of deforestation in the brazilian amazon: a panel data analysis for the 2000s. *Environmental and Resource Economics*, 54:471–494.

ICRISAT-TCI (2023). The district level database for Indian agriculture. http://data.icrisat.org/dld/src/about-dld.html.

Jack, B. K., Jayachandran, S., Kala, N., and Pande, R. (2022). Money (not) to burn: payments for ecosystem services to reduce crop residue burning. Technical report, National Bureau of Economic Research.

Jack, B. K., Jayachandran, S., Kala, N., and Pande, R. (2023). Reducing air pollution: Evidence from payments to reduce crop burning in india.

Jayachandran, S. (2009). Air quality and early-life mortality: Evidence from indonesia's wildfires. *Journal of Human Resources*, 44(4):916–954.

Jethva, H., Torres, O., Field, R. D., Lyapustin, A., Gautam, R., and Kayetha, V. (2019). Connecting crop productivity, residue fires, and air quality over northern India. *Scientific Reports*, 9(1):16594.

Kalkuhl, M., Von Braun, J., and Torero, M. (2016). *Food price volatility and its implications for food security and policy*. Springer Nature.

Kant, Y., Chauhan, P., Natwariya, A., Kannaujiya, S., and Mitra, D. (2022). Long term influence of groundwater preservation policy on stubble burning and air pollution over north-west india. *Scientific Reports*, 12(1):2090.

Krishnamurthy, M. (2012). States of wheat: the changing dynamics of public procurement in madhya pradesh. *Economic and Political Weekly*, pages 72–83.

Krishnaswamy, N. (2018). At what price? price supports, agricultural productivity, and misallocation. Technical report, Working paper.

Laborde, D., Mamun, A., Martin, W., Piñeiro, V., and Vos, R. (2021). Agricultural subsidies and global greenhouse gas emissions. *Nature Communications*, 12(1):2601.

Lai, W. (2017). Pesticide use and health outcomes: Evidence from agricultural water pollution in china. *Journal of Environmental Economics and Management*, 86:93–120.

Lan, R., Eastham, S. D., Liu, T., Norford, L. K., and Barrett, S. R. (2022). Air quality impacts of crop residue burning in India and mitigation alternatives. *Nature Communications*, 13(1):6537.

Liu, R., Sanyal, A., and Singh, N. (2021). Environmental issues, economic policies and agricultural development: The case of Punjab, India. *Economic Policies and Agricultural Development: The Case of Punjab, India (January 4, 2021)*.

Liu, T., Mickley, L. J., Singh, S., Jain, M., DeFries, R. S., and Marlier, M. E. (2020). Crop residue burning practices across north India inferred from household survey data: Bridging gaps in satellite observations. *Atmospheric Environment: X*, 8:100091.

Lundberg, C. and Abman, R. (2022). Maize price volatility and deforestation. *American Journal of Agricultural Economics*, 104(2):693–716.

Mamun, A., Martin, W., and Tokgoz, S. (2021). Reforming agricultural support for improved environmental outcomes. *Applied Economic Perspectives and Policy*, 43(4):1520–1549.

Mishra, V., Asoka, A., Vatta, K., and Lall, U. (2018). Groundwater depletion and associated co2 emissions in india. *Earth's Future*, 6(12):1672–1681.

Morales, L. E., Balie, J., and Magrini, E. (2021). How has the minimum support price policy of india affected cross-commodity price linkages? *International Food and Agribusiness Management Review*, 24(2):179–196.

Muñoz Sabater, J., Dutra, E., Agustí-Panareda, A., Albergel, C., Arduini, G., Balsamo, G., Boussetta, S., Choulga, M., Harrigan, S., Hersbach, H., Martens, B., Miralles, D. G., Piles, M., Rodríguez-Fernández, N. J., Zsoter, E., Buontempo, C., and Thépaut, J.-N. (2021). Era5-land: a state-of-the-art global reanalysis dataset for land applications. *Earth System Science Data*, 13(9):4349–4383.

Munshi, K. (2004). Social learning in a heterogeneous population: Technology diffusion in the Indian Green Revolution. *Journal of Development Economics*, 73(1):185–213.

Narayanan, A. and Tomar, S. (2023). Farm support and market distortion: Evidence from india. *American Journal of Agricultural Economics*, 105(3):966–993.

NASA (2023). Fire Information for Resource Management System-FIRMS. https://firms.modaps.eosdis.nasa.gov/active_fire/.

Negi, D. S. (2022). Global food price surge, in-kind transfers and household welfare: Evidence from India. *World Development*, 158:106009.

Newbery, D. M. and Stiglitz, J. E. (1984). Pareto inferior trade. *The Review of Economic Studies*, 51(1):1–12.

Pingali, P., Aiyar, A., Abraham, M., and Rahman, A. (2019). *Indian Food Systems towards 2050: Challenges and Opportunities*. Springer International Publishing.

Pullabhotla, H. K. and Souza, M. (2022). Air pollution from agricultural fires increases hypertension risk. *Journal of Environmental Economics and Management*, 115:102723.

Rambachan, A. and Roth, J. (2023). A more credible approach to parallel trends. *Review of Economic Studies*, 90(5):2555–2591.

Restuccia, D. and Rogerson, R. (2017). The causes and costs of misallocation. *Journal of Economic Perspectives*, 31(3):151–174.

Rud, J. P. (2012). Electricity provision and industrial development: Evidence from India. *Journal of Development Economics*, 97(2):352–367.

Saini, S. and Gulati, A. (2016). India's food security policies in the wake of global food price volatility. *Food price volatility and its implications for food security and policy*, pages 331–352.

Saini, S. and Kozicka, M. (2014). Evolution and critique of buffer stocking policy of india. Technical report, Working paper.

Sarkar, S., Singh, R. P., and Chauhan, A. (2018). Increasing health threat to greater parts of India due to crop residue burning. *The Lancet Planetary Health*, 2(8):e327–e328.

Sekhri, S., Chenault, W., Aryal, A., and Lakshmi, V. (2023). Bans without bite: Unabated stubble burning in india. Technical report, University of Virginia.

Sharma, V. P. (2016). Marketable and marketed surplus of rice and wheat in india: distribution and determinants. *Indian Journal of Agricultural Economics*, 71(2):137–159.

Shyamsundar, P., Springer, N., Tallis, H., Polasky, S., Jat, M. L., Sidhu, H. S., Krishnapriya, P., Skiba, N., Ginn, W., Ahuja, V., et al. (2019). Fields on fire: Alternatives to crop residue burning in India. *Science*, 365(6453):536–538.

Singh, A., Vishnoi, A. S., Banday, A. H., Bora, P., and Pandey, P. (2023). Influence of stubble burning on air quality of Northern India: a case study of Indo-Gangetic plains of India. *Environmental Monitoring and Assessment*, 195(4):487.

Singh, P., Roy, A., Bhasin, D., Kapoor, M., Ravi, S., and Dey, S. (2021). Crop fires and cardiovascular health–a study from North India. *SSM-Population Health*, 14:100757.

Sotelo, S. (2020). Domestic trade frictions and agriculture. *Journal of Political Economy*, 128(7):2690–2738.

Topalova, P. (2007). Trade liberalization, poverty and inequality: Evidence from indian districts. In *Globalization and poverty*, pages 291–336. University of Chicago Press.

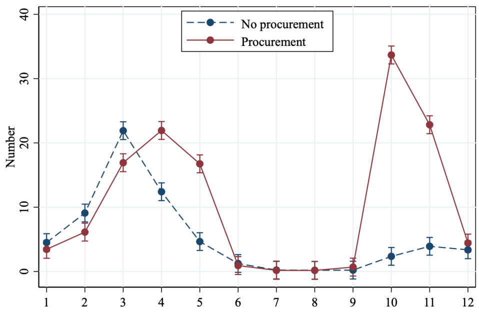
Van Donkelaar, A., Hammer, M. S., Bindle, L., Brauer, M., Brook, J. R., Garay, M. J., Hsu, N. C., Kalashnikova, O. V., Kahn, R. A., Lee, C., et al. (2021). Monthly global estimates of fine particulate matter and their uncertainty. *Environmental Science & Technology*, 55(22):15287–15300.

Viscusi, W. K. and Masterman, C. J. (2017). Income elasticities and global values of a statistical life. *Journal of Benefit-Cost Analysis*, 8(2):226–250.

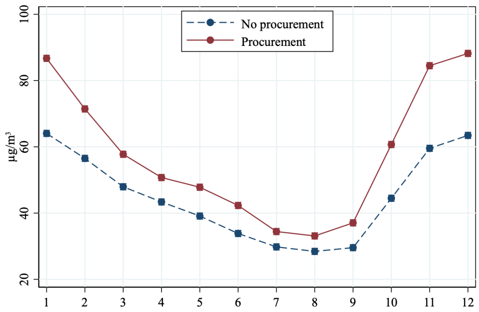
Appendix

A Figures and Tables

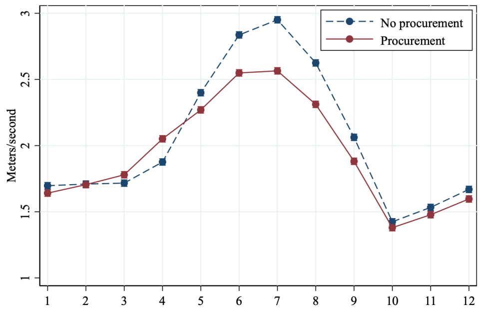
Figure A1: Seasonal Variation in Fires, Air Pollution and Wind Speed



(a) Fire Events



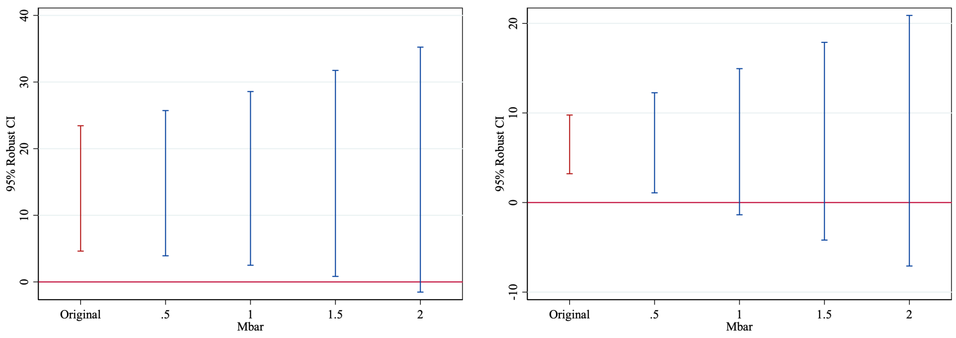
(b) PM 2.5 Levels



(c) Wind Speed

Note: Monthly averages for 2002 to 2016 with 95% confidence intervals.

Figure A2: Bounds on Relative Magnitudes



(a) Fire Events **(b) PM 2.5 Levels**

Note: Figure plots the robust confidence intervals based on Rambachan and Roth (2023) methodology. Total fire events and PM 2.5 levels for October, November and December.

Table A1: Summary Statistics

	(1) Procurement			(2) No Procurement			(3) Overall		
	Mean	SD	N	Mean	SD	N	Mean	SD	N
PM 2.5 $\frac{\mu g}{m^2}$ (Oct-Dec)	233.01	127.60	4003	168.28	113.51	4067	200.39	124.96	8070
Fire events (Oct-Dec)	60.90	223.33	4003	12.91	75.48	4067	36.72	167.88	8070
Windspeed in $\frac{mtr}{sec}$ (Oct-Dec)	1.48	0.38	3973	1.54	0.57	4007	1.51	0.49	7980
Temperature in Kelvin (Oct-Dec)	288.56	3.07	3973	288.14	5.73	4007	288.35	4.61	7980
Surface pressure in Pascal (Oct-Dec)	98363.11	2111.20	3973	96444.34	6339.73	4007	97399.64	4828.93	7980
Rainfall in meters (Oct-Dec)	0.02	0.02	3973	0.02	0.03	4007	0.02	0.02	7980
Nightlight intensity	6.13	4.53	4003	6.54	8.42	4067	6.34	6.78	8070
Road length (Km)	4325.17	2513.47	3911	4625.86	2836.25	3942	4476.11	2684.40	7853
Bank branches (No)	158.75	137.33	3911	160.13	183.76	3942	159.44	162.30	7853
=1 if election in state	0.20	0.40	4003	0.20	0.40	4067	0.20	0.40	8070
Drought (=1 if rain<1SD)	0.16	0.37	4003	0.17	0.38	4067	0.17	0.37	8070
Paddy farm harvest price (Rs/qt)	1150.27	333.11	2348	1112.73	314.24	2459	1131.07	324.11	4807
Wheat farm harvest price (Rs/qt)	1353.98	225.81	2587	1405.29	264.71	2177	1377.43	245.66	4764
Sugarvane farm harvest price (Rs/qt)	2682.92	757.11	1487	2565.57	958.92	1038	2634.68	847.71	2525
Maize farm harvest price (Rs/qt)	1058.68	254.51	2295	1086.71	291.09	2354	1072.87	273.97	4649
Cotton farm harvest price (Rs/qt)	3848.27	1026.19	837	3912.26	1046.77	1075	3884.25	1038.02	1912
Paddy/wheat farm harvest price (Rs/qt)	0.86	0.34	1662	0.82	0.24	1447	0.84	0.30	3109
Rice area (1000 hectares)	110.06	107.78	3910	48.19	54.77	3873	79.27	91.02	7783
Rice production (1000 tons)	255.39	313.44	3910	104.54	137.57	3873	180.32	253.88	7783
Wheat area (1000 hectares)	76.71	79.25	3885	33.14	45.07	3835	55.06	68.15	7720
Wheat production (1000 tons)	243.28	302.61	3877	84.76	149.91	3812	164.69	252.17	7689
Coarse cereals area (1000 hectares)	26.69	48.53	3903	71.76	125.11	3887	49.18	97.45	7790
Coarse cereals production (1000 tons)	51.84	98.59	3903	91.28	133.15	3887	71.52	118.76	7790
Pulses area (1000 hectares)	40.86	56.19	3907	50.20	89.22	3878	45.51	74.64	7785
Pulses production (1000 tons)	29.40	46.90	3907	30.88	56.78	3880	30.14	52.06	7787
Oilseed area (1000 hectares)	49.73	77.53	3301	62.00	97.71	3292	55.86	88.39	6593
Oilseed production (1000 tons)	54.08	99.87	3180	61.68	116.36	3120	57.85	108.41	6300
Sugarcane area (1000 hectares)	9.53	25.54	3851	8.79	27.80	3805	9.17	26.69	7656
Sugarcane production (1000 tons)	59.70	166.97	3854	64.23	208.51	3805	61.95	188.76	7659
Cotton area (1000 hectares)	13.47	41.65	3461	29.71	76.30	3532	21.67	62.16	6993
Cotton production (1000 tons)	5.68	18.63	3462	10.88	32.12	3532	8.31	26.44	6994
Rice acreage (Propotion)	0.41	0.29	3927	0.30	0.31	3940	0.36	0.30	7867
Wheat acreage (Propotion)	0.25	0.21	3927	0.14	0.17	3940	0.20	0.20	7867
Coarse cereals acreage (Propotion)	0.09	0.12	3927	0.22	0.21	3940	0.15	0.18	7867
Pulses acreage (Propotion)	0.15	0.19	3927	0.15	0.20	3940	0.15	0.19	7867
Oilseeds acreage (Propotion)	0.05	0.09	3927	0.07	0.12	3940	0.06	0.11	7867
Sugarcane acreage (Propotion)	0.03	0.09	3927	0.03	0.07	3940	0.03	0.08	7867
Cotton acreage (Propotion)	0.03	0.08	3927	0.06	0.13	3940	0.04	0.11	7867
Diversification Index	0.56	0.18	3927	0.61	0.21	3940	0.59	0.19	7867
Fallow land (1000 hectares)	20.46	33.54	3895	35.48	60.15	3829	27.91	49.16	7724
Forest area (1000 hectares)	99.89	140.96	3888	105.18	144.44	3825	102.51	142.71	7713
Cropped area (1000 hectares)	369.48	210.80	3901	359.81	328.72	3818	364.70	275.53	7719
Fertilizer use (Kg/ha)	134.41	93.83	3887	114.39	98.67	3797	124.52	96.77	7684
Area irrigated (Propotion)	0.54	0.31	3774	0.36	0.28	3357	0.46	0.31	7131
Male wage (Rs)	169.44	85.20	2119	177.71	101.84	1445	172.79	92.38	3564
Female wage (Rs)	100.99	46.96	1056	111.04	51.94	865	105.52	49.51	1921

Table A2: Agricultural Fires and Crop Area and Production

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)
Ln(Rice area)	9.126***													
	(2.780)													
Ln(Wheat area)		-1.181												
		(2.708)												
Ln(Coarse cereals area)			-9.154**											
			(3.676)											
Ln(Pulses area)				-4.957***										
				(1.897)										
Ln(Oilseed area)					-8.078*									
					(4.218)									
Ln(Sugarcane area)						-9.017**								
						(4.433)								
Ln(Cotton area)							-12.949							
							(8.589)							
Ln(Rice production)								2.356**						
								(1.149)						
Ln(Wheat production)									-0.113					
									(1.540)					
Ln(Coarse cereals production)										-7.209**				
										(2.962)				
Ln(Pulses production)											-4.214***			
											(1.595)			
Ln(Oilseed production)												-7.836**		
												(3.792)		
Ln(Sugarcane production)													-7.416**	
													(2.973)	
Ln(Cotton production)														-11.250
														(8.448)
Observations	7684	7623	7691	7685	6508	7559	6899	7684	7592	7691	7687	6215	7561	6900
Mean of Dep. Variable	37.08	37.20	36.58	37.07	32.45	36.44	39.00	37.08	37.34	36.58	37.07	33.87	36.43	39.04

Notes: All regressions include district and year fixed effects. Each column has an estimate from a separate regression. The dependent variable is the district-level total fire events in October, November, and December. Crop area in 1000 hectares and production in 1000 tons. Control variables include road length in kilometers, number of bank branches, average nightlight intensity, wind speed, rainfall, temperature and pressure. District-clustered standard errors are in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Table A3: Support Prices, Procurement, Land Use and Inputs

	Area (000 hectares)			Kg/hectare	Proportion	Rupees/Day	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Fallow	Forest	Cropped area	Fertilizer use	Irrigated area	Wage (M)	Wage (F)
PROC $\times$ POST	-0.054	-0.038	-0.055	-2.078	0.004	-14.229**	-2.780
	(0.055)	(0.038)	(0.035)	(4.103)	(0.006)	(6.308)	(3.108)
Observations	7417	7228	7071	7639	7071	3508	1881
Mean of Dep. Variable	2.44	3.54	4.22	124.45	0.45	172.45	105.60

Notes: Dependent variables are in logs. All regressions include district and year fixed effects. PROC is a dummy variable indicating district with government procurement of rice and wheat and POST is a dummy variable which equals one after 2006. Control variables include road length in kilometers, number of bank branches, average nightlight intensity, wind speed, rainfall, temperature and pressure. Standard errors are clustered at the district level. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Table A4: Support Prices, Procurement and Plot Level Cost of Cultivation

	Hours/Hectare		Kilogram/Hectare	Rupees/Hectares				Rupees/Hour
	(1) Labor	(2) Machine	(3) Fertilizer	(4) Total Cost	(5) Labor	(6) Machine	(7) Fertilizer	(8) Wage
A. Rice								
PROC × POST	-0.010	0.226***	-0.082	-0.021	-0.026	0.061	-0.082	-0.017
	(0.027)	(0.080)	(0.066)	(0.031)	(0.038)	(0.106)	(0.061)	(0.024)
Observations	83919	57007	77057	83923	83921	56930	77056	83919
Mean of Dep. Variable	6.74	2.27	4.64	10.11	9.57	7.92	7.65	2.83
B. Wheat								
PROC × POST	0.037	0.144	0.007	0.094**	0.091**	0.223**	0.072	0.053
	(0.068)	(0.105)	(0.090)	(0.039)	(0.041)	(0.109)	(0.079)	(0.080)
Observations	30554	29434	29496	30559	30555	29428	29494	30554
Mean of Dep. Variable	5.82	2.39	4.92	9.89	8.73	8.23	7.91	2.91

Notes: Dependent variables are logs of plot level input use and cost of cultivation for rice and wheat. All regressions include farm household, district and year fixed effects. All cost estimates are deflated by state GDP deflator. PROC is a dummy variable indicating district with government procurement of rice and wheat and POST is a dummy variable which equals one after 2006. Standard errors are clustered at the district level. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Table A5: Estimates from Sub-samples

	2002-2009		Without Punjab & Haryana	
	(1) Fires	(2) PM 2.5	(3) Fires	(4) PM 2.5
PROC × POST	7.78***	5.23***	4.41***	11.07***
	(2.19)	(1.27)	(1.13)	(1.67)
Observations	4096	4096	7190	7190
Mean of Dep. Variable	30.71	190.91	7.51	189.86

Notes: All regressions include district and year fixed effects. PROC is a dummy variable indicating district with government procurement of rice and wheat and POST is a dummy variable which equals one after 2006. Standard errors are clustered at the district level. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Table A6: Robustness to Rollout of Other Government Programs

	(1) Fires	(2) Fires	(3) Fires	(4) Fires	(5) Fires	(6) PM 2.5	(7) PM 2.5	(8) PM 2.5	(9) PM 2.5	(10) PM 2.5
PROC × POST	15.16***	15.55***	15.16***	16.14***	16.53***	14.32***	14.98***	14.42***	12.95***	13.64***
	(4.00)	(4.09)	(4.02)	(4.37)	(4.44)	(1.77)	(1.77)	(1.77)	(1.82)	(1.81)
MGNREGA	Yes	No	No	No	Yes	Yes	No	No	No	Yes
PMGSY	No	Yes	No	No	Yes	No	Yes	No	No	Yes
BANK	No	No	Yes	No	Yes	No	No	Yes	No	Yes
DCP	No	No	No	Yes	Yes	No	No	No	Yes	Yes
Observations	8040.00	8025.00	8025.00	7455.00	7440.00	8040.00	8025.00	8025.00	7455.00	7440.00
Mean of Dep. Variable	35.09	35.16	35.16	37.27	37.34	200.20	200.28	200.28	208.41	208.52

Notes: All regressions include district and year fixed effects. Control variables include road length in kilometers, number of bank branches, average nightlight intensity, wind speed, rainfall, temperature and pressure. PMGSY denotes the district-level population covered under new roads. MGNREGA is a dummy variable indicating the district-wise rollout of the MGNREGA scheme. BANK denotes the district-level number of bank branches established under the RBI's new bank branch licensing policy. DCP is a state level indicator for the adoption of the Decentralized Procurement Scheme. District clustered standard errors in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Table A7: Support Prices, Procurement and the PDS

	Real Farm Harvest Prices		Fires and Pollution	
	(1)	(2)	(3)	(4)
	Rice	Wheat	Fires	PM 2.5
PROC × POST	0.03**	-0.00	14.12***	10.62***
	(0.02)	(0.01)	(3.70)	(1.70)
SPDS × POST	-0.06**	0.03*	-7.99	-7.95***
	(0.03)	(0.02)	(5.87)	(2.18)
Observations	4529	4431	7330	7330
Mean of Dep. Variable	6.99	7.21	34.25	197.80

Notes: All regressions include district and year fixed effects. PROC is a dummy variable indicating a district with government procurement of rice and wheat, and POST is a dummy variable that equals one after 2006. SPDS is rice and wheat distributed through the PDS as a proportion of total rice and wheat production in the district. Control variables include road length in kilometers, number of bank branches, average nightlight intensity, wind speed, rainfall, temperature and pressure. Standard errors are clustered at the district level. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Table A8: Alternative Specifications

	(1)	(2)	(3)	(4)
	Fires	Fires	PM 2.5	PM 2.5
SHPROC × Ln(MSP)	394.55***		36.39*	
	(111.85)		(19.04)	
SHAWARE × Ln(MSP)		155.92***		62.99***
		(43.20)		(12.42)
Observations	7750	7750	7750	7750
Mean of Dep. Variable	35.12	35.12	200.05	200.05

Notes: All regressions include district and year fixed effects. Control variables include road length in kilometers, number of bank branches, average nightlight intensity, wind speed, rainfall, temperature, and pressure. SHPROC denotes the proportion of rice and wheat production procured by the government. SHAWARE denotes the proportion of farmers who are aware of the minimum support prices. MSP denotes the average rice and wheat minimum support prices. District clustered standard errors in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

B Local Prices, Central Market Price and Trade Frictions

Allen and Atkin (2022) consider a hierarchical market structure where district-level markets trade with state-level terminal markets. State markets, in turn, trade in the national market. At the first layer, each location has a large number of farmers who are both producers and consumers of goods. Farmers can buy and sell goods from intermediaries whose primary role is to trade between producers and the state market. In the second layer, traders at the state level trade with the central market. At every level, traders can engage in arbitrage between selling the good locally or shipping it to the market at an iceberg trade cost. Trade costs τ_i of shipping between location i and the market are heterogeneous and drawn from a Pareto distribution with shape parameter ε_i. The greater the value of ε_i, the lower the average trade costs between location i and the market. Crop production is risky, and yield per unit of land in location i depends on the state of the world $s \in S$. Farmers/consumers are risk averse. Given this structure, Allen and Atkin (2022) establish the following equilibrium relationship between local prices and production.

$$\ln p(s)_i = -\frac{1}{1+\varepsilon_i}\ln A(s)_i + \frac{\varepsilon_i}{1+\varepsilon_i}\ln \bar{p}(s)_m + \delta_i + \delta(s)_i \tag{B1}$$

where price $p(s)_i$ at location i in state s depends on the realization of productivity in that location and the price in terminal market m, i.e., $\bar{p}(s)_m$. Equation (B1) shows that in autarky or $\varepsilon_i = 0$, the price in location i has an inverse relationship with local productivity and is independent of price in the terminal market. With free trade, local prices become independent of local productivity shocks and align with prices in the terminal market m. A similar relationship exists between prices in the terminal market, production arrival in the terminal market $\bar{Q}(s)_m$ and central market price $\ln p^*(s)$.

$$\ln \bar{p}(s)_m = -\frac{1}{1+\varepsilon_m}\ln \bar{Q}(s)_m + \frac{\varepsilon_m}{1+\varepsilon_m}\ln p^*(s) + \delta_m + \delta(s)_m \tag{B2}$$

where ε_m captures the heterogenous trade costs between terminal market m and the central market. Given these relationships, it is easy to see that the elasticity of central market price to local prices is $\frac{\partial \ln p(s)_i}{\partial \ln p^*(s)} = \frac{\varepsilon_i}{1+\varepsilon_i}\frac{\varepsilon_m}{1+\varepsilon_m}$. The elasticity depends on spatial trade frictions between local and terminal market ε_i, and terminal and central market ε_m.

I use this structure to think about the relationship between national support prices and local agricultural market prices. In my case, the central market price is the MSP. I argue that the relevant spatial trade friction/distortion in this context is the large volume of rice purchased and moved across regions by government agencies. The government procurement operations spatially vary, with the government purchasing almost all grain production in some states and none in others. Therefore, the passthrough of MSP to the local price will also spatially vary based on government interference in the local markets.

C Calculation of Gains and Mortality Cost

C.1 Gains

I use the following formula to calculate the consumption expenditure gain in USD:

$$\begin{aligned} GAIN_i = \big[&MPCE_i \times \eta_{Ri} \times SARICE_i \\ &+ MPCE_i \times \eta_{Wi} \times SAWHEAT_i\big] \times 12 \times POPULATION_i \times 0.0195 \end{aligned} \tag{C1}$$

Where i denotes the district and $MPCE$ denotes the baseline monthly per capita expenditure estimates from the 61st (2004-05) round of the NSS expenditure survey. η_{Ri} and η_{Wi} are the elasticity estimates from Negi (2022), which vary based on the net producer or net consumer status of the district (Table C1). Negi (2022) uses a large-scale pan-India two-period household panel survey and a similar difference-in-difference strategy to estimate these elasticities. The two time periods of the survey correspond to a pre (2005) and post (2012) price increase year.

I categorize a district as a net producer if the total production of rice and wheat in the district is greater than the total consumption. I estimate the total consumption of rice and wheat at the district level from the 68th (2012) round of the NSS consumption expenditure survey and extract the production for that year from the ICRISAT district-level dataset. $SARICE$ and $SAWHEAT$ indicate the proportion of area under rice and wheat in the district in 2012, respectively.

Although the consumption expenditure is for the baseline year of 2005, I consider crop acreage and net producer status for the endline year of 2012 to account for any changes in area allocation and production (and net producer status) due to the price increase. Finally, $POPULATION$ is the total district population from the 2001 Census of India, and 0.0195 is the INR to USD conversion factor.

Table C1: The Monthly Per Capita Consumption Expenditure Elasticity of Global Food Price Increase Between 2005 and 2012

Elasticity	Net producer	Net consumer
Rice	0.169	0.008
Wheat	0.120	0.066

C.2 Costs

For mortality based cost calculation, I first calculate the Relative Risk (RR) of the outcome (death) associated with the exposure to baseline and endline PM 2.5 levels. The RR of mortality associated with a 10 $\frac{\mu g}{m^2}$ increase in PM 2.5 is $\eta_M = 1.2$ (de Bont et al., 2024).

The baseline average monthly PM 2.5 level in the procurement districts for the three months of October, November, and December is 70 $\frac{\mu g}{m^2}$. The endline average monthly PM 2.5 level comes out to be 74 $\frac{\mu g}{m^2}$, given the DID estimate of 4 $\frac{\mu g}{m^2}$ (= 12/3) increase in baseline PM 2.5 levels by 2012. Based on this, the $RR_{Baseline}$ and $RR_{Endline}$ can be calculated as:

$$RR_{Baseline} = \eta_m^{\frac{70}{10}} \tag{C2}$$

$$RR_{Endline} = \eta_m^{\frac{74}{10}} \tag{C3}$$

Population Attributable Fraction (PAF) is a measure to estimate the proportion of incidence or mortality in a population that can be attributed to a specific risk factor, such as exposure to PM 2.5. It captures the fraction of cases that would not have occurred if the exposure had been eliminated. The PAF for baseline and endline is defined as:

$$PAF_{Baseline} = \frac{RR_{Baseline} - 1}{RR_{Baseline}} \tag{C4}$$

$$PAF_{Endline} = \frac{RR_{Endline} - 1}{RR_{Endline}} \tag{C5}$$

Finally, the additional mortality due to an increase in PM 2.5 levels post price increase in procurement districts can be calculated as:

$$COST_i = VSL \times \frac{DEATHS_i}{365} \times \left(PAF_{Baseline} - PAF_{Endline}\right) \times 92 \tag{C6}$$

Where VSL is the value of statistical life estimated to be 0.275 million USD (Viscusi and Masterman, 2017) and $DEATHS$ is the annual baseline mortality for 2005 from the Registrar General of India.

Ideally, I should be using population totals from the baseline year of 2005 for these calculations. The Census, however, happens every ten years and the closest baseline population data is from the 2001 Census of India. To be consistent, I use population from the 2001 census for both gain and cost calculations. I also population data from the 2001 Census to calculate the gains or costs per person.