Ashoka University
Economics Discussion Paper 152

Fire in the Fields, Crime in the Air

August 2025

Hardeep Singh Amale, Indian Institute of Technology, Jammu
Digvijay S. Negi, Ashoka University

Fire in the Fields, Crime in the Air

Hardeep Singh Amale* Digvijay S. Negi†

Abstract

We exploit seasonal crop residue burning as a source of pollution and use exogenous year-to-year variation in wind direction to estimate the impact of rural sources of air pollution on crime in India. We find that short term pollution exposure leads to an increase in violent crime, public order offenses, and most worringly, violent crimes against women. Estimates suggest an unaccounted social cost of USD 600 million just from pollution exposure in the rice harvest season. We explore three channels: (i) pollution induced aggression and weakened impulse control, (ii) reduced visibility leading to poor deterrence, and (iii) income distress from reduced earnings. Heterogeneity by crime type and spatial variation in law enforcement capacity support these mechanisms. Our findings highlight the need to account for issues of public safety and social instability in environmental and agricultural policy in developing countries.

Keywords: Crime, crop residue, fires, externalities, air pollution, India
JEL codes: H23, K42, Q52, Q53

*Indian Institute of Technology Jammu, Jammu & Kashmir, 181221, India. Email: hardeep.singh@iitjammu.ac.in

†Associate Professor, Department of Economics, Ashoka University, Sonepat, Haryana, 131029, India. Email: digvijay.negi@ashoka.edu.in

1 Introduction

Air pollution persistently reaches dangerously high levels in many parts of the world, posing severe risks to public health (Amann et al., 2013; Rentschler and Leonova, 2023). At the same time, several regions around the world continue to experience social unrest manifested through violent crime, civil disturbances, and armed conflicts (Institute for Economics & Peace, 2022; Van Dijk et al., 2021). While air pollution is widely recognized for its health and productivity costs, much less is known about the impact of rural pollution sources such as biomass burning on public safety and social stability in low and middle income countries. Such downstream externalities are especially concerning given that social instability and heightened criminal activity are likely to disproportionately affect the most vulnerable populations, particularly women and children in low-income settings (Deryugina et al., 2021).

In this paper, we study the causal effect of pollution on crime in India. We exploit a major pollution source specific to rural agricultural regions: crop residue burning during the rice harvest season. Using high resolution satellite data on particulate matter (PM 2.5) and district level crime records, we estimate the impact of short term air pollution exposure on criminal activity in downwind districts. Our identification strategy exploits year-to-year random wind direction changes to determine which districts would be downwind and potentially exposed to pollution from major rice producing areas during the rice harvest and residue burning season.

We first show that districts downwind of major rice producing regions exhibit elevated PM 2.5 levels during the rice harvesting season. We find that downwind exposure leads to a 1.8% increase in overall crime rates. This increase is driven primarily by violent interpersonal crimes, public disorder events such as arson and rioting, and crimes against women. We also observe a rise in property crimes, while economic offenses, such as fraud and counterfeiting, remain unaffected. Back-of-the-envelope calculations suggest that pollution exposure during the rice harvest season generates an unaccounted social cost of approximately USD 600 million. These results are robust across a range of specification checks.

To understand how pollution influences crime, we explore several plausible mechanisms. First, pollution may increase aggression by impairing cognitive function and reducing impulse control. Second, pollution reduces visibility due to haze, weakening deterrence, and enabling opportunistic crimes in public spaces. Third, pollution, by depressing earnings, can create economic distress and create incentives for property crime. We empirically test these channels using heterogeneity by crime type, law enforcement capacity, and local income indicators. Our findings show that stronger law enforcement infrastructure attenuates the pollution-crime link for property crimes but not for violent crimes suggesting different underlying drivers. The implication is that institutional deterrence may mediate some but not all channels.

Our findings contribute to two strands of the literature. First, we show that rural pollution sources carry substantial social costs through their adverse effects on public safety and social stability. While previous studies have demonstrated that short term urban pollution shocks increase violent behavior in high income settings (Bondy et al., 2020; Burkhardt et al., 2019; Herrnstadt et al., 2021), relatively little is known about the existence of such behavioral responses in lower income contexts where the spatial and seasonal distribution of pollution sources differ substantially. Among the few studies from developing countries, Ayesh (2023) shows that crop residue burning increases crime in Pakistan, while Batkeyev and DeRemer (2023) find higher crime elasticities with respect to PM 2.5 in Kazakhstan but no effects on violent crime. Li and Meng (2023) find that air pollution increases social conflict in China. On the contrary, in the context of Bihar, India, Singh and Visaria (2021) find that high pollution days reduce property crimes by discouraging outdoor activities.

Second, we contribute to the literature examining the relationship between weather and crime. While prior studies have documented that weather induced agricultural shocks can influence criminal activity (Blakeslee et al., 2021; Blakeslee and Fishman, 2018; Mehlum et al., 2006; Miguel, 2005), we extend this literature by highlighting a novel link between weather, agricultural practices, and crime, mediated by wind-driven pollution exposure. This link emphasizes the role of environmental spillovers across space where pollution generated by agricultural burning in one region can affect criminal behavior in distant downwind areas.

Relatedly, we contribute to the literature on the gendered impacts of environmental factors by documenting that pollution exposure also leads to an increase in crimes against women.

A growing body of evidence suggests that extreme environmental conditions can increase gendered crimes directly by increasing psychological stress and aggression, and indirectly by imposing economic strain through income shocks particularly in informal or rural agriculture-dependent contexts (Blakeslee and Fishman, 2018; Burke et al., 2015; Iyer and Topalova, 2014; Sekhri and Storeygard, 2014). We add to this literature by identifying air pollution as a salient environmental risk factor with gendered consequences.

While our empirical context is India, the challenges of excessive agricultural specialization and crop residue management are global (Lin and Begho, 2022). Many countries implement agricultural support programs targeted at reducing income volatility and rural poverty (Anderson et al., 2013). An unintended consequence is that large volumes of agricultural residue are generated annually, and in the absence of alternatives, open burning remains a common practice (Liu et al., 2021). This is a critical policy issue as major economies devote substantial public resources to agriculture while often ignoring the environmental and social externalities associated with these support programs (Anderson et al., 2013).

2 Background and Context

Studies find that elevated levels of pollution, such as PM 2.5 and ozone, can lead to a rise in aggression driven crimes (Bondy et al., 2020; Burkhardt et al., 2019; Herrnstadt et al., 2021). The underlying mechanism is found in the medical literature, which documents that air pollution impairs cognitive function, alters serotonin levels, and increases physiological stress, all of which can elevate aggression and reduce impulse control. Exposure to air pollution has been shown to affect serotonin pathways linked to aggression (Coccaro et al., 2011; González-Guevara et al., 2014; Murphy et al., 2013), reduce frustration tolerance (Anderson and Bushman, 2002; Rotton, 1983), and contribute to symptoms such as lethargy, fatigue, and headaches (Winquist et al., 2012). Pollution exposure may also lead to neuroinflammation and elevated stress responses (Levesque et al., 2011; Rammal et al., 2008).

However, these studies largely focus on urban contexts in high-income countries. Much less is known about how rural pollution sources, such as crop residue burning, may influence crime and public safety in developing countries. This is particularly important because rural air pollution can reach distant downwind areas, is seasonally concentrated, and often directly linked to policy choices in agriculture.

In India, subsidies and price support policies have led to excessive specialization in rice and wheat cultivation (Liu et al., 2021). While price supports have existed in India since the colonial period, they were used in a major way to incentivize farmers to adopt new high-yielding varieties in the 1970s to achieve national food security (Saini and Gulati, 2016). Although these objectives were achieved long ago, the incentives still remain (Liu et al., 2021).

Rice and wheat alone account for nearly 30% of global food consumption, and India ranks as the world's second largest producer after China (Rada, 2016). Yet India's agricultural intensification, originally intended to achieve food security, now generates environmental externalities with widespread spillover effects (Negi, 2024). The result is excessive rice cultivation and large volumes of agricultural residue during the harvest season (Gottipati et al., 2021).

Due to labor constraints, farmers increasingly rely on mechanized harvesting followed by residue burning to rapidly clear fields for the next crop (Shyamsundar et al., 2019). Approximately 63.6% of crop residues are burned annually with Punjab and Haryana being the major contributors (Gupta and Dadlani, 2012; Hill et al., 2024; Parihar et al., 2023; Singh et al., 2021). This widespread practice triggers sharp seasonal spikes in particulate matter (PM 2.5) leading to some of the worst air quality episodes observed across Northern India (Cusworth et al., 2018). Studies estimate that open residue burning contributes nearly half of regional PM 2.5 concentrations and accounts for 40–65% of the annual elemental and organic carbon levels (Jiang et al., 2024; Mehmood et al., 2022).

3 Data and Summary Statistics

3.1 Data

3.1.1 Crime data

We source crime data from the Socio Economic Database of the Centre for Economic Data and Analysis (CEDA) at Ashoka University (CEDA, 2023). This data is collated by CEDA from the annual reports of the National Crime Records Bureau (NCRB). The NCRB annually aggregates data from the State Crime Records Bureau. The NCRB publishes this district level aggregated data under the "Crimes in India" report annually. The CEDA crime data aggregates and matches NCRB crime data to the 2011 Census district boundaries and is available up to 2020. Crimes are recorded either under the Indian Penal Code (IPC) or Special and Local Laws (SLL), where the former includes serious offenses such as rape, murder, arson, and dacoity, and the latter relates to violations of specific legal provisions prohibiting certain social practices. We specifically focus on the district level IPC crime rate (number of crimes per 100,000 population), which is calculated based on the mid year population projections of each state.

Crimes are classified into broad categories. Violent interpersonal crimes include murder, assault, and kidnapping. Property crimes cover robbery, burglary, and theft. Economic crimes include breach of trust, cheating, and counterfeiting. Crimes against public order include rioting and arson. Finally, crimes against women cover rape, sexual harassment, dowry deaths, cruelty by the husband or relatives, and assault on women. We will follow this classification in our analysis.

3.1.2 Weather data

We extract weather data from ERA5, the fifth generation reanalysis dataset produced by the European Center for Medium Range Weather Forecasts which covers the period from 1940 to the present (Muñoz Sabater et al., 2021). The ERA5 provides daily estimates of multiple atmospheric variables and is updated daily. The dataset is available at a 0.25 degree latitude and longitude grid. We primarily use data on wind, temperature, and precipitation. We use 10-meter U and V wind components. The U-component represents the East-West (horizontal axis) movement while the V-component represents the North-South (vertical axis) movement of wind at 10 meters above the Earth's surface. These components can be combined to derive wind speed and direction.

3.1.3 Fire and pollution data

We extract PM 2.5 data from the Atmospheric Composition Analysis Group (ACAG) at Washington University in St. Louis (Van Donkelaar et al., 2021). ACAG provides monthly ground level fine particulate matter (PM 2.5) for the period 1998–2023 based on NASA's satellite instruments. These estimates are calibrated using actual ground based measurements. This data is available at a relatively high spatial resolution of 0.01 degrees latitude and longitude grid.

We extract time and geo coded active biomass fire data from NASA's Fire Information for Resource Management System (FIRMS) which is available from 2000 to 2022 (NASA, 2023). FIRMS detects thermal anomalies or active fires within 1 km pixels using satellite measurements based on the Moderate Resolution Imaging Spectroradiometer (MODIS) Fire and Thermal Anomalies algorithm. This dataset provides pixel level information on fire events and also categorizes them as vegetation fires, active volcanoes, other static land sources, or offshore fires. FIRMS also provides a confidence score for each detected fire event which ranges from 0 to 100%. We focus only on vegetation based fires and exclude data points that are assigned a confidence level of zero.

3.1.4 Other data

We also use data on district-level average nightlight intensity and agricultural production. The nightlight data comes from the Socioeconomic High Resolution Rural Urban Geographic Platform for India (SHRUG) (Asher et al., 2021). SHRUG provides aggregated and gridded night light intensity data for the period 2000-2020 which we use as a proxy for economic activity. We collect district-level seasonal crop-wise cultivated area and production 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 is compiled from official government sources and covers the period from 1990 to 2019.

The visibility data is sourced from the Integrated Surface Hourly dataset of the National Oceanic and Atmospheric Administration (NOAA). NOAA provides global daily visibility data from 1929 to the present for around 9000 geo-coded weather stations. Visibility is defined as the horizontal distance at which an object can be seen and identified from a height of 2 meters. We use these observations to calculate average monthly visibility at the district level for India.

We also compile data on the number of police stations across districts by scraping multiple official government sources, including state statistical abstracts, district profiles, district statistical handbooks, and States at a Glance reports. Due to limited data availability, we were unable to compile historical records of police stations at the district level. However, such data is available for more recent years. We therefore construct measures of police station density for the endline years of 2019 and 2020.

3.1.5 Dataset and variable construction

We use the 2011 district boundaries to construct the district monthly count of fire events and average monthly PM 2.5 levels for the entire period. We construct monthly district temperature and precipitation measures in a similar fashion. Based on data availability and consistency across different data sources, we retain data on 532 districts across 19 major Indian states over a 20 year period from 2001 to 2020.

To identify the primary sources of winter air pollution caused by seasonal crop fires, we first determine the top rice producing districts by calculating their average total *Kharif* season (June to October) rice production from 2001 to 2019.[1] We rank districts by their average annual rice production from 2001 to 2019 and classify the top 25% as primary rice producers. This results in 135 districts being identified as top rice producers and the source of crop residue burning-based air pollution.

[1]The seasonal crop production data is available for that time frame only.

We construct a dyadic dataset by pairing each of these 135 top rice producing districts with every other district in the sample for each year. We also compute the linear distance between each district pair. We then use the average monthly U and V wind components and the geographic location of districts relative to the major rice producers to identify the districts downwind of pollution sources.

3.2 Summary Statistics

Since our focus is on rice residue burning during October, November, and December, we focus on rice cultivation in the main rice growing season. The *Kharif* season typically spans June to October and aligns with the South Western monsoon. Rice is one of the main crops of the Kharif season.[2] Rice sowing begins with the onset of monsoon rains around June and July, while harvesting occurs between September and October.

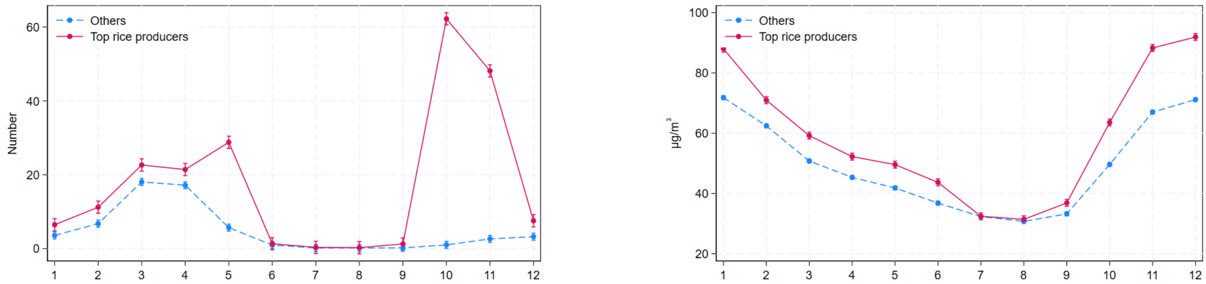
We begin by examining the spatial distribution of rice production across India. To do so, we first calculate the average district-level Kharif rice production from 2001 to 2019. Appendix Figure A1a plots the average rice production at the district level. Rice cultivation is widespread across the country with production concentrated in the Northern states of Punjab, Haryana, and Uttar Pradesh. The South Eastern region and several districts along the Eastern coastal belt also cultivate rice during the Kharif season.

Based on the average rice production patterns, Appendix Figure A1b highlights the top 25% rice-producing districts, which we identify as the primary source of crop residue burning. To verify whether these districts are the main contributors to biomass burning, Figure 1a plots the average monthly fire events in both the top rice producing and other districts. Coinciding with the Kharif rice harvest, we observe a sharp rise in fire activity in the top rice producing districts during October, November, and December. Moreover, Figure 1b shows that the average PM 2.5 levels are also elevated during these months.

We conjecture that pollution exposure from rice residue burning will essentially depend on

[2] While some rice is also cultivated in the winter (Rabi) season, around three-quarters of the rice is produced in the monsoon season.

Figure 1: Seasonal Variation in Fires and Air Pollution

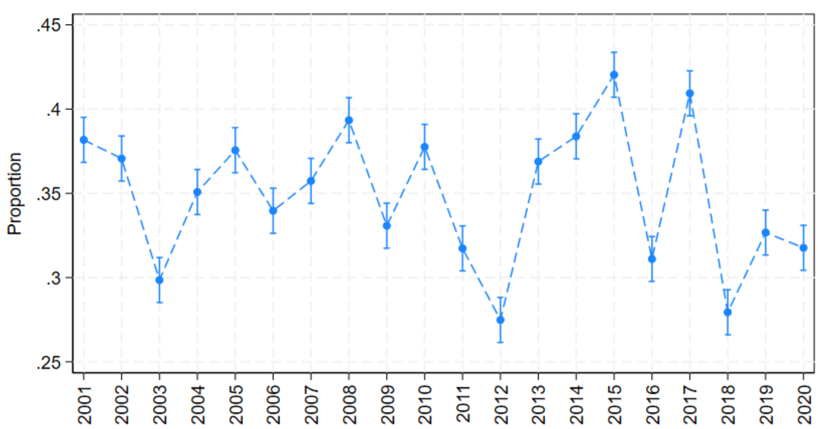


(a) Fire Events **(b) PM 2.5 Levels**

Notes: Monthly averages for 2001 to 2020 with 95% confidence intervals. These figures are based on district monthly averages.

wind direction from top rice producers to downwind areas. Hence, wind patterns play a crucial role in our empirical framework. Appendix Figure A2 visualizes wind vectors as red arrows originating from rice producing districts during October, November, and December for 2001, 2010, and 2020 respectively. In the rice growing regions of North Western and North Eastern India, winds predominantly flow Eastward, whereas in Central and Western regions, they tend to move Southward or Westward. In the Southern districts, winds primarily flow seaward. More importantly, Figure 2 shows that there is substantial variation in wind direction patterns and the likelihood of being downwind of the pollution sources.

Figure 2: Proportion of Downwind Districts Based on Wind Direction in Winter Months



Notes: A district is coded as downwind if it was downwind of a rice-producing district in any of the three months of October, November, or December. Vertical lines indicate 95% confidence intervals.

Table 1 presents summary statistics of key variables for top rice producing districts and

Table 1: Summary Statistics

	(1) Others			(2) Top rice producers		
	Mean	SD	N	Mean	SD	N
Violent interpersonal crimes (per 100000 individuals)	46.74	34.65	1035686	40.79	25.65	341943
Property crimes (per 100000 individuals)	32.02	30.82	1035686	26.29	19.83	341943
Crime against women (per 100000 individuals)	16.19	12.33	1035686	12.46	9.41	341943
Economic crimes (per 100000 individuals)	7.19	7.49	1035686	6.95	5.46	341943
Crimes against public order (per 100000 individuals)	7.05	9.37	1035686	3.57	3.51	341943
Total crimes (per 100000 individuals)	109.19	65.23	1035686	90.05	47.47	341943
Downwind dummy	0.36	0.48	1061280	0.33	0.47	356440
Wind speed Oct-Dec (meters/second)	0.98	0.43	1053240	1.13	0.42	353780
Temperature Oct-Dec (kelvin)	288.23	5.10	1053240	289.23	3.04	353780
Rainfall Oct-Dec (meters)	0.13	0.18	1053240	0.17	0.22	353780
Nightlight intensity index	6.39	6.71	1061280	7.50	4.48	356440
Distance (kilometers)	1006.58	523.62	1061280	935.40	560.42	356440
Rice production kharif (000 tons)	35.05	38.41	1061280	336.86	188.56	356440
Fire events Oct-Dec	2.25	6.56	1061280	39.29	101.52	356440
PM 2.5 $\frac{\mu g}{m^2}$ Oct-Dec	62.42	38.95	1061280	81.25	46.75	356440
Dummy for PM 2.5 > 1 SD mean	0.16	0.36	1061280	0.16	0.36	356440
Police station (100000 people)	1.20	1.05	1055920	0.96	0.49	356440
Dummy for police station density > 1 SD mean	0.08	0.28	1055920	0.03	0.17	356440

other districts in our dataset. We find that overall crime rates are slightly higher in other districts with an average of 109 crimes per hundred thousand individuals compared to 90 in top rice producing districts. However, average weather conditions during the winter months are similar across both groups. Nightlight intensity is slightly higher in top rice producing districts. Fire activity is 20 times greater in the rice producing districts yet PM 2.5 levels are only marginally higher. This suggests that pollution from crop residue burning may be dispersed by wind affecting air quality in surrounding areas beyond the immediate source. In comparison to rice producing districts, police station density is also slightly higher in downwind districts.

4 Empirical Framework

As observed earlier, top rice producing districts exhibit very high biomass based fire activity during the harvest months of October, November, and December. Since multiple districts act as pollution sources, any given district can be downwind of one or more sources. Moreover, source districts can themselves be downwind of other sources. Conceptually, we can think of the top rice producers as the origin and senders of pollution, and the downwind districts as receivers.

Wind direction essentially acts as the mechanism by which air pollution is transported from senders to receivers. To empirically model this wind mediated sender-receiver relationship, we estimate the following specification using the dyadic panel:

$$Y_{i(j)t} = \delta_1 \, Downwind_{ijt} + \mathbf{X}_{i(j)t}\beta_1 + \alpha_{ij} + \mu_{jt} + \epsilon_{ijt} \tag{1}$$

where $Y_{i(j)t}$ either represents the PM 2.5 levels or the crime rates in downwind district i in year t. The subscript (j) indicates that outcome Y for a downwind district i will be repeated j times each year to form pairs with the j source districts.[3] The variable $Downwind_{ijt}$ is a dummy that equals one if district i is downwind of source district j in either October, November or December for year t. Note that, $i \neq j$ implying that a downwind district i will always be distinct from the upwind source district j.

We include the district pair fixed effects, α_{ij}, to control for time-invariant differences in district pairs. We also include rice producing district-specific year fixed effects, μ_{jt}, to account for factors such as weather variations, differential trends, and macroeconomic policy changes in the origin districts that could influence rice production, fire activity, and pollution levels.

Vector X has weather related controls, including precipitation, temperature, and wind speed, to account for environmental conditions that may affect both pollution exposure and criminal activity in the downwind districts. Vector $\mathbf{X}$ also includes nightlight intensity for downwind districts to control for changes in economic activity which could simultaneously impact air pollution levels and crime rates.

Our key coefficient of interest is δ_1 which captures the average effect of being downwind of a pollution source district on crime in district i. We hypothesize that if being downwind of a top rice producing district increases exposure to crop residue based PM 2.5 and subsequently drives crime, then $\delta_1 > 0$.

To explore whether better law enforcement infrastructure moderates the pollution induced criminal activity, we extend our previous specification by interacting the $Downwind$ indicator

[3] Standard errors will be clustered at j level to account for this repetition.

with a measure of law enforcement infrastructure available in the downwind district. We estimate:

$$Y_{i(j)t} = \delta_2\, Downwind_{ijt} + \theta_2\, Police_i \times Downwind_{ijt} + \mathbf{X}_{i(j)t}\beta_2 + \alpha_{ij} + \mu_{jt} + \varepsilon_{ijt} \tag{2}$$

Where $Police_i$ is an indicator equal to one if the police station density per person in downwind district i is greater than one standard deviation of the mean density across downwind districts. The coefficient θ_2 captures heterogeneity in the pollution-crime relationship based on policing capacity. If greater policing capacity mitigates the effect of pollution on crime, then we expect $\theta_2 < 0$.

To account for potential differences in underlying crime trends between districts with varying levels of policing capacity, we also include the interactions between high police density dummy and year dummies as controls. This helps ensure that the estimated coefficient θ_2 captures only the mediating role of policing capacity, rather than picking up spurious trends.

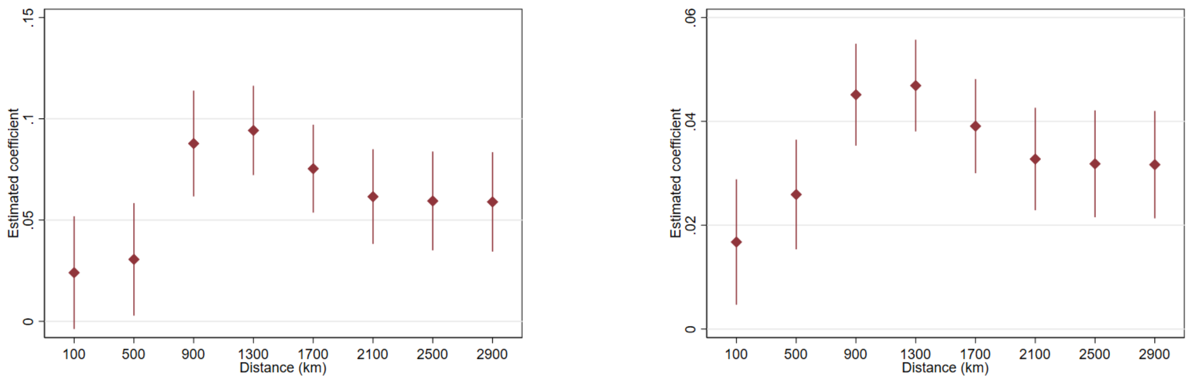
Given the structure of our data, we report two-way clustered standard errors at both the origin (j) and destination (i) district group levels. Clustering at the origin group accounts for spatial and general correlation inherent in the dyadic nature of the data, and clustering at the destination district level accounts for serial correlation and heteroscedasticity in the destination district time series.

5 Results

5.1 Rice production and downwind pollution

We begin by looking at the relationship between air pollution levels in districts located downwind of major rice producing areas. Figure 3a presents the estimated coefficients from equation (1) using standardized PM 2.5 levels as the dependent variable. The coefficients are estimated from sub samples that vary based on the distance between the pollution source and the downwind district (see Appendix Table A1 for estimates).

Figure 3: Air Pollution in Downwind Districts



(a) Standardized PM 2.5 Levels **(b) Extreme PM 2.5 Deviation**

Notes: The figures display estimated coefficients from separate regressions on the downwind dummy for district sub-samples located between 100 and 2,900 kilometers from the top rice-producing districts. In Figure 3a, the dependent variable is standardized PM 2.5 levels. In Figure 3b, the dependent variable is a binary indicator equal to one if a district's annual PM 2.5 level exceeds its mean by one standard deviation, capturing extreme positive deviations. All regressions include district-pair fixed effects and top rice-producing district-by-year fixed effects. 95% confidence intervals are based on standard errors clustered by both downwind and top rice-producing districts.

For subsamples within 500 kilometers of the source districts, we find a positive but statistically insignificant coefficient estimate. However, the estimate rises to 0.09 around the 900 to 1000 kilometer band before declining. In terms of magnitude, around the 900-kilometer distance band, downwind districts experience an increase of 4 $\mu g/m^2$ (or a 5% increase) in winter PM 2.5 levels.

Figure 3b shows a similar pattern where the dependent variable is an indicator for PM 2.5 levels going above one standard deviation of the district mean. The probability of experiencing extremely high PM 2.5 levels peaks at approximately 4-5% around the 900-1000 kilometer band before declining. This pattern suggests that while pollution levels are higher in downwind districts, pollution exposure downwind declines with distance.[4] Given that the downwind pollution exposure is highest at the 900 kilometer band, we will present estimates for districts within 900 kilometers of the top rice producers.

[4]As the distance between a source district and a downwind district increases, potential exposure from that specific source declines. However, we observe that the probability of being downwind of other source districts increases with distance, peaking at around 900 kilometers.

5.2 Criminal activity in downwind districts

Having established that being downwind of the rice production regions does increase PM 2.5 levels, we move on to explore the impact of downwind pollution exposure on criminal activity in downwind districts. Table 2 presents the estimates of equation (1) for different crime categories and overall crime rates.

Table 2: Crimes in Downwind Districts

	Crime rate per 100000 individuals					
	(1) Violance	(2) Property	(3) Economic	(4) Women	(5) Public	(6) Total
Downwind	0.81***	0.59***	−0.07	0.21**	0.31***	1.85***
	(0.30)	(0.14)	(0.06)	(0.09)	(0.08)	(0.38)
Windspeed	1.65	−1.52*	0.97**	−0.34	−0.94***	−0.18
	(2.22)	(0.87)	(0.39)	(0.49)	(0.35)	(2.61)
Temperature	−0.27	−0.61**	0.60***	0.05	−0.32***	−0.55
	(0.56)	(0.25)	(0.09)	(0.13)	(0.08)	(0.70)
Rainfall	−5.75**	1.83	−1.39***	0.22	−0.14	−5.22
	(2.59)	(1.33)	(0.50)	(0.74)	(0.57)	(3.70)
Nightlight	1.22***	1.00***	0.04	0.13**	0.07**	2.45***
	(0.25)	(0.29)	(0.05)	(0.06)	(0.03)	(0.37)
Observations	654200	654200	654200	654200	654200	654200
Mean of Dep. Var.	45.18	31.00	6.93	15.27	5.65	104.03

Notes: All regressions include district-pair fixed effects and top rice-producing district-by-year fixed effects. Each column reports estimates from a separate regression. The sample is restricted to downwind districts located within 900 kilometers of the top rice-producing districts. Standard errors, clustered by both downwind district and top rice-producing district, are reported in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

We find that being downwind leads to an additional 1.9 crimes per 100,000 individuals. In terms of numbers, this translates into approximately 24000 to 26000 additional crimes in 2020.[5] This effect appears to be primarily driven by increases in violent and property crimes. Additionally, we observe a higher incidence of crimes against women and public order offenses such as arson and rioting. In percentage terms, the largest increase is observed for public order offenses.

Based on our estimates, we do back-of-the-envelope calculations to approximate the economic costs of increased criminal activity. Estimates of economic costs per crime are not readily available for India. To approximate this figure, we draw on estimates from the Institute for Economics and Peace, which report that India lost approximately 6% of its annual GDP to violence and crime in 2022 (Institute for Economics & Peace, 2022; Raj and Kalluru, 2023). Based on this estimate, we calculate the average annual cost per crime to be approximately USD

[5] According to World Bank projections, India's population would be around 1.4 billion people in 2020.

25000. Total additional crimes (assuming 24000) due to being downwind times cost per crime (USD 25000) gives us a number of USD 600 million.

5.3 Downwind districts and types of criminal activity

While we do see an increase in overall criminal activity in the downwind districts, we now explore the effects by individual crimes. Table 3 panel A shows the estimated effects by individual crimes within the property crime category. We observe an increase in burglaries and thefts in downwind districts. In terms of magnitude, thefts increase by around 1.6% and burglaries increase by around 3%.

Table 3: Pollution and Type of Crimes in Downwind Districts

	Panel A. Property crimes per 100000 individuals			
	(1) Burglary	(2) Dacoity	(3) Robbery	(4) Theft
Downwind	0.24***	−0.01**	0.00	0.35***
	(0.06)	(0.00)	(0.01)	(0.11)
Observations	654200	654200	654200	654200
Mean of Dep. Var.	7.11	0.38	1.72	21.77

	Panel B. Public and economic crimes per 100000 individuals				
	(1) Arson	(2) Riots	(3) Cheating	(4) Counterfeiting	(5) Breach of trust
Downwind	0.07***	0.24***	−0.05	−0.00**	−0.01
	(0.03)	(0.06)	(0.05)	(0.00)	(0.01)
Observations	654200	654200	654200	654200	654200
Mean of Dep. Var.	0.85	4.79	5.78	0.10	1.06

	Panel C. Crime against women per 100000 individuals				
	(1) Assult	(2) Cruelty by husband	(3) Dowry deaths	(4) Insult	(5) Rape
Downwind	0.20***	−0.03	0.01*	−0.02	0.05**
	(0.05)	(0.04)	(0.00)	(0.01)	(0.02)
Observations	654200	654200	654200	654200	654200
Mean of Dep. Var.	5.09	6.27	0.73	0.69	2.50

	Panel D. Violent crimes per 100000 individuals					
	(1) Murder attempt	(2) Culpable homicide	(3) Death by negligence	(4) Hurt	(5) Kidnapping	(6) Murder
Downwind	0.11***	−0.01***	0.07*	0.55*	0.10***	−0.00
	(0.03)	(0.00)	(0.04)	(0.30)	(0.03)	(0.01)
Observations	654200	654200	654200	654200	654200	654200
Mean of Dep. Var.	3.05	0.31	7.97	26.91	3.98	2.97

Notes: All regressions include district-pair fixed effects, top rice-producing district-by-year fixed effects, weather controls, and nightlight intensity. Each column reports estimates from a separate regression. The sample is restricted to downwind districts located within 900 kilometers of the top rice-producing districts. Standard errors, clustered by both downwind district and top rice-producing district, are reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

We also explore whether downwind districts experience more crimes related to public disorder in Table 3 panel B. Consistent with the aggression mechanism, we observe that downwind districts show a greater rate of arson and rioting. In terms of magnitude, arson rates increase by about 8% and rioting incidence rises by around 5%.

A novel feature of our data is that we can specifically look at crimes against women. Table 3 panel C shows the estimates for individual categories of crimes committed where the victim was a woman. Again consistent with the aggression channel, we observe higher rates of assaults involving women and rapes.

Finally, we also explore the influence of pollution exposure on subcategories within violent crimes. We observe a statistically significant increase in murder attempts and kidnappings in the downwind districts (Table 3 panel D). The aggression channel appears to be the potential mechanism as we observe a decline in culpable homicides where the perpetrator did not intend to kill the victim, but a rise in actual attempted murder cases and kidnappings. A similar pattern is also reported by (Herrnstadt et al., 2021) for crimes in Chicago.

6 Potential Mechanisms

Our findings align closely with the growing body of evidence linking short-term pollution exposure to increased criminal activity, particularly crimes driven by aggression. The observed rise in violent crimes such as assaults on women, rape and murder attempts, and kidnappings is consistent with the aggression channel emphasized in Burkhardt et al. (2019), Herrnstadt et al. (2021), and Ayesh (2023), all of which document stronger effects of pollution on violent offenses relative to property crimes. Our findings on increased arson and rioting also reinforce this behavioral mechanism. In contrast, we find no significant effect on crimes such as cheating, counterfeiting, and breach of trust, which are generally planned and opportunistic.

While the physiological and psychological effects of PM 2.5 exposure have been associated with increased aggression and criminal behavior, what can possibly explain the positive effects on burglary and theft? While there is some evidence that pollution may also elevate property crimes in certain settings (Ayesh, 2023; Bondy et al., 2020), the underlying mechanisms remain less well understood.

One potential mechanism is that pollution exposure may induce criminal behavior through its adverse effects on livelihoods and earnings. Poor air quality can reduce agricultural productivity and temporarily depress labor market participation or worker productivity, particularly in outdoor and informal occupations (see, for example, Chang et al. (2016); Graff Zivin and Neidell (2012)). Prior research has also shown that weather induced income shocks can influence criminal activity in poor lower income settings (e.g., Blakeslee and Fishman (2018)). These disruptions can generate economic distress, which in turn can increase the incidence of theft and property crimes.

To test these possibilities, we check whether the downwind indicator is correlated with measures of agricultural performance, including crop yields, total agricultural production, and incomes. Appendix Table A4 presents the results. We do not find evidence that downwind pollution exposure significantly affects agricultural production or crop yields indicating no disruption to farm based livelihoods. However, we do find a statistically significant decline in income from services in districts exposed to downwind pollution (Appendix Table A4 column 5). This pattern is consistent with reduced labor market participation and earnings driven either by deteriorating air quality or heightened perceptions of public insecurity. While empirically disentangling the contribution of these two factors is difficult, we cannot rule out the additional indirect channel of economic distress due to reduced earnings in non-agricultural occupations linking pollution exposure and crime.

We discuss the heterogeneity results based on police infrastructure here, as they provide insights into potential mechanisms underlying the observed effects. Table 4 shows that better law enforcement infrastructure mitigates the impact of downwind pollution exposure on only property crimes. In fact, the magnitude of the coefficient suggests that in districts with high police station density, downwind exposure has no significant effect on property crime rates. These estimates are consistent with the argument that property crimes are typically premeditated rather than impulsive, and a stronger police presence may serve as a deterrent to such offenses. The evidence suggests that violent crimes, which are often more impulsive in nature and potentially triggered by pollution induced cognitive impairment, may not be effectively deterred by better law enforcement infrastructure.

Table 4: Police Infrastructure and Crimes in Downwind Districts

	Crime rate per 100000 individuals					
	(1) Violance	(2) Property	(3) Economic	(4) Women	(5) Public	(6) Total
Downwind	0.79**	0.61***	−0.07	0.21**	0.28***	1.82***
	(0.32)	(0.15)	(0.06)	(0.09)	(0.07)	(0.40)
Downwind × Police	0.20	−0.84***	−0.04	−0.15	0.40	−0.43
	(0.88)	(0.32)	(0.18)	(0.17)	(0.55)	(1.04)
Observations	652900	652900	652900	652900	652900	652900
Mean of Dep. Var.	45.22	31.01	6.94	15.29	5.65	104.11

Notes: All regressions include district-pair fixed effects, top rice-producing district-by-year fixed effects, weather controls, and nightlight intensity. *Police* is a dummy equal to 1 when police-station density in a district exceeds one standard deviation above the mean. Regressions also include year dummies interacted with the police-density dummy. Each column reports results from a separate regression. The sample is limited to downwind districts located within 900 kilometers of the top rice-producing districts. Standard errors, clustered on both downwind district and top rice-producing district, are shown in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Research has shown that individuals with low self-control are more likely to engage in violent crimes (Pratt and Cullen, 2000). In contrast, property crimes appear to be more influenced by deterrence mechanisms. For instance, Di Tella and Schargrodsky (2004) and Klick and Tabarrok (2005) demonstrate that increased police deployment significantly reduces theft and other property crimes, but not violent crimes. Marvell and Moody (1996) similarly report substantial declines in offenses such as larceny and auto theft, while noting limited effects on assault. To the extent that pollution exposure leads to impulsive behavior, these findings align well with existing evidence showing that police presence generally reduces non violent and property crimes, but has limited effectiveness in reducing impulsive or violent offenses.

Another possible facilitator could be visibility. Smoke from crop residue burning is also known to generate haze and significantly reduce visibility (Ravindra et al., 2021). Smog and haze, by impairing human and CCTV surveillance, can create ideal conditions for property crimes like theft and burglary. In low-income settings like India, where incentives for burglary and theft are persistently high, reduced visibility can act as additional motivation for committing crimes. Evidence suggests that visibility is an important determinant of criminal activity (Jacob et al., 2007; Tompson and Bowers, 2015). Reduced visibility can decrease the likelihood of detection, as fewer people may be present to serve as potential witnesses (Tompson and Bowers, 2013, 2015). We observe that average visibility during the three winter months decreases by 3% in downwind districts at the 900-kilometer distance band (Appendix Figure A3). These estimates account for other weather controls, including rainfall, temperature, and wind speed.

7 Robustness Tests

Appendix Table A2 presents estimates from equation (1) that include indicator variables for both downwind and upwind districts. The upwind indicator is constructed analogously to the downwind indicator but equals one for districts located upwind from major pollution source regions. If exposure to burnt crop residue pollution is the primary mechanism driving increases in crime, we should observe effects only in downwind districts, where pollutants are carried over by prevailing winds. However, no effects should be observed in upwind districts. Consistent with this prediction, Appendix Table A2 shows that the coefficients on the upwind indicator are generally statistically insignificant or of the opposite sign. Although we find a positive coefficient for economic crimes, these offenses are not significantly associated with being downwind, suggesting that the result is likely driven by other factors. The absence of positive effects in upwind districts supports the mechanism that pollution exposure from crop burning elevates crime rates only in downwind areas.

A potential concern with our identification strategy is that pollution from sources other than crop residue burning may also contribute to elevated crime rates in downwind areas. However, baseline characteristics of major rice producing districts relative to other districts suggest that this is unlikely. Top rice producing districts are more reliant on agriculture, with a larger share of district income derived from agricultural activities, and are less industrialized with industrial output accounting for only 26% of district GDP compared to around 30% in other districts. To further address this concern, we conduct a placebo test using a downwind indicator constructed for the months of June, July, and August. These months correspond to the sowing and growing season of paddy during which crop residue burning is negligible (as shown in Figure 1a). Appendix Table A3 presents the results of this placebo test. Consistent with expectations, the coefficients on the summer downwind indicator are mostly negative and statistically insignificant, providing additional support for the interpretation that the observed crime effects are driven specifically by pollution from crop residue burning during the harvest season.

We also conduct sensitivity checks by varying the procedure used to identify downwind districts. In our baseline specification, districts are classified as downwind if they lie within a 30 degrees angular range relative to the source district's wind direction. To test the robustness of our results to this threshold, we vary the downwind angle used to define downwind exposure. Appendix Table A5 reports the results from these alternative specifications. Our results remain consistent across different downwind definitions, further validating our empirical strategy.

We include rice producing districts as potential downwind districts in our main dataset. Since these districts are both sources of pollution and can themselves be downwind of other source districts, their inclusion may affect the estimates. To assess the robustness of our findings, we re-estimate the regressions after excluding rice producing districts from the dyads. The results, reported in Appendix Table A6, are very close to our original estimates, suggesting that our main findings are not driven by the inclusion of rice producing districts.

Our main downwind variable is constructed as an indicator variable which may not capture the extent or duration of a district being downwind. To address this, we construct a continuous version of the downwind variable that measures the number of days a district was downwind of the source districts during October, November, and December. We use daily U and V wind vector data to determine whether a district was downwind of the top rice-producing districts on each day during October, November, and December. We then count the total number of downwind days for each district over the three months and calculate the proportion of downwind days in October, November, and December.

Given that the day based downwind variable also captures exposure at the intensive margin, we re-estimate our main regressions without the distance restriction. The results presented in Table A7 are broadly consistent with our earlier findings. However, the estimated coefficients for crimes against women and public order offenses are not statistically significant in this specification. In Panel B of Table A7, we present estimates that include a quadratic specification of the downwind variable. The results indicate that while the linear term of the downwind variable remains mostly positive but statistically insignificant, the squared term is positive and statistically significant for most outcomes suggesting a nonlinear relationship. For crimes against women, the coefficient on the squared term is positive and weakly significant.

8 Conclusion

In this paper, we study the causal link between seasonal crop residue burning, resultant air pollution, and criminal activity. The setting is India, widely known to have a policy supported cereal centric cultivation system. Crop residue management is a major problem, and seasonal crop fires and resultant spikes in air pollution are recurring phenomena. In the larger policy relevant context of price support to agriculture, the question we ask is whether crop residue burning can have the additional social cost of heightened criminal activity.

Our results show that districts downwind of major rice producing regions experience higher PM 2.5 levels during the rice harvesting season. This pollution increase is associated with a 1.8% rise in overall crimes. Back-of-the-envelope calculations suggest an unaccounted social cost of approximately USD 600 million just from pollution exposure in the rice harvest season.

A more concerning finding is that downwind pollution exposure also leads to an increase in violent crimes against women. This finding carries broader implications for understanding the constraints on women's economic and social participation. While academic discussions on low female workforce participation often focus on factors like marriage, childcare, and gender norms, our findings suggest that rising pollution itself may discourage women from leaving their homes not only due to health concerns but also because it may contribute to a more unsafe and violent social environment.

Our results support the suggestion to shift the focus of environmental interventions from targeting the most polluted areas to prioritizing the most vulnerable populations, who may suffer disproportionately from pollution exposure. The evidence also highlights the importance of integrating environmental quality into policy discussions on safety, gender equality, and women's empowerment.

References

Amann, M., Klimont, Z., and Wagner, F. (2013). Regional and global emissions of air pollutants: Recent trends and future scenarios. *Annual Review of Environment and Resources*, 38(1):31–55.

Anderson, C. A. and Bushman, B. J. (2002). Human aggression. *Annual Review of Psychology*, 53(1):27–51.

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.

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).

Ayesh, A. (2023). Burned agricultural biomass, air pollution and crime. *Journal of Environmental Economics and Management*, 122:102887.

Batkeyev, B. and DeRemer, D. R. (2023). Mountains of evidence: The effects of abnormal air pollution on crime. *Journal of Economic Behavior and Organization*, 210:288–319.

Blakeslee, D., Chaurey, R., Fishman, R., Malghan, D., and Malik, S. (2021). In the heat of the moment: Economic and non-economic drivers of the weather-crime relationship. *Journal of Economic Behavior & Organization*, 192:832–856.

Blakeslee, D. S. and Fishman, R. (2018). Weather shocks, agriculture, and crime: Evidence from India. *Journal of Human Resources*, 53(3):750–782.

Bondy, M., Roth, S., and Sager, L. (2020). Crime is in the air: The contemporaneous relationship between air pollution and crime. *Journal of the Association of Environmental and Resource Economists*, 7(3):555–585.

Burke, M., Hsiang, S. M., and Miguel, E. (2015). Climate and conflict. *Annual Review of Economics*, 7(1):577–617.

Burkhardt, J., Bayham, J., Wilson, A., Carter, E., Berman, J. D., O'Dell, K., Ford, B., Fischer, E. V., and Pierce, J. R. (2019). The effect of pollution on crime: Evidence from data on particulate matter and ozone. *Journal of Environmental Economics and Management*, 98:102267.

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

Chang, T., Graff Zivin, J., Gross, T., and Neidell, M. (2016). Particulate pollution and the productivity of pear packers. *American Economic Journal: Economic Policy*, 8(3):141–69.

Coccaro, E. F., Sripada, C. S., Yanowitch, R. N., and Phan, K. L. (2011). Corticolimbic function in impulsive aggressive behavior. *Biological Psychiatry*, 69(12):1153–1159.

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.

Deryugina, T., Miller, N., Molitor, D., and Reif, J. (2021). Air pollution policy should focus on the most vulnerable people, not just the most polluted places. In di Mauro, B. W., editor, *Combating Climate Change: A CEPR Collection*. CEPR Press, Paris & London.

Di Tella, R. and Schargrodsky, E. (2004). Do police reduce crime? Estimates using the allocation of police forces after a terrorist attack. *American Economic Review*, 94(1):115–133.

González-Guevara, E., Martínez-Lazcano, J. C., Custodio, V., Hernández-Cerón, M., Rubio, C., and Paz, C. (2014). Exposure to ozone induces a systemic inflammatory response: Possible source of the neurological alterations induced by this gas. *Inhalation Toxicology*, 26(8):485–491.

Gottipati, R., Burra, P. M., and Menon, S. (2021). Stubble burning: Root cause, impacts and its management in Indian scenario. *Environment Conservation Journal*, 22(3):37–45.

Graff Zivin, J. and Neidell, M. (2012). The impact of pollution on worker productivity. *American Economic Review*, 102(7):3652–73.

Gupta, H. and Dadlani, M. (2012). Crop residues management with conservation agriculture: Potential, constraints and policy needs. *New Delhi: Indian Agricultural Research Institute*.

Herrnstadt, E., Heyes, A., Muehlegger, E., and Saberian, S. (2021). Air pollution and criminal activity: Microgeographic evidence from Chicago. *American Economic Journal: Applied Economics*, 13(4):70–100.

Hill, A. E., Burkhardt, J., Bayham, J., O'Dell, K., Ford, B., Fischer, E. V., and Pierce, J. R. (2024). Air pollution, weather, and agricultural worker productivity. *American Journal of Agricultural Economics*, 106(4):1329–1353.

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

Institute for Economics & Peace (2022). Global Peace Index 2022: Measuring Peace in a Complex World. Technical report.

Iyer, L. and Topalova, P. B. (2014). Poverty and crime: Evidence from rainfall and trade shocks in India. *Harvard Business School BGIE Unit Working Paper*, (14-067).

Jacob, B., Lefgren, L., and Moretti, E. (2007). The dynamics of criminal behavior: Evidence from weather shocks. *Journal of Human resources*, 42(3):489–527.

Jiang, K., Xing, R., Luo, Z., Huang, W., Yi, F., Men, Y., Zhao, N., Chang, Z., Zhao, J., Pan, B., et al. (2024). Pollutant emissions from biomass burning: A review on emission characteristics, environmental impacts, and research perspectives. *Particuology*, 85:296–309.

Klick, J. and Tabarrok, A. (2005). Using terror alert levels to estimate the effect of police on crime. *The Journal of Law and Economics*, 48(1):267–279.

Levesque, S., Taetzsch, T., Lull, M. E., Kodavanti, U., Stadler, K., Wagner, A., Johnson, J. A., Duke, L., Kodavanti, P., Surace, M. J., et al. (2011). Diesel exhaust activates and primes microglia: Air pollution, neuroinflammation, and regulation of dopaminergic neurotoxicity. *Environmental Health Perspectives*, 119(8):1149–1155.

Li, J. and Meng, G. (2023). Pollution exposure and social conflicts: Evidence from China's daily data. *Journal of Environmental Economics and Management*, 121:102870.

Lin, M. and Begho, T. (2022). Crop residue burning in South Asia: A review of the scale, effect, and solutions with a focus on reducing reactive nitrogen losses. *Journal of Environmental Management*, 314:115104.

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)*.

Marvell, T. B. and Moody, C. E. (1996). Specification problems, police levels, and crime rates. *Criminology*, 34(4):609–646.

Mehlum, H., Miguel, E., and Torvik, R. (2006). Poverty and crime in 19th century Germany. *Journal of Urban Economics*, 59(3):370–388.

Mehmood, K., Bao, Y., Saifullah, Bibi, S., Dahlawi, S., Yaseen, M., Abrar, M. M., Srivastava, P., Fahad, S., and Faraj, T. K. (2022). Contributions of open biomass burning and crop straw burning to air quality: Current research paradigm and future outlooks. *Frontiers in Environmental Science*, 10:852492.

Miguel, E. (2005). Poverty and witch killing. *The Review of Economic Studies*, 72(4):1153–1172.

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.

Murphy, S. R., Schelegle, E. S., Miller, L. A., Hyde, D. M., and Van Winkle, L. S. (2013). Ozone exposure alters serotonin and serotonin receptor expression in the developing lung. *Toxicological Sciences*, 134(1):168–179.

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

Negi, D. (2024). State mediated trade, distortions and air pollution. https://papers.ssrn.com/sol3/papers.cfm?abstract_id=4997656.

Parihar, D. S., Narang, M. K., Dogra, B., Prakash, A., and Mahadik, A. (2023). Rice residue burning in northern India: An assessment of environmental concerns and potential solutions–a review. *Environmental Research Communications*, 5(6):062001.

Pratt, T. C. and Cullen, F. T. (2000). The empirical status of gottfredson and hirschi's general theory of crime: A meta-analysis. *Criminology*, 38(3):931–964.

Rada, N. (2016). India's post-green-revolution agricultural performance: What is driving growth? *Agricultural Economics*, 47(3):341–350.

Raj, P. and Kalluru, S. R. (2023). Does crime impede economic growth? An evidence from India. *Cogent Social Sciences*, 9(1):2196814.

Rammal, H., Bouayed, J., Younos, C., and Soulimani, R. (2008). Evidence that oxidative stress is linked to anxiety-related behaviour in mice. *Brain, Behavior, and Immunity*, 22(8):1156–1159.

Ravindra, K., Singh, T., Sinha, V., Sinha, B., Paul, S., Attri, S., and Mor, S. (2021). Appraisal of regional haze event and its relationship with PM 2.5 concentration, crop residue burning and meteorology in Chandigarh, India. *Chemosphere*, 273:128562.

Rentschler, J. and Leonova, N. (2023). Global air pollution exposure and poverty. *Nature Communications*, 14(1):4432.

Rotton, J. (1983). Affective and cognitive consequences of malodorous pollution. *Basic and Applied Social Psychology*, 4(2):171–191.

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.

Sekhri, S. and Storeygard, A. (2014). Dowry deaths: Response to weather variability in India. *Journal of Development Economics*, 111:212–223.

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, G., Gupta, M. K., Chaurasiya, S., Sharma, V. S., and Pimenov, D. Y. (2021). Rice straw burning: A review on its global prevalence and the sustainable alternatives for its effective mitigation. *Environmental Science and Pollution Research*, 28(25):32125–32155.

Singh, T. P. and Visaria, S. (2021). Up in the air: Air pollution and crime–evidence from India.

Tompson, L. and Bowers, K. (2013). A stab in the dark? A research note on temporal patterns of street robbery. *Journal of Research in Crime and Delinquency*, 50(4):616–631.

Tompson, L. A. and Bowers, K. J. (2015). Testing time-sensitive influences of weather on street robbery. *Crime Science*, 4(1):1–11.

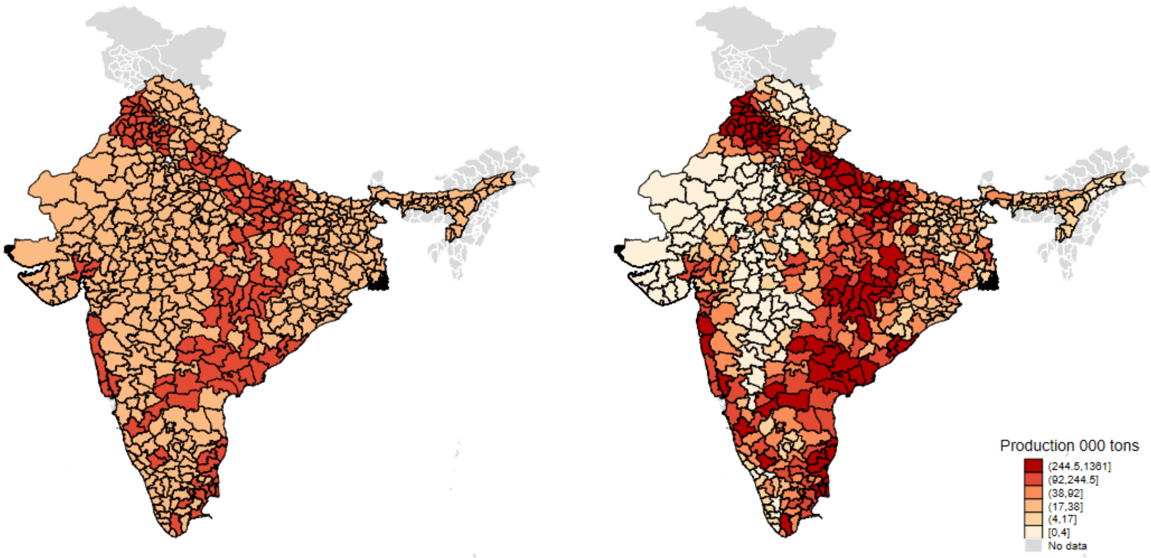
Van Dijk, J., Nieuwbeerta, P., and Joudo Larsen, J. (2021). Global crime patterns: An analysis of survey data from 166 countries around the world, 2006–2019. *Journal of Quantitative Criminology*, pages 1–36.

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 and Technology*, 55(22):15287–15300.

Winquist, A., Klein, M., Tolbert, P., Flanders, W., Hess, J., and Sarnat, S. (2012). Comparison of emergency department and hospital admissions data for air pollution time-series studies. *Environmental Health*, 11:1–14.

Appendix

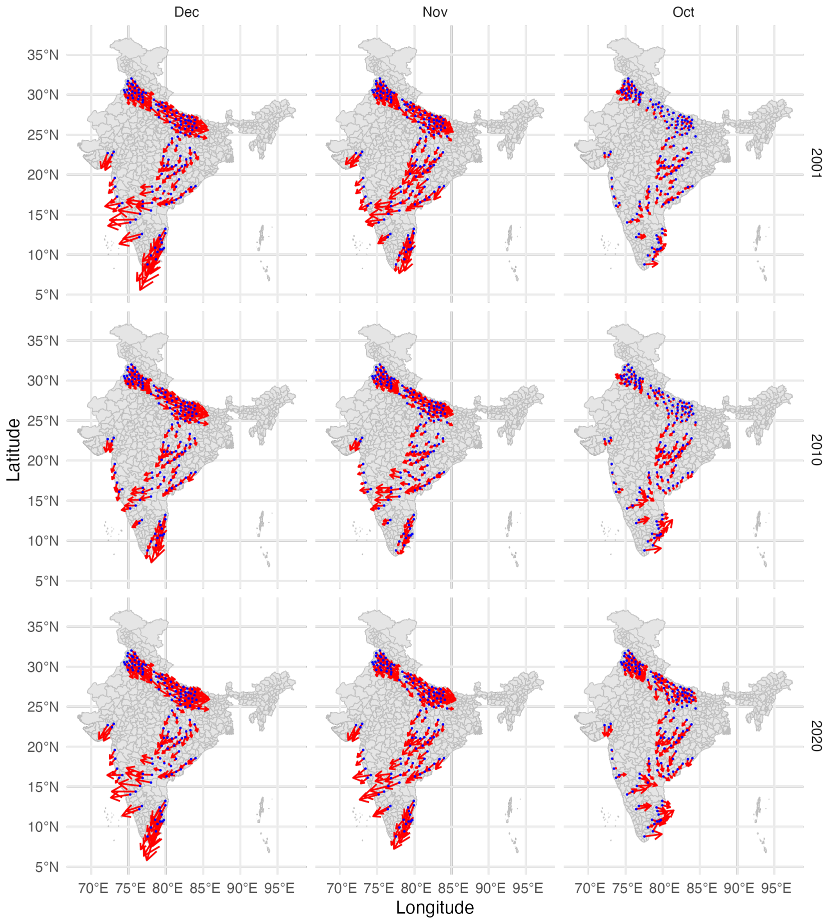
Figure A1: Spatial Distribution of Top Rice Producing Districts



(a) Rice production **(b) Top rice producers**

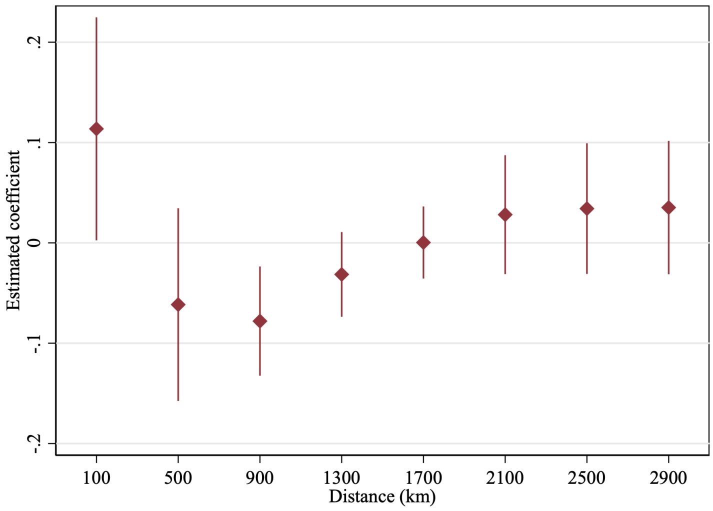
Notes: Panel (a) shows the spatial distribution of average rice production in districts from 2001 to 2019, considering only Kharif (monsoon) season. Panel (b) highlights the top 25% rice-producing districts based on average Kharif rice production.

Figure A2: Wind Vectors in Top Rice Producers During Winter Months



Notes: Red arrows show wind direction from the centroids of top rice-producing districts. Arrow length is proportional to wind speed. Vectors are based on average monthly U and V wind components for winter months.

Figure A3: Visibility in Downwind Districts



Notes: The dependent variable is average visibility (in meters) during October–December. Coefficients are from regressions on the downwind dummy across distance bands (100–2,900 km). All regressions include district-pair fixed effects, top rice-producing district-by-year fixed effects, weather controls, and nightlight intensity. Confidence intervals are based on standard errors clustered by both downwind districts and top rice-producing districts.

Table A1: Air Pollution in Downwind Districts

	Distance between top rice producers and downwind districts (kilometers)							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	100	500	900	1300	1700	2100	2500	2900
Downwind	0.02*	0.03**	0.09***	0.09***	0.08***	0.06***	0.06***	0.06***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Observations	16120	284920	672260	1022120	1248680	1363800	1405080	1407020
Mean PM 2.5 Levels	97.86	80.92	74.66	70.97	69.06	68.02	67.24	67.19

	Distance between top rice producers and downwind districts (kilometers)							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	100	500	900	1300	1700	2100	2500	2900
Downwind	0.02***	0.03***	0.05***	0.05***	0.04***	0.03***	0.03***	0.03***
	(0.01)	(0.01)	(0.00)	(0.00)	(0.00)	(0.00)	(0.01)	(0.01)
Observations	16120	284920	672260	1022120	1248680	1363800	1405080	1407020
Mean of Dep. Var.	0.16	0.16	0.16	0.16	0.16	0.16	0.16	0.16

Notes: Dependent variable in panel (a) is district-level standardized average PM 2.5 for October–December. In panel (b), it is an indicator for episodes when PM 2.5 exceeds one standard deviation above the district mean. All regressions include district-pair fixed effects, top rice-producing district-by-year fixed effects, weather controls, and nightlight intensity. Standard errors, clustered on both downwind district and top rice-producing district, are shown in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Table A2: Pollution and Crime in Upwind vs. Downwind Districts

	Pollution		Crime rate per 100000 individuals					
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	PM 2.5	Extreme PM 2.5	Violance	Property	Economic	Women	Public	Total
Downwind	0.08***	0.04***	0.75**	0.59***	−0.06	0.21**	0.30***	1.79***
	(0.01)	(0.00)	(0.30)	(0.14)	(0.06)	(0.09)	(0.07)	(0.38)
Upwind	−0.05***	−0.03***	−0.94***	0.03	0.16***	0.03	−0.08	−0.80*
	(0.02)	(0.01)	(0.29)	(0.14)	(0.06)	(0.09)	(0.07)	(0.41)
Observations	672260	672260	654200	654200	654200	654200	654200	654200
Mean of Dep. Var.	−0.00	0.16	45.18	31.00	6.93	15.27	5.65	104.03

Notes: All regressions include district-pair fixed effects, top rice-producing district-by-year fixed effects, weather controls, and nightlight intensity. Sample restricted to downwind districts within 900 km of top rice-producing districts. Standard errors, clustered on both downwind district and top rice-producing district, are shown in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Table A3: Crime in Downwind Districts in Summer

	Pollution		Crime rate per 100000 individuals					
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	PM 2.5	Extreme PM 2.5	Violance	Property	Economic	Women	Public	Total
Downwind (summer)	−0.02	0.01	−0.21	−0.19	−0.03	−0.20**	0.21*	−0.42
	(0.02)	(0.01)	(0.28)	(0.14)	(0.06)	(0.09)	(0.12)	(0.37)
Windspeed (summer)	0.15***	0.05***	0.26	1.50***	0.51***	−0.33	0.39***	2.34**
	(0.03)	(0.01)	(0.63)	(0.51)	(0.13)	(0.21)	(0.11)	(0.96)
Temperature (summer)	0.26***	0.04***	1.16**	0.38	0.68***	0.30*	0.32*	2.84***
	(0.02)	(0.01)	(0.58)	(0.35)	(0.09)	(0.16)	(0.19)	(0.81)
Rainfall (summer)	0.11***	0.07***	−5.55***	−0.59	−0.03	0.60*	−0.70***	−6.25***
	(0.03)	(0.02)	(1.08)	(0.54)	(0.18)	(0.32)	(0.13)	(1.58)
Nightlight	−0.00	−0.01***	1.23***	1.01***	0.03	0.13**	0.08***	2.48***
	(0.00)	(0.00)	(0.25)	(0.29)	(0.05)	(0.06)	(0.03)	(0.37)
Observations	672260	672260	654200	654200	654200	654200	654200	654200
Mean of Dep. Var.	−0.00	0.16	45.18	31.00	6.93	15.27	5.65	104.03

Notes: All regressions include district-pair fixed effects and top rice-producing district-by-year fixed effects. Sample limited to downwind districts within 900 km. Standard errors, clustered on both downwind district and top rice-producing district, are shown in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Table A4: Crop Yields, Agricultural Production, and Income in Downwind Districts

	Agricultural outcomes		GDP (rupees per person)		
	(1) Production	(2) Yield	(3) Agriculture	(4) Industry	(5) Services
Downwind	15.69	86.60***	−20.88	−66.22**	−246.05***
	(10.35)	(29.87)	(35.80)	(30.17)	(75.56)
Observations	626999	624282	504195	504195	504195
Mean of Dep. Var.	701.38	2394.69	6232.49	8123.68	13846.49

Notes: Dependent variables in columns 1 and 2 are overall crop production and yield at the district level. Dependent variables in columns 3 to 5 are district-level Gross Domestic Product (GDP) in rupees per person at constant prices. All regressions include district-pair fixed effects, top rice-producing district-by-year fixed effects, weather controls, and nightlight intensity. Sample limited to downwind districts within 900 km. Standard errors, clustered on both downwind district and top rice-producing district, are shown in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Table A5: Sensitivity Based on Different Wind Angle Thresholds for Downwind Districts

	Crime rate per 100000 individuals					
	(1) Violance	(2) Property	(3) Economic	(4) Women	(5) Public	(6) Total
Downwind 20	0.54**	0.47***	−0.07	0.15*	0.26***	1.35***
	(0.27)	(0.14)	(0.06)	(0.08)	(0.10)	(0.36)
Observations	654200	654200	654200	654200	654200	654200
Mean of Dep. Var.	45.18	31.00	6.93	15.27	5.65	104.03

	Crime rate per 100000 individuals					
	(1) Violance	(2) Property	(3) Economic	(4) Women	(5) Public	(6) Total
Downwind 40	0.97***	0.87***	−0.06	0.32***	0.36***	2.45***
	(0.34)	(0.16)	(0.06)	(0.09)	(0.07)	(0.42)
Observations	654200	654200	654200	654200	654200	654200
Mean of Dep. Var.	45.18	31.00	6.93	15.27	5.65	104.03

	Crime rate per 100000 individuals					
	(1) Violance	(2) Property	(3) Economic	(4) Women	(5) Public	(6) Total
Downwind 60	1.18***	1.03***	−0.03	0.28***	0.41***	2.87***
	(0.36)	(0.18)	(0.07)	(0.10)	(0.10)	(0.47)
Observations	654200	654200	654200	654200	654200	654200
Mean of Dep. Var.	45.18	31.00	6.93	15.27	5.65	104.03

Notes: All regressions include district-pair fixed effects, top rice-producing district-by-year fixed effects, weather controls, and nightlight intensity. Sample limited to downwind districts within 900 km. Standard errors, clustered on both downwind district and top rice-producing district, are shown in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Table A6: Sensitivity Analysis Excluding Pollution Source Districts

	Crime rate per 100000 individuals					
	(1) Violance	(2) Property	(3) Economic	(4) Women	(5) Public	(6) Total
Downwind	0.92**	0.63***	−0.08	0.22**	0.35***	2.04***
	(0.38)	(0.17)	(0.07)	(0.11)	(0.10)	(0.46)
Windspeed	3.50	−2.19*	1.13**	−0.48	−1.01**	0.94
	(2.74)	(1.11)	(0.52)	(0.60)	(0.44)	(3.26)
Temperature	−0.27	−0.54*	0.60***	0.01	−0.30***	−0.50
	(0.64)	(0.28)	(0.11)	(0.15)	(0.09)	(0.80)
Rainfall	−12.63***	2.03	−1.32**	0.88	−0.53	−11.57***
	(3.09)	(1.86)	(0.66)	(0.82)	(0.85)	(4.31)
Nightlight	1.42***	1.32***	0.01	0.10	0.05	2.91***
	(0.34)	(0.37)	(0.06)	(0.08)	(0.04)	(0.47)
Observations	481851	481851	481851	481851	481851	481851
Mean of Dep. Var.	47.32	32.92	7.04	16.20	6.48	109.97

Notes: All regressions include district-pair fixed effects, top rice-producing district-by-year fixed effects, weather controls, and nightlight intensity. The sample excludes source districts and is restricted to downwind districts located within 900 kilometers. Standard errors, clustered at both the downwind district and top rice-producing district levels, are shown in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Table A7: Estimates for Downwind based on Daily Wind Direction Changes

Panel A: Linear Specification

	Crime rate per 100000 individuals					
	(1) Violance	(2) Property	(3) Economic	(4) Women	(5) Public	(6) Total
Downwind	7.98***	3.18***	0.29	0.39	0.75	12.59***
	(1.71)	(0.81)	(0.29)	(0.46)	(0.73)	(2.61)
Windspeed	−0.62	−1.55*	0.85**	−1.19**	−1.01**	−3.51
	(1.70)	(0.81)	(0.34)	(0.50)	(0.48)	(2.41)
Temperature	−0.89**	−0.53***	0.61***	−0.02	−0.27***	−1.11**
	(0.41)	(0.20)	(0.09)	(0.11)	(0.07)	(0.55)
Rainfall	−5.11**	1.49	−1.25***	−0.52	−0.06	−5.45
	(2.24)	(1.20)	(0.45)	(0.69)	(0.50)	(3.30)
Nightlight	1.82***	0.97***	0.04	0.17***	0.13***	3.12***
	(0.28)	(0.25)	(0.05)	(0.06)	(0.04)	(0.43)
Observations	1360034	1360034	1360034	1360034	1360034	1360034
Mean of Dep. Var.	45.09	30.35	7.01	15.21	6.21	103.86

Panel B: Quadratic Specification

	Crime rate per 100000 individuals					
	(1) Violance	(2) Property	(3) Economic	(4) Women	(5) Public	(6) Total
Downwind	1.985	−0.653	3.339 * **	−0.983	−1.115	2.573
	(2.68)	(1.27)	(0.62)	(0.87)	(0.94)	(3.87)
Downwind Square	8.939 * *	5.722 * **	−4.552 * **	2.050*	2.782	14.940 * **
	(3.76)	(1.72)	(0.72)	(1.12)	(2.41)	(5.70)
Windspeed	−0.623	−1.552*	0.852 * *	−1.187 * *	−1.014 * *	−3.523
	(1.70)	(0.81)	(0.34)	(0.50)	(0.49)	(2.41)
Temperature	−0.880 * *	−0.528 * **	0.602 * **	−0.022	−0.270 * **	−1.098 * *
	(0.41)	(0.20)	(0.09)	(0.11)	(0.07)	(0.55)
Rainfall	−5.101 * *	1.500	−1.256 * **	−0.516	−0.053	−5.427
	(2.24)	(1.20)	(0.45)	(0.69)	(0.50)	(3.30)
Nightlight	1.817 * **	0.966 * **	0.037	0.166 * **	0.135 * **	3.121 * **
	(0.28)	(0.25)	(0.05)	(0.06)	(0.04)	(0.43)
Observations	1360034	1360034	1360034	1360034	1360034	1360034
Mean of Dep. Var.	45.09	30.35	7.01	15.21	6.21	103.86

Notes: The downwind variable represents the proportion of days in October, November, and December during which a given district was downwind of the source districts. All regressions include district-pair fixed effects, top rice-producing district-by-year fixed effects, weather controls, and nightlight intensity. Regressions are estimated on the full sample without distance restrictions. Standard errors, clustered at both the downwind district and top rice-producing district levels, are shown in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.