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Political Cycles in Crop Residue Burning: Evidence from India

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Abstract

This paper examines the relationship between electoral incentives and crop residue burning (CRB) in India. Exploiting the asynchronous nature of state legislative assembly elections, we investigate whether the proximity to election timing influences CRB incidence. We construct a novel dataset combining 1-km resolution daily NASA remote sensing data on CRB with state electoral constituency information. Our findings reveal a significant increase in CRB before elections, suggesting political incentives play a role in its persistence. We provide evidence that this pre-electoral spike is unlikely to be driven by increased crop production, pointing instead to the relaxed law enforcement for political gain.

Keywords: Political cycles, crop residue burning, environmental regulation

JEL classification: D72, O13, O17, O18, Q53, Q54, Q58

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1 Introduction

The large-scale burning of crop residue has well-documented negative effects on health, education, and productivity (Awasthi, Singh, Mittal, Gupta, & Agarwal, 2010; Raza et al., 2022; Singh et al., 2022). Despite this, crop residue burning (CRB) remains a widespread practice, particularly in northern India[1]. It has often been argued that a lack of political will is responsible for the persistence of crop residue burning. In this paper, we test this hypothesis by analyzing patterns in CRB based on the proximity to the legislative assembly election timings in each constituency.

India is a particularly important setting to study the effect of political cycles on CRB given that the majority of the Indian population is dependent on agriculture. Despite being illegal, CRB is an inexpensive and widespread practice among farmers (Shyamsundar et al., 2019; Jack, Jayachandran, Kala, & Pande, 2022). It remains prevalent, particularly in regions of northern India where crop residue is abundant and there is a lack of profitable alternatives for this residue..

Political cycles can affect crop residue burning in several ways. Firstly, disposable income might increase before elections. Cole (2009) shows that farm loans disbursed by government banks increase by 5-10 percentage points in election years. Banerjee, Kumar, Pande, and Su (2011) note the presence of cash or kind-based vote buying before elections using data from a field experiment in New Delhi. Additionally, lax implementation of environmental laws is often observed in the lead-up to elections (Pailler, 2018; Bhuvaneshwari, Hettiarachchi, & Meegoda, 2019). This combination of increased income and resources along with lax regulatory enforcement, is a possible avenue through which the likelihood of CRB can potentially increase.

There is a large literature on the effects of political cycles in the context of both developed and developing countries. Many of these studies focus on macroeconomic outcomes (Aidt, Asatryan, Badalyan, & Heinemann, 2020; Akhmedov & Zhuravskaya, 2004; Alesina, 1988; Brender & Drazen, 2005; Galli & Rossi, 2002; Katsimi & Sarantides, 2012; McCallum, 1978;

[1] As the world's second-largest crop producer, India generates approximately 500 million metric tons (MT) of crop residue annually. Approximately 100 metric tons are burnt as residue. (Lan, Eastham, Liu, Norford, & Barrett, 2022)

Nordhaus, 1975).

The literature on political cycles and environmental outcomes is relatively novel and growing. Li, Wei, Liao, and Huang (2015) show that local governments in China tend to relax environmental regulations before major political events to boost short-term economic growth, leading to increased pollution. Some studies identify evidence of political cycles in deforestation (Pailler, 2018). Balboni, Burgess, Heil, Old, and Olken (2021) explore the effect of political cycles on forest fires in Indonesia, finding that forest fires significantly reduce during election years and increase in the years following elections.

In the Indian context, several studies have documented the effects of political cycles on various outcomes. Khemani (2004) finds evidence of political cycles both in public service delivery, such as road construction, and fiscal instruments, such as commodity taxes. Baskaran, Min, and Uppal (2015) show that electricity provision increases significantly during bye-election years. Fagernäs and Pelkonen (2018) find that teacher hiring and teacher transfers increase after legislative assembly elections. Bhattacharjee (2022) finds significant improvements in child health outcomes before elections. Additionally, Aggarwal, Chatterjee, and Jha (2024) find the role of political cycles in influencing the Minimum Support Price (MSP) for food grains.

Building on this literature, we investigate the specific relationship between political cycles and CRB. The fact that all states do not have elections at the same time provides us with the required variation to study this effect. We employ a fixed effects regression model with climatic, population, and political variables as controls. We find a significant increase in the likelihood of crop residue burning during the winter months immediately preceding elections, while no comparable effect is observed for summer months or post-election periods. Notably, the results are robust to the inclusion of rice yield, the crop that contributes to over half of all crop residue burnt in India. To capture long-term policy changes and economic developments within states, our empirical strategy includes state-specific year trends.

Our paper makes several contributions to the literature. Firstly, we add to the body of work on the relationship between political institutions and environmental outcomes (Lemos & Agrawal, 2006; Ribot, Agrawal, & Larson, 2006; Cabrales & Hauk, 2011; Oldekop, Sims, Karna, Whittingham, & Agrawal, 2019). Some of these papers study the effect of democracy on environmental outcomes (Congleton, 1992; Bernauer & Koubi, 2009; Fredriksson & Neumayer, 2013; Lv, 2017; Von Stein, 2022; Acheampong, Opoku, & Dzator, 2022). Since elections are one of the key features of a democracy, this paper makes an important contribution to the existing literature by studying the effect of the timing of elections on crop residue burning, a major contributor to air pollution in India and other emerging economies.

To the best of our knowledge, this is one of the first papers to analyze the effect of political incentives on crop residue burning in India, and more broadly in the context of developing countries. Previous research has primarily focused on macroeconomic outcomes and policy instruments. However, the effect on environmental regulations remains relatively unexplored. Secondly, an advantage of this study is that while most of the previous studies in India used yearly data, we use monthly data to uncover evidence of political cycles. This allows us to cleanly identify the pre-election effects. This is not possible using yearly data since the data corresponding to the electoral year is composed of both pre and post-election months. Finally, we contribute to the literature on environmental externalities of agricultural production (Hargrave & Kis-Katos, 2013; Börner, Kis-Katos, Hargrave, & König, 2015; Gatto, Wollni, Asnawi, & Qaim, 2017; Krishna, Euler, Siregar, & Qaim, 2017). In the Indian context, there is evidence that shows that the Subsoil Water Act, which mandates a delay in the sowing of paddy so that the pressure on groundwater is lessened, actually leads to an increase in crop residue burning (Agarwala, Bhattacharjee, & Dasgupta, 2022).

The paper is divided into six sections. Section 2 provides the institutional background on state assembly elections and legislation on CRB in India. Section 3 describes the data sources and variables used in the study, and Section 4 outlines the empirical strategy, including the regression model and controls. Section 5 presents the findings of the study and Section 6 has the concluding remarks.

2 Background

2.1 State Assembly Elections in India

The Constitution of India delineates the responsibilities between the central and state governments, which is crucial in understanding their roles in legislative matters including environmental regulation. The central government is responsible for legislating on items listed in the Union List, such as defence and foreign affairs, while state governments handle issues listed in the State List, which includes public order, police, and agriculture. The Concurrent List provides for shared jurisdiction, where both levels of government can create laws.

In India, State Assembly elections are held to elect Members of State Legislative Assemblies (MLAs), distinct from national elections that elect members to the Lok Sabha, the lower house of Parliament. These elections are conducted every five years in designated assembly constituencies, with the party or coalition securing a majority being invited by the governor to form the state government. The number of assembly constituencies varies depending on the state's population and different states have elections in different years. This structure underscores the autonomy and responsibility of state governments in addressing local issues, including environmental concerns such as crop residue burning.

The umbrella legislation governing environmental protection in India is the Environment (Protection) Act of 1986. As per the law, both central and state governments have the power to legislate on various aspects of the environment. The shared responsibility for enforcing environmental regulations between different levels of government often results in inconsistencies, especially during election seasons when political motivations may impact the rigour with which these laws are implemented.

2.2 Legislation on CRB

India has implemented a comprehensive legislative framework to address CRB. The Air (Prevention and Control) Pollution Act of 1981 prohibits the burning of non-fuel materials likely to cause air pollution, while the Environmental Protection Act of 1986 bars activities that emit pollutants above the prescribed standards and imposes legal consequences for violations. Additionally, Section 144 of the Civil Procedure Code (CPC) has also been invoked to specifically ban paddy burning.

In 2014, the Indian Ministry of Agriculture introduced the National Policy for Management of Crop Residue (NPMCR), aimed at reducing CRB through efficient utilization and promotion of on-site management practices. This was followed by the National Green Tribunal's (NGT) 2015 directive banning CRB in several states, including Rajasthan, Uttar

Pradesh, Haryana, and Punjab, with fines ranging from INR 2,500 to 15,000 for violations.

The central government plays a key role in formulating broad environmental policies and regulations, such as the NPMCR and directives from the NGT. While the central government is responsible for drafting national-level laws, the enforcement and implementation of these laws primarily fall under state jurisdiction. State governments are tasked with monitoring compliance, imposing penalties for violations, and implementing specific initiatives within their jurisdictions. For instance, until 2019, the Punjab government provided financial incentives to small farmers who refrained from burning crop residue. This scheme, although discontinued due to financial constraints and logistical challenges, highlights the state's proactive role in implementing CRB laws. Additionally, capacity-building efforts by organizations like the Confederation of Indian Industry (CII), which adopted over 100,000 acres of farmland in Punjab and Haryana to provide machinery, technical training, and awareness campaigns, further demonstrate the state's responsibility in tackling CRB challenges.

3 Data

3.1 CRB data

The data used in the analysis comes from the Moderate Resolution Imaging Spectroradiometer (MODIS) sensor aboard Terra and Aqua satellites. These two satellites are operated by NASA, a US space agency. The fire count data is combined from MODIS products Aqua MYD14A2 and Terra MOD14A2 to create raster layers for burnt areas date-wise from the available data. The raw data can be conveniently accessed from `https://doi.org/10.5067/MODIS/MOD14A2.006` for Terra MOD14A2 and `https://doi.org/10.5067/MODIS/MYD14A2.006` for Aqua MYD14A2. These two satellites identify fires at 1-km resolution on the Earth's surface every one to two days. Data is available every 8 days from mid-2002. While Terra MODIS is available from 2000, Aqua MODIS is only available since mid-2002. Our study uses data collected for the period 2003-2018 over Indian Regions.

Our study only accounts for agricultural fires and not forest fires. To mask out non-agricultural areas, we have used the Land Use Land Cover dataset created by the European

Space Agency's Climate Change Initiative Land Cover Maps. The data can be accessed at `http://maps.elie.ucl.ac.be/CCI/viewer/index.315.php`. Moreover, we consider the harvest months of October and November for winter burning and April and May for summer burning. These are the months when fires on agricultural land usually reflect CRB.

CRB is observed seasonally during winters and summers and occurs mainly after the two primary harvesting seasons of India: Rabi and Kharif. Major crop residue that contributes to CRB is paddy residue during the winter season (October-November), and wheat residue during the summer season (April-May). The monthly CRB data has been generated from the fire count data available from 2003 to 2018.[2]

Our unit of analysis is an assembly constituency. State elections are held in India at the level of assembly constituencies. On average, each district consists of 7 assembly constituencies. The issue observed with the use of assembly constituency as the unit of analysis is that constituency borders changed in 2008. Delimitation commissions are created by the Indian parliament in the years 1952, 1963, 1973 and 2002 to redefine the boundaries of state assembly constituencies. The recommendations of the last 2002 delimitation commission were implemented in 2008. The redefinition of constituency boundaries makes it difficult to compare within the same assembly constituencies over time. As a solution to this problem, we created the data for the entire period according to the post-2008 delimitation definition of constituency boundaries. This enables us to include constituency fixed effects in our estimating equation as the pre-2008 and the post-2008-CRB data have a consistent definition of constituency boundary.

A limitation of the used data is that it only captures large fires. We cannot use other available data sets due to data issues.[3] To understand the limitations of MODIS Fire prod-

[2]For agricultural burning, fire detects are combined from the data collection by two satellites operated by US space agency NASA: Aqua MYD14A2 (`https://doi.org/10.5067/MODIS/MYD14A2.006`) and Terra MOD14A2 (`https://doi.org/10.5067/MODIS/MOD14A2.006`). These are Moderate Resolution Imaging Spectroradiometer (MODIS) sensors aboard the Terra and Aqua satellites. To exclude fire data from non-agriculture areas like forest fires, we used European Space Agency's Climate Change Initiative Land Cover Maps (ESA CCI-LC Maps version 2.0.7, available at `http://maps.elie.ucl.ac.be/CCI/viewer/index.php`). The agricultural fire areas are extracted for every assembly constituency date-wise from the available imagery. The daily CRB data is aggregated at the monthly level.

[3]The unavailability of the data for several years makes the use of available alternate higher resolution data like Landsat-based classification and indices difficult. The data from VIIRS is available for a shorter period than MODIS as VIIRS was commissioned in the year 2012.

ucts, it leads only to the estimation of the effects of the subsoil water act on large agricultural fires in our study.

In our analysis, we control for several potential confounding factors, including climatic factors, policy, demographic and agricultural variables to isolate the effect of political cycles on crop residue burning that we describe below.

3.2 Biophysical Variables

We use precipitation and wind speed as controls in our regressions. The precipitation data comes from the Tropical Rainfall Measuring Mission (TRMM) 3B42 launched in 1997 to study rainfall for research related to weather and climate. It is available at a 3-hour resolution, however, the daily resolution data (in millimetres) is downloaded. The raw data for precipitation is available at `https://doi.org/10.5067/TRMM/TMPA/3H/7`. We used GLDAS 2.1 version of the Global Land Data Assimilation System (GLDAS) for daily data on wind speed (in metre per second). The raw wind speed data is available at `https://doi.org/10.5067/E7TYRXPJKWOQ`.

The daily data on the above biophysical variables is converted into a month-level assembly constituency using the average of the daily observations over months in a given constituency.

3.3 Policy Variables

We define the proximity to the state election by an indicator variable that takes the value 1 for 0 to 11 months before the election and 0 otherwise. The election data is available at `https://eci.gov.in/statistical-report/statistical-reports/`.

We also control for the timing of the introduction of the Mahatma Gandhi National Employment Guarantee Scheme (MGNREGA). MGNREGA is a rural workfare scheme that provides 100 days of guaranteed work at a state-level minimum wage. It was introduced in three phases in years 2006, 2007 and 2008. The number of districts included in Phases 1, 2 and 3 were 200, 130 and 295 respectively. Since MGNREGA can affect rural wages, it can also affect CRB by affecting the demand for agricultural workers. An indicator variable is included for all years following the implementation of MGNREGA in the district. The data is available at `https://nrega.nic.in/MNREGA_Dist.pdf`.

3.4 Demographic and Agricultural variables

We include controls for demographic characteristics at the district level, such as the proportions of Scheduled Castes and Scheduled Tribes, Muslims, urban population, and the sex ratio from the 2001 and 2011 census. The figures corresponding to the intercensal years are calculated using linear interpolation. These variables are used for robustness checks performed in Table 5.

The agricultural production data is obtained from the official website of the Ministry of Agriculture & Farmers Welfare at the district level available at `https://aps.dac.gov.in/APY/Public_Report1.aspx`. The data consists of the total rice production (in 1000 tons) and yield in the Kharif season and total wheat production and yield data in the Rabi season. These variables are used as controls in the regressions reported in column 3 of Table 4.

4 Estimation Strategy

To determine how the proximity to the state election influences the crop residue burning (CRB) we run the following regression model:

$$Y_{csmt} = \alpha_c + \tau_t + \delta_m + \beta E_{smt} + \gamma X_{csmt} + \psi_s \times t + \epsilon_{csmt} \tag{1}$$

Where Y_{csdmt} is an indicator variable for the presence of CRB in constituency c, state s, and month m year t. E_{smt} takes the value 1 if the month m is between 0 and 12 months before election and 0 otherwise. X_{csmt} denotes the different controls- climatic, political and demographic characteristics.

In our context, unobserved variables such as regional economic conditions, variations in local governance, and cultural practices related to agriculture could confound the relationship between election timing and CRB. For instance, regions with higher economic prosperity might have better access to alternative residue management techniques, reducing CRB independently of election cycles. Additionally, variations in local governance and enforcement of environmental regulations can lead to differential impacts on CRB, unrelated to political cycles. Social and cultural factors, such as traditional farming practices and community norms, may also play a significant role in influencing CRB behaviours.

The control variables include climatic controls (precipitation and wind speed), population controls (district-level proportions of Scheduled Castes and Scheduled Tribes, urban population proportions, literacy rates, and sex ratio), and political controls (incumbent's political party and the sex of the incumbent MLA). We also control for the presence of the large-scale workfare scheme, MGNREGA, which was introduced in a phased manner during our sample period.

Additionally, we include assembly constituency fixed effects, year-fixed effects, month-fixed effects, and state-specific year trends. Since the variation in our independent variable comes at the state-month-year level, we cluster the standard errors at the state level. Moreover, we acknowledge the possibility of endogenous election timing, where electoral schedules might be strategically chosen based on anticipated favourable conditions. We address this by exploiting the exogenous variation in election timing across states, which reduces the likelihood of endogeneity bias. We implement wild bootstrap cluster to account for the small number of clusters.

5 Results

Table 2 shows the effect of political cycles on the likelihood of CRB with separate analyses for the summer and winter months. Each column progressively adds various controls to isolate any electoral effect on CRB. We find that the probability of CRB during the winter months increases at a statistically significant level during the period immediately before assembly elections. For example, as shown in column (7), when all controls are accounted for, the likelihood of CRB in the winter months in the period 0-11 months before elections increases by around 0.6%. Panel B shows that largely no such effects are seen for the likelihood of CRB in summer, although the statistical significance is maintained for the same period. One potential explanation for this comes from the cropping cycle of CRB-emitting crops. Rice, wheat and sugarcane have the highest crop residue burnt, accounting for 93% of all CRB in India (Jain, 2014). Rice, the most dominant food grain in India and one that accounts for 43% of all CRB in the country is harvested primarily during the winter months. Sugarcane has a long and diverse harvesting period that spans the late winter and early summer months while wheat is harvested during summer, potentially explaining why the results are primarily significant for the winter months, while some significance is maintained for the period 0-11 months before elections for summer months when all control factors are accounted for.

When CRB is measured as a count variable, as shown in Table 3, no significant results are found. This could be because of a few larger fires driving the count variable which makes it more difficult for smaller, more widespread fires to be detected. Moreover, because the data is aggregated at the constituency level, it is harder to detect smaller fires which are more likely to occur at a more localised level.

Next, we try to find the mechanisms behind our results. We identify two possible channels - an increase in the amount of residue generated due to increased production in election years or due to the lax implementation of laws immediately before elections. To identify whether increased residue being left behind is what drives our results, we estimate our regression, controlling for the production of rice which is the main producer of residue in winter. The results are presented in Table 4. Aligning with our results in Table 2, across all specifications, the coefficients for the periods 12-23 months before elections, 13-24 months after elections, and 1-12 months after elections are statistically insignificant, while that of the period 0-11 months before elections is significant, indicating that the observed increase in CRB is specifically related to the months immediately preceding elections. This supports the hypothesis that temporal proximity to the elections leads to an increase in CRB, indicating that the phenomenon is not driven by an increase in crop production as the inclusion of yield controls does not negate the pre-election effect.

Lastly, to ensure the robustness of our findings, Table 5 presents various checks. Column (1) controls for seasonal variation and maintains a positive and significant coefficient for 0-11 months before elections. Columns (2) and (3) control for Punjab and Haryana, known to be significant drivers of CRB. Column (2) excludes the two states and still yields a positive and significant coefficient for the main period of interest. In contrast, Column (3) tests the model only for these two states. The fact that this does not yield a significant result further strengthens the argument, demonstrating that these states cannot be said to be the sole drivers of the trend. Column (4) includes the post-delimitation data to account for the changes in electoral boundaries and shows that the positive coefficient remains significant. Lastly, column (5) tests for 0-5 months and 6-11 months separately - The robustness checks maintain the validity of the results and confirm that the conclusion that CRB increases in the months leading up to elections is consistent across various controls (Table 4).

6 Conclusion

This paper examines the link between political incentives and crop residue burning in India. We focus on how the proximity to a state legislative assembly election influences crop residue burning. Our results which are robust across a range of specifications find that CRB increases significantly in the period immediately preceding an assembly election, suggesting that political incentives play an important role in sustaining a practice that is detrimental to both the environment and health. The results majorly align with the previous literature on political cycles which suggests political incentives affect the willingness of politicians to relax regulations.

Interestingly, however, comparing these results with studies from other contexts, such as the observed decrease in forest burning in Indonesia during election years, reveals a notable contrast. In Indonesia, increased public awareness and the direct health impacts of forest fires may prompt stricter environmental policies during elections (Balboni et al., 2021). Conversely in India, farmers constitute a significant and influential lobby, and electoral incentives may prioritize agricultural stakeholders over environmental quality. For example, Aggarwal et al. (2024) demonstrate how India's Minimum Support Prices (MSP) can be manipulated for political incentives, especially around election times. This contrast underscores how different factors, including electorate preferences and public awareness, shape the relationship between political cycles and environmental outcomes. Overall, our study contributes to the understanding of how political cycles influence environmental practices. The findings have important policy implications in the context of designing appropriate policies to reduce crop residue burning in the context of developing countries.

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Table 1: Summary statistics

	(1)	(2)	(3)
Variable	**Mean**	**Std. Dev.**	**N**
CRB Dummy	0.071	0.257	141757
0-11 Months Before Elections	0.222	0.416	134577
Precipitation	42.214	51.488	141750
Wind Speed	5.136	1.483	140490
Temperature	15105.279	256.467	141393
Proportion of SC	0.167	0.076	123585
Proportion of ST	0.084	0.143	123585
Proportion of Urban	0.272	0.198	141470
Sex Ratio	0.929	0.042	141470
Proportion of Literates	0.592	0.115	141470
Female MLA	0.066	0.249	134577

Notes: The table presents the mean and the standard deviation of the main variables used in this analysis.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 2: Elections and Crop Burning: Likelihood

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Panel A: Winter							
0-11 Months Before Elections	0.0104**	0.0092**	0.0099**	0.0097**	0.0094**	0.0092**	0.0060*
	(0.0115)	(0.0124)	(0.0160)	(0.0169)	(0.0233)	(0.0292)	(0.0784)
	[0.0192]	[0.0188]	[0.0249]	[0.0258]	[0.0366]	[0.0406]	[0.0729]
12-23 Months Before Elections							-0.0009
							(0.8168)
							[0.8159]
13-24 Months After Elections							-0.0095
							(0.1309)
							[0.2246]
1-12 Months After Elections							-0.0013
							(0.8614)
							[0.8990]
Observations	137085	135567	119681	119681	119681	119681	119681
Mean of Dependent Variable	0.0716	0.0724	0.0794	0.0794	0.0794	0.0794	0.0794
Number of Constituencies	3998	3960	3472	3472	3472	3472	3472
Panel B: Summer							
0-11 Months Before Elections	-0.0091	-0.0103	-0.0070	-0.0068	-0.0062	-0.0074	-0.0164*
	(0.3031)	(0.2031)	(0.4063)	(0.3983)	(0.4762)	(0.3598)	(0.0871)
	[0.3308]	[0.2255]	[0.4210]	[0.4324]	[0.5204]	[0.3646]	[0.0687]
12-23 Months Before Elections							-0.0157
							(0.0969)
							[0.1231]
13-24 Months After Elections							-0.0040
							(0.7295)
							[0.7455]
1-12 Months After Elections							-0.0140
							(0.2908)
							[0.3122]
Observations	93295	92407	81707	81707	81707	81707	81707
Climatic Controls	NO	YES	YES	YES	YES	YES	YES
Population Controls	NO	NO	YES	YES	YES	YES	YES
Political Controls	NO	NO	NO	YES	YES	YES	YES
MNREGS Control	NO	NO	NO	NO	YES	YES	YES
State Specific Trends	NO	NO	NO	NO	NO	YES	YES

Notes: Each column in each panel represents a separate regression. The dependent variable is a dummy variable indicating whether crop burning occurred in the given constituency. Panel A shows results for the winter months (August to December), while Panel B shows results for the summer months (February to May). All specifications include fixed effects for assembly constituencies, years, and months. The controls used in the regressions are listed in the last five rows. Climatic controls include temperature, precipitation, and wind speed. Population controls cover the district-level proportions of the SC population, ST population, urban population, sex ratio, and literacy rate. Political controls consist of a dummy variable for female legislators and dummies for the parties of the legislators. The p-values are shown in parentheses. Wild bootstrap cluster p-values are reported in square brackets. Significance stars are based on wild bootstrap cluster p-values.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 3: Elections and Crop Burning: Intensity

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Panel A: Winter							
0-11 Months Before Elections	-0.0598	-0.1132	-0.1494	-0.1592	-0.1629	-0.2084	-0.2170
	(0.6751)	(0.5520)	(0.5584)	(0.5584)	(0.5528)	(0.4861)	(0.4973)
	[0.8760]	[0.8474]	[0.8189]	[0.8192]	[0.8118]	[0.7624]	[0.6697]
12-23 Months Before Elections							0.1341
							(0.3103)
							[0.2223]
13-24 Months After Elections							-0.2106
							(0.2517)
							[0.2498]
1-12 Months After Elections							0.0651
							(0.6589)
							[0.6025]
Observations	134577	133095	117741	117741	117741	117741	117741
Panel B: Summer							
0-11 Months Before Elections	-0.0671	-0.0496	-0.0201	-0.0138	-0.0061	-0.0294	-0.0914
	(0.4732)	(0.5707)	(0.8375)	(0.8909)	(0.9516)	(0.7955)	(0.5237)
	[0.5060]	[0.5523]	[0.8175]	[0.8801]	[0.9466]	[0.7801]	[0.5229]
12-23 Months Before Elections							-0.1765
							(0.3328)
							[0.3577]
13-24 Months After Elections							-0.0030
							(0.9880)
							[0.9880]
1-12 Months After Elections							-0.0203
							(0.9233)
							[0.9293]
Observations	93295	92407	81707	81707	81707	81707	81707
Climatic Controls	NO	YES	YES	YES	YES	YES	YES
Population Controls	NO	NO	YES	YES	YES	YES	YES
Political Controls	NO	NO	NO	YES	YES	YES	YES
MNREGS Control	NO	NO	NO	NO	YES	YES	YES
State Specific Trends	NO	NO	NO	NO	NO	YES	YES

Notes: Each column in each panel represents a separate regression. The dependent variable is the number of crop-burning incidents that occurred in the given constituency. Panel A shows results for the winter months (August to December), while Panel B shows results for the summer months (February to May). All specifications include fixed effects for assembly constituencies, years, and months. The controls used in the regressions are listed in the last five rows. Climatic controls include temperature, precipitation, and wind speed. Population controls are the district-level proportions of the SC population, ST population, urban population, sex ratio, and literacy rate. Political controls consist of a dummy variable for female legislators and dummies for the parties of the legislators. The p-values are shown in parentheses. Wild bootstrap cluster p-values are reported in square brackets. Significance stars are based on wild bootstrap cluster p-values.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 4: Elections and Crop Burning: With Yield Controls

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
0-11 Months Before Elections	0.0117**	0.0102**	0.0102**	0.0101**	0.0098**	0.0097**	0.0065**
	(0.0113)	(0.0121)	(0.0136)	(0.0143)	(0.0205)	(0.0238)	(0.0539)
	[0.0163]	[0.0162]	[0.0200]	[0.0205]	[0.0315]	[0.0320]	[0.0499]
12-23 Months Before Elections							-0.0010
							(0.8073)
							[0.8068]
13-24 Months After Elections							-0.0096
							(0.1331)
							[0.2302]
1-12 Months After Elections							-0.0013
							(0.8570)
							[0.8963]
Observations	119481	118933	118933	118933	118933	118933	118933
Mean of Dependent Variable	0.0794	0.0798	0.0798	0.0798	0.0798	0.0798	0.0798
Number of Constituencies	3476	3458	3458	3458	3458	3458	3458
Climatic Controls	NO	YES	YES	YES	YES	YES	YES
Population Controls	NO	NO	YES	YES	YES	YES	YES
Political Controls	NO	NO	NO	YES	YES	YES	YES
MNREGS Control	NO	NO	NO	NO	YES	YES	YES
State Specific Trends	NO	NO	NO	NO	NO	YES	YES

Notes: Each column in each panel represents a separate regression. The dependent variable is a dummy indicating whether crop burning occurred in the given constituency. The months included are from August to December. All specifications include fixed effects for assembly constituencies, years, and months. The controls used in the regressions are listed in the last five rows. Climatic controls consist of temperature, precipitation, and wind speed. Population controls are district-level proportions of the SC population, ST population, urban population, sex ratio, and literacy rate. Political controls include a dummy variable for female legislators and dummy variables for the parties of the legislators. The p-values are shown in parentheses. Wild bootstrap cluster p-values are reported in square brackets. Significance stars are based on wild bootstrap cluster p-values.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 5: Robustness

	(1) Excluding August-December	(2) Excluding Punjab Haryana	(3) Only Punjab Haryana	(4) Including Post Delimitation	(5) 0-5,6-11 Months Before
0-11 Months Before Elections	0.0100**	0.0097*	0.0709	0.0042**	
	(0.0362)	(0.0473)	(0.1231)	(0.0186)	
	[0.0355]	[0.0894]	[0.1666]	[0.0223]	
0-5 Months Before Elections					0.0089
					(0.4123)
					[0.5629]
6-11 Months Before Elections					0.0097
					(0.3904)
					[0.4219]
Observations	72182	112481	7200	244292	119681
Mean of Dependent Variable	0.0792	0.0583	0.4082	0.1080	0.0794
Number of Constituencies	3472	3266	206	3454	3472

Notes: Each column in each panel represents a separate regression. The dependent variable is a dummy indicating whether crop burning occurred in the given constituency. All specifications include fixed effects for assembly constituencies, years, and months, climatic controls, population controls, political controls, control for the public workfare program MNREGS and state-specific year trends. Climatic controls consist of temperature, precipitation, and wind speed. Population controls are district-level proportions of the SC population, ST population, urban population, sex ratio, and literacy rate. Political controls include a dummy variable for female legislators and dummy variables for the parties of the legislators. The p-values are shown in parentheses. Wild bootstrap cluster p-values are reported in square brackets. Significance stars are based on wild bootstrap cluster p-values.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$