The Effect of Political Institutions on Crop Residue Burning

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Abstract: While crop residue burning (CRB) is held responsible for air pollution across northern India, there is lack of scientific evidence on the determinants of CRB. We put together a unique dataset on CRB using 1-km resolution disaggregated data from NASA's remote sensing products and test our hypotheses using novel causal estimation techniques to look at the impact of plausible factors such as legislation change, mechanization, labour shortage, and political factors on CRB in India. Our preliminary results show that the intensity of CRB increases before elections in constituencies which have a narrower margin of victory.

1. Introduction

Crop residue burning (CRB) is a major contributor to North India's air pollution problem (Gadde et al., 2009; Liu et al., 2018; Singh & Kaskoutis, 2014; Cusworth et al., 2018), yet there is a paucity of scientific evidence investigating the determinants of CRB. Several possible explanations for increase in CRB exist in the public domain such as mechanization, labour shortage, seasonal and political factors, and laws regulating paddy cultivation. The causal impacts of these factors have not been tested rigorously, and this paper addresses this research gap by causally testing the determinants of CRB in India. In this paper we contribute to the literature on social norms and welfare outcomes and also examine the potential spill-over effects of a public policy.

Of the many hypotheses regarding drivers of crop-burning in the public domain, mechanization in agriculture is considered the most important factor driving CRB. Punjab and Haryana contribute 48 percent of CRB emissions and have seen mechanization of agriculture in the last 30 years (Badrinath et al., 2006). In multi-cropping agricultural production systems, combined harvesters increase time efficiency, but result in increased height of post-harvest paddy stalks. Paddy straws are not used as animal-feed nor do they have any non-feed use. Farmers dispose the residue by burning it in order to clear the land for planting wheat. With increasing mechanization, the need for bulls as draught labour is effectively reduced which may affect livestock ownership and thus fodder demand by livestock owners. This further confounds the problem of crop residue management. Current government initiatives to reduce CRB are focussed on reducing the impact of combined harvesters through subsidizing the purchase and use of machines such as Happy Seeder that reduce height of paddy stalks or allow planting in an uncleared field[1]. Yet, adoption of Happy Seeder is low because of knowledge gap, high capital costs (1.5 lakhs per machine), resistance to behavioural change and capital

[1]the government announced 1151 crore subsidy in Feb 2018:https://www.pressreader.com/india/hindustan-times-delhi/20180202/281715500059148).

investment in existing machinery (Punjab Agricultural Commissioner). Schemes are not translating to behavioural change, perhaps because motivations for farmer behaviour are still unclear.

A second popular hypothesis suggests that CRB may have increased as a result of restricting paddy cultivation in the summer months in order to prevent diversion of scarce water resources in the summer. This has resulted in a very short window of time between paddy harvesting and cultivation of wheat at the end of the Kharif season. For example, Punjab and Haryana enacted the "Preservation of Sub-Soil Water Act, 2009" (ordinance in 2008), which led to a temporal shift in paddy production so that post-paddy burning now occurs later in the winter where it may interact with the winter temperature to create lower air quality standards (Liu et al., 2018). Therefore, this law may be responsible for increase in CRB as farmers switch to time-saving cultivation practices like CRB to maximise profits from agriculture.

The removal of paddy stalk is a labour-intensive process which typically involves seasonal, migrant workers from the states of Uttar Pradesh and Bihar. It is argued that agricultural labour has become a scarce commodity in parts of Punjab and Haryana due to the implementation of NREGS. Therefore, implementation of NREGS may be associated with increase in CRB due to lower labour availability. Therefore, the NREGS[2], which aimed to implement a minimum wage in rural areas, may have led to incidental costs such as increased CRB as the increase in labour costs may have led to farms shifting to labour saving agricultural practices. Further, lower availability of labour can interact with the limited time window for preparing the field for wheat cultivation (law regulating paddy cultivation) to further increase CRB. In addition to district-level labour availability, there may be individual variation in ability to hire labour based on economic class of farmer hiring labour and the number of family members who can serve as unpaid labour.

Paddy variety influences whether the crop is hand-harvested or machine harvested. For example, Basmati is hand-harvested unless it is the 11-21 variety, while Parmal is machine harvested. Therefore, Parmal and 11-21 variety are more likely to be burnt than Basmati. Similarly, variety of wheat also influences crop burning as a new variety of wheat, CSW18, can be sowed as early as October 15 in Punjab and Haryana, which leaves no time for burning the crop residue as fields need at least a week to recover after burning; paddy season is from June to October/November, while wheat season is from November to April (conversations with agricultural commissioners of Punjab and Haryana). Therefore, it is important to understand the impact of crop variety on CRB as well.

Due to farmers forming an important political constituency, there may be political reasons for lack of suppression of CRB. As a result, incidence of CRB may be related to temporal proximity to an election year. Temporal proximity to election year has been shown to be a significant factor influencing a number of policy outcomes like public goods provision, availability of agricultural credit and development outcomes such as infant mortality rate (Khemani, 2004; Bhattacharjee, 2017), and it may influence CRB as well. Therefore, it is also important to test whether political factors play a role in year-to year variation in CRB incidences; in particular, whether CRB incidence is related to electoral cycles and whether it increases in election years. In addition we can test differential effects of election year on close election constituencies, i.e. constituencies with a narrower margin of victory in the previous election.

[2]The National Rural Employment Guarantee Scheme (NREGS) is a workfare program which entitles every rural household to upto 100 days of work per year at a minimum wage. The program was implemented across India in different phases, with the poorest 200 districts included in February, 2006, another 130 districts included in April, 2007 and finally all-India implementation in the remaining districts in April, 2008.

Current literature has focussed on contribution of CRB to pollution patterns in Delhi and north India. Some papers have focussed on the “Preservation of Sub-soil Water Act, 2009” in Punjab (Liu et al., 2018), but causal analysis on the causes for CRB has not been attempted. Proposals to stem CRB assume that farmers burn their crops once they are mechanized, but this does not explain the annual variation in CRB.

One limitation to doing this analysis traditionally has been the availability of data on CRB across India and the resolution at which it is available. Few studies have attempted to use CRB data itself to understand drivers of CRB (e.g. Gupta 2010 relies on farmer reports and find mechanization to be the main driver of CRB). Of the studies that do, most are limited to Punjab or investigate impacts of CRB on pollution in Delhi (Liu et al., 2018; Cusworth et al., 2018). This paper uses remote sensing and GIS products to obtain CRB data at a highly disaggregated resolution that can be used to derive CRB area and intensity at different spatial resolutions (assembly constituency or district level). Remote sensing products are extremely useful in generating large sample sizes for hypothesis testing, and providing data where data access is restricted due to time, costs and access. These products can also provide information on biophysical variables prior to the present. These products are frequently used to understand forest fires and their impacts. In this study, we extend these techniques to crop burning similar to previous papers (Liu et al., 2018; Cusworth et al., 2018). However, unlike previous papers, the spatial extent of this study ranges across India and data for our predictor variables are collected at a similar scale and resolution (see Methods section).

Literature has quantified the economic impacts of pollution and laws regulating pollution, and such studies are very important in establishing public support for anti-pollution measures. Although there are studies examining the role of pollution on health across Indian cities, our study extends such an analysis to rural areas. Establishing the impact of CRB in rural areas may be critical in gaining support of states responsible for CRB for countering CRB. It is important to understand drivers of CRB in order to devise ways to dis-incentivise it. This paper addresses this research gap by causally testing whether (a) Mechanization; (b) “Preservation of Sub-Soil Water Act, 2009”; (c) NREGS; (d) Crop Variety and (d) Political cycles are associated with higher levels of CRB.

2. Methods

2.1 Data

2.1.1 Crop Residue Burning

For CRB, we used NASA’s MODIS 14A1 (reverb.echo.gov.in) to create raster layers for area burnt for every date that fire radiative power (FRP) was collected. Data is available for every 8 days from 2000 to 2017 at 1-km resolution. We masked out non-agricultural areas using the dataset compiled by the Global Land Cover National Mapping Organizations (GLCNMO, version 1, 2003) from MODIS images, which classifies land cover into 20 categories, including cropland (paddy, other and miscellaneous). We created datasets that quantify total area burnt (km^2), mean, mode and standard deviation of the intensity of burns per month (W/m^2) for every district and electoral constituency.

2.1.2 Biophysical variables

Since biophysical variables such as temperature, precipitation, distance to surface water, and soil type influence burning intensity and length as well as influence cropping patterns, we collect data on these sources. Precipitation data was obtained from Tropical Rainfall Measuring Mission (TRMM) 3B3, a joint mission of NASA and the Japan Aerospace Exploration Agency. TRMM was launched in 1997 to study rainfall for weather and climate research, and is available at a 3-hour resolution, but we downloaded the data at a daily resolution. We used MODIS 21A2 Land Surface Temperature and Emissivity dataset for temperature data at 1-km spatial resolution and 8-day temporal resolution. Data on Soil Type is obtained from Food and Agriculture Organization's soil portal. This dataset is "compiled using field surveys backed up by remote sensing and other environmental data, expert opinion and laboratory analysis."[3] Proximity to surface water was calculated using ArcMap on shapefiles of all-India water bodies.

2.1.3 Socio-economic variables

We collected data on socio-economic variables from the Agricultural Census, conducted by the Department of Agriculture and Cooperation, Ministry of Agriculture, Govt. of India. The Agriculture Census is conducted quinquennially since 1970-71. For the purpose of our analysis, we use rounds 7-9 which ranged temporally from 2000-01 to 2010-11. From these, we extracted district-level data on area under cultivation (single, double cropping), area under paddy and wheat cultivation, mechanization (combine harvesters), agricultural loans and livestock. Area under cultivation and area under paddy and wheat cultivation are recorded in the first two phases of each Census respectively whereas data on mechanization, agricultural loans and livestock is recorded under the Input survey phase or the 3rd phase of each Agricultural Census. We also collected information on level of infrastructure development in the districts. For this purpose, we use Global Night Light dataset generated by National Oceanographic and Atmospheric Administration (NOAA).

2.1.4 Policy-related variables

NREGS: NREGS was introduced in three phases in different districts across the country. The first phase was introduced in 2006, the second phase in 2007 and the third phase in 2008. We use the planning commission reports to identify the relative ranking of districts in terms of development index which was used for assigning the districts to the different NREGS phases following Zimmerman (2012). 200 districts belong to Phase 1, 130 districts belong to Phase 2 and 295 districts belong to Phase 3. We coded all districts with the particular phase in which NREGS was introduced in them. For example, NREGS was introduced in Katihar, Bihar in Phase 1; in Mewat, Haryana in Phase 2 and in Kullu, Himachal Pradesh in Phase 3. Therefore, Katihar, Mewat and Kullu are codified as 1, 2 and 3 respectively.

Political Cycles: We used the election dataset compiled by the Election Commission of India. Variables included all relevant information pertaining to state level elections for the post 2000 period[4] such as age andsex of the candidates. We also collected information on whether the seat was a reserved seat or not, the number of votes polled by each of the candidates and their party affiliations.

2.2Estimation Strategy

2.2.1Impact of "Preservation of Sub-Soil Water Act, 2009"

Because the "Preservation of Sub-Soil Water Act, 2009" restricts the transplanting of paddy to after June 1 in the states of Punjab and Haryana, we expect this act to impact winter burning (post-

[3]http://www.fao.org/soils-portal/soil-survey/soil-maps-and-databases/en/

[4] https://www.eci.nic.in/eci_main1/ElectionStatistics.aspx

September) and not summer burning (pre-September). Based on patterns of CRB in Punjab and Haryana (and neighbouring states with similar precipitation regimes such as Rajasthan and Madhya Pradesh)(Fig 1), we restricted our analysis to CRB after September 1 in each year. One confounding variable in this analysis is that the overall CRB was much higher in Punjab and Haryana than in states such as Rajasthan and Madhya Pradesh (control states where a similar act was not implemented; hence we scaled the response variable in the difference-in-difference analysis to the maximum area burnt in winter in a state for any year.

The main estimating equation is

$$y_{st} = \alpha_s + \tau_t + \beta T_s \times post_t + \gamma X_{st} + \epsilon_{st} \text{ …(1)}$$

where y_{st}denotes the CRB intensity in state s in year t. $post_t$is a dummy variable equal to 1 if year t corresponds to the post 2009 period. $T_s$is a dummy variable denoting the treated states (Punjab and Haryana). $\alpha_s$and $\tau_t$denote state and time fixed effects respectively. X_{st}denotes the set of controls which included annual precipitation. We tested impact at different windows of time before and after t ranging from 1 to 5 years. We used the date when 10% of maximum burns were recorded in each year (winter) as the start date of burning for each year to test whether there had been any change in the date of CRB onset. We also used date of peak burning (date of maximum area burnt) for each year to test whether there had been any change in peak CRB.

2.2.2 Impact of National Rural Employment Guarantee Act (NREGS)

We plan to use both difference in difference and regression discontinuity for this part of the analysis. The estimating equation for the difference in difference analysis is:

$$y_{dt} = \alpha_d + \tau_t + \beta N_{dt} + \gamma X_{dt} + \epsilon_{dt} \text{ ……(2)}$$

Where $y_{dt}$is the extent of crop burning (defined as the mean area burned) in district d and year t.$\alpha_d$denotes district fixed effects which controls for the factors that remained constant in a district over time.$\tau_t$denotes year fixed effects and controls for the factors common to all districts in a given year. N_{dt} is a dummy variable equal to 1 if NREGS was in operation in district d at the time period t. We additionally control for population characteristics such as the proportion of literates and the proportion of females in a district, political factors such as a dummy for the state assembly election year, proportion of female candidates, average poll percentage in the district during the last election, and weather controls like district level rainfall and temperature.

In addition to the preliminary DID analysis, we plan to use a regression discontinuity estimation strategy to analyse the role of NREGS on CRB. The regression discontinuity strategy relies on the fact that districts around the treatment threshold of the development index (used to classify NREGS phases) are similar except for the fact that some have been randomly selected for treatment. We first also plan to test the mechanism underlying this pattern by testing whether NREGS had an impact on wages and employment, where data on changes wages and employment are obtained from different rounds of the National Sample Survey (NSSO).

2.2.3 Impact of political cycles

We investigated whether timing of election affects the intensity of crop residue burning. Here the main estimating equation is

$$y_{csdmt} = \alpha_c + \tau_{tm} + \beta_1 E_{smt} + \beta_2 E_{smt} \times Margin_{csmt} + \gamma X_{csmt} + \epsilon_{csdmt} \text{……(3)}$$

Where $y_{csdmt}$is the extent of crop burning (defined as the mean area burned) in constituency c, state s, day d, month m and year t.$\alpha_c$and τ_{tm}denote constituency fixed and year-month fixed effects respectively. E_{smt} is the election dummy equal to 1 if the month m in year t in state s is 12 months before an assembly election. Since crop burning is concentrated in only a few months, we consider a window of 12 months before elections to allow complete exposure to all states.$Margin_{csmt}$denotes the margin of victory of the legislator in the last assembly election in constituency c of state s in month m and year t. X_{csmt}denotes a set of controls including a dummy for female candidate, poll percentage in the constituency during the last election, population characteristics like proportion of literates, proportion of females at the constituency level, weather controls like constituency level rainfall, temperature.

However the issue with using constituency fixed effects is that we cannot run the regression for the entire sample (2000-2017). The constituency boundaries changed with the 2008 delimitation. Thus we have to separately analyse the samples corresponding to the 2000-2007 time period and the 2008-2017 time period. Additionally we can use district fixed effects for the entire sample. The preliminary results given in this paper is based on the post 2008 delimitation sample.

3. Results

3.1 Descriptive results

Annual patterns in CRB shows that burning in summer (~June) is much higher than burning in winter (Nov-December), and there is substantial annual variation in CRB (Fig 1) (Similar figures for all states in Supplementary Information S1). Within this, some states have lower temporal annual variation in the summer (e.g. Punjab, Haryana, Madhya Pradesh) than others (e.g. Maharashtra, Andhra Pradesh). Summer burning is significantly higher than winter burning (t-test, p-value 2.2e-16, Fig 2). Interestingly, winter burning in Punjab and Haryana appears to be starting at a later date since 2008.

3.2 Impact of “Preservation of Sub-Soil Water Act, 2009”

Although the difference in difference analysis showed that The interaction of time (post-2009 and pre-2009) and treatment (Punjab and Haryana had this Act while Rajasthan and Madhya Pradesh with similar patterns did not) was significant (t-value -6.8, p-value 6.9e-12) for winter burning (post Sep 1), the significance levels were lower than for only treatment and the coefficient of interaction was negative. There was no significant difference in onset date of CRB after the act, but there was a significant increase in date of peak CRB after the act (DID, 13.410, SE 2.445, p-value4.89e-08). Therefore, there was an average delay of 13 weeks in Punjab and Haryana since the act (Figure 3).

3.3 Impact of NREGS

Mean annual CRB varies by the three phases of NREGS (Figure 4). It increased for all the districts however the patterns are different for the different NREGS roll-out phases. The spike in CRB appears to happen first for phase 1 districts which got the program first. We plan to see if the CRB trajectory can be explained by the onset of NREG in the different phases after controlling for other factors.

3.4 Impact of Political Cycles

Table 1 presents the results. Column 1 shows that the CRB intensity falls just before elections but the effect is not statistically significant. However column 2 shows that CRB intensity is higher in close election constituencies (with a lower margin of victory) compared to constituencies where the margin was higher just before elections. The same relationship is presented in Figure 5.

4. Discussion

4.1 Impact of “Preservation of Sub-Soil Water Act, 2009”

Previous studies have found a pattern of later onset date of CRB in Punjab after this act, however, they were not able to test this (Liu et al., 2018). Our study, in comparing patterns in Punjab and Haryana with comparable states is able to establish the impact of the act. However, there was no impact of the act on total burning, which suggests that the main impact may be due to interaction of CRB with colder temperatures due to later burning. Colder temperatures lead to stronger temperature inversion--and there is evidence of a cold front causing temperature inversion in north India later in the winter (Liu et al., 2017)--which prevents dispersal of aerosols thus increasing pollution levels. Further studies will need to establish this relationship with pollution.

4.2 Impact of NREGS

Implementation of NREGS was associated with increase in CRB for Phase 1 and Phase 2 but not with Phase 3. Phase 1 and Phase 2 districts were those that scored higher on a backwardness index, thus the implementation of NREGS, and its associated increase in wages, may have led to a significant change in labour dynamics. Because districts in Phase 3 were more developed, the implementation of NREGS may not have had a strong impact as the labour may already have been better compensated.

However, the analysis still does not include many control variables such as mechanization, crop variety, which may influence results. Also, because NREGS work often focussed on tasks such as watershed management, these associated factors may be responsible for the increase in CRB. Ground surveys scheduled in October-November 2018 will help establish the motivation and mechanism behind these patterns.

4.3 Impact of election cycle

The higher intensity ofCRB in close election constituencies during the 12 months preceding elections may be explained by the need of politicians to appease their constituents prior to elections. We include time fixed effects to control for confounding factors such as Minimum Support Price, which is set for the entire country annually. Model Code of Conduct, where politicians are not allowed to do any development work in the 12 months prior to elections may be another factor, but its mechanism on the ground is unclear; it is counter-intuitive that enforcement would be stronger in the year prior to elections. Ground studies scheduled in October-November 2018 will help understand this phenomenon.

4.4 Ways forward

Greenstone and Hannah (2014) present a systematic evaluation of India’s environmental regulations and highlights the role of institutions and politics in influencing environmental conditions. They find that the air regulations have led to improvements in air pollution, while the water pollution regulations have been ineffective. Thus the potential for resolving air pollution crises in India is high given that we understand its drivers.

This study has yielded surprising results regarding the pattern of CRB across India and causally tested the impact of legislation regarding water conservation and political cycles on CRB. As a next step, we will causally test the impact of NREGS, mechanization, crop variety and awareness schemes on CRB and conduct fieldwork in Oct-November 2018 to understand farmers' motivations in selecting a burning strategy. We expect that these results will inform policy-makers on ways to disincentivise CRB. We also find that policies directed towards good in one sector (e.g. water conservation, labour wages) may have unintended consequences for other sectors (air pollution).

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Figures and Tables

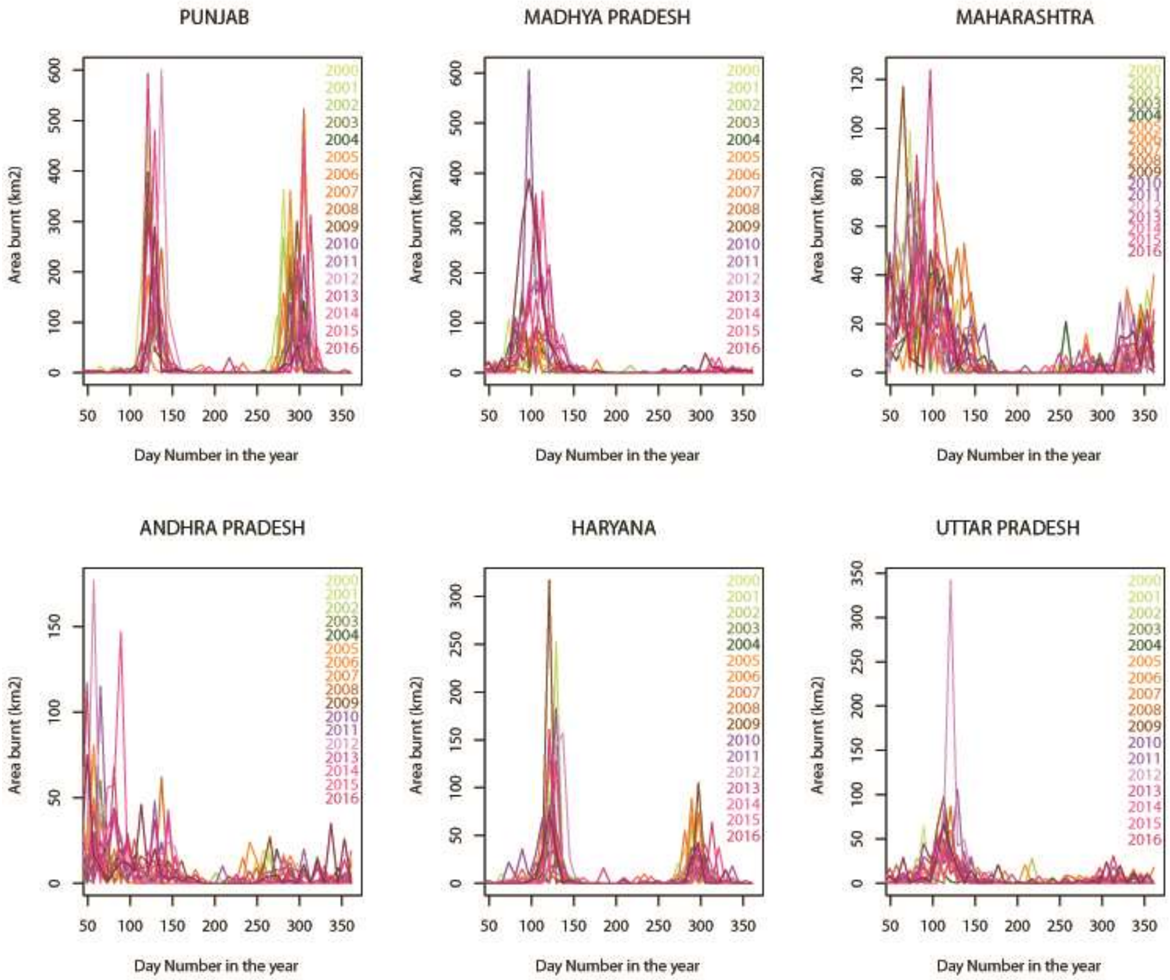

Fig 1. Patterns of crop-residue burning (CRB) in 6 states that had highest mean CRB from 2000 to 2017.

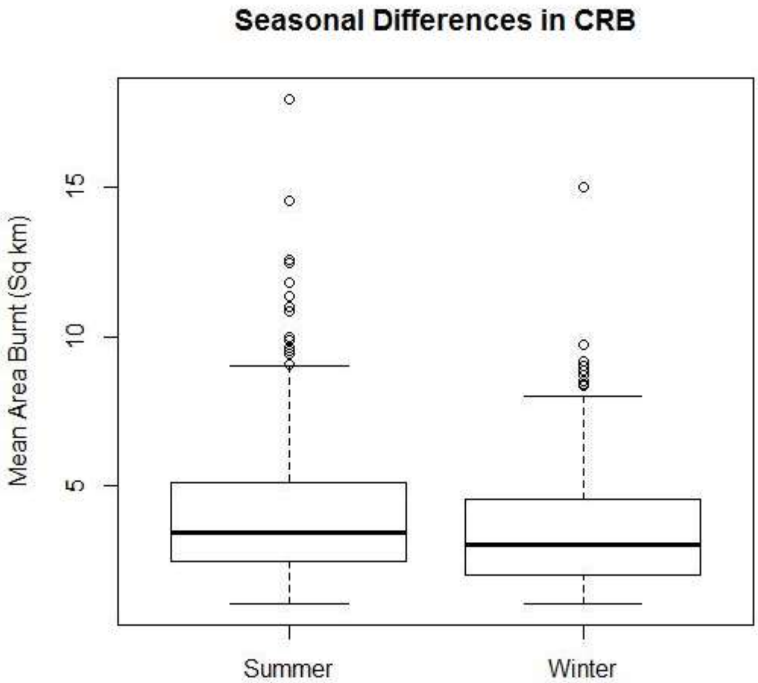

Fig 2. Significantly higher CRB in summer than in winter (all India)

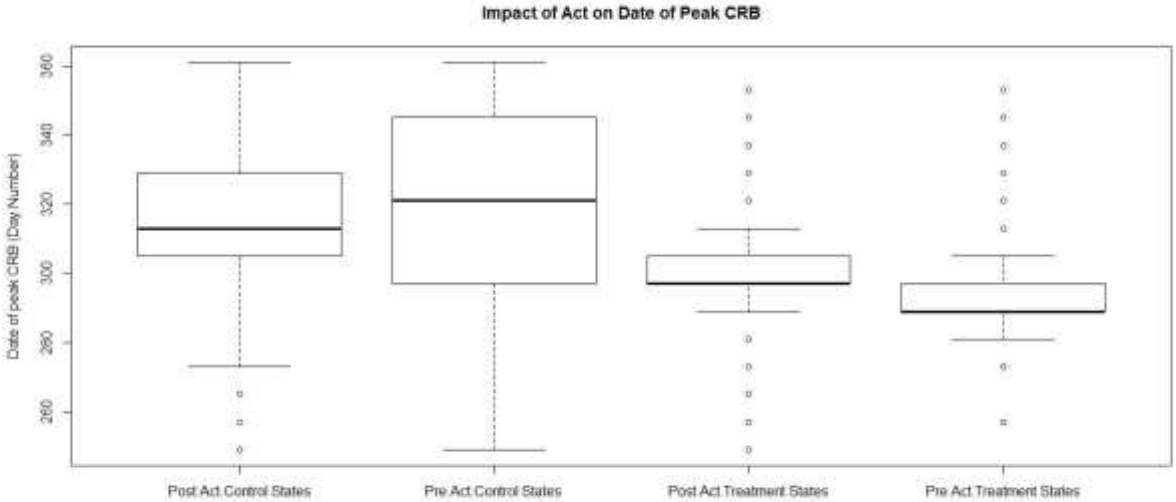

Fig 3. Significantly later CRB peak for treatment states after "Preservation of Sub-Soil Water Act, 2009"

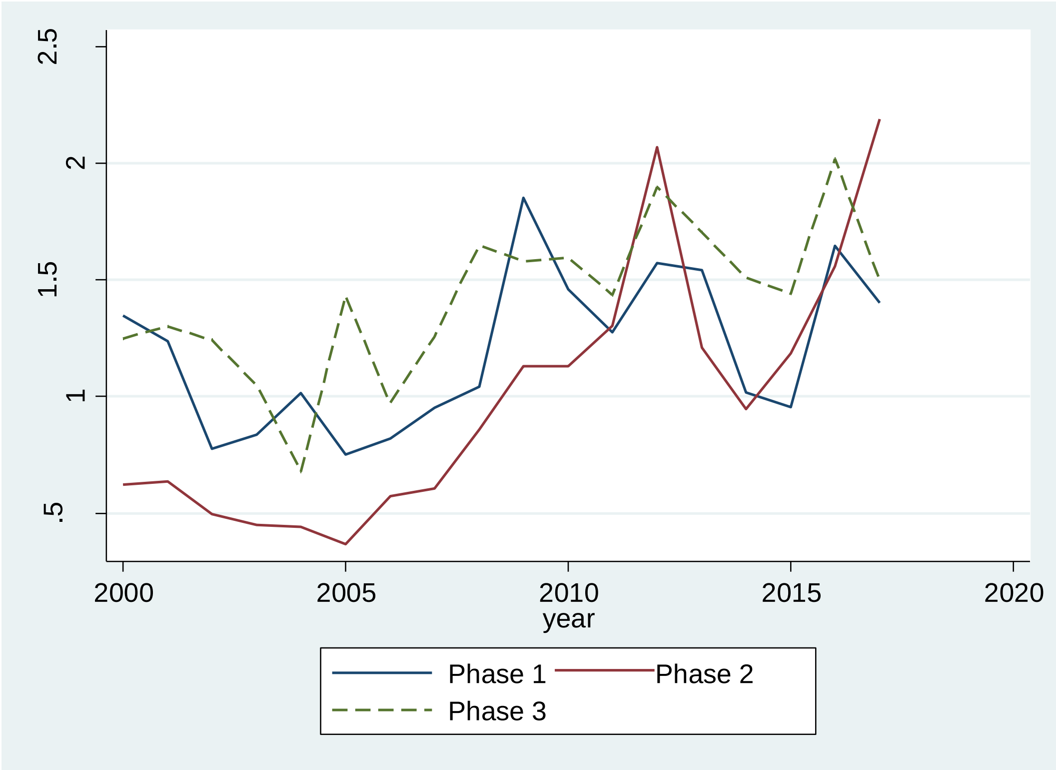

Fig 4. Impact of NREGA phases on CRB

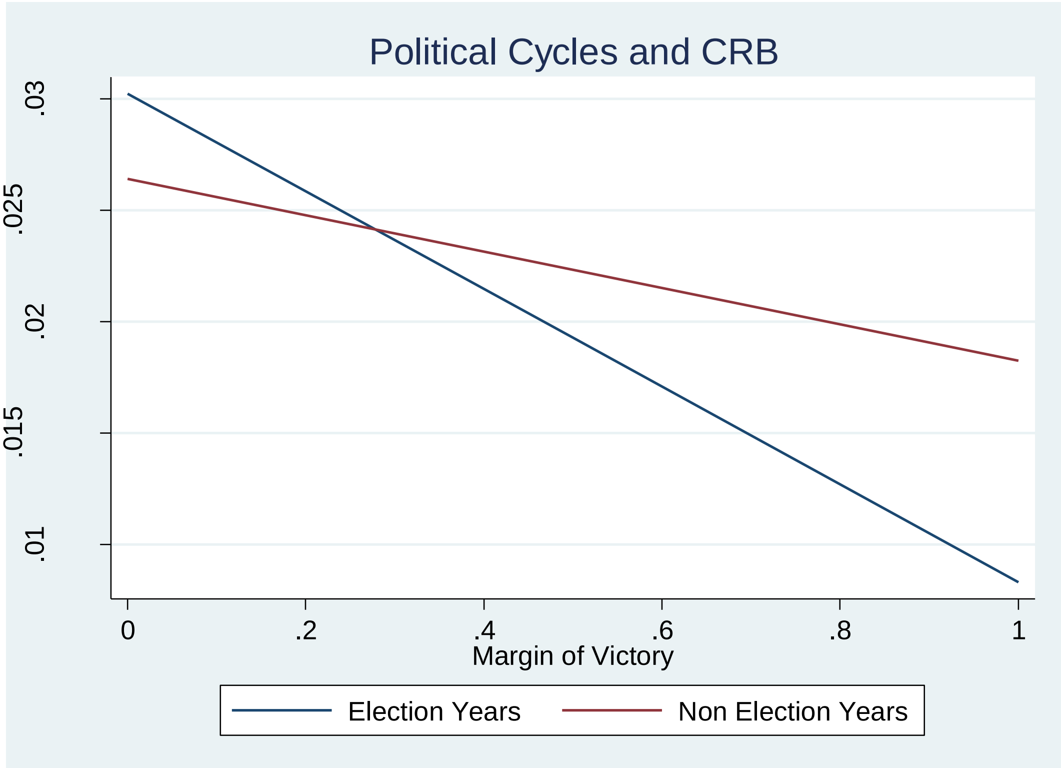

Fig 5. Political Cycles and CRB

Table 1: Political Cycles and CRB

	(1)	(2)
12 months Bef Elec	-0.0016	0.00096
	(-1.45)	(0.50)
12 months Bef Elec*Margin		-0.011**
		(-2.06)
Margin		-0.0042
		(-0.95)
Observations	1199620	1199620
r2	0.0252	0.0252

t statistics in parentheses. * p<0.10 ** p<0.05 *** p<0.01

Supplementary Information

S1. Patterns of CRB in other states

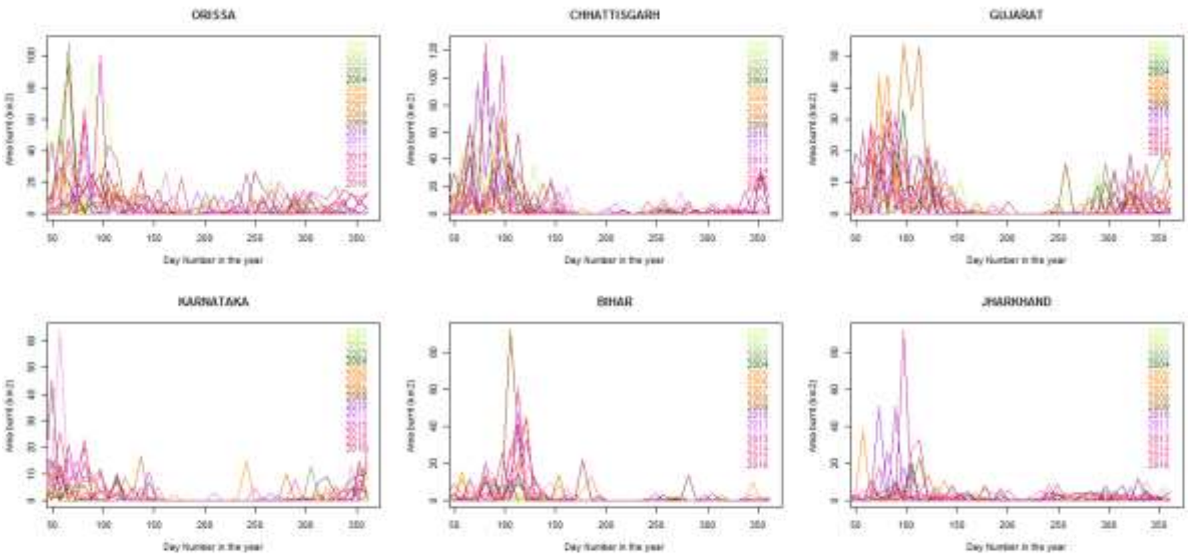

Fig S1.1 Patterns of crop-residue burning (CRB) in 6 states that had 7-12 highest mean CRB from 2000 to 2017

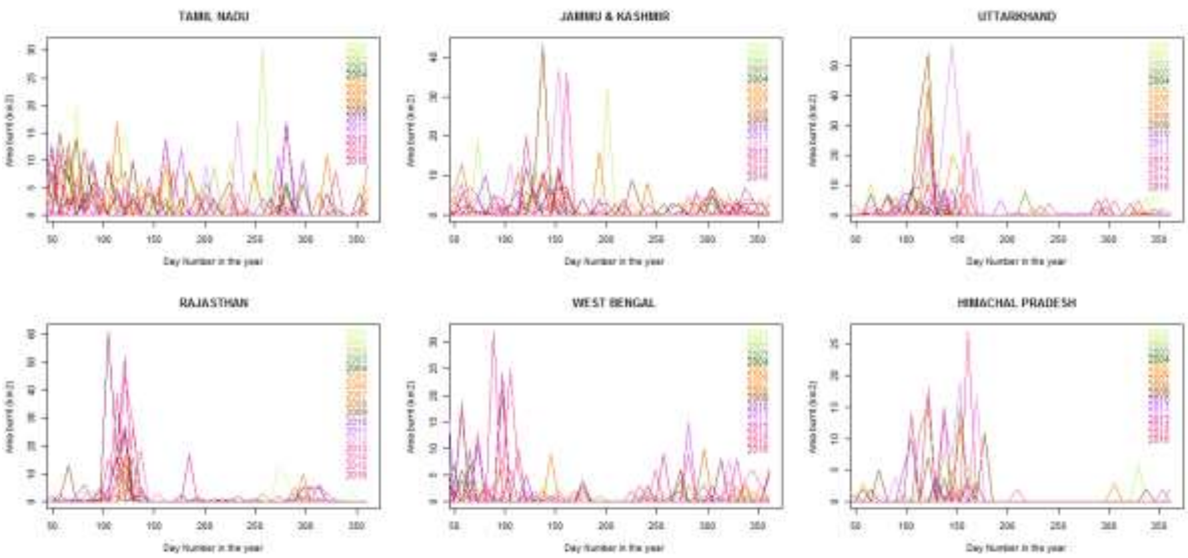

Fig S1.2 Patterns of crop-residue burning (CRB) in 6 states that had 13-18 highest mean CRB from 2000 to 2017