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Unintended Consequences of Indian Groundwater Preservation Law on Crop Residue Burning

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Abstract

Crop residue burning is a major concern for many countries since it leads to a deterioration of air quality, which has a number of health implications. This paper examines the unintended consequences of a policy aimed at improving the groundwater level on crop residue burning in India. The Preservation of Subsoil Water Act, 2009 was implemented in the Indian states of Punjab and Haryana in March 2009, and it bans the transplantation of paddy before mid-June to preserve groundwater. Theoretically, this leaves a short window of time for clearing the crop residue before the next crop and thus increases the likelihood of farmers adopting time saving methods like crop residue burning. Exploiting the spatial and temporal variation of the Preservation of Subsoil Water Act, we compare the bordering areas of Punjab and Haryana with that of the neighbouring states and find that the ban results in both delay and an increase in crop residue burning in the winter months. The findings have important implications for environmental policy design.

Keywords: Crop Residue Burning, Groundwater, Water Policy, Waste Management, Air Pollution, India

JEL Codes: Q10, Q18, Q25, Q53, O13, K32

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1 Introduction

Crop residue burning (hereafter, CRB) is a common farming practice in many parts of the world and is an important source of air pollution (Liu et al. (2021), Zhao et al. (2017), Awasthi et al. (2011), McCarty et al. (2009), Korontzi et al. (2006)). The problem is particularly severe in the northwest India (Liu et al. (2018), Cusworth et al. (2018), Guo (2017), Singh and Kaskaoutis (2014), Gadde et al. (2009)). While there has been some research on the effects of CRB on health and educational outcomes (He et al. (2020), Zivin et al. (2020), Rangel and Vogl (2019)), a causal understanding of the factors responsible for it is limited. In the Indian context, some recent studies have tested the association between CRB and the timing of government policies and suggest that CRB may have been delayed because of the enactment of the Preservation of Subsoil Water Act, 2009 (hereafter, subsoil water act) (Sembhi et al. (2020), McDonald et al. (2019)). However, the causal impact of the subsoil water act on CRB has not been tested rigorously. The current paper addresses this gap in literature.

Over-extraction of groundwater is an acute problem in India (Sayre and Taraz (2019)). In March 2009, the Indian states of Punjab and Haryana implemented the subsoil water act to reduce the use of groundwater for irrigation. The law prohibits the transplantation of paddy before mid-June, and existing literature suggests that the subsoil water act has been successful in increasing groundwater levels (Tripathi et al. (2016)). However, the subsoil water act also delays paddy cultivation (McDonald et al. (2019)) and the time of paddy harvest, resulting in a very short temporal window between paddy harvest and sowing of the next crop. This can induce farmers to adopt less time intensive techniques like using fires to clear their paddy residue.

The subsoil water act provides us with an exogenous policy variation across the treated states of Punjab and Haryana and their neighbouring states. We employ a difference in difference (DID) estimation strategy, comparing the bordering areas of Punjab and Haryana with those of the neighbouring states in the post-period relative to the pre-period. Our main variable of interest is CRB during the months of October and November when paddy is harvested. We control for a large number of factors by including area fixed effects, time fixed effects and state specific linear time trends in our regressions. We also control for climatic factors and policy variables that are likely to influence CRB.

The DID results show that CRB during the winter months of October and November increases by 19% to 47% in the post-period in the treated states. Such effects are absent for the summer months of April and May. Summer CRB is largely due to wheat residue burning and is unlikely to be affected by the subsoil water act.

We also estimate a triple difference model comparing October and November with the other months of the year across the bordering areas of Punjab and Haryana and the neighbouring states in the post-period relative to the pre-period. The triple difference results are similar to the DID results and show a significant increase CRB in the months of October and November relative to other months. Estimating the effects separately for October and November, we find that the results are driven by a large increase in CRB during the month of November relative to other months. However, the monthly results are statistically insignificant.

Regarding mechanisms, our results show that the increase in CRB in the post-period occurs in November. This is consistent with previous literature, which shows that the law leads to a delay in paddy harvest such that most of it now occurs in late October or early November as compared to before October 26 in the pre-period (McDonald et al. (2019)). We also show that the law has no effects on summer burning, confirming that the results are driven by the delay in paddy cultivation and not a general increase in CRB.[1]

The study has important contributions. To the best of our knowledge, this is the first paper to causally test the unintended consequences of the subsoil water act on CRB which has important policy implications. The previous studies, which test the association between the timing of the subsoil act and CRB, find that there is a *delay* in CRB following the implementation of the act. Ours is the first paper to show that in addition to a delay, winter CRB *increases* following the implementation of the subsoil water act.

The paper is divided into several sections. The next section gives a brief description of the evolution of CRB in India over our sample period. Section 3 describes the data used in this paper. Section 4 explains our estimation strategy. Section 5 contains the results and section 6 concludes the paper.

2 Crop Residue Burning in India

In India, CRB is seasonal and occurs mostly at the end of the two main harvesting seasons: Rabi and Kharif. Kharif or the monsoon crop season lasts from June to October-November. Rabi crops are sown in November and are harvested in April-May. In north India, the main Kharif crop is paddy, and the main Rabi crop is wheat. Paddy residue burning mostly contributes to CRB in winter (October-November), and wheat residue burning contributes to summer CRB (April-May).

Figure 1a shows the monthly average of CRB before and after the implementation of

[1] Appendix table A6 shows that the subsoil water act did not affect agricultural production or agricultural yield.

the subsoil water act. To make our treatment and control groups closely comparable, we restrict our sample to the bordering assembly constituencies of Punjab and Haryana and the neighbouring states of Uttar Pradesh, Rajasthan and Himachal Pradesh.[2] It can be seen that most of CRB takes place at the end of the Rabi season (April-May) and Kharif season (October-November).[3] Thus we focus on these two seasons: April-May for summer burning and October-November for winter burning.[4] Figure 1a also shows a large increase in November burning in the post-period.

Figure 1b shows the evolution of winter CRB by months. We can see that CRB in November is quite low till 2008 and increases sharply after that. On the other hand, burning in the month of October has remained relatively stable over time.

3 Data

3.1 Crop Residue Burning

We have generated the CRB data by combining fire count data from MODIS products Aqua MYD14A2 and Terra MOD14A2 for the period 2003-2018. The data is available at 8 day intervals and 1 km resolution. We have masked out non-agricultural areas such that we only consider agricultural fires and not forest fires.[5]

The unit of observation for the CRB data is an assembly constituency. State elections in India are held at the level of assembly constituencies.[6] The use of assembly constituencies in place of state or districts is particularly useful. We compare across bordering assembly constituencies, and this implies we are comparing across regions which are more homogeneous than bordering districts or bordering states. At the same time, assembly constituencies are typically larger than villages. Thus they are less likely to be contaminated by spillover effects than a comparison across bordering villages.[7]

The CRB data identifies whether there is any fire incident in a given square kilometre. In other words, it does not identify the fraction of area burnt in a given square kilometre. We cumulate this data to generate monthly data on the number of square kilometres which had a fire incident in a given assembly constituency. We interpret it as the monthly area

[2]Our unit of analysis is an assembly constituency, as explained in section 3.

[3]Appendix figure A3 shows that April-May and November-December are the relevant months, even considering all assembly constituencies and not just the bordering assembly constituencies.

[4]Appendix figures A4 and A5 show the evolution of winter and summer CRB over time.

[5]We have included the details in section A2 of the appendix.

[6]Voters of each assembly constituency elect each member of the state legislative assembly.

[7]One problem with the use of assembly constituency as the unit of analysis is that constituency borders changed in 2008. For consistency, we have generated the data for the entire sample period according to the post-2008 delimitation definition of constituency boundaries, as explained in section A2 of the appendix.

burnt in a given assembly constituency. Thus the dependent variable is essentially a count variable.

3.2 Biophysical variables

Biophysical variables such as precipitation and wind speed can influence crop burning intensity and length. Thus we use controls for these variables in our regressions.

We have obtained daily precipitation data from the Tropical Rainfall Measuring Mission (TRMM) 3B42. For daily data on wind speed, we use GLDAS 2.1 version of Global Land Data Assimilation System (GLDAS).

3.3 Policy Variables

During our sample period (2003-2018), the government of India launched the Mahatma Gandhi National Employment Guarantee Scheme (MGNREGS). Previous literature points out the labour market impacts of the policy in driving up rural wages (Imbert and Papp (2015)), and this can lead to increased use of cost effective methods like CRB to clear fields. We control for the policy by using the phase wise implementation of the policy at the district-year level. The data comes from the official website of the Mahatma Gandhi National Rural Employment Guarantee Act.

It is also argued that CRB increases before elections because of the relaxed implementation of the laws preventing it. Thus we have also controlled for whether a particular year corresponds to a state election year.[8] The data comes from the official website of the election commission of India.

4 Estimation Strategy

We implement a difference in difference estimation strategy, comparing Punjab and Haryana with the bordering states of Rajasthan, Uttar Pradesh and Himachal Pradesh in the post-period relative to the pre-period.

As discussed earlier, the dependent variable is a count variable. The usual choices in such cases are Poisson or Negative Binomial regression models. Poisson regression model assumes that the conditional mean and variance of the dependent variable are the same. Negative Binomial models, on the other hand, relaxes this assumption. The standard deviation of the

[8]We include month-year fixed effects in our regressions, which controls for the timing of parliamentary elections.

CRB variable is more than twice its sample mean.[9] This indicates that Negative Binomial is a better fit for our data. We formally test the hypothesis of the overdispersion parameter to be 0. The test results in a chi-square value that is significant at 1% level and confirms the presence of overdispersion. Thus we use a Negative Binomial model for this analysis.

Let Y_{ismt} be the dependent variable which denotes the extent of CRB in assembly constituency i of state s in month m and year t. Also assume that Z_i is a vector containing all the covariates. The regression specification is given by

$$E(Y_{ismt}|Z_i, \epsilon_i) = exp(\alpha + \theta post_t \times Treat_s + \gamma X_{ist} + \delta_i + \tau_{mt} + \rho_s \times t + \epsilon_i) \tag{1}$$

Where $E(Y_{ismt}|Z_i) < Var(Y_{ismt})$. In the above regression, δ_i and τ_{mt} denote assembly constituency and month-year fixed effects, respectively. Constituency fixed effects control for the time invariant factors, which result in the differential level of CRB across constituencies. Month-year fixed effects account for heterogeneity across the different time periods. We saw that winter burning shows an increasing trend. We include state specific linear time trends, $\rho_s \times t$, so that this does not bias our results. The vector X_{ist} includes a number of controls for climatic factors and policy change. The climatic controls are mean precipitation, and wind-speed in the assembly constituency i, month m, and year t. We also include an election dummy and a dummy variable indicating whether the workfare scheme MNREGS is in place in year t in the district containing assembly constituency i. Appendix table A5 shows that the results are robust to controls for agricultural production, agricultural yield and demographic variables. We estimate this equation separately for the winter (October-November) and the summer (April-May) months.

The Negative Binomial regression coefficient can be interpreted as the log change in the outcome variable as the independent variable increases by one unit. Thus we can interpret the coefficient, θ, as the percentage change in the dependent variable as a result of the subsoil water act.

One issue in this analysis is the potential heterogeneity across treatment and control groups. The states in our sample can be dissimilar in many respects, like mechanization in agriculture[10] and attitude towards CRB. We control for time-invariant heterogeneity across assembly constituencies by including assembly constituency fixed effects. We also include state specific linear time trends which control for the factors responsible for a state-wise consistent linear trend in the outcome variable. However, there might be non-linear trends, which can bias our results. Thus we restrict our analysis to the assembly constituencies along the administrative border of Punjab and Haryana and their neighbouring states that

[9] Appendix table A1 shows this.

[10] Combined harvesters leave more residue in fields and are positively associated with crop burning (Sahai et al. (2011), Gupta et al. (2004)).

are likely to share similar changes in mechanization and attitude towards CRB over time. The resulting sample includes *109* assembly constituencies.

We use state-time level variation for this analysis. We thus cluster the standard errors at the state level. Since we consider 5 states for this analysis, we use wild bootstrapping to account for the small number of clusters.

In order to show the robustness of our results, we also estimate a triple difference equation. We find the subsoil water act only affects winter burning and not summer burning. We thus estimate the effect of the scheme comparing the months of October and November with the other months of the year in the treated states in the post-period. The estimating equation is given by:

$$E(Y_{ismt}|Z_i, \epsilon_i) = exp(\alpha + \theta post_t \times Treat_s \times Oct\text{-}Nov_m + \gamma X_{ist} + \delta_i + \tau_{mt} + \rho_{st} + \phi_{sm} + \epsilon_{ist}) \quad (2)$$

where $Oct\text{-}Nov_m$ is a dummy equal to 1 for the months of October and November, ρ_{st} indicates state-year fixed effects and ϕ_{sm} indicates state-month fixed effects.

5 Results

5.1 Main Results

Table 1 shows the baseline results. Panel A shows the results for the winter months of October and November, and Panel B shows the results for the summer months of April and May. Column 1 only includes the climatic controls of precipitation and wind speed. Column 2 additionally includes dummies for election years and MGNREGS. Column 3 includes constituency specific year trends[11], and column 4 includes state-month fixed effects. Panel A of table 1 indicates that the subsoil water act leads to an increase in CRB in winter months. The magnitude of the effect ranges from 19% to 47%. The results are smaller in magnitude and statistically insignificant for summer CRB as shown in panel B.

One concern with the above analysis is the skewness of the CRB data. Only 18% of the observations are greater than the mean. The outliers can potentially lead to errors, and hence we estimate the effect of the subsoil act on winter CRB for two subsamples excluding the outliers. The results are shown in Panels C and D of table 1. Panel C shows the results excluding the three observations for which the monthly area burnt is greater than 800 square kilometres. In panel D, the sample is further reduced to include only those observations for which CRB is less than 500 square kilometres. We can see that the results are similar to our baseline estimates.

[11] The other columns include state specific linear time trends.

5.2 Robustness Tests

5.2.1 Parallel Trends

Figure 2 shows the evolution of CRB across treatment and control states between 2003 and 2018. It shows that CRB in the treatment states is much higher than that of the control states. In order to account for this, we include assembly constituency fixed effects in our analysis. We also control for state specific linear time trends to control for pre-existing linear trends in CRB which varies by states.

In order to further test for the presence of pre-existing trends across treated and control states, we do a set of robustness checks in table 2. In columns 1 and 2, we restrict the sample to the pre-2009 period and perform two placebo tests. We estimate equation (1), assuming that the policy change took place in 2005 in column 1 and 2006 in column 2. We see that the results are very small in magnitude and are statistically insignificant, as expected.

5.2.2 Spillover Effects

One problem of considering the neighbouring assembly constituencies is the possibility of spillover effects. In column 3 of table 2, we estimate regression (1) on the sample of all constituencies belonging to bordering districts. We find that the magnitude of the effect remains unchanged. In column 4, we estimate regression (1) on the sample of assembly constituencies belonging to the bordering districts but not including the bordering assembly constituencies. This again leaves the magnitude of the effect unchanged. However, the effects turn statistically insignificant.

5.2.3 Inclusion of Other Months

In our main analysis, we considered the months of October and November, when most of the post-monsoon CRB takes place. However, it can be argued that our results are driven by the choice of months. In column 5 of table 2, we estimate regression (1) for the months of August-December. The result is again similar to the inclusion of only October and November.

5.2.4 Robustness to the exclusion of states

We previously saw that CRB is much higher in treated states than in control states. Among the two treated states, the CRB is higher in Punjab compared to Haryana. In column 1 of table 2, we estimate regression (1), excluding the state of Punjab. The magnitude of the effect remains unchanged. In the remaining columns, we estimate the same specification, omitting one state at a time. Again, the sign and magnitude of the results remain relatively unchanged.

5.3 Triple Difference

In table 3, we present the results from the triple difference specification. The results show that compared to other months of the year, CRB increases by about 60% in October and November in the treated states compared to the control states in post-period. In column 2, we estimate the effects separately for October and November and find that the effect is driven by the increase in CRB in November. CRB increases by more than 100% in November compared to other months. However, the results are statistically insignificant.

6 Conclusion and Discussion

CRB is an important problem in the India and our results show that the subsoil water act which has been otherwise successful in addressing the over-extraction of groundwater, has exacerbated the CRB problem. We find that the subsoil water act leads to an increase in winter CRB, particularly in the month of November. The delay in rice harvesting following the subsoil act is likely to have incentivised the farmers to increase the practice of CRB. Moreover, the fact that CRB rises in winter may have particular implications in further worsening air quality in north India which deteriorates during this time.

In terms of policy implications, we are not recommending the removal of the subsoil water act, which has proved effective in preserving the groundwater level. However, it is important to be cognisant of the spillover effects of this act in increasing CRB. We present evidence on how an otherwise beneficial environmental policy can have unintended welfare consequences in exacerbating another environmental concern that policymakers should be wary about.

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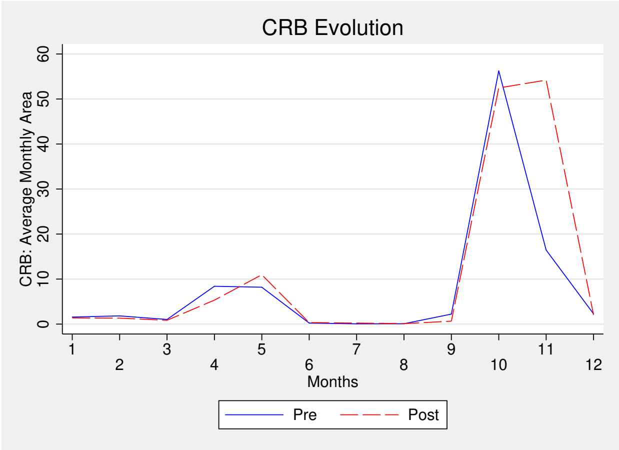
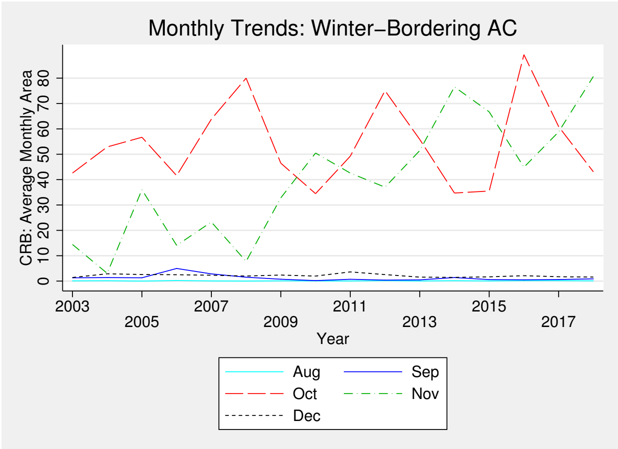
Figure 1: Evolution of CRB (Bordering AC): by Month



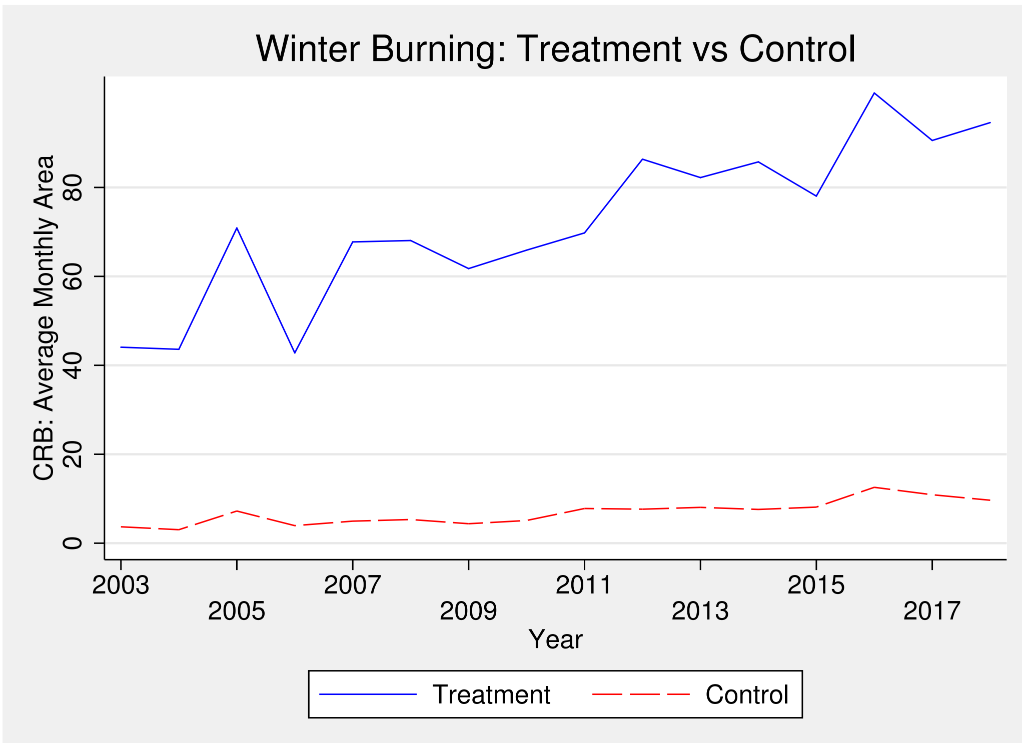
(a) Pre and Post



(b) Winter Months

Figure (a) shows average CRB in the pre and the post-period across the different months. Figure (b) the evolution of CRB separately for each of the months, August-December. We restrict the sample to bordering assembly constituencies.

Figure 2: Evolution of CRB (Bordering AC) across Treatment and Control States



The figure shows evolution average CRB across the treatment and control states. The sample consists of the bordering assembly constituencies.

Table 1: Effect on CRB

	(1)	(2)	(3)	(4)
Panel A: Winter: October and November				
Treatment × Post	0.2950**	0.2812**	0.1869*	0.4682*
	[0.0397]	[0.0386]	[0.0603]	[0.0720]
Observations	3120	3120	3120	3120
Panel B: Summer-April and May				
Treatment × Post	0.1007	0.1123	-0.0286	-0.0250
	[0.7465]	[0.7077]	[0.9335]	[0.9406]
Observations	3120	3120	3120	3120
Panel C: Winter CRB<800				
Treatment × Post	0.3060**	0.2938**	0.1993*	0.4802**
	[0.0382]	[0.0389]	[0.0806]	[0.0425]
Observations	3117	3117	3117	3117
Panel D: Winter CRB<500				
Treatment × Post	0.3414*	0.3219**	0.2127	0.4843**
	[0.0526]	[0.0349]	[0.1853]	[0.0420]
Observations	3076	3076	3076	3076
Political Controls	No	Yes	Yes	Yes
AC Specific Year Trends	No	No	Yes	No
State-Month Fixed Effects	No	No	No	Yes

Notes: Each cell represents a separate regression. Area Burnt is the dependant variable in all the regressions. Panel A shows the results for winter CRB (Months: October and November) and panel B presents the results for summer CRB (April and May). The sample in panel C and D correspond to winter burning. The sample in panel C only includes observations where the monthly area burnt is less than 800 square kilometres in a constituency. Panel D includes observations where the monthly area burnt is less than 500 square kilometres. Apart from the reported variables, all regressions include assembly constituency fixed effects, month-year fixed effects and climatic controls. Columns 1, 2 and 4 additionally include linear state specific year trends. Column 3 includes assembly constituency specific year trends. Columns 4 includes state-month fixed effects. Columns 2, 3 and 4 includes policy controls. Sample includes data from neighbouring constituencies of the states Punjab, Haryana, Himachal Pradesh, Rajasthan and Uttar Pradesh for the years 2003-2017. Errors are clustered at state level. Wild bootstrapped p-values are reported in the brackets.

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

Table 2: Robustness Checks

	(1)	(2)	(3)	(4)	(5)
	Panel A: Pre-Trends and Sample Restrictions				
Treatment × Post	-0.0643	0.0278	0.3009	0.3089	0.2285*
	[0.8036]	[0.7577]	[0.1056]	[0.1210]	[0.0947]
Observations	1248	1248	8010	4890	7800
Sample	Pre-2009	Pre-2009	Neighbouring Districts	Neighbouring Districts	Months: August-December
	Panel B: Excluding States				
Treatment × Post	0.3092	0.2582*	0.1821*	0.5653	0.2738*
	[0.1094]	[0.0601]	[0.0616]	[0.1428]	[0.0589]
Observations	2340	1980	2640	2760	2760
State Excluded	Punjab	Haryana	Rajasthan	Uttar Pradesh	Himachal Pradesh

Notes: Each cell represents a separate regression. Area Burnt is the dependant variable in all columns. Columns 1 and 2 of panel A only includes the pre-2009 period. The post dummy in column 1 corresponds to the post 2004 period. In column 2 it corresponds to the post 2005 period. The sample in columns 3 and column 4 of panel A includes the neighbouring districts instead of neighbouring assembly constituencies. In column 4, we include assembly constituencies in the neighbouring districts but exclude the bordering assembly constituencies. The sample in column 5 includes the months August-December instead of only October and November. Panel B shows the estimates from regressions, excluding one state at a time. The states excluded in each column is mentioned in the last row. Apart from the reported variables, all regressions include assembly constituency fixed effects, month-year fixed effects, state specific linear year trends, climatic and policy controls. Errors are clustered at state level. Wild bootstrapped p-values are reported in the brackets.

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

Table 3: Triple Difference

	(1)	(2)
Treatment×Post×October-November	0.5907*	
	[0.0741]	
Treatment×Post×October		0.0384
		[0.6971]
Treatment×Post×November		1.0492
		[0.1068]
Treatment×Post	0.0562	0.0747
	[0.6082]	[0.4408]
Observations	18720	18720

Notes: Each column represents a separate regression. Area Burnt is the dependant variable in all columns. Apart from the reported variables, all regressions include assembly constituency fixed Effects, month-year fixed effects, state specific linear year trends, climatic controls and policy controls. Sample includes data from neighbouring constituencies of the states Punjab, Haryana, Himachal Pradesh, Rajasthan and Uttar Pradesh for the years 2003-2017. Errors are clustered at state level. Wild bootstrapped p-values are reported in the brackets.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Appendix

A1 Preservation of Subsoil Water Act, 2009

In India, the importance of groundwater in irrigation has steadily increased over the decades. Gandhi and Bhamoriya (2011) note that the contribution of groundwater to total irrigation has increased from 28% to 61% between 1951 and 2008-09. Factors like electricity access in rural areas and improvement in pumping technology are considered responsible for the increased use of groundwater for irrigation (Gandhi and Bhamoriya (2011)). Over-extraction of groundwater has massively reduced the groundwater level (Sayre and Taraz (2019)).

The Preservation of Subsoil Water Act was implemented in the Indian states of Punjab and Haryana in 2009 to reduce the depletion in groundwater. The law prohibits transplantation of paddy before mid-June (McDonald et al. (2019)). The delay in transplantation date brings paddy cultivation closer to the monsoon season and thus reduces the need of groundwater for irrigation.

The law imposes a huge penalty on the farmers who defy the law. The law states that those who violate the provisions of the law have to pay 10,000 Indian rupees (equivalent to about 140 US dollars at the current exchange rate) per hectare per month for the period of violation. In addition, paddy planted in the nursery or transplanted in the field before the notified date are destroyed. Existing literature suggests that the subsoil water act is successful in increasing groundwater level (Tripathi et al. (2016)).

A2 Data Appendix

A2.1 CRB data

The data comes from the Moderate Resolution Imaging Spectroradiometer (MODIS) sensor, which is on board Terra and Aqua satellites. Terra and Aqua are operated by the US space agency, NASA. We combine fire count data from MODIS products Aqua MYD14A2 and Terra MOD14A2 to create raster layers for area burnt for each date for which the data is available. We have obtained the raw data from `https://doi.org/10.5067/MODIS/MOD14A2.006` for Terra MOD14A2 and `https://doi.org/10.5067/MODIS/MYD14A2.006` for Aqua MYD14A2. Terra MODIS and Aqua MODIS view Earth's surface every one to two days and identify fires at 1-km resolution. We have used the data collected over Indian regions. Data is available every 8 days from mid-2002. While Terra MODIS is available from 2000, Aqua MODIS is only available from mid-2002. We have used data for the period 2003-2018 in this analysis.

We have masked out non-agricultural areas using Land Use Land Cover dataset, created by European Space Agency's Climate Change Initiative Land Cover Maps and available at `http://maps.elie.ucl.ac.be/CCI/viewer/index.315.php`. Thus we only consider agricultural fires and not forest fires. Moreover, we consider the harvest months of October and November for winter burning and April and May for summer burning, when fires on agricultural land usually reflect CRB.

Our unit of analysis is an assembly constituency. State elections are held in India at the level of assembly constituencies. Assembly constituencies are typically smaller than districts, with each district having 7 assembly constituencies on average. One problem 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 from time to time to define and redefine the boundaries of state assembly constituencies. Four such delimitation commissions have been formed: 1952, 1963, 1973 and 2002. The recommendations of the last delimitation commission, constituted in 2002, were implemented in 2008. This change in constituency boundary makes it difficult to compare within the same assembly constituencies over-time. In order to avoid this problem, we have generated the data for the entire period according to the post-2008 delimitation definition of constituency boundaries. Thus the pre-2008 and the post 2008-CRB data have the same constituency boundary definition. This enables us to include constituency fixed effects in our estimating equation.

One limitation of this data is that it only captures large fires. Using alternate data is not possible due to data issues.[12] Understanding the limitations of MODIS Fire products, our study is limited in that we are only estimating the effects of the subsoil water act on large agricultural fires.

A2.2 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, 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. However, we downloaded the data at daily resolution (in millimetre). The raw data for precipitation is available at `https://doi.org/10.5067/TRMM/TMPA/3H/7`. For daily data on wind speed (in metre per second), we use GLDAS 2.1 version of Global Land Data Assimilation System (GLDAS). The raw wind speed data is available at `https://doi.org/`

[12] Using higher resolution data such as Landsat-based classification and indices is not possible because of data unavailability for a number of years. VIIRS was commissioned in 2012. Thus the data is available for a shorter time period than MODIS.

10.5067/E7TYRXPJKWOQ.

We convert the daily data on all these biophysical variables into assembly constituency-month level by averaging the daily observations over months in a given constituency.

A2.3 Policy Variables

We control for the timing of the introduction of the Mahatma Gandhi National Employment Guarantee Scheme (MGNREGS) in our regressions. MGNREGS is a rural workfare scheme and provides 100 days of guaranteed work at a state-level minimum wage. MGNREGS was introduced in three phases. The first phase was introduced in 2006, the second phase in 2007 and the third phase in 2008. 200 districts belong to Phase 1, 130 districts belong to Phase 2 and 295 districts belong to Phase 3. Since MGNREGS can affect rural wages, it can also affect CRB by affecting the demand for agricultural workers. We create a dummy variable equal to 1 for all years following the implementation of MGNREGS in the district and include it in our regressions as a control. The data is available at https://nrega.nic.in/MNREGA_Dist.pdf.

We also include a dummy for the year of state-assembly elections in our regressions. The data is available at https://eci.gov.in/statistical-report/statistical-reports/.

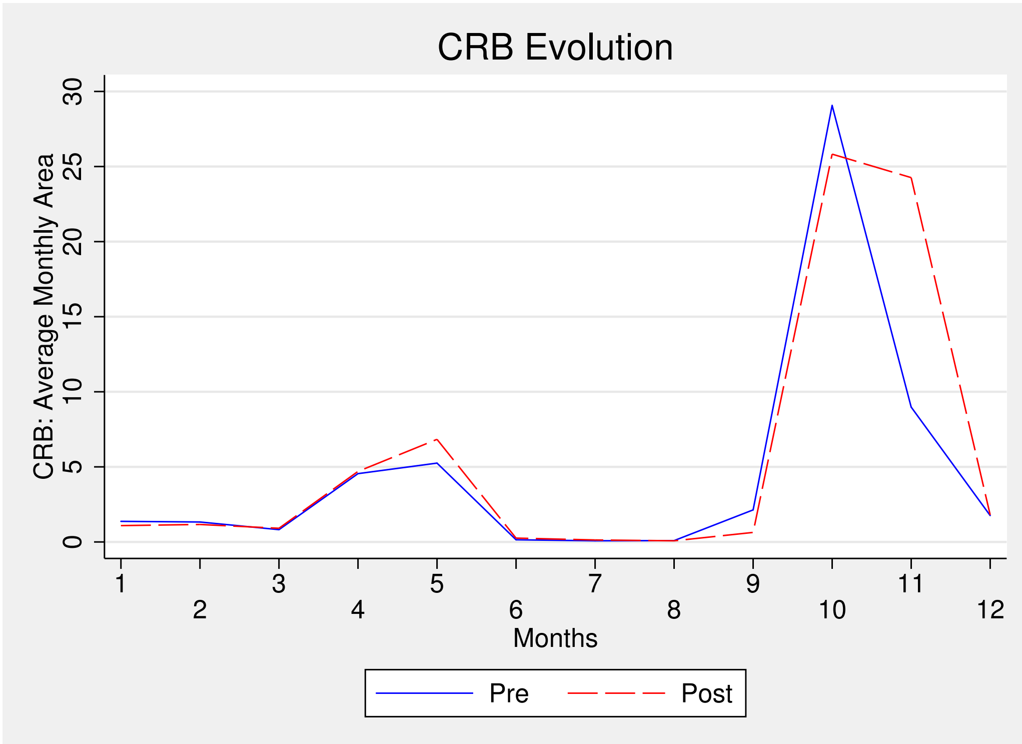
A2.4 Demographic and Agricultural variables

We have collected data on demographic variables from the 2001 and 2011 census. The data is at the district level and the variables used in the analysis are proportion of Scheduled Castes and Scheduled Tribes, proportion of Muslims, proportion of urban population and sex ratio. We have used linear interpolation for figures corresponding to the intercensal years. We use these variables for robustness checks performed in table A5.

We have obtained agricultural production data from the official website of the Ministry of Agriculture & Farmers Welfare. The data is available at https://aps.dac.gov.in/APY/Public_Report1.aspx. The data is at district-year level. We have used data on the total rice production (in 1000 tons) and yield in the Kharif season and total wheat production and yield data in the Rabi season. We use these variables as controls in the regressions reported in column 3 of table A5 as well as dependent variables in table A6.

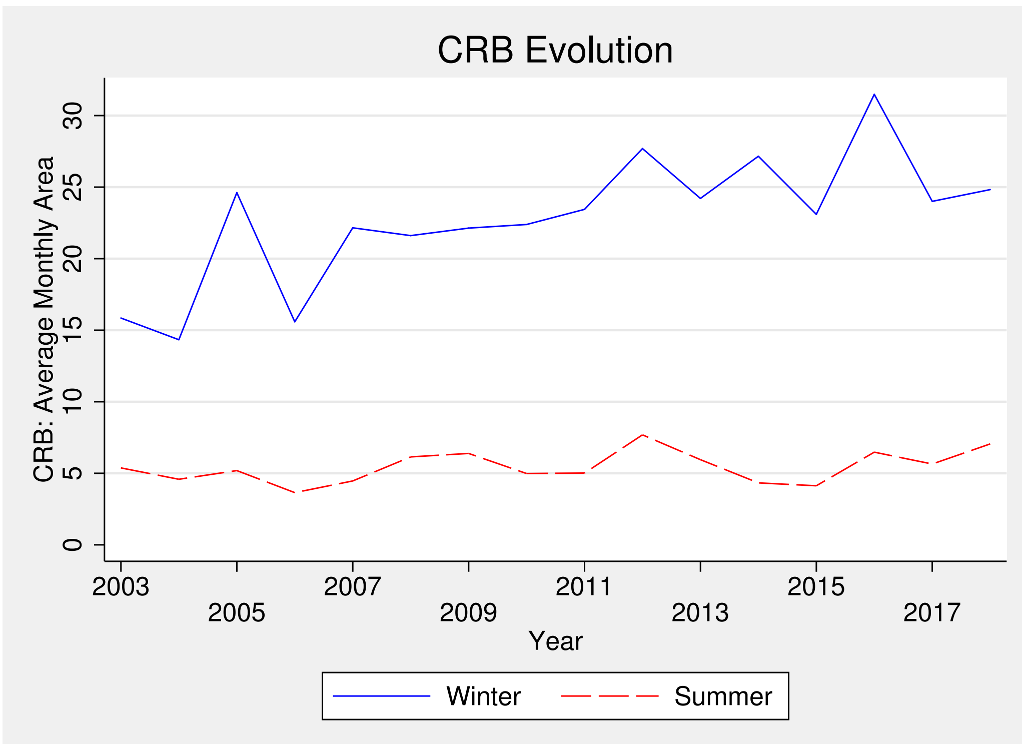
A3 Appendix Figures and Tables

Figure A3: Average Monthly Burning



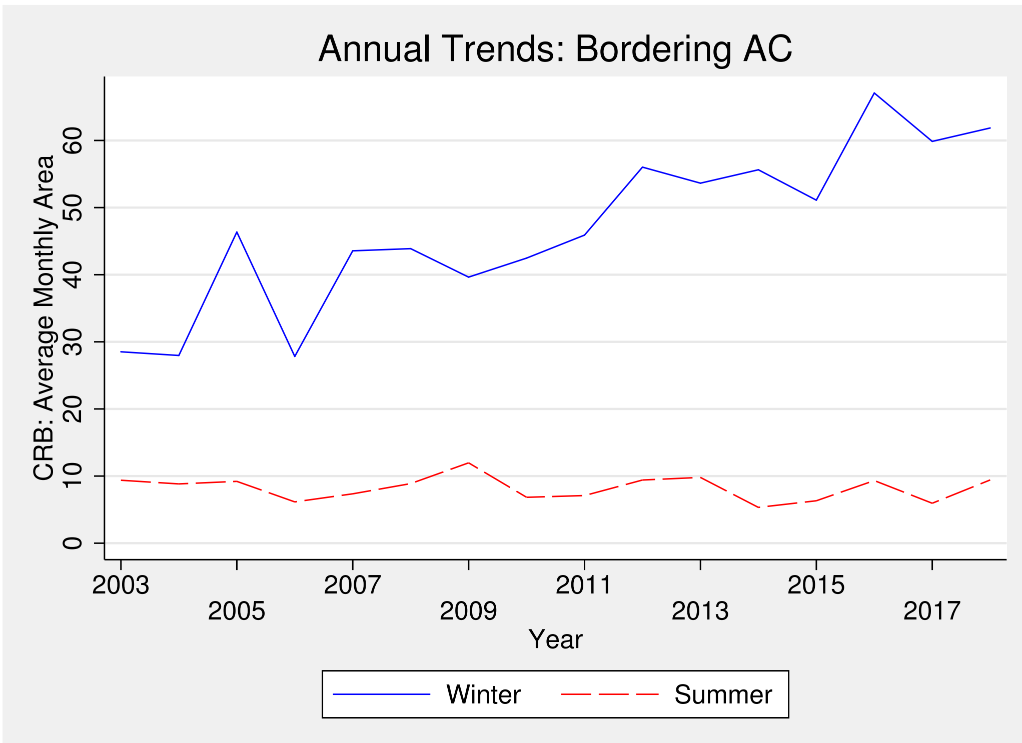
The figure shows the average crop residue burning in the pre and the post period across the different months of the year. The sample consists of all constituencies of the treated and control states.

Figure A4: Evolution of CRB across years



The figure shows the evolution of winter and summer CRB across the different years. The sample consists of all constituencies of Punjab and Haryana and the neighbouring states

Figure A5: Evolution of CRB (Bordering AC)



The figure shows the evolution of winter and summer CRB across the different years. The sample consists of the bordering constituencies of Punjab and Haryana and the neighbouring states

Table A4: Summary statistics

Variable	**Mean**	**Std. Dev.**	**N**
Winter: October-November			
Area Burnt	48.144	115.375	3120
Wind Speed	3.135	0.475	3120
Precipitation	0.076	0.146	3120
Summer: April-May			
Area Burnt	8.477	16.695	3120
Wind Speed	4.569	0.723	3120
Precipitation	0.294	0.258	3120
Policy Variables			
MNREGA	0.691	0.462	3120
Election Year	0.208	0.406	3120
Agricultural Controls			
Rice Production(1000 tons): Kharif	271.253	395.795	2968
Wheat Production(1000 tons): Rabi	642.5	505.794	2968
Rice Yield: Kharif	2.964	0.945	2604
Wheat Yield: Rabi	3.695	1.056	2968
Demographic Controls			
Proportion of SC/ST	0.237	0.072	3120
Proportion of Muslims	0.089	0.138	3120
Proportion of Urban Population	0.254	0.114	3120
Proportion of Literates	0.61	0.081	3120
Sex Ratio (Age 0-6)	0.843	0.038	3120

Notes: The table presents the mean and variance of the variables used in the regressions. Sample consists of the bordering constituencies of Punjab, Haryana and the control states between 2003 and 2018.

Table A5: Effect on CRB

	(1) Baseline	(2) Demographic Controls	(3) Agricultural Controls
Panel A: Winter: October and November			
Treatment × Post	0.2812**	0.2669**	0.3677*
	(0.0632)	(0.0636)	(0.0377)
	[0.0383]	[0.0374]	[0.0649]
Observations	3120	3120	2604
Panel B: Summer-April and May			
Treatment × Post	0.1123	0.1577	0.0721
	(0.6737)	(0.4813)	(0.7855)
	[0.7077]	[0.5138]	[0.8067]
Observations	3120	3120	2604

Notes: Each cell represents a separate regression. Area Burnt is the dependant variable in all the regressions. Panel A shows the results for winter burning (Months: October and November) and panel B report results for summer burning (April and May). Apart from the reported variables, all regressions include assembly constituency fixed effects, year-month fixed effects, state specific linear year trends, climatic controls and policy controls. Column 2 includes demographic controls and column 3 includes controls for agricultural production and yield in addition to the above-mentioned controls. Sample includes data from neighbouring constituencies of the states Punjab, Haryana, Himachal Pradesh, Rajasthan and Uttar Pradesh for the years 2003-2017. Errors are clustered at state level. Wild bootstrapped p-values are reported in the brackets.

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

Table A6: Effects on Rice and Wheat Production

	(1) Production	(2) Yield
Panel A: Kharif Rice		
Treatment × Post	-7.0482	-0.0316
	[0.8431]	[0.8352]
Observations	718	602
Panel B: Rabi Wheat		
Treatment × Post	-13.5733	-0.0341
	[0.6503]	[0.7442]
Observations	718	718

Notes: Each cell represents a separate regression. The dependent variables are mentioned at the top of the cell. The unit of observation is a district-year. Apart from the reported variables, all regressions include assembly climatic controls, political controls, district and year fixed effects and state specific year trends. Sample include data from neighbouring districts of the states Punjab, Haryana, Himachal Pradesh, Rajasthan and Uttar Pradesh. Errors are clustered at state level. Wild bootstrapped p-values are reported in the brackets.