Technology in Agriculture and Religious Conflict*

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Abstract

I examine the effect of the Green Revolution on religious riots in India between 1957 and 1985. Using an instrumental variable framework on a district level panel dataset, I find that riots are longer after the Green Revolution is introduced, with a 1% increase in the duration of a riot. Employing alternative measures of riot intensity and incidence, I find suggestive evidence of an overall increase in religious conflict after the introduction of mechanization via the Green Revolution. I show that the Green Revolution reduces the opportunity cost of engaging in conflict by reducing the demand for labor in agriculture due to mechanization. There is suggestive evidence to show that religious violence is exacerbated in an election year. Additional results indicate the mitigation of the effects of the Green Revolution on conflict in a good rainfall year and an increase in the intensity of conflict in districts in north India. My findings shed light on the unintended consequences of technology in agriculture as well as the mechanisms through which this technology influences ethnic conflict.

Keywords: Green Revolution, Riots, Conflict

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1 Introduction

There has been evidence to show that even in ethnic and religious conflict, where violence seems to be instigated due to cultural differences, economic factors play a key role (Mitra and Ray, 2014). The introduction of technology in labor intensive sectors is one such economic channel through which conflict can be influenced. This paper examines the effect of the introduction of new technology in agriculture on religious conflict. I examine the effects of the Green Revolution (henceforth GR), which introduced mechanisation and improved cropping methods in Indian agriculture in 1967, on the onset and duration of Hindu Muslim riots.

A major component of the Green Revolution was the introduction of High Yielding Variety (HYV) seeds, which required large amounts of controlled irrigation (Parayil, 1992). As a result, the Green Revolution targeted the new technology more towards districts with greater pre existing irrigation infrastructure. I use this variation in pre existing irrigation intensity to construct an instrument for the spread of the Green Revolution in an instrumental variable framework. I use the 1966 level irrigation intensity in the district as a measure of suitability to the adoption of HYV seeds. I interact this cross sectional measure of suitability with a time dummy representing the introduction of the Green Revolution in India in 1967. This instrument has been used to plausibly identify the effects of the Green Revolution on other outcomes, such as political outcomes and insurance networks (Munshi and Rosenzweig, 2009; Dasgupta, 2017). I combine district level agricultural data and data on Hindu-Muslim riots from 1957-1985 to construct a panel dataset, which allows test the effect of the introduction of GR on religious conflict between 1957-85.

The empirical strategy addresses endogeneity concerns that can arise from examining the effect of area under HYV cultivation on religious riots. It is possible that districts with higher HYV adoption rates may have differential incidence and intensity The baseline specification includes district fixed effects which controls for all the time invariant district characteristics which are associated with the instrument and which also affect religious rioting. State by year fixed effects control for variation in year wise pattern of riots across states. This identification strategy thus allows me to compare the *change* in riot outcomes as a result of HYV crop adoption within a district in a given year.

I find a statistically significant effect on the duration of riots, with a 1 percent increase in the length of a riot after the introduction of the Green Revolution. The effects on other measures of conflict, though statistically insignificant, suggest an increase in the incidence and intensity of conflict. I interact the instrument for share of district area under HYV cultivation and find that in a year with a good rainfall shock, the exacerbating effects of the Green Revolution on conflict reduce, but this effect is marginal in nature. I find suggestive evidence of increased conflict in rice growing districts as well as districts in the northern region. In a year of political change, my results suggest a heightened exacerbatory role of the Green Revolution. My results are robust to the inclusion of district level controls, as well as fixed effects and a state time trend. I conduct various robustness checks to provide evidence of the validity of the exclusion restriction and present additional results wherein I control for rainfall shocks, crop variety and geographical location. I also use alternative specifications which does not alter my result.

The availability of income or resources may not always have the same effect on conflict (Lyall, Zhou and Imai, 2018; Dube and Vargas, 2013; Adhvaryu et al., 2018). The effect that new technology could have on conflict is ambiguous a priori: it leads to an increase in agricultural productivity, leading to an increase in prosperity in farms and potentially reducing conflict. However, if the new technology improvement is not diffused evenly, it could lead to an increase in conflict. My results suggest that the inequality channel may be in operation, as a result of the labor displacement that followed the Green Revolution. As a result of the Green Revolution creating disparities in rural income, people may have greater incentives to grab resources and engage in conflict.

The existing literature has tried to determine the causal factors that affect ethnic and religious conflict. Dal Bó and Dal Bó (2011) estimate a model wherein they find that a rise in the price of the labour intensive good reduces conflict, whereas a rise in the price of either the capital intensive good will increase conflict. This ambiguous relationship of conflict with its causal factors has been validated by Dube and Vargas (2013), who find that price shocks generate contradictory pressures on conflict. A price rise may generate greater rents to fight over or may increase wages, which raises the opportunity cost of fighting. Since income and conflict are endogenous, instrumental variables such as rainfall have been used to study the impact of economic growth on conflict, and these studies find a reduction in conflict in areas which receive more rainfall (Miguel, Satyanath and Sergenti (2004); Sarsons (2015); Bai and Kung (2011)). Field et al. (2008) find that imperfect property rights are an important determinant of religious conflict. Other studies have studied the impact of social welfare programs on the incidence of conflict. Fetzer (2014) studies the impact of social insurance on conflict, measured by the introduction of a large scale employment guarantee scheme in India, and finds a decline in both the incidence and intensity of conflict. Khanna and Zimmermann (2014) assess the effect of a large scale employment guarantee scheme in India on insurgency related violence and find that there is more police action and a reduction in the incidence of such violence. Nunn and Qian (2014) study the impact of frequency of US food aid provision as well as wheat production in the US on both the frequency and the incidence of conflict in recipient countries. They find a significant effect on the incidence of conflict but no such effect on the intensity margin. Additional mechanisms may also play a role, such as prosperous farmers being able to invest in protection, which may reduce the incidence of conflict (Mitra and Ray, 2014).

However, the role of technology in influencing conflict has been relatively understudied. Moreover, the underlying mechanisms through which technology might affect conflict is also not the same across studies. Pierskalla and Hollenbach (2013) find that the spread of cell phone technology across Africa allows for better intragroup coordination and significantly increases the probability of violence. Acemoglu, Fergusson and Johnson (2017) focus on the impact of health technology on the effect of population and social conflict in a cross country analysis and find that countries with higher exogenous increases in population experienced more social conflict. The paper closest to my study is by Iyigun, Nunn and Qian (2017), who use the introduction of the potato to study the effect permanent increase in agricultural productivity in the period from 1400-1900 in a cross country analysis. They exploit variation in suitability to potato cultivation to examine the effect on the incidence of conflict, and find that the introduction of the potato reduced conflict in areas more suitable to potato cultivation. My paper adds to the existing literature on the causal effect of agriculture on conflict (Wischnath and Buhaug, 2014; Roy, 2012), as well as the literature on economic factors determining religious conflict in India (Iyer and Shrivastava, n.d.; Field et al., 2008; Bohlken and Sergenti, 2010). My paper contributes to the growing literature on the introduction of new technology in agriculture, as well as the literature on adaptation to climate shocks (Burke, Hsiang and Miguel, 2015).

The paper is organised as follows: Section 2 provides background information on the Green Revolution and religious conflict in India, Section 3 discusses the empirical strategy, Section 4 describes the data, Section 5 provides the results, Section 6 examines the validity of the exclusion restriction, Section 7 includes some additional results, Section 8 discusses mechanisms at work and Section 9 concludes.

2 Background

2.1 Riots in India

Religious violence has a long history in India. The violence is primarily between Hindus and Muslims and dates back to the period before Partition. After India gained independence, religious riots have been sporadic but occur at regular intervals. While these riots are often attributed to underlying religious tension, several researchers argue that they are also sparked by economic conditions. There is evidence to show that economic factors play a role in this context, just as they do in religious or ethnic violence elsewhere. Income shocks make it easier for elites to gain support, particularly if Hindus and Muslims blame each other for unemployment or falling wage (Esteban and Ray, 2011; Mitra and Ray, 2014; Bohlken and Sergenti, 2010). Figure 1 shows the average number of religious riots in India which occurred between 1950 and 1990. In the period corresponding to the Green Revolution, that is between 1967 and 1985, the figure shows a sudden spike in the incidence of conflict, which makes the case for examining the potential effect of the Green Revolution on religious conflict.

2.2 The Green Revolution

The Green Revolution can be defined as a global effort to increase agricultural yields worldwide. The Green Revolution ushered a technological revolution in Indian agriculture in 1967 as a response to the famine in 1965-66. It aimed to increase the output of wheat and rice in the country through the introduction of High Yielding Variety(HYV) seeds as well as the introduction of double cropping methods (Janaiah, 2005). These genetically engineered seeds allowed for significantly greater production of foodgrains than had been possible earlier. It was introduced in the districts which had adequate pre existing irrigation infrastructure. The program led to a huge increase in yields from 1966-1985, with 17 million tons of wheat produced in 1968 compared to 6 million tons of wheat produced in 1947 (Moscona, 2017). HYV crops were taken up widely across India over the next two decades, but the takeup rate depended on the water intensity of the district (Dasgupta, 2017). The effects of the Revolution began to dissipate after 1985, with agricultural yields declining as a result of diminishing returns to land. Moreover, the program was highly selective in spread effects and was largely restricted to the original treatment districts. By the 2000's, investment in agriculture saw a sharp decline (Pingali, 2012). This is also the reason I restrict the sample for my study to 1985, in order to capture the effect of the Green Revolution while it was in still in operation. There have been several studies which have studied the effects of the Green Revolution in India on several outcomes such as agricultural productivity (Moscona, 2016), single party dominance in electoral politics (Dasgupta, 2017), insurance (Munshi and Rosenzweig, 2009) and social networks (Munshi, 2004). However, to the best of my knowledge, there has been no study to examine the causal relation that the Green Revolution may have with religious conflict.

Figures 2 and 3 show the average share of land under HYV wheat and rice cultivation respectively. The mean share of land used for HYV cultivation sees an increase post 1967, and these increases are more pronounced for rice and wheat. The same holds true for the mean share of land under HYV cultivation for jowar, bajra and maize. Figure 4 depicts the spread of the share of agricultural land under HYV cultivation by the years 1973 and 1985. The maps depict the gradual increase in area under HYV cultivation after the Green Revolution in 1967.

3 Empirical Strategy

The OLS specification regresses the outcome of interest on the share of agricultural land in a district under HYV cultivation. The specification for the same is as follows:

$$y_{dt} = \beta_0 + \beta_1 HYVshare_{dt} + \gamma_d + \delta_{st} + \theta_t + \phi X_{dt} + \epsilon_{dt} \quad (1)$$

where d represents district, s represents state and t represents year. β_1 is the coefficient of interest, which shows the marginal effect of land under HYV on conflict. I include district level demographic controls. The specification also includes district fixed effects, γ_d, year fixed effects,

θ_t as well as a state time year trend, δ_{st}. This allows me to look at changes *within* districts over time in HYV crop adoption on conflict, while controlling for any state specific time shocks or trends as well as unobservable changes over time. To control for correlation between errors within districts over time, I cluster standard errors at the district level.

The main concern is that there are unobservables which caused both HYV and conflict, including direct effects of conflict on HYV. Moreover, there is an issue of sampling error in agricultural surveys from which HYV adoption data is compiled. Hence, I adopt an instrumental variable approach to address the potential bias. This approach also minimizes measurement error, which could arise from sampling error in the agricultural survey from which HYV crop adoption data is obtained (Dasgupta, 2017).

The instrument I employ uses one of the key features of the Green Revolution: areas which already had the requisite irrigation infrastructure in place prior to the Green Revolution had a greater share of agricultural area under HYV cultivation. This is because HYV seeds were water intensive and delivered high yields only in areas with access to controlled irrigation facilities. The first stage equation measures the strength of the instrument and is specified as follows:

$$HYVShare_{dt} = \alpha_0 + \alpha_1 Int_d \times After_t + \alpha_2 Int_d + \alpha_3 After_t + \gamma_d + \delta_{st} + \theta_t + \phi X_{dt} + \epsilon_{dt} \quad (2)$$

where d represents district, s represents state and t represents time. $HYVShare_{dt}$ is the share of agricultural area in a district under HYV cultivation. $After_t$ is the dummy which takes the value of 1 for the years post 1967, when the Green Revolution was introduced. Int_d is the cross sectional measure of irrigation intensity in 1966. Irrigation intensity is defined as the share of net cropped area that is under irrigation. $Int_d \times After_t$ is the instrument, which is the interaction of irrigation intensity in 1966 interacted with a time dummy that 'switches on' for the year 1967 and after. α_1 is the coefficient of interest, which measures the correlation between the instrument and the instrumented variable. The equation includes district fixed effects, γ_d as well as a state time year trend, $delta_{st}$ and district level demographic controls,X_{dt}.

The reduced form specification estimates the effect of the instrument on the outcome of interest in a difference in differences framework. The reduced form equation assesses whether the Green Revolution affected religious rioting more in districts that got a greater share of HYV seeds. The reduced form equation takes the form:

$$y_{dt} = \pi_0 + \pi_1 Int_d \times After_t + \pi_2 Int_d + \pi_3 After_t + \gamma_d + \delta_{st} + \theta_t + \phi X_{dt} + \epsilon_{dt} \quad (3)$$

where d represents district, s represents state and t represents time. $After_t$ is the dummy which takes the value of 1 for the years post 1967, when the Green Revolution was introduced. Int_d is the cross sectional measure of irrigation intensity in 1966. Irrigation intensity is defined as the share of net cropped area that is under irrigation. The equation also includes district fixed effects, γ_d as well as a state time year trend, $delta_{st}$. $Int_d \times After_t$ is the instrument, which is the interaction of irrigation intensity in 1966 interacted with a time dummy that 'switches on' for the year 1967 and after. The identifying assumption for this specification exploits the fact that exposure to HYV seeds was more in districts with higher investment in irrigation before the GR was introduced. This provides the necessary cross sectional variation to estimate the causal effect. I include district level demographic controls in all specifications.

The second stage regression is the specification in equation (1). In equations (1) and (3), y_{dt} is an outcome variable which measures a different dimension of conflict. I divide these dimensions of conflict into incidence and intensity measures. Incidence measures include an indicator variable for whether a riot took place in a particular district in a give year, and the number of riots that a district experienced in a given year. Intensity measures include an indicator variable for whether anyone was killed in a riot, the number of people killed in a riot and the number of days over which a given riot was spread out. The exclusion restriction requires that, conditional on covariates, areas with greater 1966 irrigation intensity experienced an increase in conflict after 1967 only through differentially higher rates of HYV crop adoption over time and not due to other factors. I test the plausibility of this assumption with various robustness checks, which follow the main results.

4 Data

The variables on conflict have been constructed using the Varshney and Wilkinson (2006) dataset, which is an exhaustive dataset of religious riots in India covering the period from 1950 to 1995. This dataset provides information on all Hindu-Muslim riots reported in the The Times of India, a major national Indian newspaper, from January 1950 through December 1995. The dataset contains district wise information on location, number of casualties, duration of the riot, reported causes, official involvement, policing arrangements, among other characteristics. A total number of 1192 riots were reported over the entire timeline of the dataset. In this paper, I look at riots between 1957 and 1985, which correspond to the pre GR period, introduction of the GR and diffusion periods. Despite being a comprehensive dataset, it has its shortcomings: since it is based only the *reported* number of riots, it could potentially be an underestimate of the *actual* number of riots which occurred in this time period.

The agricultural technology and climate variables are derived from the Evenson and McKinsey dataset, compiled by Sanghi, Kumar and James Jr (1998). It covers 271 districts in 13 states of India from the period of 1957-1985. This dataset contains detailed district level data on crops grown, area under HYV and non HYV cultivation, soil characteristics, area of land under irrigation as well as demographic factors such as population density, labor employed in agriculture and percentage of literate males in the district.

4.1 Descriptive Statistics

Table 1 displays descriptive statistics for both the explanatory as well as dependent variables. The first column represents the pre GR period, that is, the period from 1957-66. The second column depicts descriptive statistics for the post GR period, which covers the period from 1968-85. On an average, there is an increase in both incidence and intensity measures of riots. The average number of riots increase by 0.22 riots per year after the Green Revolution. The average duration of a riot also sees an increase of about 0.03 days per riot in a year. However,there is substantial variation in the number of people killed as well as the occurrence of a riot. There is an increase in net irrigated area as well as the share of land under HYV cultivation, both in terms of area as well as percentage share. The share of land under HYV cultivation increases by 23% in the period from 1968-85. The average district had about 21% of its cropped land under irrigation in 1966.

5 Results

5.1 OLS Results

Tables 3 and 4 report the OLS estimates from equation (1). The estimates show insignificant effects of the GR on whether a riot took place, the number of riots, number of people killed, whether anyone was killed and the duration of a riot in days. The estimates remain consistent with the addition of a state time trend, which controls any unobservable state specific characteristics that may be changing over time. The estimates also remain consistent with the inclusion of controls. The OLS results could be biased as unobservables which affect both conflict and the spread of HYV seeds may be driving the results. This is indicative of omitted variable bias, since measures of conflict may be correlated with unobservables in the error term.

5.2 First Stage and Reduced Form Results

Table 2 displays results from the first stage regression of HYV share on the instrument, which is the dummy for the post GR period($After$) interacted with the 1966 irrigation intensity. The results show a strong and positive first stage relationship, which is robust to the addition of controls as well as inclusion of a state time trend. Areas with higher 1966 irrigation levels also had a higher share of area under HYV cultivation, with a 34.7 percentage point increase in area under HYV seed cultivation for districts with greater pre existing irrigation infrastructure.

Tables 3 and 4 report the reduced form estimates, wherein the instrument is regressed on the outcomes of interest. This is analogous to a differences in difference estimation, where I exploit the variation in irrigation intensity across districts and interact it with the post GR dummy. To account for the excess number of zeros in both the count variables, I add a small number of 0.01 to the log of the count variable, as done by Mitra and Ray (2014). This allows for a percentage point interpretation of the coefficients. I find a significant increase in the duration of riots in days. The length of a riot increases by about 0.40 percent in areas with greater pre existing irrigation after the introduction of the Green Revolution. The estimates on other measures of conflict suggest an increase in conflict, but these estimates are insignificant at the 5 percent level.

5.3 2SLS Estimates

The instrumental variable results are reported in Tables 3 and 4. There is a positive and significant effect on the number of days a given riot occurs, with a 1 percent increase in the length of a riot (measured in days) post the Green Revolution. On other margins, however, the effects are greater than those in the reduced form estimates but remain statistically insignificant. The estimates are robust with the inclusion of controls. The instrumental variable estimates represent effects of HYV crop adoption in areas which had high water availability and hence conducive to HYV crop adoption.

These results are suggestive of the fact that an increase in productivity in rural areas may not have had spillovers in the urban areas and could be a possible explanation for why we do not see any results on the intensity of religious riots, which occurred in larger proportions in urban areas as compared to rural areas. This explanation is also given by Roy (2012) in her paper studying the effects of land reform in rural India on Hindu Muslim rioting. I examine the plausibility of the labor displacement channel which could explain the increase in the length of a riot in section 8 of the paper.

6 Robustness Checks

6.1 Testing the Exclusion Restriction

The exclusion restriction requires that district wise 1966 irrigation intensity levels interacted with a time dummy for the Green Revolution should not affect conflict through any other channel other than its effect on the HYV share of agricultural land. The reduced form results rule this effect out and the inclusion of fixed effects and state year time trends rule out any time invariant characteristics or state time trends that may threaten the exclusion restriction. However, the exclusion restriction may not hold if districts with higher levels of 1966 irrigation intensity would have had higher levels of conflict even without the introduction of the Green Revolution in 1967. Though the exclusion restriction cannot be tested directly, I conduct several tests in order to provide evidence in support of the exclusion restriction.

6.2 Parallel Trend and Pre Trend Results

To identify the *timing* of the emergence of a positive reduced form relationship between irrigation intensity in 1966 and conflict, I estimate a regression of the form:

$$y_{dt} = \sum_{k=1957}^{1985} \theta_k Int_d \times Year_t^k + \epsilon_{dt} \tag{4}$$

where y_{dt} is a measure of conflict, $Year_t^k$ is a dummy variable representing a particular year between 1957 and 1985 and Int_d is the district level irrigation intensity in 1966. This specification includes district fixed effects and year fixed effects. For the parallel trend assumption to hold, unobservable trends from the pre Green Revolution period should not be driving the increase in conflict after the introduction of the Green Revolution. That is, θ_k for any k in the pre Green Revolution period should not be significant. Figure 5 displays the coefficients θ_k for the indicator variable representing whether a riot took place. I include additional results on the other outcome variables in the Appendix and the results suggest that trends unrelated to area under HYV cultivation do not drive the results on any of the measures of conflict. There is no detectable positive pre trend in areas with greater 1966 irrigation intensity.

6.3 Placebo Test

I also construct a placebo test in Tables 5 and 6, where I interact the 1966 irrigation intensity measure with year dummies for the period from 1957-1966, since these years are unrelated to the introduction of the Green Revolution in India. The specification for the placebo test takes the form:

$$y_{dt} = \beta_0 + \beta_1 Int_d \times PseudoAfter_t + \beta_2 Int_d + \beta_3 PseudoAfter_t + \gamma_d + \delta_{st} + \theta_t + \phi X_{dt} + \epsilon_{dt} \tag{5}$$

where $PseudoAfter_t$ represents the year 1966, a year prior to the introduction of the Green Revolution and hence unrelated to the introduction of HYV crops in India. β_1 is the coefficient of interest, which shows the correlation between the period before the introduction of the Green Revolution. If the exclusion restriction is valid, β_1 should have no effect on any of the measures of conflict. I find small and statistically insignificant coefficients on the placebo interaction variables, which indicate that districts with higher irrigation intensity saw greater conflict only after the Green Revolution took place, and not before it was introduced, thus providing further evidence in support of the exclusion restriction.

7 Additional Results

7.1 Rainfall Shocks

Rainfall shocks have been shown to reduce religious and ethnic conflict(Miguel, Satyanath and Sergenti, 2004; Bai and Kung, 2011), where areas with higher rainfall are shown to have higher incomes and hence a lower incidence and intensity of conflict. I therefore run the instrumental variable regression with an interaction term for the rainfall shock. The baseline specification for this regression is given as

$$y_{dt} = \beta_0 + \beta_1 HYVshare_{dt} \times RainShock_{dt} + \beta_2 HYVshare_{dt} + \beta_3 RainShock_{dt} + \gamma_d + \delta_{st} + \theta_t + \phi X_{dt} + \epsilon_{dt} \quad (6)$$

where β_1 is the coefficient of interest, which gives us the effect of the Green Revolution interacted with a yearly rainfall shock in a district. I use two measures of rainfall shocks, both of which account for seasonality in rainfall. The first measure is the fractional deviation of rainfall from its average level (calculated from 1957 to 1985) summed over all months, used previously by Sarsons (2015) and Duflo and Pande (2007) . I then sum over all 12 months to find a district's yearly shock. I construct the second measure as follows: for a particular month, I compare the actual amount of rainfall to the average amount and define a positive shock as rainfall that is above the eightieth percentile and a negative shock as rainfall below the twentieth percentile (Sarsons, 2015; Jayachandran, 2006). I then take the average of this measure over all months. I interact the rainfall shock measures with my instrument and find that some of the exacerbating effects of the Green Revolution are countered in a district in a year with a positive rainfall shock. There is a 0.3 percent decrease in the duration of a riot post the Green Revolution in a year with greater rainfall than normal, which is significant at the 5 percent level(Table 9). I find similar results for the other measures of conflict, where in a year with greater than normal rainfall, conflict actually *reduces*. However, these results are only suggestive, as they are insignificant at the 5 percent level.

7.2 Heterogeneity across Crops

The Green Revolution increased yields for five crops, and in particular, for wheat and rice. Wheat growing regions may have different trends due to geographic characteristics from rice growing regions, and the relative importance of the crop grown may influence the direction of conflict. For instance, in an area with greater wheat production where wheat based food is not a staple form of diet, districts which get more HYV wheat seeds may not see too much of an effect on conflict. I split my sample to compare wheat growing districts to rice growing districts to see if there was a differential increase in conflict in districts which was determined by the crops they grew after the Green Revolution. I find that most measures of conflict have increased more in rice growing districts rather than wheat growing districts, but this increase is insignificant across most measures(Table 10).

7.3 Heterogeneity across Regions

To test heterogeneity in treatment effects across the country in response to the Green Revolution, I split my sample into regions, North and non North to examine heterogeneous effects across countries. The northern region of India comprises of the Hindi speaking states of Bihar, Madhya Pradesh, Haryana, Uttar Pradesh, Rajasthan and Punjab. The non North regions include the South(Andhra Pradesh, Karnataka, Tamil Nadu), East(West Bengal and Orissa) and the West(Gujarat and Maharashtra). The argument for doing so stems from the fact that the northern part of India is culturally different from the other regions. I find a significant 1.78 percent increase in the number of people killed in the northern regions post the Green Revolution. There is evidence to suggest that the intensity of conflict may have actually *reduced* in the non North regions post the Green Revolution (Table 11), but these estimates are statistically insignificant.

7.4 Alternate Specifications

The intensity measures control for state and time fixed effects and use the negative binomial model. My results for the count variables are robust to alternative specifications such as the Poisson and negative binomial distributions. Count variables suffer from the problem of over dispersion and an excess number of zeros, and the negative binomial regression adjusts for this and provides an estimate for the log count of a variable. I include the reduced form results from these regressions in the Appendix, and the estimates from these regressions also suggest an increase in conflict. However, the measures are statistically insignificant.

8 Discussion

As discussed earlier, there are two potential mechanisms through which the Green Revolution could be affecting conflict. The Green Revolution could increase agricultural prosperity, and hence reduce the incentives for conflict. On the other hand, the Green Revolution might perpetuate inequalities between the treatment and control districts and hence increase the incidence of conflict. My results seem to suggest that the latter effect may be in operation.

One of the channels through which the Green Revolution may have increased conflict is through displacing labor. The Green Revolution was known to have increased agricultural yields through mechanization (E. Evenson and W. McKinsey, 1999). This has come at the cost of displacing labor from the rural farmland, and I test this hypothesis by regressing the quantity of labor in agriculture on the instrumented HYV share in Table(insert number here). The specification takes the form:

$$y_{dt} = \beta_0 + \beta_1 HYVshare + \gamma_d + \delta_{st} + \theta_t + \phi X_{dt} + \epsilon_{dt} \tag{7}$$

where y_{dt} is defined as the outcome variable measuring the percentage change in number of men whose primary job is cultivation. I also test this hypothesis for the total number of males working in the agricultural sector, and this work includes activities related to both cultivation and non cultivation in Table 12.

I find a decrease in the labor whose primary job is cultivation as well as a decrease in the quantity of labor post the Green Revolution. The quantity of labor is defined as the weighted sum of labor involved in agriculture and labor involved in cultivation, multiplied by the number of days worked in the state by farm workers.

8.1 Election Cycles

There has been evidence linking religious riots in India with political outcomes Iyer and Shrivastava (n.d.) Iyer and Shrivastava, Varshney, Wilkinson). I explore whether this channel, in conjunction with the GR, affects religious rioting. Dasgupta (2017) finds that a decline in Congress vote share and seat share is negatively correlated with the adoption of HYV wheat and rice. This happened due to the steadily increasing clout of politically excluded agricultural groups and farmers unionising in the face of lower prices for their produce (Nellis, Weaver and Rosenzweig, 2016). It is possible that the unionisation and collective action by both rich and poor farmers could also have religious undertones. The theoretical model drawn up by Esteban and Ray (2011) throws light on ethnic conflict which is guided by both income and relative clout of the two groups.

To examine the interaction between political cycles and the Green Revolution, I interact the instrument with a dummy which represents occurrence of a national election in a given year. There were seven national elections that took place in the period of study. The specification I use takes the following form:

$$y_{dt} = \beta_0 + \beta_1 HYVshare_{dt} \times Election_t + \beta_2 HYVshare_{dt} + \beta_3 Election_t + \gamma_d + \delta_{st} + \theta_t + \phi X_{dt} + \epsilon_{dt} \tag{8}$$

where $Election_t$ is a dummy variable which takes the value of 1 in an election year. β_1 is the coefficient of interest, which shows the effect of the interaction of an election year with the timing of the Green Revolution on religious conflict in a particular district. As mentioned before, $HYVshare_{dt}$ is the instrument used for the HYV share. This specification me to tease out the top down vs bottom up approach and determine whether the effect on conflict is purely due to the economic implications of the Green Revolution or because of the influence that politicians have on the implementation of the Green Revolution and over the farmers (**?**). Tables 13 and 14 present the results for both the incidence and intensity measures of the riot. The coefficients are statistically insignificant, but are suggestive of conflict spiking up even more in years where a national election was held in districts which experienced a greater spread of the Green Revolution.

9 Conclusion

There is scarce evidence linking technological change to conflict. This paper examines the effect of the introduction of new technology in agriculture on the incidence and intensity of religious conflict among the Hindus and Muslims. I use an instrumental variable framework to plausibly identify the effects of the introduction of the Green Revolution. I find a statistically significant increase in the duration of riots and suggestive evidence of an increase other measures of religious conflict. Additional estimates suggest that in years of good rainfall, the effects of the Green Revolution are countered. This is in line with existing evidence that shows that rainfall reduces ethnic conflict (Miguel, Satyanath and Sergenti, 2004; Burke, Hsiang and Miguel, 2015). I find that one of the mechanisms through which this operates is the labor displacement in agriculture following the Green Revolution. I find statistically significant and negative results on the quantity of labor employed in the post Green Revolution period. I find that in the year coinciding with an election, there is evidence to suggest an increase in conflict in districts with a greater spread of the Green Revolution.

This demonstrates that the inequality channel may be at play here: since the Green Revolution was known to increase rural inequality (Pingali, 2012), it may have led to increased incentives to grab resources from those who benefitted more from the availability of the new seeds. A future avenue of research would be to examine the religious composition of farmers benefiting from the Green Revolution, in order to determine which group may be inciting the violence and to further understand the incentives underlying engagement in conflict. Other questions to explore are the extent of landholding in rural areas between Hindus and Muslims at the district level and how that may affect religious conflict.

10 Declaration

- **Ethical Approval**: This paper uses secondary data which is publicly available and does not contain any personal identifiable information. It is not a human study and hence is exempt from ethics requirement.

- **Funding**: There was no funding received for this project.

- **Availability of data and materials**: Data is available at https://github.com/bhattashreya/Drafts

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11 Tables

Table 1: Descriptive Statistics

	1957-66 (1)	1968-85 (2)
Whether Any Riot Took Place	0.022	0.031
	(0.147)	(0.173)
Number of Riots	0.348	0.563
	(2.742)	(3.588)
Anyone Killed	0.009	0.018
	(0.096)	(0.133)
Number Killed	0.037	0.227
	(0.49)	(8.754)
Duration of Riot in Days	0.026	0.054
	(0.191)	(0.397)
Net Irrigated Area('000 hectares)	82.14	123.5
	(90.33)	(119.1)
Total Area Under HYV('000 hectares)	1899.4	112208.8
	(8994.4)	(114615.3)
Share Under HYV Cultivation	0.004	0.234
	(0.018)	(0.187)
1966 Irrigation Intensity	0.213	0.213
	(0.199)	(0.199)
Total Agricultural Area ('000 hectares)	438603.3	472838.2
	(231790.2)	(235456.4)
N	3005	4911

Notes: There are 270 districts in the dataset, covering the years from 1957-1985. The table contains mean coefficients on the dependent and independent variables in the sample. Column (1) represents the period before the introduction of the Green Revolution and Column (2) represents the period after the introduction of Green Revolution. Standard errors are in parentheses. A unit of observation is a district year. *Whether Any Riot Took Place* is an indicator variable which takes the value of 1 if a riot took place in a district in a year. *Number of Riots* is a numerical count of riots in a district in a year. *Anyone Killed* is an indicator variable which takes the value of 1 if anyone was killed in a riot in a district in a year. *Number Killed* is a numerical count of the number of people killed in a riot in a district in a year. *Duration of Riot in Days* represents the number of days over which a riot takes place in a district in a year. *Net Irrigated Area* is the net cropped area under irrigation in thousand hectares. *Total Area under HYV* is the total cropped area cultivated with HYV seeds. *Share Under HYV Cultivation* is defined as the proportion of the total cropped area in a district which is under HYV cultivation. *1966 Irrigation Intensity* is the cross sectional measure of district level irrigation intensity. *Total Agricultural Area* is the total area under cultivation in a district in a year.

Table 2: First Stage: Effect of HYV Instrument on HYV Share

	(1)	(2)	(3)
After×1966 Irrigation Intensity	0.347	0.364	0.43
	(0.035)	(0.037)	(0.043)
t stat	9.9	9.61	9.98
R^2	0.879	0.871	0.84
Controls	Y	N	Y
District Fixed Effects	Y	Y	Y
Year Fixed Effects	Y	Y	Y
State Time Trend	Y	Y	N
Observations	6815	7961	6815

Notes: Table 2 presents results for equation (2). Columns (1), (2) and (3) represent results from two separate regressions. *HYV Share* is the dependent variable, which is defined as the proportion of agricultural land cultivated with HYV seeds. The independent variable, *After* $\times$ *1966 Irrigation Intensity*, is the instrument, the interaction between the time dummy which switches on for years greater than 1967 and the cross sectional measure of district level irrigation intensity in 1966. Irrigation intensity is defined as the proportion of net cropped area that is irrigated. Standard errors are in parentheses and clustered at the district level. A unit of observation is a district year from the period 1957-85. There are 270 districts covered in the dataset. Controls include male literacy rate and population density.

Table 3: IV, Reduced Form and OLS Estimates: Incidence of Riots

	I(Riot) (1)	Number of Riots (2)
IV Estimate	0.203	1.479
	(0.113)	(0.83)
Reduced Form Estimate	0.071	0.516
	(0.039)	(0.287)
OLS Estimate	-0.035	-0.262
	(0.027)	(0.207)
Observations	6831	6831

Notes: Table 3 shows results from the estimations of equations (1) and (3). The first row estimates the 2SLS coefficients from equation (1), whereas the OLS estimates are shown in the third row. The coefficients in each cell represent the result from a separate regression. I measure incidence of riots using two outcome variables. *I(Riot)* is an indicator variable for whether a riot took place in a particular district in a particular year. *Number of Riots* is a count variable which represents the number of riots in a district in a year. To adjust for excess zeros, I add 0.01 to the count and take the log, which provides a percentage interpretation to the coefficients. A unit of observation is a district year from the period 1957-85. There are 270 districts covered in the dataset Standard errors are in parentheses and clustered at the district level. Controls include male literacy rate and population density. All specifications include district fixed effects, a state time trend and year fixed effects.

Table 4: IV, Reduced Form and OLS Estimates: Intensity of Riots

	Number Killed	I(Killed)	Duration
IV Estimate	0.66	0.114	1.13
	(0.491)	(0.085)	(0.559)
Reduced Form Estimate	0.228	0.039	0.395
	(0.171)	(0.297)	(0.192)
OLS Estimate	-0.024	-0.004	-0.088
	(0.106)	(0.018)	(0.132)
Observations	6831	6831	6831

Notes: Table 4 shows results from the estimations of equations (1) and (3). The first row estimates the 2SLS coefficients from equation (1), whereas the OLS estimates are shown in the third row. The coefficients in each cell represent the result from a separate regression. I measure intensity of riots using three outcome variables. *Number Killed* is a count variable which represents the number of people killed in a riot in a district in a year. *Duration* is a count variable representing the duration of a riot in days. *I(Killed)* is an indicator variable for whether anyone was killed in a riot in a particular district and year. To adjust for excess zeros, I add 0.01 to the count variables and take the log, which provides a percentage interpretation to the coefficients. A unit of observation is a district year from the period 1957-85. There are 270 districts covered in the dataset. Standard errors are in parentheses and clustered at the district level. Controls include male literacy rate and population density. All specifications include district fixed effects, a state time trend and year fixed effects.

Table 5: Placebo Test for Incidence of Riot Measures

	I(Riot)	Number of Riots
	(1)	(2)
IV Estimate	-0.030	-0.197
	(0.051)	(0.335)
Observations	6831	6831

Notes: Table 5 shows results from the estimation of equation 5. Each column in the table represents the results from a separate regression. I measure incidence of riots using two outcome variables. *I(Riot)* is an indicator variable for whether a riot took place in a particular district in a particular year. *Number of Riots* is a count variable which represents the number of riots in a district in a year. To adjust for excess zeros, I add 0.01 to the count and take the log, which provides a percentage interpretation to the coefficients. Standard errors are in parentheses and clustered at the district level. A unit of observation is a district year from the period 1957-85. There are 270 districts covered in the dataset Controls include male literacy rate and population density. All specifications include district fixed effects, a state time trend and year fixed effects.

Table 6: Placebo Test for Intensity of Riot Measures

	Number Killed (1)	I(Killed) (2)	Duration (3)
IV Estimate	-0.254	-0.037	-0.164
	(0.233)	(0.386)	(0.247)
Observations	6831	6831	6831

Notes: Table 6 shows results from the estimation of equation 5. Each column in the table represents the results from a separate regression. Standard errors are in parentheses and clustered at the district level. A unit of observation is a district year from the period 1957-85. There are 270 districts covered in the dataset. I measure intensity of riots using three outcome variables. *Number Killed* is a count variable which represents the number of people killed in a riot in a district in a year. *I(Killed)* is an indicator variable for whether anyone was killed in a riot in a particular district and year.*Duration* is a count variable representing the duration of a riot in days. To adjust for excess zeros, I add 0.01 to the count variables and take the log, which provides a percentage interpretation to the coefficients. Controls include male literacy rate and population density. All specifications include district fixed effects, a state time trend and year fixed effects.

Table 7: IV with Rainfall Shock

	I(Riot) (1)	(2)
Instrumented HYV Share	0.148	0.215
	(0.131)	(0.12)
Rain Shock	-0.026	0.0001
	(0.02)	(0.001)
Instrumented HYV Share × Rain Shock	0.089	-0.032
	(0.084)	(0.036)
Controls	Y	N
District Fixed Effects	Y	Y
Year Fixed Effects	Y	Y
State Year FE	Y	Y
Observations	6831	7916

Notes: Table 7 shows results from the estimation of equation 6. Each column represents the results from a separate regression. Standard errors are in parentheses and clustered at the district level. A unit of observation is a district year from the period 1957-85. There are 270 districts covered in the dataset. *Instrumented HYV Share* is the coefficient on the instrument for HYV share. The coefficient of interest is *Instrumented HYV Share × Rain Shock*, which interacts the IV estimate with a rainfall shock in a given district in a given year. *Rain Shock* is calculated as the monthly deviation of a district's rainfall above or below its average amount, summed over all months. *I(Riot)* is an indicator variable for whether a riot took place. I control for district level male literacy rate and population density. All specifications include district fixed effects, a state time trend and year fixed effects.

Table 8: IV with Alternate Rainfall Shock Measure

	I(Riot)	
	(1)	(2)
Instrumented HYV Share	0.190	0.186
	(0.114)	(0.108)
Rain Shock	-0.126	-0.126
	(0.121)	(0.128)
Instrumented HYV Share × Rain Shock	-0.050	-0.054
	(0.056)	(0.056)
Controls	Y	N
District Fixed Effects	Y	Y
Year Fixed Effects	Y	Y
State Year FE	Y	Y
Observations	6831	7916

Notes: Table 8 shows results from the estimation of equation 6. Each column represents the results from a separate regression. Standard errors are in parentheses and clustered at the district level. A unit of observation is a district year from the period 1957-85. There are 270 districts covered in the dataset. *Instrumented HYV Share* is the coefficient on the instrument for HYV share. The coefficient of interest is *Instrumented HYV Share × Rain Shock*, which interacts the IV estimate with a rainfall shock in a given district in a given year. *Rain Shock* is measured as a categorical variable which takes the value 1 if the district's average rainfall is above the 80th percentile, -1 if it is below the 20th percentile, and 0 otherwise. *I(Riot)* is an indicator variable for whether a riot took place. I control for district level male literacy rate and population density. All specifications include district fixed effects, a state time trend and year fixed effects.

Table 9: IV Estimates for Other Measures with Rainfall Shocks

	Number of Riots	Number Killed	I(Killed)	Duration in Days
	(1)	(2)	(3)	(4)
Instrumented HYV Share	1.695	0.938	0.157	1.308
	(0.902)	(0.588)	(0.103)	(0.606)
Instrumented HYV Share×Rain Shock	-0.416	-0.325	-0.51	-0.324
	(0.411)	(0.221)	(0.382)	(0.267)
Rain Shock	-1.912	-0.449	-0.059	-1.233
	(0.371)	(0.177)	(0.030)	(0.244)
N	6831	6831	6831	6831

Notes: Table 9 shows results from the estimation of equation 6. Each column represents the results from a separate regression. Standard errors are in parentheses and clustered at the district level. A unit of observation is a district year from the period 1957-85. There are 270 districts covered in the dataset. *Instrumented HYV Share* is the coefficient on the instrument for HYV share. The coefficient of interest is *Instrumented HYV Share × Rain Shock*, which interacts the IV estimate with a rainfall shock in a given district in a given year. *Rain Shock* is calculated as the monthly deviation of a district's rainfall above or below its average amount, summed over all months. *Number of Riots* is a count variable which represents the number of riots in a district in a year. *Number Killed* is a count variable which represents the number of people killed in a riot in a district in a year. *I(Killed)* is an indicator variable for whether anyone was killed in a riot in a particular district and year. *Duration* is a count variable representing the duration of a riot in days. To adjust for excess zeros, I add 0.01 to the count variables and take the log, which provides a percentage interpretation to the coefficients. I control for district level male literacy rate and population density. All specifications include district fixed effects, a state time trend and year fixed effects.

Table 10: IV Estimates for Wheat and Rice Growing Districts in India

	I(Riot)	Number of Riots	Number Killed	I(Killed)	Duration in Days
	(1)	(2)	(3)	(4)	(5)
Wheat Growing	0.178	1.292	0.623	0.106	0.963
	(0.095)	(0.702)	(0.407)	(0.070)	(0.485)
Observations	6488	6488	6488	6488	6488
Rice Growing	0.268	1.959	0.836	0.145	1.476
	(0.157)	(1.160)	(0.665)	(0.114)	(0.795)
Observations	6125	6125	6125	6125	6125

Notes: Table 10 shows results from the 2SLS estimation of equation (1). The coefficient in each cell represents the result from a separate regression. Standard errors are in parentheses and clustered at the district level. A unit of observation is a district year from the period 1957-85. There are 270 districts covered in the dataset. *I(Riot)* is an indicator variable representing whether a riot took place in a district in a year. *Number of Riots* is a count variable which represents the number of riots in a district in a year.*Number Killed* is a count variable which represents the number of people killed in a riot in a district in a year. *I(Killed)* is an indicator variable for whether anyone was killed in a riot in a particular district and year. *Duration in Days* is a count variable representing the duration of a riot in days. To adjust for excess zeros, I add 0.01 to the count variables and take the log, which provides a percentage interpretation to the coefficients. I control for district level male literacy rate and population density. All specifications include district fixed effects, a state time trend and year fixed effects.

Table 11: IV Estimates for North and Non North Regions of India

	I(Riot)	Number of Riots	Number Killed	I(Killed)	Duration in Days
	(1)	(2)	(3)	(4)	(5)
North	0.268	1.818	1.786	0.29	1.469
	(0.159)	(1.107)	(0.89)	(0.154)	(0.072)
Observations	3774	3774	3774	3774	3774
Non North	0.105	0.834	-0.48	-0.067	0.68
	(0.135)	(1.047)	(0.388)	(0.067)	(0.064)
Observations	3057	3057	3057	3057	3057

Notes: Table 11 shows results from the 2SLS estimation of equation (1). The coefficient in each cell represents the result from a separate regression. Standard errors are in parentheses and clustered at the district level. A unit of observation is a district year from the period 1957-85. There are 270 districts covered in the dataset. *I(Riot)* is an indicator variable representing whether a riot took place in a district in a year. *Number of Riots* is a count variable which represents the number of riots in a district in a year *Number Killed* is a count variable which represents the number of people killed in a riot in a district in a year. *I(Killed)* is an indicator variable for whether anyone was killed in a riot in a particular district and year. *Duration in Days* is a count variable representing the duration of a riot in days. To adjust for excess zeros, I add 0.01 to the count variables and take the log, which provides a percentage interpretation to the coefficients. I control for district level male literacy rate and population density. All specifications include district fixed effects, a state time trend and year fixed effects.

Table 12: IV Estimates of Effect of HYV Share on Labor in Agriculture

	Labor in Cultivation (1)	Total Agricultural Labor (2)
Instrumented HYV Share	-0.176 (0.170)	-0.013 (0.162)
Observations	6831	6831

Notes: Table 12 shows results from the estimation of equation 7. Each column in the table represents the results from a separate regression. Standard errors are in parentheses and clustered at the district level. A unit of observation is a district year from the period 1957-85. There are 270 districts covered in the dataset. *Instrumented HYV Share* is the coefficient on the instrument for HYV share. *Labor in Cultivation* is the log transformation of the number of rural males whose primary job classification is cultivation. *Total Agricultural Labor* is the log transformation of the total number of people working in agriculture, weighted by the number of days worked on the farm. Controls include male literacy rate and population density. All specifications include district fixed effects, a state time trend and year fixed effects.

Table 13: IV with Election Year

	I(Riot)	
	(1)	(2)
Instrumented HYV Share	0.239	0.288
	(0.218)	(0.191)
Election Year	0.019	0.002
	(0.074)	(0.077)
Instrumented HYV Share × Election Year	0.002	0.032
	(0.031)	(0.008)
Controls	Y	N
District Fixed Effects	Y	Y
Year Fixed Effects	Y	Y
State Year FE	Y	Y
Observations	6831	7916

Notes: Table 13 shows results from the estimation of equation 8. Each column represents the results from a separate regression. Standard errors are in parentheses and clustered at the district level. A unit of observation is a district year from the period 1957-85. There are 270 districts covered in the dataset. *Instrumented HYV Share* is the coefficient on the instrument for HYV share. The coefficient of interest is *Instrumented HYV Share* × *Election*, which interacts the IV estimate with a election dummy in a given district in a given year. *Election* is measured as a categorical variable which takes the value 1 in a national election year and 0 otherwise. There are 7 national elections that took place in the period of study. The years in which national elections took place are 1957, 1962, 1967, 1971, 1977, 1980 and 1984. *I(Riot)* is an indicator variable for whether a riot took place. I control for district level male literacy rate and population density. All specifications include district fixed effects, a state time trend and year fixed effects.

Table 14: IV Estimates for Other Measures with Election Year

	Number of Riots	Number Killed	I(Killed)	Duration in Days
	(1)	(2)	(3)	(4)
Instrumented HYV Share	1.570	1.291	0.231	1.238
	(1.467)	(1.050)	(0.176)	(1.034)
Instrumented HYV Share×Election	0.173	-0.181	-0.044	0.095
	(0.548)	(0.374)	(0.063)	(0.351)
Election	0.0141	0.123	0.282	0.037
	(0.223)	(0.149)	(0.025)	(0.143)
N	6831	6831	6831	6831

Notes: Table 14 shows results from the estimation of equation 8. Each column represents the results from a separate regression. Standard errors are in parentheses and clustered at the district level. A unit of observation is a district year from the period 1957-85. There are 270 districts covered in the dataset. *Instrumented HYV Share* is the coefficient on the instrument for HYV share. The coefficient of interest is *Instrumented HYV Share* × *Election*, which interacts the IV estimate with a election dummy in a given district in a given year. *Election* is measured as a categorical variable which takes the value 1 in a national election year and 0 otherwise. There are 7 national elections that took place in the period of study. The years in which national elections took place are 1957, 1962, 1971, 1977, 1980 and 1984. *Number of Riots* is a count variable which represents the number of riots in a district in a year. *Number Killed* is a count variable which represents the number of people killed in a riot in a district in a year. *I(Killed)* is an indicator variable for whether anyone was killed in a riot in a particular district and year. *Duration* is a count variable representing the duration of a riot in days. To adjust for excess zeros, I add 0.01 to the count variables and take the log, which provides a percentage interpretation to the coefficients. I control for district level male literacy rate and population density. All specifications include district fixed effects, a state time trend and year fixed effects.

12 Figures

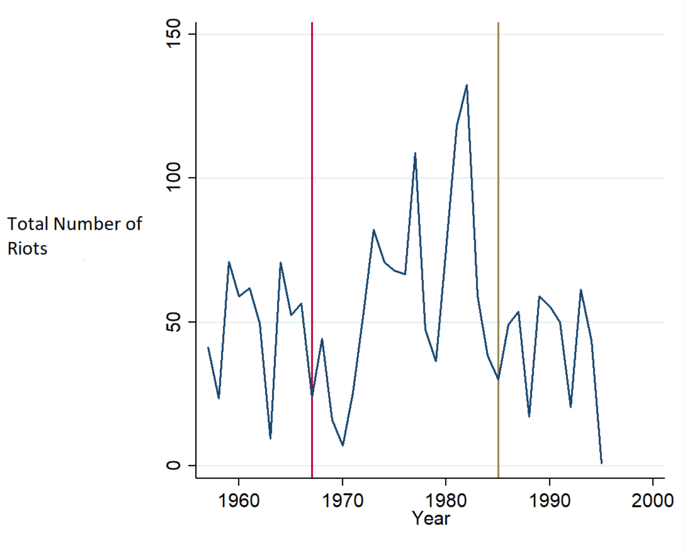

Figure 1: Total number of riots

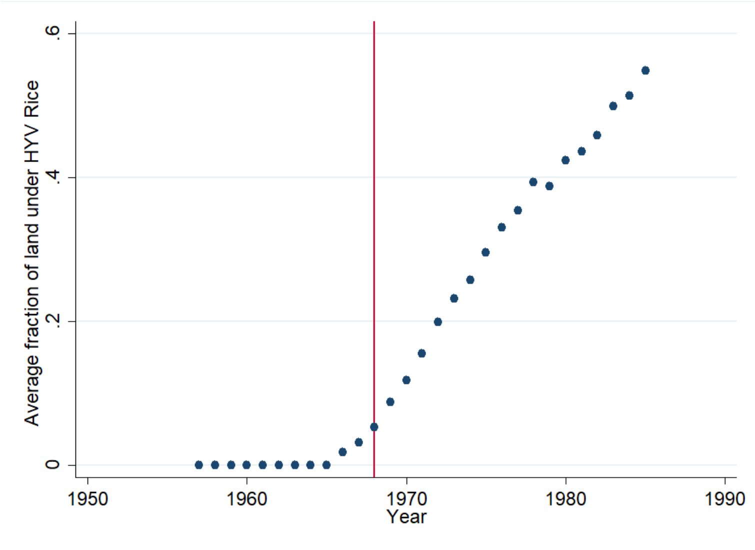

Figure 2: Area of land under HYV Rice cultivation

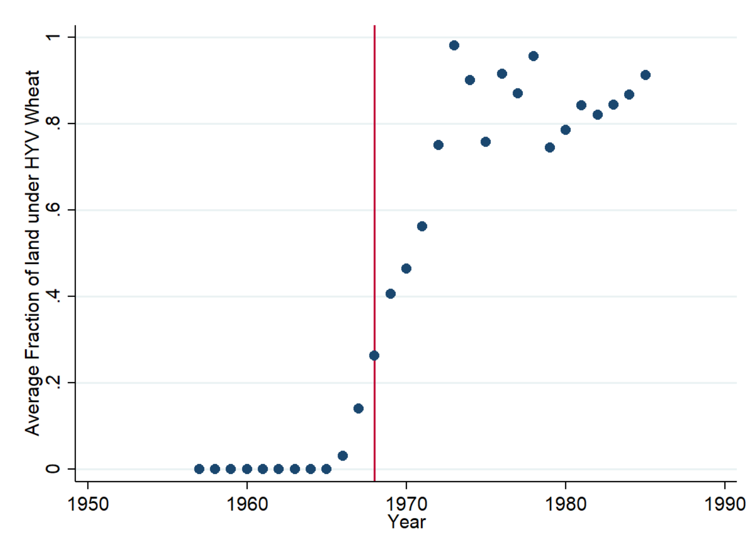

Figure 3: Area of land under HYV Wheat cultivation

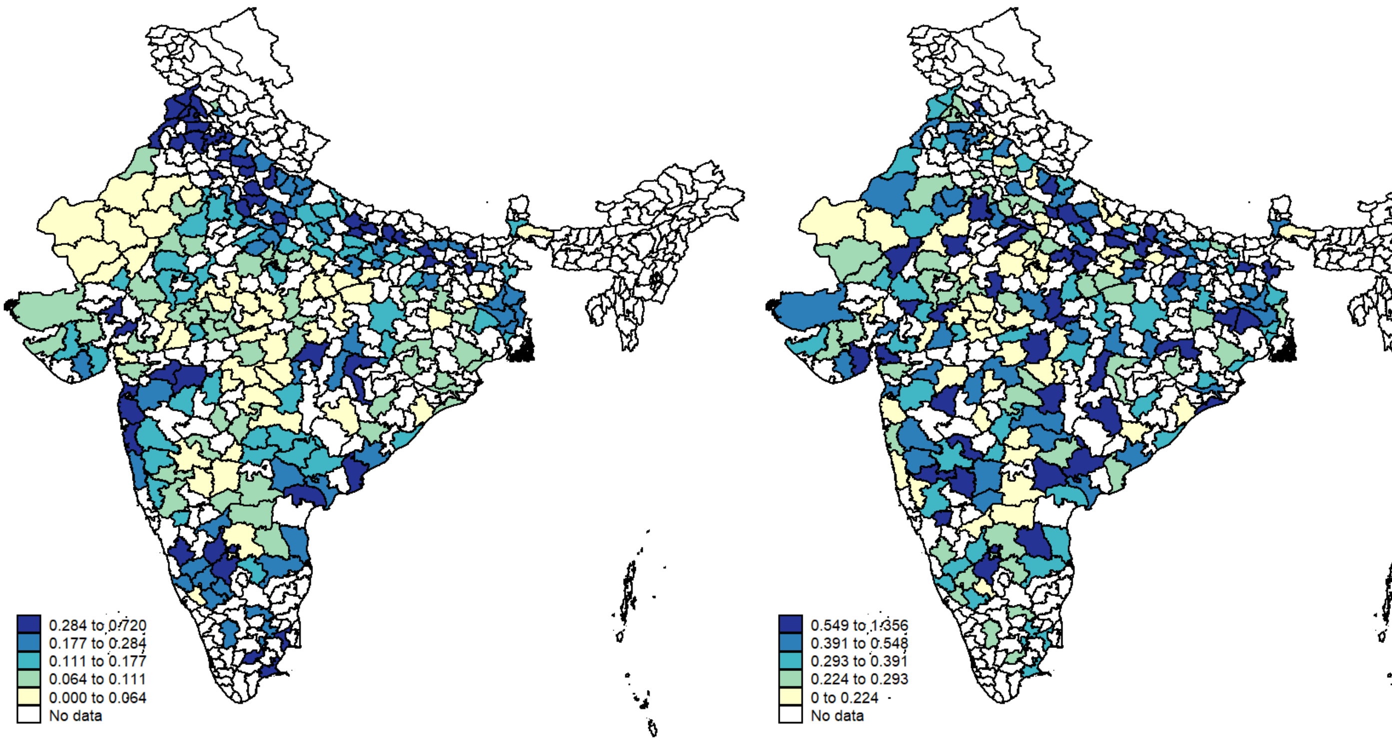

Figure 4: District Wise Share of HYV Cultivation in 1973 and 1985

Notes:The left panel represents the mean share of HYV seeds in districts across the country in 1973 and the right panel represents the correspnding share in 1985.

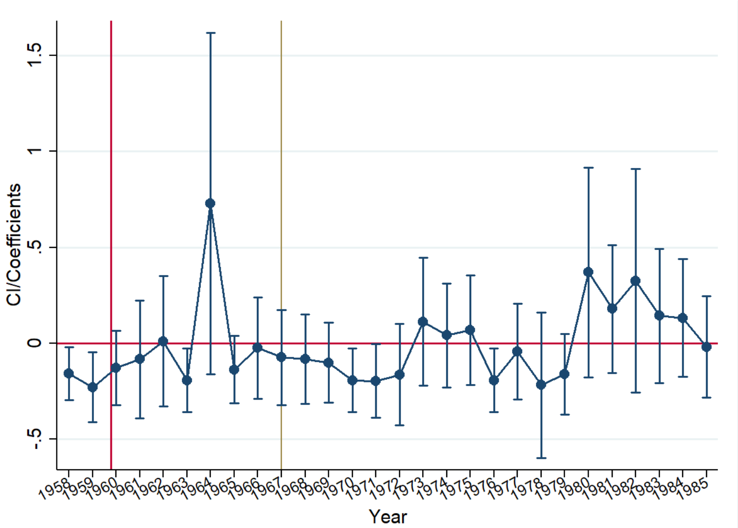

Figure 5: Parallel Trend Assumption

Notes:The Y axis represents the coefficients for the indicator variable for whether a riot took place. The brown line represents 1967, the year that the Green Revolution was introduced.

13 Appendix

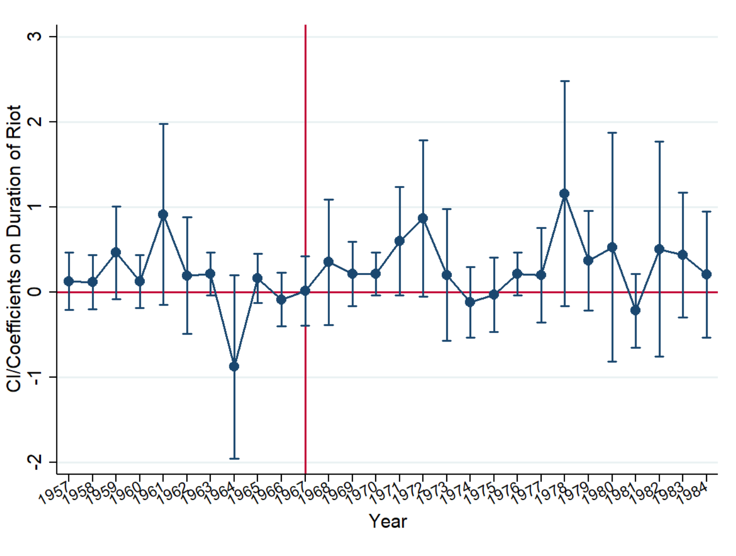

Figure 6: Parallel Trend Assumption Using Duration of Riot

Notes: The Y axis represents the coefficients on the count variable for the duration of a riot in days. The red line represents the year 1967, which is when the Green Revolution was introduced.

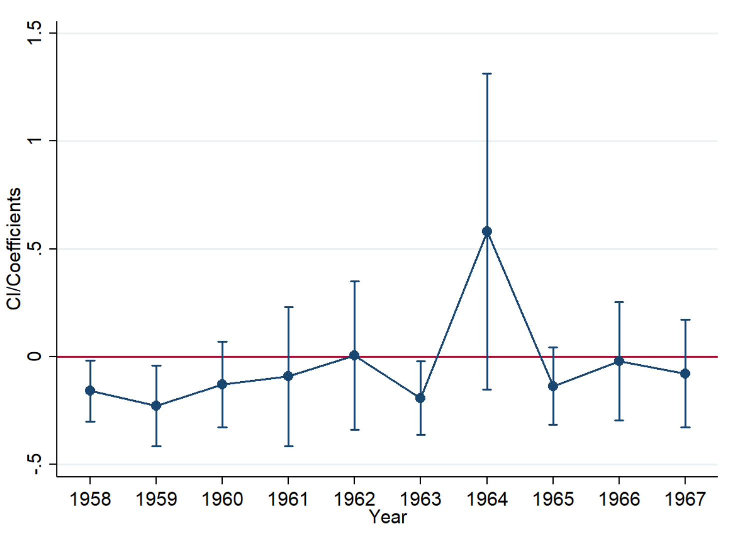

Figure 7: Pre Trend

Notes: The Y axis represents the coefficients on the indicator variable for whether a riot took place.

Table 15: Reduced Form Estimates Using 1966 Level Irrigation Intensity and Negative Binomial Regressions

	Number of Riots (1)	Number Killed (2)	Duration (3)
1966 Irrigation×After	0.182	5.937	4.959
	(0.466)	(1.738)	(1.073)
Controls	Y	Y	Y
District Fixed Effects	N	N	N
Year Fixed Effects	Y	Y	Y
State Fixed Effects	Y	Y	Y
State Time Trend	N	N	N
Observations	6759	6759	6759

Notes: Standard errors in parentheses and clustered at district level. A unit of observation is a district year from the period 1957-85. There are 270 districts covered in the dataset. Controls include male literacy rate, agricultural income and population density. The dependent variables which are counts have been estimated using the negative binomial regressions, and the probability measures using OLS.