Rainfall and Conflict: A Cautionary Tale

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A large literature uses rainfall variation as an instrument to study the impacts of income shocks on civil conflict, arguing that in agriculturally-dependent regions, negative rain shocks lower income which incites violence. This identification strategy relies on the assumption that rainfall shocks affect conflict only through their impacts on income. This paper evaluates this exclusion restriction in the context of religious conflict in India. Using data on dam construction, I identify districts that are downstream from irrigation dams and show that income in these areas is much less sensitive to rainfall fluctuations. However, rain shocks remain equally strong predictors of riot incidence in these districts. As rainfall fails to satisfy the exclusion restriction in this case, I then explore other channels through which rainfall might affect conflict.

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1 Introduction

Intrastate conflict has become widespread over the past 30 years, particularly in developing countries. Economists have linked various forms of intrastate conflict, such as civil wars, riots, and political demonstrations, to income fluctuations in these countries. Collier and Hoeffler (1998, 2002), for example, argue that poverty lowers the opportunity cost of fighting, making rebellion and civil war more likely to occur. Fearon and Laitin (2003) argue that poor economic growth reduces the state or the elites' capacity to quell protests and rebellions. Mitra and Ray (2010) find that changes in relative income levels between ethnic groups make the disadvantaged group more likely to engage in conflict. Regardless of the mechanism, there is a wide consensus that low levels of income are correlated with high levels of conflict.

As income is endogenous to conflict, however, most researchers rely on rainfall as a source of exogenous variation for income. Rainfall became a popular instrument for income in developing countries following Miguel, Satyanath, and Sergenti's seminal 2004 paper that provides evidence for a causal link between economic growth and civil war outbreak in sub-Saharan Africa. As the region is economically dependent on agriculture, the authors assert that periods of low rainfall cause crop failure which consequently lowers income levels. When instrumenting for GDP with rainfall growth (the change in rainfall from one year to the next), the authors find that economic conditions significantly impact conflict incidence. Specifically, negative rainfall growth lowers the economic growth rate and increases the probability of civil war by approximately 2% per year.

A critical assumption underlying the use of rainfall as an IV is that rainfall affects conflict only through its impact on income. While Miguel et al. are unable to test for this directly, their analysis is supported by the fact that, along with having 60% of the population employed in the agricultural sector, only 6% of cropland in Africa is irrigated. Income in Africa is therefore strongly tied to rainfall. This is not so in other countries where Miguel et al.'s work has been replicated[1], including in India, which is the focus of this paper. India has seen substantial investment in irrigation infrastructure over the past 50 years, primarily in the form of irrigation dams. These dams protect against weather shocks, something that earlier research does not account for.

This paper explores the relationship between agricultural production and income and religious conflict in India but also fits within the larger literature on conflict, serving as a note of caution for analyses using rainfall as an instrument for income. It proceeds in two parts. I first use data on dam construction in India to evaluate whether rainfall satisfies the exclusion restriction. Specifically, I identify districts that are downstream from dams and as a result receive water during droughts. These districts are also somewhat protected against heavy rainfall as water is stored behind dam walls, mitigating floods. Therefore, while agricultural production in districts that are not downstream of dams (rain-fed districts) is dependent on rainfall, production in downstream (dam-fed) districts is uncorrelated with the weather. There should then be no correlation between production and rioting in dam-fed districts if rainfall is a valid instrument for income.

Overall, I find that rain-fed districts behave in the same way as previous studies have found: a negative rain shock lowers the value of production and income levels and increases the likelihood of conflict. In dam-fed districts, however, production value is much less sensitive to rain shocks. Yet despite having little influence on production in these districts, rainfall still predicts riot incidence, suggesting that rainfall affects conflict through some other channel. This "placebo test" provides evidence against rainfall's validity as an instrument, particularly in the Indian context, and casts doubt on whether income shocks have causal effects on rioting.

I then investigate other channels through which rainfall might be affecting rioting in the second part of the paper. I specifically check to see whether cross-

[1]Numerous studies in other countries have also used rainfall as an IV for income when considering various political and economic outcomes. For example, Bruckner and Ciccone (2011) use rainfall variation to examine the effect of economic shocks on democratic institutions in Africa. Mehlum, Miguel, and Torvik (2006) use rainfall to instrument for grain prices when looking at the relationship between economic conditions and violent crime in 19th-century Germany. Bohlken and Sergenti (2010) use rainfall to instrument for state-level GDP in India to look at the effect of income shocks on religious riots.

district migration or violence spillovers could be affecting rioting but find no evidence for either.

The paper proceeds as follows. Section 2 provides an overview of rioting and intuition as to why income might affect religious riots. I then describe dam construction in India and the data used in my estimation. The estimation framework and the main results are presented in section 3. In section 4, I investigate various channels through which rainfall might affect conflict. Robustness checks are presented in section 5 and section 6 concludes.

2 Background and Data

2.1 Riots

Religious violence has a long history in India. Conflict between Hindus and Muslims has become particularly widespread since the India-Pakistan partition in 1947. While these riots are often attributed to underlying religious tension, several researchers argue that they are also sparked by economic conditions [2]. As most riots are believed to be premeditated, with political elites or community leaders recruiting civilians to riot, income shocks make it easier for elites to gain support, particularly if Hindus and Muslims blame each other for unemployment or falling wages. A negative income shock should thus increase the number of riots in a district. Indeed, Bohlken and Sergenti (2010) find that, instrumenting for GDP growth with rainfall growth, a 1% increase in the growth rate lowers the number of riots in a state by 10%.

To measure rioting, I draw on the Varshney-Wilkinson Dataset on Hindu-Muslim Riots in India (2006). This dataset lists all riots between Hindus and Muslims reported in The Times of India, a major national Indian newspaper, between 1950 and 1995. Nearly 1200 riot cases of varying intensity and duration were reported over the 45-year period. For example, some riots lasted less than a day and claimed no casualties while others spanned several weeks, resulting in dozens of deaths and injuries. All riots were, however, reported in the newspaper as arising due to conflict between Hindu and Muslim groups. The specific event triggering the riot is recorded when possible but is missing in many cases.

[2] See Bohlken and Sergenti (2010), Mitra and Ray (2013), Brass (2003), and Wilkinson (2004)

The Varshney-Wilkinson dataset is the best available for religious violence in India but has some biases. First, the number of riots reported in the dataset is likely an underestimate of the number of actual riots that occurred over the time period. Riots that occur in small, remote towns, for example, may not be reported in the newspaper. Similarly, small-scale riots are unlikely to receive much media attention. Secondly, approximately 250 of the 627 Indian districts do not appear in the dataset and it is unclear as to whether no riots occurred in these districts or riots that did occur went unreported.

To deal with the latter issue, I exclude districts not listed in the dataset from my analysis. This is in line with other authors' treatment of these districts (see Mitra and Ray, 2013; Bohlken and Sergenti, 2010). The overall riot counts presented in this paper are thus likely to be underestimates. I use both an indicator for whether a district experiences a riot and a count of the number of riots as my main dependent variables.

2.2 Dams

India has rapidly increased its investment in dams, building more than 3000 between 1947 and 2001 (Pande, 2008). Over 95% of dams constructed since 1947 have been for irrigation purposes as they remain India's primary form of irrigation infrastructure (World Commission, 2000b). The World Commission for Dams and the Indian Ministry of Water Resources have kept record of dam construction, making it possible to identify districts that contain an irrigation dam.

Irrigation dams are primarily constructed as embankment dams where a wall is built across a river valley. Water is then channeled to districts downstream of the dam through a series of spillways and canals (Biswas and Tortajada, 2001). These dam-fed districts receive water during drought periods and are also somewhat protected against floods as the reservoir holds excess rainwater. Being protected against rainfall shocks, dam-fed districts should be less prone to volatility in crop yields and subsequent income fluctuations. In the context of Bohlken and Sergenti's paper, dam-fed districts should also be less prone to rioting driven by weather-induced income shocks. The area immediately surrounding or directly upstream of the dam, "rain-fed" districts, receives little or no irrigation benefit, making farmers in the area prone to weather shocks (Thakkar, 2000).

To identify dam-fed and rain-fed districts, I draw on Duflo and Pande's dataset (2007) of dam construction in India. Their data comes from the World Registry of Large Dams and provides information on the number of irrigation dams constructed both within and upstream of a district in a year.

Two concerns arise when including data on dams. The first is whether an entire district can be correctly categorized as either dam or rain-fed. Even if a district is labeled as being downstream, for example, it is unlikely that the entire district benefits from irrigation. This shows up in the estimation results as dams imperfectly protecting against rain shocks. However, the district is the smallest administrative unit for which weather and agricultural shocks can be analyzed, and the relatively small size of districts (3500 km^2 on average) should allay the concern that some districts will be mislabeled.

There is also the issue of whether dam allocation is independent of district wealth. In their analysis, Duflo and Pande (2007) show that dam construction is correlated with state wealth, as construction is largely the responsibility of state governments. Because this paper exploits differences in dam construction across districts, focusing on inter-district variation should somewhat reduce any bias coming from the correlation between state wealth and dam construction.

Still, as Duflo and Pande note, dam construction is likely dependent on factors other than state wealth, such as an area's agricultural productivity, making OLS estimates inconsistent (Duflo and Pande, 2007). Therefore, instead of using the actual number of dams in a district, I use the predicted number to create a dummy variable indicating whether a district is dam-fed. The number of predicted dams is based on a district's geographic suitability for dam construction (having the proper river gradient and length) as well as differences in dam construction across years in India and the contribution of each state to this increase.[3] A dam-fed district is then one that has both a predicted dam and an actual dam.

Over the entire time period analyzed (1961-1991), approximately 30% of districts are in dam-fed regions. However, the proportion of dam-fed districts increases significantly over the 30-year time period. By 1991, 57% of districts were dam-fed. Figure 1 contains maps showing the distribution of dams in 1961 (Panel A) and 1991 (Panel B)[4]. It is possible for a district to be both down-

[3] See Duflo and Pande (2007) for a more detailed description of how this variable is estimated.

[4] 142 districts are included in the sample. The districts that are excluded are done so because they did not appear in one or more of the datasets.

stream of a dam and contain a dam. For the purpose of this paper, all districts downstream of dams are called dam-fed districts and all districts not downstream of dams are called rain-fed districts, regardless of whether it contains a dam itself.

2.3 Agricultural Production and Wages

Most of the literature on conflict and income uses GDP per capita as its primary measure of income. As GDP per capita is not available at the district level, I use the value of agricultural production to capture agricultural income. For robustness, I also use the log of agricultural wages as a secondary measure of income. I focus on the value of production as agricultural wages may not adequately capture the income going to self-employed farmers. For example, the agricultural wage data that is available is the average wage (measured in rupees per hour) of a male ploughman or a male field labourer. While this should roughly reflect farmers' incomes, the value of production broadly captures what is happening in the agricultural sector. Regardless, the two variables are highly correlated and the results change very little when wages are used instead of production. Both of these measures are taken from the Evenson-McKinsey India Agriculture and Climate Dataset which covers 271 Indian districts from 1950 through 1997. The value of production is measured in rupees per 1000 tonnes of agricultural output. Average crop prices from 1960 to 1965 are used and the variable specifically includes the value of rice, wheat, sugarcane, jowar, millet, and maize, India's main crops. Agricultural wages are weighted by month to account for the intensity of field work during harvest months and was originally constructed using data from the Indian Ministry of Agriculture's Directorate of Economics and Statistics.

2.4 Rainfall

The University of Delaware's Center for Climatic Research provides rainfall estimates at 0.5 degree longitude and latitude nodes across the world, starting in 1945. I use this data to derive monthly rainfall estimates for the longitude and latitude points within India. I then use the World Bank's India Agricultural Database, which has the longitude and latitude coordinates for each district, to match these rainfall estimates to a district.[5] The distance between the identified grid points from the rainfall dataset and the in-district weather stations ranges from 1 km to 63km. The mean distance is 21 km. This method assumes that all areas within a district receive the same amount of rainfall, a reasonable assumption given the relatively small size of Indian districts.

Two points regarding the rainfall data should be noted. First, the rain shock variable that I use as an instrument is constructed to account for seasonality in rainfall. Some months receive more rainfall than others and farmers can, to an extent, anticipate this. In defining a rain shock, I follow the approach used by Kaur (2012) and Jayachandaran (2006). For a given 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. For robustness, I use a secondary measure of a rainfall shock where it is defined as the fractional deviation of rainfall from its average level, summed over all months. For example, if a district's average rainfall level in June is 150 mm, the monthly rainfall shock in a year in which June rainfall is 100 mm would be -50 mm.

Second, I do not treat positive rain shocks as detrimental. While unexpected flooding might destroy crops, most positive shocks occur during the monsoon season which is known and accounted for when farmers plan their planting schedule. This treatment of a rain shock is in accordance with other authors' treatment of the variable (see Jacoby and Skoufias, 1997; Rose, 2001). Furthermore, the Indian Ministry of Agriculture groups areas that have had below-average rainfall together and areas that have had average or above-average rainfall together when tracking agricultural productivity. This suggests that below-average rainfall is of greater concern than above-average rainfall (Jayachandran, 2006).

2.5 Control Variables

Previous studies on conflict identify several demographic factors correlated with violence. For India, the percent of the population that is either Muslim, young and male, migrant, or literate is associated with an increased incidence of violence. I use variables from the Census of India to control for each of these.

[5] Districts and rainfall estimates are matched using an interpolation algorithm provided by Seema Jayachandaran and used in her 2006 paper.

I also control for a district's total population as well as the percentage of its populace living in a rural area.

2.6 Descriptive Statistics

Panel A of Table I displays descriptive statistics for the main dependent and independent variables as well as various controls that are used for robustness checks. The average district has 0.16 riots per year, but this varies widely with some districts experiencing as many as 20 riots in a year. There is also substantial variation in the number of deaths, casualties, and arrests. The 1984 riot in Thane district, for example, claimed 161 lives whereas 117 of riot incidences had no casualties. Districts receive 1078 millimetres of rainfall on average and produce 22,522,000 rupees worth of agricultural output each year, again with substantial variation across districts. The mean wage is 5.45 rupees per hour. Other welfare measures that are used in later specifications include a district's headcount ratio, poverty gap measure, and gini coefficient of household expenditure. A district's headcount ratio is the proportion of the population living below the national poverty line. The poverty gap measure is the average distance below the poverty line and is expressed as a proportion of the poverty line. The gini coefficient is measured using average household consumption expenditure which comes from the Indian National Sample Surveys. On average, young males, defined as men under the age of 35, compose 31% of the population; 36% of the population is literate; 76% of the population lives in a rural area; and 12% of the population is Muslim.

Panel B shows descriptive statistics and tests for balance for the main dependent and independent variables across dam-fed and rain-fed districts. While the number of riots is higher in dam-fed districts, this is somewhat driven by Ahmedabad district which experienced 35 riots between 1985 and 1987. When removing Ahmedabad from the sample (Panel C), the average number of riots in dam-fed districts falls substantially, but there is still a statistically significant difference between dam-fed and rain-fed districts. Finally, production and wages are higher in rain-fed than dam-fed districts but have a larger standard deviation, likely due to agriculture's dependence on weather.

3 Estimation Framework and Main Results

3.1 Predictions

To test whether rainfall satisfies the exclusion restriction, I analyze the first stage relationship between rain shocks and income,

$$Y_{i,t} = \alpha + b_1(rain_{i,t}) + \theta_i + \nu_{st} + u_{ist} \tag{1}$$

and the reduced form relationship between rain shocks and conflict,

$$conflict_{i,t} = \alpha + \beta_1(rain_{i,t}) + \theta_i + \nu_{st} + u_{ist}. \tag{2}$$

For district i in year t, $rain_{i,t}$ is the district rain shock, $conflict_{i,t}$ is a dummy variable that equals one if the district experiences a riot that year, and $Y_{i,t}$ is the log of the value of agricultural output in the district. I also include a district fixed effect, θ_i and a state-year time trend, θ_{st}.

Looking only at rain-fed districts, one would expect b_1 to be positive: abundant rainfall improves agricultural production whereas insufficient rainfall worsens it. β_1 should then be negative as a positive rain shock that increases production, and consequently income, should lower the probability that a riot occurs. When considering only dam-fed districts, however, the first-stage relationship should be diminished as these regions are protected against rain shocks. If rainfall is a valid instrument, the reduced-form relationship in equation (2) should also be diminished.

I test whether this holds by including an interaction term in the above equations:

$$Y_{i,t} = \alpha + b_1(rain_{i,t}) + b_2(rain_{i,t} * damfed) + b_3(damfed_{i,t}) + \theta_i + \nu_{st} + u_{ist} \tag{3}$$

$$conflict_{i,t} = \alpha + \beta_1(rain_{i,t}) + \beta_2(rain_{i,t} * damfed_{i,t}) + \beta_3(damfed_{i,t}) + \theta_i + \nu_{st} + u_{ist} \tag{4}$$

where $damfed_{i,t}$ is a dummy indicating whether a district is dam-fed. If there is no first-stage relationship between rainfall and production in dam-fed districts so that b_1 is positive and b_2 is negative, we would expect β_1 to be negative and β_2 to be positive in rainfall is satisfies the exclusion restriction.

3.2 Estimation Results

I first exclude information on dams and show that, absent this information, production shocks appear to drive conflict in the same way shown in previous work. Using rainfall shocks as an instrument for the value of production, I estimate the following equation (5) where all of the variables are defined as in Section 3.1:

$$conflict_{i,t} = \alpha + \beta_1(Y_{i,t}) + \theta_i + \nu_{st} + u_{ist} \tag{5}$$

The results are reported in column 1 of Table II. In line with the earlier literature, an increase in production value significantly lowers the probability of rioting when a rain shock is used as an instrument. Specifically, when controlling for district and state-year effects, a R1000 increase in value lowers the probability that a district will experience a riot by 64% per year, a substantial drop considering that the average district experiences 0.2 riots per year. Including information on dams now allows me to test whether rainfall satisfies the exclusion restriction.

I estimate equation (1) first without dam information and then including the dam-fed interaction and dummy terms. The results are reported in columns 2-5 of Table II. A negative rain shock appears to lower a district's average production value by 4.4% when no information on dams is included. However, the sample split in columns 3-5 show that rain shocks are no longer significant determinants of agricultural production in dam-fed districts. While being downstream from a dam does result in generally higher production value, the results in column 3 show that dams mitigate extreme rainfall, thereby reducing agriculture's dependency on rain. The p-value reported in column 3 tests whether rain shocks have the same effect in dam-fed and rain-fed districts. This hypothesis is strongly rejected. Columns 4 and 5 split the sample to more clearly show the relationship between rainfall and production value in each district type. In rain-fed districts, a negative rain shock lowers the value of production by 8.2% but in dam-fed districts, there is no significant relationship between rain shocks and production value.

As a robustness check, I estimate equation (1) using agricultural wages and the main dependent variable. The results are similar and are reported in column 1 of Appendix Table II. Again, a negative rain shock lowers a district's wage by 1.1% but the effect of a shock is reversed in dam-fed districts.

Given the first stage results, any observable correlation between rainfall and rioting (β_1) should disappear when the sample is restricted to districts downstream of dams. Otherwise, rainfall is affecting rioting either directly or through a variable other than wages, thereby violating the exclusion restriction.

As with equation (1), equation (2) is first estimated excluding dam information and then including the dam interaction and dummy terms. The results, reported in columns 6-7 of Table II, reveal that rainfall remains a significant predictor of rioting regardless of which type of district is considered. The effect of rainfall is slightly larger in dam-fed districts, with a positive rain shock lowering the likelihood of conflict by an additional 3% per year (over the 3% decrease that all districts experience). Here, we can not reject the null that the difference between the rain shock coefficient across the two types of districts is zero.

I run several tests to ensure that the results are robust to different specifications and are not being driven by other factors. These are presented in the appendix tables and are discussed in Section 5.

4 Possible Channels

Having shown that rainfall does not satisfy the exclusion restriction in this context, I now investigate other channels through which rainfall might be affecting conflict in India.

4.1 Spillovers

Although rain shocks do not affect production in dam-fed districts, it is plausible that rioting spills over from rain-fed to dam-fed regions. For example, while specific details on what happened during the riot are missing for most of the reported incidences, there are some cases in which a religious monument was desecrated during a riot. Imagine, then, that an extended drought causes production and income to fall and rioting to erupt in a rain-fed district. A mosque being burned could incite anger in nearby districts, including those that are protected against weather shocks. Since rainfall is strongly correlated across districts, a negative rain shock could thus appear to be affecting rioting in dam-fed districts when we are actually witnessing a spillover effect.

To explore this possibility, I take each dam-fed district and calculate what proportion of its neighbouring districts are rain-fed. I then control for rain shocks in these neighbouring districts by including an interaction term between the proportion of neighbours that are rain-fed and the average rain shock in these districts:

$$conflict_{i,t} = \alpha + \beta_1(rain_{i,t}) + \beta_2(rainfed_{i,t} * nbrain_{i,t}) + \beta_3(rainfed_{i,t}) + \theta_i + \nu_{st} + u_{ist} \tag{6}$$

In the above equation, $rainfed_{i,t}$ is the proportion of district i's neighbours that are rain-fed and $nbrain_{i,t}$ is the average rain shock in those districts.

The results are shown in Table III. The dependent variable in column 1 is an indicator variable for whether a district experienced a riot in a given year. The dependent variable in columns 2 and 3 is the number of riots that occurred in a district in a given year. From column 1 we see that rain shocks do not have as strong of an effect on the probability of conflict after controlling for spillovers. However, the neighbouring rain shock term is insignificant so there does not appear to be any direct spillover effect. The effect of a rain shock on the number of riots a district experiences remains significant after controlling for spillovers and the interaction term is again insignificant (columns 2-3). There is thus little evidence of conflict spilling over from rain-fed to dam-fed districts.

4.2 Migration

Rainfall could also be affecting conflict through migration. Since production and wages in rain-fed districts are still responsive to rain shocks, a prolonged drought could induce farmers in rain-fed districts to migrate to dam-fed districts, instigating conflict over land. If this is the case, a negative rain shock in rain-fed districts should increase the number of migrants to dam-fed districts. To test this, I estimate the equation

$$migrants_{i,t} = \alpha + \beta_1(rain_{i,t}) + \beta_2(rainfed_{i,t} * rain_{i,t}) + \beta_3(rainfed_{i,t}) + \theta_i + \nu_{st} + u_{ist} \tag{7}$$

where the interaction and $rainfed$ variables are defined as in Section 3. While the coefficients on the variables have the expected signs (a negative rain shock in neighbouring rain-fed districts increases the number of migrants to dam-fed districts), they are small and insignificant. Prior literature suggests that migration across districts due to weather shocks is unlikely. Duflo and Pande (2007), for example, state that "districts are relevant markets and social units within which people might relocate ... but migration across district lines in response to shocks is rare" (pg. 11). A negative rain shock could thus instigate conflict over land issues within a rain-fed district but there is unlikely to be an effect across districts. Unfortunately I can not test for whether migration within a district results in land conflict as the migration data available is at the district level. This is an avenue that could be further explored given finer data.

4.3 Riot Potential

In Table V, I check to see whether dam-fed districts have greater "riot potential"; that is, whether it takes a smaller production shock to spark a riot. If this were true, we might not need a strong first-stage relationship between rainfall and production even though rainfall is still working through the income channel. To test this, I interact rainfall shocks with variables that are positively correlated with rioting: the percent of the population that is Muslim, the percent living in a rural area, the log of the district's total population, and the number of past riots. When using the number of past riots as the control, I restrict the sample to the years after 1970 and interact the rain shock variable with the number of riots a district had before 1970.

The effect of a rain shock on conflict is consistent across the specifications. When controlling for a district's religious composition (column 1), the effect of a rain shock increases with the percent of the population that is Muslim. The results are similar using the percent of the population that is in a rural area and the number of past riots a district has experienced as controls. Surprisingly, the coefficient on the rain shock variable changes signs when the log population is used as the control in column 3. However, to interpret the effect of a rain shock on conflict, the shock*control interaction term has to be multiplied by the mean log population, which is 14.44. Multiplying this by the interaction coefficient, we get a coefficient of -0.592, offsetting the positive coefficient on rain shock. For the average rain-fed district, then, the effect of a rain shock on conflict is close to zero. The effect in a dam-fed district is approximately -0.026*14.44 = -0.0375. A positive rain shock decreases the probability of rioting by 3.75%.

4.4 Other Channels

Heavy rainfall could be ruining infrastructure like roads, making it difficult for groups to organize and protest. However, including the percentage of paved roads in a district, with the idea being that rainfall would have a more detrimental effect in districts with more dirt roads, does not produce any significant results.

Finally, it is possible that rain directly deters people from engaging in conflict. Several papers demonstrate that people are unlikely to organize themselves during extreme weather conditions. Madestam et al. (2011), show that individuals are unlikely to show up to political protests in the United States when it is raining. Collins and Margo (2007) use rainfall as an instrument for rioting when looking at the effect of the 1960 U.S. riots on housing prices. As previously mentioned, it is widely believed that religious riots in India are planned ahead of time. Given the research indicating that citizens are unlikely to attend planned political rallies if the weather is bad, it is conceivable that heavy rainfall could deter people from participating in a riot. However, given the nature of the riot data, it is difficult to discern whether rainfall actually prevents riots from starting, calms riots that have already started, or both.

5 Robustness Checks

In Appendix Table I, I see whether the reduced form relationship between rainfall and rioting is robust to various specifications. In columns 1 and 2, I reestimate equation (4), using the number of riots in a district as the dependent variable instead of the probability of rioting. I estimate the equation using a negative binomial model. District fixed effects and the state-year time trend are included in column 1. Under this specification, a positive rain shock lowers the number of riots by 0.25 per dam-fed district and 0.7 per rain-fed district. In column 2, I drop the district fixed effects and instead include the set of control variables discussed in Section 2.5. Rainfall remains a significant predictor of violence in both rain-fed and dam-fed districts.

Given that dam construction often disadvantages or displaces those peoples living in the area immediately surrounding the dam, there is reason to believe that dam construction could itself invoke conflict (Pande, 2008). While this should not directly affect the impact that rainfall has on rioting, I include a dummy variable indicating whether a dam was built within a district in a given year as a control variable in equation (4). The results in columns 3-4 show that the construction of a dam does not have a significant impact on rioting, nor does it detract from rainfall's effect. I also look up to three years following dam construction but find no evidence of a lagged response (results not shown).

In his analysis of Hindu-Muslim violence, Steven Wilkinson (2004) finds that an area's history of violence has a significant impact on whether it experiences violence in the future. To control for previous conflict, I include first the number of riots that a district experienced over the past year and then the number it experienced over the past five years, and reestimate (4). I estimate the model using random effects since panels that include lagged dependent variables as controls often give inconsistent estimates (Angrist and Pischke, 2009). The results are reported in columns 5-8. Both the one-year and the five-year riot variables are positive and significant in all specifications. A district that had a riot in the previous year is 5% more likely to have one in the current year. A district that experiences one additional riot over a five-year period is 2.3% more likely to experience a riot in the current year. The coefficient on the rain shock variable, however, remains significant and falls only slightly in magnitude after controlling for previous riots.

Even if rainfall is not significantly affecting agricultural production in dam-fed districts, it could be working through other welfare measures to provoke conflict. In Appendix Table II, the production variable is substituted with four other welfare measures: the headcount ratio, poverty gap, gini coefficient (measured over expenditure), and mean expenditure. These variables are defined in Section 2.6. Rainfall has no effect on the gini coefficient nor on mean expenditure in rain-fed districts (columns 3-4). It has a positive effect on the headcount ratio in rain-fed districts. As with the value of production, however, the effect is mitigated and even reversed in dam-fed districts and a t-test shows that we can reject the hypothesis that a rain shock has the same effect in both districts. Surprisingly, rain shocks have a small and positive effect on the poverty gap: a positive shock increases the wealth gap between the rich and the poor. The effect is barely significant, however, and is small relative to a mean coefficient of 0.16. Furthermore, the effect goes in the opposite direction needed to support the hypothesis that rain shocks inversely affect conflict through welfare.

In Appendix Table III, I run quantile regressions to look at the impact that rain shocks have on income at different income percentiles. I find no effect of a rain shock on mean expenditure (columns 1-3) in either type of district when looking at the 25th, 50th, and 75th quantiles. Looking at log wages, however, I find that a rain shock only affects wages above the 50th percentile suggesting that the poorest do not feel much of a shock. However, the negative coefficient on the dam-fed*shock interaction term shows that dam-fed regions are still protected from shocks. It is possible that if the poorest do not receive any benefit from a positive wage shock, they might riot. However, there is no first-stage effect in dam-fed districts for any income percentile. Therefore, the fact that people at the 25th income percentile in rain-fed districts are unaffected by a shock does not explain why there is still a reduced form relationship between shocks and rioting in dam-fed districts. Given that there is still no first-stage effect even when looking at the sample by income quantile, we should not see a reduced-form effect of rainfall on rioting.

Two alternative sample splits are shown in Appendix Table IV. In Panel A, the sample is divided into urban and rural districts. The Census of India defines rural districts as those in which at least 78% of the population resides in a rural area. A rural area is defined as an area with a population density below 400 people per square kilometer. While the effect of a rain shock on the probability of a riot is weaker in rural districts, the general result still holds. There is no significant correlation between rainfall and agricultural production in urban areas (where agriculture is not being widely produced), but there is still a strong and negative relationship between rain shocks and rioting.

The sample is split according to whether a district is predominantly agricultural or industrial in Panel B. These categories are defined using the Census of India's data on employment in each type of sector. On average, 24% of workers are directly engaged in agricultural production. I therefore define an agricultural district as one in which at least 24% of workers are farmers. All other districts are called industrial. Column 2 shows a weak relationship between rainfall and agricultural production in industrial districts so the same conclusions can not be drawn. However, the relationship between rainfall and rioting is larger in manufacturing districts than in agricultural districts despite the relationship between rainfall and production being much stronger in the latter.

6 Conclusion

The widely established finding that negative income shocks drive conflict rests on the assumption that rainfall shocks affect conflict only through their effects on income. It is not obvious that this assumption holds, particularly in countries with some irrigated farmland. This paper contributes to the literature relating income shocks to conflict in two ways. First, it cautions against using rainfall as an instrument for income in some contexts. While rainfall may be a valid instrument when looking at certain types of conflict in certain areas of the world, it may be a poor instrument for others, such as rioting in India. In districts downstream of dams in India, income is insensitive to rain shocks. Yet rain shocks continue to have an effect on conflict with a positive shock lowering the probability of conflict by an additional 2.9% per year.

Second, it begins to explore other mechanisms through which rainfall affects riot incidence. While I find no conclusive evidence that rainfall is working through a specific channel, it is an important avenue for future research. For example, the absence of any cross-district effects may suggest that rain shocks affect migration patterns or the spread of violence within districts which subsequently affects the degree of violence that a district incurs. Finer data would enable such an analysis.

Generally speaking, however, future researchers should be careful when using rainfall as an instrument for income and search for a case in which the first-stage should not hold so that they can test their instrument's validity.

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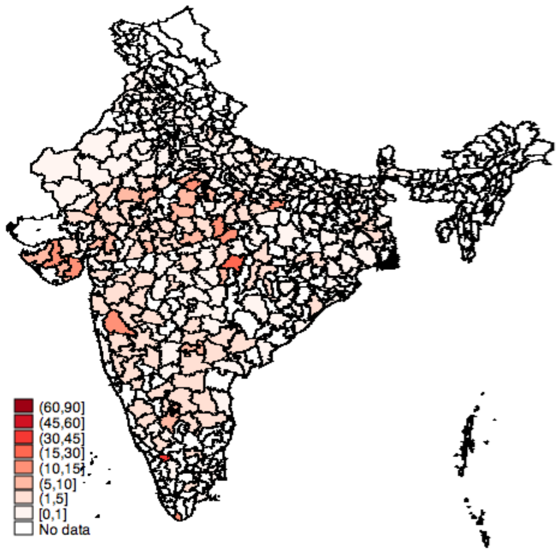
FIGURE 1: District Maps of India

a) Dams in 1961



b) Dams in 1991

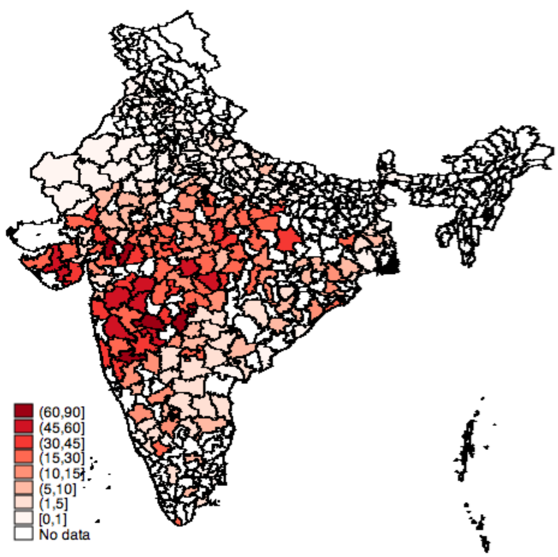


Table I
Summary Statistics

	Mean	SD	Min	Max	Observations	Data Source
Panel A: Full Sample						
Conflict						
Number of Riots	0.16	0.75	0	20	4303	Varshney-Wilkinson
Deaths	0.85	11.34	0	601	4303	Varshney-Wilkinson
Injured	3.02	27.13	0	893	4289	Varshney-Wilkinson
Arrests	15.07	135.52	0	4000	4289	Varshney-Wilkinson
Annual Rainfall (mm)	1077.59	504.15	55.7	5919.9	4303	Univ. of Delaware
Welfare Measures						
Value of Production (000 rupees)	22,552	22,703	0	259,494	4256	Evenson/McKinsey
Wage	5.45	2.91	0.82	41.97	4272	Evenson/McKinsey
Headcount Ratio	0.44	0.15	0.07	0.82		Duflo/Pande
Poverty Gap	0.16	0.10	0.01	0.40		Duflo/Pande
Gini Coefficient	0.28	0.04	0.15	0.39		Duflo/Pande
Dams (%)						
Dam-fed	28.2	45.0	0	100	4292	Duflo/Pande
Dam-fed (predicted)	30.2	45.9	0	100	4292	Duflo/Pande
Population Variables						
Total Population	1,884,971	1,154,017	423,815	13,000,000	4303	Census (1961 - 91)
Percent of Population:						
Young Male	31.0	1.7	23.7	37.9	4303	Census (1961 - 91)
Literate	35.6	11.5	12.2	71.8	4303	Census (1961 - 91)
Rural	76.0	13.8	23.6	97.5	4303	Census (1961 - 91)
Muslim	11.9	9.8	0.2	61.4	4303	Census (1961 - 91)
Migrants	30.3	6.1	12.0	48.6	4303	Census (1961 - 91)
Panel B: Rain-fed vs. Dam-fed	Rain-fed Mean	Rain-fed SD	Dam-fed Mean	Dam-fed SD		p-value
Number of Riots	0.11	0.56	0.26	1.07		0.001
Annual Rainfall (mm)						
Value of Production	21,355	20,220	23,679	24,765		0.001
Wage	5.32	2.54	5.57	3.19		0.001
% Muslim	0.17	0.23	0.15	0.21		0.343
% Rural	0.82	0.14	0.76	0.15		0.001
Panel C: Dropping Ahmedabad	Rain-fed Mean	Rain-fed SD	Dam-fed Mean	Dam-fed SD		
Number of Riots	0.11	0.53	0.17	0.66		0.001
Annual Rainfall (mm)						
Value of Production	23,699	24,775	21,359	19,867		0.001
Wage	5.57	3.19	5.32	2.55		0.001
% Muslim	0.16	0.25	0.15	0.24		0.365
% Rural	0.84	0.13	0.80	0.13		0.001

Notes: There are 142 districts in the dataset, covering the years 1961-1995. The headcount ratio is the proportion of the population living below the poverty line. The poverty gap is the average shortfall of a district's population from the poverty line, expressed as a percentage of the poverty line. The gini coefficient is measured using average household consumption expenditure which comes from the Indian National Sample Surveys. I interpolate between years for all variabes from the Census of India, assuming a constant rate of population growth. Young males are those males less than 35 years of age. Migrants include migrants from other states and countries.

Table II
First Stage, Reduced Form Results, and Instrumental Variable Results

	IV	Reduced Form (OLS)					
Dep. Variable:	Conflict	Log Value of Production				Conflict	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Rain Shock		0.044*** (0.013)	0.036*** (0.005)	0.028 (0.018)	0.082*** (0.013)	-0.032*** (0.008)	-0.032*** (0.006)
Shock x Downstream			-0.022*** (0.002)				-0.029** (0.013)
Downstream Dummy			0.012*** (0.003)				0.009 (0.016)
Log Wage Shock	-0.643*** (0.184)						
p-value			0.001				0.879
District Fixed Effects	x	x	x	x	x	x	x
State-Year Fixed Effects	x	x	x	x	x	x	x
Sample	full	full	full	dam-fed	rain-fed	full	full
Observations	4392	4763	4689	1865	2898	4470	4396

Notes: Standard errors are reported in parentheses and are clustered by district. The rain shock variable takes the value 1 if the district's average rainfall is above the 80th percentile, -1 if it is below the 20th percentile, and is otherwise 0. All specifications include district and state-year fixed effects. Column 1 replicates Miguel et al.'s IV specification where rain shock is used to instrument for the wage shock. This specification is estimated on the full sample and no dam information is included. The dependent variable in columns 1 and 6-7 is a dummy variable indicating whether a district experienced a riot in a given year. The dependent variable in columns 2-5 is the log of the value of a district's agricultural production, measured in 1000 rupees. Specifications 2-7 are estimated using OLS. The p-value that is displayed is for the test that a rain shock has the same effect in rain-fed and in dam-fed districts.

Table III
Spillovers

	OLS	Negative Binomial	
Dep. Variable:	Conflict	Number of Riots	Number of Riots
	(1)	(2)	(2)
Rain Shock	-0.101*	-0.943**	-1.268***
	(0.056)	(0.429)	(0.445)
Rain Shock x % Neighbouring Rain-Fed Districts	-0.044	-0.770	-1.220
	(0.151)	(1.518)	(1.664)
% Neighbouring Rain-Fed Districts	0.310	-2.410*	-1.318
	(0.262)	(1.269)	(1.162)
Controls			x
District Fixed Effects	x	x	
State-Year Fixed Effects	x	x	x
Sample	Dam-Fed	Dam-Fed	Dam-Fed
Observations	972	867	837

Notes: Standard errors are reported in parentheses and are clustered by district. The rain shock variable takes the value 1 if the district's average rainfall is above the 80th percentile, -1 if it is below the 20th percentile, and is otherwise 0. The dependent variable in column 1 is a dummy variable indicating whether a district experienced a riot in a given year. The dependent variable in columns 2 and 3 is the number of riots that occur within a district in the current year. Specifications 1 and 2 include both district and state-year fixed effects. Specification 3 includes state-year fixed effects and the following vector of control variables: percent of the population that is Muslim, percent that is male and under 35 years of age, percent that is literate, the proportion of the population living in a rural area, the number of migrants, and the log of the total population. The construction of each control variable is described in Section 2 of the paper. All specifications are run on the sample of dam-fed districts.

Table IV
Spillovers: Migrants

	OLS	
	Migrants (%)	
	(1)	(2)
Rain Shock	0.002 (0.003)	-0.001 (0.003)
District Fixed Effects	x	x
State-Year Fixed Effects	x	x
Sample	dam-fed	rain-fed
Observations	1899	1725

Notes: Standard errors are reported in parentheses and are clustered by district. The rain shock variable takes the value 1 if the district's average rainfall is above the 80th percentile, -1 if it is below the 20th percentile, and is otherwise 0. The dependent variable is the percent of the population who are migrants from another district. All specifications include district and state-year fixed effects.

Table V
Interactions with Proxies for Rioting

Dep. Variable:	Conflict			
Control:	Muslim	Rural	Log(Pop)	Past Riots
	(1)	(2)	(3)	(4)
Rain Shock	0.001	-0.124**	0.579***	-0.023***
	(0.010)	(0.056)	(0.186)	(0.009)
Shock*Control	-0.177**	0.135**	-0.041***	-0.021**
	(0.082)	(0.066)	(0.013)	(0.010)
Downstream* Shock	-0.028**	-0.026**	-0.026**	-0.029**
	(0.012)	(0.012)	(0.012)	(0.012)
Downstream* Shock*Control	0.025	-0.002	-0.000	0.010
	(0.136)	(0.018)	(0.001)	(0.017)
Control	0.147*	-0.252***	0.039**	-0.021**
	(0.085)	(0.073)	(0.015)	(0.010)
Downstream Dummy	-0.010	-0.007	-0.010	-0.013
	(0.016)	(0.016)	(0.016)	(0.018)
State-Year Fixed Effects	x	x	x	x
Observations	4152	4152	4152	2852

Notes: Standard errors are reported in parentheses and are clustered by district. The rain shock variable takes the value 1 if the district's average rainfall is above the 80th percentile, -1 if it is below the 20th percentile, and is otherwise 0. All specifications include district and state-year fixed effects. The dependent variable is a dummy variable indicating whether a district experienced a riot in a given year. All specifications include state-year fixed effects and the set of control variables specified in Table III. The controls that are interacted with rain shock are defined as follows. Muslim is the percent of a district's population that is Muslim. A rural district is one in which more than 78% of the population resides in an area defined as rural by the Indian Census. Log(Pop) is the log of a district's total population. Past riots is the number of riots that a district had prior to 1971. The specification in Column 4 is run on the post-1971 sample.

Appendix Table I
Robustness Checks on Reduced Form Regression

	Riot Count		Dam Built in Year t		One-year Riot Lag		Five-year Riot Lag	
Dep. Variable:	Number Riots	Number Riots	Conflict	Number Riots	Conflict	Number Riots	Conflict	Number Riots
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Rain Shock	-0.252***	-0.284***	-0.036***	-0.275***	-0.016***	-0.220***	-0.024***	-0.258***
	(0.072)	(0.076)	(0.007)	(0.074)	(0.005)	(0.069)	(0.006)	(0.071)
Shock x Downstream	-0.452***	-0.559***	-0.026**	-0.417***	-0.025**	-0.367***	-0.024**	-0.354***
	(0.144)	(0.146)	(0.013)	(0.144)	(0.011)	(0.136)	(0.012)	(0.137)
Downstream Dummy	0.498**	0.073	0.004	0.445**	-0.001	0.233	0.002	0.218
	(0.202)	(0.193)	(0.017)	(0.206)	(0.013)	(0.172)	(0.013)	(0.171)
Dam Built			0.003	0.139				
			(0.013)	(0.145)				
Number of riots in year t-1					0.056***	0.140***		
					(0.006)	(0.020)		
Number of riots in five-year lag							0.023***	0.041***
							(0.002)	(0.009)
Controls		x						
District Fixed Effects	x	x	x	x				
State-Year Fixed Effects	x		x	x	x	x	x	x
Random Effects					x	x	x	x
p-value	0.2416	0.1099	0.4948	0.4136	0.4767	0.3646	0.9941	0.5641
Observations	4853	4244	4260	4532	4260	4756	3759	4249

Notes: Standard errors are reported in parentheses and are clustered by district. "Dam Built" is a dummy variable indicating whether a dam was built in district i in year t. Specifications 5-6 include the number of riots that a district experienced in past year as a control variable, and specifications 7-8 include the number of riots in the past five years. Specifications including past riots as a control are estimated using a random effects model. All specifications include a state-year time trend and specifications 1 and 3-4 also include district fixed effects. In specification 2, I drop district fixed effects and include the vector of control variables described in Table III. I use a negative binomial model for estimation when the number of riots is the dependent variable and OLS when the conflict dummy is the dependent variable.

Appendix Table II
Robustness: Other Welfare Measures

	OLS				
Dep. Variable:	Log Wage	Headcount Ratio	Poverty Gap	Gini Coefficient	Expenditure
	(1)	(2)	(3)	(4)	(5)
Rain Shock	0.011*	0.007**	0.003*	0.001	0.000
	(0.006)	(0.003)	(0.002)	(0.001)	(0.009)
Shock x Downstream	-0.036**	-0.017**	-0.004	-0.007**	0.021
	(0.014)	(0.009)	(0.004)	(0.003)	(0.019)
Downstream Dummy	0.094***	0.018	-0.051***	-0.004	0.103*
	(0.029)	(0.021)	(0.010)	(0.005)	(0.058)
District Fixed Effects	x	x	x	x	x
State-Year Fixed Effects	x	x	x	x	x
p-value	0.010	0.0298	0.1154	0.019	0.3915
Observations	4536	4896	4896	4896	4896

Notes: Log Wage is log of the agricultural wage, described in Section 2.3 of the paper. The headcount ratio is the proportion of the population living below the poverty line. The poverty gap is the average shortfall of a district's population from the poverty line, expressed as a percentage of the poverty line. The gini coefficient is measured using average household consumption expenditure which comes from the Indian National Sample Surveys. Expenditure is the mean household consumption expenditure in a district, measured in rupees. Standard errors are reported in parentheses and are clustered by district. The p-value that is displayed is for the test that a rain shock has the same effect in rain-fed and in dam-fed districts.

Appendix Table III
Robustness: Income Percentiles

Dep. Variable:	Mean Expenditure			Log Wage		
Percentile:	25th	50th	75th	25th	50th	75th
	(1)	(2)	(3)	(4)	(5)	(6)
Rain Shock	0.003	0.005	0.002	0.007	0.013**	0.016*
	(0.005)	(0.005)	(0.005)	(0.007)	(0.006)	(0.008)
Shock x Downstream	-0.004	-0.014	-0.006	-0.019	-0.026**	-0.038**
	(0.008)	(0.010)	(0.008)	(0.014)	(0.012)	(0.017)
Downstream Dummy	0.084***	0.047***	0.025*	0.131***	0.100***	0.022
	(0.014)	(0.016)	(0.014)	(0.018)	(0.016)	(0.022)
District Fixed Effects	x	x	x	x	x	x
State-Year Fixed Effects	x	x	x	x	x	x
p-value	0.527	0.114	0.4082	0.1122	0.0064	0.0053
Observations	3341	3341	3341	4536	4536	4536

Notes: Log Wage is log of the agricultural wage, described in Section 2.3 of the paper. Mean expenditure is the mean household consumption expenditure in a district, measured in rupees. The p-value that is displayed is for the test that a rain shock has the same effect in rain-fed and in dam-fed districts. Standard errors are reported in parentheses.

Appendix Table IV
Robustness: Other Sample Splits

	Panel A: Rural vs. Urban Districts			
Dep. Variable:	Log Production Value		Conflict	
	(1)	(2)	(3)	(4)
Rain Shock	0.061*** (0.013)	0.026 (0.022)	-0.016* (0.009)	-0.051*** (0.014)
District Fixed Effects	x	x	x	x
State-Year Fixed Effects	x	x	x	x
Sample	Rural	Urban	Rural	Urban
Observations	2915	1848	2831	1639

	Panel B: Agricultural vs. Industrial Districts			
Dep. Variable:	Log Production Value		Conflict	
	(1)	(2)	(3)	(4)
Rain Shock	0.060*** (0.015)	0.038* (0.021)	-0.028*** (0.009)	-0.042*** (0.014)
District Fixed Effects	x	x	x	x
State-Year Fixed Effects	x	x	x	x
Sample	Farming	Industrial	Farming	Industrial
Observations	2177	2334	1997	2222

Notes: In Panel A, districts are divided according to whether it is predominantly rural or urban. A rural district is one in which more than 78% of the population resides in an area defined as rural by the Indian Census. In Panel B, districts are divided by industry type. Farming districts are those in which more than 24% of the population is employed in the farming sector. Standard errors are reported in parentheses and are clustered by district.