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Rainfall and conflict: A cautionary tale

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ABSTRACT

There is evidence that, in some contexts, income shocks cause conflict. The literature demonstrating this relationship uses rainfall shocks to instrument for income shocks, 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. I explore other channels through which rainfall might affect conflict.

1. Introduction

Intrastate conflict has become widespread in recent decades, 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 (2014) 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, several researchers have relied on rainfall as a source of exogenous variation for income. Miguel et al. (2004) instrument GDP growth in sub-Saharan Africa with rainfall growth and find that lower economic growth increases the probability of civil war. Bohlken and Sergenti (2010) conduct the same analysis in India, instrumenting for state-level GDP with rainfall. They too find that low rainfall growth increases the number of riots that a state experiences in a given year. Rainfall is a plausible candidate instrument if the country or region in question is economically dependent on rain-fed agriculture. Low levels of rainfall result in crop failure, thereby depressing rural income.

A critical assumption underlying the use of rainfall as an IV is that rainfall affects conflict only through its impact on income. This paper uses heterogeneity in the effect of rainfall on income in India to test this assumption. 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, providing districts downstream of the dam with water during droughts and holding excess rainwater during periods of heavy rainfall. I identify districts that are downstream of dams (dam-fed districts) and find that while agricultural production in rain-fed districts (those upstream of a dam) is dependent on rainfall, production in dam-fed districts is uncorrelated with the amount of rain. 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 paper fits into the literature on the economic determinants of conflict and contributes to the debate over whether rainfall should be used a driver of income shocks when looking at the relationship between income and conflict. Authors[1] who use rainfall as an instrument for income argue that the effect of rainfall on conflict arises through the income channel. Other authors refute this hypothesis, however. Couttenier and Soubeyran (2014) argue that the relationship between rainfall and civil war is driven by global climate shocks. Using a new, country-specific drought measure, the authors find a weaker relationship between drought and civil war than had previously been measured. Ciccone (2011) revisits Miguel et al.'s (2004) analysis of civil war in sub-Saharan Africa and shows that there is actually a positive correlation between twice-lagged rainfall levels and current conflict. This point is further developed in Ciccone (2013), where the author looks at the effect of transitory shocks on civil conflict risk to test whether income

[1] Bohlken and Sergenti (2010), Fetzer (2013), Vanden Eynde (2011) use rainfall to look at the effect of income shocks on various forms of conflict, including religious riots and Naxalite conflict, in India. Miguel et al (2004), Hendrix and Salefyan (2012), and Adano et al. (2012) all find an effect of rainfall on conflict in sub-Saharan Africa.

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shocks lower the opportunity cost of participating in violence. Ciccone again finds that, in contrast to Miguel et al.'s finding, negative income shocks lower the risk of civil conflict.

My analysis yields an overall effect in India, but the difference in the effect across dam-fed and rain-fed districts is inconsistent with the income channel. While this paper cannot be generalized, nor does it claim to apply to other settings, it serves as a word of caution when using rainfall to instrument for income in regions that have seen development in irrigation systems or other public services that might weaken the dependency of income on rainfall.

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. Several robustness checks are presented in Sections 5 and 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 (Bohlken and Sergenti, 2010; Mitra and Ray, 2014).

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. 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.

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 actual number of 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. I exclude districts not listed in the dataset from my analysis, thereby focusing on the marginal effect of rain on conflict in regions where at least one riot occurred over the sample period. This is in line with other authors' treatment of these districts (see Bohlken and Sergenti, 2010; Mitra and Ray, 2014). The overall riot counts presented in this paper are 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 on Dams, 2000). The World Commission for Dams and the Indian Ministry of Water Resources has 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, a “rain-fed” district, 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 might be mislabeled. Districts containing a dam typically do not benefit from irrigation. The land immediately surrounding the reservoir is submerged and other surrounding regions suffer loss of agricultural land due to increased soil salinity (McCully, 2001; Singh, 2002). Therefore, while there may be some beneficial economic activity in the reservoir area, such as fishing, the agricultural benefit in terms of access to irrigation occurs in the command, or downstream, area (Duflo and Pande, 2007; Thakkar, 2000).

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 reduce 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. I therefore follow their strategy of using geographic characteristics to predict the number of dams that a district would contain. There are three main geographic characteristics that determine an area's

[2] See Bohlken and Sergenti (2010), Mitra and Ray (2014), Brass (2003), and Wilkinson (2004).

suitability for dam construction: river gradient, district elevation, and river length. For example, Duflo and Pande show that gentle river gradients between 1.5 and 3% or very steep gradients (above 6%) are conducive for dam construction while gradients less than 1.5% or between 3 and 6% are not. The authors use these characteristics to predict whether a district contains a dam in a given year. Specifically, the authors estimate the first-stage equation

$$\hat{D}_{ist} = \alpha_1 + \sum_{k=2}^{5} \alpha_{2k}(RGr_{ki} * \overline{D}_{st}) + \sum_{k=2}^{4} \alpha_{3k}(El_{ki} * \overline{D}_{st}) + \sum_{k=2}^{5} \alpha_{4k}(Gr_{ki} * \overline{D}_{st}) + \ldots \\ \ldots + (X_i * \overline{D}_{st})\alpha_5 + v_i + \mu_{st} + w_{ist} \tag{1}$$

where districts are divided into five gradient areas and four elevation categories, each indexed by k. The variable RGr_{ki} is the fraction of river area within a district that is in an area with gradient k. Gr_{ki} is the fraction of a district that has gradient k, and El_{ki} is the fraction of a district that has elevation level k. $\overline{D}_{st}$ is the number of dams that have been built in state s up to and including year t. X_i is a vector of controls which includes district area and river length, and district and state-year fixed effects. Using the predicted number of dams, $\hat{D}_{ist}$, from Eq. (1), I then create a variable $da\hat{m}fed_{ist}$ which is equal to 1 if a district is downstream of a district predicted to contain one or more dams in year t. That is, if $\hat{D}_{jst} \geq 1$ and district j is upstream of district i, then $da\hat{m}fed_{ist} = 1$. In the remainder of the paper, anytime I refer to a "dam-fed" district, I am using this predicted dam measure.

Over the entire time period analyzed, 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. Fig. 1 contains maps showing the distribution of (actual) dams in 1961 (Panel A) and 1991 (Panel B).[3] It is possible for a district to be both downstream 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. The agricultural wage data that is available is the average wage (measured in rupees per hour) of a male ploughman or a male field laborer. 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 calculated as the price per tonne of output multiplied by the number of tonnes produced in a district in a year. 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 were originally constructed using data from the Indian Ministry of Agriculture's Directorate of Economics and Statistics.

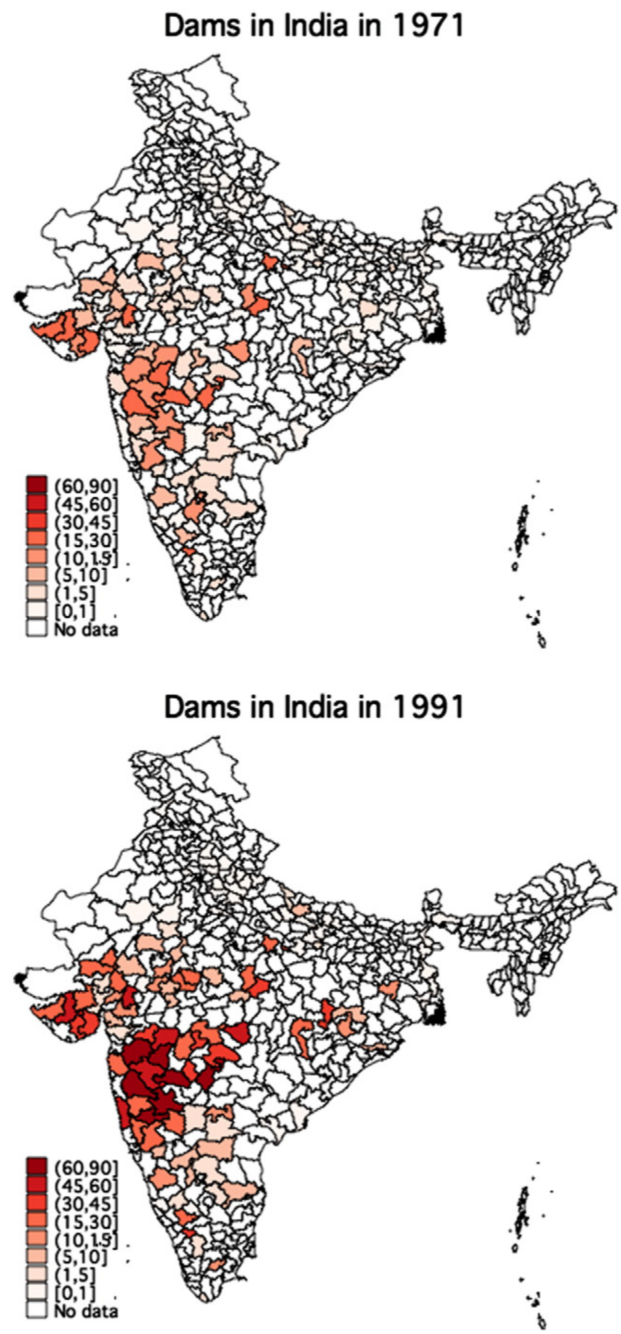

Fig. 1. District maps of India.

2.4. Rainfall

The University of Delaware's Center for Climatic Research provides rainfall estimates at 0.5° 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.[4] The distance between the

[3] 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.

[4] Districts and rainfall estimates are matched using an interpolation algorithm provided by Seema Jayachandaran and used in her 2005 paper.

identified grid points from the rainfall dataset and the in-district weather stations ranges from 1 km to 63 km. 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.

I use two measures of rainfall shocks, both of which are constructed to account for seasonality in rainfall. The first measure is the fractional deviation of rainfall from its average level (calculated over 1961–1995), summed over all months. For example, if a district's average rainfall level in June is 150 mm, the monthly rain shock for a year in which the district received 100 mm of rainfall in June would be −50 mm. I then sum over all 12 months to find a district's yearly shock. This is the measure that Duflo and Pande (2007) use when looking at dams, agricultural productivity, and welfare in India. The second definition follows 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. I then take the average of this measure over all months. This definition has been used in the literature due to the somewhat non-linear relationship between rainfall and agricultural output (see Kaur, 2012, for more discussion).

In accordance with other authors' treatment of the variable (see Jacoby and Skoufias, 1997; Rose, 2001), positive rain shocks are not treated as detrimental. The Indian Ministry of Agriculture groups areas that have had below-average rainfall together to track agricultural productivity. This suggests that below-average rainfall is of greater concern than above-average rainfall (Jayachandaran, 2006).

I do not use the rainfall growth measure, calculated as $100\times\frac{\text{rainfall}_t-\text{rainfall}_{t-1}}{\text{rainfall}_{t-1}}$, that was used in earlier literature[5] as it can misclassify a rain shock. For example, rainfall that is abnormally high in year $t-1$ and reverts back to its usual level in year t will be classified as a negative shock (Ciccone, 2011). However, Appendix Table 6 repeats the following analysis using rainfall growth.

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. 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 1 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 mm 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. There are significant differences in the number of riots that each district type experiences. Two concerns arise from this difference. First, there could be some unobserved variable X that is correlated with a district being dam-fed and that variable also increases the marginal effect of rainfall on rioting through a non-income channel. For example, dam-fed districts could all have dirt roads and an increase in rainfall destroys these roads, making it more difficult for people to organize and riot. While this is possible, it does not validate the use of rainfall as an instrument for income. There is now a non-income through which rainfall is affecting rioting in dam-fed districts. The vast majority of studies using rainfall as an instrument do not conduct tests to see whether there are certain regions in which the exclusion restriction fails. Without running these diagnostic checks, researchers cannot be sure that rainfall satisfies the exclusion restriction.

Another concern might be that there is an unobserved variable that is correlated with a district being dam-fed and also correlates with rioting. In this case, however, the effect of that variable would be picked up by the dam-fed dummy. We see that the dam-fed dummy is correlated with rioting in most regressions but the impact of rainfall on rioting in these areas remains.

3. Estimation framework and main results

In what follows, I refer to districts being dam-fed or rain-fed. Dam-fed districts are defined using the predicted dam measure.

3.1. Estimating equations

I first analyze the first stage relationship between rain shocks and income,

$$Y_{i,t} = a + b_1\left(\text{rain}_{i,t}\right) + v_i + v_{st} + u_{ist} \quad (2)$$

and the reduced form relationship between rain shocks and conflict,

$$\text{conflict}_{i,t} = \alpha + \beta_1\left(\text{rain}_{i,t}\right) + \theta_i + \theta_{st} + \epsilon_{ist}. \quad (3)$$

For district i in year t, $\text{rain}_{i,t}$ is the district rain shock, $\text{conflict}_{i,t}$ is a dummy variable that equals one if the district experience 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 Eq. (3) should also be diminished. To test for such effects of predicted dams, I include interaction terms

[5] Such as Miguel et al. (2004) and Bohlken and Sergenti (2010).

Table 1
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		Dam-fed		p-Value
	Mean	SD	Mean	SD	
Number of riots	0.13	0.57	0.20	0.92	0.001
Value of production	23,196	24,205	21,355	20,220	0.015
Wage	5.45	3.12	5.32	2.54	0.012
% Muslim	0.17	0.25	0.15	0.24	0.044
% rural	0.82	0.13	0.79	0.14	0.001

Notes: There are 142 districts in the dataset, covering the years 1961–1995. The value of production is the price per tonne of output multiplied by the number of tonnes produced in a district in a year. 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 variables 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.

in the above equations:

$$Y_{i,t} = a + b_1\left(\text{rain}_{i,t}\right) + b_2\left(\hat{\text{rain}}_{i,t} * \hat{damfed}_{it}\right) + b_3(\hat{damfed}_{it}) + \theta_i + \theta_{st} + u_{ist} \tag{4}$$

$$\text{conflict}_{i,t} = a + \beta_1(\text{rain}_{it}) + \beta_2\left(\hat{rain}_{i,t} * \hat{damfed}_{i,t}\right) + \beta_3\left(\hat{damfed}_{i,t}\right) + \theta_i + \theta_{st} + u_{ist} \tag{5}$$

where $\hat{damfed}_{it}$ is the dummy variable defined in Section 2.2.

Table 2
First stage, reduced form results, and instrumental variable results.

Dep. variable:	Categorical shock				Fractional shock			
	Log value of prodn.		Conflict		Log value of prodn.		Conflict	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Rain shock	0.054***	0.055***	−0.023***	−0.036**	0.271***	0.363***	−0.114***	−0.052*
	(0.011)	(0.015)	(0.008)	(0.013)	(0.042)	(0.053)	(0.024)	(0.030)
Shock × downstream		−0.049**		−0.013**		−0.187***		−0.134***
		(0.022)		(0.019)		(0.069)		(0.050)
Downstream dummy		0.104***		0.003		0.127***		0.005
		(0.028)		(0.020)		(0.026)		(0.019)
p-Value		0.003		0.382		0.001		0.269
District fixed effects	x	x	x	x	x	x	x	x
State-year fixed effects	x	x	x	x	x	x	x	x
Observations	4697	3564	4400	3267	4697	3564	4400	3267

Notes: Standard errors are reported in parentheses and are clustered by district. The categorical rain shock variable used in columns 2–5 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 fractional rain shock variable used in columns 6–9 is the monthly deviation of a district's rainfall above or below its average amount, summed over all months. All specifications include district and state-year fixed effects. The dependent variable in columns 1–2 and 5–6 is the log of the value of a district's agricultural production (defined in Table 1), measured in 1000 rupees. The dependent variable in columns 3–4 and 7–8 is a dummy variable indicating whether a district experienced a riot in a given year. All specifications 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.
***, **, and * indicate significance at the 1%, 5%, and 10% levels respectively.

3.2. Estimation results

Table 2 contains the main results of estimating Eqs. (2)–(5) using the two rain shock definitions described in Section 2.4. Using the categorical shock variable, a negative rain shock appears to lower a district's average production value by 5.4% across all regions (column 1). However, in column 2, rain shocks are not significant determinants of agricultural production in dam-fed districts. The p-value reported in column 2 tests whether rain shocks have the same effect in dam-fed and rain-fed districts. This hypothesis is strongly rejected.

Given the first stage results, if the effect of rain on conflict arises through agricultural production, rainfall shocks should have a negative effect on conflict across all regions but not in dam-fed regions. The results in column 3 show that positive rain shocks do lower conflict across all regions. However, when I estimate separate effects of rain shocks for dam-fed regions and rain-fed regions in column 4, the effect of rain shocks on conflict is actually stronger in dam-fed regions. This result is inconsistent with income being the channel through which rainfall affects conflict.

Columns 5–8 repeat the analysis using the fractional rain shock measure.[6] I again find a positive effect of rain shocks on agricultural production across all regions (column 5) but the effect is again weaker in dam-fed regions (column 6). In contrast to column 2, however, the effect of rainfall on income is still marginally significant in dam-fed regions. Turning to the effect of rain shocks on conflict, I find that positive rain shocks lower the risk of conflict across all regions but again have a stronger effect in dam-fed regions (column 8). The same rainfall-driven shock to agricultural production appears to be more likely to lead to conflict in dam-fed regions than in rain-fed regions which is again inconsistent with the income hypothesis.

4. Robustness

I now investigate other channels through which rainfall might affect conflict, such as conflict spillover and migration. I then test whether the above findings are robust to accounting for heterogeneity in riot potential across districts, the potential for conflict to erupt when dams are being built, and to alternative specifications.

4.1. Spillovers

It is possible that rioting spills over from rain-fed to dam-fed regions. For example, Varsheny and Wilkinson's dataset contains some details on what happened during a riot and in some instances a religious monument was desecrated during the conflict. 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 the proportion of its neighboring districts that are rain-fed. I then control for rain shocks in the neighboring districts by including an interaction term between the proportion of neighbors that are rain-fed and the average rain shock in these districts:

$$\text{conflict}_{i,t} = \alpha + \beta_1\left(\text{rain}_{i,t}\right) + \beta_2\left(\text{rainfed}_{i,t} * \text{nbrain}_{i,t}\right)\beta_3\left(\text{rainfed}_{i,t}\right) + \theta_i + \theta_{st} + u_{ist}.$$

In the above equation, $\text{rainfed}_{i,t}$ is the proportion of district i's neighbors that are rain-fed and $\text{nbrain}_{i,t}$ is the average rain shock in those districts.

The results are shown in Table 3. 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 neighboring rain shock term is insignificant 11 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), providing little evidence of conflict spilling over from rain-fed to dam-fed districts.

Table 3
Spillovers.

Dep. variable	OLS	Negative binomial	
	Conflict	Number of riots	Number of riots
	(1)	(2)	(2)
Rain shock	−0.124**	−1.122***	−1.089**
	(0.052)	(0.399)	(0.457)
Rain shock × % neighboring rain-fed districts	−0.097	−1.298	−1.540
	(0.145)	(1.924)	(2.073)
% neighboring rain-fed districts	0.300***		
	(0.106)		
Controls			x
District fixed effects	x	x	
State-year fixed effects	x	x	x
Sample	Dam-fed	Dam-fed	Dam-fed
Observations	972	972	943

Notes: Standard errors are reported in parentheses and are clustered by district. The rain shock variable is the monthly deviation of a district's rainfall above or below its average amount, summed over all months. 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.
***, **, and * indicate significance at the 1%, 5%, and 10% levels respectively.

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

$$\text{migrants}_{i,t} = \alpha + \beta_1\left(\text{rain}_{i,t}\right) + \beta_2\left(\text{rainfed}_{i,t} * \text{rain}_{i,t}\right) + \beta_3\left(\text{rainfed}_{i,t}\right) + \theta_i + \theta_{st} + u_{ist}$$

[6] Appendix Table 6 shows the results using rainfall growth (defined in Section 2.4) as the rainfall measure. This is the measure used in Miguel et al. (2004) and in Bohlken and Sergenti (2010), and tested in Ciccone (2011).

Table 4
Spillovers: migrants.

	OLS	
	Migrants (%)	
	(1)	(2)
Rain shock	0.002	−0.001
	(0.005)	(0.003)
District fixed effects	x	x
State-year fixed effects	x	x
Sample	Dam-fed	Rain-fed
Observations	1796	1828

Notes: Standard errors are reported in parentheses and are clustered by district. The rain shock variable is the monthly deviation of a district's rainfall above or below its average amount, summed over all months. The dependent variable is the percent of the population who are migrants from another district. All specifications include district and state-year fixed effects.

where the interaction and rainfed variables are defined as in Section 3. The results are shown in Table 4. While the coefficients on the variables have the expected signs (a negative rain shock in neighboring 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 cannot 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.

Table 5
Interactions with proxies for rioting.

Dep. variable:	Conflict			
Control:	Muslim	Rural	Log(Pop)	Total riots
	(1)	(2)	(3)	(4)
Rain shock	−0.111***	−2.044	5.504	−0.058**
	(0.036)	(1.564)	(4.612)	(0.025)
Shock ∗ control	0.536*	2.525	−0.383	0.004
	(0.304)	(1.965)	(0.319)	(0.003)
Downstream ∗ shock	−0.002***	−0.005*	−0.003	−0.002***
	(0.001)	(0.003)	(0.003)	(0.001)
Downstream ∗ shock ∗ control	−0.264	−0.002	−0.016	−0.013***
	(0.429)	(0.130)	(0.0.016)	(0.003)
Control	0.201**	−0.940**	0.119**	0.005
	(0.086)	(0.407)	(0.047)	0.001
Downstream dummy	−0.002	0.123***	0.113***	0.001
	(0.016)	(0.039)	(0.041)	(0.012)
State-year fixed effects	x	x	x	x
Observations	3158	3624	3624	3158

Notes: Standard errors are reported in parentheses and are clustered by district. The rain shock variable is the monthly deviation of a district's rainfall above or below its average amount, summed over all months. 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 3. 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. Total riots are the total number of riots a district experienced over the sample period, leaving out year t.
***, **, and * indicate significance at the 1%, 5%, and 10% levels respectively.

4.3. Riot potential

In Table 5, 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 is 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 total number of riots that occur in a district over the sample period. The total riots control is calculating leaving out the current year (ie past riots$_t$ = total riots over period − riots$_{st}$).

The effect of a rain shock on conflict is consistent across the specifications although insignificant in column 2 which controls for the relative size of the rural population. 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 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 −5.53, offsetting the positive coefficient on rain shock. The effect of a rain shock is thus close to zero when looking at dam-fed districts. Controlling for total riots over the period does not alter the results (column 4).

4.4. Other factors

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

5.1. Number of riots

In Appendix Table 1, I see whether the reduced form relationship between rainfall and rioting is robust to various specifications. In columns 1 and 2, I reestimate Eq. (5), using the number of riots in a district as the dependent variable instead of the dummy variable. 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 0.62 per dam-fed district and 0.6 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.

5.2. Conflict during dam construction

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 Eq. (5). 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. The coefficients remain stable with this control. I also look up to three years following dam construction but find no evidence of a lagged response (results not shown).

5.3. History of violence

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 (5). 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 5–6. The one-year riot variable is positive and significant but the 5-year lag is insignificant which could be due to the fact that riots are typically short-lived. A riot that occurred five years ago probably does not weigh as heavily in people's minds as one that occurred last year. The coefficient on the rain shock variable remains significant and stable in magnitude.

5.4. Alternative welfare measures

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 2, the production variable is substituted with five other welfare measures: the log of agricultural wages, the headcount ratio, poverty gap, Gini coefficient (measured over expenditure), and mean expenditure. These variables are defined in Section 2.6. Rainfall has no significant effect on any of the measures except for the agricultural wage. It does, however, have a negative impact on the poverty gap in dam-fed districts. This means that an abundance of rainfall decreases the poverty gap. If rainfall is working through this channel to affect rioting, this could explain why we see a reduced-form effect of rainfall on rioting even when there is no first stage between rainfall and agricultural income. Given that rain shocks do not affect the poverty gap in rain-fed districts, though, it would have to be some combination of these poverty and income measures that rainfall is working through. Otherwise, when using the poverty gap as the income measure, we should not see any correlation between rainfall and rioting in rain-fed areas.

In Appendix Table 3, I run quantile regressions to look at the impact that rain shocks have on income at different income percentiles. I find no significant effects of rain shocks on these income measures.

5.5. Alternative sample splits

Three alternative sample splits are shown in Appendix Table 4. 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 cannot 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.

Appendix Table 5 addresses concerns that might arise regarding the dam variable. In columns 1–4, I call a district dam-fed if it was downstream of a dam at the beginning of the sample period. This allays the concern that building dams during the sample period could be affecting rioting. In columns 5 and 6, I omit the 5 years before and after a dam is built in a district. The effect of a rain shock on agricultural production remains the same: dams mitigate weather shocks. However, as seen in columns 4 and 6, dams do not mitigate the effect of rain shocks on conflict.

5.6. Geography

In Appendix Table 7, I include the geographic characteristics used to predict dams to see if these characteristics also make regions more or less prone to conflict. The characteristics that are significant (high district elevation or a district gradient between 3 and 6°) are actually less conducive for dam construction.[7] Therefore, while these areas may have fewer conflicts, they are also unlikely to contain a dam, allaying the worry that this might be driving the results.

6. Conclusion

This paper evaluates the use of rainfall as an instrumental variable for income when looking at the relationship between income and conflict in India. My analysis confirms earlier findings that positive rainfall shocks reduce conflict in India. For India as a whole, the effect would seem consistent with the income hypothesis: negative rain shocks lower agricultural production and income, thereby spurring violence. However, I also find that the effect of rain shocks on conflict is stronger in areas downstream of dams even though irrigation makes agricultural production less sensitive to rain shocks.

This paper contributes to the literature in two ways. First, it cautions against using rainfall as an instrument for income in regions that have some irrigation technology that reduces the dependency of agriculture on rainfall. Researchers searching for an instrument for income should test to see whether the first stage holds in such subsamples. 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.

[7] See Table 2 in Duflo and Pande's working paper version of "Dams".

Appendix A

Appendix Table 1
Robustness checks on reduced form regression.

Dep. variable:	Riot count		Dam built in year t		1-year riot lag	5-year riot lag
	Number riots	Number riots	Conflict	Number riots	Conflict	Conflict
	(1)	(2)	(3)	(4)	(5)	(6)
Rain shock	−0.604*	−0.580**	−0.065**	−0.595*	−0.061**	−0.064**
	(0.335)	(0.290)	(0.026)	(0.338)	(0.026)	(0.026)
Shock × downstream	−0.016***	−0.017***	−0.002***	−0.016***	−0.002***	−0.002***
	(0.006)	(0.006)	(0.001)	(0.006)	(0.001)	(0.001)
Downstream dummy	0.866***	0.121	0.004	0.839***	0.005	0.006
	(0.223)	(0.194)	(0.019)	(0.220)	(0.018)	(0.019)
Dam Built			0.005	0.234		
			(0.016)	(0.193)		
Number of riots in year t − 1					0.018**	
					(0.009)	
Number of riots in five-year lag						0.002
						(0.003)
Controls		x				
District fixed effects	x	x	x	x		
State-year fixed effects	x		x	x	x	x
Random effects					x	x
p-Value	0.0828	0.0548	0.0186	0.0179	0.0222	0.0179
Observations	3834	3624	3342	3834	3342	3342

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. Specification 5 includes the number of riots that a district experienced in past year as a control variable, and specification 6 includes 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 3. 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.
***, **, and * indicate significance at the 1%, 5%, and 10% levels respectively.

Appendix Table 2
Robustness: other welfare measures.

Dep. variable:	OLS				
	Log wage	Headcount ratio	Poverty gap	Gini coefficient	Expenditure
	(1)	(2)	(3)	(4)	(5)
Rain shock	0.003***	−0.011	0.001	0.003	−0.020
	(0.011)	(0.014)	(0.007)	(0.004)	(0.039)
Shock × downstream	−0.075***	−0.016	−0.014**	−0.008	0.045
	(0.019)	(0.016)	(0.007)	(0.005)	(0.038)
Downstream dummy	0.088***	0.024	−0.093***	−0.003	0.229***
	(0.029)	(0.018)	(0.008)	(0.006)	(0.045)
District fixed effects	x	x	x	x	x
State-year fixed effects	x	x	x	x	x
p-Value	0.001	0.845	0.255	0.149	0.371
Observations	3407	619	619	619	619

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.
***, **, and * indicate significance at the 1%, 5%, and 10% levels respectively.

Appendix Table 3
Robustness: income percentiles.

Dep. variable:	Mean expenditure			Log wage		
Percentile:	25th	50th	75th	25th	50th	75th
	(1)	(2)	(3)	(4)	(5)	(6)
Rain shock	0.186*	0.134	0.108	0.025	0.035	0.039
	(0.097)	(0.084)	(0.099)	(0.024)	(0.023)	(0.030)
Shock × downstream	−0.002	−0.002	−0.002	−0.001	−0.001**	−0.001
	(0.002)	(0.002)	(0.002)	(0.001)	(0.001)	(0.001)
Downstream dummy	0.207***	0.200***	0.164**	0.184***	0.131***	0.071***
	(0.071)	(0.061)	(0.072)	(0.019)	(0.019)	(0.024)
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	654	654	654	3474	3474	3474

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.
***, **, and * indicate significance at the 1%, 5%, and 10% levels respectively.

Appendix Table 4
Robustness: other sample splits.

Dep. variable:	Log production value		Conflict	
	(1)	(2)	(3)	(4)
Panel A: rural vs. urban districts				
Rain shock	0.061***	0.026	−0.016*	−0.051***
	(0.013)	(0.022)	(0.009)	(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				
Rain shock	0.060***	0.038*	−0.028***	−0.042***
	(0.015)	(0.021)	(0.009)	(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.
***, **, and * indicate significance at the 1%, 5%, and 10% levels respectively.

Appendix Table 5
Robustness: variants on dam variable.

Dam variable:	Dams existing at beginning of sample period				Excl. 5 years before and after dam built	
Dep. variable:	Log value production		Conflict		Log value prod.	Conflict
	(1)	(2)	(3)	(4)	(5)	(6)
Rain shock	0.259***	0.455***	−0.107***	−0.127***	0.352***	−0.097***
	(0.048)	(0.080)	(0.024)	(0.038)	(0.057)	(0.036)
Shock * dam-fed	−0.328***		0.066	−0.001	−0.002***	
		(0.094)		(0.046)	(0.001)	(0.001)
Dam-fed		0.201*		0.018		
		(0.106)		(0.016)		
Controls		x		x		
District FEs					x	x
State-year fixed effects	x	x	x	x	x	x
Observations	3441	3441	3150	3150	2202	2320

Notes: Standard errors are reported in parentheses and are clustered by district. The rain shock variable is the fractional deviation of rainfall from its historical average. In specifications 1–4, “dam-fed” is a dummy that equals 1 if a district contained a dam at the beginning of the sample period. Because it does not vary over time, I include a vector of controls instead of district fixed effects. The controls included are 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. In specifications 5–6, I exclude the four years before and after a dam is built. These specifications include district fixed effects which absorbs the dam-fed dummy. All specifications include a state-year time trend. The dependent variable in columns 1, 2, and 5 is the log of the value of a district's agricultural production, measured in 1000 rupees. The dependent variable in columns 3, 4, and 6 is a dummy variable indicating whether a district experienced a riot in a given year.
***, **, and * indicate significance at the 1%, 5%, and 10% levels respectively.

Appendix Table 6
Robustness: rainfall growth.

Dep. variable:	Log value production		Conflict	
	(1)	(2)	(3)	(4)
Rainfall growth	0.003***	0.003***	0.000	0.000
	(0.000)	(0.001)	(0.000)	(0.000)
Growth * dam-fed		−0.001		0.000
		(0.001)		(0.000)
Dam-fed		0.038*		−0.061**
		(0.021)		(0.024)
District fixed effects	x	x	x	x
State-year fixed effects	x	x	x	x
Observations	3109	2240	3109	2240

Notes: Standard errors are reported in parentheses and are clustered by district. Rainfall growth is the percent change in rainfall from one year to the next. All specifications include district fixed effects and a state-year time trend. The dependent variable in columns 1 and 2 is the log of the value of a district's agricultural production, measured in 1000 rupees. The dependent variable in columns 3 and 4 is a dummy variable indicating whether a district experienced a riot in a given year.
***, **, and * indicate significance at the 1%, 5%, and 10% levels respectively.

Appendix Table 7
Robustness: geographic characteristics.

Geographic var:	Elevation		River gradient		District gradient	
Dep. variable:	Conflict		Conflict		Conflict	
	(1)	(2)	(3)	(4)	(5)	(6)
Rain shock	−0.088***	−0.089**	−0.087***	−0.087**	−0.087***	−0.087**
	(0.023)	(0.043)	(0.023)	(0.043)	(0.023)	(0.043)
Slope 0–1.5/elev 0–250 m	0.039	0.038	0.021	0.021	0.036	0.036
	(0.033)	(0.033)	(0.022)	(0.022)	(0.030)	(0.030)
Slope 1.5–3/elev 250–500 m	0.044	0.045	0.125	0.137	0.260	0.260
	(0.028)	(0.028)	(0.259)	(0.262)	(0.228)	(0.228)
Slope 3–6/elev 500–1000 m	−0.010	−0.010	−0.424	−0.461	−0.687*	−0.698*
	(0.026)	(0.026)	(0.542)	(0.555)	(0.371)	(0.368)
Slope 6–10/elev > 1000 m	−0.166*	−0.165*	0.552	0.593	0.417	0.438
	(0.088)	(0.089)	(0.530)	(0.551)	(0.394)	(0.388)
Shock * slope 0–1.5/elev 0–250 m		0.041		0.040		0.001
		(0.067)		(0.058)		(0.065)
Shock * slope 1.5–3/elev 250–500 m		−0.075		−0.152		−0.569
		(0.068)		(0.837)		(0.599)
Shock * slope 3–6/elev 500–1000 m		0.019		−0.231		1.650
		(0.055)		(1.820)		(1.166)
Shock * slope 6–10/elev > 1000 m		−0.171		−0.138		−1.541
		(0.094)		(1.694)		(1.363)
Controls	x	x	x	x	x	x
State-year fixed effects	x	x	x	x	x	x
Observations	3218	3218	3218	3218	3218	3218

Notes: Standard errors are reported in parentheses and are clustered by district. "Elev 0-250" is the percent of the upstream district with mean elevation between 0 and 250 m and is used as the independent variable for columns 1 and 2. "Slope 1–1.5" is, for columns 3 and 4, the percent of rivers in the upstream district with mean slope between 0 and 1.5. For columns 5 and 6, it is the percent of the upstream district with a slope between 0 and 1.5 and is used as the independent variable for columns 3–6. The rain shock variable is the fractional deviation of rainfall from its historical average. In specifications 1–4, "dam-fed" is a dummy that equals 1 if a district contained a dam at the beginning of the sample period. Because it does not vary over time, I include a vector of controls instead of district fixed effects. The controls included are 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. In specifications 5–6, I exclude the four years before and after a dam is built. These specifications include district fixed effects which absorbs the dam-fed dummy. All specifications include a state-year time trend. The dependent variable is a dummy variable indicating whether a district experienced a riot in a given year.
***, **, and * indicate significance at the 1%, 5%, and 10% levels respectively.

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