RAINFALL AND CONFLICT*

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ABSTRACT

Starting with Miguel, Satyanath, and Sergenti (2004), a large literature has used rainfall variation as an instrument to study the impacts of income shocks on civil war and conflict. These studies argue that in agriculturally-dependent regions, negative rain shocks lower income levels, which in turn incites violence. This identification strategy relies on the assumption that rainfall shocks affect conflict only through their impacts on income. I evaluate this exclusion restriction by identifying districts that are downstream from dams in India. In downstream districts, income is much less sensitive to rainfall fluctuations. However, rain shocks remain equally strong predictors of riot incidence in these districts. These results suggest that rainfall affects rioting through a channel other than income and cast doubt on the conclusion that income shocks incite riots.

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I Introduction

In a seminal paper, Miguel, Satyanath, and Sergenti (2004) provide evidence for a causal link between economic growth and civil war outbreak in Sub-Saharan Africa. Because the region is economically dependent on agriculture, the authors use rainfall as an instrumental variable for GDP growth, arguing that during periods of low rainfall, crops fail and income levels drop. 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. A negative shock induced by poor rainfall significantly increases the probability of civil war in the region.

Since Miguel et al.'s publication, rainfall has been widely adopted as an instrument for income levels. Researchers have used it to establish causality when looking at a host of political and economic outcomes. Bruckner and Ciccone (2011), for example, 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. Chaney (2010) combines rainfall and flood data to estimate the effect of economic shocks on political stability in Egypt and Bohlken and Sergenti (2010) replicate Miguel et al.'s study for India, using rainfall fluctuation to predict state-level GDP and its effect on rioting.

A critical assumption underlying this literature is that rainfall shocks affect civil conflict only through their impacts on income. In this paper, I use data on dam construction in India to evaluate whether rainfall satisfies the exclusion restriction. I identify districts that are downstream from dams and consequently receive water from dams during droughts. They are similarly somewhat protected against heavy rainfall as water is stored behind dam walls, thereby mitigating floods. Therefore, while wages in districts not downstream of dams, which I call rain-fed districts, are dependent on rainfall, wages in downstream, or dam-fed, districts are uncorrelated with the weather. There should then be no correlation between wages and rioting in downstream 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 income levels and increases the likelihood of conflict. In dam-fed districts, however, wages are much less sensitive to rain shocks. Yet despite having little influence on wages in these districts, rainfall still predicts riot incidence, suggesting that rainfall affects conflict through a channel other than income. This "placebo test" provides evidence against rainfall's validity as an instrument and casts doubt on whether income shocks have causal effects on conflict.

The remainder of the paper proceeds as follows. Section 2 describes the data used in the paper and provides an overview of dam construction in India. The estimation framework is outlined and the results are presented in section 3. Section 4 concludes.

II Data

The data used for the estimation is detailed in the appendix. However, several key points should be outlined.

First, I depart from Miguel et al.'s use of rainfall growth, calculated as $(\mathrm{R}_{i,t} - \mathrm{R}_{i,t-l})/\mathrm{R}_{i,t-1}$ where R denotes a yearly rainfall estimate. As Ciccone (2011) argues, rainfall growth could inadequately capture a rainfall's effect on crops and income. For example, a country with above-average rainfall in year t and average rainfall in year t+1 will, according to Miguel et al.'s definition, be identified as experiencing a negative rain shock when in fact rainfall levels are simply returning to the mean. Any observed relationship between income levels and conflict could therefore be wrongfully attributed to poor rainfall and crop yields. I instead use rainfall's fractional deviation from its average level. To calculate this variable, I sum over a district's monthly rainfall levels as well as its average monthly levels and find the yearly difference. For example, if a district's average rainfall level is 1075 mm, the rainfall shock in a year in which rainfall is 1000 mm would be -75 mm. This measure accounts for seasonality and sidesteps Ciccone's criticism of Miguel et al.'s definition.

Secondly, two concerns may arise when including dam information. The first is whether an entire district can be correctly categorized as either dam or rain-fed and the second is whether dam placement is correlated with income. I will first outline the nature of dam construction in India and then address these concerns.

India has rapidly increased its investment in dam construction, building more than 3000 dams between 1947 and 2001 (Pande, 2008). Over 95% of dams constructed since 1947 have been for irrigation purposes and dams remain India's primary form of irrigation infrastructure (World Commission, 2000b). These 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, known as command districts, through a series of spillways and canals (Biswas and Tortajada, 2001). Dam-fed districts therefore receive water during drought periods and are also somewhat protected against floods as the reservoir holds excess rainwater. The area immediately surrounding or directly upstream of the dam (rain-fed districts) receives no irrigation benefit (Thakkar, 2000). To identify downstream districts, I draw on Duflo and Pande's dataset (2007) of dam construction in India.

However, even if a district is labeled as being downstream, 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 income 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 concern that wealthier areas can build more dams. If this is the case, an estimation that includes dam variables may suffer from reverse causality. However, dam construction is the responsibility of the state and this paper exploits differences in dam construction across districts. As India has 28 states but 627 districts, focusing on inter-district variation should reduce any bias coming from state wealth and dam construction. Furthermore, the decision to construct a dam is not only dependent on the availability of state funds. An area viable for dam construction must contain a river of a certain length and gradient. For example, rivers flowing on a gradient of less than 1.5% or more than 6% are not suitable for dam construction. The national government of India, which approves all dam projects, also helps to fund projects in drought-prone areas when the state is suffering from a lack of funding (Duflo and Pande, 2007). Dam construction is therefore dependent on more than state wealth.

Table I displays descriptive statistics for the main variables of interest as well as various control variables that are used in the specifications in the appendix. The average district has approximately 0.2 riots per year, but this varies widely across district. Average annual rainfall is 1076 millimetres and the average wage is 4.78 rupees per hour.

III Estimation Framework and Results

I first exclude information on dams and replicate Miguel et al.'s two-stage least squares specification. Using rainfall shocks as an instrument for wages, I estimate equation (1) where $conflict_{i,t}$ is a dummy variable that equals one if district i experiences a riot in year t, $Y_{i,t}$ is the average agricultural wage in district i in year t, and θ_t and ν_i are time and district fixed effects.

$$conflict_{i,t} = \alpha + \beta_1(Y_{i,t}) + \theta_t + \nu_i + u_{i,t} \tag{1}$$

The result of this estimation is reported in column 1 of Table II and are similar to Miguel et al.'s earlier findings: an increase in wages lowers the probability of conflict when a rain shock is used as an instrument. Specifically, when controlling for district and year effects, an increase in the hourly wage lowers the probability that a district will experience a riot by nearly 25% per year. However, it is not clear that rainfall is working through wages to affect rioting. Splitting the sample into rain-fed and dam-fed districts now allows me to test whether rainfall satisfies the exclusion restriction.

As in Miguel et al.'s paper, I estimate three equations to capture the relationship between rainfall, income, and conflict. The following first-stage equation measures the relationship between rainfall and wages and is estimated using a simple ordinary least squares model:

$$Y_{i,t} = \alpha + b_1(rain_{i,t}) + \theta_t + \nu_i + u_{i,t} \tag{2}$$

All variables are defined as before and $rain_{i,t}$ is the fractional deviation of rainfall from district i's average rainfall in year t.

I estimate equation (2) first on the full sample and then separately for dam-fed and rain-fed districts. The results are reported in columns 2-4 of Table II. A negative rain shock appears to lower a district's average wage by 0.345 rupees per hour when the full sample is considered. However, splitting the sample by district type shows that rain shocks are no longer significant determinants of wages in dam-fed districts. Dams appear to mitigate extreme rainfall, thereby reducing the dependency of agriculture on rainfall. In rain-fed districts, however, a negative rain shock lowers the district wage by approximately 0.5 rupees per hour. With 5% confidence, a t-test shows that the wage differential between these two districts is significant.

The following reduced-form equation captures correlation between rainfall and rioting:

$$conflict_{i,t} = \alpha + \beta_1(rain_{i,t}) + \theta_t + \nu_i + u_{i,t} \tag{3}$$

Given the first stage results, any observable correlation (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 (2), equation (3) is also estimated on the full sample and then separately for rain-fed and dam-fed districts. The results, reported in columns 5-7 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 similar across regions, suggesting that rainfall has a significant effect on rioting even when the link between rainfall and wages is broken. A positive rain shock lowers the likelihood of rioting in a district by 7-8% per year.

The above results are summarized in Figure I. Panels (a) and (b) show the relationship between wages and rainfall for rain-fed and dam-fed districts respectively. The slope of the line in panel (b) becomes very flat, indicating a weak relationship between wages and rainfall in dam-fed districts. Panels (c) and (d), however, are nearly identical for both rain-fed and dam-fed districts, indicating that rainfall is a significant predictor of riot incidence regardless of how sensitive wages are to rainfall.

For robustness, I repeated the above analysis using different measures of conflict and replacing the fixed effects with controls. First, I used the number of riots in a district as my dependent variable in equation (3), estimating it with a negative binomial model. I then included a district-specific time trend in place of the district fixed effects. Finally, I replaced the fixed effects altogether with district-level controls that came from the Census of India. These included various demographic controls, such as the portion of the population that is male, Muslim, or under the age of 30, as well as the number of migrants, the literacy rate, and the total population. The results were largely unchanged. Wages in dam-fed districts remain uncorrelated with rainfall but a rain shock remains a significant predictor of riot incidence.

IV Conclusion

Miguel et al.'s well-known finding that negative income shocks drive conflict rests on the assumption that rainfall shocks affect conflict only through their effects on income. In this paper, I present evidence suggesting that this assumption does not hold. In districts downstream of dams, 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 nearly 8% per year.

The mechanisms through which rainfall affects riot incidence remains unclear. I attempted to test several possible avenues but the results were inconclusive. For example, rainfall could be affecting conflict by influencing migration patterns. Since 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, thereby instigating conflict over land. I tested for this by first including the percentage of migrants as a regressor in the reduced-form equation to see whether an influx of migrants increases the probability of conflict. Even when excluding the rain shock variable, the coefficient on migrant is near zero, though imprecisely estimated. I also regressed the rain shock variable against the proportion of migrants to see whether rain shocks influence migration at all. When considering only rain-fed districts, a negative rain shock does result in outmigration, although this effect becomes insignificant when I include both district and year fixed effects. When considering only dam-fed districts, rain shocks appear to have no effect on migration. This is surprising since one would expect negative rain shocks that push farmers in rain-fed districts to migrate would also be positively correlated with migration into dam-fed districts. This mixed evidence does not fully support the migration hypothesis, but it is something that could be further explored.

Heavy rainfall could also ruin infrastructure like roads, making it difficult for groups to organize and protest. Unfortunately, there is currently no data available to test this hypothesis. Finally, it is plausible that rain directly deters people from engaging in conflict. Several papers demonstrate that people are unlikely to organize themselves during extreme weather conditions. Shoag and Yanagizawa-Drott (2011), for example, show that individuals are unlikely to show up to tea party rallies 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 riots on housing prices in the U.S. Given the nature of the riot data, it is also difficult to discern whether rainfall actually prevents riots from starting, calms riots that have already started, or both.

Future research might further test various mechanisms through which rainfall affects conflict. The main contribution of this paper is the evidence it provides that rainfall does not satisfy the exclusion restriction.

References

1. Biswas, A. and C. Tortajada. 2001. "Development and Large Dams: A global perspective." International Journal of Water Resources Development: 9–21.

2. Blattman, Christopher and Edward Miguel. 2010. "Civil War." Journal of Economic Literature 48(1): 3-57.

3. Bohlken, Anjali and Thomas Sergenti. 2010. "Economic Growth and Ethnic Violence: An Empirical Investigation of Hindu-Muslim Riots in India." Journal of Peace Research 47(5): 589-600.

4. Brückner and Ciccone. 2010. "Rain and the Democratic Window of Opportunity." Econometrica 79(3): 923-947.

5. Chaney, Eric. 2010. "Revolt on the Nile: Economic Shocks, Religion, and Institutional Change." Harvard Working Paper.

6. Ciccone, Antonio. 2011. "Economic Shocks and Civil Conflict: A Comment." Forthcoming in AEJ: Applied Economics.

7. Collins, William and Robert Margo. 2007. "The Economic Aftermath of the 1960s Riots in American Cities: Evidence from Property Values." The Journal of Economic History 67: 849-883.

8. Duflo, Esther and Rohini Pande. 2007. "Dams." The Quarterly Journal of Economics 122 (2): 601-646.

9. Fearon, James D. and David D. Laitin. 2003. "Ethnicity, Insurgency, and Civil War." American Political Science Review 97 (March): 75-90.

10. Foster, Andrew D., and Mark R. Rosenzweig. 2003. "Agricultural Productivity Growth, Rural Economic Diversity, and Economic Reforms: India, 1970–2000." Manuscript, Harvard University.

11. Jayachandaran, Seema. 2006. "Selling Labor Low: Wage Responses to Productivity Shocks in Developing Countries." Journal of Political Economy 114 (3): 538-575.

12. Mehlum, Halvor, Edward Miguel, and Ragnar Torvik. 2006. "Poverty and Crime in 19th Century Germany." Journal of Urban Economics 59(3): 370-388.

13. Miguel, Edward, Shanker Satyanath, and Ernest Sergenti. 2004. "Economic Shocks and Civil Conflict: An Instrumental Variables Approach." Journal of Political Economy 112 (4): 725-53.

14. Nashik District, Government of India. District Map of India. http://nashik.gov.in/

15. Pande, Rohini. 2008. "Large Dams in India." The Oxford Companion to Economics in India. Edited by Kaushik Basu, Oxford University Press.

16. Shoag, Daniel and David Yanagizawa-Drott. 2011. "Do Political Protests Work? Evidence from the Tea Party Movement." Harvard Kennedy School Working Paper.

17. Thakkar, H. 2000. Assessment of Irrigation in India. World Commission of Dams.

18. Varshney, Ashutosh and Steven Wilkinson. 2004. Dataset on Hindu-Muslim Violence in India. October 8.

19. Wilkinson, Steven I. 2004. Electoral Competition and Ethnic Riots in India. New York:Cambridge University Press.

20. World Commission on Dams. 2000b. "Large Dams: India's Experience." World Commission on Dams Report.

Data Appendix

I draw on five data sources to conduct my analysis. All of the data, with exception to the rainfall data, are in panel form where an observation is a district-by-year.

Hindu-Muslim Riots

Riot data is drawn from the Varshney-Wilkinson Dataset on Hindu-Muslim Riots in India (2006). The dataset lists all riots reported in The Times of India, a national Indian newspaper, between 1955 and 1995. All riotslisted in the dataset are reported as being between Hindu and Muslim groups. The dataset gives the district name and date at which each riot occurred as well as the number of people killed, injured, and arrested at each riot

The dataset is the best available for religious violence but has obvious 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. Riots are particularly underreported for the 1950s and early 1960s due to difficulty in accessing newspaper records. 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 these issues, I restrict my analysis to the years after 1970 so as to avoid studying the years during which the riot count is substantially underestimated. I also 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, Bohlken and Sergenti). It should be noted that the overall riot counts presented in this paper are likely to be underestimates.

Rainfall

The University of Delaware's Center for Climatic Research provides monthly rainfall estimates at 0.5 degree longitude and latitude nodes across the world, starting in 1945. I use this data, along with information from the World Bank's India Agricultural Database (IAD) to derive monthly rainfall estimates for each Indian district. The World Bank IAD provides the longitude and latitude points of weather stations within each district. I match these points to the rainfall data using an interpolation algorithm provided by Seema Jayachandaran.

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 thesame amount of rainfall, a reasonable assumption given the relatively small size of Indian districts.

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 data on agricultural wages, drawn from Robert Evenson and James McKinsey's India Agriculture and Climate dataset, to measure income growth. While the agricultural wage does not capture the wages of those employed outside of the agricultural sector, it is the best available data at the district level. Data on average expenditure levels is available at five-year periods, and I find that for these years, the agricultural wage is strongly correlated with expenditure levels. Furthermore, since nearly 75% of the Indian population lives in rural areas, the agricultural wage should provide an adequate measure of general income levels (Jayachandaran, 2006). It is also the measure of income that is most closely tied to rainfall.

Evenson and McKinsey's dataset covers 271 Indian districts from 1950 through 1997. They use data from the Indian Ministry of Agriculture's Directorate of Economics and Statistics, which gathers information on various wages and incomes by district, to construct the wage variable. Measured in rupees per hour, it is a weighted average of wages for various agricultural occupations. It accounts, for example, for agricultural labour wages as well as market yield prices. It also weights wages by month to account for the fact that farmers' incomes will be higher in the months immediately following harvest.

Dams

To identify rain-fed and dam-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 within a district in a year as well as the number of dams constructed upstream of a district in a year. From this, I create a dummy variable labeled downstream that equals 1 if a district is located downstream from a dam.

Approximately 62% of districts are in dam-fed and nearly 60% contain a dam themselves. 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.

Table I
Descriptive Statistics

	Mean	Standard Deviation	Observations	Data Source
Number of Riots	0.19	0.85	2925	Varshney-Wilkinson
Annual Rainfall (mm)	1076	507	2925	University of Delaware
Wage	4.78	1.99	2908	Evenson/McKinsey
Dam-fed	0.64	0.48	2925	Duflo/Pande
Control Variables				Census (1971, 81, 91)
Total Population	2,499,853	1,397,569	2828	
Percent of Population:				
Young Male	30.92	1.73	2828	
Literate	35.08	11.56	2828	
Literate Male	23.66	5.89	2828	
Rural	76.64	13.94	2828	
Muslim	11.74	9.63	2698	
Migrants	30.20	6.09	2828	

Notes: There are 142 districts in the dataset, covering the years 1971-1991. Dam-fed is the portion of districts that are downstream from a dam. The wage is the average agricultural wage in a district and is measured in rupees per hour. All control variabes are from the Census of India which is conducted every 10 years. Because of this, I interpolate between years. Young males are those males less than 40 years of age. Migrants include migrants from other states and countries. Literate is the district's literacy rate, defined as the number of individuals who can read and write in any language.

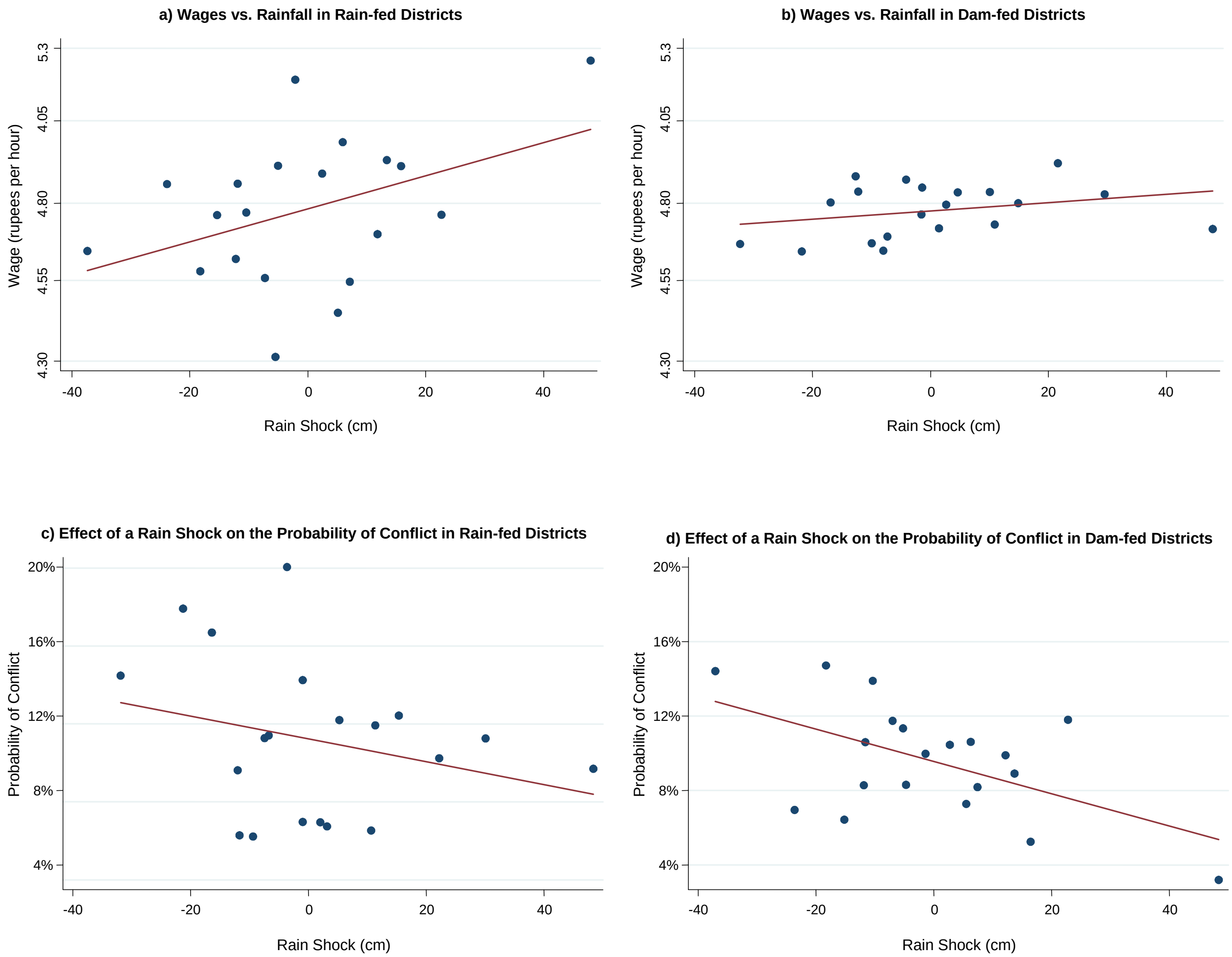
Table 2
IV, First Stage, and Reduced Form Results

	IV	First Stage (OLS)			Reduced Form (OLS)		
Dep. Variable:	Conflict	Agricultural Wage			Conflict		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Rain Shock		0.345*** (0.093)	0.057 (0.120)	0.501*** (0.180)	-0.076*** (0.025)	-0.070** (0.034)	-0.078** (0.037)
Agricultural Wage	-0.243** (0.111)						
District & Year Fixed Effects	x	x	x	x	x	x	x
Sample	full	full	dam-fed	rain-fed	full	dam-fed	rain-fed
Number of Districts	142	142	92	56	142	92	56
Number of Obs.	2908	2908	1854	1054	2908	1854	1054

Notes: Standard errors are reported in parentheses and are clustered by district. All specifications include district and year fixed effects. Column 1 replicates Miguel et al.'s IV specification. This specification is estimated on the full sample and no dam information is included. The exogenous regressor is the rain shock, which is the yearly fractional deviation of rainfall from its district average . The independent variable in specifications 2-7 is the rain shock. The dependent variable in column 1 and columns 5-7 is a dummy variable for whether a district experiences a riot in year t. The dependent variable in columns 2-4 is a district's average agricultural wage in year t. For details on how this variable is measured, refer to the Data Appendix. Specification 1 is estimated using two-stage least squares, 2-4 are estimated using OLS, and 5-7 are estimated using a negative binomial model.

FIGURE 1

Effect of Rain Shocks on Wages and Riots in Dam-fed and Rain-fed Districts



NOTE– Panels (a) and (b) show the effect of a rain shock on wages in rain-fed and dam-fed districts respectively. Panels (c) and (d) show the effect of a rain shock on the probability that a riot will occur in a district in a given year. A rain shock is defined as the yearly fractional deviation of rainfall from its district average. A dam-fed district is one that is downstream from a dam whereas a rain-fed district is not. To construct each plot, I regress both the y- and x-axis variable on the district and year fixed effect dummies to calculate residuals. I then group the observations into twenty equal-sized (5 percentile-point) bins based on the x-axis residual and plot the average value of both the y- and x-axis residuals within each bin, adding back the sample means of each variable for ease of interpretation. The solid line shows the best linear fit estimated on the underlying data using OLS. The coefficients and standard errors corresponding to each panel are presented in columns (3)-(4) and (6)-(7) of Table II. Standard errors are clustered at the district level.