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Conflict in Ethiopia: The Impact of Precipitation and Its Transmission Mechanism

Negar Habibi[1]

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Abstract:

In this paper we examine the impact of precipitation variations on the probability of conflict in Ethiopia using subnational data at 0.5×0.5 decimal degrees resolution for the period 1997 to 2013. We find that lower precipitation levels, after accounting for the long-term average, are associated with higher probability of conflict. Our results are robust to alternative model specifications. The impact of precipitation on conflict remains significant for intra-state conflict but loses significance for non-state conflict. Moreover, using a two-stage estimation method we find evidence for the hypothesis that precipitation affects conflict through affecting total production levels.

Keywords: conflict, precipitation, climate, Ethiopia.

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[1] King's College London

1. Introduction:

Despite being among the fastest growing economies in Africa, Ethiopia has periodically experienced conflict over the past decade. The most recent chain of protests triggered by government's plan for extending Addis Ababa's administration into Oromia resulted in announcement of a six months state of emergency on 8th October 2016. Recent unrests have involved attacks against foreign firms and disruption of movement of goods to cities by farmers. Therefore, it seems that a combination of political and economic factors have contributed to the outbreak of recent protests.

Political power in Ethiopia has been in the hands of the Ethiopian People's Revolutionary Democratic Front (EPRDF) for more than two decades. The government has been successfully following a public sector investment-based development plan since the EPRDF seized power in 1991. However, GDP per capita levels remain low and political exclusion of opposition parties has been a source of concern in Ethiopia. The EPRDF and its allies have repeatedly obtained a majority at the parliament over the past parliamentary elections. However, lack of transparency has resulted in major disputes over the election results. Unrests following the 2005 elections resulted in the death of nearly 200 protestors. The 2010 elections in which EPRDF won more than 90% of the seats was criticized by the US and EU observers as falling short of international standards.

Ethiopian government's economic development strategy has largely relied on public sector investment. A major goal of the development plan has been to increase the share of industry versus agriculture in the country's GDP. Although high growth levels have been achieved following the government's development strategy, the economy remained largely reliant on agriculture, and for most of the past decade the share of industry has been lagging behind the targets. Agriculture constitutes 40% of the GDP and an estimated 75% of jobs in Ethiopia are in the agriculture sector.

As an agrarian economy Ethiopia remains highly vulnerable to severe climate conditions. Climate conditions over the past decade have not been favorable and Ethiopia has periodically experienced drought and famine. The Famine Early Warning Systems Network (FEWS NET 2011) estimates a 15-20 percent decline in spring and summer rains in parts of Ethiopia since the mid-1970s. Increasing temperature at the same time has exacerbated the dryness.

2. The link between climate variations and conflict:

Security implications of climate change have been a source of concern amongst policy makers and researchers over the recent years. While there is no consensus yet amongst the policy makers on whether human conflict is affected by climate change, the idea has attracted more support over time. In the academic realm there are competing claims on whether prolonged heat and low rainfall affect the risk of conflict. Availability of geo-data at high resolution on conflict, climatic variables and some socioeconomic factors has enabled rigorous quantitative research on the subject. However, methodological differences and focus on different types of conflict have resulted in contrasting claims on the role of climate change in incidence of conflict. While some studies find a strong causal impact from climate change on conflict others explain number or onset of conflict with mere socioeconomic factors such as income and ethnic diversity.

Hsiang et al. (2013) find that a one standard deviation increase in temperature results in a four percent increase in interpersonal violence and a 14 percent increase in the frequency of intergroup violence. Hendrix et al. (2012) find a significant impact from variations in climate indicators on both low-scale and high-scale conflict in a sample of African countries. Miguel et al. (2004) use rainfall variations as a proxy for economic conditions and find a significant negative relationship between rainfall and conflict in a sample of 41 African countries. Burke et al (2009) estimates a 54% rise in armed conflict incidence by 2030 based on historical linkage between temperature and conflict and using climate model projections.

Buhaug (2010), on the other hand, finds no impact of climate variables on conflict in Africa using various model specifications. O'Loughlin et al. (2012) examine the impact of climatic factors on conflict in East Africa while controlling for country and time fixed effects. They discover little evidence for climate change driven conflict in the region, finding a small but significant positive impact of warmer than normal temperatures and a small negative impact of higher than normal precipitation on conflict.

One source of contradiction in the results is that some socioeconomic factors such as income are themselves affected by climate change. Therefore, having them as control variables in the model might absorb the impact of the climate variable and result in underestimation of the statistical significance or size of the related coefficients (Hsiang et al. 2013). Once attention is restricted to studies that account for the impact of unobserved geographical characteristics (country or subnational geographic unit fixed effect) and occasional shocks (time specific dummy variables) there is more convergence in the results. Hsiang et al. (2013) conduct a meta-analysis on 60 such quantitative studies on the impact of climate change on conflict in various fields from Economics to psychology and show that there is more agreement in the literature on the significant influence of climate variables on conflict than previously thought.

An important follow up question on this subject is the mechanisms through which climate variations affect conflict. It is impossible to design appropriate policy responses to the negative consequences of climate change for human conflict without identifying these mechanisms. Attempts to answer this question have usually used an instrumental variable approach. Intuitively, the estimation method tests whether climatic variables of the model such as precipitation and temperature affect conflict through affecting a third variable.

It is more feasible to pin down the mechanisms through which climate change affects conflict at the subnational level where the units of analysis are more homogeneous. In a case study on Somalia Maystadt and Ecker (2014) test whether climate variables affect conflict through affecting livestock prices. In the first stage of the estimation they test whether precipitation and temperature are good predictors of livestock prices. In the second stage they use the predicted livestock prices of the first stage to estimate conflict. They find livestock prices to be a credible channel for the impact of climate variations on conflict in Somalia.

While most of the studies on the link between climate variables and conflict have been done at the cross-national level, there is a deficit of case studies at the subnational level on the subject. We try to fill in this gap by focusing on subnational data on Ethiopia between 1997 and 2013. We aim to test whether precipitation variations have an impact on the probability of conflict in Ethiopia.

We further examine whether the impact of precipitation variations on conflict is mediated through the impact of precipitation on total production levels. We can also interpret the analysis provided here as a test of whether total production affects probability of conflict using precipitation as an instrument. Use of precipitation as an instrument will resolve the endogeneity problem that exists in the study of the impact of economic factors on conflict as this relationship works both ways i.e. conflict affects economic factors (Shortland et al 2013) and economic factors affect probability of conflict.

The indicator of economic factors in our model is a variable measuring the dollar value of *total production* in the geographic units of this study. This variable can be seen as an approximation for the level of *agricultural production*, which is a major determinant of food security in Ethiopia (Barrios et al 2008). This is a reasonable approximation since a large part of production in Ethiopia either directly or indirectly comes from agriculture (World Bank 2006). The results of this hypothesis test can provide some insight on whether changes in precipitation affect conflict through affecting agricultural production.

3. Data and variables of interest:

3.1. PRIO-GRID:

Subnational study of conflict is less likely to suffer from the risks associated with unobserved heterogeneity among the units of analysis, as many unobserved factors such as culture and the quality of the political system are constant within a country. However, one of the challenges of such analysis is lack of data at the subnational level. PRIO-GRID collects and provides spatially disaggregated data on climate and socioeconomic variables at 0.5×0.5 decimal degrees resolution i.e. for cells of 55×55 kilometers at the equator (3025 square kilometers area). Ethiopia occupies approximately 1.1 square kilometers of land that corresponds to 372 cells with the mentioned resolution level (Tollefsen et al 2012).

The main variable of interest for the purpose of this study is precipitation variations. We use precipitation data provided by Global Precipitation Climatology Centre. The data provides information on the yearly total amount of precipitation (in millimeters) in each cell (Schneider et al 2015).

Moreover, we control for a number of variables that are likely to correlate with both precipitation and conflict. We control for population density, which is a common control in the literature, as where there is no people there is no conflict. Data on population measures population size in a cell, taken from the Gridded Population of the World (Center for International Earth Science Information Network and Centro Internacional de Agricultura Tropical 2005). Population estimates have been obtained every five years since 1995. We have used linear interpolation to obtain population levels in the middle years. To calculate population density we divide total population of each cell by its land area. The data on land area measures the total area in a cell covered by land and is taken from Weidmann et al (2010). Moreover, we control for the interaction of the percentage of agricultural land in a cell and the cell's precipitation levels to assess whether having access to more agricultural land can reduce adverse impact of lack of rainfall on conflict. The variable measuring the percentage of agricultural land is based on ISAM-HYDE land use data (Meiyappan et al 2012). The other interaction variable included in the model aims to assess whether higher irrigation alleviates the impact of precipitation on conflict in Ethiopia. Irrigation data measures the area of a cell equipped for irrigation. The data is taken from the Historical Irrigation dataset v.1, which indicates pixelated data on areas equipped for irrigation across time (Siebert et al 2015). This data is only available for the years 1950, 1960, 1970, 1980, 1985, 1990, 1995, 2000, and 2005. Therefore, we rely on linear interpolation and extrapolation to obtain figures for the missing years.

In section 5.2 we test whether variations in precipitation affect conflict through affecting total production of a cell. The data on production levels indicates the gross cell product, measured in billion USD using purchasing-power-parity, based on the G-Econ dataset (Nordhaus 2006).[2] G-Econ dataset on total production value suffers from serious inconsistencies for some countries. However, their data quality on Ethiopia is coded as one, which indicates that the economic data on Ethiopia in G-Econ data is consistent. It should be noted that, G-Econ quality information does not capture the quality of the underlying country statistics. Total production measures have been obtained in 5-year intervals between 1990 and 2005. We assumed a linear trend in production levels and used linear interpolation and extrapolation to obtain production levels in the missing years.

3.2. Armed Conflict Location and Event Dataset:

We spatially join the PRIO-GRID data on climate and socio-economic factors with the ACLED-PRIO geo-coded data on conflict incidence (Raleigh et al 2010). The Armed Conflict Location and Event Dataset (ACLED) compiles real time data on conflict incidence based on news reports of various sources. The dataset contains information on the location, date, number of fatalities reported, actors involved in conflict and the type of their interaction. The location information provided in ACLED-PRIO shapefiles is reported based on grid cell identifiers that correspond to the grid cell identifiers used for PRIO-GRID data on precipitation, and the control variables in the model. We merged the

[2] http://gecon.yale.edu

two datasets based on the grid cell identifiers. Therefore, our analysis here is at the cell level.[3]

A total number of 1927 conflict incidences have been recorded by ACLED-PRIO in Ethiopia between 1997 and 2013. These conflict incidences vary from local tensions with no fatalities to major violent clashes between armed groups or between the Ethiopian military forces and protestors.

The quality of governance of adverse climate variations has an important role in whether they lead to higher probability of conflict or not (Theisen et al. 2013). In many of the agrarian economies of Africa such as Ethiopia, rainfall variations have an important impact on the country's production (Miguel 2004). Lack of resources resulted from lower precipitation might result in protests against the government. One the other hand it might also result in formation of groups fighting amongst themselves (Buhaug et al 2010). To assess what type of conflict results from lack of precipitation in Ethiopia, we distinguish between two types of conflict namely intra-state and non-state conflict defined as below:

Intra-State: An event is classified as intra-state, if one of the actors is the Ethiopian government, military or police forces of Ethiopia and the other actor is internal.
Non-State: An event is classified as non-state if the government has not been involved in it.

The above definitions also correspond to the definitions used by Uppsala Conflict Data program.

Intra-state conflict has been the most common type of conflict during 1997-2013 in Ethiopia with 530 such events taking place across all geographic units of our study. A large proportion of intra-state conflict events over this period have been Ethiopian government's response to protests and riots. The other important component of this conflict type is clashes between the Ethiopian government and the Ogaden national liberation front, in Ogaden region, and clashes with the Oromo national liberation front in the Oromia region.

Non-state conflict is the second most common conflict type in our sample with 228 cells experiencing such incidence between 1997 and 2013. This type of conflict mainly consists of clashes between local militia groups such as Borena and Garre ethnic militias in Oromia and Tigray and Oromo ethnic militias.

Ethiopia has frequently experienced tensions with its neighboring countries particularly Eritrea and Somalia. However, for the period of this study (1997-2013) interstate tensions have not been very prevalent in Ethiopia. ACLED has recorded 21 inter-state conflicts

[3] We use version 5 of the ACLED dataset here that has been last updated in 2014. Therefore, any possible changes to the administrative boundaries over the period before 2014 have been counted for in our data.

over this period. These include Ethiopia-Eritrea war in 1999 and continued tensions in the border with Eritrea over the following years. Figure 2 provides a map of Ethiopia showing the geographic distribution of all the conflict incidences over 1997-2013. Trends in intra-state and non-state conflicts in 1997-2013 are illustrated in Figure 3.

Figure 2: Geographic Distribution of Conflict Incidences in Ethiopia 1997-2013:

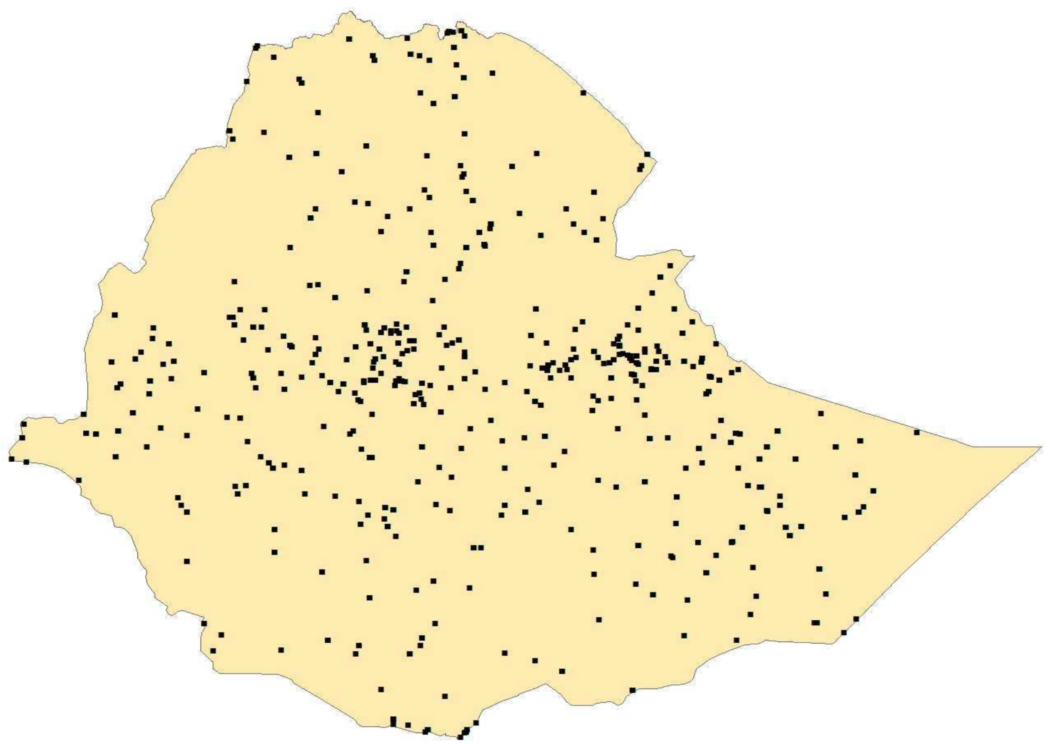
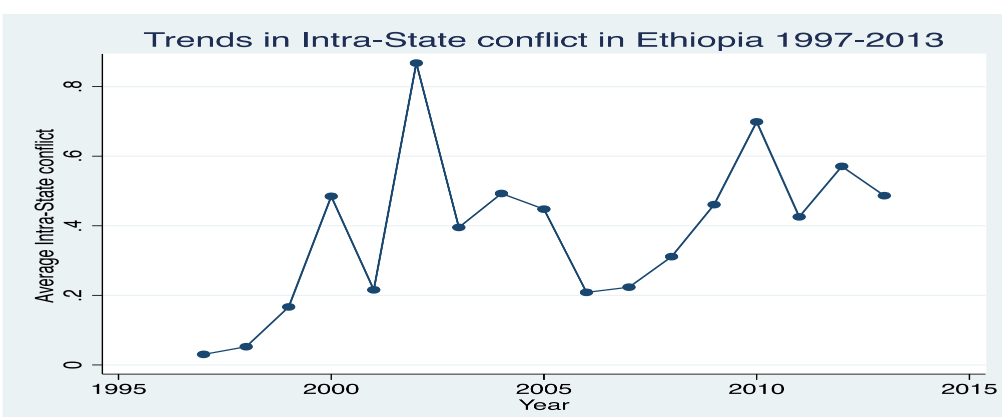
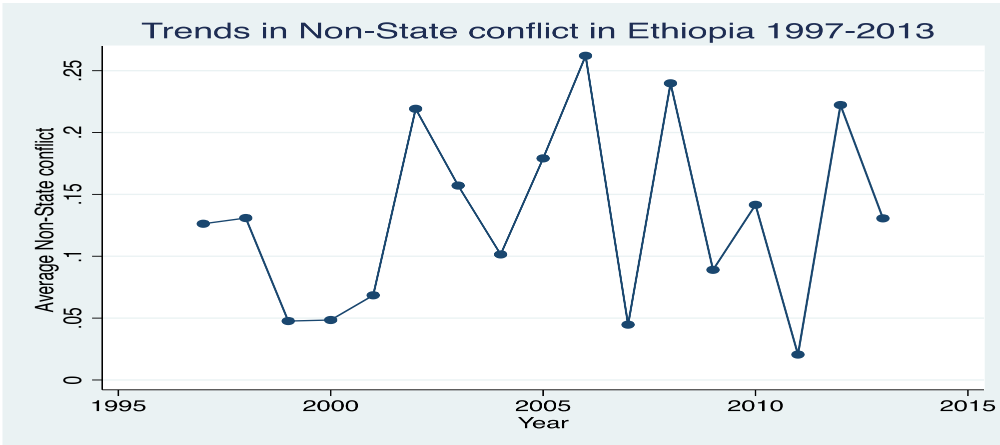


Figure 3





3.3. Descriptive statistics of the data:

The time span of our study is 1997 to 2013, which is the longest period for which data on conflict is available. The time unit of analysis is years. Therefore, the final dataset is a panel of yearly information on conflict, precipitation and control variables at the cell level. Descriptive statistics of the variables in presented in table 1:

Table 1: Descriptive Statistics of the variables:

Variable	Observations	Mean	Std. Dev.	Min	Max
%Agricultural Land	6324	12.05	12.725	0	79.584
Population	6324	191774.50	252238.4	1942.008	2713806
Production	6324	0.124	0.168	0.0007176	1.263
Conflict Count	6324	0.294	1.525	0	32
Precipitation	6324	220.39	117.948	7.947	572.932

4. Case Control Sampling:

Considering the very high resolution of our data (55km×55km cells) it is likely that no conflict is reported for the whole period of the study in a large proportion of the cells. In fact, conflict incidence has only been reported in around 10% of the cells in our sample. Therefore, we face the problem of "rare events" and "excess number of zeros" (non-onset cells) in our sample. Estimation of rare events such as conflict with usual binary response methods such as logit can be problematic as these methods are likely to underestimate the probability of rare events. A more efficient sampling design that enables valid inferences in such cases is sampling of all available events and a fraction of nonevents (King and Zeng 2001). This sampling strategy is widely used in medicine to study determinants of rare events such as being diagnosed with cancer where the diseased individuals (cases) are rare compared to a sample of non-diseased individuals from the population (controls).

The other problem that might arise in using high-resolution geo-coded data on conflict is the possibility of spatial correlation of observations in nearby cells. In a study of the impact of income on conflict, Buhaug et al. (2011) use a case control logit method to resolve both of these problems. The method compares the conflict onset cells with a sub-sample of non-onset cells. Spatial correlation decays as the distance between two cells increases.[4] While the non-onset zeros are chosen randomly from all cells it is unlikely that neighboring or close by cells appear in the case control sample. Therefore, the case control sample is less likely to exhibit spatial correlation. However, this claim can be challenged as the case control sample contains all the onset cells. Therefore, it is equally likely to have neighboring or close by onset cells in the original data and the case control sample.

It is recommended in case control analysis that the ratio of controls to cases in the final sample is 4:1. Following this approach and considering the distribution of onset and non-onset cells in our original sample, our case control samples will consist of approximately 52% of the observations in the original sample.[5] The large size of the case control samples relative to the original sample has the advantage of providing more consistent estimates in repeated sampling. On the downside, while more than half of the original cells are sampled it is unlikely that the problem of spatial correlation is resolved. However, the case control method resolves the rare event problem and therefore, we continue our analysis on case control samples.

We ran all the regression analysis on 100 random samples of the original dataset containing all the cells where at least one conflict event has been observed over this period and a random subsample of 47% of the cells where no conflict has been observed over the whole period of the study. The reported results indicate average coefficients and average standard deviations of estimations on the 100 random samples.

5. Hypotheses Tests:

5.1. Impact of precipitation on conflict onset:

In this section we test whether precipitation variations have an impact on probability of conflict. It is common practice in the literature to use a fixed effect specification and include year dummies in the model to account for the impact of unobserved and periodic factors. We follow the same approach. Our precipitation variable in the fixed effect estimation measures the "within variation" in precipitation i.e. it measures the difference between precipitation in each year in a cell and average precipitation in that cell over the

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[4] Buhaug et al. (2011) show that in their data the correlation reaches zero for cells that are 1000km or more apart

[5] Using this sampling strategy will affect the estimates for intercept. Intercept estimates must be adjusted for the relative share of 1s and zeros using: $\beta_0 = \hat{\beta}_0 - ln\left[\left(\frac{1-\gamma}{\gamma}\right)\left(\frac{\bar{y}}{1-\bar{y}}\right)\right]$ where γ is the proportion of 1s in the population and $\bar{y}$ is the proportion of 1s in the estimation sample.

1997-2013 period. Here we use a logistic functional form. The fixed effect model specification is as below:

$$Conflict\ Onset_{it} = G\ (\beta_1 Precipitaion_{it-1} + \beta_k X + \mu_i + \tau_t + \epsilon_{it})$$

Where G is the logistic function:

$$G(z) = \exp\,(z)/1 + \exp\,(z)$$

And X is the vector of control variables. For the purpose of identification all of our explanatory variables are measured at $t - 1$. Therefore, changes in precipitation and other explanatory variables precede conflict onset in each cell by one year. We focus on the impact of a one year lag of precipitation on conflict as adaptation and outside intervention are less likely to take place in the short term and short-term variations in precipitation are more relevant for the study of the impact of precipitation on conflict (Theisen et al. 2013).

5.1.1 Results and Discussion:

Estimation results are presented in Table 2 and 3. Model 1 in table 2 provides the results of the fixed effect estimation method on the impact of precipitation on conflict. The random and pooled estimations include a constant (not reported in the table). The coefficient estimates and standard errors reported in the tables are the average of the coefficient and standard error estimates of 100 random samples obtained by using all the cells that experienced conflict at least once between 1997 to 2013 and a random sub-sample of cells where no conflict has taken place over this period as explained in section 4. To assess whether a coefficient is statistically significant or not we look at the average z-scores of each of the coefficients over the 100 samples.

As table 2 shows we find a negative and statistically significant effect from annual precipitation on conflict in model 1 where a fixed effect specification is used. The precipitation coefficient is robust to inclusion of the control variables and stays significant in model 2. The results of random effect and pooled cross section estimations reported in models 3 to 6 provide a check on robustness of our results to model specifications excluding a cell fixed effect. As the fixed effect estimation removes the impact of unobserved time invariant cell characteristics we carry out the rest of this analysis using only fixed effect estimation method.

We run the model for the two types of conflict defined in section 3.2 i.e. intrastate and non-state conflict types (table 3). The results for intrastate conflict (model 8) are very similar to model 2. However, the impact of precipitation on non-state conflict is not statistically significant. As described in section 3.2 non-state conflict type mainly consists of clashes between ethnic militia groups motivated by ethnic problems. Therefore, this result is not surprising.

The Irrig_Prec variable aims to test whether the impact of precipitation on conflict is different in cells with higher than median irrigation or not. The negative sign of Irrig_Prec indicates that the impact of precipitation on conflict is lower in cells with higher than median irrigation. Although this variable is significant in the random and pooled estimations in models 4 and 6, it is not statistically significant in the fixed effect estimation in model 2. At the same time cells with higher than median irrigation levels are more likely to experience conflict compared to other cells. This might be an indication that cells with higher than median access to irrigation equipment are located in more developed areas and are targeted more often in conflict incidents. Again the impact is significant in the pooled and random effect models but not in the fixed effect model.

The Agr_Prec variable measures whether the impact of precipitation on conflict in cells with higher than median share of agricultural land is different from other cells. The coefficient on this variable is very small in magnitude and is not significant for none of the estimation methods. The High Agricultural Land variable is a dummy taking the value of one if the share of agricultural land in a cell is higher than median and zero otherwise. This variable is also never significant. Therefore, we do not find any evidence for an impact from having access to more land for agriculture on the probability of conflict.

As expected more populated areas are more likely to experience conflict and the population variable is significant in all model specifications and for both conflict types.

Table 2:

	Model 1	Model2	Model3	Model4	Model5	Model6
	Fixed Effect	Fixed Effect	Pooled*	Pooled*	Random* Effect	Random Effect*
Conflict Onset						
Precipitation	-0.001** (0.0004)	-0.002*** (0.001)	-0.001*** (0.0003)	-0.002*** (0.0006)	-0.001*** (0.0004)	-0.002*** (0.0008)
High Irrigation		0.47 (0.325)		0.567** (0.241)		0.555* (0.317)
Irrig_Prec		-0.002 (0.001)		-0.002** (0.001)		-0.002* (0.001)
High Agriculture Land		0.021 (0.318)		0.05 (0.227)		0.033 (0.3)
Agr_Prec		0.00002 (0.001)		-0.00006 (0.001)		-0.00004 (0.001)
Population density		0.005*** (0.001)		0.005*** (0.0006)		0.006*** (0.001)
N	3327	3327	3327	3327	3327	3327

Regression estimates with time fixed effect included; SEs are in parentheses. ***P < 0.01 , **P < 0.05, *P < 0.1.
*cell clustered SE used.

Table 3: Conflict Types:

	Model7	Model8
	Non_State	Intra-State
Precipitation	-0.002	-0.002**
	(0.001)	(0.001)
High Irrigation	0.336	0.346
	(0.46)	(0.348)
Irrig_Prec	-0.001	-.001
	(0.001)	.001
High Agricultural Land	-0.018	0.083
	(0.457)	(0.341)
Agr_Prec	0.0006	0.0001
	(0.001)	(0.0013)
Population Density	0.002***	0.004***
	(0.001)	(0.001)
N	3327	3327

5.2. Mechanism through which precipitation affects conflict:

In this section we test whether precipitation affects conflict through affecting total production levels. Our attempt is to disentangle the relationship observed between precipitation and conflict in the "reduced form equation" of section 5.1. To test whether the impact of precipitation on conflict is channeled through affecting production levels we use a two-stage estimation method. The reduced form equation estimated in section 5.1 was:

$$Conflict\ Onset_{it} = G\ (\beta_1 Precipitaion_{it-1} + \beta_k X + \mu_i + \tau_t + \epsilon_{it})$$

We begin the two stage estimation by testing whether precipitation and cell production are partially correlated i.e. whether precipitation has a significant impact on cell production levels once we control for all the control variables. In the first stage we regress cell production on precipitation and other control variables and obtain the "predicted production" levels. The equation estimated here is:

$$log\_Production_{it-1} = \alpha_0 + \alpha_1 Precipitaion_{it-1} + \alpha_k X + \mu_{i1} + \tau_{t1} + \epsilon_{it}$$

In stage two, we use the predicted production values obtained from stage one as an explanatory variable to regress conflict onset, while controlling for the vector of control variables *X*. The second stage equation is:

$$Conflict\ Onset_{it} = G\ (\gamma_1 \widehat{log\_Production}_{it-1} + \gamma_k X + \mu_{i2} + \tau_{t2} + \varepsilon_{it})$$

A significant coefficient estimate for predicted production level (γ_1) in stage two would suggest that precipitation affects conflict through affecting total cell production levels.

5.2.1. Results and Discussion:

The results of the two-stage estimation method are presented in table 4. As in previous sections, the coefficients and standard errors reported in table 4 are averages of estimates of 100 random samples of our data.

The first stage results in table 4 show that partial correlation exists, as the coefficient on precipitation is statistically significant. The precipitation coefficient is also positive as expected. Therefore, based on the first stage results higher precipitation is associated with higher production in the cells. Manual implementation of a two-stage estimation has the problem of generating wrong standard errors in the second stage. However, the sampling structure of our analysis resolves this problem as it runs the analysis on 100 random samples.

First stage results also provide some information on associations between other variables of the model. Production levels are higher in cells where irrigation levels are higher than the median irrigation in the whole sample. The same applies to cells where the share of the agricultural land is higher than median. Interaction variables appear with the expected signs i.e. the impact of precipitation on production is lower in cells with higher than median irrigation levels and higher in cells with higher than median share of agricultural land. However, these coefficients are not statistically significant. Moreover, production levels are higher in cells with higher population density.

In the second stage of the estimation we use predicted values of the first stage dependent variable i.e. total production as a regressor. Based on the second stage results production levels as predicted by precipitation and other variables of the model have a negative and significant impact on conflict. Therefore, cells with higher production levels are less likely to experience conflict. The combination of the first and second stage estimations supports the hypothesis that precipitation affects probability of conflict through affecting production levels.

Table 4: Two-Stage Estimation

	First Stage	Second Stage
	Production	Conflict
Precipitation	0.001***	
	(0.0002)	
Production		-1.564***
		(0.541)
High Irrigation	0.287***	0.918***
	(0.087)	(0.33)
Irrig_Prec	-0.0001	-0.002
	(0.0003)	(0.001)
High Agricultural Land	0.897***	1.422***
	(0.08)	(0.341)
Agr_Prec	0.0002	0.0003
	(0.0003)	(0.001)
Population Density	0.007***	0.017***
	(0.004)	(0.001)
N	3327	3327

6. Conclusions:

We look at the impact of precipitation on conflict in Ethiopia in 1997-2013. We use high-resolution subnational data on precipitation and conflict. Therefore, a large proportion of the geographic units in our sample have never experienced conflict and very often our binary dependent variable takes the value of zero. To overcome this problem we use case control sampling method and run our estimations on 100 random samples of our original dataset.

Our results show that over this period places with lower precipitation have been more likely to experience conflict. Although the impact is not very large in magnitude the precipitation coefficient is consistently significant in several model specifications. Moreover, we find a negative and significant impact from precipitation on probability of intra-state conflict. However, non–state conflict is not affected by precipitation. This is consistent with the observation that most of the non-state conflict events reported in our dataset involve fights between militia groups with ethnic motivations.

Moreover, we include two interaction variables in the model to test whether having access to more agricultural land and higher irrigation alleviate the adverse impact of low precipitation on conflict. In our data the impact of precipitation on conflict is lower in cells with higher than median irrigation and higher in cells with higher than median agricultural land. However, none of these coefficients are statistically significant.

Furthermore, we find evidence for the hypothesis that precipitation affects conflict through affecting total production levels using a two-stage estimation method. As most of Ethiopia's production either comes directly from the agricultural sector or relies on agriculture for its raw material (World Bank 2006), here we can look at the total production figures as an approximation for the level of agricultural production. Therefore, it can be inferred from our model that lack of precipitation results in lower agricultural production levels which in turn results in higher conflict.

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