Economic Shocks and Civil Conflict: Fifteen Years Later

By Harvey Barnhard*

Miguel, Satyanath, and Sergenti (2004) argue that negative economic shocks increase the likelihood of civil conflict in sub-Saharan Africa in the period from 1981 to 1999. Economic activity is endogenous with conflict, so the authors instrument growth in per-capita GDP by growth in rainfall to derive their results. Since 2004, the validity of rainfall as an instrument for economic activity has been called into question. Using fine-grained conflict data from 1997-2017, I attempt to replicate the authors' results, and I confirm that rainfall remains a weak instrument: it does not allow us to infer a relationship between economic shocks and the measure of conflict used by Miguel, Satyanath, and Sergenti. However, I do find significant relationships between economic shocks and alternative measures of conflict that were unavailable to the authors in 2004. I continue on to find that promising results can be obtained from disaggregating the analysis of conflict to the sub-national level.

Social scientists have long tried to prove the existence of a causal relationship between income shocks and conflict. There are two major theoretical mechanisms through which negative income shocks could increase conflict: the opportunity cost mechanism and the state capacity mechanism. Following Gary Becker's model of criminal behavior, adherents of the opportunity cost mechanism theorize that negative economic shocks increase conflict by suppressing wages and lowering the opportunity cost of fighting. Negative economic shocks can also hinder the state's capacity to field a proper military and address grievances among the populace, thereby increasing conflict incidence.

Though perhaps counter-intuitive, negative income shocks could potentially reduce conflict through a different set of mechanisms. If individuals earn less and hold less valuable items, then there is less for rebel groups to loot, so there are fewer economic incentives for individuals to join militant groups. Secondly, rebel groups may not be able to function if they are not sufficiently well-funded (ammunition can be expensive). Third, if wages are supressed but the state is still well-funded then the state has a greater ability to "pay-off" potential militants.

So it is not exactly clear what the relationship is between civil conflict and economic downturns, if such a relationship even exists. Determining the sign and magnitude of this relationship is a necessary step to reducing future conflict. With such information, policy-makers can be more proactive against reducing conflict through price-stabilization and unemployment insurance programs.

* Harvey Barnhard: University of Chicago, harveybarnhard@uchicago.edu.

Miguel, Satyanath, and Sergenti (whom I will refer to as MSS) made a major contribution to understanding this relationship in their seminal paper "Economic Shocks and Civil Conflict: An Instrumental Variables Approach" (2004). Using cross-national panel data in sub-Saharan Africa, MSS found that negative economic shocks were positively correlated with conflict incidence from 1981-1999. MSS define conflict incidence to be at least 25 deaths in a given year (or 1000 deaths in a given year, for some specifications). There are multiple problems with using this measurement after 1999. In the past two decades, many conflicts have decreased in magnitude and may not cross the threshold of 25 deaths to be covered in this measure. Moreover, there are many different types of conflict that a simple death count can not address. Such conflict types include battles, riots, violence against civilians, and acts of terrorism. I address these problems in the extension portion of my paper.

MSS use an instrumental variable strategy when estimating the effect of economics shocks on conflict because there is a particularly strong reverse causility issue—economic activity can increase conflict, and civil conflict can greatly reduce a country's economic activity. When a country is embroiled in civil conflict, fewer individuals are working in non-military roles, investments decline, and capital depreciates at a much higher rate (e.g. factories being bombed). In other words, economic activity is an endogenous predictor of conflict. Time series can partially circumvent this endogeneity concern. However, when looking at first-differences in conflict and economic activity from one year to the next, researchers assume that individuals are not forward-looking and do not anticipate conflict. That is, if a conflict seems eminent, the economy may sink as individuals become less productive, consume less, or emigrate out of the country in anticipation of civil conflict. Thus, the endogeneity concern remains.

MSS cleverly use growth in rainfall to instrument growth in GDP in sub-Saharan Africa. There are a few reasons why ex-ante this instrument is a good choice. Clearly, rainfall avoids the endogeneity concern because rainfall is nearly random and is not affected by conflict. Moreover, rainfall is particularly random in sub-Saharan Africa and is much more difficult to predict than in other regions of the world. Most sub-Saharan economies remain heavily reliant on subsistence agriculture and few regions have access to reliable irrigation technologies. This means that droughts can have major consequences in regions where households rely heavily on crops and livestock for their livelihoods.

There are two pitfalls with using rainfall as an instrument, one minor and one major. MSS's findings have received criticism for there not existing enough theoretical basis showing that rainfall fulfills the exclusion restriction—this is the minor pitfall. It is possible that rainfall can *directly* affect conflict, rather than indirectly affecting conflict through economic activity which is what we want for inferring causality. For example, rainfall can have an effect on conflict by deteriorting infrastructure used by the state to suppress rebel activity.

The larger concern when instrumenting economic activity with rainfall is that rainfall is not a particularly strong instrument, even in sub-Saharan Africa. That is, rainfall trends capture only a small portion of the total variation in economic activity, even in heavily agricultural regions. In the original paper, MSS find that current and lagged rainfall growth produce an F-statistic of only 4.5, well below the rule-of-thumb for a strong instrument ($F \geq 10$). MSS admit this flaw in their design, noting that, "the instrumental variable two-stage least squares (IV-2SLS) estimates may be somewhat biased toward ordinary least squares (OLS) estimates." However, if rainfall truly fulfills the exogeneity assumption, then this bias may be greatly diminished.

In this paper, I attempt to replicate the results of MSS (2004) and determine if we can find a relationship between economic shocks and civil conflict when economic shocks are instrumented with rainfall shocks. MSS kindly provided all replication materials on the Harvard Dataverse, and all that is required to reproduce their baseline results is running a Stata do file. In the analyses covered in this paper, I provide my own original results using different data than MSS (2004). My data is different in two ways. First, I observe conflict from 1997-2017 whereas MSS observe conflict from 1981-1999. Second, I use a different datasource for conflict that provides much more detailed information on a wider range of conflict events, and geo-locates each conflict event to allow for analysis at the sub-national level. I use the same rainfall and country-characteristic data as MSS but corresponding to my period of observation.

I find that rainfall remains a weak instrument for economic growth and the second stage results of MSS no longer hold across multiple specifications—there is no significant relationship between economic growth and civil conflict when economic growth is instrumented by rainfall. The signs of my estimates, however, are in most cases the same as MSS, indicating that the original results are not necessarily false but just specific to the observed period of 1981-1999. Despite the lack of results when using the same measure of conflict as MSS, I recover some significance when using more specific measures of conflict. In particular, the same 2SLS procedure shows that current economic growth *increases* the likelihood of violence against civilians and prior economic growth *increases* the likelihood of remote violence (e.g. mortar strikes, improvised explosive devices (IEDs)). Finally, I provide preliminary results indicating that we may see similar results when we disaggregate data to the sub-national level.

I. Empirical Strategy

As discussed in the introduction, MSS implement a two-stage least squares procedure to determine the effects of economic growth on civil conflict, where economic growth is instrumented by rainfall growth. The equations for the first and second stage of the 2SLS procedure are identical to the one used by MSS in their 2004 paper. The unit of analysis is a country in a given year.

A. First Stage

$$\text{growth}_{it} = a_i + X'_{it}\beta + c_0\Delta R_{it} + c_1\Delta R_{i,t-1} + d_i\text{year}_t + \epsilon_{it}$$

The equation for the first stage is reported above. The dependent variable growth_{it} is the growth in GDP per capita in country i from year $t-1$ to year t. The main dependent variables of interest are ΔR_{it} and $\Delta R_{i,t-1}$, the current and one-year-lagged growth in rainfall in country i.

$$\text{growth}_{it} = \frac{\text{GDP}_{it} - \text{GDP}_{i,t-1}}{\text{GDP}_{i,t-1}} \qquad \Delta R_{it} = \frac{R_{it} - R_{i,t-1}}{R_{i,t-1}}$$

As for the control variables, country fixed effects (a_i) are used in some specifications to account for time-invariant unobserved characteristics. In other specifications, I use a host of observed country characteristics (X_{it}) as discussed in the data section. The final variable is a time-trend given by year_t. When combined with a country-specific coefficient δ_i, we allow for the passage of time to have heterogeneous effects on GDP per capita. We therefore call these variables country-specific time trends since they let each country's GDP per capita have a different linear relationship with time. This is a more reasonable assumption than year fixed effects or global time trends across all sub-Saharan countries; individual economies may experience more growth than others over time.

B. Second Stage

$$\text{conflict}_{it} = \alpha_i + X'_{it}\beta + \gamma_0\text{growth}_{it} + \gamma_1\text{growth}_{i,t-1} + \delta_i\text{year}_t + \epsilon_{it}$$

The second stage is a linear probability model, where the dependent variable is an indicator variable equalling one if there was civil conflict exceeding 25 deaths within a country for a given year. In some specifications, civil conflicts exceeding 1,000 deaths are observed. The main independent variables of interest are growth_{it} and $\text{growth}_{i,t-1}$, which are the current and lagged growth in GDP per capita instrumented by rainfall. The fixed effects, country characteristics, and country-specific time trends are employed just as in the first stage. Since linear probability models necessarily introduce heteroskedasticity, robust standard errors are used for inference procedures.

II. Data

MSS focused their analyses on conflict in sub-Saharan Africa in the period from 1981-1999. Since that time, there has been nearly 20 years of conflict, 20 years of regime change, and 20 years of economic development in sub-Saharan Africa.

In my analyses, I attempt to replicate the results of MSS with two modifications. First, I look at new data from 1997-2017. Second, I use a conflict dataset that provides more fine-grained information on conflict events. I obtained conflict data from The Armed Conflict Location & Event Data Project (ACLED), a comprehensive and detailed collection of violent events across Africa and around the world. MSS used the UCDP/PRIO dataset on conflict, which aggregates all conflict to the level of the country and most often to the level of the year. I used the same rainfall data source as MSS, from the Global Precipitation Climatology Project (GPCP) but corresponding to the period from 1995-2017 (1995 and 1996 included for lagged effects). I also used the same data sources for country characteristics, appropriately updated to match the period of observation.

The unit of analysis used by MSS is a country in a particular year, observing 41 countries in sub-Saharan Africa over the course of 19 years. This results in 779 units of observation. However, due to data-availability issues, the authors exclude certain country-year observations (such as for Somalia and Liberia) and end up analyzing 743 country-year observations. I focus my analyses on the same 41 countries in sub-Saharan Africa over the course of 21 years—861 country-year observations in total. In the following three subsections, I touch on some key differences between my data and the data MSS use in their analyses. A table of summary statistics is provided at the end of the data section.

The period observed by MSS covers a particularly violent era in sub-Saharan Africa with such devastating events as the Rwandan Genocide and the Ethiopian Civil War. Contained within this period of observation is the decline of the Cold War and the collapse of the Soviet Union. The United States and the Soviet Union took advantage of conflict in sub-Saharan Africa to establish another front in the Cold War, most notably in Angola during an extended civil war beginning in 1975 and only concluding in 2002. While my period of observation is perhaps more peaceful, there is one major shock to consider—the global financial crisis of 2007-2008. I consider this shock in the discussion section of this paper.

A. Conflict Data

There is a large qualitative difference in how conflict incidence is reported in the PRIO dataset used by MSS and the ACLED dataset used in this paper. The PRIO dataset codes only relatively large civil conflicts (at least 25 deaths in a given year) and aggregates all information to the country level. On the other hand, the ACLED dataset includes events with below 25 fatalities, including events with zero fatalities such as riots and protests. Figure 1 below displays all such conflict events from 1997-2019 in the ACLED dataset (approximately 170,000 total events).

To resemble the empirical strategy of MSS (2004), I created an indicator variable equalling one if there were at least 25 civil-conflict related deaths in a country for a given year, and zero otherwise. I made a similar indicator variable for 1,000 civil-conflict related deaths. More indicator variables were made for other measures of civil conflict, and those will be the focus of analysis in the extension portion of this paper.

In MSS (2004), approximately 27% of country-year observations had civil conflict events with at least 25 fatalities, and 17% of country-year observations had civil conflict events with at least 1,000 fatalities. In the data I use, 43.2% of country-year observations had conflict events with at least 25 fatalities but only 12% of observations had events with at least 1,000 fatalities. The standard deviations on these estimates are remarkably similar between the two datasets. There are fewer large-scale civil conflicts in sub-Saharan Africa, but small and moderate size civil conflicts have become more frequent. This fact leads us to believe that prior measurements of conflict, such as those used by MSS, are perhaps no longer relevant as many conflict events may float just below the threshold of detection by indicator variables.

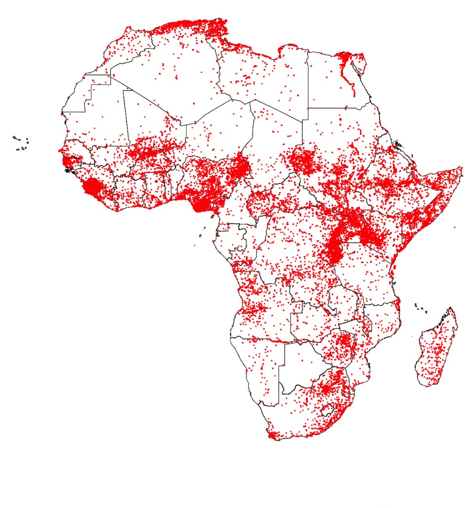

Figure 1. Conflict Events (1997-2019)

Note: Each point represents a reported conflict event in the ACLED dataset. Note that these events include major riots and protests. Northern Africa was included in the figure but is not considered for the remainder of the paper.
Source: Armed Conflict Location & Event Data Project (ACLED)

B. *Rainfall Data*

As discussed in previous sections, I use the same datasource on rainfall as MSS, but for the period corresponding to 1997-2017. GPCP Precipitation data provided by the NOAA/OAR/ESRL PSD, Boulder, Colorado, USA, from their website at https://www.esrl.noaa.gov/psd/. The rainfall data is formatted as a three-dimensional array to cover latitude, longitude, and time. In particular, the data gives us average monthly rainfall (measured in mm/day) for each 2.5×2.5 longitude-latitude cell. Just as MSS did in their 2004 paper, I located the centroid (a "node") of each cell within a country so that each grid-cell was associated with a particular country. For each country, I found the average annual rainfall by taking the mean annual rainfall of each node contained within the country, and then averaged over all nodes. See Figure 2 for an example of what these grid-cells look like when superimposed over Africa.

Some small African countries, like Rwanda, do not contain rainfall measurement nodes. I associate a rainfall node with each of these small countries by using the Hausdorff distance to find the closest rainfall node, and let the average annual rainfall of that node be the average annual rainfall node of the small country. Of course, this measurement is quite coarse, and I believe this measure of rainfall growth can be improved through implementing a kriging procedure where rainfall growth is interpolated among the several closest nodes. I expect this to provide a more accurate measure of rainfall in countries that do not contain a rainfall node.

MSS do not provide much justification for why average *annual* rainfall would be the best measure of rainfall to instrument economic growth. For example, there could be unexpected seasonal droughts within years with no average rainfall growth. Such seasonal components would not be captured when taking the average rainfall over the course of the year. In future work, I believe different measures of rainfall deviations should be used to account for seasonal droughts. I propose one alternative measure: Let D_{it} be the longest length of time in which rainfall was below expected seasonal average in country i during year t, and $D_{i,t-1}$ the same measure for year $t-1$. Then $D_{it} - D_{i,t-1}$ would capture the relative change in seasonal droughts from one year to the next. These sorts of measures may become more important as climate change affects weather patterns.

Despite covering different decades, my rainfall data is quite similar to those in MSS (2004). In particular, the annual average daily rainfall (mm/day) was 1,001.6 in 1981-1999 and 1022.4 in 1997-2017. The standard deviations were 501.7 and 521.6, respectively. The average annual *growth* in rainfall was 1.8% in 1981-1999 and 2.4% in 1997-2017 (standard deviation are slightly larger in the latter period as well). This tells us that rainfall deviations are more extreme in my period of observation, which could mean that rainfall is a better instrument for the latter period (though this is ultimately not the case).

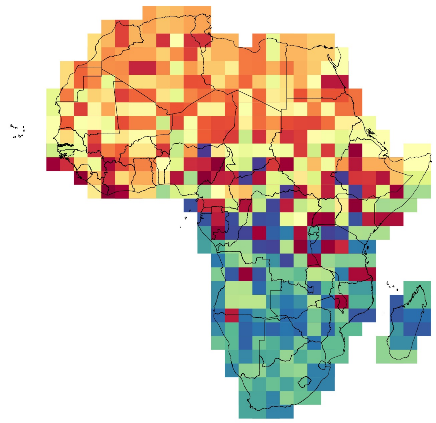

Figure 2. Average Yearly Rainfall (2015)

Note: Monthly rainfall estimates, averaged over each month of 2015. Each square corresponds to a 2.5 × 2.5 longitude-latitude square (approximately the size of Yosemite National Park). The color scaling is from red to yellow to green to blue, where red inciates low average rainfall and blue indicates high average rainfall. The center of each square is the location at which rainfall estimates were made.
Source: Global Precipitaiton Climatology Project (GPCP).

C. Other Country Characteristics

I obtained per-capita GDP data from the World Bank. All observations are in current US dollars (2017). Some yearly observations of GDP per capita for Somalia and Liberia are missing, so I imputed them with per capita GDP estimates from the UN. From 1981-1999 the average yearly growth in GDP per capita was about -0.5% and from 1997-2017 the average annual growth was about 5%. Though these numbers are quite different, this corresponds to the economic trends reported by the World Bank—sub-Saharan Africa experienced many years of negative growth in the early 1980s and relatively high postive growth from the mid 1990s onwards. Also, my standard deviations are larger than those in MSS indicating that I am observing a period of greater economic volatility.

Although most specifications in MSS use country fixed effects, some specifications use data on country characteristics. These characteristics include the lagged logarithm of national population (obtained from the World Bank) and the democracy level of a country as measured by the Polity IV index, from the Integrated Network for Societal Conflict Research (INSCR). I included other time-invariant characteristics such as ethnolinguistic fractionalization, religious fractionalization, whether or not a country exports oil, a measure of how mountainous a country is. These values are the same as in MSS (2004), so I forward impute them from 1999 onwards. MSS obtained these values from the replication files of Fearon and

Laitin (2003). Finally, I include the logarithm of GDP per capita in 1995 for each country, two years prior to observing conflict data. MSS did the same for their paper but chose log(GDP per capita) in 1979. This piece of data gives us a baseline for how wealthy a country is while avoiding potential endogeneity issues.

I have chosen to exclude "growth in terms of trade" from my summary statistics for three reasons. First, the statistic was found to be unhelpful for predicting conflict for any of MSS's empirical specifications. Second, the inclusion is not theoretically useful since we are mostly concerned with the effect of the magnitude of economic shocks, not the effect of the *type* of economic shock. Various work has been done on the relationship between external shocks and civil conflict. In particular, see Berman and Couttenier (2004) for evidence that external income shocks are important determinants for the onset and intensity of conflict. Third, I have chosen to exclude growth in terms of trade from my analysis because such data is more sparse (i.e. MSS only have information on 661 of 743 observations in their original paper).

Table 1—Descriptive Statistics

Statistic	N	Mean	St. Dev.
At least 25 deaths in year t	861	0.432	0.496
At least 1000 deaths in year t	861	0.123	0.329
Annual rainfall (mm/year), GPCP measure	861	1022.408	521.640
Annual growth in rainfall, time t	861	0.024	0.226
Annual growth in rainfall, time $t-1$	861	0.023	0.224
Annual economic growth rate, time t	861	0.059	0.208
Annual economic growth rate, time $t-1$	861	0.059	0.210
Log(GDP per capita), 1995	861	6.021	0.924
Democracy level, time $t-1$	861	1.501	4.848
Ethnolinguistic fractionalization	861	0.716	0.196
Religious fractionalization	861	0.477	0.194
Oil-exporting country	861	0.098	0.297
Log(mountainous)	861	1.590	1.412
Log(national population), time $t-1$	861	16.071	1.236

Note: GDP per capita for Somalia and Libera were imputed for several years using various online sources. These two countries were embroiled in major civil conflict during these years, and standard measurements of GDP per capita do not exist for the late 1990s and the early 2000s.
Source: Conflict statistics are from ACLED. Rainfall data is from the Global Precipitation Data Set. GDP per capital and national population is obtained from the World Bank online datasets. The remainder of the country characteristics were forward-imputed from Fearon and Laitin 2003 (the same data source used by MSS).

III. Empirical Results

A. Reduced Form

What is the relationship betwen growth in rainfall and civil conflict? In Table 2 below, we see that a postive growth in rainfall in the year $t-1$ is associated with lower conflict in year t. In other words, a drought in the previous year increases the likelihood of conflict in the following year. However, these coefficients are not significiantly different from zero with 90% confidence. We do see a positive relationship between growth in rainfall in the current period and conflict incidence in the current period, but the standard errors are too large to say if this is necessarily the case. The sign on lagged rainfall are in both specifications the same as in MSS (2004), but with smaller magnitude and less significance—MSS found that an increase in lagged rainfall decreased the probability of conflict with 95% confidence. Despite the reduced form giving little indication that droughts increase the likelihood of conflict in sub-Saharan Africa, a strong first stage could ultimately expose a relationship between rainfall and conflict through economic growth (though we see that this is not the case for the given measures of conflict incidence).

Table 2—Rainfall and Civil Conflict (Reduced-Form)

	Dependent variable:	
	OLS	
	Conflict $\geq$ 25 Deaths	Conflict $\geq$ 1,000 Deaths
	(1)	(2)
Growth in Rainfall, t	0.049	-0.017
	$(0.053)^r$	$(0.025)^r$
Growth in Rainfall, $t-1$	-0.057	-0.012
	$(0.057)^r$	$(0.024)^r$
Country fixed effects	yes	yes
Country-specific time trends	yes	yes
Observations	861	861
R^2	0.779	0.721
Adjusted R^2	0.756	0.691
Residual Std. Error (df = 777)	0.325	0.195
F Statistic (df = 84; 777)	32.690^{***}	23.899^{***}
Note:		*p<0.1; **p<0.05; ***p<0.01

Note: Huber-White robust standard errors denote with superscript r.

B. First Stage

$$\text{growth}_{it} = a_i + X'_{it}\beta + c_0\Delta R_{it} + c_1\Delta R_{i,t-1} + d_i\text{year}_t + \epsilon_{it}$$

In Figure 3, I compare economic activity and rainfall for each of the 41 countries. Each chart displays growth in GDP per capita in red and lagged growth in rainfall in blue from 1996-2017. Some countries appear to experience major volatility in rainfall growth, like Botswana and Namibia, while others have more stable rainfall like Madagascar and Sudan. Lagged rainfall growth and growth in GDP correspond relatively nicely with each other for some countries, a promising indicator for a strong first stage. Such countries include Cameroon, the Central African Republic, Madagascar, and Togo.

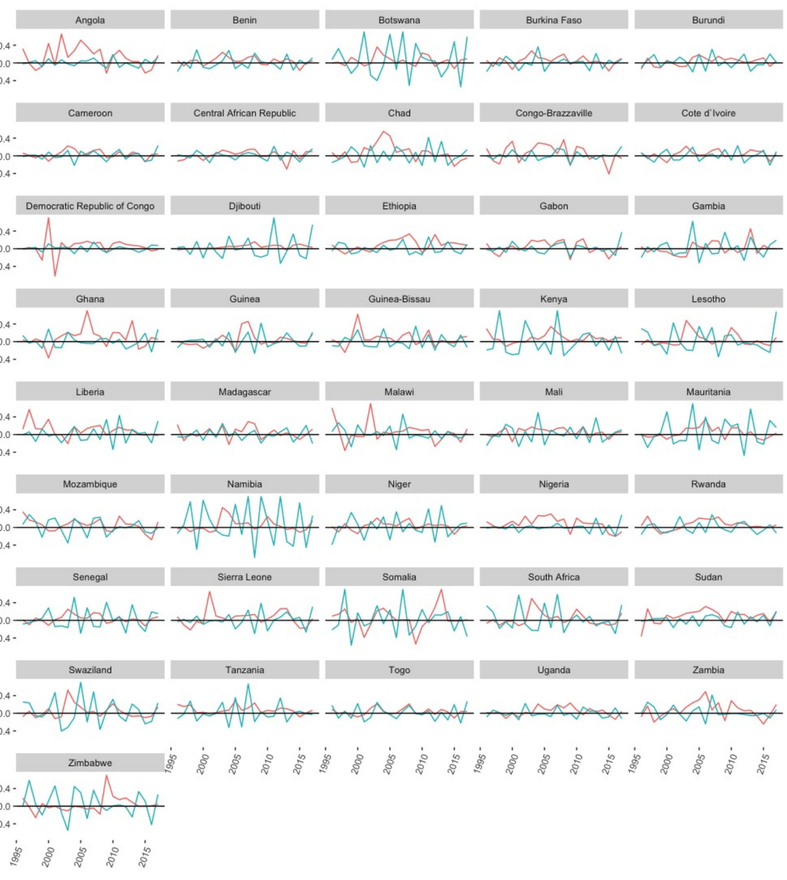

Figure 3. Rainfall and Economic Growth

Note: Red lines represent growth in per capita GDP at time t and blue lines represent lagged growth in rainfall (time $t-1$). Both variables are topcoded at 0.7.

Just as in MSS (2004), the first-stage relationship between rainfall and income growth is strongly positive. Both current and lagged rainfall exhibit a positve relationship with economic growth with 95% confidence. Not only are all of the coefficients on rainfall growth of the same sign, but they are also of greater magnitude than in MSS (2004). For example, MSS report a coefficient of .049 on cureent growth in rainfall in the third specification, while my estimates give a coefficient of .090. This indicates that perhaps rainfall growth has a larger impact on economic growth in 1997-2017 than in 1981-1999. These results are robust to the inclusion of country characteristics, country fixed effects, and country-specific time-trends.

Table 3—Rainfall and Economic Growth (First-Stage)

	Dependent variable: Economic Growth Rate, t			
	(1)	(2)	(3)	(4)
Growth in rainfall, t	0.120***	0.086**	0.090***	0.120***
	$(0.030)^r$	$(0.030)^r$	$(0.034)^r$	$(0.032)^r$
Growth in rainfall, $t-1$	0.120***	0.091***	0.092***	0.108***
	$(0.029)^r$	$(0.029)^r$	$(0.033)^r$	$(0.031)^r$
Growth in rainfall, $t+1$				0.049
				(0.038)
Log(GDP per capita), 1995		−0.023		
		$(0.015)^r$		
Democracy (Polity IV), $t-1$		0.005**		
		$(0.002)^r$		
Ethnolinguistic fractionalization		0.020		
		$(0.073)^r$		
Religious fractionalization		0.151*		
		$(0.093)^r$		
Oil-exporting country		0.126*		
		$(0.049)^r$		
Log(mountainous)		−0.011		
		$(0.009)^r$		
Log(national population), $t-1$		0.007		
		$(0.006)^r$		
Country fixed effects	no	no	yes	yes
Country-specific time trends	no	yes	yes	yes
Observations	902	902	902	902
R^2	0.018	0.126	0.141	0.142
Adjusted R^2	0.016	0.075	0.052	0.053
Residual Std. Error	0.213	0.206	0.209	0.208
F-Statistic on Joint Significance	8.273***	4.442**	4.442***	5.217***
Heteroskedasticity Robust F-Statistic	9.443***	5.014***	3.853**	7.211***
F-Statistic from MSS (2004)	...	...	4.5***	...
Note:	*p<0.1; **p<0.05; ***p<0.01			

Note: Huber-White robust standard errors denoted with superscript r. The Wald-test was used to obtain heteroskedasticity-robust F statistic on the joint significance of rainfall growth. All reported F-statistics are testing against the null hypothesis that current rainfall growth and lagged rainfall growth do not improve the linear relationship when compared to the reduced model.

As a placebo test, the fourth specification includes future rainfall growth, which should be independent from current economic growth due to the unpredictabile nature of rainfall in much of sub-Saharan Africa. The coefficient on future rainfall growth is not significantly different from zero, so we conclude that the temporal ordering of rainfall growth matters.

In the first stage, we see that none of the F-statistics on the joint significance of current and lagged rainfall growth surpass 10, the rule of thumb proposed by Staiger and Stock (1997) for assesing whether or not the strength of an instrument. MSS (2004) reported an F-statistic of 4.5 for specification 3, similar to my results. Note that the heteroskedasticity robust F-statistics produce higher values, but remain below 10. This indicates that all of the 2SLS estimates will be somewhat biased towards the standard OLS estimates.

C. *Second Stage*

$$\text{conflict}_{it} = \alpha_i + X_{it}'\beta + \gamma_0\text{growth}_{it} + \gamma_1\text{growth}_{i,t-1} + \delta_i\text{year}_t + \epsilon_{it}$$

Current economic growth is negatively correlated with the likelihood of conflict incidence in all specifications in Table 4 except specification 5, the 2SLS regression that includes country characteristics. Similarly, lagged economic growth is negatively correlated with the likelihood of conflict occurring in a given year. MSS had very similar results for specifications 1 through 4 in their second stage. However, these correlations are only statistically significant in the third and fourth OLS specifications, and we have yet to deal with the fact that economic growth is likely endogenous with conflict. All significance on the coefficients for economic growth disappear when we introduce rainfall as an instrument in regression 5, 6, and 7. Although the magnitude of the coefficients on lagged economic growth greatly increase in specifications 5 and 6, so do the standard errors so our estimates are imprecise.

The results using a probit regression produce the same signs on the coefficients with little difference in significance levels, so I continue using the linear probability model. I ran the second stages of specifications 5 and 6 using a probit model, and the results were about the same except that the coefficient on lagged growth in specification 5 became significantly negative with 90% confidence. However, the residual standard error almost doubled when using the probit model so I do not put much faith in this result.

Part of the difference in the magnitude of coefficients on economic growth between the OLS and 2SLS models could perhaps be explained by measurment error of per capita GDP in sub-Saharan Africa, as MSS discuss in their paper. Perhaps one reason we are seeing larger standard errors in the 2SLS specifications is that African economies have diversified away from subsistence agriculture since 1999, and are therefore more resilient against rainfall shocks. Many sub-national regions remain heavily reliant on subsistence agriculture, which could explain why. We should not infer that there is no significant relationship between economic shocks and conflict, just that disaggregated analysis remains an essential next step.

Table 4—Economic Growth and Civil Conflict

	Dependent Variable: Conflict ≥ 25 Deaths						Dependent Variable: Conflict ≥ 1,000 Deaths
	Probit	*OLS*	*OLS*	*OLS*	*IV-2SLS*	*IV-2SLS*	*IV-2SLS*
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Economic growth rate, t	-0.172	-0.044	-0.064	-0.101^{*}	0.125	-0.036	-0.162
	(0.217)	$(0.072)^{r}$	$(0.061)^{r}$	$(0.056)^{r}$	$(0.812)^{b}$	(0.546)	(0.324)
Economic growth rate, $t-1$	-0.345	-0.102	-0.119^{**}	-0.129^{**}	-0.988	-0.814	0.220
	(0.216)	$(0.082)^{r}$	$(0.065)^{r}$	$(0.051)^{r}$	$(0.704)^{b}$	(0.546)	(0.328)
Log(GDP per capita), 1995	-0.514^{***}	-0.132^{***}	-0.115^{***}		-0.129		
	(0.051)	$(0.011)^{r}$	$(0.026)^{r}$		$(0.041)^{b}$		
Democracy (Polity IV), $t-1$	-0.023^{**}	-0.007^{**}	-0.014^{***}		-0.011		
	(0.010)	$(0.003)^{r}$	$(0.005)^{r}$		$(0.007)^{b}$		
Ethnolingusitic fractionalization	1.183^{***}	0.312^{***}	-0.147		-0.132		
	(0.311)	$(0.092)^{r}$	$(0.190)^{r}$		$(0.226)^{b}$		
Religious fractionalization	-0.554^{*}	-0.095	-0.058		0.054		
	(0.285)	$(0.081)^{r}$	$(0.193)^{r}$		$(0.261)^{b}$		
Oil-exporting country	0.409^{**}	0.125^{**}	0.367^{***}		0.454		
	(0.169)	$(0.052)^{r}$	$(0.107)^{r}$		$(0.181)^{b}$		
Log(mountainous)	0.258^{***}	0.081^{***}	0.089^{***}		0.083		
	(0.041)	$(0.012)^{r}$	$(0.027)^{r}$		$(0.031)^{b}$		
Log(National population), $t-1$	0.120^{***}	0.058^{***}	0.067^{***}		0.071		
	(0.027)	$(0.008)^{r}$	$(0.018)^{r}$		$(0.022)^{b}$		
Country fixed effects	no	no	no	yes	no	yes	yes
Country-specific time trends	no	no	yes	yes	yes	yes	yes
Observations	861	861	861	861	861	861	861
R^2	...	0.566	0.717	0.781	...	...	...
Residual Std. Error		0.435	0.360	0.324	0.361	0.325	0.195

*p<0.1; **p<0.05; ***p<0.01

Note: Bootstrapped standard errors for IV estimates are denoted with the superscript b, Huber-White robust standard errors denoted with superscript r. Bootstrapped standard errors were derived from bootstrapping the second-stage residual over 2000 simulations for each specification. I also obtained bootstrap standard errors using case resampling, but these standard errors were substantially smaller so I opted for the more conservative approach of bootstrapping the residuals. I do not report the significance for estimates with boostrapped standard errors.

IV. Discussion and Extensions

A. Are Results being Driven by Outliers?

There are some observations that contain extraordinarily high values of growth in GDP and others that contain extraordinarily high values of growth in rainfall. Do these outliers influence our estimations? To check, I top-coded growth in GDP per capita and growth in rainfall at 0.7—approximately the 99th percentile for both variables. I then reran the third specification in the first-stage (Table 3), and found similar results for the OLS estimates on the effect of rainfall and lagged rainfall on GDP growth. Results are reported in the first column of Table 5. In fact, the F-statistic on the joint significance of the instrument on explaining economic growth actually increases slightly (though is still well below the threshold for rejecting the null hypothesis that rainfall and lagged rainfall are together weak instruments for growth in GDP per capita). The reported robust F-statistics are even lower, so we conclude that rainfall remains a weak instrument. However, we can now have more faith that our second-stage estimates in Table 4 are not being driven by a handful of extraordinary cases.

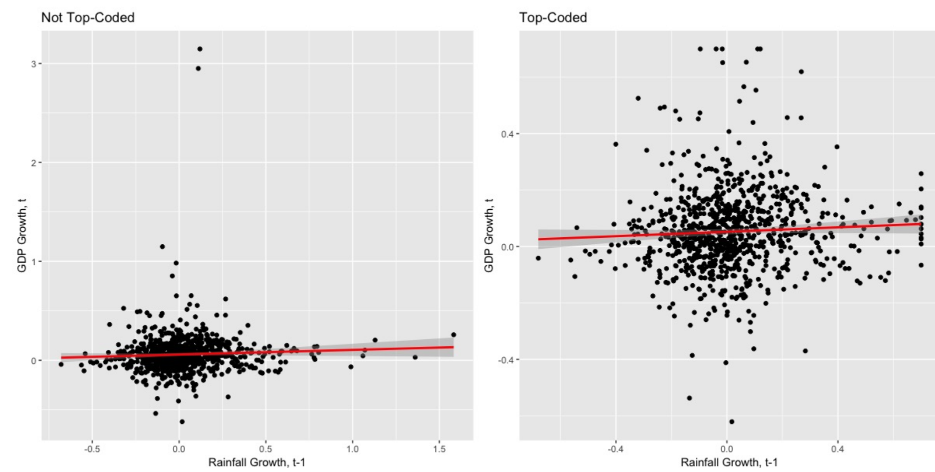

Figure 4. Top-Coding (First-Stage)

B. What is the Effect of the Global Financial Crisis?

Berman and Couttenier (2015) show that exogenous financial shocks increase civil conflict in sub-Saharan Africa, particularly for regions that are near a major seaport. The causal mechanism is the same for local economic shocks (perhaps caused by drought): when the North American financial markets tanked in 2007, imports of all kinds decreased, so exports from sub-Saharan Africa decreased. Less exports led to lower wages, and the opportunity cost of fighting decreased. Berman and Couttenier, however, only observe relatively minor financial crises and withold from analyzing the global financial crisis.

My conflict data span from 1997-2017, which includes the global financial crisis of 2007-2008 (GFC). When determining the relationship between economic growth and civil conflict, it would be foolish to create a model that does not account for a period of such great financial stress. There are two main ways I can extend my model to include the GFC. First, I can look for a structural change in the model that occurs somewhere between 2007-2009. Second, I can include a dummy variable for 2007-2008 that indicates years in which the global financial markets were experiencing the greatest stress. The first model extension assumes that the GFC had a permanent impact on economic growth in sub-Saharan Africa while the second model assumes that the GFC had an immediate impact on growth, but growth continued after the darkest part of the crisis passed.

To test the first extension of the model, I perform a Chow test to look for a structural break in GDP growth around 2007-2009. Upon observing the plot of GDP growth by year, it seems as though a structural break actually occurs starting in 2009. This would make sense given that most of the impact of the GFC on sub-Saharan Africa likely took place in the latter portion of 2008. I perform a Chow test by breaking up the topcoded rain and GDP data into two datasets, one ranging from 1996-2008 and the other from 2009-2017. I then run the first first-stage specification in Table 5 on both datasets, and compare the sum of the resulting sum of square residuals to the sum of square residuals for the combined data. I end up with a Chow F-statistic that garners a p-value of less than 10^{-7} so I reject the null hypothesis that there is no structural break in the data. See Figure 5 below for visual evidence of such a structural break using a local polynomial regression, and Figure 6 using OLS. Note that in Figure 6 economic growth increases in sub-Saharan Africa from 1996 to 2008 (i.e. the second derivative of GDP per capita is positive), but decreases on average from 2009 onwards.

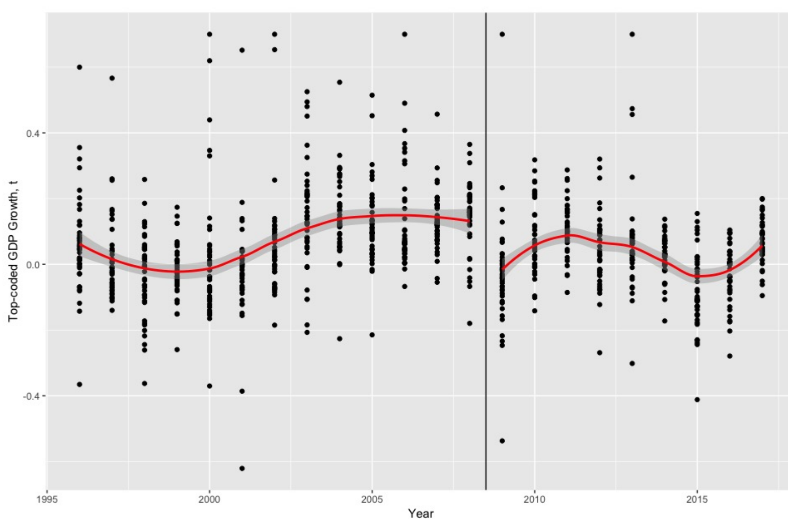

FIGURE 5. STRUCTURAL BREAK IN ECONOMIC GROWTH DUE TO GLOBAL FINANCIAL CRISIS

Note: The two red curves represent local polynomial regressions fitted from 1996-2008 and 2009-2017. The shaded areas represent 95% confidence intervals. No controls are included.

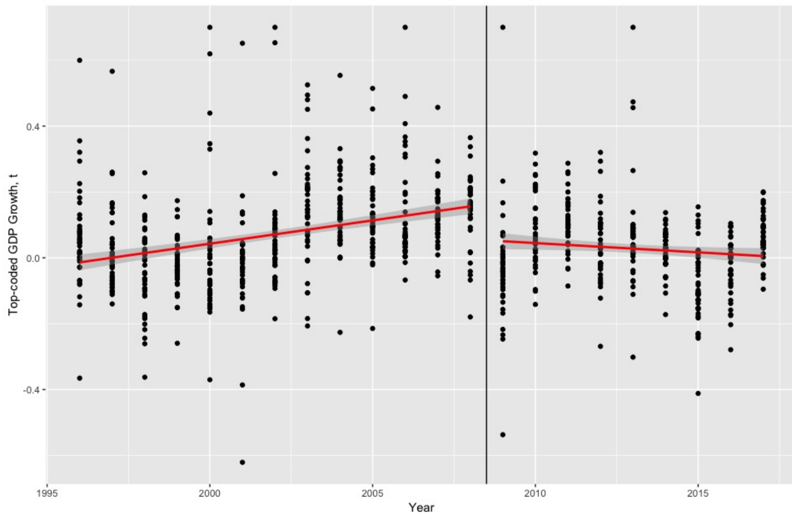

Figure 6. Structural Break in Economic Growth due to Global Financial Crisis

Note: The two red curves represent OLS regressions fitted from 1996-2008 and 2009-2017. The shaded areas represent 95% confidence intervals. No controls are included.

To test the second extension of the model, I include a dummy variable that equals one if the year is 2007 or 2008 and zero otherwise. I report the results of including the dummy in Table 5. The results are surprising: the coefficient on the dummy is found to be *positive* and significant at the $\alpha = .001$ level. To test whether or not introducing this dummy into the model helps explain variation in economic growth, I performed a Wald-test where the reduced model is specification 1 in Table 5 and the full model is specification 1 with a financial crisis dummy. I obtain a p-value less than 5×10^{-14}, so I decidedly reject the null-hypothesis that the dummy does not help explain variation in GDP growth.

Ultimately, I believe modeling the financial crisis with a structural break is a more realistic representation of the effect of the GFC on sub-Saharan Africa. There is more theoretical justification for why the magnitude of the GFC would have a lingering effect on economic growth than for why economic growth would be higher than average during the GFC (as the sign on the coefficient for the financial crisis dummy tells us). However, implementing this model with country-specific time trends greatly increased standard errors as I had to include a dummy variable for the year being greater than 2008, and interactions with each of the 41 country specific time-trends, so the degrees of freedom dropped by 42 (results not reported in this paper). However, if I backpedal from using the country-specific time-trends and use a global linear time-trend instead, I only need to add two variables to model the strucutral change: a dummy for the year being greater than 2008 and an interaction with global linear time-trend. The results for this specification are provided in column 3 of Table 5. Rainfall remains a weak instrument.

TABLE 5—RAINFALL AND ECONOMIC GROWTH (FIRST-STAGE, TOP-CODED)

	Dependent variable: Economic Growth Rate, t		
	OLS	OLS	OLS
Growth in Rainfall, t	0.074***	0.077***	0.066**
	(0.028)	(0.027)	(0.026)
Growth in Rainfall, $t-1$	0.082***	0.067***	0.067***
	(0.028)	(0.027)	(0.026)
GFC Dummy (2007 and 2008)		0.095***	
		(0.017)	
GFC Dummy (Year > 2008)			0.184***
			(0.056)
Global Linear Time Trend			0.014***
			(0.002)
Time Trend:GFC Dummy (Year > 2008)			-0.020***
			(0.003)
Country fixed effects	yes	yes	yes
Country-specific time trends	yes	yes	no
Observations	861	861	861
R^2	0.181	0.214	0.240
Adjusted R^2	0.092	0.132	0.199
Residual Std. Error	0.149	0.146	0.141
F-Statistic on Joint Significance	4.770***	4.886***	4.520**
Heteroskedasticity Robust F-statistic	4.427**	4.365**	4.201**

*p<0.1; **p<0.05; ***p<0.01

Note: Growth in GDP and growth in rainfall both top-coded at 0.7. Financial crisis dummy equals one for 2007 and 2008, zero otherwise. Reported F-statistics are for the joint significance of current and lagged rainfall growth.

V. Further Extensions

In this section, I look for potential reasons why the second stage of the 2SLS procedure does not produce the same significant results as in MSS (2004). In the first subsection, I explore alternative measures of conflict such as violence against civilians and total fatalities. In the second subsection, I look for indications that disaggregating data to the subnational level could lead to more fruitful results.

A. *Introducing More ACLED Variables at the Country Level*

The ACLED conflict dataset is much more detailed than the UCDP/PRIO dataset used by MSS. As mentioned in the data section, the ACLED dataset reports conflict events with fewer than 25 fatalities and also has more detailed descriptions of the type of each conflict. In particular, the ACLED dataset codes conflict events into the following categories: battles between the government and non-state actors, riots/protests, violent acts directed towards civilians, and remote violence. Remote violence captures assymetric warfare such as mortar strikes and the detonation of improvised explosive devices (IEDs). I created indicator variables for each of these event types; if at least one of a particular type of event occurred in a country in a given year, then that indicator equals one, and zero otherwise. For example, if a battle occurred in Sierra Leone in 2007, then the indicator variable for battles would equal one for Sierra Leone in 2007. Summary statistics of these variables are provided in Table 6.

Note that these types of events are much more common (battles, riots, and violence against civilians all occur in at least 80% of observations). For these types of conflict, it might be more informative to observe the count of events or let the indicator variable equal one for higher thresholds (e.g. the indicator for battles equalling one if at least three battles occurred). For now, I stick with whether or not any event occurred in a given year.

In Table 7, I reproduce the second-stage results of Table 4 column 5 but with alternative measures for conflict incidence as the dependent variable. The main independent variables are current and lagged growth in GDP instrumented by current and lagged growth in rainfall. Country fixed effects and country-specific time trends are included to account for both time-invariant and time-dependent unobserved characteristics. The results are much more promising, and perhaps a little surprsing.

Lagged economic growth is negatively correlated with the incidence of battles, the incidence of riots, and the logarithm of fatalities. This is exactly what we would expect if we assume the opportunity cost mechanism. However, none of these coefficients are significantly different from zero.

Current economic growth is *positively* correlated with the incidence of battles, riots, and violent acts directed against civilians. Moreover, current economic

TABLE 6—DESCRIPTIVE STATISTICS (ACLED DATA)

Statistic	N	Mean	St. Dev.
$\geq$ 25 deaths in year t	861	0.432	0.496
$\geq$ 1000 deaths in year t	861	0.123	0.329
log(fatalites+1) in year t	861	3.204	2.658
$\geq$ one battle in time t	861	0.724	0.447
$\geq$ one riot/protest in year t	861	0.868	0.339
$\geq$ one violent event against civilians in year t	861	0.857	0.350
$\geq$ one remote violence incident in year t	861	0.357	0.479

growth is positively related with acts of violence against civilians with 90% confidence. Even more surprisingly, acts of remote violence (insurgent attacks) are more likely to occur after a period of economic growth. The opportunity cost mechanism does not help explain why these two forms of violence would increase due to economic growth. However, there are two potential mechanisms through which positive economic growth could increase violence in this way. First, increased economic growth could lead to greater economic incentives to join militia groups as looting becomes more profitable. Second, positive economic growth could disproportionately fund militant groups, facilitating the purchase of guns and ammunition. I favor the second mechanism, as we more often associate acts of violence against civilians and insurgent activity as ideologically motivated.

TABLE 7—ECONOMIC GROWTH AND CIVIL CONFLICT (SECOND STAGE, ACLED VARIABLES)

	Dependent variable:				
	Battles	Riots and Protests	Violence Against Civilians	Remote Violence	Log(Fatalities+1)
	(1)	(2)	(3)	(4)	(5)
Economic growth rate, t	0.150	0.079	0.840*	-0.804	-2.714
	(0.564)	(0.493)	(0.504)	(0.619)	(2.114)
Economic growth rate, $t-1$	-0.912	-0.359	0.417	1.362**	-1.414
	(0.571)	(0.499)	(0.509)	(0.626)	(2.138)
Country fixed effects	yes	yes	yes	yes	yes
Country-specific time trends	yes	yes	yes	yes	yes
Observations	861	861	861	861	861
R^2	0.856	0.908	0.903	0.649	0.916
Note:					*p<0.1; **p<0.05; ***p<0.01

Note: Battles are coded in three categories (all government fighting against non-state actors): first, battles in which the government regains territory. Second, battles in which there is no change in territory. Third, battles in which the non-state actor overtakes territory. Reported standard errors are incorrect 2SLS estimates that do not take into account the fact that growth in GDP was estimated.

B. Analysis at the sub-National Level

MSS obtained rainfall data at a sub-national level. Why not also analyze conflict at a sub-national level as well? MSS were limited to cross-country analysis since in 2004 there were no datasets available to independent researchers (of course the U.S. military has great geo-located data, the SIGACTS dataset, but this data is not released for obvious security reasons). In this final section, I produce reduced-form estimates akin to the reduced form in Table 2, but this time with the unit of analysis disaggregated down from the country level to the grid-cells from the rainfall dataset. Afterward, I lay out a framework for developing the first stage of the 2SLS procedure with this more granular unit of analysis.

Performing analysis at the sub-national level provides a slew of benefits when performing inference. For instance, we massively expand our sample size and increase variance in rainfall observations since we are no longer averaging across countries.

However, observing conflict at the sub-national level presents an additional set of problems. I list a few of these problems, though there are likely many more. First, we will likely observe a spillover effect among adjacent grid cells. For example, if the economy takes a nose-dive in one grid-cell, then we are likely to see higher conflict in the adjacent grid-cells as well. Second, the error terms of adjacent grid cells could be correlated with each other. We would expect correlated errors among adjacent cells due to unobserved characteristics like culture and geography. Clustering standard errors at a higher-level than the grid cell but still at a sub-national level could mitigate this problem. Third, since grid-cells are smaller and conflict events tend to be heavy-tailed and regionally distributed, we could potentially see many cells that never experience a conflict event. That is, any dependent variable for conflict (conflict events, conflict incidence, total deaths, etc.) would likely be heavily zero inflated. While not problematic for binary dependent variables, if we chose to focus on number of conflict events, then a negative binomial regression may be more appropriate than linear regression since we would be dealing with count data.

Unfortunately, obtaining GDP data at the subnational level is in most cases impossible, and available data is hardly reliable. To estimate a first stage between economic growth and rainfall at the subnational level, I plan on using publicly available data from space. There is an expanding literature on using nighttime-light to proxy economic activity. For a recent example, see the working paper by Luis Martinez (Harris School of Public Policy), "How Much Should We Trust the Dictator's GDP Growth Estimates?" In this paper, Martinez finds that GDP is systematically larger in more authoritatrian regimes by using nighttime lights to proxy true economic activity. Satellite data on nighttime light is publicly available from the National Centers for Environmental Information. Henderson et al. (2012, AER) have made their satellite data and replication files publicly available as well.

In Table 8, I provide summary statistics on grid-level rainfall and conflict data.

In Table 9, I provide reduced form estimates of the effect of rainfall growth on various measures of conflict. None of the effects are significant when we include cell fixed effects, but neither my original reduced form nor the reduced form in MSS (2004) produced significant results.

Table 8—Grid Level Descriptive Statistics

Statistic	N	Mean	St. Dev.
Annual rainfall (feet), GPCP measure	6,888	2.301	1.646
Growth in rainfall, t	6,888	0.091	0.625
Growth in rainfall, t-1	6,888	0.088	0.623
$\geq$ 25 deaths in year t	6,888	0.196	0.397
$\geq$ 1000 deaths in year t	6,888	0.014	0.115
log(Fatalites+1)	6,888	1.429	2.023
$\geq$ one battle in time t	6,888	0.396	0.489
$\geq$ one riot/protest in time t	6,888	0.373	0.484
$\geq$ one violent event against civilians in time t	6,888	0.438	0.496
$\geq$ one remote violence incident in time t	6,888	0.121	0.326

Table 9—Grid Level Rainfall and Civil Conflict (Reduced-Form)

	Dependent variable:						
	Conflict $\geq$ 25 deaths		log(Fatalities + 1)	Battles	Riots/Protest	Violence Against Civilians	Remote Violence
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Growth in rainfall, t	-0.036^{***}	-0.002	-0.006	-0.0002	-0.003	0.007	-0.006
	(0.008)	(0.007)	(0.030)	(0.008)	(0.007)	(0.008)	(0.006)
Growth in rainfall, $t-1$	-0.034^{***}	0.00002	0.001	-0.004	-0.0001	0.008	-0.003
	(0.008)	(0.007)	(0.030)	(0.008)	(0.007)	(0.008)	(0.006)
Grid fixed effects	no	yes	yes	yes	yes	yes	yes
Year fixed effects	yes	yes	yes	yes	yes	yes	yes
Observations	6,888	6,888	6,888	6,888	6,888	6,888	6,888
R^2	0.215	0.544	0.700	0.680	0.700	0.713	0.405
Adjusted R^2	0.212	0.519	0.684	0.663	0.684	0.698	0.373
F Statistic	81.762^{***}	22.268^{***}	43.572^{***}	39.642^{***}	43.642^{***}	46.456^{***}	12.732^{***}

Note: *p<0.1; **p<0.05; ***p<0.01

VI. Conclusion

My attempt to replicate MSS's findings showed that rainfall is a weak instrument for GDP growth when we try to estimate the relationship between economic shocks and conflict. Since the orginal paper on economic shocks and civil conflict was published in 2004, many authors have shown that observing conflict at the subnational level produces significant estimates on economic correlates of conflict. For example, Dube and Vargas (2008) show that exogenous price shocks effect conflict in oil and coffee producing regions of Colombia. In many cases, observing conflict at the national level is simply too coarse; Cross-country analyses of data assume homogeneity of economic conditions within a country and rely on country level estimates of GDP per capita. For small countries in Europe, these assumptions may be valid. However, countries in sub-Saharan Africa are far from homogenous both in terms of ethnicity and regional economies.

There are two main takeaways from this paper. First, my attempts to replicate MSS's findings do not indicate that there no relationship exists between economic shocks and conflict. All my replication shows is that rainfall is simply too weak of an instrument to estimate GDP growth at the national level.

Second, any research on the correlates of conflict must be performed at a more granular level. There are multiple measures of conflict, and the binary indicator of conflict that MSS use in their analyses is not always the most policy-relevant. We are often more interested in the total number of deaths per-capita or type of events (battles, IEDs, riots, etc.) than whether or not 25 people died within the span of a year.

Civil conflict must also be observed at a sub-national level. For example, Boko Haram is relegated to northeast Nigeria, and Joseph Kony's LRA operated along the border of Uganda and South Sudan. In both examples, conflict is not contained within a single country. There are certainly cases of country-wide conflict such as the civil war in Sierra Leone and the genocide in Rwanda. Fortunately, however, conflicts of these magnitude are becoming more rare. The nature of conflict is changing, and our measures of conflict must adapt accordingly.