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Adverse Rainfall Shocks and Civil War: Myth or Reality?

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Abstract

News reports and policymakers frequently link African civil conflicts and wars to agricultural crises caused by droughts. However, empirical studies of the relationship between rainfall and civil conflict or war remain inconclusive. I reexamine this relationship focusing on rainfall over each country's agricultural land during the growing seasons. I also incorporate that the relationship between rainfall and agricultural output is hump-shaped, as rainfall beyond a threshold decreases output. I find a U-shaped relationship between rainfall and the risk of civil conflict and war in (Sub-Saharan) African countries. This relationship mirrors the hump-shaped relationship between rainfall and agricultural output.

Keywords

civil war, civil conflict, rainfall, weather, Africa

Introduction

According to a recent BBC news report, "Ethiopia has suffered periodic droughts and famines that lead to a long civil conflict in the 20th Century" (BBC 2015). Similar news reports are frequent. Their message—that droughts in Africa lead to food shortages that trigger civil conflict and war—seems plausible, and the idea that adverse rainfall shocks are a cause of civil conflict and war has by now become pervasive in policy circles. For example, U.S. President Barack Obama linked the

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rise of the terrorist group Boko Haram in Nigeria to droughts and the Secretary General of the United Nations Ban Ki-moon stated that droughts fueled the 1983-2005 civil war in Sudan (Ki-moon 2007; Obama 2015).

However, the empirical evidence on the relationship between rainfall and civil conflict or war in Africa is inconclusive. While some empirical studies find that Sub-Saharan African countries are more likely to see civil conflict or war following adverse rainfall shocks, others studies do not find such a link (Miguel, Satyanath, and Sergenti 2004; Ciccone 2011; Miguel and Satyanath 2011; Couttenier and Soubeyran 2014). I contribute to this literature with an empirical approach that differs from previous work in two main ways. Existing studies of the relationship between rainfall and civil conflict or war in African countries link the presence of civil conflict or war in a country to annual rainfall over a country's entire territory. I use new satellite data on African countries' growing seasons and data on their agricultural areas to focus on rainfall over countries' agricultural land during their growing seasons.[1] This should yield a rainfall measure that is more closely related to a country's agricultural output than rainfall during calendar years over a country's entire territory. In addition, my approach takes into account the evidence in agricultural economics showing that the relationship between rainfall and agricultural output is hump-shaped, with rainfall beyond a threshold decreasing output (Guiteras 2009; Lobell, Schlenker, and Costa-Roberts 2011; Schlenker and Roberts 2009; Schlenker and Lobell 2010).

My empirical analysis proceeds in three steps. I first combine data on rainfall and agricultural land use with new, high-resolution satellite data on growing seasons for 51 African countries to construct a country-level measure of rainfall over agricultural land during growing seasons from 1980 to 2013. I refer to this new measure of country-level rainfall as agricultural rainfall.[2] I then combine the agricultural rainfall data with data on agricultural output to confirm the hump-shaped relationship between rainfall and agricultural output documented in agricultural economics in my data. In the last step I examine the effect of agricultural rainfall on the risk of civil conflict and war in all African countries and the subsample of Sub-Saharan African countries as many previous studies focused on Sub-Saharan Africa. A key feature of my analysis is that I allow for a U-shaped relationship between agricultural rainfall and the risk of civil conflict or war. This permits the relationship between agricultural rainfall and civil conflict or war to mirror the hump-shaped relationship between agricultural rainfall and agricultural output.

My main finding is a robust, U-shaped relationship between agricultural rainfall and the risk of civil war onset and incidence in (Sub-Saharan) African countries. The U-shaped relationship implies that the quantitative effect of rainfall shocks on the risk of civil war depends on the base level of rainfall. A quantitatively similar U-shape relationship is also obtained when using the literature's standard measure of annual rainfall over a country's entire territory, albeit the statistical fit worsens. This suggests that previous inconclusive results on the impact of rainfall on civil war risk were not due to measurement error in the rainfall data but rather because these analyses did not account for the non-monotonic impact of rainfall on civil war risk. I also find a robust U-shaped relationship between agricultural rainfall and the risk of civil conflict incidence. However, one cannot reject the hypothesis that rainfall is unrelated to civil conflict incidence risk when rainfall is measured over the calendar year and a country's entire territory. This, in turn, highlights the importance of using rainfall measures that better predict agricultural output when examining the impact of rainfall on civil war and civil conflict risk.

I find that a negative rainfall shock that takes a country from the 50th to the 25th percentile of the distribution of agricultural rainfall increases the risk of civil war onset and incidence in Africa by 2.2 and 2.3 percentage points, respectively. A positive shock that takes a country from the 50th to the 75th percentile of the distribution of agricultural rainfall decreases the risk of civil war onset and incidence by 0.6 and 0.8 percentage points, respectively. Nevertheless, large enough positive shocks have the opposite effect, increasing civil war onset and incidence risk. Going from the 50th to the 90th percentile of the distribution of agricultural rainfall increases the risk of civil war onset and incidence by 1 and 0.7 percentage points, respectively. The effect of rainfall on civil war onset and incidence risk is qualitatively the same in Sub-Saharan Africa.

Determining if and when rainfall shocks cause civil conflicts and especially civil wars is important because of the enormous cost of civil conflict and war in terms of human lives and living conditions (Sambanis 2002). A better understanding of whether civil conflicts and wars might be triggered by rainfall shocks informs policymakers on how the risk of civil conflicts and wars might be diminished. A better understanding of the effect of rainfall shocks on civil conflicts and wars has also become pressing given the consensus that climate change will make extreme rainfall events more likely (IPCC 2014). Simulations from twelve global circulation models predict increased heavy precipitation in east Africa and the opposite in the southern region of the continent (Seneviratne et al. 2012). These new weather patterns are expected to affect food security in many poor and agricultural countries. In Sub-Saharan Africa, predicted reductions in agricultural yields by the mid-century range between 8% and 22%, depending on the crop (Schlenker and Lobell 2010).

The remainder of the paper is structured as follows. Related Literature discusses the related empirical and theoretical literature on the impact of rainfall shocks on the risk of civil conflict and war. Theoretical Framework: Economic Shocks and Civil War section characterizes the equilibrium of an extension of the dynamic game of civil war of Chassang and Padró i Miquel (2009) to show that the hump-shaped relationship between rainfall and agricultural productivity implies that there is a U-shaped relationship between rainfall and civil war risk. Data section introduces the data and discusses the construction of the agriculture-relevant rainfall measure. Rainfall and Agriculture section draws from the agricultural economics literature to inform the mapping from rainfall onto agricultural output and civil war. Rainfall and

Civil War outlines the empirical strategy and presents the main results. The last section concludes.

Related Literature

My work is closely related to empirical studies examining whether Sub-Saharan African countries were more likely to experience civil conflict or war following low-rainfall years. In a seminal study, Miguel, Satyanath, and Sergenti (2004) find that Sub-Saharan African countries experiencing low year-on-year rainfall growth were more likely to see civil conflict and war over the 1981-1999 period. Their civil conflict and war indicators are based on the Uppsala Conflict Data Program and the Peace Research Institute Oslo's (UCDP-PRIO) Armed Conflict Dataset. Civil conflict is defined as "a contested incompatibility that concerns government or territory or both where the use of armed forces between two parties results in at least 25 battle-related deaths. Of these two parties, at least one is the government of a state" (Gleditsch et al. 2002, 618-619). Civil war is defined as a civil conflict with more than a 1,000 deaths per year. An attractive feature of the panel-data approach by Miguel, Satyanath, and Sergenti (2004) is that it allows controlling for unobservables that translate into permanently greater civil conflict risk in some countries (country fixed effects) or some years (year fixed effects), as well as country-specific trends in conflict risk. Later studies with the same panel-data approach for Sub-Saharan Africa but for longer time periods do not find a statistically significant relationship between rainfall levels or year-on-year rainfall growth on the one hand and civil conflict or war on the other. See Ciccone (2011) and Miguel and Satyanath (2011) for Sub-Saharan African countries over the 1981-2009 period and Couttenier and Soubeyran (2014) for Sub-Saharan African countries over the 1945-2005 period, the latter only considers rainfall in levels.

The rainfall measures used in these empirical studies of the link between rainfall and civil conflict or war, aggregate rainfall during calendar years and over the totality of a country's territory. Recent research in agricultural economics on the relationship between rainfall and agricultural output has taken a different approach. At the local level, Schlenker and Roberts (2009) construct crop-specific measures of rainfall for U.S. counties by aggregating rainfall during the growing season and over the counties' cropland.[3] Schlenker and Lobell (2010) and Lobell, Schlenker, and Costa-Roberts (2011) have generalized these crop-specific rainfall measures to the country level for Sub-Saharan Africa and a world panel, respectively. Additionally, this literature has documented the existence of a hump-shaped relationship between rainfall and agricultural output; the evidence comes from India (Guiteras 2009), the U.S. (Schlenker and Roberts 2009), Sub-Saharan Africa (Schlenker and Lobell 2010), and a world panel (Lobell, Schlenker, and Costa-Roberts 2011). Following this literature, I measure rainfall during the growing season and over a country's agricultural land. Further, I allow my rain measure and agricultural output to have a hump-shaped relationship and confirm it holds at the country level in my sample.

There is also empirical work examining the link between rainfall and inter-group violent events at the local level. For Africa, between 1960 and 2004, Theisen, Holtermann, and Buhaug (2011) find no statistically significant relationship between year-on-year rainfall growth or rainfall anomalies on the one hand and civil war battle locations on the other hand. Their data on battle location is derived from UCDP-PRIO's Armed Conflict Dataset. von Uexkull (2014) uses the UCDP Georeferenced Event Dataset (UCDP-GED) for Sub-Saharan Africa between 1989 and 2008 and finds that sustained drought is more likely to lead to conflict in locations with rainfed agriculture. Harari and Ferrara (2018) find that negative shocks to the so-called standardized precipitation evapotranspiration index (SPEI) during the growing season increase the risk of inter-group violence incidence in Africa between 1997 and 2011 using UCDP-PRIO's Armed Conflict Location and Event Data Project (ACLED) dataset. This effect is mainly driven by increased battle risk, increased violence against civilians, and increased riot risk. My result on the existence of a significant relationship between civil conflict and war at the *country* level and rainfall over agricultural areas during the growing season resonate with those of Harari and Ferrara (2018) at the *local* level. Outside the African context, my paper relates to a recent study by Crost et al. (2018) on the relationship between seasonal rainfall and inter-group violence in Philippine provinces over the 2001-2009 period. Using military reports, the authors find that more rainfall during the dry season decreases the risk of violent events while more rainfall during the wet season increases the risk of violent events.

There is also a growing theoretical literature in the social sciences that has examined the relationship between income and civil war (Besley and Persson 2011; Chassang and Padró i Miquel 2009; Dal Bó and Dal Bó 2011; Fearon 2007; Grossman 1991), highlighting that civil war risk is increasing in the size of the appropriable resources (i.e., the loot) and decreasing in the opportunity cost of participating in civil war (e.g., foregone agricultural income).[4] Empirical tests of the opportunity cost mechanism, however, need to address the issue that the size of appropriable resources is seldom observable and that it will often be correlated with the opportunity cost of fighting (Chassang and Padró i Miquel 2009; Fearon 2007), leading to omitted-variable bias. For instance, consider the decision of an agricultural worker that has to choose whether to work on the fields or, alternatively, become a rebel and fight over the control of the state's resources. A negative and persistent agricultural shock (e.g., soil erosion, long-lasting pest) would reduce the returns to working the land, increasing the likelihood of conflict. However, at the same time, it would reduce the value of the economy—in the present and into the future—and, hence, the incentives to capture the state. A way to test for the opportunity cost mechanism is to look at the effect of transitory rainfall shocks or transitory rainfall-induced income shocks on civil war. Chassang and Padró i Miquel (2009) have developed a model that underscores that while transitory income shocks have a direct impact on the opportunity cost of engaging in war, the effect on the total value of the economy is orders of magnitude smaller. By definition, the transitory shock will quickly dissipate and the size of the economy in the future will go back to its pre-shock value.

Other studies examining the impact of transitory income shocks on civil war risk have focused on downfalls in international commodity prices (see Blattman and Miguel 2010, for a review), with the most recent evidence being mixed (Brückner and Ciccone 2010; Bazzi and Blattman 2014; Ciccone 2018). Because there is no empirical evidence or theoretical channel suggesting that downfalls in international commodity prices have a non-monotonic impact on income, these studies use linear specifications when examining the impact of these downfalls on civil war risk. Methodologically, this paper extends the linear panel-data approach of earlier studies examining the impact of transitory shocks (e.g., rainfall, international commodity prices) on civil war risk by allowing for non-monotonic effects.

Theoretical Framework: Economic Shocks and Civil War

The dynamic game of civil war of Chassang and Padró i Miquel (2009) predicts that these occur following sufficiently adverse transitory shocks to (agricultural) productivity. This is because transitory shocks reduce the opportunity cost of fighting without affecting the future value of the economy. In particular, they show that the most efficient subgame perfect equilibrium of their game is characterized by stationary threshold ($\tilde{\theta}$) strategies that depend only on the period's stochastic land productivity (θ_t) and where groups chose to fight if and only if $\theta_t < \tilde{\theta}$. Chassang and Padró i Miquel (2009) show further that a solution to $\tilde{\theta}$ exists whenever θ has a continuous support on $(0, +\infty)$ and a well defined expected value.[5]

In this section, I characterize the solution of an extension of the dynamic game of civil war of Chassang and Padró i Miquel (2009), where I incorporate (i) that agricultural productivity depends on rainfall as well as on other factors (e.g., agricultural technology, pests, soil erosion) and (ii) that the relationship between rainfall and agricultural productivity is hump-shaped. A full description of the extended game is provided in online appendix A. In the augmented model, sufficiently low or high rainfall shocks can reduce agricultural productivity beyond a level where war is inevitable. The intuition for this result is straightforward: as negative or positive rainfall shocks become more extreme (leading to droughts and floods) agricultural output decreases, effectively reducing the opportunity cost of fighting and increasing civil war risk.

The first extension consists of decomposing land productivity into a component that depends on rainfall (r) and another one that does not (ε):

$$\theta_t = f(r_t) + \varepsilon_t \tag{1}$$

where the relationship between rainfall and agricultural productivity is given by function f. The second extension assumes that f is hum-shaped, i.e. it is continuous, strictly positive, and strictly increasing in rainfall up to a turning point ($r^{\max} > 0$)

where it becomes strictly decreasing. Assume further that (i) r_t and ε_t have continuous support on $(0, +\infty)$ and well defined expected values and (ii) as droughts and floods are increasingly severe, rain-related agricultural productivity converges to zero, i.e. $\lim_{r\to 0} f(r) = 0$ and $\lim_{r\to\infty} f(r) = 0$.

Because the differences between the original model of Chassang and Padró i Miquel (2009) and this extension are fully summarized in equation 1, there is one-to-one mapping between the solution to the original model and the augmented one. That an equilibrium in threshold strategies $(\tilde{\theta})$ exists follows from the fact that the above assumptions guarantee that θ has a continuous support on $(0, +\infty)$ and a well defined expected value.

In equilibrium, groups fight whenever $f(r_t) + \varepsilon_t < \tilde{\theta}$. Because $f(r_t) \in (0, f(r^{\max})]$ is bounded, it follows, first, that for a sufficiently high realization of the non-rainfall agricultural productivity, i.e. $\varepsilon_t \geq \tilde{\theta}$, there is no possible (adverse) realization of $f(r_t)$ for which a war occurs. Second, that if the maximum rain-related agricultural productivity alone cannot avert war ($f(r^{\max}) < \tilde{\theta}$), and if non-rainfall agricultural productivity is sufficiently low, i.e. $0 < \varepsilon_t < \tilde{\theta} - f(r^{\max})$, there is no possible (favorable) realization of $f(r_t)$ which prevents war. Further, for intermediate values of $\varepsilon_t \in (\max\{0, \tilde{\theta} - f(r^{\max})\}, \tilde{\theta})$ there are thresholds $r_{low}(\varepsilon_t) \leq r_{high}(\varepsilon_t)$, such that war occurs whenever $r_t < r_{low}(\varepsilon_t)$ or $r_t > r_{high}(\varepsilon_t)$. These thresholds are given by the minimum and maximum solutions to $f(r_t) = \tilde{\theta} - \varepsilon_t$, respectively. That a solution to r_{low} (r_{high}) exists follows from the fact that f is continuous and strictly increasing (decreasing) in the $(0, r^{\max}]$ interval ($[r^{\max}, \infty)$ interval).

That, in equilibrium, there is a U-shaped relationship between rainfall and civil war risk follows directly from the observation that the probability of civil war, $Pr\{f(r_t) + \varepsilon_t < \tilde{\theta}\}$ is decreasing in r_t up to $r^{\max}$, after which it becomes increasing. That this U-shaped relationship mirrors the hump-shaped relationship between rainfall and agricultural productivity follows from the fact that civil war risk is minimized when the rainfall level is such that agricultural productivity is maximized.

Data

Agricultural Weather and Agricultural Output

To construct the new country-level measure of agricultural rainfall, I combine raw data on rainfall with data on growing seasons and land use in Africa. I also construct an analogous variable for agricultural temperature. The sources of the data are:

- Precipitation data (in mm) come from the Global Precipitation Climatology Project (GPCP Version 2.2) in a 2.5° latitude by 2.5° longitude global grid. The dataset combines gauge station information with satellite instruments to produce monthly rainfall estimates.[6]

- Growing season data for Africa are based on satellite images from the Advanced Very High Resolution Radiometer (AVHRR) sensor (Vrieling, De Leeuw, and Said 2013), and are available on an 8 km by 8 km grid. The sensor effectively monitors phenological changes on land surface, and allows for the detection of green-up and senescence of vegetation for every year between 1981 and 2011. Because growing seasons—whether there is just one or two within 12 months—can span more than one calendar year, data from two calendar years are used to determine the start and end of the growing season(s) each year. The dataset reports the average start and end dates of the growing season(s), over the whole sample, for each grid cell.
- Land use data come from the Land Degradation Assessment in Drylands Project (LADA Version 1.1), which indicates whether the area of any cell on a 5 by 5 arc minutes grid (approximately 9 km by 9 km at the Equator) was used for agricultural purposes in the year 2000 (Nachtergaele and Petri 2013).
- Temperature data (in $^\circ$ K) come from the National Center for Environmental Prediction and the U.S. Department of Energy (NCEP-DOE R2) in a T62 Gaussian grid.[7] The dataset combines gauge station, marine, aircraft, and satellite data, among other, using a climate model, to produce 6-hour temperature estimates.[8]

I use the data to construct country-level rainfall and temperature measures over agricultural land during the growing seasons following the agricultural economics literature (Guiteras 2009; Schlenker and Roberts 2009; Schlenker and Lobell 2010; Lobell, Schlenker, and Costa-Roberts 2011). Gridded data are mapped into political maps using country borders from Weidmann, Kuse, and Gleditsch (2010). Given that the growing seasons data is at a higher resolution than the weather data, I first construct mean growing season start and end dates for grid cells in Africa that match the resolution of the rainfall and temperature grids. For precipitation, I calculate the total amount of rainfall (in dm) during the growing season in each cell.[9] For temperature, I calculate the fraction of time (i.e., 6-hour readings) during the growing season that every cell was exposed to temperatures in the following temperature bins (in $^\circ$ C): $(-\infty, 0)$, $[0, 3)$, $[3, 6), \ldots, [36, 39)$, $[39, +\infty)$.[10] Additionally, and for the sake of comparability with previous work that controls for average temperature, I also calculate the mean temperature (in $^\circ$ C) during the growing season. I then aggregate spatially these annual data to the country level. For any given country, I first select all the cells that "touch" the country (i.e., that lie fully or partially within the country's borders). Then, for each of these cells, I calculate the amount of agricultural land from the selected country that lies within the respective cell. Aggregation is done by averaging the annual weather measurements of these cells, weighting them by their share of the country's agricultural land.

For comparability with previous work in the conflict literature, I also construct rainfall and temperature measures over countries' entire territories and during the calendar year. I term these variables aggregate rainfall and aggregate temperature, respectively. Aggregate rainfall corresponds exactly to the rainfall measure used by Miguel, Satyanath, and Sergenti (2004); the reader is referred to their paper for the details on how this variable is constructed. For temperature, the method for constructing the aggregate data is slightly different in that all cells that touch a country are used in the construction of the aggregate variable, and not just those whose centers lie within a given country. I do this for two reasons: (i) there is always some cell that touches a country, while there is not always a cell whose center lies within a country, thus, my process is discretion-free in the assignment of cells to countries and (ii) for comparability with the agricultural rainfall data.

The agricultural production data—which is at the country level—come from FAO's Statistical Division FAOSTAT. In particular, I measure agricultural production using the crops gross production index (GPI) as it is a quantity index of agricultural production (the base period is 2004-2006).

Civil War and Civil Conflict

Civil war and civil conflict data come from UCDP-PRIO's Armed Conflict Dataset (Gleditsch et al. 2002), version 4. The original dataset codes dyads made out of the government of a state and an armed group that result in at least 25 or 1,000 deaths per year for civil conflict and civil war, respectively. I construct a civil war incidence measure, at the country level, by coding a country as experiencing civil war in a given year if and only if it experienced an internal civil war (with or without foreign intervention) with at least one armed group. I, thus, exclude all dyads that involve extrasystemic (colonial) wars and interstate wars. To study the start of civil wars, I construct a civil war onset variable that is unity in period t if there was no civil war in $t-1$ but there was a civil war in t. It takes the value of zero if there was no war at $t-1$ nor at t. The civil war onset variable is not defined if a civil war was ongoing in $t-1$. Civil conflict incidence and onset variables are defined in an analogous way.

Table 1 shows that the average African country experienced civil war in 7.28% of the years during the 1981-2013 period and experienced the onset of a civil war in 2.21% of the years, the numbers are 21.54% and 5.75%, respectively, for civil conflict.

Rainfall and Agriculture

Opportunity cost theories of the link between rain and civil war in Africa are based on the premise that rainfall affects agricultural output. I therefore start by investigating the effect of agricultural rain on agricultural output. Following the agricultural economics literature, I use a quadratic specification in agricultural rainfall—which allows for a hump-shaped relationship—to approximate the conditional expectation function (CEF) of agricultural output for African countries. The quadratic specification allows the effect of rainfall increments on output to depend on the base rainfall level. Hence, increased rainfall at low levels can have a positive effect on agricultural output, while the same increment at high rainfall levels (i.e., floods) could have

Table 1. Descriptive Statistics.

	Obs	Mean	S.D.	Min	Max
Civil war incidence	1,662	0.073	0.260	0	1
Civil conflict incidence	1,662	0.215	0.411	0	1
Civil war onset	1,538	0.022	0.147	0	1
Civil conflict onset	1,305	0.057	0.233	0	1
Crops GPI†	1,650	85.306	28.307	25.190	234.520
Agg. rain (dm)	1,662	9.249	5.893	0.191	26.197
Agg. mean temp (° C)	1,662	23.431	2.740	14.357	28.238
Agri. rain (dm)	1,662	8.036	4.314	0.320	24.929
Agri. mean temp (° C)	1,662	23.133	3.435	14.672	29.900

Notes: Author's calculations, see the Data section for details on data sources and variable construction. The sample is made out of 51 African countries between 1981-2013. Aggregate (Agg.) variables summarize temporally and spatially disaggregated weather data over the entire calendar year and the totality of a country's territory. Agricultural (Agri.) variables summarize information during the growing seasons and over agricultural land. †Data on the crops gross production index (GPI) for Ethiopia between 1981 and 1992 are missing.

a negative effect. Additionally, I also report results with linear agricultural rainfall. Table 2, columns 1 to 4, presents results from OLS estimations of the following equation

$$y_{c,t} = \beta_1 rain_{c,t} + \beta_2 rain_{c,t}^2 + \gamma temp_{c,t} + \delta_c + \delta_t + t_c + \varepsilon_{c,t}, \tag{2}$$

where y is agricultural production, *rain* is agricultural rainfall, *temp* is either mean agricultural temperature or a full set of agricultural temperature bins, δ_c are country fixed-effects, δ_t are year fixed-effects, t_c are linear trends, and ε is an error term. Subscripts c and t index countries and years, respectively. The vector $[\beta_1\ \beta_2\ \gamma]$ of regression coefficients is identified exploiting (exogenous) agricultural weather variation after controlling for country fixed effects, yearly shocks common to all African countries, and country-specific linear trends. Results from column 1, where rainfall enters linearly ($\beta_2 = 0$), indicate that rainfall does not have an effect on agricultural output. Column 2, follows Guiteras (2009), Lobell, Schlenker, and Costa-Roberts (2011), Schlenker and Lobell (2010), and Schlenker and Roberts (2009) in using a quadratic relationship between agricultural output and agricultural rainfall. The results indicate that agricultural rainfall significantly affects agricultural output, both the linear and quadratic terms are significant at the 99% confidence level. At low rainfall levels, increased rain is positive for agricultural output, while the opposite is true at high levels. The significance of the quadratic term confirms the non-monotonicity of the effect of rainfall on agricultural output and rejects a linear relationship between these two variables.[11] In my sample, about 19% of the country-year observations lie on the decreasing section of the estimated relationship.

Table 2. Agricultural Production and Rainfall in Africa between 1981 and 2013.

	Agricultural Weather				Aggregate Weather			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
rain	0.883	5.380***	0.796	5.128***	0.257	4.417***	0.207	4.323***
	(0.603)	(1.217)	(0.583)	(1.173)	(0.450)	(0.997)	(0.459)	(1.018)
$rain^2$		−0.214***		−0.203***		−0.158***		−0.155***
		(0.047)		(0.046)		(0.032)		(0.031)
Observations	1,650	1,650	1,650	1,650	1,650	1,650	1,650	1,650
Obs. decreasing section (%)	n.a.	19.27	n.a.	19.21	n.a.	24.79	n.a.	25.03
Adjusted R-squared	0.822	0.828	0.826	0.831	0.819	0.824	0.823	0.827
Adjusted R-squared (p)	−0.056	−0.023	−0.033	−0.006	−0.076	−0.049	−0.052	−0.026
Mean temperature	Y	Y	N	N	Y	Y	N	N
Temp. bins	N	N	Y	Y	N	N	Y	Y

Notes: Author's calculations, see the Data section for details on data sources and variable construction. The dependent variable is the crops gross production index. Rainfall is measured in decimeters (dm). Estimation method is OLS. All regressions include country fixed-effects, year fixed-effects, and country-specific linear time trends. Robust standard errors are clustered at the country level and are presented in parentheses. The adjusted R-squared (p) is the adjusted R-squared from regressions where country fixed-effects, year fixed-effects, and country-specific linear time trends have been partialled out from all variables. Obs. decreasing section (%) refers to the percentage of the observations that lie on the decreasing section of the estimated relationship between agricultural output and rainfall. Agricultural variables summarize information during the growing seasons and over agricultural land. Aggregate weather variables summarize temporally and spatially disaggregated weather data over the entire calendar year and the totality of a country's territory. Significance: ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.

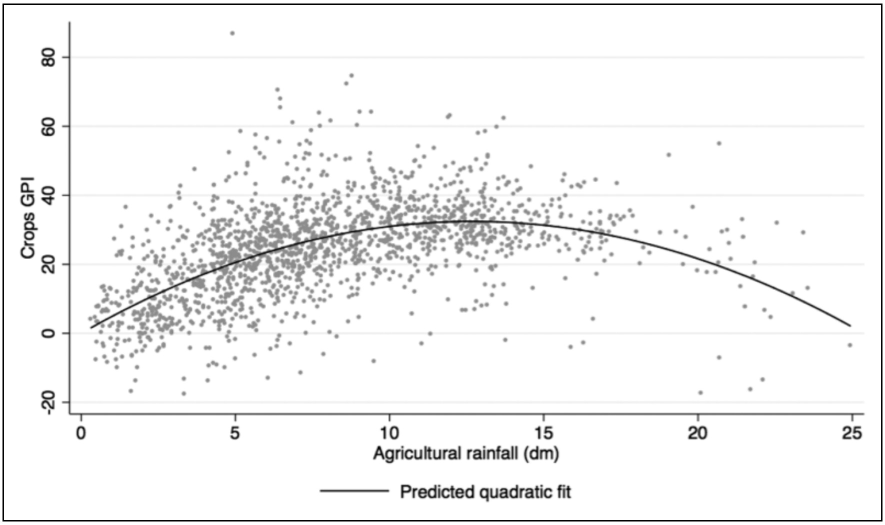

Figure 1. Agricultural output and agricultural rainfall.

Notes: Author's calculations, see the Data section for details on data sources and variable construction. The graph shows an augmented component-plus-residual plot of the relationship between agricultural output and agricultural rainfall. The underlying regression corresponds to the specification in column 4 of Table 2.

Columns 3 and 4 in Table 2 replace mean agricultural temperature with a full set of agricultural temperature bins so as to control for temperature more flexibly. The adjusted R^2 for the quadratic specification with the temperature bins controls (column 4) is larger than the one controlling for mean temperature (column 2). The effect of agricultural rain on agricultural output remains qualitatively and quantitatively the same. In what follows I only report results that flexibly control for temperature and relegate results controlling for average temperature to the online appendix.

Figure 1 illustrates the hump-shaped relationship between agricultural rain and agricultural output in an augmented component-plus-residuals plot. It depicts the fitted values of agricultural output (as predicted by linear and quadratic agricultural rain) from OLS estimation of equation 2 plus the residuals, against agricultural rainfall. In the construction of the augmented component-plus-residuals plot, the estimation of equation 2 takes *temp* to be the full set of agricultural temperature bins.[12]

Columns 5 to 8 in Table 2 estimate columns 1 to 4 using aggregate weather variables instead of agricultural weather variables. It is worth noting that the adjusted R^2s are always larger in the regressions that use agricultural weather variables. Moreover, in the quadratic specification with temperature bins, in columns 4 and 8, the share of the residual variation in agricultural output—after controlling for country fixed effects, year fixed-effects, and linear trends—that is explained by agricultural weather variables alone (R^2 (p)) is over four times larger than that explained by aggregate weather variables. This is what one would expect if the use of rainfall data from outside the growing season and from places where little or nothing is grown adds measurement error to the aggregate rainfall measure. As shown in Table OA.II in the online appendix, the hump-shaped relationship between agricultural output and agricultural rainfall holds for Sub-Saharan Africa (SSA) also.

Theory only predicts an unambiguous negative effect of adverse rainfall shocks or rain-induced income shocks, when these are transitory (Chassang and Padró i Miquel 2009). To test if agricultural rainfall shocks are indeed short-lived, I estimate a modified version of equation 2, augmented with once-lagged weather variables. Lagged agricultural rainfall is never significant, whether one controls for mean temperature or a full set of temperature bins (results are presented in the online appendix Table OA.III).

Rainfall and Civil War

The section above has provided evidence, supporting previous work in agricultural economics, showing that (i) agricultural rainfall is a better predictor of agricultural output than aggregate rainfall, and (ii) transitory agricultural rainfall shocks have non-monotonic effects on agricultural output. Additionally, Table 2 showed that a linear specification relating agricultural rainfall to agricultural output masks this relationship. These pieces of evidence beg the question of whether previous inconclusive findings relating rainfall to civil war are due to a true no-effect (i.e., civil war risk being independent of rainfall in a statistical sense) or a combination of mismeasurement and misspecification.[13]

Empirical Strategy

To estimate the effect of agricultural rainfall shocks on civil war onset (*war*), I relate the latter to a linear and quadratic term in agricultural rain, some measure of agricultural temperature (either mean agricultural temperature or a full set of agricultural temperature bins), country fixed-effects, year fixed-effects, country-specific linear trends, and an error term. This specification (equation 3) allows rainfall and civil war to have a U-shaped relationship, mirroring the hump-shaped relationship between rainfall and agricultural output.

$$war_{c,t} = \beta_1 rain_{c,t} + \beta_2 rain^2_{c,t} + \gamma temp_{c,t} + \delta_c + \delta_t + t_c + \varepsilon_{c,t} \qquad (3)$$

The coefficients of interest are β_1 and β_2, and these are identified out of the (exogenous) rainfall variation, after controlling for time-invariant country differences, shocks common to all countries in a given year, country-specific linear trends, and temperature. $\beta_1 < 0$ and $\beta_2 > 0$ would be consistent with the opportunity cost mechanism, whereby decreased agricultural production, either due to droughts or excess rain, leads to increased civil war outbreak risk.

To study the effect of agricultural rainfall shocks on civil war incidence, I relate this variable to all the independent variables in equation 3. Additionally, and to account for the fact that civil wars tend to be persistent events, I also control for lagged civil war incidence—note that, by construction, civil war onset is not persistent. Again, a negative β_1 and a positive β_2 would be consistent with the theoretical effects of rainfall shocks on civil war.

The effect of agricultural rainfall shocks on civil conflict onset and incidence risk is estimated in an analogous way.

Estimates of the Effect of Agricultural Rainfall Shocks on Civil War and Civil Conflict

Column 1, in (panel A) Table 3, reports the OLS estimates of the effect of agricultural rainfall shocks on civil war onset risk for Africa (1981-2013) using a quadratic specification. Robust standard errors clustered at the country level are presented in parenthesis. Both the linear and quadratic agricultural rainfall coefficients are significant at the 95% confidence level—with $\beta_1 < 0$ and $\beta_2 > 0$—evidencing a U-shaped relationship between civil war onset risk and agricultural rainfall shocks. Column 2 presents the estimates of a modified version of equation 3, where the quadratic agricultural rainfall term has been eliminated. Linear agricultural rain is not significantly related to civil war onset. This result comes as no surprise, if agricultural rain has non-monotonic effects on agricultural output and it, in turn, affects civil war risk; using a linear specification will mask the link between agricultural rain and both agricultural output (as shown in the section above) and civil war. Column 3 presents estimates from regressions using agricultural rainfall growth rates for comparison with previous work in the conflict literature. Again, the results are of the no-effect type.

Panel a, in Figure 2, illustrates the quadratic, U-shaped relationship between civil war onset risk and agricultural rainfall in an augmented component-plus-residuals plot. It depicts the fitted values of civil war onset risk (as predicted by linear and quadratic agricultural rain) from OLS estimation of equation 3 plus the residuals, against agricultural rainfall.[14]

Columns 4 to 6 and 7 to 9, in (panel A) Table 3, replicate the analysis in columns 1 to 3, but for SSA between 1981-1999 and 1981-2013, respectively. The first of these samples corresponds to the one analyzed by Miguel, Satyanath, and Sergenti (2004) and the second one to an updated version of it. While I find no effect of linear agricultural rainfall or agricultural rainfall growth on civil war onset risk, I find that a more flexible specification—the quadratic—uncovers a significant relationship between agricultural rainfall and civil war onset risk in SSA.

The U-shaped relationship implies that the quantitative effect of agricultural rainfall on civil war onset risk depends on the baseline level of rainfall. A negative rainfall shock that takes a country from the 50th to the 25th percentile of the distribution of agricultural rainfall increases the risk of civil war onset in Africa (1981-2013), SSA (1981-1999), and SSA (1981-2013) by 2.2, 3.1, and 2.3 percentage

Table 3. The Effect of Agricultural Rainfall on Civil War Onset and Incidence Risk.

	Africa 1981-2013			SSA 1981-1999			SSA 1981-2013		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Panel A: Civil war onset									
rain	−0.237**	0.021		−0.439**	0.035		−0.296**	0.023	
	(0.107)	(0.040)		(0.221)	(0.069)		(0.131)	(0.051)	
$rain^2$	0.012**			0.022**			0.014**		
	(0.006)			(0.010)			(0.006)		
rain growth			0.110			0.047			0.143
			(0.079)			(0.171)			(0.105)
Observations	1,538	1,538	1,536	662	662	662	1,228	1,228	1,227
Panel B: Civil war incidence									
rain	−0.239**	0.015		−0.456*	−0.019		−0.312**	0.022	
	(0.120)	(0.047)		(0.242)	(0.076)		(0.148)	(0.058)	
$rain^2$	0.012**			0.021**			0.015**		
	(0.006)			(0.010)			(0.007)		
rain growth			0.143			−0.240			0.112
			(0.098)			(0.223)			(0.128)
lagged dep. variable	0.369***	0.370***	0.370***	0.185**	0.186**	0.186**	0.338***	0.341***	0.341***
	(0.073)	(0.072)	(0.072)	(0.073)	(0.075)	(0.074)	(0.070)	(0.070)	(0.070)
Observations	1,660	1,660	1,660	743	743	743	1,343	1,343	1,343
Agricultural temp. bins	Y	Y	Y	Y	Y	Y	Y	Y	Y

Notes: Author's calculations, see the Data section for details on data sources and variable construction. Rainfall is measured in meters (m). Estimation method is OLS. All regressions include country fixed-effects, year fixed-effects, and country-specific linear time trends. Robust standard errors are clustered at the country level and are presented in parentheses. Agricultural variables summarize information during the growing seasons and over agricultural land. Columns 4 to 6 correspond to the sample used in Miguel, Satyanath, and Sergenti (2004) with the only difference being that these regressions treat rainfall for Namibia in 1989 as a missing value—the country obtained its independence only in 1990. Columns 7 to 9 correspond to the same set of countries as in Miguel, Satyanath, and Sergenti (2004), but extend the sample up to 2013. Significance: ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.

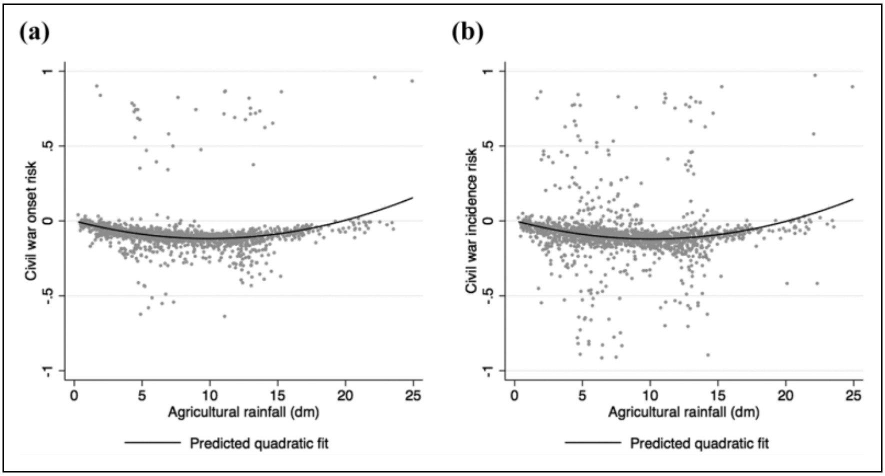

Figure 2. Civil war onset and incidence risk and agricultural rainfall. (a) Civil war onset. (b) Civil war incidence.

Notes: Author's calculations, see the Data section for details on data sources and variable construction. Panel a (b) shows an augmented component-plus-residual plot of the relationship between civil war onset (incidence) and agricultural rainfall. The underlying regression corresponds to the specification in column 1, panel A (B), of Table 3.

points, respectively. A positive shock that takes a country from the 50th to the 75th percentile of the distribution of agricultural rainfall decreases the risk of the outbreak of civil war by 0.6, 0.1, and 0.8 percentage points, in the respective samples. Nevertheless, large enough positive shocks increase civil war onset risk. Going from the 50th to the 90th percentile of the distribution of agricultural rainfall increases the risk of civil war outbreak by 1, 2.8 and 0.6 percentage points, respectively.

Column 1, in (panel B) Table 3, reports the OLS estimates of the effect of agricultural rainfall shocks on civil war incidence risk for Africa (1981-2013) using a quadratic specification. Again, both the linear and quadratic agricultural rainfall coefficients are significant at the 95% confidence level—with $\beta_1 < 0$ and $\beta_2 > 0$—evidencing a U-shaped relationship between civil war incidence risk and agricultural rainfall shocks. This quadratic relationship is illustrated in in Panel b, in Figure 2, by means of an augmented component-plus-residuals plot.[15] Column 2 and column 3 present results from specifications using linear agricultural rainfall ($\beta_2 = 0$) and agricultural rainfall growth. Once again, neither linear agricultural rainfall nor agricultural rainfall growth are significantly related to civil war onset risk. The (quadratic) relationship between agricultural rainfall and civil war onset risk is qualitatively similar in SSA for the 1981-1999 period and the 1981-2013 period.

Quantitatively, a negative rainfall shock that takes a country from the 50th to the 25th percentile of the distribution of agricultural rainfall increases the risk of civil war incidence in Africa (1981-2013), SSA (1981-1999), and SSA (1981-

2013) by 2.3, 3.9, and 2.4 percentage points, respectively. A positive shock that takes a country from the 50th to the 75th percentile of the distribution of agricultural rainfall decreases the risk of civil war incidence by 0.8, 1.5, and 0.8 percentage points, in the respective samples. However, large enough positive shocks increase civil war incidence risk. Going from the 50th to the 90th percentile of the distribution of agricultural rainfall increases the risk of civil war incidence by 0.7, 0.3 and 0.7 percentage points, respectively. The quantitative effect of agricultural rainfall on civil war onset and incidence risk, for all three samples and for a larger combination of rainfall shocks, is presented in online appendix Table OA.VII.

Table 4, presents the same analysis as Table 3 but for civil conflict. Panel A shows that, unlike the results for civil war onset, agricultural rainfall shocks are not significantly related to the start of conflicts that do not exceed the 1,000 deaths threshold. Panel B presents the estimates of the effect of agricultural rainfall on civil conflict incidence. The results largely mimic those for civil war incidence, indicating that agricultural rainfall shocks not only have non-monotonic effects on the incidence of fully fledged war, but also on the incidence of smaller scaled conflicts. The quantitative effect of agricultural rainfall on civil conflict onset and incidence risk, for all three samples and for a larger combination of rainfall shocks, is presented in online appendix Table A.VIII.

The estimated hump-shaped relationship between agricultural rainfall and agricultural output implies the existence of a turning point beyond which extra rainfall decreases agricultural output. Similarly, the estimated U-shaped relationships between agricultural rainfall and civil war and civil conflict imply the existence of turning points beyond which extra rainfall increases civil war and civil conflict risk. Importantly, when equations 2 and 3, for civil war incidence and onset and civil conflict incidence, are estimated in a seemingly unrelated regression (SUR) framework, I cannot reject the joint, null hypothesis that the estimated turning points from civil war and civil conflict regressions are the same as the turning point in the agricultural output regression at the 95% confidence level, for Africa (1981-2013), SSA (1981-1999), or SSA (1981-2013).[16]

The equivalents of Tables 3 and 4 using aggregate rainfall data are presented in Tables B.I and B.II, respectively, in the Appendix. When using the aggregate rainfall measure instead of the agricultural one, I find a quantitatively similar U-shape relationship with the risk of civil war onset and incidence, albeit the statistical fit worsens. However, while there is a significant U-shaped relationship between agricultural rainfall and the risk of civil conflict incidence, one cannot reject the hypothesis of no-relationship when using aggregate rainfall data.[17]

Conclusions

Policymakers and the media around the world have associated crop failures caused by droughts to civil war and conflict in African countries. However, empirical work on the effect of adverse rainfall shocks on African civil wars and conflicts has been inconclusive. I argue that to better understand whether rainfall shocks affect the risk of

Table 4. The Effect of Agricultural Rainfall on Civil Conflict Onset and Incidence Risk.

	Africa 1981-2013			SSA 1981-1999			SSA 1981-2013		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Panel A: Civil conflict onset									
rain	−0.002	−0.044		−0.022	−0.038		−0.091	−0.070	
	(0.127)	(0.047)		(0.172)	(0.077)		(0.152)	(0.058)	
rain^2	−0.002			−0.001			0.001		
	(0.005)			(0.008)			(0.005)		
rain growth			−0.124			0.025			−0.253
			(0.209)			(0.285)			(0.313)
Observations	1,305	1,305	1,303	575	575	575	1,032	1,032	1,031
Panel B: Civil conflict incidence									
rain	−0.316**	−0.036		−0.417*	−0.131		−0.433**	−0.047	
	(0.154)	(0.082)		(0.237)	(0.104)		(0.192)	(0.104)	
rain^2	0.013*			0.014			0.017**		
	(0.008)			(0.009)			(0.008)		
rain growth			−0.281			−0.625*			−0.488*
			(0.205)	–		(0.334)			(0.282)
lagged dep. variable	0.386***	0.389***	0.389***	0.076	0.078	0.078	0.373***	0.378***	0.378***
	(0.055)	(0.056)	(0.056)	(0.073)	(0.073)	(0.073)	(0.056)	(0.059)	(0.059)
Observations	1,660	1,660	1,660	743	743	743	1,343	1,343	1,343
Agricultural temp. bins	Y	Y	Y	Y	Y	Y	Y	Y	Y

Notes: Author's calculations, see the Data section for details on data sources and variable construction. Rainfall is measured in meters (m). Estimation method is OLS. All regressions include country fixed-effects, year fixed-effects, and country-specific linear time trends. Robust standard errors are clustered at the country level and are presented in parentheses. Agricultural variables summarize information during the growing seasons and over agricultural land. Columns 4 to 6 correspond to the sample used in Miguel, Satyanath, and Sergenti (2004) with the only difference being that these regressions treat rainfall for Namibia in 1989 as a missing value—the country obtained its independence only in 1990. Columns 7 to 9 correspond to the same set of countries as in Miguel, Satyanath, and Sergenti (2004), but extend the sample up to 2013. Significance: ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.

civil war and conflict through agricultural productivity, it is useful to first examine the effect of rainfall shocks on agricultural output. Following recent work in agricultural economics, I relate the agricultural output of African countries to rainfall over agricultural land during the growing seasons and allow for a hump-shaped effect of rainfall. This yields a robust, hump-shaped relationship between rainfall and agricultural output. Hence, increases in rainfall raise agricultural output at low levels and decrease agricultural output at high levels. If rainfall affects civil war and conflict through its effect on agricultural productivity, the effect of rainfall on the risk of civil war and conflict should therefore be U-shaped. I find this to be the case. Hence, increases in rainfall lower the risk of civil war and conflict at low levels and raise the risk of war and conflict at high levels. In particular, I find that a negative rainfall shock that takes a country from the 50th to the 25th percentile of the distribution of agricultural rainfall increases the risk of civil war onset and incidence in Africa by 2.2 and 2.3 percentage points, respectively. A positive shock that takes a country from the 50th to the 75th percentile of the distribution of agricultural rainfall decreases the risk of civil war onset and incidence by 0.6 and 0.8 percentage points, respectively. However, large enough positive shocks have the opposite effect, increasing civil war onset and incidence risk. Going from the 50th to the 90th percentile of the distribution of agricultural rainfall increases the risk of civil war onset and incidence by 1 and 0.7 percentage points, respectively. The effect of rainfall on civil war onset and incidence risk is qualitatively the same for Sub-Saharan African countries. These results resonate with a recent literature that has linked rainfall shocks to other *local* forms of political violence and inform the policy debate on the effects of adverse rainfall shocks, in general, and climate change, in particular.

Appendix

A. The Model: Economic Shocks and Civil War

In this appendix, I present an extension of the dynamic model of civil war of Chassang and Padró i Miquel (2009) where, in equilibrium, civil wars occur following sufficiently low or high rainfall shocks.

There are two groups $i \in 1, 2$, each initially controlling one unit of land of a shared territory of size 2.[18] In each period ($t = 1, 2, 3...$), each group controls one unit of labor which can be used to produce crops or to launch an attack aimed at seizing the neighbor's land and production. Crops are produced according to the following production function:

$$c(\theta_t, L_t, l_t) = \theta_t L_t l_t \tag{1}$$

where L is the amount of land controlled at the beginning of the period, l is the amount of labor used for crop production, and θ is land productivity. I, first, augment the original model of Chassang and Padró i Miquel (2009) by decomposing land productivity into a component that depends on rainfall (r) and another one that does not (ε):

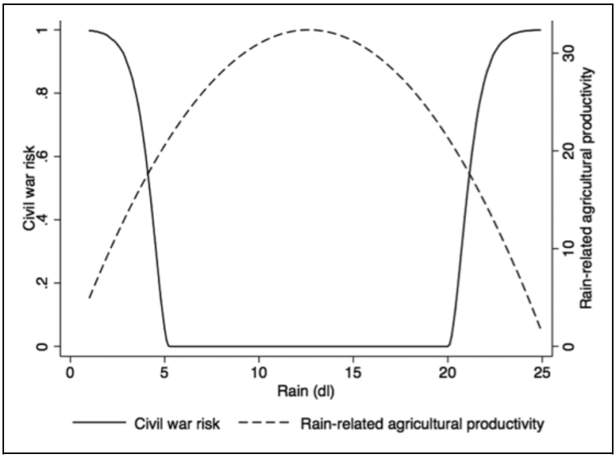

Figure A.1. Rainfall, agricultural productivity, and civil war risk in a dynamic model of civil war.
Notes: Author's calculations based on equilibrium strategies in the augmented, dynamic model of civil war of Chassang and Padró i Miquel (2009).

$$\theta_t = f(r_t) + \varepsilon_t \tag{2}$$

where the relationship between rainfall and agricultural productivity is given by function f. In addition, following the agricultural economics literature, assume that f is hum-shaped, i.e. it is continuous, strictly positive, and strictly increasing in rainfall up to a turning point ($r^{\max} > 0$) where it becomes strictly decreasing. Assume further that, as droughts and floods are increasingly severe, rain-related agricultural productivity converges to zero, i.e. $\lim_{r\to 0} f(r) = 0$ and $\lim_{r\to\infty} f(r) = 0$.

At the beginning of each period r_t and ε_t are drawn independently according to well defined cumulative distributions with continuous support on $(0, +\infty)$ and with well defined expected values. These draws are common knowledge, which implies that the period's land productivity (θ_t) is also common knowledge.

Groups seek to maximize the present discounted value of crop consumption:

$$U = \sum_{t=1}^{\infty} \delta^t c_t \tag{3}$$

where $\delta \in (0, 1)$ is a discount factor.

If a group unilaterally launches an attack, it obtains an offensive advantage and wins with probability $p > 0.5$. If both groups launch attacks there is a symmetric war where each group wins with probability $p = 0.5$. In case of conflict, both groups divert $k \in (0, 1]$ units of labor from production to fight. If war occurs, the game ends, the winning group seizes the opponent's production from that period ($\theta_t(1 - k)$) as well as their land, which is used for future production. The defeated group obtains a payoff of zero for the rest of the game.

In their model, Chassang and Padró i Miquel (2009) show that the most efficient subgame perfect equilibrium of this game (in terms of reducing the probability of a war) is characterized by stationary threshold strategies that depend only on the period's land productivity and where groups chose to fight if and only if $\theta_t < \tilde{\theta}$. Chassang and Padró i Miquel (2009) note, however, that when the offensive advantage is sufficiently high, $p > 1/(2(1-k))$, there is no equilibrium that avoids war in the first period. I focus here on the case where $p < 1/(2(1-k))$, which allows examining the role of rainfall-induced productivity shocks on civil war risk.

Because the differences between the original model of Chassang and Padró i Miquel (2009) and this extension are fully summarized in Appendix equation 2, there is one-to-one mapping between the solution to the original model and the augmented one. To determine whether the threshold for the most efficient subgame perfect equilibrium ($\tilde{\theta}$) exists in the augmented model, it suffices to examine whether θ has a continuous support on $(0, +\infty)$ and a well defined expected value. That θ has a continuous support on $(0, +\infty)$ follows directly from the fact that the distribution of $f(r_t)$ has continuous support on $(0, f(r^{\max})]$, that the distribution of ε has continuous support on $(0, +\infty)$, so that the distribution of the sum of these variables will have continuous support on $(0, +\infty)$.[19] It is straightforward to see that θ has a well-defined expected value as f is bounded and ε has a well defined expected value by assumption.

The equilibrium solution of this extended game is presented in Theoretical Framework: Economic Shocks and Civil War section.

For illustration purposes, I next parametrize the augmented model described above, solve numerically for $\tilde{\theta}$, and plot the probability of civil war risk, as a function of rainfall only, by integrating numerically over the distribution of ε. Assume that rainfall realizations follow a Gamma distribution with a shape parameter of 2.5 and scale parameter of 3.8, where these numbers were chosen to fit the mean and variance of the distribution of rainfall for African countries (1981-2013). The non-rainfall agricultural productivity shock also follows a Gamma distribution with shape and scale parameters equal to 2. The hump-shaped relationship between rainfall and agricultural productivity is parametrized as a quadratic function $f(r_t) = 5.128r_t - 0.203r_t^2$ based on estimates from Rainfall and Agriculture section.[20] Under these assumptions, θ has a mean of 27.5 units of agricultural productivity.[21] The discount factor (δ) is 0.8, the offensive advantage (p) is 0.55, and labor that's used for war (k) is 0.8. Solving for the equilibrium threshold numerically, I obtain $\tilde{\theta} = 21.3$, so that war occurs whenever agricultural productivity is about 23% below its mean value. Given the equilibrium strategies, one can calculate the probability of civil war, for any rainfall value, by integrating over ε, which is plotted in Figure A.1 (left axis). The figure also shows rain-related agricultural productivity (f) as a function of rainfall (right axis). As expected, the hump-shaped relationship between rainfall and rain-related agricultural productivity is mirrored by a U-shaped relationship between rainfall and civil war risk: at low rainfall levels, more rainfall increases rain-related agricultural productivity and reduces civil war risk, while the converse is true at high rainfall levels.

Table B.I. The Effect of Aggregate Rainfall on Civil War Onset and Incidence Risk.

	Africa 1981-2013			SSA 1981-1999			SSA 1981-2013		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Panel A: Civil war onset									
rain	−0.214**	−0.004		−0.309**	0.038		−0.306***	0.001	
	(0.090)	(0.035)		(0.127)	(0.053)		(0.110)	(0.046)	
rain^2	0.008**			0.013**			0.011***		
	(0.004)			(0.006)			(0.004)		
rain growth			0.005			−0.006			−0.115
			(0.143)			(0.167)			(0.204)
Observations	1,538	1,538	1,536	662	662	662	1,228	1,228	1,227
Panel B: Civil war incidence									
rain	−0.204**	−0.008		−0.399**	−0.008		−0.305**	−0.000	
	(0.103)	(0.037)		(0.176)	(0.059)		(0.131)	(0.053)	
rain^2	0.007*			0.015**			0.011**		
	(0.004)			(0.006)			(0.005)		
rain growth			0.036			−0.174			−0.130
			(0.171)			(0.284)			(0.251)
lagged dep. variable	0.370***	0.372***	0.372***	0.181**	0.179**	0.179**	0.340***	0.342***	0.342***
	(0.074)	(0.074)	(0.074)	(0.076)	(0.078)	(0.077)	(0.072)	(0.072)	(0.072)
Observations	1,660	1,660	1,660	743	743	743	1,343	1,343	1,343
Aggregate temp. bins	Y	Y	Y	Y	Y	Y	Y	Y	Y

Notes: Author's calculations, see the Data section for details on data sources and variable construction. Rainfall is measured in meters (m). Estimation method is OLS. All regressions include country fixed-effects, year fixed-effects, and country-specific linear time trends. Robust standard errors are clustered at the country level and are presented in parentheses. Columns 4 to 6 correspond to the sample used in Miguel, Satyanath, and Sergenti (2004) with the only difference being that these regressions treat rainfall for Namibia in 1989 as a missing value—the country obtained its independence only in 1990. Columns 7 to 9 correspond to the same set of countries as in Miguel, Satyanath, and Sergenti (2004), but extend the sample up to 2013. Significance: ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.

Table B.II. The Effect of Aggregate Rainfall on Civil Conflict Onset and Incidence Risk.

	Africa 1981-2013			SSA 1981-1999			SSA 1981-2013		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Panel A: Civil conflict onset									
rain	−0.044	−0.021		0.061	−0.004		0.035	−0.020	
	(0.109)	(0.042)		(0.200)	(0.064)		(0.155)	(0.053)	
$rain^2$	−0.002			−0.003			−0.002		
	(0.004)			(0.006)			(0.005)		
rain growth			0.223			0.299			0.399
			(0.187)			(0.398)			(0.293)
Observations	1,305	1,305	1,303	575	575	575	1,032	1,032	1,031
Panel B: Civil conflict incidence									
rain	−0.164	0.032		−0.229	0.049		−0.283	0.047	
	(0.151)	(0.058)		(0.261)	(0.082)		(0.199)	(0.074)	
$rain^2$	0.007			0.011			0.012*		
	(0.006)			(0.009)			(0.007)		
rain growth			0.206			0.032			0.161
			(0.254)			(0.424)			(0.380)
lagged dep. variable	0.382***	0.384***	0.384***	0.077	0.082	0.082	0.370***	0.373***	0.374***
	(0.056)	(0.056)	(0.057)	(0.074)	(0.074)	(0.075)	(0.057)	(0.058)	(0.059)
Observations	1,660	1,660	1,660	743	743	743	1,343	1,343	1,343
Aggregate temp. bins	Y	Y	Y	Y	Y	Y	Y	Y	Y

Notes: Author's calculations, see the Data section for details on data sources and variable construction. Rainfall is measured in meters (m). Estimation method is OLS. All regressions include country fixed-effects, year fixed-effects, and country-specific linear time trends. Robust standard errors are clustered at the country level and are presented in parentheses. Columns 4 to 6 correspond to the sample used in Miguel, Satyanath, and Sergenti (2004) with the only difference being that these regressions treat rainfall for Namibia in 1989 as a missing value—the country obtained its independence only in 1990. Columns 7 to 9 correspond to the same set of countries as in Miguel, Satyanath, and Sergenti (2004), but extend the sample up to 2013. Significance: ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.

Author's Note

The author is now affiliated with Amazon, Seattle, WA, USA. This paper was written before the author joined Amazon.

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Supplemental Material

Supplemental material for this article is available online.

Notes

1. The Food and Agriculture Organization (FAO) defines growing seasons as time periods when temperature and soil moisture allow for crop growth (Fischer et al. 2012).
2. Monthly satellite rainfall data are available since 1979. However, because data from two calendar years are needed to measure rainfall during the growing season, agricultural rainfall data are available starting in 1980.
3. Guiteras (2009) measures rainfall in Indian districts during the growing season but does not take into account land use.
4. A comprehensive review of the theoretical literature on the causes of civil wars is beyond the scope of this paper. The reader is referred to Blattman and Miguel (2010) and Sambanis (2002).
5. Chassang and Padró i Miquel (2009) note, however, that under certain model parametrization there is no equilibrium that avoids war in the first period (see Appendix A). I focus here on the case where peace can be at least temporarily attained, which allows one to examine the role of rainfall-induced productivity shocks on civil war risk.
6. Miguel, Satyanath, and Sergenti (2004) use this same rainfall dataset. The reader is referred to their paper for an introduction to the data and to Adler et al. (2003) for a technical discussion.

7. The T62 Gaussian grid is made out of 192 point along each parallel and 94 points along each meridian. Points are equally spaced along the longitude dimension at a distance of 1.875°, and unequally spaced along the latitude dimension at a distance of approximately 1.904°—with the spacing becoming (marginally) smaller as one approaches the poles.
8. The reader is referred to Kalnay et al. (1996) for an introduction to the data set and Kanamitsu et al. (2002) for a description of the latest improvements to the data. This data set also provides 6-hour estimates for precipitation, but I do not use them in this paper because of reliability problems (see Kalnay et al. (1996, 448))—which are not present in the temperature data.
9. For example, if the average growing season start and end months in a grid-cell are June and September, respectively, for each calendar year, rainfall is aggregated between those months in the same calendar year. When growing seasons span different calendar years (e.g., starts in November and ends in March), for each calendar year, rainfall is aggregated between the start month of the previous calendar year and the end month of the corresponding calendar year.
10. I do this following the agricultural economics literature that has highlighted the need to exploit high-frequency temporal variation in the study of the effect of temperature on agricultural yields. As Schlenker and Roberts (2009, 15594) put it "... similar average temperatures may arise from two very different days, one with little temperature variation and one with wide temperature variation. Holding the average temperature constant, days with more variation will include more exposure to extreme outcomes, which can critically influence yields."
11. In the online appendix Table OA.I, I also compare the quadratic specification to several other parametric specifications that have been used in the conflict literature. The quadratic specification always has a higher explanatory power in terms of adjusted R^2.
12. See Ashraf and Galor (2013), Ashraf and Michalopoulos (2015), Duranton, Morrow, and Turner (2014), and Liebman, Katz, and King (2004) for other applications of augmented component-plus-residuals plots and Mallows (1986) for a general discussion. Standard partial residual plots of agricultural output on linear and quadratic agricultural rainfall terms are presented in Figure OA.1a-b in the online appendix.
13. The non-conclusive findings using aggregate rainfall are also true in my data as I show in the online appendix Tables OA.IV, OA.V, and OA.VI.
14. Standard partial residual plots of civil war onset risk on linear and quadratic agricultural rainfall terms are presented in Figure OA.2a-b in the online appendix.
15. Standard partial residual plots of civil war incidence risk on linear and quadratic agricultural rainfall terms are presented in Figure OA.2c-d in the online appendix.
16. Standard errors for each regression are clustered at the country level. The p-values for the joint, null hypotheses for Africa (1981-2013), SSA (1981-1999), and SSA (1981-2013) are 0.072, 0.051, and 0.104, respectively. I do not include civil conflict onset estimates in the multiple-hypotheses test because linear and quadratic agricultural rainfall are not significant in any of the samples.
17. The equivalents of Tables 3 and 4, controlling for average temperature instead of the flexible set of temperature bins can be found in the online appendix Tables OA.IX and OA.X. All results remain qualitatively the same.

18. Chassang and Padró i Miquel (2009) show that the parameter space where war is inevitable in a model with equal land holdings and no bargaining is the same as the one where war is inevitable in a model with unequal land holdings but where land transfers are possible through bargaining. Because of this, I focus on the case of equal land holdings without bargaining.
19. Note that the probability density function (pfd) of θ is the convolution of the pdf of $f(r)$ and ε.
20. The quadratic parametrization implies that $f(r_t) < 0$ for $r_t > 5.128/0.203$. Since f ought to be positive, f is truncated at zero.
21. Mean was calculated based on 10,000 draws of $f(r)$ and ε.

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