Adverse rainfall shocks and civil war: Myth or reality?*

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Abstract

News reports and policy makers 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.

1 Introduction

According to a recent BBC news report, "Ethiopia has suffered periodic droughts and famines that lead to a long civil conflict in the 20^{th} 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

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Barack Obama linked the 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 et al., 2004; Burke et al., 2009; Ciccone, 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 as agricultural output should be unaffected by rainfall before planting, after harvest, or in places where little or nothing is grown. In addition, my approach takes into account the evidence in agricultural economics that the relationship between rainfall and agricultural output is hump-shaped, with rainfall beyond a threshold decreasing output (Guiteras, 2009; Lobell et al., 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 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

[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.

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 conflict or war depends on the base level of rainfall.

I find that a negative rainfall shock that takes a country from the 50^{th} to the 25^{th} 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 50^{th} to the 75^{th} 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 50^{th} to the 90^{th} percentile of the distribution of agricultural rainfall increases the risk of civil war onset and incidence by 1 and 0.7 percentage points, respectively. I also find a robust, U-shaped relationship between agricultural rainfall and the risk of civil conflict incidence. Moreover, the effect of rainfall on civil war and civil conflict 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).

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 et al. (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, pp. 168-619). Civil war is defined as a civil conflict with more than a 1000 deaths per year. An attractive feature of the panel-data approach by Miguel et al. (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 et al. (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 et al., 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 intergroup violent events at the local level. For Africa, between 1960 and 2004,

[3]Guiteras (2009) measures rainfall in Indian districts during the growing season but does not take into account land use.

Theisen et al. (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 La Ferrara (2013) 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 La Ferrara (2013) at the local level. Outside the African context, my paper relates to a recent study by Crost et al. (2015) 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

[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).

cost mechanism is to look at the effect of 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. All in all, theory predicts that following adverse transitory rainfall shocks in agricultural economies one should observe an increased risk of civil war.

The remainder of the paper is structured as follows. Section 2 introduces the data and discusses the construction of the agriculture-relevant rainfall measure. Section 3 draws from the agricultural economics literature to inform the mapping from rainfall onto agricultural output and civil war. Section 4 outlines the empirical strategy and presents the main results. Section 5 concludes.

2 Data

2.1 Agricultural weather and agricultural output data

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:

- The 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.[5]
- The growing season data for Africa come from a new data set, on an 8 km by 8 km grid, based on satellite images from the Advanced Very High Resolution Radiometer (AVHRR) sensor (Vrieling et al., 2013). 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

[5]Miguel et al. (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.

and end dates of the growing season(s), over the whole sample, for each grid cell.

- The 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 9km by 9 km at the Equator) was used for agricultural purposes in the year 2000 (Nachtergaele and Petri, 2013).
- The temperature data (in °K) come from the National Center for Environmental Prediction and the U.S. Department of Energy (NCEP-DOE R2) in a T62 Gaussian grid.[6] The dataset combines gauge station, marine, aircraft, and satellite data, among other, using a climate model, to produce 6-hour temperature estimates.[7]

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 et al., 2011). Gridded data are mapped into political maps using country borders from Weidmann et al. (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.[8] 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 °C): $(-\infty, 0)$, $[0, 3)$, $[3, 6)$, ..., $[36, 39)$, $[39, +\infty)$.[9] Additionally, and for the sake of comparability with previous work that controls for average temperature, I also calculate the mean temperature

[6]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.

[7]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, p. 448)) – which are not present in the temperature data.

[8]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.

[9]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.

(in °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 a 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 et al. (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. (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).

2.2 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 (see section above). The original dataset codes dyads made out of the government of a state and an armed group that result in at least 25 or 1000 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

As Schlenker and Roberts (2009, p. 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."

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.

[Insert Table1 about here]

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

$$y_{c,t} = \beta_1 rain_{c,t} + \beta_2 rain^2_{c,t} + \gamma temp_{c,t} + \delta_c + \delta_t + t_c + \epsilon_{c,t}, \qquad (1)$$

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 has no effect on agricultural output. Column 2, follows Guiteras (2009), Lobell et al. (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 high 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.[10] In my sample, about 19% of the country-year observations lie on the decreasing section of the estimated relationship.

[Insert Table 2 about here]

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 appendix.

[Insert Figure 1 about here]

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 1 plus the residuals, against agricultural rainfall. In the construction of the augmented component-plus-residuals plot, the estimation of equation 1 takes *temp* to be the full set of agricultural temperature bins.[11]

Columns 5-8 in Table 2 estimate columns 1-4 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

[10] In Table OA1 in the online appendix, 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.

[11] See Ashraf and Galor (2013), Ashraf and Michalopoulos (2013), Duranton et al. (2014), and Liebman et al. (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 A1(a)-A1(b) in the Appendix.

– 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 OA2 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 1, 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 Table A1 in the appendix).

4 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.[12]

4.1 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 2) allows rainfall and civil war to have a U-shaped relationship, mirroring the hump-shaped relationship between rainfall and agricultural output.

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

[12]The non-conclusive findings using aggregate rainfall are also true in my data as I show in appendix Tables A2, A3, and A4.

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 2. 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.

4.2 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 2, 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.

[Insert Table 3 about here]

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 2 plus the residuals, against agricultural rainfall.[13]

[Insert Figure 2 about here]

Columns 4-6 and 7-9, in (panel A) Table 3, replicate the analysis in columns 1-3, but for SSA between 1981-1999 and 1981-2013, respectively. The first of these samples corresponds to the one analyzed by Miguel et al. (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 50^{th} to the 25^{th} 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 points, respectively. A positive shock that takes a country from the 50^{th} to the 75^{th} 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 50^{th} to the 90^{th} 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.[14] 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.

[13] Standard partial residual plots of civil war onset risk on linear and quadratic agricultural rainfall terms are presented in Figure A2(a)-A2(b) in the Appendix.

[14] Standard partial residual plots of civil war incidence risk on linear and quadratic agricultural rainfall terms are presented in Figure A2(c)-A2(d) in the Appendix.

Quantitatively, a negative rainfall shock that takes a country from the 50^{th} to the 25^{th} 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 50^{th} to the 75^{th} 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 50^{th} to the 90^{th} 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 appendix Table A5.

[Insert Table 4 about here]

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 necessarily exceed the 1000 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 smaller scaled conflicts. Further, linear agricultural rainfall and growth rates are never significantly related to civil conflict onset or incidence risk. 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 appendix Table A6.

The equivalents of Tables 3 and 4, controlling for average temperature instead of the flexible set of temperature bins can be found in appendix Tables A7 and A8. All results remain qualitatively the same.

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 1 and 2, 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 90%

confidence level, for Africa (1981-2013) and SSA (1981-1999).[15]

5 Conclusions

Policy makers 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 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 50^{th} to the 25^{th} 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 50^{th} to the 75^{th} 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 50^{th} to the 90^{th} 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 and conflict 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 particular, and climate change, in general.

[15] 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.

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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: 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.

Table 2: Agricultural production and rainfall in Africa 1981-2013

	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: The dependent variable is the crops gross production index. 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 brackets. 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.

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	-0.024**	0.002		-0.044**	0.003		-0.030**	0.002	
	(0.011)	(0.004)		(0.022)	(0.007)		(0.013)	(0.005)	
rain^2	0.001**			0.002**			0.001**		
	(0.001)			(0.001)			(0.001)		
rain growth			0.011			0.005			0.014
			(0.008)			(0.017)			(0.011)
Observations	1,538	1,538	1,536	662	662	662	1,228	1,228	1,227
Panel B: Civil war incidence									
rain	-0.024**	0.001		-0.046*	-0.002		-0.031**	0.002	
	(0.012)	(0.005)		(0.024)	(0.008)		(0.015)	(0.006)	
rain^2	0.001**			0.002**			0.001**		
	(0.001)			(0.001)			(0.001)		
rain growth			0.014			-0.024			0.011
			(0.010)			(0.022)			(0.013)
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
Temp. bins	Y	Y	Y	Y	Y	Y	Y	Y	Y

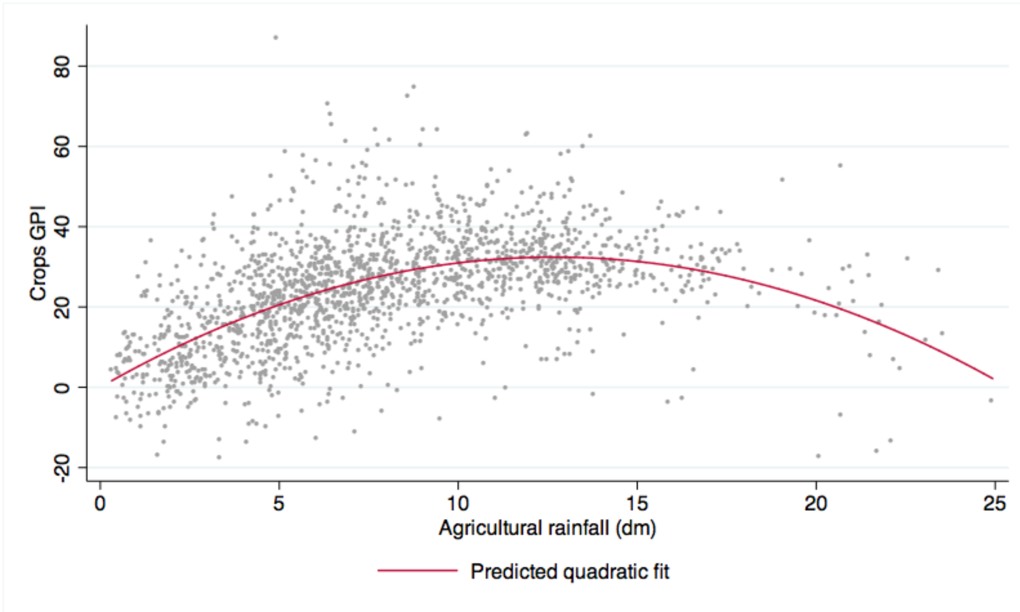
Notes: Estimation method is OLS. All regressions include country fixed-effects, year fixed-effects, and country-specific linear time trends. Robust standard errors are clustered at the country level and are presented in brackets. Agricultural variables summarize information during the growing seasons and over agricultural land. Columns 4-6 correspond to the sample used in Miguel et al. (2004) with the only difference being that these regressions treat rainfall for Namibia in 1989 as a mising value –the country obtained its independence only in 1990. Columns 7-9 correspond to the same set of countries as in Miguel et al. (2004), but extend the sample up to 2013. Significance: *** p<0.01, ** p<0.05, * p<0.1.

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	-0.000	-0.004		-0.002	-0.004		-0.009	-0.007	
	(0.013)	(0.005)		(0.017)	(0.008)		(0.015)	(0.006)	
$rain^2$	-0.000			-0.000			0.000		
	(0.000)			(0.001)			(0.001)		
rain growth			-0.012			0.002			-0.025
			(0.021)			(0.029)			(0.031)
Observations	1,305	1,305	1,303	575	575	575	1,032	1,032	1,031
Panel B: Civil conflict incidence									
rain	-0.032**	-0.004		-0.042*	-0.013		-0.043**	-0.005	
	(0.015)	(0.008)		(0.024)	(0.010)		(0.019)	(0.010)	
$rain^2$	0.001*			0.001			0.002**		
	(0.001)			(0.001)			(0.001)		
rain growth			-0.028			-0.062*			-0.049*
			(0.020)			(0.033)			(0.028)
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
Temp. bins	Y	Y	Y	Y	Y	Y	Y	Y	Y

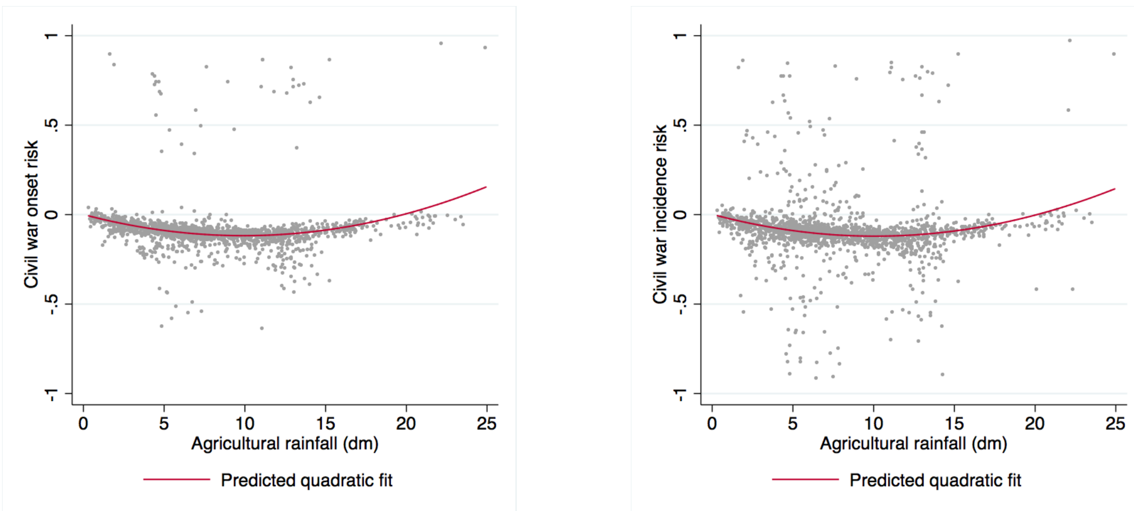
Notes: Estimation method is OLS. All regressions include country fixed-effects, year fixed-effects, and country-specific linear time trends. Robust standard errors are clustered at the country level and are presented in brackets. Agricultural variables summarize information during the growing seasons and over agricultural land. Columns 4-6 correspond to the sample used in Miguel et al. (2004) with the only difference being that these regressions treat rainfall for Namibia in 1989 as a mising value –the country obtained its independence only in 1990. Columns 7-9 correspond to the same set of countries as in Miguel et al. (2004), but extend the sample up to 2013. Significance: *** p<0.01, ** p<0.05, * p<0.1.

Figure 1: Agricultural output and agricultural rainfall



Notes: 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.

Figure 2: Civil war onset and incidence risk and agricultural rainfall



(a) Civil war onset (b) Civil war incidence

Notes: 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.

Appendix

Table A1: Agricultural production and rainfall in Africa 1981-2013

	Agricultural weather				Aggregate weather			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
rain	0.917*	5.173***	0.869*	5.091***	0.272	4.310***	0.154	4.089***
	(0.540)	(1.172)	(0.520)	(1.093)	(0.393)	(0.965)	(0.393)	(0.969)
rain^2		-0.201***		-0.195***		-0.152***		-0.146***
		(0.043)		(0.040)		(0.030)		(0.030)
l.rain	-0.438	1.109	-0.556	0.877	-0.110	2.529***	-0.080	2.474***
	(0.523)	(1.076)	(0.516)	(1.108)	(0.444)	(0.980)	(0.412)	(0.935)
l.rain^2		-0.066		-0.059		-0.093***		-0.090***
		(0.058)		(0.060)		(0.034)		(0.033)
Observations	1,648	1,648	1,648	1,648	1,648	1,648	1,648	1,648
Adjusted R-squared	0.823	0.829	0.827	0.832	0.819	0.826	0.826	0.832
Adjusted R-squared (p)	-0.055	-0.022	-0.031	-0.002	-0.076	-0.039	-0.035	-0.002
Mean temperature & lag	Y	Y	N	N	Y	Y	N	N
Temp. bins & lags	N	N	Y	Y	N	N	Y	Y

Notes: The dependent variable is the crops gross production index. 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 brackets. 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. 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: *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Table A2: The effect of aggregate rainfall on civil war and civil conflict onset risk

Dep. variable	1981-1999				1981-2013			
	Civil war		Civil conflict		Civil war		Civil conflict	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
rain	0.004		-0.002		0.001		-0.001	
	(0.005)		(0.007)		(0.004)		(0.005)	
l.rain	-0.005		-0.009		-0.003		-0.009	
	(0.005)		(0.009)		(0.004)		(0.006)	
rain growth		0.015		0.023		0.001		0.038
		(0.020)		(0.037)		(0.018)		(0.032)
l.rain growth		0.004		-0.011		0.014		-0.048
		(0.028)		(0.061)		(0.013)		(0.035)
Observations	662	661	575	574	1,227	1,226	1,031	1,030
Mean temperature & lag	Y	Y	Y	Y	Y	Y	Y	Y

Notes: Estimation method is OLS. All regressions include country fixed-effects, year fixed-effects, and country-specific linear time trends. Columns 1-4 correspond to the sample used in Miguel et al. (2004) with the only difference being that these regressions treat rainfall for Namibia in 1989 as a mising value –the country obtained its independence only in 1990. Columns 5-8 correspond to the same set of countries as in Miguel et al. (2004), but extend the sample up to 2013. Robust standard errors are clustered at the country level and are presented in brackets. Aggregate weather variables summarize temporally and spatially disaggregated weather data over the entire calendar year and the totality of a country's territory. Significance: *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Table A3: The effect of aggregate rainfall on civil war and civil conflict incidence risk (no lagged dependent variable)

Dep. variable	1981-1999				1981-2013			
	Civil war		Civil conflict		Civil war		Civil conflict	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
rain	-0.002		0.003		-0.000		0.007	
	(0.006)		(0.009)		(0.006)		(0.010)	
l.rain	-0.007		-0.004		-0.004		-0.005	
	(0.007)		(0.010)		(0.007)		(0.012)	
rain growth		-0.004		-0.011		-0.006		-0.010
		(0.027)		(0.060)		(0.025)		(0.046)
l.rain growth		-0.019		-0.001		0.001		-0.041
		(0.036)		(0.045)		(0.012)		(0.038)
Observations	743	742	743	742	1,343	1,342	1,343	1,342
Mean temperature & lag	Y	Y	Y	Y	Y	Y	Y	Y

Notes: Estimation method is OLS. All regressions include country fixed-effects, year fixed-effects, and country-specific linear time trends. Columns 1-4 correspond to the sample used in Miguel et al. (2004) with the only difference being that these regressions treat rainfall for Namibia in 1989 as a mising value –the country obtained its independence only in 1990. Columns 5-8 correspond to the same set of countries as in Miguel et al. (2004), but extend the sample up to 2013. Robust standard errors are clustered at the country level and are presented in brackets. Aggregate weather variables summarize temporally and spatially disaggregated weather data over the entire calendar year and the totality of a country's territory. Significance: *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Table A4: The effect of aggregate rainfall on civil war and civil conflict incidence risk (including lagged dependent variable)

	1981-1999				1981-2013			
Dep. variable	Civil war		Civil conflict		Civil war		Civil conflict	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
rain	-0.002		0.003		-0.000		0.005	
	(0.005)		(0.008)		(0.005)		(0.007)	
l.rain	-0.008		-0.004		-0.005		-0.008	
	(0.007)		(0.010)		(0.005)		(0.008)	
rain growth		-0.015		-0.009		-0.011		-0.008
		(0.028)		(0.061)		(0.023)		(0.047)
l.rain growth		-0.026		-0.001		-0.002		-0.049
		(0.040)		(0.046)		(0.015)		(0.035)
l.dep variable	0.187**	0.186**	0.080	0.080	0.343***	0.343***	0.378***	0.378***
	(0.077)	(0.077)	(0.075)	(0.076)	(0.070)	(0.071)	(0.058)	(0.058)
Observations	743	742	743	742	1,343	1,342	1,343	1,342
Mean temperature & lag	Y	Y	Y	Y	Y	Y	Y	Y

Notes: Estimation method is OLS. All regressions include country fixed-effects, year fixed-effects, and country-specific linear time trends. Columns 1-4 correspond to the sample used in Miguel et al. (2004) with the only difference being that these regressions treat rainfall for Namibia in 1989 as a mising value –the country obtained its independence only in 1990. Columns 5-8 correspond to the same set of countries as in Miguel et al. (2004), but extend the sample up to 2013. Robust standard errors are clustered at the country level and are presented in brackets. 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.

Table A5: The quantitative effect of agricultural rainfall on civil war onset and incidence risk when moving from/to different percentiles of the distribution of agricultural rainfall

	Africa 1981-2013					SSA 1981-1999					SSA 1981-2013				
Panel A: Onset															
from\to	10	25	50	75	90	10	25	50	75	90	10	25	50	75	90
10	0	-3.18	-5.40	-6.01	-4.41	0	-3.20	-6.29	-6.38	-3.52	0	-2.44	-4.77	-5.54	-4.22
25	3.18	0	-2.22	-2.83	-1.23	3.20	0	-3.09	-3.18	-0.32	2.44	0	-2.33	-3.10	-1.78
50	5.40	2.22	0	-0.61	0.98	6.29	3.09	0	-0.09	2.77	4.77	2.33	0	-0.77	0.55
75	6.01	2.83	0.61	0	1.60	6.38	3.18	0.09	0	2.86	5.54	3.10	0.77	0	1.32
90	4.41	1.23	-0.98	-1.60	0	3.52	0.32	-2.77	-2.86	0	4.22	1.78	-0.55	-1.32	0
Panel A: Incidence															
from\to	10	25	50	75	90	10	25	50	75	90	10	25	50	75	90
10	0	-3.25	-5.55	-6.32	-4.85	0	-3.65	-7.57	-9.03	-7.32	0	-2.56	-5.00	-5.77	-4.35
25	3.25	0	-2.31	-3.07	-1.61	3.65	0	-3.93	-5.38	-3.67	2.56	0	-2.44	-3.21	-1.79
50	5.55	2.31	0	-0.76	0.70	7.57	3.93	0	-1.45	0.25	5.00	2.44	0	-0.77	0.65
75	6.32	3.07	0.76	0	1.46	9.03	5.38	1.45	0	1.71	5.77	3.21	0.77	0	1.43
90	4.85	1.61	-0.70	-1.46	0	7.32	3.67	-0.25	-1.71	0	4.35	1.79	-0.65	-1.43	0

Notes: The table shows the change in civil war onset and incidence risk when when moving from(rows)/to(columns) different percentiles of the distribution of agricultural rainfall (in the respective sample). Results are based on the estimates from the quadratic specifications in Table 3. The unconditional probabilties of civil war onset (incidence) risk for Africa 1981-2013, SSA 1981-1999, and SSA 1981-2013 are 2.21% (7.28%), 3.02% (11.04%), and 2.61% (8.48%), respectively.

Table A6: The quantitative effect of agricultural rainfall on civil conflict onset and incidence risk when moving from/to different percentiles of the distribution of agricultural rainfall

	Africa 1981-2013					SSA 1981-1999					SSA 1981-2013				
Panel B: Onset															
from\to															
10	0	-0.37	-1.02	-2.40	-3.79	0	-0.44	-1.24	-2.45	-3.43	0	-1.28	-3.07	-5.48	-7.06
25	0.37	0	-0.65	-2.03	-3.42	0.44	0	-0.79	-2.00	-2.99	1.28	0	-1.79	-4.20	-5.79
50	1.02	0.65	0	-1.38	-2.77	1.24	0.79	0	-1.21	-2.20	3.07	1.79	0	-2.41	-4.00
75	2.40	2.03	1.38	0	-1.39	2.45	2.00	1.21	0	-0.99	5.48	4.20	2.41	0	-1.59
90	3.79	3.42	2.77	1.39	0	3.43	2.99	2.20	0.99	0	7.06	5.79	4.00	1.59	0
Panel B: Incidence															
from\to															
10	0	-4.71	-8.55	-11.25	-11.06	0	-4.16	-9.59	-14.40	-16.10	0	-4.09	-8.58	-11.88	-11.94
25	4.71	0	-3.83	-6.54	-6.35	4.16	0	-5.43	-10.25	-11.94	4.09	0	-4.49	-7.78	-7.85
50	8.55	3.83	0	-2.71	-2.52	9.59	5.43	0	-4.81	-6.50	8.58	4.49	0	-3.30	-3.36
75	11.25	6.54	2.71	0	0.19	14.40	10.25	4.81	0	-1.69	11.88	7.78	3.30	0	-0.06
90	11.06	6.35	2.52	-0.19	0	16.10	11.94	6.50	1.69	0	11.94	7.85	3.36	0.06	0

Notes: The table shows the change in civil conflict onset and incidence risk when when moving from(rows)/to(columns) different percentiles of the distribution of agricultural rainfall (in the respective sample). Results are based on the estimates from the quadratic specifications in Table 4. The unconditional probabilties of civil conflict onset (incidence) risk for Africa 1981-2013, SSA 1981-1999, and SSA 1981-2013 are 5.75% (21.54%), 6.26% (23.42%), and 6.49% (23.36%), respectively.

Table A7: The effect of agricultural rainfall on civil war onset and incidence risk (controlling for mean agricultural temperature)

	Africa 1981-2013			SSA 1981-1999			SSA 1981-2013		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Panel A: Civil war onset									
rain	-0.023**	0.002		-0.036*	0.006		-0.028**	0.003	
	(0.010)	(0.004)		(0.019)	(0.006)		(0.013)	(0.005)	
rain^2	0.001**			0.002**			0.001**		
	(0.001)			(0.001)			(0.001)		
rain growth			0.011			0.020			0.019*
			(0.009)			(0.016)			(0.011)
Observations	1,538	1,538	1,536	662	662	662	1,228	1,228	1,227
Panel B: Civil war incidence									
rain	-0.021*	0.002		-0.040*	0.001		-0.028**	0.003	
	(0.011)	(0.004)		(0.022)	(0.007)		(0.014)	(0.006)	
rain^2	0.001*			0.002**			0.001**		
	(0.001)			(0.001)			(0.001)		
rain growth			0.016*			0.003			0.018
			(0.009)			(0.018)			(0.012)
lagged dep. variable	0.370***	0.372***	0.372***	0.186**	0.186**	0.185**	0.342***	0.344***	0.344***
	(0.073)	(0.073)	(0.072)	(0.075)	(0.077)	(0.077)	(0.071)	(0.070)	(0.070)
Observations	1,660	1,660	1,660	743	743	743	1,343	1,343	1,343
Mean temperature	Y	Y	Y	Y	Y	Y	Y	Y	Y

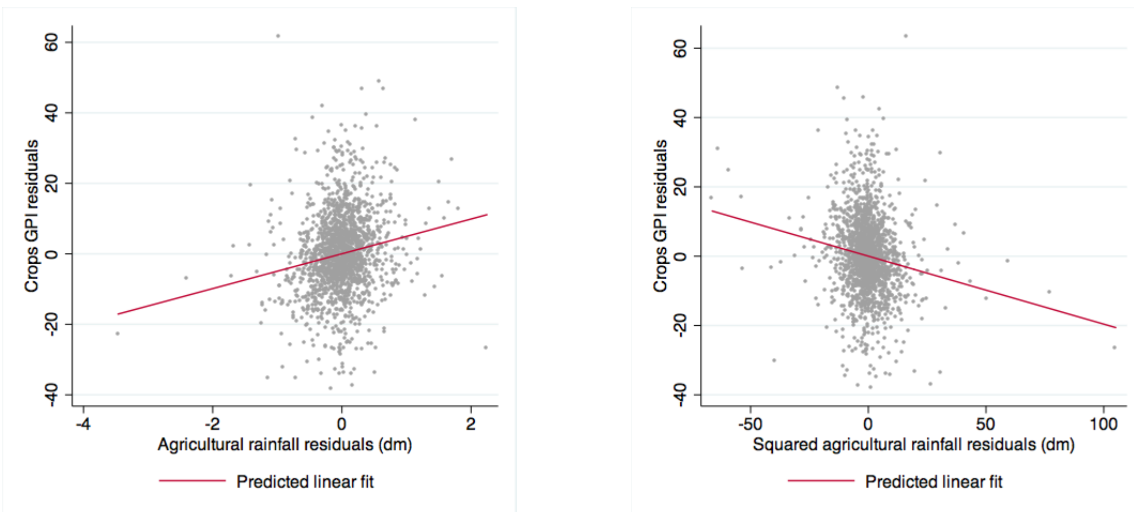
Notes: Estimation method is OLS. All regressions include country fixed-effects, year fixed-effects, and country-specific linear time trends. Robust standard errors are clustered at the country level and are presented in brackets. Agricultural variables summarize information during the growing seasons and over agricultural land. Columns 4-6 correspond to the sample used in Miguel et al. (2004) with the only difference being that these regressions treat rainfall for Namibia in 1989 as a mising value –the country obtained its independence only in 1990. Columns 7-9 correspond to the same set of countries as in Miguel et al. (2004), but extend the sample up to 2013. Significance: *** p<0.01, ** p<0.05, * p<0.1.

Table A8: The effect of agricultural rainfall on civil conflict onset and incidence (controlling for mean agricultural temperature)

	Africa 1981-2013			SSA 1981-1999			SSA 1981-2013		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Panel A: Civil conflict onset									
rain	0.000	-0.004		-0.002	-0.004		-0.007	-0.007	
	(0.012)	(0.005)		(0.017)	(0.007)		(0.015)	(0.006)	
$rain^2$	-0.000			-0.000			0.000		
	(0.000)			(0.001)			(0.001)		
rain growth			-0.012			0.021			-0.019
			(0.022)			(0.029)			(0.031)
Observations	1,305	1,305	1,303	575	575	575	1,032	1,032	1,031
Panel B: Civil conflict incidence									
rain	-0.031**	-0.004		-0.035	-0.010		-0.042**	-0.004	
	(0.016)	(0.008)		(0.024)	(0.010)		(0.020)	(0.010)	
$rain^2$	0.001*			0.001			0.002*		
	(0.001)			(0.001)			(0.001)		
rain growth			-0.028			-0.041			-0.044
			(0.021)			(0.034)			(0.029)
lagged dep. variable	0.385***	0.388***	0.388***	0.081	0.082	0.083	0.375***	0.379***	0.380***
	(0.055)	(0.057)	(0.057)	(0.075)	(0.076)	(0.076)	(0.056)	(0.059)	(0.059)
Observations	1,660	1,660	1,660	743	743	743	1,343	1,343	1,343
Mean temperature	Y	Y	Y	Y	Y	Y	Y	Y	Y

Notes: 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 brackets. Agricultural variables summarize information during the growing seasons and over agricultural land. Columns 4-6 correspond to the sample used in Miguel et al. (2004) with the only difference being that these regressions treat rainfall for Namibia in 1989 as a mising value –the country obtained its independence only in 1990. Columns 7-9 correspond to the same set of countries as in Miguel et al. (2004), but extend the sample up to 2013. Significance: *** p<0.01, ** p<0.05, * p<0.1.

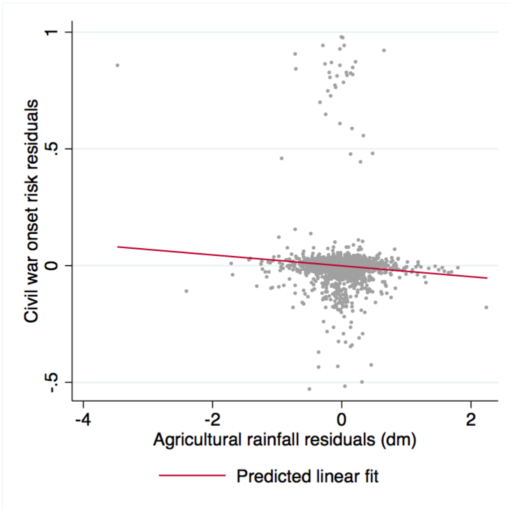
Figure A1: Agricultural output and agricultural rainfall



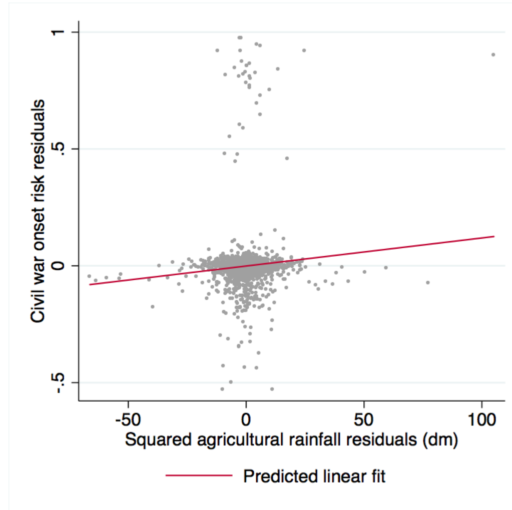
(a) First-order effect (b) Second-order effect

Notes: This figure illustrates the positive first-order- and negative second-order- partial effects of agricultural rainfall on agricultural output, in Panel a and b, respectively. Panel a (b) plots the residuals of agricultural output from a regression on quadratic (linear) agricultural rainfall, country fixed-effects, year fixed-effects, country-specific linear time trends, and the full set of agricultural temperature bins against the residuals of linear (quadratic) agricultural rainfall on quadratic (linear) agricultural rainfall and same set of controls.

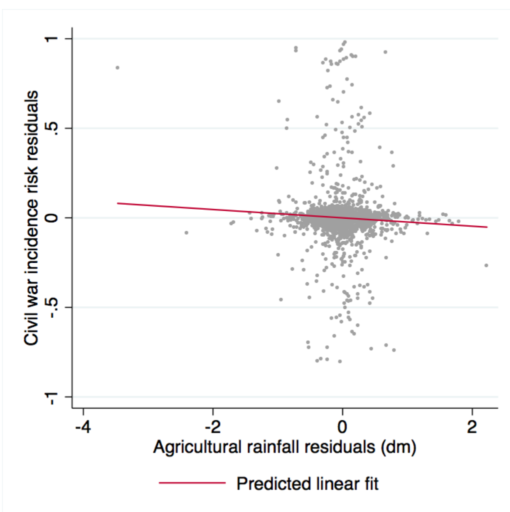
Figure A2: Civil war onset and incidence risk and agricultural rainfall



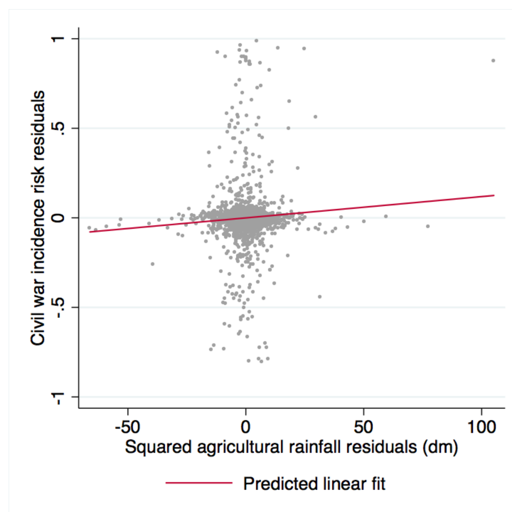
(a) Civil war onset risk: first-order effect



(b) Civil war onset risk: second-order effect



(c) Civil war incidence risk: first-order effect



(d) Civil war incidence risk: second-order effect

Notes: This figure illustrates the negative first-order- and positive second-order- partial effects of agricultural rainfall on civil war onset (Panels a and b) and incidence (Panels c and d), respectively. Panel a (b) plots the residuals of civil war onset risk from a regression on quadratic (linear) agricultural rainfall, country fixed-effects, year fixed-effects, country-specific linear time trends, and the full set of agricultural temperature bins against the residuals of linear (quadratic) agricultural rainfall on quadratic (linear) agricultural rainfall and same set of controls. Panel c (d) plots the residuals of civil war incidence risk from a regression on quadratic (linear) agricultural rainfall, lagged civil war incidence, country fixed-effects, year fixed-effects, country-specific linear time trends, and the full set of agricultural temperature bins against the residuals of linear (quadratic) agricultural rainfall on quadratic (linear) agricultural rainfall and same set of controls.

Online Appendix: not for publication

Table OA1: Agricultural production and rainfall in Africa 1981-2013

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A: Agricultural variables								
rain	0.883			5.380***	0.796			5.128***
	(0.603)			(1.217)	(0.583)			(1.173)
rain^2				-0.214***				-0.203***
				(0.047)				(0.046)
log rain		11.178***				9.983***		
		(3.474)				(3.324)		
rain growth			4.446***				4.177***	
			(1.340)				(1.296)	
Adjusted R-squared	0.822	0.825	0.824	0.828	0.826	0.828	0.827	0.831
Adjusted R-squared (p)	-0.056	-0.039	-0.052	-0.023	-0.033	-0.022	-0.030	-0.006
Panel B: Aggregate variables								
rain	0.257			4.417***	0.207			4.323***
	(0.450)			(0.997)	(0.459)			(1.018)
rain^2				-0.158***				-0.155***
				(0.032)				(0.031)
log rain		8.318***				7.992***		
		(3.055)				(3.096)		
rain growth			1.684				1.623	
			(1.075)				(1.244)	
Adjusted R-squared	0.819	0.821	0.820	0.824	0.823	0.825	0.824	0.827
Adjusted R-squared (p)	-0.076	-0.064	-0.074	-0.049	-0.052	-0.042	-0.051	-0.026
Observations	1,650	1,650	1,648	1,650	1,650	1,650	1,648	1,650
Mean temperature	Y	Y	Y	Y	N	N	N	N
Temp. bins	N	N	N	N	Y	Y	Y	Y

Notes: The dependent variables is the crops gross production index. 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 brackets. The adjusted R-squared (p) is the R-squared from regressions where country fixed-effects, year fixed-effects, and country-specific linear time trends have been partialled out from all variables. 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.

Table OA2: Agricultural production and agricultural rainfall in Sub-Saharan Africa 1981-2013

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
agri. rain	0.796	0.776	5.540***	5.338***	0.853	0.887	5.329***	5.179***
	(0.627)	(0.562)	(1.229)	(1.105)	(0.626)	(0.550)	(1.168)	(1.013)
agri. rain^2			-0.210***	-0.196***			-0.198***	-0.185***
			(0.050)	(0.041)			(0.049)	(0.037)
l.agri. rain		-0.115		2.387*		-0.288		1.878
		(0.672)		(1.270)		(0.679)		(1.283)
l.agri. rain^2				-0.101				-0.087
				(0.067)				(0.068)
Observations	1,332	1,331	1,332	1,331	1,332	1,331	1,332	1,331
Adjusted R-squared	0.831	0.830	0.835	0.836	0.835	0.838	0.839	0.842
Adjusted R-squared (p)	-0.068	-0.070	-0.039	-0.035	-0.040	-0.025	-0.014	0.004
Mean temperature	Y	Y	Y	Y	N	N	N	N
Temp. bins	N	N	N	N	Y	Y	Y	Y

Notes: The dependent variable is the crops gross production index. 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 brackets. 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. Agricultural (agri.) variables summarize information during the growing seasons and over agricultural land. Significance: *** p<0.01, ** p<0.05, * p<0.1.

Table OA3: Agricultural production and rainfall in Africa 1981-2013

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A: Agricultural variables								
rain	0.917*			5.173***	0.869*			5.091***
	(0.540)			(1.172)	(0.520)			(1.093)
l.rain	-0.438			1.109	-0.556			0.877
	(0.523)			(1.076)	(0.516)			(1.108)
rain^2				-0.201***				-0.195***
				(0.043)				(0.040)
l.rain^2				-0.066				-0.059
				(0.058)				(0.060)
log rain		11.139***				10.428***		
		(3.370)				(3.194)		
l.log rain		-0.914				-2.102		
		(2.250)				(2.311)		
rain growth			6.958***				7.026***	
			(1.717)				(1.882)	
l.rain growth			3.339**				2.626*	
			(1.369)				(1.458)	
Adjusted R-squared	0.823	0.825	0.821	0.829	0.827	0.829	0.826	0.832
Adjusted R-squared (p)	-0.055	-0.040	-0.050	-0.022	-0.031	-0.021	-0.024	-0.002
Observations	1648	1648	1598	1648	1648	1648	1598	1648
Panel B: Aggregate variables								
rain	0.272			4.310***	0.154			4.089***
	(0.393)			(0.965)	(0.393)			(0.969)
l.rain	-0.110			2.529***	-0.080			2.474***
	(0.444)			(0.980)	(0.412)			(0.935)
rain^2				-0.152***				-0.146***
				(0.030)				(0.030)
l.rain^2				-0.093***				-0.090***
				(0.034)				(0.033)
log rain		8.209***				7.549**		
		(3.005)				(2.972)		
l.log rain		3.046				3.302		
		(2.908)				(2.863)		
rain growth			3.202**				2.771**	
			(1.385)				(1.342)	
l.rain growth			2.987*				3.133**	
			(1.592)				(1.478)	
Adjusted R-squared	0.819	0.822	0.820	0.826	0.826	0.828	0.827	0.832
Adjusted R-squared (p)	-0.076	-0.063	-0.073	-0.039	-0.035	-0.024	-0.031	-0.002
Observations	1,648	1,648	1,646	1,648	1,648	1,648	1,646	1,648
Mean temperature & lag	Y	Y	Y	Y	N	N	N	N
Temp. bins & lags	N	N	N	N	Y	Y	Y	Y

Notes: The dependent variables is the crops gross production index. Estimation method is OLS. All regressions include country fixed-effects, year fixed-effects, and country-specific time trends. Robust standard errors are clustered at the country level and are presented in brackets. The adjusted R-squared (p) is the R-squared from regressions where country fixed-effects, year fixed-effects, and country-specific time trends have been partialled out from all variables. 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.