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# Climate (change) and conflict: resolving a puzzle of association and causation

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# DISCUSSION PAPERS

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# Climate (change) and conflict: resolving a puzzle of association and causation*

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There is an ongoing discussion especially among political scientists and economists whether and how climate variability affects civil conflicts and wars in developing countries. Given the predicted climatic changes, several studies argue that increasing temperatures or decreasing precipitation will lead to more conflicts in the future. This paper aims at linking the different strands of the literature by analyzing the causal mechanisms at work. We use short-term weather variability as well as long-term changes in Sub-Saharan Africa and find that climate (change) significantly affects agricultural output, to some extent also GDP, and has no robust direct effects on civil wars. Negative shocks in GDP, however, have the expected fostering effects on civil conflicts.

**Keywords:** Civil conflict, climate change, economic shocks, Africa.

**JEL classification:** D74, Q54, C36, N47

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## 1 Introduction

There is a long history of research on the sources and consequences of civil wars.[1] Scholars in the social sciences in particular are increasingly concerned about the impact that climate and climate change may have on human prosperity and development. Given the predicted changes in climatic conditions for the next half century and the expected increase in extreme weather events (IPCC 2007), climate change may impose a serious threat especially to poor countries if it fosters the incidence of civil conflicts and wars. A recent example has been the disastrous drought at the Horn of Africa that led to a food crisis[2] in a region already heavily affected by civil wars.[3]

In this paper, we shed light on the question whether and how different short-run and long-run climatic conditions cause civil wars in Sub-Saharan Africa – one of the poorest (Easterly and Levine 1997), most unstable (Fearon and Laitin 2003) and, with respect to climate change, most vulnerable (Boko et al. 2007) regions in the world. In particular, the contributions of our paper are twofold. First, we disentangle the channels through which weather variability might affect the incidence of conflicts. So far, the literature has not been conclusive regarding the existence of direct and/or indirect effects, the latter mainly via effects on economic output. Second, we use observed rather than predicted changes in climate to estimate their impact on civil war. This is of major relevance as different causal channels would lead to totally different policy conclusions. Knowing the exact mechanisms, however, is crucial for policy-makers in order to be able to prevent or mitigate the otherwise highly destructive impact that civil conflicts and wars usually have (Fearon and Laitin 2003, Burke et al. 2009).

For that purpose, we analyze a panel of 36 Sub-Saharan countries from 1985 to 2008. This period has been chosen because Sub-Saharan Africa shows an abnormal high prevalence of wars in comparison to other regions of the world during that time (Collier and Hoeffler 2002). We employ some static but mainly dynamic country-level fixed effects models that are estimated by a robust two-step system GMM procedure while accounting for different types of endogeneity. These include a range of dynamic interdependencies among the variables of interest, which are instrumented using panel internal information. By applying over-identification and autocorrelation tests we evaluate the sensitivity of our results to the inclusion of different sets of instruments.

In addressing this topic, our paper links three strands of the literature that are so far discussed separately but actually are highly related. First, there is the literature that directly associates weather variation or weather related natural disasters to social conflicts (Tol and Wagner 2010, Hsiang et al. 2011, Dell et al. 2012). Based on this literature, there is no clear consensus if (extreme) weather events trigger civil conflicts, or not. However, by applying a reduced form analysis of this kind it is impossible to

[1] For two recent surveys on the topic see Blattman and Miguel (2010) and Solow (2011).
[2] The Economist: The Horn of Africa: Chronicle of a famine foretold, July 30th 2011.
[3] The New York Times: Somalia, December 28th 2011; article can be found at: *http://topics.nytimes.com/top/news/international/countriesandterritories/somalia/index.html.*

state anything about the underlying causal channels that are at work, and hence any conclusion that is drawn highly depends on the particular setting (see also the discussion in Dell et al. (2012)). Do people start wars because climatic shocks result in declining economic conditions, and/or health problems, and/or mental stress (Miguel et al. 2004, Kudamatsu et al. 2010, Larrick et al. 2011)?

Second, there is an ongoing debate about the impact that climatic conditions have on civil wars in Sub-Saharan Africa when factors like economic output and the quality of political institutions are taken into account (Nel and Righarts 2008, Salehyan 2008, Burke et al. 2009, Buhaug 2010, Sutton et al. 2010). Findings of this literature, however, are often based on the independence of civil conflicts, economic conditions and political institutions, especially in terms of dynamic effects. Moreover, most papers focus on weather variation rather than variation in the long-term climate. They use precipitation and temperature as measured in current-year levels or year-to-year growth concluding that, given a significant effect, predicted climatic changes will lead to more conflicts.

Third, there is a literature that focuses on the effects of income shocks on civil wars taking weather variation as instrument for GDP. Implicitly, this literature assumes that variations in temperature and precipitation do only affect civil wars through a change in income (Miguel et al. 2004, Miguel and Satyanath 2011, Ciccone 2011). Any other causal channel, e.g. the previously mentioned "direct" effects, would yield inconsistent results as instruments would no longer be independent of conflicts.

In this light, the findings of our paper are at least threefold. First, we find clear evidence for climatic conditions to affect agricultural output (Schlenker and Lobell 2010, Dell et al. 2012). These effects include short-run effects – both for log-levels and year-to-year growth – such as higher precipitation (temperature) leading to more (less) output. We thus confirm the underlying arguments in the economic literature: weather shocks do have an impact on agricultural production which in turn influences GDP (Miguel et al. 2004). For climate change, defined as deviation from the long-term trend, we also find the expected impact: a larger growth in temperatures over the medium and long-run decreases agricultural output while additional rainfall increases it. These effects also hold for GDP (Dell et al. 2012) but with less economic and statistical significance, and they totally vanish (except for some extreme weather events) if agricultural output is controlled for. Thus, climatic conditions affect economic output in Sub-Saharan Africa, but mainly through agricultural production at least for the sample under investigation. Second, we do not find much evidence for a non-economic channel of climatic conditions on civil conflicts except for some static FE estimates where precipitation and temperature both have a positive effect on the incidence of civil wars (Tol and Wagner 2010, Dell et al. 2012). Third, negative shocks in GDP and to a lesser extent in agricultural output increase the likelihood of civil conflicts. We therefore confirm the results found by Miguel et al. (2004), but using a different set of instruments and a different time period.

The remainder of the paper discusses the following aspects. In section 2 we describe the sources and properties of our data. Sections 3 and 4 contain the results, first for several reduced form models, and then for a structural model of climate (change), output, and conflict. A detailed discussion is provided in section 5. Finally, section 6 summarizes our findings and highlights some policy implications.

## 2 Data

The data under investigation covers 36 Sub-Saharan African countries (see Table 8 in the appendix) over the period 1985 to 2008. The incidence of internal civil conflicts is taken from the Peace Research Institute Oslo (PRIO) and Uppsala University (Gleditsch et al. 2002). The variable indicates whether there has been a conflict (at least 25 battle deaths) in a given country and year. Information on GDP per capita and agricultural output stems from the Africa Development Indicators published by the World Bank. The information on climatic conditions are taken from two sources. Average temperature and precipitation originates from the CRU 3.1 dataset provided by the Climatic Research Centre at the University of East Anglia. We aggregated the grid based (0.5 to 0.5 degree) monthly data to country and year level by taking averages over grids and months. Information on extreme weather events like droughts, floods, and storms is taken from EM-DAT provided by the Catholic University of Louvain.

We consider several transformations of the temperature and precipitation data in order to measure the effect of changing climatic conditions.[4] The reason for additionally including these alternative measures is that so far all inference is based on predicted climatic changes. That is, papers usually estimate the relationship between temperature, precipitation and civil conflict in a first step and then use climate change predictions to forecast the likelihood of civil conflicts in the far distant future. The two implicit assumptions for such an analysis are that (i) people will not (be able to) adapt, and (ii) climate change predictions are accurate. In other words, all factors that we treat to be fixed when analyzing current available data need to remain constant in the future. This is a very questionable assumption. In addition, climate change predictions are expected to be highly uncertain. On the downside, already realized changes may be less severe than far distant predictions, but the results can be treated as estimates of realized events rather than potentially inaccurate predictions.

The variables on climate change are generated on the basis of average temperature and precipitation data included in the CRU dataset. In particular, we calculate three additional sets of variables in order to capture medium and long-term climatic changes. First, we calculate the 5-years moving average (MA) for precipitation and temperature for each country and year and build a variable capturing the percentage deviation of the current climate from its 5-years MA. That is, we use the following transformation:

$$cc_{it}^5 = (c_{it} - f_{it}(c_{it-1}, c_{it-5}))/f_{it}(c_{it-1}, c_{it-5})) \qquad (1)$$

[4] In addition, we also included several lags of temperature and precipitation as in Dell et al. (2012), non-linear effects (e.g., Schlenker and Roberts (2009)), and interactions (Kudamatsu et al. 2010). However, for our sample neither of these turned out to be important.

where $f(.)$ constitutes the 5-years moving average of climate measures $c$ (temperature or precipitation) lagged by one year. A variable constructed that way reflects the percentage deviation of current average temperature, or precipitation, from the MA of the past 5 years. In order to include changes in the longer term, we also use deviations from the 10-years moving average:

$$cc_{it}^{10} = (c_{it} - f_{it}(c_{it-1}, c_{it-10}))/f_{it}(c_{it-1}, c_{it-10})). \tag{2}$$

Finally, we build two variables (for temperature and precipitation) capturing the percentage deviation from the predicted climate for that year. In doing so, we follow a three-steps process. First, we regress temperature and precipitation on a constant and a linear trend given our panel of Sub-Saharan African countries for the years 1901 to 1950, using the within-country variation of the climate data. Second, we predict both climate variables until 2008 on the basis of the panel estimates. In a third step, we calculate the percentage deviation of the actual climate measures from these predictions:

$$cc_{it}^{50} = (c_{it} - \hat{c}_{it}^{50})/\hat{c}_{it}^{50} \tag{3}$$

where $\hat{c}_{it}^{50}$ represents the prediction based on the 50-years benchmark period (1901-1950). Taking this period as the benchmark ensures that our $cc_{it}^{50}$ variables capture exactly those climatic developments prior to any observable anthropogenic climate change.

Overall, our different measures of climate change may give some first evidence on the adaptive capacity of Sub-Saharan Africa with respect to global warming (Dell et al. 2012). Significant results for the long-term change (1901-1950) could be a signal for a lack of adaptation in general. However, a combination of insignificant results for the long-term and significant estimates for the medium term variables could reflect some adaptation with time lags. These adaptation effects may be less important for civil conflicts but are definitely of interest for agricultural output and GDP growth.

Table 1 summarizes all variables (with their means, standard deviations, minima and maxima) in the format they are included in the analysis. Overall, for about 22 percent of the country-year observations we have a civil conflict or war. The average GDP growth is slightly positive with 0.8 percent, but there is a considerable variation over countries and time ranging from $-46.9$ percent to $+37.8$ percent. Analogously, for agricultural output we observe a wide spread between the smallest and largest records and a standard deviation that is more than 1.2 billion US dollars.

Regarding the climate variables, the maximum average yearly temperature is almost 30 degrees Celsius, the maximum average yearly precipitation is about 200mm. For the latter in particular, we observe a substantial variation over countries and years with the lowest average yearly precipitation only about 5mm. The medium and long-term changes in precipitation and temperatures are constructed such that they capture different trends in climatic conditions in Sub-Saharan African countries, and the differences in the standard deviations can be taken as an indicator of this heterogeneity. The counts of the extreme weather events show that on average floods occurred more frequently than droughts and storms, but again there is a lot of variation over countries and years.

**Table 1:** Summary statistics

| Variable | Mean | Std. Dev. | Min. | Max. | N |
|---|---|---|---|---|---|
| Incidence of conflict | 0.224 | 0.417 | 0 | 1 | 851 |
| GDP growth | 0.008 | 0.054 | -0.469 | 0.378 | 847 |
| Agricult. output (Mio. US$) | 1124.8 | 1238.4 | 63.12 | 6374.4 | 825 |
| log(temp) | 3.178 | 0.166 | 2.448 | 3.380 | 864 |
| log(precip) | 4.121 | 0.722 | 1.652 | 5.324 | 864 |
| temp growth | 0.001 | 0.017 | -0.102 | 0.058 | 864 |
| precip growth | 0.024 | 0.191 | -0.670 | 1.374 | 864 |
| $cc^5$ temp | 0.003 | 0.015 | -0.064 | 0.093 | 864 |
| $cc^5$ precip | 0.027 | 0.161 | -0.473 | 2.023 | 864 |
| $cc^{10}$ temp | 0.007 | 0.015 | -0.054 | 0.090 | 864 |
| $cc^{10}$ precip | 0.023 | 0.151 | -0.441 | 1.895 | 864 |
| $cc^{50}$ temp | -0.008 | 0.144 | -0.528 | 0.197 | 864 |
| $cc^{50}$ precip | -0.113 | 0.462 | -0.939 | 1.417 | 864 |
| drought | 0.140 | 0.351 | 0 | 2 | 864 |
| storm | 0.116 | 0.442 | 0 | 4 | 864 |
| flood | 0.498 | 0.854 | 0 | 7 | 864 |

## 3 Reduced form effects of climate and climate change

### 3.1 Empirical methodology

In the first part of the empirical analysis, we look at the reduced form effects of various climatic conditions on three outcomes: the log of agricultural output, year-to-year growth in GDP and the incidence of civil conflicts. We focus on these outcomes as they will constitute the endogenous ingredients of our structural model below. The reduced form approach has been followed by, for example, Tol and Wagner (2010) and Hsiang et al. (2011). If climate and climate change are assumed exogenous, at least at the country level, then the reduced form effects can be informative to the extent that they summarize all possible direct and indirect effects on the considered outcomes.

We estimate models of the form

$$y_{it} = \sum_{p=1}^{P} \alpha_p y_{i,t-p} + \beta' climatic\ conditions_{it} + \gamma_i + \delta_t + u_{it} \tag{4}$$

where $y_{it}$ is the outcome of interest (agricultural output, GDP growth, civil conflict) in country $i$ at time $t$, $\gamma_i$ is an unobserved time-constant country effect, $\delta_t$ is a time fixed effect (modeled by year dummies), and $u_{it}$ is the reduced form error.

Equation (4) is a standard dynamic linear panel model. Estimation by ordinary least squares generally yields biased estimates because of the $P$ lagged dependent variable(s) on the right-hand side and the presence of $\gamma_i$ (which may be correlated with the climate variables). Consistent estimation of (4) can proceed by first-differencing the equation and using instruments for the differenced lagged dependent variables (the latter are correlated with the differenced errors by definition of the model).

The original Arellano and Bond (1991) estimator employs all suitable lagged levels as instruments to construct an efficient generalized method of moments (GMM) estimator. This procedure, however, has been shown to perform poorly under certain properties of the data (e.g., if the variables are close to a random walk) or if the time dimension is large (because far distant lags may be weak instruments). To overcome these problems we follow two suggestions in the methodological literature. First, we consider a system of (4) in levels and (4) in differences, and instrument the former using suitable lags of the first differenced variables under the additional assumption that differences are uncorrelated with the country fixed effect $\gamma_i$ (Arellano and Bover 1995). Second, we do not employ all possible lags as instruments. Instead, we estimate a pooled first-stage and carefully select those instruments that convincingly pass the relevance condition (Wooldridge 2005). In this way we can still conduct overidentifying and serial correlation tests to provide additional plausibility checks for the imposed assumptions. Moreover, in all models (with or without the restriction $\alpha_p = 0$) we calculate standard errors using a heteroscedasticity and autocorrelation (HAC) robust covariance matrix.

The climatic variables comprise the following six types, as introduced above:

- the log of contemporaneous temperature and precipitation
- the growth rates of temperature and precipitation
- the 5-years moving average transformations
- the 10-years moving average transformations
- the relative deviation from the 50-years benchmark
- the number of extreme events drought, storm, and flood

These variables allow us to differentiate between short-, medium- and long-term impacts of weather variability. Moreover, by including them block-wise we can separate climate from climate change and evaluate their relative predictive power.

### 3.2 Agriculture

Table 2 shows the estimated reduced form effects of climatic conditions on the log of agricultural output. The results suggest that temperature and precipitation, in all transformations, are strong predictors (see also, e.g. Schlenker and Lobell (2010), Dell et al. (2012)). For example, a temperature raise by 1 percent is predicted to reduce output by about 1.37 percent, and an increase in precipitation by 1 percent leads to an additional output of about 0.15 percent (see column 1). Similar predictions hold for the growth rates (column 2), which by definition account for the relative changes in temperatures and precipitation observed from the previous to the current year.

The climate change variables have a significant impact on agricultural output, too. All three, the deviations from the 5- and 10-years moving averages and the relative difference to the long-term prediction affect agricultural output in the expected direction: Higher temperatures reduce output whereas higher precipitation increases it. Overall the impact of temperature tends to be stronger relative to the impact of precipitation, although several factors influence this interpretation, like the type of crops produced, agricultural productivity and technology in general, and the processing standards. The more pronounced impact of temperature is confirmed by the extreme weather events which indicate that only the number of droughts has a significant impact, the effects of storms and floods are both small and insignificant.

Regarding the dynamics in agricultural output, we find a stable and significant elasticity of around 0.7, i.e., if output has increased by 1 percent in the previous year, we expect an increase in output in the current period of about 0.7 percent. The two-period lagged output has a weaker negative impact (mostly insignificant at the 5 percent level), pointing to the existence of some cyclicality. If we drop the dynamics and estimate a standard static panel data model with country fixed effects (FE, see Table 9 in the appendix), then we mainly confirm the reduced form effects of the temperature measures. The impact of precipitation, however, becomes smaller and mostly insignificant. This might be explained by the dynamic dependence of agricultural processes on climatic conditions, and rainfall in particular. An increase in precipitation leads to a higher output in the current year which partly passes through to the next period, an effect that is missed by the static model leading to an underestimation of the true effect.

### 3.3 GDP growth

The reduced forms for GDP growth are displayed in Table 3. The results suggest that short-term, medium-term and long-term increases in temperature significantly reduce GDP growth rates (Dell et al. 2012). For example, an increase in current temperatures by 1 percent is predicted to decrease GDP growth by almost 0.3 percentage points (column 1). For the climate change variables, the largest reduction of about 0.4 percentage points is estimated for one additional percentage point deviation from the 50-years benchmark. For precipitation, the effects on GDP growth are relatively weak and mostly insignificant. It might be conjectured that a too high temperature negatively impacts the overall economy, reducing GDP growth, whereas the main effects of precipitation are on agricultural output. Extreme weather events affect GDP growth, too, with one additional drought per year reducing GDP growth by almost 1 percentage point, and one additional flood increasing it by about 0.6 percentage points.

**Table 2:** Climate (Change) and agricultural output: System GMM estimation

| Dependent variable: log(agricultural output) | | | | | | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| L1.log(agricultural output) | 0.745 | 0.683 | 0.651 | 0.640 | 0.857 | 0.680 |
| | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) |
| L2.log(agricultural output) | -0.336 | -0.389 | -0.331 | -0.337 | -0.324 | -0.260 |
| | (0.065) | (0.023) | (0.052) | (0.052) | (0.090) | (0.120) |
| log(temp) | -1.370 | | | | | |
| | (0.043) | | | | | |
| log(precip) | 0.146 | | | | | |
| | (0.000) | | | | | |
| temp growth | | -1.101 | | | | |
| | | (0.023) | | | | |
| precip growth | | 0.0817 | | | | |
| | | (0.000) | | | | |
| $cc^5$ temp | | | -1.185 | | | |
| | | | (0.042) | | | |
| $cc^5$ precip | | | 0.0802 | | | |
| | | | (0.017) | | | |
| $cc^{10}$ temp | | | | -1.280 | | |
| | | | | (0.039) | | |
| $cc^{10}$ precip | | | | 0.0935 | | |
| | | | | (0.007) | | |
| $cc^{50}$ temp | | | | | -2.314 | |
| | | | | | (0.003) | |
| $cc^{50}$ precip | | | | | 0.0914 | |
| | | | | | (0.009) | |
| drought | | | | | | -0.0263 |
| | | | | | | (0.069) |
| storm | | | | | | 0.00530 |
| | | | | | | (0.672) |
| flood | | | | | | 0.00713 |
| | | | | | | (0.146) |
| Observations | 816 | 816 | 816 | 816 | 816 | 816 |
| F statistic | 211.5 | 328.5 | 155.4 | 191.9 | 191.1 | 161.3 |
| ar1p | <0.001 | <0.001 | <0.001 | <0.001 | <0.001 | <0.001 |
| ar2p | 0.207 | 0.139 | 0.158 | 0.155 | 0.262 | 0.244 |
| ar3p | 0.174 | 0.163 | 0.217 | 0.216 | 0.169 | 0.171 |
| hansenp | 0.741 | 0.807 | 0.768 | 0.710 | 0.823 | 0.764 |

*Notes:* L1 (L2) denote one (two) period lagged variables. $p$-values in parentheses. Year dummies included in all models. Estimates from pooled first-stage two-step system GMM with HAC robust standard errors using Windmeijer's finite-sample correction. *ar1p, ar2p, ar3p* indicate $p$-values for the Arellano and Bond (1991) autocorrelation tests of order 1, 2, and 3. *hansenp* indicates the $p$-values for the over-identification test as proposed by Hansen (1982).

We find some evidence for a persistence in GDP growth in Sub-Saharan Africa: the one- and two-year lags of GDP growth are both small and insignificant, but the three-year lagged impact is about 0.1 percentage points, and marginally significant at the 10 percent level. If we drop the lagged GDP growth variables from the model (see Table 10 in the appendix), then the estimated reduced form effects become somewhat smaller and statistically weaker suggesting similar mechanisms as for agricultural output.

Overall, the results for the impact of climate and climate change on GDP growth are largely consistent with our findings for agricultural output, but the estimated effects on GDP are weaker throughout. One explanation could be that the direct effects are less pronounced. Another explanation could be that the effects of climatic conditions solely go through agricultural output which is one of the driving forces of GDP.

We therefore add (the log of) agricultural output to the estimated equations to evaluate such a mechanism. Table 4 shows the results. As one would expect, agricultural output is a strong and significant predictor of GDP growth. Once agricultural output is controlled for, all climate and climate change variables with exception of the extreme weather events turn small and insignificant. This indicates that for countries in Sub-Saharan Africa, the causal mechanism running from climate (change) to GDP growth mainly stems from agricultural production. The effect of the extreme weather events on GDP growth becomes a bit smaller, too, suggesting the presence of at least some indirect effects, but the direct effects remain significant. This may be explained by the fact that extreme weather events affect public infrastructure well beyond the agricultural sector, and often trigger international help for stabilizing the local economy.

### 3.4 Civil conflicts

As a final outcome, we look at the reduced form effects of climate and climate change on the incidence of civil conflicts (see Table 5). Overall, there is little evidence for a reduced form effect. The estimated coefficients are small and insignificant. However, the results highly depend on the dynamics in the incidence of civil conflicts. Our results suggest an almost 25 percentage points higher chance of observing a conflict in the current year if there has been a conflict in the previous year. If we do not account for this persistence (see Table 11 in the appendix), then the impact of temperature is large and significant. The effects of precipitation also become more important, though only marginally significant or insignificant at the 10 percent level.

To summarize, climate and climate change seem to have little impact on the incidence of conflicts once past conflicts are kept fixed. Looking at the causal mechanisms, there can be alternative explanations for such a result. First, this could be due to inherently no effects of climatic conditions. Second, there could be indirect effects that run through past conflicts and/or economic outcomes and balance out. And finally, there could be yet another non-economic channel that is not visible in the reduced form. At this stage, we cannot tell these explanations apart, or whether any combination of them justifies the observed patterns in conflicts. In order to shed more light on the underlying causal channels we estimate a structural model in the next section.

**Table 3:** Climate (Change) and GDP growth: System GMM estimation

| Dependent variable: GDP growth | | | | | | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| L1.GDP growth | -0.0172 | 0.0347 | -0.0366 | -0.0183 | -0.0541 | 0.0143 |
| | (0.959) | (0.920) | (0.910) | (0.955) | (0.865) | (0.966) |
| L2.GDP growth | -0.0588 | -0.0296 | -0.0902 | -0.0743 | -0.0928 | -0.0432 |
| | (0.863) | (0.933) | (0.786) | (0.822) | (0.776) | (0.899) |
| L3.GDP growth | 0.114 | 0.114 | 0.115 | 0.116 | 0.112 | 0.126 |
| | (0.079) | (0.078) | (0.077) | (0.082) | (0.080) | (0.078) |
| log(temp) | -0.275 | | | | | |
| | (0.048) | | | | | |
| log(precip) | 0.0196 | | | | | |
| | (0.075) | | | | | |
| temp growth | | -0.277 | | | | |
| | | (0.012) | | | | |
| precip growth | | 0.00520 | | | | |
| | | (0.442) | | | | |
| $cc^5$ temp | | | -0.183 | | | |
| | | | (0.146) | | | |
| $cc^5$ precip | | | 0.0140 | | | |
| | | | (0.174) | | | |
| $cc^{10}$ temp | | | | -0.243 | | |
| | | | | (0.066) | | |
| $cc^{10}$ precip | | | | 0.0151 | | |
| | | | | (0.131) | | |
| $cc^{50}$ temp | | | | | -0.405 | |
| | | | | | (0.024) | |
| $cc^{50}$ precip | | | | | 0.00501 | |
| | | | | | (0.703) | |
| drought | | | | | | -0.00973 |
| | | | | | | (0.046) |
| storm | | | | | | -0.00429 |
| | | | | | | (0.182) |
| flood | | | | | | 0.00572 |
| | | | | | | (0.009) |
| Observations | 837 | 837 | 837 | 837 | 837 | 837 |
| F statistic | 14.85 | 18.96 | 14.90 | 14.35 | 15.02 | 16.24 |
| ar1p | 0.0997 | 0.0822 | 0.0882 | 0.0847 | 0.0934 | 0.0917 |
| ar2p | 0.870 | 0.885 | 0.727 | 0.765 | 0.770 | 0.912 |
| ar3p | 0.885 | 0.976 | 0.796 | 0.831 | 0.781 | 0.962 |
| hansenp | 0.576 | 0.548 | 0.598 | 0.565 | 0.614 | 0.509 |

*Notes:* See Table 2. $p$-values in parentheses. Year dummies included in all models. Estimates are based on the same specification as in Table 2.

**Table 4:** Climate (Change), agriculture and GDP growth: System GMM estimation

| Dependent variable: GDP growth | | | | | | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| L1.GDP growth | 0.0141 | 0.0213 | 0.0134 | 0.0153 | 0.0130 | 0.0136 |
| | (0.890) | (0.839) | (0.898) | (0.884) | (0.899) | (0.892) |
| L2.GDP growth | 0.0159 | 0.0218 | 0.0124 | 0.0141 | 0.0132 | 0.00432 |
| | (0.827) | (0.777) | (0.877) | (0.861) | (0.858) | (0.958) |
| L3.GDP growth | 0.0952 | 0.0937 | 0.0921 | 0.0923 | 0.0948 | 0.0914 |
| | (0.029) | (0.045) | (0.049) | (0.048) | (0.030) | (0.059) |
| log(agricultural output) | 0.315 | 0.297 | 0.301 | 0.299 | 0.312 | 0.295 |
| | (0.002) | (0.004) | (0.003) | (0.004) | (0.002) | (0.001) |
| log(temp) | -0.0195 | | | | | |
| | (0.947) | | | | | |
| log(precip) | -0.0182 | | | | | |
| | (0.168) | | | | | |
| temp growth | | -0.0836 | | | | |
| | | (0.436) | | | | |
| precip growth | | -0.00971 | | | | |
| | | (0.332) | | | | |
| $cc^5$ temp | | | 0.0548 | | | |
| | | | (0.819) | | | |
| $cc^5$ precip | | | -0.00767 | | | |
| | | | (0.433) | | | |
| $cc^{10}$ temp | | | | 0.0101 | | |
| | | | | (0.966) | | |
| $cc^{10}$ precip | | | | -0.00846 | | |
| | | | | (0.418) | | |
| $cc^{50}$ temp | | | | | 0.122 | |
| | | | | | (0.643) | |
| $cc^{50}$ precip | | | | | -0.0167 | |
| | | | | | (0.329) | |
| drought | | | | | | -0.00743 |
| | | | | | | (0.064) |
| storm | | | | | | -0.00655 |
| | | | | | | (0.029) |
| flood | | | | | | 0.00504 |
| | | | | | | (0.007) |
| Observations | 814 | 814 | 814 | 814 | 814 | 814 |
| F statistic | 16.29 | 23.04 | 14.02 | 17.12 | 15.37 | 64.27 |
| ar1p | 0.00582 | 0.00613 | 0.00680 | 0.00673 | 0.00612 | 0.0105 |
| ar2p | 0.632 | 0.563 | 0.638 | 0.623 | 0.665 | 0.535 |
| ar3p | 0.823 | 0.753 | 0.756 | 0.738 | 0.808 | 0.616 |
| hansenp | 0.341 | 0.329 | 0.335 | 0.336 | 0.344 | 0.393 |

*Notes:* See Table 2. $p$-values in parentheses. Year dummies included in all models. Estimates are based on the same specification as in Table 2.

**Table 5:** Climate (Change) and civil war: System GMM estimation

| Dependent variable: civil conflict | | | | | | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| L1.civil conflict | 0.243 | 0.249 | 0.248 | 0.249 | 0.239 | 0.247 |
| | (0.105) | (0.097) | (0.099) | (0.098) | (0.111) | (0.088) |
| log(temp) | 0.239 | | | | | |
| | (0.811) | | | | | |
| log(precip) | 0.0334 | | | | | |
| | (0.624) | | | | | |
| temp growth | | 0.370 | | | | |
| | | (0.519) | | | | |
| precip growth | | 0.0486 | | | | |
| | | (0.306) | | | | |
| $cc^5$ temp | | | -0.0899 | | | |
| | | | (0.915) | | | |
| $cc^5$ precip | | | 0.0134 | | | |
| | | | (0.786) | | | |
| $cc^{10}$ temp | | | | -0.0613 | | |
| | | | | (0.938) | | |
| $cc^{10}$ precip | | | | 0.00477 | | |
| | | | | (0.928) | | |
| $cc^{50}$ temp | | | | | 0.553 | |
| | | | | | (0.675) | |
| $cc^{50}$ precip | | | | | 0.0596 | |
| | | | | | (0.370) | |
| drought | | | | | | -0.00335 |
| | | | | | | (0.939) |
| storm | | | | | | -0.00503 |
| | | | | | | (0.836) |
| flood | | | | | | -0.00416 |
| | | | | | | (0.799) |
| Observations | 847 | 847 | 847 | 847 | 847 | 847 |
| F statistic | 6.340 | 6.982 | 9.435 | 8.765 | 5.264 | 28.65 |
| ar1p | 0.00293 | 0.00302 | 0.00317 | 0.00316 | 0.00281 | 0.00270 |
| ar2p | 0.641 | 0.679 | 0.637 | 0.645 | 0.645 | 0.652 |
| ar3p | 0.209 | 0.207 | 0.208 | 0.210 | 0.209 | 0.209 |
| hansenp | 0.266 | 0.270 | 0.273 | 0.272 | 0.267 | 0.269 |

*Notes:* See Table 2. $p$-values in parentheses. Year dummies included in all models. Estimates are based on the same specification as in Table 2.

## 4 Disentangling the impacts of climate (change) and output on civil conflicts

### 4.1 Structural model estimation

In the second part of our analysis, we estimate a model that explains the incidence of civil conflicts in dependence of economic outcomes and that accounts for the possibility of a "direct" effect of climatic conditions, with "direct" meaning that the estimated effects do not run through GDP growth or agricultural output.

The general model is specified as

$$\begin{aligned} conflict_{it} &= \alpha_1 conflict_{i,t-1} + \alpha_2 GDP\ growth_{it} + \alpha_3 \log(agri\ output)_{it} \\ &\quad +\beta' climatic\ conditions_{it} + \gamma_i + \delta_t + \varepsilon_{it} \end{aligned} \tag{5}$$

where $conflict_{it}$ is an indicator of civil conflict in country $i$ at time $t$. Its one-period lag[5] appears together with GDP growth and the log of agricultural output as endogenous right-hand side variables. As before, $\gamma_i$ is an unobserved time-constant country effect, $\delta_t$ is a time fixed effect, and $\epsilon_{it}$ is the structural error.

Equation (5) can be estimated by the pooled first-stage system GMM approach discussed above. An additional difficulty arises in the structural model due to the endogeneity of GDP growth and agricultural output. We construct supplemental moment conditions using further lags (and differences) of these two variables as instruments in the differenced (and in the level) equation. Like before, we calculate standard errors using a heteroscedasticity and autocorrelation (HAC) robust covariance matrix.

We will further impose and relax two types of restrictions. First, we set $\alpha_3$ equal to zero allowing for indirect effects of climatic conditions through agricultural output but not through GDP growth (which is included in the model). We then add agricultural output to see how the estimated effects change. Second, we evaluate the sensitivity of our results to setting $\alpha_1$ equal to zero. The results above suggest some persistence in civil conflicts, but it is yet unclear whether this is inherent to conflicts, or induced by certain economic conditions that are affected by the incidence of a civil conflict.

### 4.2 Climate (change), GDP growth, and civil conflicts

Table 6 shows the results under the restriction $\alpha_3 = 0$, i.e., without adjusting for agricultural output. Compared to the reduced form models, the persistence in civil conflicts is smaller and less significant. GDP growth reduces the likelihood of conflicts by about 0.7 percentage points with each additional percentage point. The point estimates are stable over the six models and about significant at the 5 percent level.

[5] **Further lags have been investigated but turned out to be not relevant here.**

Regarding the climate variables, we still do not find a significant impact on civil conflicts. However, compared to Table 5 we observe some changes in the signs of the estimated coefficients of temperature growth and the deviations from the 5-years and 10-years MA (although all not statistically significant). This suggests some sensitivity of the estimates of climate (change) as a response to economic output. These effects are modest at best and may be moderated by agricultural output, as indicated by Tables 3 and 4. In the next subsection, we therefore add the log of agricultural output to the model.

### 4.3 Adding agricultural output to the model

Estimating equation (5) without restrictions bears two major difficulties: i) endogeneity of lagged conflicts, and ii) endogeneity of GDP growth and agricultural output. Instrumenting the former with its two- and four-period lags, and the latter two with their one- and three-period lags in the difference equation, and using first order lagged differences as instruments in the level equation, we obtain the results shown in Table 7. The lag structure of the instruments is chosen such that each of them convincingly passes the relevance condition in a first stage regression (with t-stats at least 2.5).

The impact of GDP on the incidence of civil wars is about -0.75 percentage points with each additional percentage point in growth. Increases in agricultural output do not have a significant effect on conflicts. This is in line with the hypothesis that the impact of agricultural output on conflicts only runs through GDP growth, and once the latter is kept fix, there is no remaining residual influence. All in all, these results (including the persistence in conflicts) are robust irrespective of the chosen specification in the climate (change) variables which are still insignificant in all models.

As indicated by Table 6, but also Tables 5 and 11, the specification of a dynamic model heavily influences the results. Under the restriction $\alpha_1 = 0$, the model is static and we can employ a linear FE estimation strategy with GDP growth and agricultural output instrumented as above. The results under $\alpha_1 = 0$ do not entirely confirm the effects for GDP growth in the full model (see Table 13 in the appendix), and neglecting model dynamics also matters for agricultural output. The impact of the former is somewhat weaker, of the latter somewhat stronger (in absolute magnitude). Moreover, ignoring the endogeneity of GDP growth and agricultural output makes a significant difference (see Table 12 in the appendix), with the estimated impact of GDP growth too strong, and the estimated impact of agricultural output highly significant and almost double the size as in the model using panel internal instruments.

## 5 Discussion

Given the results presented in the preceding two sections, there are three main conclusions that can be drawn. First, we do not find evidence for a "direct" effect of climate

**Table 6:** Climate (Change), GDP growth and civil war: System GMM estimation

| Dependent variable: civil conflict | | | | | | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| L1.civil conflict | 0.165 | 0.165 | 0.167 | 0.167 | 0.158 | 0.166 |
| | (0.189) | (0.192) | (0.192) | (0.190) | (0.205) | (0.195) |
| GDP growth | -0.749 | -0.744 | -0.735 | -0.735 | -0.736 | -0.733 |
| | (0.056) | (0.050) | (0.051) | (0.050) | (0.055) | (0.053) |
| log(temp) | 0.265 | | | | | |
| | (0.784) | | | | | |
| log(precip) | 0.0691 | | | | | |
| | (0.354) | | | | | |
| temp growth | | -0.426 | | | | |
| | | (0.524) | | | | |
| precip growth | | 0.0489 | | | | |
| | | (0.263) | | | | |
| $cc^5$ temp | | | 0.115 | | | |
| | | | (0.892) | | | |
| $cc^5$ precip | | | 0.0353 | | | |
| | | | (0.515) | | | |
| $cc^{10}$ temp | | | | 0.0194 | | |
| | | | | (0.981) | | |
| $cc^{10}$ precip | | | | 0.0351 | | |
| | | | | (0.532) | | |
| $cc^{50}$ temp | | | | | 0.231 | |
| | | | | | (0.836) | |
| $cc^{50}$ precip | | | | | 0.0294 | |
| | | | | | (0.648) | |
| drought | | | | | | 0.0236 |
| | | | | | | (0.568) |
| storm | | | | | | -0.00176 |
| | | | | | | (0.937) |
| flood | | | | | | -0.00111 |
| | | | | | | (0.938) |
| Observations | 834 | 834 | 834 | 834 | 834 | 834 |
| F statistic | 3.475 | 4.841 | 2.822 | 2.746 | 3.534 | 7.177 |
| ar1p | 0.00336 | 0.00354 | 0.00344 | 0.00345 | 0.00327 | 0.00339 |
| ar2p | 0.967 | 0.923 | 0.970 | 0.978 | 0.977 | 0.933 |
| ar3p | 0.444 | 0.424 | 0.445 | 0.444 | 0.452 | 0.471 |
| hansenp | 0.212 | 0.213 | 0.217 | 0.218 | 0.219 | 0.213 |

*Notes:* See Table 2. $p$-values in parentheses. Year dummies included in all models. GDP growth in addition to lagged dependent variable treated as endogenous.

**Table 7:** Climate (Change), GDP growth, agriculture and civil war: System GMM

| Dependent variable: civil conflict | | | | | | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| L1.civil conflict | 0.148 | 0.153 | 0.153 | 0.153 | 0.141 | 0.156 |
| | (0.205) | (0.212) | (0.216) | (0.215) | (0.232) | (0.211) |
| GDP growth | -0.757 | -0.774 | -0.742 | -0.745 | -0.721 | -0.727 |
| | (0.044) | (0.054) | (0.058) | (0.057) | (0.053) | (0.068) |
| log(agricultural output) | -0.0847 | -0.0298 | -0.0624 | -0.0597 | -0.0479 | -0.0573 |
| | (0.647) | (0.837) | (0.693) | (0.704) | (0.804) | (0.724) |
| log(temp) | -0.0623 | | | | | |
| | (0.934) | | | | | |
| log(precip) | 0.0945 | | | | | |
| | (0.255) | | | | | |
| temp growth | | -0.712 | | | | |
| | | (0.302) | | | | |
| precip growth | | 0.0487 | | | | |
| | | (0.268) | | | | |
| $cc^5$ temp | | | -0.0870 | | | |
| | | | (0.906) | | | |
| $cc^5$ precip | | | 0.0476 | | | |
| | | | (0.391) | | | |
| $cc^{10}$ temp | | | | -0.193 | | |
| | | | | (0.796) | | |
| $cc^{10}$ precip | | | | 0.0516 | | |
| | | | | (0.375) | | |
| $cc^{50}$ temp | | | | | -0.262 | |
| | | | | | (0.801) | |
| $cc^{50}$ precip | | | | | 0.0393 | |
| | | | | | (0.613) | |
| drought | | | | | | 0.00979 |
| | | | | | | (0.796) |
| storm | | | | | | -0.00618 |
| | | | | | | (0.799) |
| flood | | | | | | -0.00742 |
| | | | | | | (0.529) |
| Observations | 807 | 807 | 807 | 807 | 807 | 807 |
| F statistic | 11.90 | 8.799 | 9.116 | 9.723 | 9.011 | 15.93 |
| ar1p | 0.00412 | 0.00437 | 0.00406 | 0.00409 | 0.00456 | 0.00407 |
| ar2p | 0.960 | 0.874 | 0.984 | 0.974 | 0.921 | 0.965 |
| ar3p | 0.455 | 0.434 | 0.453 | 0.452 | 0.457 | 0.464 |
| hansenp | 0.541 | 0.535 | 0.547 | 0.549 | 0.510 | 0.523 |

*Notes:* $p$-values in parentheses. Year dummies included in all models. GDP growth and agricultural output in addition to lagged dependent variable treated as endogenous.

and climate change on civil conflicts (see also Dell et al. (2012)) in our sample of Sub-Saharan African countries and the years 1985 to 2008. This result is even stronger given that we analyze a period of time where Sub-Saharan Africa shows an abnormal high prevalence of civil conflicts relative to other regions in the world (Collier and Hoeffler 2002). We therefore cannot confirm the results by Hsiang et al. (2011) or Burke et al. (2009) who find significant effects of (extreme) weather variation on civil conflicts.

Second, we obtain a strong and significant impact of short-, medium- and long-run climatic conditions on agricultural production (Schlenker and Lobell 2010), and to a lesser extent on GDP growth (Miguel et al. 2004, Dell et al. 2012). That is, climatic conditions affect civil conflicts primarily via such intermediate economic factors. We therefore find clear evidence for a causal chain where climate affects economic output, and shocks in economic output increase the likelihood of civil conflicts (Miguel et al. 2004). Moreover, we can conjecture that the impact is via agricultural production on GDP growth and then on conflicts, as agricultural output renders insignificant if GDP growth is fixed.

Third, we find that all our measures for medium- and long-term climate change have an effect on agricultural output. A higher temperature change exerts a negative impact whereas additional precipitation has a positive impact on agricultural production. In addition, we find the largest effects for the long-term changes followed by the deviations from the 10-years and the 5-years MA. This could be interpreted as evidence for a lack of adaptation capacities in Sub-Saharan Africa. Moreover, droughts do have the expected negative impact on agriculture although the effect is rather small.

From a methodological point of view, our results indicate the need for an econometric model that accounts for a large number of challenges the researcher faces in this context. First, countries in general, and Sub-Saharan African countries in particular, differ with respect to their prevalence of civil conflicts, the level of GDP growth, agricultural output and climatic conditions. Moreover, all these factors are subject to change over time or exhibit cycling behavior. We therefore think that accounting for country and year fixed effects is imperative when analyzing panel data for such a set of heterogeneous countries.[6] Second, almost all explanatory variables in a model for civil conflicts are likely endogenous (Miguel et al. 2004, Burke et al. 2009, Blattman and Miguel 2010, Miguel and Satyanath 2011, Ciccone 2011). Third, there is evidence for a persistence in civil conflicts, calling for a fully fletched dynamic panel data model.

An appealing way for dealing with these challenges is to apply a system GMM estimator as proposed by Arellano and Bover (1995) and Blundell and Bond (1998).[7] However, in a country-level panel of the present form one has to be careful when applying system GMM as the time dimension is relatively long (Miguel and Satyanath 2011). The data structure therefore deviates from the typical short panel (large $N$, small $T$) for which system GMM has been originally developed. One problem this might cause is that the

[6] See also the discussion in Buhaug (2010).
[7] See also the discussion in Miguel and Satyanath (2011) and Ciccone (2011).

number of instruments becomes very large when using the standard specification. In order to account for the specific data structure (fixed $N$ and $T$) we used a pooled first-stage system GMM estimator to ensure that the number of instruments does not exceed the number of countries (i.e., $N$). The reason for using a system GMM approach in the present setting is that although the Nickell bias (Nickell 1981) is less of a problem in the long panel under investigation (Miguel and Satyanath 2011) we make use of internal instruments for other covariates to account for their potential endogeneity. Relying solely on internal instruments is certainly not the first choice for identification but the only solution in cases where external instruments are rare.

Of course, as we are dealing with a binary dependent variable one would obtain more efficient estimates when using nonlinear estimation techniques (Buhaug 2010). However, in order to ensure unbiased estimates one would have to account for the specific data structure that comes with the research question at hand and solutions for dynamic panel data models with limited dependent variables are still non-standard especially for long panels and endogenous regressors (Carro 2007, Fernandez-Val and Vella 2011).

We also agree that it would be interesting to additionally analyze the onset of civil conflicts (Buhaug 2010, Dell et al. 2012). However, there are again several challenges to solve as one would have to account for the fact that onsets of civil conflicts are rather rare events (King and Zeng 2001) especially in our sample, and at the same time one needs to take care of country and time fixed effects, different types of endogeneity, dynamics, etc. Despite these enormous challenges and the resulting lack of appropriate estimators it would certainly be interesting to know more about how and why civil conflicts start.

## 6 Conclusion

The present paper sheds light on the influence of short-, medium-, and long-run climatic conditions on civil conflicts in Sub-Saharan Africa. Our analysis identifies a causal chain where climate (change) affects civil unrest exclusively via intermediate factors such as GDP growth or agricultural output. Although regularly postulated in the literature, we do not find evidence for a "direct" impact of climate (change) on civil conflicts. Reduced form models may provide important insights into the association between climatic conditions and conflicts, but we think that it is now crucial to identify the exact causal mechanisms at work. In particular, it has been discussed that there may be further factors that are influenced by climatic conditions and at the same time cause civil conflicts, like general health conditions associated with the outbreak of certain diseases, or mental distress (Kudamatsu et al. 2010) that we do not address in our analysis.

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## Appendix

**Table 8:** Included countries

| | |
|---|---|
| Angola | Lesotho |
| Benin | Madagascar |
| Botswana | Malawi |
| Burkina Faso | Mali |
| Burundi | Mauritania |
| Cameroon | Mozambique |
| Central African Republic | Namibia |
| Chad | Niger |
| Congo, Dem. Rep. | Rwanda |
| Cote d'Ivoire | Senegal |
| Eritrea | South Africa |
| Ethiopia | Sudan |
| Gabon | Swaziland |
| Gambia | Tanzania |
| Ghana | Togo |
| Guinea | Uganda |
| Guinea-Bissau | Zambia |
| Kenya | Zimbabwe |

**Table 9:** Climate (Change) and agriculture: FE estimation

| Dependent variable: log(agricultural output) | | | | | | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| log(temp) | -2.101 | | | | | |
| | (0.000) | | | | | |
| log(precip) | 0.0587 | | | | | |
| | (0.259) | | | | | |
| temp growth | | -0.650 | | | | |
| | | (0.070) | | | | |
| precip growth | | 0.0147 | | | | |
| | | (0.492) | | | | |
| $cc^5$ temp | | | -0.765 | | | |
| | | | (0.161) | | | |
| $cc^5$ precip | | | 0.0635 | | | |
| | | | (0.212) | | | |
| $cc^{10}$ temp | | | | -1.166 | | |
| | | | | (0.010) | | |
| $cc^{10}$ precip | | | | 0.0657 | | |
| | | | | (0.173) | | |
| $cc^{50}$ temp | | | | | -2.086 | |
| | | | | | (0.000) | |
| $cc^{50}$ precip | | | | | 0.0813 | |
| | | | | | (0.206) | |
| drought | | | | | | -0.00934 |
| | | | | | | (0.472) |
| storm | | | | | | -0.0220 |
| | | | | | | (0.094) |
| flood | | | | | | 0.0187 |
| | | | | | | (0.049) |
| Observations | 825 | 825 | 825 | 825 | 825 | 825 |
| F statistic | 615017.4 | 83294.9 | 94051.1 | 89184.8 | 45102.3 | 143612.0 |

*Notes:* $p$-values in parentheses. Linear FE estimation using Driscoll-Kraay standard errors. Year dummies included in all models.

**Table 10:** Climate (Change) and GDP growth: FE estimation

| Dependent variable: GDP growth | | | | | | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| log(temp) | -0.183 | | | | | |
| | (0.161) | | | | | |
| log(precip) | 0.00623 | | | | | |
| | (0.653) | | | | | |
| temp growth | | -0.219 | | | | |
| | | (0.029) | | | | |
| precip growth | | -0.000431 | | | | |
| | | (0.996) | | | | |
| $cc^5$ temp | | | -0.114 | | | |
| | | | (0.337) | | | |
| $cc^5$ precip | | | 0.00862 | | | |
| | | | (0.488) | | | |
| $cc^{10}$ temp | | | | -0.153 | | |
| | | | | (0.192) | | |
| $cc^{10}$ precip | | | | 0.00772 | | |
| | | | | (0.552) | | |
| $cc^{50}$ temp | | | | | -0.260 | |
| | | | | | (0.103) | |
| $cc^{50}$ precip | | | | | 0.00145 | |
| | | | | | (0.933) | |
| drought | | | | | | -0.00530 |
| | | | | | | (0.269) |
| storm | | | | | | 0.00238 |
| | | | | | | (0.461) |
| flood | | | | | | 0.00638 |
| | | | | | | (0.014) |
| Observations | 847 | 847 | 847 | 847 | 847 | 847 |
| F statistic | 6809.6 | 3620.3 | 68010.7 | 80817.0 | 26613.0 | 35595.9 |

*Notes:* $p$-values in parentheses. Linear FE estimation using Driscoll-Kraay standard errors. Year dummies included in all models.

**Table 11:** Climate (Change) and civil war: FE estimation

| Dependent variable: civil conflict | | | | | | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| log(temp) | 2.233 | | | | | |
| | (0.021) | | | | | |
| log(precip) | 0.0742 | | | | | |
| | (0.229) | | | | | |
| temp growth | | 0.361 | | | | |
| | | (0.534) | | | | |
| precip growth | | 0.0734 | | | | |
| | | (0.102) | | | | |
| $cc^5$ temp | | | 1.644 | | | |
| | | | (0.021) | | | |
| $cc^5$ precip | | | 0.0690 | | | |
| | | | (0.158) | | | |
| $cc^{10}$ temp | | | | 2.379 | | |
| | | | | (0.005) | | |
| $cc^{10}$ precip | | | | 0.0703 | | |
| | | | | (0.184) | | |
| $cc^{50}$ temp | | | | | 2.378 | |
| | | | | | (0.036) | |
| $cc^{50}$ precip | | | | | 0.0374 | |
| | | | | | (0.538) | |
| drought | | | | | | -0.00150 |
| | | | | | | (0.958) |
| storm | | | | | | -0.0354 |
| | | | | | | (0.143) |
| flood | | | | | | -0.00860 |
| | | | | | | (0.587) |
| _cons | -7.220 | 0.162 | 0.168 | 0.155 | 0.220 | 0.230 |
| | (0.019) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) |
| Observations | 851 | 851 | 851 | 851 | 851 | 851 |

*Notes:* $p$-values in parentheses. Linear FE estimation using Driscoll-Kraay standard errors. Year dummies included in all models.

**Table 12:** Climate (Change), GDP growth, agriculture and civil war: FE estimation

| Dependent variable: civil conflict | | | | | | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| GDP growth | -0.804 | -0.805 | -0.804 | -0.801 | -0.798 | -0.791 |
| | (0.000) | (0.000) | (0.000) | (0.000) | (0.001) | (0.000) |
| log(agricultural output) | -0.206 | -0.225 | -0.221 | -0.212 | -0.209 | -0.229 |
| | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) |
| log(temp) | 1.660 | | | | | |
| | (0.104) | | | | | |
| log(precip) | 0.0733 | | | | | |
| | (0.249) | | | | | |
| temp growth | | 0.137 | | | | |
| | | (0.833) | | | | |
| precip growth | | 0.0688 | | | | |
| | | (0.116) | | | | |
| $cc^5$ temp | | | 1.316 | | | |
| | | | (0.095) | | | |
| $cc^5$ precip | | | 0.0806 | | | |
| | | | (0.166) | | | |
| $cc^{10}$ temp | | | | 2.020 | | |
| | | | | (0.026) | | |
| $cc^{10}$ precip | | | | 0.0790 | | |
| | | | | (0.172) | | |
| $cc^{50}$ temp | | | | | 1.844 | |
| | | | | | (0.108) | |
| $cc^{50}$ precip | | | | | 0.0614 | |
| | | | | | (0.325) | |
| drought | | | | | | -0.00974 |
| | | | | | | (0.760) |
| storm | | | | | | -0.0419 |
| | | | | | | (0.078) |
| flood | | | | | | -0.00322 |
| | | | | | | (0.831) |
| Observations | 818 | 818 | 818 | 818 | 818 | 818 |
| F statistic | 6571.1 | 13873.9 | 13504.1 | 15697.1 | 12611.9 | 37880.7 |

*Notes:* $p$-values in parentheses. Linear FE estimation using Driscoll-Kraay standard errors. Year dummies included in all models. GDP growth and agricultural output treated as exogenous.

**Table 13:** Climate (Change), GDP growth, agriculture and civil war: FE estimation

| Dependent variable: civil conflict | | | | | | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| GDP growth | -0.661 | -0.706 | -0.668 | -0.670 | -0.667 | -0.678 |
| | (0.166) | (0.146) | (0.159) | (0.158) | (0.166) | (0.153) |
| log(agricultural output) | -0.147 | -0.0983 | -0.128 | -0.126 | -0.106 | -0.121 |
| | (0.485) | (0.576) | (0.490) | (0.494) | (0.622) | (0.519) |
| log(temp) | -0.0416 | | | | | |
| | (0.952) | | | | | |
| log(precip) | 0.0864 | | | | | |
| | (0.238) | | | | | |
| temp growth | | -0.690 | | | | |
| | | (0.306) | | | | |
| precip growth | | 0.0445 | | | | |
| | | (0.254) | | | | |
| $cc^5$ temp | | | -0.0133 | | | |
| | | | (0.984) | | | |
| $cc^5$ precip | | | 0.0416 | | | |
| | | | (0.384) | | | |
| $cc^{10}$ temp | | | | -0.121 | | |
| | | | | (0.862) | | |
| $cc^{10}$ precip | | | | 0.0482 | | |
| | | | | (0.341) | | |
| $cc^{50}$ temp | | | | | -0.240 | |
| | | | | | (0.799) | |
| $cc^{50}$ precip | | | | | 0.0334 | |
| | | | | | (0.609) | |
| drought | | | | | | -0.00429 |
| | | | | | | (0.907) |
| storm | | | | | | -0.0198 |
| | | | | | | (0.432) |
| flood | | | | | | 0.000950 |
| | | | | | | (0.946) |
| N | 809 | 809 | 809 | 809 | 809 | 809 |
| F | 3.655 | 3.582 | 3.195 | 3.125 | 3.982 | 5.177 |

*Notes:* $p$-values in parentheses. Linear FE estimation using HAC robust standard errors. Year dummies included in all models. GDP growth and agricultural output treated as endogenous.