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Mehdi Shiva, Hassan Molana, Andrzej Kwiatkowski

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Climatic Conditions and Internal Armed Conflicts
An Empirical Study

Mehdi Shiva* **Hassan Molana**** **Andrzej Kwiatkowski***

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Abstract

While climatic conditions are believed to have some influence on triggering conflicts, the existing empirical results on the nature and statistical significance of their explanatory role are not conclusive. We construct a dataset for a sample of 139 countries which records the occurrence of an armed conflict, the annual average temperature and precipitation levels as well as the relevant socio-economic, demographic and geographic measures over the 1961-2011 period. Using this dataset and controlling for the effect of relevant non-climate variables, our regression analyses support the significant explanatory role of climatic factors. Our results are consistent with the hypothesis that climate warming is instrumental in raising the probability of onset of internal armed conflicts and suggest that, along with regulating population size and promoting political stability, controlling climate change is one of the most effective factors for inducing peace by way of curtailing the onset of armed conflicts.

Keywords: climate change; armed conflict; logit model, average marginal effects

* University of Dundee
** Universities of Dundee and Aberdeen
Contact author and correspondence address: Hassan Molana
School of Social Sciences
University of Dundee
Dundee DD1 4HN, Scotland, UK
e-mail: h.h.molana@dundee.ac.uk
Tel: 0044(0)1382384339

1. Introduction

This paper focuses on the role of climatic factors in influencing the likelihood of onset of internal armed conflicts. A glance through the wider literature reveals that, albeit to different extents, economic, sociological and geographical factors – e.g., natural resources, historical grievance, ethnic dominancy, rough terrain and climatic conditions – all play direct and indirect roles in triggering and/or prolonging internal armed conflicts. However, despite the fact that climatic factors feature in quite a number of studies, the existing results on their impact does not convey a clear message. This paper addresses this issue. Our purpose is not to single out climatic factors as the main, or the most important, determinants of such conflicts. Instead, we wish to investigate if they feature significantly and robustly amongst the potential explanatory variables, and to measure the extent of their influence. By doing so, we hope to contribute to the debate on whether climate change issues should remain on the global policy agenda.

The majority of studies on the climate-conflict nexus agree with the neo-Malthusian interpretation that sees conflicts arising as a result of scarcity brought about by climatic changes – see, e.g., Fischer et al. (2002) and Hertel and Rosch (2010). A relatively large share of the literature on intrastate conflicts puts the primary emphasises on the role of natural resources seeking to explain the riddle of insurgency by linking the motivation of the rebels with their claims on such resources. Amongst the studies which examine the role of sociological and geographical factors, grievance is considered as one of the main causes of civil war: it is claimed that grievance is rooted in a behavioural paradigm which emphasises relative deprivation, social exclusion and inequality – see, amongst others, Gurr (1971), Scott (1977), Muller (1985) and Connor (1994). Collier and Hoeffler (2004) propose ethnic dominancy[1] as a civil war triggering factor but also agree that the ability to 'loot natural resources' motivates rebellion. Fearon and Laitin (2003) emphasise the facilitating role of rough terrain[2], whose relevance as an explanatory factor had been previously highlighted by Collier et al. (2001). The end of the cold war and decolonisation process, which are commonly accepted as the greatest political destabilising events of the past century, are considered also considered by a number of studies. Although these events are known to have proceeded with new conflicts in the nations that were affected by them, evidence on their direct role in triggering conflicts is somewhat controversial. Fearon and Laitin (2003) explain that the correlation between these events and prevalence of conflict could be due to the fact that in most cases the newly formed independent states were financially, bureaucratically, and militarily weak, but for instance, Collier (2008) examines countries involved in decolonisation and does not find a significant pattern.

There is also a parallel literature on identifying causes of conflict and/or violence at the individual level. Although the focus of these studies differs from ours, their analyses and findings can lend support to our motivation in attempting to understand whether climatic factors influence internal armed conflicts, especially to the extent that they could result from a form of collaborative aggressive behaviour fuelled by some kind of 'perceived injustice' – see

[1] This is defines as a situation in which one ethnic group makes up to 45-90% of the population.
[2] This is defined as the proportion of the country that is mountainous.

Muller and Opp (1986) and Stott and Reicher (1998). Anderson (2001), Anderson and DeLisi (2011), Hsiang et al. (2013) and Prediger et al. (2014) report evidence which associates the psychological effects of weather fluctuations (in the short-run) and climatic trends (in the long-run) with aggressive behaviour.

Despite a substantial, and ongoing, research on what provokes an armed conflict, however, a clear consensus on a coherent set of factors does not yet seem to exist. In particular, the role of climatic factors remains rather ambiguous with mixed results that vary between one extreme that regards them as critical and the other which dismisses them as irrelevant. We focus on filling this specific gap by carrying out a systematic statistical/econometric scrutiny of the explanatory role of variables that are commonly regarded in the literature as relevant, including measures of temperature and precipitation which capture the role of both the short-run, year-to-year, change in the weather as well as its long-run, historical, trend – similar to that used by Anderson and DeLisi (2011). We construct and use a sample of 139 countries over the 1961-2011 period. Our results, based on econometric analysis of regression equations whose dependent variable is the onset of intrastate armed conflicts, suggest that both temperature and precipitation play significant explanatory roles once the contribution of other relevant factors is accounted for. More specifically, we find that, ceteris paribus, the likelihood of starting a new conflict increases as the average temperature rises and precipitation level falls.

The rest of this paper is organised as follows. Section 2 reviews the literature. Section 3 describes our data and empirical methodology. Section 4 provides and discusses our evidence and Section 5 concludes the paper.

2. Literature review

While there is not a general agreement in the literature on what motivates a rebellion, a core set of explanatory variables can be deduced by sifting through the existing empirical studies. Collier and Hoeffler (2004), Gurr (1971) and Fearon and Laitin (2003) identify looting, religious reform, nationalistic and/or economic grievance, and demand of more favourable conditions as leading causes. Resource wealth, especially crude oil, is also thought to increase the probability of civil war since a resource-rich region has a strong incentive to seek a high level of autonomy (Fearon and Laitin, 2003) or even to go as far as wanting to form a separate independent state (Le Billon, 2001; Fearon, 2005). Ross (2004) distinguishes between different types of resources and finds that on the whole richness in fuel and nonfuel minerals and illicit drugs appears to be influential while other types of resource wealth – especially agricultural commodities – do not seem to provoke conflicts.

As far as the role of climate is concerned, the influencing channels identified in the literature are usually separated in terms of time horizon and the underlying mechanism, i.e. long-term climate change alters the risk factors involved while short-term climatic shocks raise the survival pressure; Gleditsch (2012) stresses the importance of recognising the distinct role of each channel. Various studies have examined the indirect effects of climatic factors which are exerted through, e.g., food scarcity, malnutrition and poverty. Based on their experiments in Namibia Prediger et al. (2014) find persistent food scarcity to increase anti-social behaviour and aggression. Following a birth cohort of children in Mauritius, Liu et al. (2004) analyse the relationship between malnutrition and subsequent antisocial behaviour and conclude that malnourished children exhibit symptoms of more aggressive behaviour. White et al. (2013) show that a greener habitat – e.g. larger park and recreation areas in cities (whose provision is facilitated by more favourable climatic conditions) – reduces the incidence of aggression. Fearon and Laitin (2003), Collier and Hoeffler (2004), Buhaug and Gates (2002) and Fearon and Laitin (2003) provide evidence on the impact of topological characteristics of a territory on facilitating or preventing an uprising.

A number of studies have examined the impact of sudden changes in the weather conditions: Hendrix and Glaser (2007) and Fjelde and Uexkull (2012) study the effect of precipitation; Burke et al. (2009), Buhaug (2010) and Hsiang et al. (2013) consider the role of temperature shocks; Raleigh and Urdal (2007) and Salehyan and Hendrix (2014) examine the impact of water level fluctuations; and last but not least, Bergholt and Lujala (2012) and Slettebak (2012) analyse the influence of natural disasters. However, the evidence presented in these studies does not lead to a clear conclusion about the size and significance of the estimated impact of climatic factors on conflicts. For instance, Hendrix and Glaser (2007) and Fjelde and Uexkull (2012) report a positive effect on probability of armed conflicts, Bergholt and Lujala (2012) and Raleigh and Urdal (2007) find the effect to be rather small or negligible, while Salehyan and Hendrix (2014) and Slettebak (2012) suggest negative effects. A novel study by Hsiang and Burke (2014) examines 50 rigorous quantitative studies on the association between violent conflict and socio-political stability and deviations of temperature and precipitation from their norm. They use meta-analysis methodology and a broad range of aggressive behaviour from individual-level violence to country-level political instability and civil war and conclude "*… the majority of studies suggest that conflict increases and social stability decreases when temperatures are hot and precipitation is extreme…*". Buhaug et al. (2014) criticise this methodology claiming that their study "*suffers from shortcomings with respect to sample selection and analytical coherence*". Buhaug et al. (2014,) argue that statistical analysis which pool different types of aggressive behaviour "*from non-violent land grabbing via urban riots to major civil war*" that have occurred in "*a wide range of spatial scales, from municipalities via countries to the entire world*", and use as explanatory variables "*a wide range of climatic events, from heat waves via excess rainfall to global ENSO* [El Niño–Southern Oscillation] *cycles*", are bound to result in inaccurate and biased estimates.

Although the link between temperature levels and incidence of individual-level aggression is not directly related to our focus, the existing findings on heat induced violence are worthwhile mentioning here. This is because the same underlying change in individual behaviour could lie at the core of inducing a collective violent action (some form of collaborative use of destructive forces) provided that a collective incentive existed a priori. Anderson (1989, 2001) and Baron and Bell (1976) find high temperature to increase the tendency to aggressive behaviour. Anderson (1989) reports that on average higher levels of individual-level aggressive behaviour and crime (e.g. murder, rape, assault, riot, wife beatings, etc.) are committed in hotter regions of the world. Anderson et al. (2000) estimate the effect of temperature on violent crime rates in different cities while controlling for the geographical location (*southness*), population size and socioeconomic status of the cities and find that a higher level of violence level is likely to be committed in hotter cities. Kenrick and MacFarlan (1986) find that aggressive horn honking is increased in hotter temperatures only by drivers who do not have air-conditioned cars. Using a field experiment in which a group of Dutch police officers participated in a simulated burglary scenario under different conditions, Vrij et al. (1994) found that on the whole officers were less aggressive and less likely to draw their weapons in cooler temperature conditions. Interestingly, while it is acknowledged that, in general, people living in extreme temperature conditions – hot or cold – are likely to experience relatively higher levels of aggression and violence, evidence suggests that the temperature effect is not symmetric: low temperature conditions are found to be less provoking – see, e.g., Anderson and Anderson (1998). This is explained by the fact that it is easier to overcome the environmental aspects of low temperature and is also supported by medical research on fluctuations in the level of tritiated paroxetine platelet in body which is negatively correlated with impulsivity and aggression and is found to be reduced in higher temperatures – see Tiihonen et al. (1997).

In sum, there is already a sufficiently convincing volume of evidence on the link between climatic conditions and aggressive and violent behaviour in general, and the incidence of armed conflicts in particular. However, there is not yet a clear cut evidence on the explanatory role of climatic factors on internal armed conflicts. Given the importance of understanding what causes the latter, there are sufficient grounds for constructing an appropriate dataset that enables a systematically examination of a well-specified regression equation with a view to assess the role of specific climatic factors in predicting the likelihood of onset of internal armed conflicts.

3. Definitions, data and preliminary evidence

The Uppsala Conflict Data Program (UCDP) defines conflict as: "*a contested incompatibility that concerns government and/or territory where the use of armed force between two parties, of which at least one is the government of a state, results in at least 25 battle-related deaths*". We use the conflict data provided by UCDP and the Peace Research Institute Oslo (PRIO) where an '*internal armed conflict*' is classified as occurring between the government of a state and one or more internal opposition groups without intervention from other states and is distinguished from an '*internationalised internal armed conflict*' in which there are foreign interventions in the form of supporting one or both sides involved in the conflict.[3] We shall use 'internal armed conflicts' as the dependent variable for which two main measures are available in the dataset: the '*incidence*' which records the existence of an active – or ongoing – conflict in a country in a specific year, and the '*onset*' which registers (in a country in a specific year) either the starting of a new conflict or the restarting of an old one when more than one year has passed since it was last recorded as being 'dormant'. Table 1 provides a summary of the conflict categories in the sample and Table A1 in the Appendix lists all the conflicts included in our sample which covers 139 countries over the 1961-2011 period. There

[3] The actual data can be found at http://www.ucdp.uu.se/gpdatabase/search.php and Gleditsch et al. (2002) and Harbom and Wallensteen (2012) provide further detail.

are 229 occurrences of the onset which account for 4.15% of the total observations. Our dependent variable is therefore a dichotomous categorical variable which takes the value of 1 if a new conflict has occurred in a country in a specific year. The ongoing conflicts in the sample are treated as 'missing' so as to avoid the confusion that would arise from the similarity between observations corresponding to a country-year where (i) there is a continuing conflict that had started before, and (ii) there is no conflict. Acknowledging the potential risk of truncating our sample, we believe this is the right procedure to avoid counting observations with an active conflict as 'no-conflict'.[4] Also, in order to avoid confusion in terminology, hereafter the word 'conflict' is used interchangeably with "the onset of an internal armed conflict".

[Tables 1]

Turning our attention to the choice of variables that influence the onset of a conflict, while the existing studies mentioned in the previous section provide helpful information on the relevance of different variables there is no consensus on a common or core set of variables. Hegre and Sambanis (2006) identify 88 variables that are frequently used in the literature to explain civil wars. They group these under 18 'concept' categories and use the specification strategy proposed by Levine and Renelt (1992) and implemented in Sala-i-Martin (1997) to choose a parsimonious set of explanatory variables for their regression analysis. Subject to data availability, we have used the information they provide on the relevance of these variables (regarding the statistical robustness of parameter estimates) as the main guide in selecting our set of regressors. Table 2 provides the list and definition of our non-climatic variables whose expected explanatory role and the way they have featured in other studies is briefly explained below:

Political Instability is expected to have a negative and direct influence on the onset of conflicts as well as exerting an indirect effect via its impact on economic performance (see, e.g., Alesina et al., 1996), and has been measured in different ways. For instance, Fearon and Laitin (2003) and Collier and Rohner (2008) use a dummy variable which takes the value of unity for those country-year observations in which there has been a substantial political change. We construct our measure following the method proposed by Hegre and Sambanis (2006) and use a decay function of the *Regime Durability* which corresponds to the length of time since the most recent regime change – and is defined by a three-point change in the Polity score over a period of three years or less. We use Polity IV data to construct our series – see Marshall and Jaggers (2002) and Marshall and Gurr (2013) for details.

Peace Fragility is inversely related to the length of time during which a country has not experienced any conflicts and is therefore expected to have a positive effect. On the whole, the length of peace period is considered as one of the main influencing factors in the literature.

[4] This method has been widely used in the literature by some of the most established scholars such as Collier and Hoeffler (2004) and Hegre and Sambanis (2006). The alternative, treating ongoing conflicts as 'no conflict', has been tested in robustness checks.

Collier (2008) explains this using the concept of 'conflict trap' deduced from the evidence that a country has a higher risk of starting another conflict in the post-conflict period. Collier and Hoeffler (2004) highlight the positive role of conflict-free years in keeping peace in the long run – see also Fearon (2005) and Hegre et al. (2013). Starting at 1946, we approximate the effective length of a peace period by the number of days from the end of the last conflict up to two years before the beginning of the next conflict so as to avoid endogeneity and to allow for the post conflict reconstruction time. We then apply the definition of peace fragility in Sambanis (2004) and Hegre and Sambanis (2006) who use a decay function of the peace period.

Ethnic Heterogeneity or ***Ethnic Fragmentation*** is thought to have a positive influence on triggering conflicts. The ideas was originally introduced by Gurr (1971) using grievance motives provoked by social exclusion and was further developed later by Fearon and Laitin (2003) and Collier and Hoeffler (2004) who studied the role of ethnic dispersion or diversity. Others, e.g. Hegre and Sambanis (2006), Collier and Rohner (2008) and Slettebak (2012), have investigated the contribution of different measures of ethnic diversity. Vanhanen (1999) initially used the racial, linguistic and religious diversity indices to represent ethnic heterogeneity but these were later combined into one index to represent the overall diversity index.

Rough Terrain measures the proportion of the area of the country that is mountainous and poorly served by roads and communication infrastructure, usually located farther away from where the state's power is concentrated. Since it takes time to arrive at destinations located in such areas and it is more difficult to operate there, their existence is expected to have a positive impact as it facilitates insurgency. The idea was first introduced conceptually by Fearon and Laitin (1999) and Buhaug and Gates (2002), and was later quantified in the study of conflict by Fearon and Laitin (2003) to capture the hide-out opportunity for rebels. Since then, a measure of rough terrain has featured as one of the important explanatory variables which pool data across different countries – see, e.g., Collier and Hoeffler (2004) and Collier and Rohner (2008).

Population is expected to have a positive impact. The main reason for this is based on the way a conflict is defined and requires a certain threshold of deaths in order for it to be classified as an armed violence against the state. Hegre and Sambanis (2006) maintain that the larger is the population the more likely are larger casualties. Fearon and Laitin (2003) further justify the positive effect of population on conflict on two other grounds: higher cost of surveillance and tracking suspects for the authorities and better recruitment opportunities for the opposition.

Per Capita GDP, is used in most studies and while it is commonly believed to capture the effect of level of development other justifications have also been provided for its role, e.g. Collier and Hoeffler (2004) argue that it reflects the (economic) opportunity cost of a conflict and Fearon and Laitin (2003) maintain that it captures the state's sovereignty embodied in military capabilities. On the whole, therefore, one would expect to find a negative relationship between per capita GDP and conflict.

GDP Growth too has been commonly used, in most cases in conjunction with per capita GDP and intended to capture the pace of those variables whose level is explained by the latter. Its impact therefore is not well-defined a priori and in fact appears to be unambiguous in the literature. For instance, Collier and Hoeffler (2004) find a negative effect and conjecture that, ceteris paribus, a higher is growth is likely to render conflicts more costly and therefore reduce the probability of starting a conflict. However, Heston (1994) and Hendrix and Glaser (2007), among others, have argued that poor data quality and measurement problems could undermine the reliability of this variable.

[Tables 2]

The list and definition of variables which are typically used for capturing the direct effect of climate change are given in Table 3. It is believed that the appropriate measure should adequately reflect both the long-run trend in climate change as well as the short-run climatic volatility so as to capture the resilience building phenomenon linked to the adaptation strategies (see Bloomfield and Nychka, 1992; Rea et al., 2011; and Koubi et al. 2012). Therefore, while we shall experiment with all the variables listed in Table 3, using each as an alternative explanatory variable to represent the role of climate change, it might be argued that $CT_{i,t}$ or $T_{i,t}$ – or, $CP_{i,t}$ or $P_{i,t}$ – represent the long-run pattern while $TD_{i,t}$, $\Delta T_{i,t}$ or $\%\Delta T_{i,t}$ – or, $PD_{i,t}$, $\Delta P_{i,t}$ or $\%\Delta P_{i,t}$ – better embody the short-run volatility in climate. In addition, the humidity index, $HI_{i,t}$, which adjusts $T_{i,t}$ for the impact of humidity so as to provide a more accurate measure of 'how hot the weather feels to the average person' is used as an alternative to $T_{i,t}$ and is expected to have a similar effect.

[Tables 3]

Given that we wish to focus on the role of the latter, here we provide a preliminary analysis of their relevance. Figure 1 plots, for the countries included in the sample and over the sample period: (i) deviation in the average annual temperature from its last 30 years' moving average[5]; (ii) the total number of onsets of conflicts; and (iii) total incidences of conflicts.

[Figure 1]

Three points are worth noting. First, the temperature deviation series is not stationary: a linear trend regression yields a mild but highly significant trend coefficient estimate of 0.024 with *t*-ratio of 9.20, and unit root tests cannot reject the null hypothesis that series is integrated of first order and hence nonstationary. To further support this evidence, which indicates a long-run pattern in climatic evolution, we also estimated the autocorrelation coefficients of the annual temperature deviations using

[5] IPCC defines climate as the 'average weather'. World Meteorological Organization (WMO) suggest the average should be taken over 30 years. We follow the latter method.

$$r_{t,t-s} = \frac{\sum_{i=1}^{N}\left(TD_{i,t} - \overline{TD}_t\right)\left(TD_{i,t-s} - \overline{TD}_{i,t-s}\right)}{\sqrt{\sum_{i=1}^{N}\left(TD_{i,t} - \overline{TD}_t\right)^2 \sum_{i=1}^{N}\left(TD_{i,t-s} - \overline{TD}_{i,t-s}\right)^2}}$$

where $TD_{i,t}$ is the annual temperature deviation from its climate level in country i in year t as defined in Table 3. As shown in Figure 2, although $r_{t,t-s}$ reduces with s, the estimates remain positive and statistically significant. As a result, we cannot rule out a systematic rise in the temperature that indicates global warming – namely, a gradual increase in the overall temperature of the atmosphere of Earth. Second, while we cannot reject the stationarity of the onset series, the incidence series too exhibits very similar characteristics to temperature deviation series and the corresponding linear trend regression yields a trend coefficient estimate of 0.253 with *t*-ratio of 5.46 and this non-stationarity is also supported by unit root tests.

Third, the simple static cointegration regression of incidence of conflicts on temperature deviation yields a highly significant cointegration coefficient with *t*-ratio of 4.3 and the Durbin-Watson statistic of 0.5 where the hypothesis that the cointegration residual series is stationary cannot be rejected. Together, these results suggest that we cannot rule out the hypotheses that some degree of climate warming has occurred over the sample period and that there is a positive causal association between climate warming and armed conflicts.

[Figure 2]

4. Evidence

To provide a systematic examination of the impact of climate, we shall estimate different versions of the following regression equation

$$y_{i,t} = z'_{i,t}\beta_z + \beta_x x_{i,t} + \mu_r + \theta_t + \alpha + u_{i,t},\ t \in [1,T],\ \ i \in [1,N], \quad (1)$$

where $y_{i,t} = 1$ if there is an onset of internal armed conflict in country i in year t and $y_{i,t} = 0$ otherwise. The explanatory variables consist of: $z_{i,t}$, the vector of non-climate (conditioning) explanatory variables listed in Table 2; $x_{i,t}$, a typical climatic factor, represented by one of the variables in Table 3; μ_r, the region fixed effect where each country in the sample is associated with a specific geo-political region denoted by the subscript $r \in [1,R]$;[6] θ_t, the year fixed effect. α is the constant intercept and the country-time specific disturbance term $u_{i,t}$ reflects all the omissions and is assumed to be independently distributed; at this stage we do not include a country fixed or random effect but allow for within country correlations by means of clustered errors.[7] Given the binary form of the dependent variable, our regression equation in (1) is

[6] We associate each country with one of the following six political regions: 'Western Europe and the US', 'Eastern Europe and Central Asia', 'South and East Asia and Oceania', 'Central and South America', 'Sub-Saharan Africa' and 'Middle East and North Africa'. The proposed categorisation is intended to reflect the tendency towards conflict in regions.

[7] It is more sensible to cluster errors on countries rather than on regions, of which there are only six in the current sample, to reduce the bias in standard errors. See Nichols and Schaffer (2007) and Wooldridge (2003) for details.

modified to reflect the assumption that its right-hand-side determines the conditional probability of onset subject to an unpredictable random error, namely,

$$Prob(y_{i,t} = 1 | (x_{i,t}, z'_{i,t}), \mu_r, \theta_t) = F(z'_{i,t}\beta_z + \beta_x x_{i,t} + \mu_r + \theta_t + \alpha) + u^*_{i,t}.$$

Two specification issues are worth noting at the outset. First, since there is evidence in the literature suggesting that the long-run effect of climate tends to be nonlinear, we shall use quadratic form for $\beta_{1x}x_{i,t} + \beta_{2x}x^2_{i,t}$ when $x_{i,t}$ is one of $CT_{i,t}$, $T_{i,t}$, $CP_{i,t}$ and $P_{i,t}$. Second, although in the interest of comparability with evidence available in the literature we shall include *GDP Growth* and the logarithm of *Population* and *Per Capita GDP*, it should be borne in mind that the sign and significance of their coefficient estimates might be affected by their interdependence. More precisely, given that *GDP Growth* is simply the change in logarithm of GDP between two subsequent periods, the effect captured by including $\beta_p \log(Population) + \beta_{gp} \log(GDP/Population) + \beta_g \log(GDP / GDP_{-1})$ is equivalent to that captured by using $\beta^*_p \log(Population) + \beta_{gdp} \log(GDP) + \beta_{gdpl} \log(GDP_{-1})$ instead, which enables the three parameters β^*_p, β_{gdp} and β_{gdpl} to be freely estimated. It follows that, since the restrictions $\beta_p = \beta^*_p + \beta_{gdp} + \beta_{gdpl}$, $\beta_{gp} = \beta_{gdp} + \beta_{gdpl}$ and $\beta_g = -\beta_{gdpl}$ should hold, direct estimates of β_p, β_{gp} and β_g might not exactly correspond to a priori conjectures especially if the distributed effect of income over the two subsequent periods, embodied in β_{gdp} and β_{gdpl}, does not support the underlying restriction.

4.1. The main results

We have used the logit model[8] to estimate different specifications based on equation (1) and in Table 4 report estimates of the average marginal effects (AMEs) of the main explanatory variables where each columns B to L corresponds to capturing the climate effect using one of the variables defined in Table 3; column A does not include any climate factor as explanatory variable and provides a benchmark with which the estimates reported in the other columns can be compared. The coefficient estimates reported in column A do not change much as we move across columns from B to L, which is an indication of robustness of our specification strategy. We find that most of the non-climate variables have the expected signs and are statistically significant. The exceptions are *Per Capita GDP* and *GDP Growth* which do not seem to play a statistically significant role, although coefficient estimates of the former have the correct sign. This anomaly was, to some extent, anticipated above and should not raise much concern since coefficient estimates of *Population* have the correct sign and are highly significant. We have also included (dummy) variables to represent whether a country is an oil exporter, or it has been affected by the collapse of the Soviet Union or by a conflict in one of its neighbouring countries, as well as its political regime type and geo-political region. We found that the corresponding coefficient estimates were on the whole insignificant and only report in Table 4

[8] While both logit and probit models are appropriate in these circumstances, the former is less restrictive regarding the assumptions on the distribution function representing the conditional probability.

the coefficient capturing the effect of belonging to the MENA region because it is one of the most troubled regions: the estimated coefficient is always positive but is only statistically significant at 10% critical level in very few cases.

[Table 4]

Turning our attention to climate variables, columns B and C show their long-run impact captured by the quadratic forms of $CT_{i,t}$ and $CP_{i,t}$ respectively: the AMEs have the correct sign – consistent with the role of climate in contributing to onset of conflict – but only temperature exerts a significant impact; a one s.d. rise in climate-level temperature (in Fahrenheit) raises the probability of conflict by 3.1 percentage points. Very similar results are obtained in columns D and E where we use $T_{i,t}$ and $P_{i,t}$ instead. Thus, precipitation does not seem to act as a significant proxy for the long-term effect of climate. However, this changes when we focus on the short-term effect and use the deviation in climate: as shown in columns F and G, the AMEs associated with both $TD_{i,t}$ and $PD_{i,t}$ are both statistically significant with correct signs. But replacing deviations with changes or growth rates to capture the short- term effect reverts to only temperature effect being significant as shown in columns H to J. In particular, a 2% rise in the current temperature (equivalent to one s.d.) increases the probability of onset of conflict by 0.7 percentage points. Finally, in the last column we report the role of humidity index whose effect turns out to be positive and significant but, as expected, its impact is lower than that of $T_{i,t}$, i.e. 0.015 < 0.032, since the former adjusts the latter for the impact of humidity. To summarise, as far as the impact of climate is concerned, measures which are based on temperature levels always play a positive and statistically significant role. While precipitation effect too always has the correct sign, it is only found to be significant when its deviation from the long-run climate level is used to proxy the short-run effect.

Based on the estimates of AMEs presented in Table 4, the annual average temperature and peace fragility have the highest impact followed by population size. In other words, we find that controlling climate change, along with promoting political stability and regulating the growth of population, can be most effective in reducing the likelihood of the onset of armed conflicts.

4.2. A further focus climate effects

In order to compare the quantitative impact of climate variables, in Figure 3 we show plots of the representative predictive margins calculated at different sample values of the relevant variable. These plots suggests a positive association between climate warming and the probability of onset of conflicts. In addition, to understand better the effectiveness of temperature levels, in Figure 4 we plot the AME of average annual temperature levels at different values which shows that the impact becomes significant at extreme heat levels.

[Figures 3 & 4]

To find which one of the measures used as a proxy for climate is more effective, in Table 5 we report the AMEs based on using the actual data (rather than standardised data used in obtaining the estimates reported in Table 4) for those climatic factor whose effect we found to be significant as reported in Table 4. The results are revealing in that they highlight the particular effectiveness of climate control policies that target reducing the deviation of current temperature from the long-run: a 1^{o} F increase above the climate average increases the probability of conflict by 0.8 percentage point.

[Table 5]

The above results were based on the assumption that each of the two main climate factors, temperature and precipitation, on their own represent a good proxy. However, treating these as independent and using them as alternative indicators disregards the possibility that they could play a complementary role. For instance, Lilleør and Van den Broeck (2011) argue that the impact of temperature is likely to be higher in drought-prone areas. We therefore estimated a more general regression equation that allows for an interaction between temperature and precipitation on the grounds that while only one measure – on the basis of the above evidence, a temperature-based measure – is more likely to capture the direct effect of climate, the impact is bound to be influenced by the extent to which the other measure varies. We experimented with different specifications by keeping the sample and all other control variables intact and using different combinations of temperature and precipitation measures and found that data supports the following model

$$y_{i,t} = z'_{i,t}\beta_z + \beta_{\%\Delta T}\left(\%\Delta T_{i,t}\right) + \beta_P P_{i,t} + \beta_{\%\Delta T,P}\left(\%\Delta T_{i,t} \times P_{i,t}\right) + \mu_r + \theta_t + \alpha + v_{i,t}. \qquad (2)$$

This specification is justified on the grounds that $\%\Delta T_{i,t}$ and $P_{i,t}$, which are less likely to be correlated, are respectively used to capture the short-run and long-run impacts of climate, and their interaction provides a better reflection of the hypothesis put forward by Lilleør and Van den Broeck (2011) since now $\frac{\partial y_{i,t}}{\partial(\%\Delta T_{i,t})} = \beta_{\%\Delta T} + \beta_{\%\Delta T,P}\, P_{i,t}$ and the impact of temperature fluctuations is enhanced in dryer climates or, put differently, a rise in precipitation moderates the impact of growing temperature. We found $\hat{\beta}_P = -0.00006\ (0.46)$, $\hat{\beta}_{\%\Delta T} = 0.166\ (2.60)$ and $\hat{\beta}_{\%\Delta T,P} = -0.00013\ (1.72)$ – t-ratio in parentheses – thus, as expected, the direct effect of $P_{i,t}$ remains insignificant but its impact upon the effect exerted by $\%\Delta T_{i,t}$ is significant at 10% critical level.

4.2. Robustness of evidence on the climate effects

The evidence so far supports the hypothesis that, ceteris paribus, the warming of climate significantly raises the probability of onset of conflicts. We now address a number of points that might throw some doubt on the reliability of this evidence by undermining its robustness. The first point concerns the possibility that the effectiveness of the climate factor might be diminishing over time. To examine this, we re-estimated the regression equations corresponding to columns D and E in Table 4 over the shorter period of 1967-2011 where we used the current and lagged climate factors, $T_{i,t-s}$ and $P_{i,t-s}$, in order to check if their impact is reduced as s rises. We present the estimated distributed lag effects in Table 6. Given that all regressions are estimated using an identical sample, the evidence suggests the passage of time does not significantly erode the climate effect.

[Table 6]

The next point arises since our sample is constructed by pooling all the countries regardless of their climatic characteristics. This imposes the implicit restriction that the impact of climate is homogeneous across different climatic conditions. One way to relax this restriction is to divide our sample into three groups of countries in terms of their general climate, namely *cold*, *mild* and *hot*, where the *mild* climate is assumed to prevail when the temperature is within one s.d. of the sample mean; *cold* and *hot* climates then correspond to temperatures below and above the lower and the upper bounds of the interval. Respectively, *cold*, *mild* and *hot* climate occur in 22.6%, 66.83% and 10.56% of observations in the sample. Accordingly, we construct three dummy variables, denoted by $DC_{i,t}$, $DM_{i,t}$ and $DH_{i,t}$ and assign them unity if the observation corresponds to a *cold*, *mild* and *hot* climate respectively and zero otherwise. Using these, we experimented with the following regression equation

$$y_{i,t} = z_{i,t}'\beta_z + \beta_x x_{i,t} + \gamma_m DM_{i,t} + \gamma_h DH_{i,t} + \beta_{xm} DM_{i,t} x_{i,t} + \beta_{xh} DH_{i,t} x_{i,t} + \mu_r + \theta_t + \alpha + \varepsilon_{i,t}, \quad (3)$$

which augments equation (1) with the dummies and their interactions with the climate variable, $x_{i,t}$, and treats the *cold* climate as the baseline. Table 7 reports estimates of the γ_j coefficients, associated with the dummies, and the interaction effects β_{xj}, when $x_{i,t}$ is set to one of $TD_{i,t}$, $\%\Delta T_{i,t}$, $PD_{i,t}$ or $\%\Delta P_{i,t}$. Clearly, in all cases estimates of γ_j are positive and statistically significant: as expected, ceteris paribus, the onset of a conflict is more likely in countries with warmer climate and $\hat{\gamma}_h > \hat{\gamma}_m$ holds in all cases. To illustrate how the impact of climate is likely to evolve in each case in Figures 5 and 6 we show how the AMEs of $DM_{i,t}$ and $DH_{i,t}$ vary when evaluated at different values of $\%\Delta T_{i,t}$ and $PD_{i,t}$. These confirm the expected result that on the whole the effect of a rise in temperature is less substantial in *cold* climates compared to *mild* and *hot* climates.

[Table 7 and Figures 5 & 6]

A number of studies which use cross country data (e.g. Burke et al., 2009, and Hsiang et al., 2013) have argued in favour of replacing the country characteristics, captured in equation (1) above by $\mu_r + z_{i,t}'\beta_z$, with country fixed effects, hence they recommend using the following regression equation instead,

$$y_{i,t} = \beta_x x_{i,t} + c_i + \theta_t + \alpha + \epsilon_{i,t}, \quad (4)$$

where c_i is the country specific fixed effect. This approach is worth considering when assessing the robustness of our evidence. However, we note that the specification in (4) restricts the sample since all the observations pertaining to countries that did not experience any conflict will have to be excluded. Besides reducing the sample size considerably (limiting the number of countries to 75 out of original 139) and eliminating the possibility of distinguishing between countries on the basis of a specific characteristic, this approach also raises the likelihood of introducing a sample selection problem since those countries which have experienced a conflict tend to have a number of common or very similar characteristics. In addition, the sample mean and median of 'risks of onset' for countries with a history of conflict are respectively 11.3% and 5%, which are noticeably larger than the corresponding values for the whole sample, namely 7.3% and 1.8% – see Table 1 above for other details. In Table 8 we compare our estimates based on this approach with those based on equation (1). The set of estimates entitled (A) are our original estimates which can be compared with those entitled (B); climatic factors retain their sign and significance but, as expected, their effects are considerably larger. To make direct comparison between the two specifications possible, the corresponding estimates based on identical samples are also reported in the table, entitled (C) and (D) respectively. These results too support our original conclusions regarding the sign of the impacts. While there are certain drawbacks in using this method – which stem from eliminating important observations from the sample and hence over-estimating the effects and introducing sample selection bias – it should be noted that it could be more appropriate in situations where the focus is on countries with a history of conflict and/or there are data availability issues regarding the country-specific characteristics.

[Table 8]

The next set of point concern the overall adequacy of our sample and estimation method. In this connection we consider the following main issues:[9]

(i) The 'rare event' characteristic of the dependent variable: King and Zeng (2001) and Tomz et al. (2003) discuss this problem in general and propose using an adjusted logit model specifically designed for estimating regression equations when the dependent variable measures the occurrence of a rare event. In particular, the results presented in King and Zeng (2001) suggest that standard logit estimates may under predict the probability of the occurrence such events and Tomz et al. (2003) show how their modified estimator yields lower mean squared errors when the dependent variable is data on outbreak of war, political activism or an epidemiological infection. Given that our dependent variable could be classified as rare-event since $y_{i,t} = 1$ only for less than 5% of the observations, we re-estimated equation (1) using the modified logit estimator and the results support our original conclusions regarding the impact of climate factors.[10]

[9] The results for these modified regressions are not reported in the paper but are available from authors on request.
[10] The software is made available for Stata by Tomz et al. (2003) and can be downloaded from https://gking.harvard.edu/relogit.

(ii) Treatment of observations corresponding to on-going conflicts: Our sample so far only includes those observations in which at least one new conflict has started but all the on-going conflicts (defined as an active conflict that had started before that specific observation) are excluded. An alternative would be to include the latter observations too but treat them as 'no conflict'. Although this modification skews the sample (since observations corresponding to an 'active conflict' are not distinguished from those corresponding to 'no conflict'), it is worthwhile checking if it affects the estimated impact of climatic effect. We therefore re-estimated equation (1) using the modified sample for the climate variable $x_{i,t} = \beta_{1T} T_{i,t} + \beta_{2T} T_{i,t}^2$ as an example (whose estimates based on the original sample are given in column D of Table 4) and found that the results support our original conclusion with the estimated AME 0.0211 being statistically significant at 5%.

(iii) Omission of 'internationalised internal armed conflicts': There is a clear distinction between *internal* and *internationalised* internal armed conflicts based on the definition introduced earlier: there is evident involvement of a foreign state in the later. It is therefore important to test if the presumption that internal armed conflicts that involve a third-party support are fundamentally different from other purely internal conflicts. We re-estimated equation (1) using a modified sample whose dependent variable accounts for both *internal* and *internationalised* conflicts but did not find any noticeable change in our main findings regarding the impact of climate factors.

(iv) Exclusion of the observations corresponding to high leverage cases: Since there are a number observations within the sample which could be described as 'outliers' and/or 'influential', due to the country-specific characteristics, it is important to ensure that their inclusion does not skew the parameter estimates. We therefore experimented with two methods that deal with this problem: (i) the approach recommended in Pregibon (1981) that identifies and omits observations with high leverage from the sample; (ii) the method advocated by Hosmer and Lemeshow (1989) and Hosmer et al. (2013) which identifies and omits observations with large residuals based on Pearson and Deviance residual measures. Re-estimating equation (1) after these sample modifications for the climate variable $x_{i,t} = \beta_{1T} T_{i,t} + \beta_{2T} T_{i,t}^2$ as an example did not alter the general conclusions, yielding an AME of 0.026 (statistically significant at 5%) and 0.037 (statistically significant at 1%) for the above methods, respectively.

(v) Omission of potentially relevant country-specific explanatory variables: In the interest of maintaining a parsimonious specification, we have used a selected subset of explanatory variables identified in the literature. We list the additional relevant variables in Table 9 where for each variable we report the study which uses that variable and/or the corresponding source. The corresponding coefficient estimates were statistically insignificant and including them as additional explanatory variables did not alter the effect of climate variables reported above.

[Table 9]

5. Summary and conclusion

The existence of reliable information on what triggers an intrastate armed conflict is essential for upholding peace. While numerous studies have addressed this issue by focussing on quantifying the influence of different factors, there is yet no firm consensus in the literature on whether a worsening of climatic conditions facilitates the onset of such a conflict. In this paper we have focussed on the existence and robustness of an empirical relationship between intrastate armed conflicts and climatic factors. We have constructed a dataset for a sample of 139 countries over the 1961-2011 period which, for each country-year observation, includes the relevant socio-economic, demographic, geographic and climatic measures as well as recording whether there has been an armed conflict. Our econometric analysis based on this dataset reveals that climate plays a consistent and statistically significant role once other relevant control variables are accounted for: rising temperature and reducing precipitation increase the probability of onset of internal armed conflicts, and this result holds when it is subjected to a battery of robustness checks. In addition, based on the estimated impacts of the standardised measures of different explanatory variables, represented by their corresponding average marginal effects on the probability of an onset, we find that the annual average temperature, peace fragility and population size exert the highest impact. Thus, according to our results, controlling climate change, protecting and promoting stability, and regulating the growth rate of population size are the most effective tools when targeting a reduction in the onset of internal armed conflicts as means of promoting peace.

References

Alesina, A., Özler, S., Roubini, N. and Swagel, P. (1996). Political instability and economic growth. *Journal of Economic growth*, 1(2), 189-211.

Anderson, C.A. (1989). Temperature and aggression: ubiquitous effects of heat on occurrence of human violence. *Psychological bulletin*, 106(1), 74.

Anderson, C. and Anderson K. (1998). Temperature and aggression: Paradox, controversy, and a (Fairly) clear picture. *Academic Press*, 247-298.

Anderson, C.A., Anderson, K. B., Dorr, N., DeNeve, K.M. and Flanagan, M. (2000). Temperature and aggression. *Advances in experimental social psychology*, 32, 63-133.

Anderson, C.A. (2001). Heat and violence. *Current directions in psychological science*, 10(1), 33-38.

Anderson, C.A. and DeLisi, M. (2011). Implications of global climate change for violence in developed and developing countries. In J. Forgas, A. Kruglanski, and K. Williams (Eds.), *The Psychology of Social Conflict and Aggression*. (pp. 249-265). New York, NY: Psychology Press.

Baron, R.A. and Bell, P.A. (1976). Aggression and heat: The influence of ambient temperature, negative affect, and a cooling drink on physical aggression. *Journal of Personality and Social Psychology*, 33(3), 245.

Bergholt, D. and Lujala, P. (2012). Climate-related natural disasters, economic growth, and armed civil conflict. *Journal of Peace Research*, 49(1), 147-162.

Bloomfield, P. and Nychka, D. (1992). Climate spectra and detecting climate change. *Climatic Change*, 21(3), 275-287.

Buhaug, H. (2010). Climate not to blame for African civil wars. *Proceedings of the National Academy of Sciences*, 107(38), 16477-16482.

Buhaug, H. and Gates, S. (2002). The geography of civil war. *Journal of Peace Research*, 39(4), 417-433.

Buhaug, H., Nordkvelle, J., Bernauer, T., Böhmelt, T., Brzoska, M., Busby, J.W., Ciccone, A., Fjelde, H., Gartzke, E., Gleditsch, N.P. and Goldstone, J.A. (2014). One effect to rule them all? A comment on climate and conflict. *Climatic Change*, 127(3-4), 391-397.

Burke, M.B., Miguel, E., Satyanath, S., Dykema, J.A. and Lobell, D.B. (2009). Warming increases the risk of civil war in Africa. *Proceedings of the national Academy of sciences*, 106(49), 20670-20674.

Cheibub, J.A., Gandhi, J. and Vreeland, J.R. (2010). Democracy and dictatorship revisited. *Public choice*, 143(1-2), 67-101.

Collier, P. (2008). *The bottom billion: Why the poorest countries are failing and what can be done about it*. New York, NY: Oxford University Press.

Collier, P. and Hoeffler, A. (2004). Greed and grievance in civil war. *Oxford economic papers*, 56(4), 563-595.

Collier, P. and Rohner, D. (2008). Democracy, development, and conflict. *Journal of the European Economic Association*, 6(2-3), 531-540.

Collier, P., Hoeffler, A. and Soderbom, M. (2001). On the duration of civil war. *World Bank Policy Research Working Paper*, No. 2681.

Connor, W. (1994). Ethnonationalism: The quest for understanding. Princeton, NJ: Princeton University Press.

Fearon, J.D. (2003). Ethnic and cultural diversity by country. *Journal of Economic Growth*, 8(2), 195-222.

Fearon, J.D. (2005). Primary commodity exports and civil war. *Journal of conflict Resolution*, 49(4), 483-507.

Fearon, J.D. and Laitin, D.D. (1999). Weak states, rough terrain, and large-scale ethnic violence since 1945. In *Annual Meetings of the American Political Science Association*, Atlanta, GA.

Fearon, J.D. and Laitin, D.D. (2003). Ethnicity, insurgency, and civil war. *American political science review*, 97(1), 75-90.

Fischer, G., Shah, M.M. and Van Velthuizen, H.T. (2002). Climate change and agricultural vulnerability. *International Institute for Applied Systems Analysis*. Laxenburg: IIASA Publications Department.

Fjelde, H. and von Uexkull, N. (2012). Climate triggers: Rainfall anomalies, vulnerability and communal conflict in sub-Saharan Africa. *Political Geography*, 31(7), 444-453.

Freedom House (2013). Freedom in the World 2013: Democratic breakthroughs in the balance. *Freedom House*. Washington, DC: Freedom House.

Gallup, J.L., Sachs, J.D. and Mellinger, A.D. (1999). Geography and economic development. *International regional science review*, 22(2), 179-232.

Gleditsch, K.S. and Ward, M.D. (1999). A revised list of independent states since the Congress of Vienna. *International Interactions*, 25(4), 393-413.Gleditsch, N.P. (2012). Whither the weather? Climate change and conflict. *Journal of Peace Research*, 49(1), 3-9.

Gleditsch, N.P., Wallensteen, P., Eriksson, M., Sollenberg, M. and Strand, H. (2002). Armed conflict 1946-2001: A new dataset. *Journal of peace research*, 39(5), 615-637.

Gurr, T.R. (1971). Why men rebel. Princeton, NJ: Harvard University Press.

Harbom, L. and Wallensteen, P. (2012). Armed conflict, 1989-2011. *Journal of Peace Research*, 49(4).

Harris, I., Jones, P.D., Osborn, T.J. and Lister, D.H. (2014). Updated high-resolution grids of monthly climatic observations–the CRU TS3. 10 Dataset. *International Journal of Climatology*, 34(3), 623-642.

Hegre, H. and Sambanis, N. (2006). Sensitivity analysis of empirical results on civil war onset. *Journal of conflict resolution*, 50(4), 508-535.

Hegre, H., Karlsen, J., Nygård, H.M., Strand, H. and Urdal, H. (2013). Predicting armed conflict, 2010–2050. *International Studies Quarterly*, 57(2), 250-270.

Hendrix, C.S. and Glaser, S.M. (2007). Trends and triggers: Climate, climate change and civil conflict in Sub-Saharan Africa. *Political geography*, 26(6), 695-715.

Hertel, T.W. and Rosch, S.D. (2010). Climate change, agriculture, and poverty. *Applied Economic Perspectives and Policy*, 32, 355–385

Heston, A. (1994). A brief review of some problems in using national accounts data in level of output comparisons and growth studies. *Journal of development Economics*, 44(1), 29-52.

Hosmer, D.W. Lemeshow, S. (1989). *Applied regression analysis*. New York, NY: John Willey.

Hosmer Jr, D.W., Lemeshow, S. and Sturdivant, R.X. (2013). *Applied logistic regression* (Vol. 398). New York, NY: John Wiley and Sons.

Hsiang, S.M., Burke, M. and Miguel, E. (2013). Quantifying the influence of climate on human conflict. *Science*, 341(6151), 1212-1227.

Hsiang, S.M. and Burke, M. (2014). Climate, conflict, and social stability: what does the evidence say? *Climatic Change*, 123(1), 39-55.

Kenrick, D.T. and MacFarlane, S.W. (1986). Ambient temperature and horn honking a field study of the heat/aggression relationship. *Environment and behavior*, 18(2), 179-191.

King, G. and Zeng, L. (2001). Logistic regression in rare events data. *Political analysis*, 9(2), 137-163.

Koubi, V., Bernauer, T., Kalbhenn, A. and Spilker, G. (2012). Climate variability, economic growth, and civil conflict. *Journal of peace research*, 49(1), 113-127.

La Porta, R., Lopez-de-Silanes, F., Shleifer, A. and Vishny, R. (1999). The quality of government. *The Journal of Law, Economics, and Organization*, 15(1), 222-279.

Le Billon, P. (2001). The political ecology of war: natural resources and armed conflicts. *Political geography*, 20(5), 561-584.

Levine, R. and Renelt, D. (1992). A sensitivity analysis of cross-country growth regressions. *The American Economic Review*, 82(4), 942-963.

Lilleør, H.B. and Van den Broeck, K. (2011). Economic drivers of migration and climate change in LDCs. *Global Environmental Change*, 21(1), S70-S81.

Liu, J., Raine, A., Venables, P.H. and Mednick, S.A. (2004). Malnutrition at age 3 years and externalizing behavior problems at ages 8, 11, and 17 years. *American Journal of Psychiatry*, 161(11), 2005-2013.

Marshall, M.G. and Jaggers, K. (2002). Polity IV project: Political regime characteristics and transitions, 1800-2002.

Marshall, M.G. and Gurr, T.R. (2013). Polity IV project: Political regime characteristics and transitions, 1800-2013.

Masterton, J.M. and Richardson, F.A. (1979). Humidex; a method of quantifying human discomfort due to excessive heat and humidity. Downsview, Ont: Environment Canada, Atmospheric Environment.

Mellinger, A.D., Sachs, J.D. and Gallup, J.L. (2000). Climate, coastal proximity, and development. In G.L. Clark, M.P. Feldman, and M.S. Gertler (eds.), The Oxford handbook of economic geography (pp. 169-194). New York, NY: Oxford University Press.

Muller, E.N. (1985). Income inequality, regime repressiveness, and political violence. *American Sociological Review*, 50(1), 47-61.

Muller, E.N. and Opp, K.D. (1986). Rational choice and rebellious collective action. *American Political Science Review*, 80(2), 471-487.

Nichols, A. and Schaffer, M. (2007). Clustered errors in Stata. In *United Kingdom Stata Users' Group Meeting*. London, UK.

Prediger, S., Vollan, B. and Herrmann, B. (2014). Resource scarcity and antisocial behavior. *Journal of Public Economics*, 119, 1-9.

Pregibon, D. (1981). Logistic regression diagnostics. *The Annals of Statistics*, 9(4), 705-724.

Raleigh, C. and Urdal, H. (2007). Climate change, environmental degradation and armed conflict. *Political geography*, 26(6), 674-694.

Rea, W., Reale, M. and Brown, J. (2011). Long memory in temperature reconstructions. Climatic Change, 107(3), 247-265.

Ross, M.L. (2004). How do natural resources influence civil war? Evidence from thirteen cases. *International organization*, 58(01), 35-67.

Ross, M.L. (2013). Oil and gas data, 1932-2011. Harvard Dataverse Network. https://dataverse.harvard.edu/dataset.xhtml?persistentId=hdl:1902.1/20369

Sala-i-Martin, X.X. (1997). I just ran two million regressions. *The American Economic Review*, 87(2), 178-183.

Salehyan, I. and Hendrix, C.S. (2014). Climate shocks and political violence. *Global Environmental Change*, 28, 239-250.

Sambanis, N. (2004). What is civil war? Conceptual and empirical complexities of an operational definition. *Journal of conflict resolution*, 48(6), 814-858.

Scott, J.C. (1977). The moral economy of the peasant: Subsistence and rebellion in Southeast Asia. New Haven, CT: Yale University Press.

Slettebak, R.T. (2012). Don't blame the weather! Climate-related natural disasters and civil conflict. *Journal of Peace Research*, 49(1), 163-176.

Stott, C. and Reicher, S. (1998). Crowd action as intergroup process: Introducing the police perspective. *European Journal of Social Psychology*, 28(4), 509-529.

Tiihonen, J., Räsänen, P. and Hakko, H. (1997). Seasonal variation in the occurrence of homicide in Finland. *American Journal of psychiatry*, 154(12), 1711-1714.

Tomz, M., King, G. and Zeng, L. (2003). ReLogit: Rare events logistic regression. *Journal of statistical software*, 8(i02).

Vanhanen, T. (1999). Domestic ethnic conflict and ethnic nepotism: A comparative analysis. *Journal of Peace Research*, 36(1), 55-73.

Vrij, A., Van der Steen, J. and Koppelaar, L. (1994). Aggression of police officers as a function of temperature: An experiment with the Fire Arms Training System. *Journal of community and applied social psychology*, 4(5), 365-370

World Bank (2014). World Development Indicators 2014. Washington, DC: World Bank Publications.

Wooldridge, J.M. (2003). Cluster-sample methods in applied econometrics. *The American Economic Review*, 93(2), 133-138.

Table 1. Conflict data categories

Onset of conflicts (ongoing treated as missing)	Number	%	Onset of conflicts	Number	%	Incidence of conflicts	Number	%
No conflict	5,286	95.85	**No conflict**	6,123	95.97	**No conflict**	5,286	82.85
Minor	190	3.45	**Internal conflict**	229	3.59	**Internal conflict**	938	14.7
Major	39	0.70	**Internationalised**	28	0.44	**Internationalised**	156	2.45
Total	5,515	100	**Total**	6,380	100	**Total**	6,380	100

Table 2. List of the main country-specific explanatory variables

Variable	Description	Sample Size[6]	Sample Mean	Standard Deviation	Minimum Value	Maximum Value
Political Instability	2^{-2RS} where RS represents a measure of regime stability[1]	6330	0.1077	0.2897	0	1
Peace Fragility	$2^{-PD/8}$ where PD is a measure of peace duration[2]	6380	0.4312	0.3770	0.0036	1
Ethnic Heterogeneity Index	Ascending from perfectly homogenous to most heterogeneous[3]	6380	45.5611	34.0722	0	144
Rough Terrain	Percentage of total area[4]	6380	2.0575	1.4418	0	4.5570
Population	Mid-year estimates (in natural logarithm)[5]	6377	16.002	1.5125	12.3051	21.019
Per Capita GDP	Annual, in constant 2005 US$ prices[5]	5719	7.6941	1.5884	3.9129	11.3138
GDP Growth	Percentage change in annual GDP in constant 2005 US$ prices[5]	5712	3.9967	6.8355	-64.0471	189.8299

1. Constructed using Polity IV data, available at http://www.edac.eu/indicators_desc.cfm?v_id=63.
2. Constructed using Conflict Dataset, available at http://www.ucdp.uu.se/gpdatabase/search.php.
3. Data based on combining sub-indices of racial, linguistic, and religious diversity, from Vanhanen (1999).
4. Data are from Fearon and Laitin (2003).
5. Data from World Bank (2014).
6. The sample consists of 6380 country-year observations consisting of 139 countries for the period 1961-2011. The full list of countries with a conflict can be found in Table A1 in the Appendix. However, the sample is not balanced as not all the countries existed throughout the years, e.g. the countries formed after the collapse of the Soviet Union.

Table 3. Measures of climatic factors used as the explanatory variable of interest[1]

Variables	Notation and Description	Sample Mean	Standard Deviation	Minimum Value	Maximum Value
Temperature	$T_{i,t}$: Annual average temperature in Fahrenheit	66.1540	14.6904	18.6800	85.6400
Precipitation	P_{it}: Annual total precipitation in mm in natural logarithm	6.6501	0.9733	2.5953	8.2095
Climate Temperature	$CT_{i,t}$: Moving averages of $T_{i,t}$ of over the last 30 years	65.8012	14.7283	22.0820	83.8400
Climate Precipitation	CP_{it}: Moving averages of $P_{i,t}$ of over the last 30 years	1093.597	758.2622	37.3833	3164.580
Temperature Deviation from Climate	$TD_{i,t} = T_{i,t} - CT_{i,t}$	0.3528	0.8678	-3.4800	4.3560
Precipitation Deviation from Climate	$PD_{i,t} = P_{i,t} - CP_{i,t}$	-0.2021	163.2015	-919.5800	1340.117
Change in Temperature	$\Delta T_{i,t} = T_{i,t} - T_{i,t-1}$	0.0196	0.9753	-5.4000	5.2200
Change in Precipitation	$\Delta P_{i,t} = P_{i,t} - P_{i,t-1}$	0.0189	221.8989	-1864.200	1745.200
Growth Rate of Temperature	$\%\Delta T_{i,t} = \Delta T_{i,t}/T_{i,t-1}$	0.0551	2.0603	-20.8655	26.0171
Growth Rate of Precipitation	$\%\Delta P_{i,t} = \Delta P_{i,t}/P_{i,t-1}$	3.0104	28.1862	-82.5723	471.371
Humidity Index[2]	$HI_{i,t}$: Annual index value	22.4561	11.9048	-11.6894	40.5765

1. The raw data is based on daily record of temperature and precipitation and were obtained from the Climatic Research Unit (Harris et al. 2014) which provides monthly gridded fields based daily values and is calculated on high-resolution (0.5x0.5 degree) grids based on an archive of monthly values provided by thousands of weather stations distributed globally. $T_{i,t}$ and P_{it} country i and year t were calculated by matching each weather station with its host country and obtaining the corresponding annual average values for each i and t. The sample consists of 6380 country-year observations for the period 1961-2011. The full list of countries with a conflict can be found in Table A1 in the Appendix. However, the sample is not balanced as not all the countries existed throughout the years, e.g. the countries formed after the collapse of the Soviet Union.
2. $HI_{i,t} = T'_{i,t} + 0.5555\left[6.11e^{5417.7530\left(\frac{1}{273.16}-\frac{1}{Dew_{i,t}}\right)} - 10\right]$ where $T'_{i,t}$ is the Centigrade transformation of $T_{i,t}$, $Dew_{i,t} = \frac{5}{9}\times\left(T'_{i,t} + 459.67\right) - \frac{9}{25}\left(100 - RH_{i,t}\right)$, and RH_{it} is the annual average percentage air humidity (Masterton and Richardson, 1979).

Table 4. Logit estimates of equation (1) with different climatic factors: average marginal effects (AMEs) of the explanatory variables

	A	**B**	**C**	**D**	**E**	**F**	**G**	**H**	**I**	**J**	**K**	**L**
$\boldsymbol{x_{i,t}}$**:**	--	$\boldsymbol{CT_{i,t}}$	$\boldsymbol{CP_{i,t}}$	$\boldsymbol{T_{i,t}}$	$\boldsymbol{P_{i,t}}$	$\boldsymbol{TD_{i,t}}$	$\boldsymbol{PD_{i,t}}$	$\boldsymbol{\Delta T_{i,t}}$	$\boldsymbol{\Delta P_{i,t}}$	$\boldsymbol{\%\Delta T_{i,t}}$	$\boldsymbol{\%\Delta P_{i,t}}$	$\boldsymbol{HI_{i,t}}$
Political Instability	0.0115***	0.0122***	0.0115***	0.0121***	0.0116***	0.0114***	0.0116***	0.0115***	0.0116***	0.0115***	0.0116***	0.0117***
Peace Fragility	0.0300***	0.0289***	0.0300***	0.0288***	0.0298***	0.0301***	0.0300***	0.0302***	0.0300***	0.0301***	0.0300***	0.0290***
Ethnic Heterogeneity	0.0147***	0.0112***	0.0147***	0.0111***	0.0149***	0.0147***	0.0146***	0.0147***	0.0147***	0.0147***	0.0147***	0.0127***
Rough Terrain	0.0066	0.0154***	0.0065	0.0157***	0.0049	0.0069*	0.0065	0.0066	0.0065	0.0066	0.0066	0.0118**
Population	0.0197***	0.0222***	0.0195***	0.0222***	0.0182***	0.0194***	0.0197***	0.0196***	0.0197***	0.0195***	0.0197***	0.0219***
Per Capita GDP	-0.008	-0.0065	-0.0077	-0.0065	-0.0078	-0.0078	-0.0079	-0.0078	-0.0077	-0.0079	-0.0077	-0.0073
GDP Growth	0.0026	0.00244	0.0026	0.0024	0.00257	0.00253	0.0026	0.0025	0.0026	0.0025	0.0026*	0.0024
MENA region dummy	0.0212	0.0332*	0.0209	0.0334*	0.0273*	0.0229	0.0217	0.0218	0.0214	0.0219	0.0211	0.0285*
Climate: $\beta_{1x}x_{i,t} + \beta_{2x}x_{i,t}^2$	--	0.0307***	-0.0004	0.0317***	-0.0028	--	--	--	--	--	--	--
Climate: $\beta_{1x}x_{i,t}$	--	--	--	--	--	0.0068*	-0.0042**	0.0055*	-0.0026	0.0071**	0.0005	0.0150**
R^2	0.2746	0.2814	0.2747	0.2819	0.2760	0.2780	0.2757	0.2760	0.2751	0.2765	0.2747	0.2781
L	-603.29	-597.66	-603.29	-597.23	-602.14	-600.52	-602.39	-602.19	-602.94	-601.76	-603.28	-600.46

- The dependent variable is the ‘onset of an internal armed conflict’ which is a dummy set to unity if there an onset has occurred in a country during a year, and is zero otherwise.
- Lagged values of *Population*, *Per Capita GDP* and *GDP Growth* are used in order to avoid introducing an endogeneity bias and allow for the time required these to exert their impact.
- In order to facilitate comparison, all non-dummy explanatory variables are standardised so that the marginal effects reflect the impact of a one s.d. change in the value of the variables.
- The sample size in all regressions is 4463, consisting an unbalanced combination of 139 countries over the period 1961-2011.
- We only report the coefficient of the regional dummy associated with *MENA*; the base line region is Sub-Saharan Africa.
- ‘*’, ‘**’ and ‘***’ respectively denote significance at 10%, 5% and 1% critical values based on standard errors clustered at the country level. R^2 and L are the pseudo goodness of fit measure and pseudo log-likelihood values respectively.

Table 5. AMEs for different climatic factors[1]

Climatic Factor	$CT_{i,t}$[3]	$T_{i,t}$[3]	$\Delta T_{i,t}$	$\%\Delta T_{i,t}$	$TD_{i,t}$	$PD_{i,t}$
	Climate Temperature	Temperature	Change in Temperature	Growth Rate of Temperature	Temperature Deviation from Climate	Precipitation Deviation from Climate
AME[2]	0.21	0.22	0.6	0.4	0.8	-0.3

1. See the note below Table 4. The difference between these estimates and those reported in Table 4 is due to use of raw rather than standardised data.
2. These measure the impact of 1o F or 100mm rise in temperature or precipitation on the probability of onset of conflict.
3. These variables appear in quadratic form as in Table 4.

Table 6. Comparing the AMEs of current and past temperature

Climate Factor / s:	0	1	2	3	4	5	6
Temperature: $\beta_{1T}T_{i,t-s} + \beta_{2T}T_{i,t-s}^2$	0.0305	0.0291	0.0296	0.0301	0.0292	0.0286	0.0275
	(2.40)	(2.35)	(2.40)	(2.38)	(2.35)	(2.29)	(2.27)
R^2	0.295	0.294	0.294	0.294	0.294	0.294	0.293
AIC	1228	1229	1229	1229	1229	1230	1230
Precipitation: $\beta_{1P}P_{i,t-s} + \beta_{2P}P_{i,t-s}^2$	-0.00363	-0.00237	-0.00351	-0.00433	-0.00207	-0.00394	-0.00215
	(0.78)	(0.52)	(0.77)	(0.92)	(0.43)	(0.83)	(0.47)
R^2	0.290	0.289	0.289	0.289	0.288	0.290	0.288
AIC	1236	1237	1238	1237	1238	1236	1238

See the notes below Table 4. The dependent variable and the set of regressors are identical to that used in Table 4, but the sample size is reduced to 4212 since we have dropped the observations for 1961-1966 to allow for maximum of 6 lags. The numbers in parentheses are the corresponding t-ratios (standard errors are clustered at the country level).

Table 7. Effect of climatic factors in different climates based on estimates of equation (3)

$x_{i,t}$:	$TD_{i,t}$	$\%\Delta T_{i,t}$	$PD_{i,t}$	$\%\Delta P_{i,t}$
γ_m	0.955**	1.011**	0.977**	0.978**
γ_h	1.788***	1.920***	1.891***	1.881***
β_x	0.0780	0.110**	0.00497*	0.00858
β_{xm}	0.0512	-0.0124	-0.00590**	-0.00903
β_{xh}	0.176	0.103	-0.00590**	-0.00719
Constant	-11.85	-11.70	-11.96	-11.87
R^2	0.2857	0.2873	0.2883	0.2852
L	-594.08	-592.78	-591.96	-594.50

- See the notes below Table 4. The dependent variable, the set of regressors and the sample are identical to that used in Table 4. The '*cold*' case is used as the baseline.
- This table exceptionally reports Log odds, as interpreting joint role and interaction terms separately, is not possible having just marginal effects.

Table 8. Comparing estimates of specifications (1) and (4)

Dependent: conflict onset					
climatic factor used:	$\boldsymbol{\beta_{1T}T_{i,t} + \beta_{2T}T_{i,t}^2}$	$\%\Delta \boldsymbol{T_{i,t}}$	$\boldsymbol{TD_{i,t}}$	$\boldsymbol{PD_{i,t}}$	**--**
	Temperature	Growth Rate of Temperature	Temperature Deviation from Climate	Precipitation Deviation from Climate	**--**
(A) Estimates based on equation (1) with full sample, reported in Table 4; sample size: 4463					
Estimated AME	0.0317***	0.00707**	0.00677*	-0.0042**	--
R^2	0.2819	0.2765	0.2780	0.2757	0.2746
L	-597.23	-601.76	-600.52	-602.39	-603.29
AIC	1326.47	1333.53	1335.055	1334.78	1334.59
BIC	1749.11	1749.77	1764.09	1751.02	1744.42
(B) Estimates based on equation (4) with *reduced* sample; sample size: 2678					
Estimated AME	0.21*	0.00821**	0.015**	-0.0116***	--
R^2	0.2542	0.2533	0.2558	0.2551	0.2520
L	-577.9	-578.65	-576.67	-577.28	-579.67
AIC	1251.8	1253.30	1253.35	1250.56	1253.35
BIC	1534.66	1536.15	1547.99	1533.41	1530.31
(C) Estimates based on equation (1) with *restricted* sample; sample size: 2224					
Estimated AME	0.0374	0.0173**	0.0154*	-0.00754*	--
R^2	0.1994	0.1983	0.1995	0.1966	0.1955
L	-542.0861	-542.8295	-542.0183	-543.9887	-544.7094
AIC	1216.172	1215.659	1218.037	1217.977	1217.419
BIC	1592.838	1586.618	1600.41	1588.936	1582.671
(D) Estimates based on equation (4) with *restricted* sample; sample size: 2224					
Estimated AME	0.317*	0.0162**	0.0182**	-0.00891**	--
R^2	0.2563	0.2546	0.2567	0.2535	0.2518
L	-503.5323	-504.7215	-503.2512	-505.4388	-506.583
AIC	1103.065	1103.443	1104.502	1104.878	1105.166
BIC	1377.004	1371.675	1384.148	1373.11	1367.691

- See the notes below Table 4. The dependent variable in all cases, the set of regressors in (A) and (C) and the sample in (A) are identical to that used in Table 4. The set of regressors in (B) and (D) replace the country-specific explanatory variables with country-specific fixed effects. The sample size in (A) and (B) is the maximum possible number of observations in each case and in (C) and (D) is the maximum possible common observations.

Table 9. Additional country-specific variables, description and source

- *Crop Production Index*: annual agricultural production index, 2004-2006 = 100 – World Bank (2014)
- *Soil Quality*: share of area with suitable soil for crop production – Gallup et al. (1999)
- *Latitude*: absolute value of capital city's latitude over 90 – La Porta et al. (1999)
- *Tropical Area*: share of 1995 population living in the tropic or sub-tropic areas – Mellinger et al. (2000)
- *Tropical Region*: dummy set to unity if the country is located in a tropical zone with latitudes within an interval of 23.26º from the equator – Mellinger et al. (2000)
- *Malaria*: share of 1995 population exposed to risk of Malaria – Gallup et al. (1999)
- *Ethnic Fractionalisation Index*: structural distance between languages as a proxy for the cultural groups in a country – Fearon (2003)
- *Ethnic Dominance*: actual share of largest ethnicity in total population – Fearon and Laitin (2003) – or whether the share exceeds 45% – Collier and Hoeffler (2004)
- *Language Diversity*: number of languages in Ethnologue or linguistic component of – Fearon and Laitin (2003) and Vanhanen (1999)
- *Ethnolinguistic Diversity:* the probability that two randomly selected individuals belong to different ethnolinguistic groups – Collier and Hoeffler (2004)
- *Religion Diversity*: component of *Ethnic Heterogeneity Index* – Vanhanen (1999)
- *Oil Production*: oil production in metric tons – Ross (2013)
- *Oil Exports*: barrels per day – Ross (2013)
- *Partially Free Polity*: dummy set to unity for a country with limited respect for political rights and civil liberties – Freedom House (2013)
- *Presidential Democracy*: presidential democracy system – Cheibub et al. (2010)
- *Autonomy*: dummy set to unity if the country has de facto autonomous regions – Hegre and Sambanis (2006)
- *Military Personnel*: number of armed forces personnel per 1000 people – World Bank (2014)

Figure 1. Number of conflicts and temperature deviation from climate

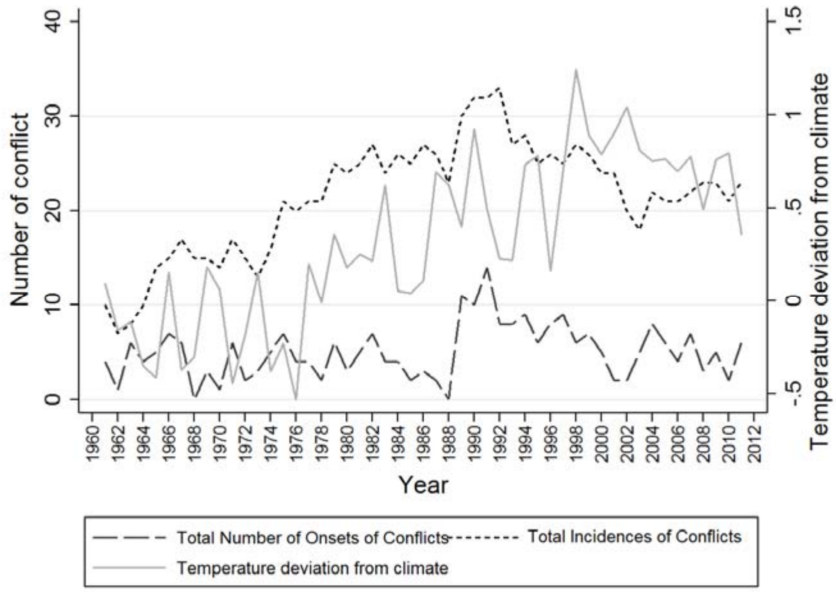


Figure 2. Sample autocorrelation coefficients with 90% CIs for $TD_{i,t}$

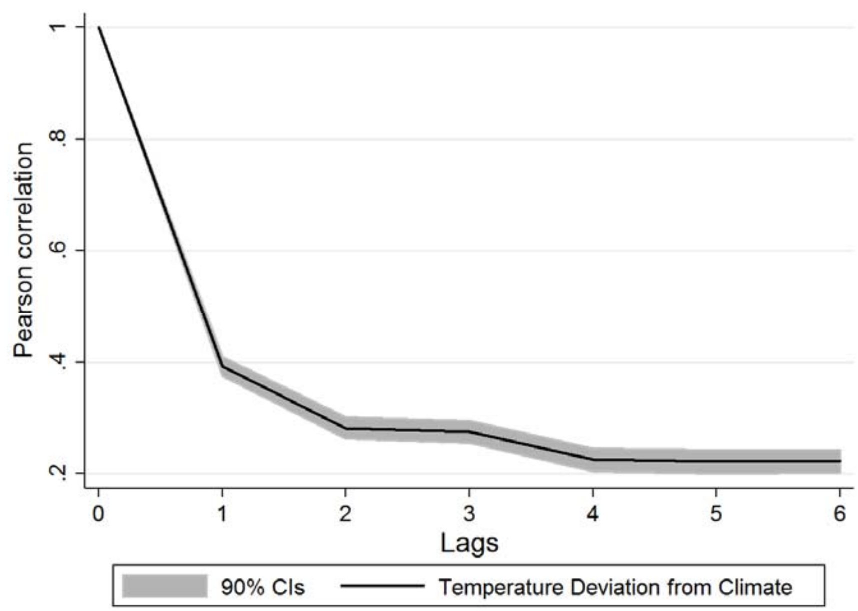


Figure 3. Predictive margins of selected climate variables with 90% confidence intervals based on the estimates reported in Table 4

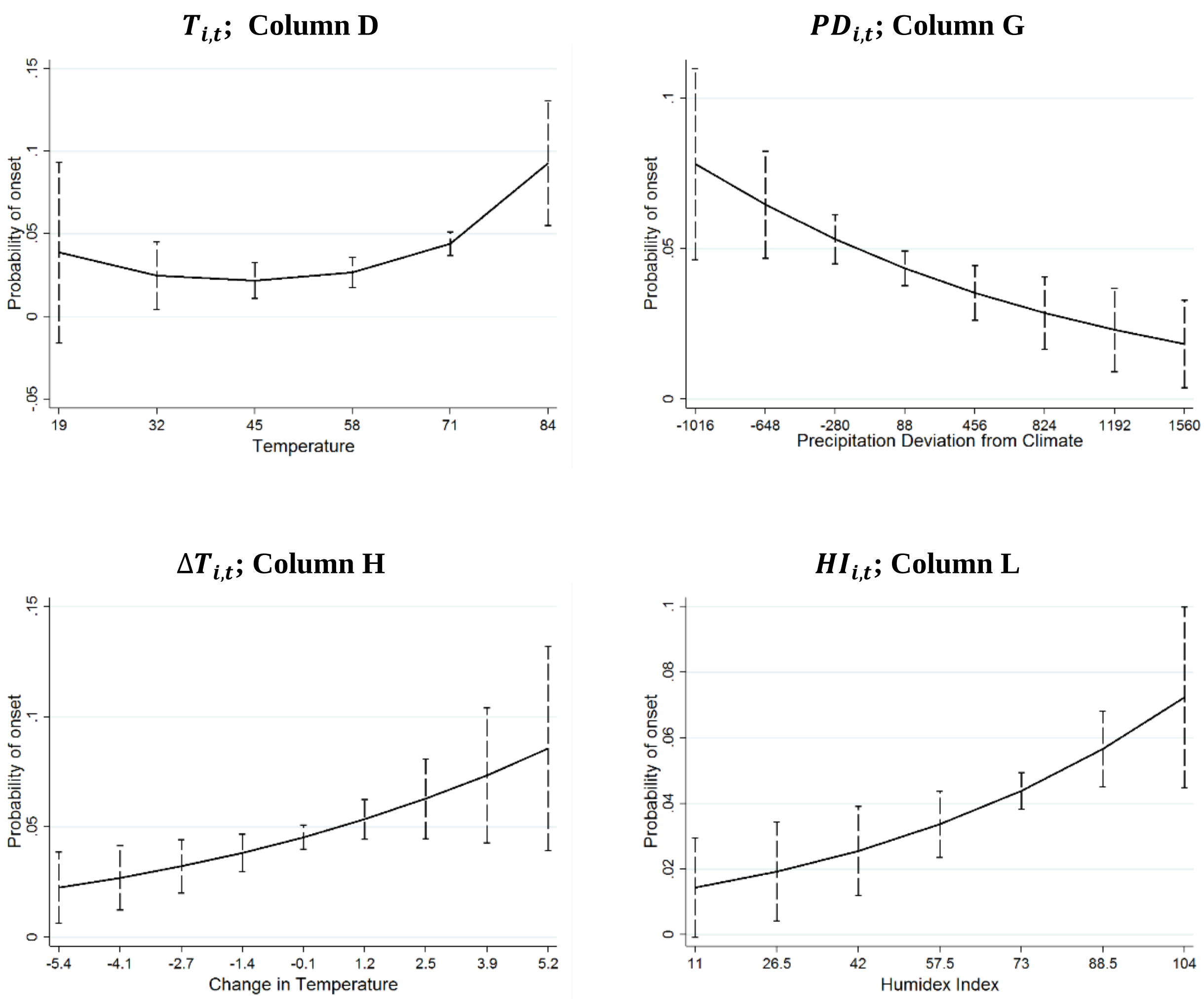


Figure 4. AMEs of $T_{i,t}$ with 90% confidence intervals (based on Column D of Table 4)

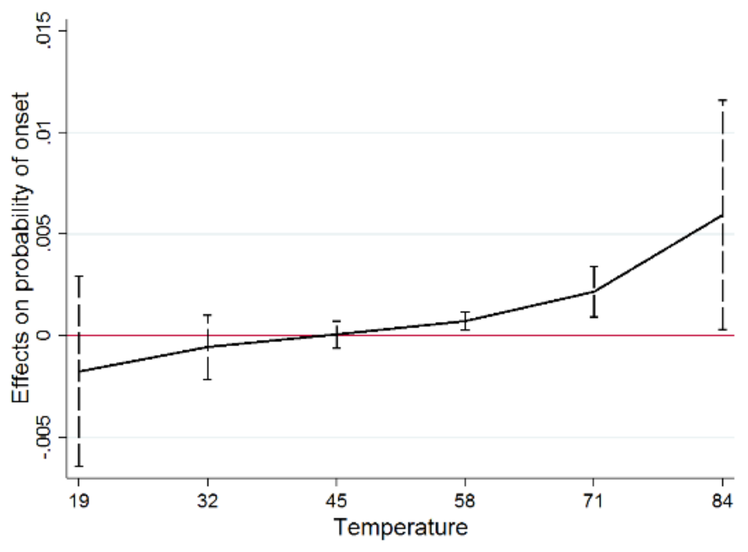


Figure 5. AMEs of belonging of Mild or Hot climate with 90% confidence intervals based on estimates of equation (3)

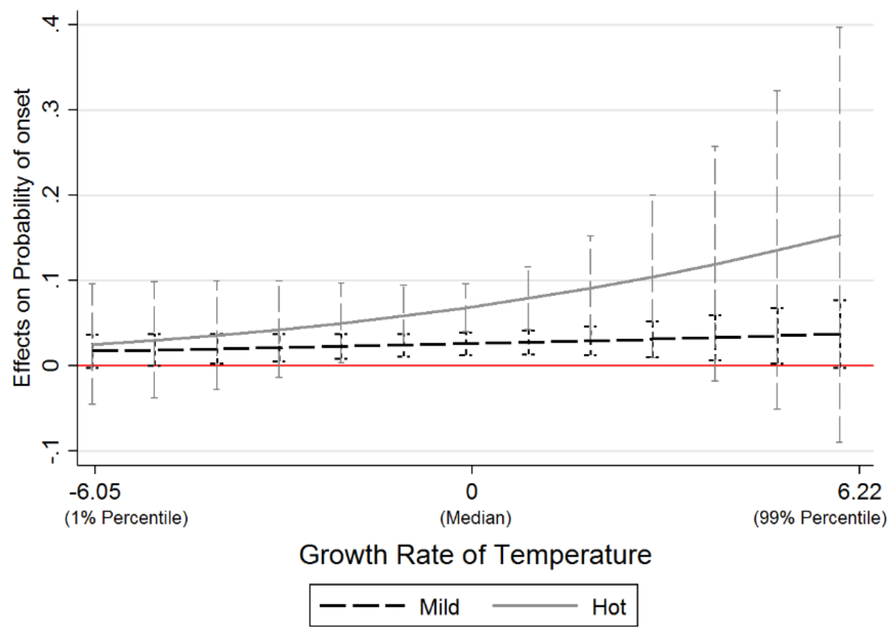
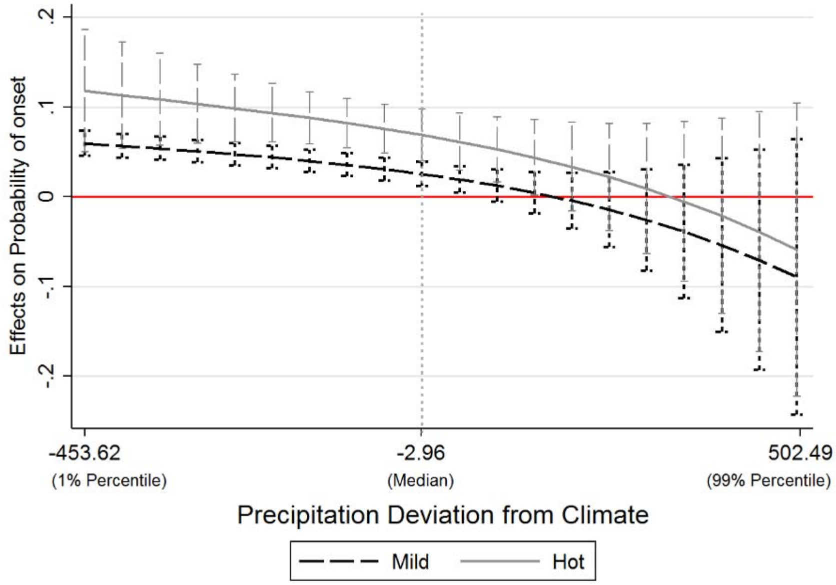


Figure 6. AMEs of belonging of Mild or Hot climate with 90% confidence intervals based on estimates of equation (3)



Appendix
Table A1. Full list of conflicts in the sample

Year[1]	GWNO[2]	State	Opposition[3]	Year[1]	GWNO[2]	State	Opposition[3]
89	41	Haiti	Military faction (forces of Himmler Rebu and Guy Francois)	98	540	Angola	UNITA
91	41	Haiti	Military faction (forces of Raol Cédras)	02	540	Angola	FLEC-FAC, FLEC-R
04	41	Haiti	FLRN, OP Lavalas (Chimères)	04	540	Angola	FLEC-FAC
65	42	Dominican Republic	Military faction (Constitutionalists)	07	540	Angola	FLEC-FAC
90	52	Trinidad and Tobago	Jamaat al-Muslimeen	09	540	Angola	FLEC-FAC
94	70	Mexico	EZLN	77	541	Mozambique	Renamo
96	70	Mexico	EPR	67	552	Zimbabwe (Rhodesia)	ZAPU
63	90	Guatemala	FAR I	73	552	Zimbabwe (Rhodesia)	ZANU, ZAPU
65	90	Guatemala	FAR I	66	560	South Africa	SWAPO
72	92	El Salvador	Military faction (forces of Benjamin Mejia)	81	560	South Africa	ANC
79	92	El Salvador	ERP, FPL	85	560	South Africa	ANC
77	93	Nicaragua	FSLN	71	580	Madagascar (Malagasy)	Monima
82	93	Nicaragua	Contras/FDN	71	600	Morocco	Military faction (forces of Mohamed Madbouh)
89	95	Panama	Military faction (forces of Moisés Giroldi)	75	600	Morocco	POLISARIO
64	100	Colombia	FARC	91	615	Algeria	Takfir wa'l Hijra
62	101	Venezuela	Military faction (navy)	80	616	Tunisia	Résistance Armée Tunisienne
82	101	Venezuela	Bandera Roja	11	620	Libya	NTC, Forces of Muammar Gaddafi
92	101	Venezuela	Military faction (forces of Hugo Chávez)	63	625	Sudan	Anya Nya
65	135	Peru	ELN, MIR	71	625	Sudan	Sudanese Communist Party
82	135	Peru	Sendero Luminoso	76	625	Sudan	Islamic Charter Front
07	135	Peru	Sendero Luminoso	83	625	Sudan	SPLM/A
67	145	Bolivia	ELN	11	625	Sudan	Republic of South Sudan
89	150	Paraguay	Military faction (forces of Andres Rodriguez)	66	630	Iran	KDPI
73	155	Chile	Military faction (forces of Augusto Pinochet, Toribio Merino and Leigh Guzman)	79	630	Iran	KDPI
63	160	Argentina	Military faction (Colorados)	79	630	Iran	MEK
74	160	Argentina	ERP	79	630	Iran	APCO
72	165	Uruguay	MLN/Tupamaros	86	630	Iran	MEK
71	200	United Kingdom	PIRA	90	630	Iran	KDPI

1. Years are from 1961 to 2011 and the first two digits of the year are deleted.
2. GWNO (Gleditsch-Ward numbers) is the most common way of identifying countries by digits (Gleditsch and Ward, 1999).
3. For the description of the opposition organisation see Gleditsch et al. (2002) and Harbom and Wallensteen (2012).

Table A1. Full list of conflicts (continued)

Year	GWNO	State	Opposition	Year	GWNO	State	Opposition
98	200	United Kingdom	RIRA	91	630	Iran	MEK
61	220	France	OAS	93	630	Iran	KDPI
78	230	Spain	ETA	96	630	Iran	KDPI
85	230	Spain	ETA	97	630	Iran	MEK
91	230	Spain	ETA	99	630	Iran	MEK
92	359	Moldova	PMR	05	630	Iran	PJAK
89	360	Rumania	NSF	84	640	Turkey	PKK
90	365	Russia (Soviet Union)	Republic of Armenia	91	640	Turkey	Devrimci Sol
90	365	Russia (Soviet Union)	APF	05	640	Turkey	MKP
93	365	Russia (Soviet Union)	Parliamentary forces	61	645	Iraq	KDP
94	365	Russia (Soviet Union)	Chechen Republic of Ichkeria	63	645	Iraq	Military faction (forces of Abd as-Salam Arif), NCRC
99	365	Russia (Soviet Union)	Chechen Republic of Ichkeria	73	645	Iraq	KDP
99	365	Russia (Soviet Union)	Wahhabi movement of the Buinaksk district	82	645	Iraq	SCIRI
07	365	Russia (Soviet Union)	Forces of the Caucasus Emirate	87	645	Iraq	SCIRI
91	372	Georgia	National Guard and Mkhedrioni	91	645	Iraq	SCIRI
92	372	Georgia	Republic of Abkhazia	95	645	Iraq	PUK
92	372	Georgia	Republic of South Ossetia	93	651	Egypt	al-Gama'a al-Islamiyya
04	372	Georgia	Republic of South Ossetia	66	652	Syria	Military faction (forces loyal to Nureddin Atassi and Youssef Zeayen)
93	373	Azerbaijan	Military faction (forces of Suret Husseinov)	79	652	Syria	Muslim Brotherhood
95	373	Azerbaijan	OPON forces	11	652	Syria	FSA
90	432	Mali	MPA	75	660	Lebanon	LNM
94	432	Mali	FIAA	82	660	Lebanon	LNM
07	432	Mali	ATNMC	90	666	Israel	Hezbollah
90	433	Senegal	MFDC	00	666	Israel	Fatah, PNA
92	433	Senegal	MFDC	06	666	Israel	Hezbollah
95	433	Senegal	MFDC	79	670	Saudi Arabia	JSM
97	433	Senegal	MFDC	92	702	Tajikistan	UTO
00	433	Senegal	MFDC	98	702	Tajikistan	Forces of Khudoberdiyev, UTO
03	433	Senegal	MFDC	10	702	Tajikistan	IMU
11	433	Senegal	MFDC	99	704	Uzbekistan	IMU

Table A1. Full list of conflicts (continued)

Year	GWNO	State	Opposition	Year	GWNO	State	Opposition
75	435	Mauritania	POLISARIO	04	704	Uzbekistan	JIG
91	436	Niger	FLAA	61	750	India	NNC
94	436	Niger	CRA	66	750	India	MNF
95	436	Niger	FDR	69	750	India	CPI-ML
97	436	Niger	UFRA	79	750	India	TNV
07	436	Niger	MNJ	82	750	India	PLA
00	438	Guinea	RFDG	83	750	India	Sikh insurgents
87	439	Burkina Faso	Popular Front	89	750	India	Kashmir Insurgents
80	450	Liberia	Military faction (forces of Samuel Doe)	89	750	India	ABSU
89	450	Liberia	NPFL	90	750	India	PWG
00	450	Liberia	LURD	90	750	India	ULFA
66	452	Ghana	NLC	92	750	India	NSCN - IM
81	452	Ghana	Military faction (forces of Jerry John Rawlings)	92	750	India	ATTF
83	452	Ghana	Military faction (forces of Ekow Dennis and Edward Adjei-Ampofo)	92	750	India	PLA
86	461	Togo	MTD	93	750	India	NDFB
84	471	Cameroon	Military faction (forces of Ibrahim Saleh)	94	750	India	ULFA
66	475	Nigeria	Military faction (forces of Patrick Nzeogwu)	95	750	India	NLFT
67	475	Nigeria	Republic of Biafra	96	750	India	MCC, PWG
04	475	Nigeria	Ahlul Sunnah Jamaa	97	750	India	ATTF, NLFT
04	475	Nigeria	NDPVF	97	750	India	KNF
09	475	Nigeria	Jama'atu Ahlis Sunna Lidda'awati wal-Jihad	00	750	India	NSCN - IM
11	475	Nigeria	Jama'atu Ahlis Sunna Lidda'awati wal-Jihad	03	750	India	UNLF
09	482	Central African Republic	CPJP	06	750	India	NLFT
66	483	Chad	Frolinat	08	750	India	DHD - BW
76	483	Chad	FAN	08	750	India	PULF
89	483	Chad	Islamic Legion, Revolutionary Forces of 1 April, MOSANAT	09	750	India	NDFB - RD
97	483	Chad	FARF, MDD	71	770	Pakistan	Mukti Bahini
05	483	Chad	FUCD	74	770	Pakistan	BLF
93	484	Congo	Ninjas	90	770	Pakistan	MQM
64	490	DR Congo (Zaire)	CNL	95	770	Pakistan	MQM

Table A1. Full list of conflicts (continued)

Year	GWNO	State	Opposition	Year	GWNO	State	Opposition
67	490	DR Congo (Zaire)	Opposition militias	04	770	Pakistan	BLA
06	490	DR Congo (Zaire)	CNDP	07	770	Pakistan	TNSM
07	490	DR Congo (Zaire)	BDK	11	770	Pakistan	BLA
71	500	Uganda	Military faction (forces of Idi Amin)	75	771	Bangladesh	JSS/SB
74	500	Uganda	Military faction (forces of Charles Arube)	71	780	Sri Lanka	JVP
94	500	Uganda	LRA	84	780	Sri Lanka	LTTE, TELO
82	501	Kenya	Military faction (forces of Hezekiah Ochuka)	89	780	Sri Lanka	JVP
65	516	Burundi	Military faction (forces loyal to Gervais Nyangoma)	03	780	Sri Lanka	LTTE
91	516	Burundi	Palipehutu	05	780	Sri Lanka	LTTE
94	516	Burundi	CNDD	96	790	Nepal	CPN-M
08	516	Burundi	Palipehutu-FNL	74	800	Thailand	CPT
96	517	Rwanda	ALiR	03	800	Thailand	Patani insurgents
91	522	Djibouti	FRUD	67	811	Cambodia (Kampuchea)	KR
99	522	Djibouti	FRUD - AD	90	811	Cambodia (Kampuchea)	FUNCINPEC, KPNLF, KR
64	530	Ethiopia	ELF	89	812	Laos	LRM
64	530	Ethiopia	Ogaden Liberation Front	63	820	Malaysia	CCO
75	530	Ethiopia	ALF	74	820	Malaysia	CPM
76	530	Ethiopia	EPRP, TPLF	81	820	Malaysia	CPM
76	530	Ethiopia	WSLF	69	840	Philippines	CPP
77	530	Ethiopia	OLF	70	840	Philippines	MIM
77	530	Ethiopia	SALF	93	840	Philippines	ASG, MNLF
83	530	Ethiopia	OLF	97	840	Philippines	CPP
83	530	Ethiopia	SLM	99	840	Philippines	CPP
91	530	Ethiopia	IGLF	65	850	Indonesia	OPM
93	530	Ethiopia	AIAI	67	850	Indonesia	OPM
94	530	Ethiopia	OLF	75	850	Indonesia	Fretilin
96	530	Ethiopia	ONLF, AIAI	76	850	Indonesia	OPM
96	530	Ethiopia	ARDUF	81	850	Indonesia	OPM
98	530	Ethiopia	ONLF	84	850	Indonesia	OPM
98	530	Ethiopia	OLF	90	850	Indonesia	GAM

Table A1. Full list of conflicts (continued)

Year	GWNO	State	Opposition	Year	GWNO	State	Opposition
97	531	Eritrea	EIJM - AS	92	850	Indonesia	Fretilin
99	531	Eritrea	EIJM - AS	97	850	Indonesia	Fretilin
03	531	Eritrea	EIJM - AS	99	850	Indonesia	GAM
91	540	Angola	FLEC-R	89	910	Papua New Guinea	BRA
94	540	Angola	FLEC-FAC, FLEC-R	92	910	Papua New Guinea	BRA
96	540	Angola	FLEC-FAC				

Table A2. Summary statistics of the variables in Tables 2, 3 and 9, based on subsamples by history of conflict within the sample period

Variable	Sample Size	Sample Mean	Standard Deviation	Minimum Value	Maximum Value	Sample Size	Sample Mean	Standard Deviation	Minimum Value	Maximum Value
	History of conflict					No history of conflict				
Political Instability	4004	0.135	0.320	0	1	2326	0.061	0.221	0	1
Peace Fragility	4052	0.5826	0.3632	0.0055	1	2328	0.1678	0.2249	0.0036	1
Ethnic Heterogeneity	4052	50.945	32.174	1	144	2328	36.189	35.241	0	144
Rough Terrain	4052	2.180	1.380	0	4.421	2328	1.844	1.520	0	4.557
Population	4052	16.231	1.429	12.534	20.923	2325	15.602	1.570	12.305	21.019
Per Capita GDP	3691	7.171	1.333	3.913	10.724	2028	8.646	1.573	4.424	11.314
GDP Growth	3676	4.0058	7.5616	-64.05	189.829	2036	3.9801	5.2789	-41.8	33.991
Temperature	4052	70.886	11.695	20.12	85.64	2328	57.917	15.704	18.68	84.38
Precipitation	4052	1127.26	806.02	21.5	3635.8	2328	1034.4	721.27	13.4	3675.7
Climate Temperature	4052	70.572	11.698	22.364	83.84	2328	57.498	15.742	22.082	82.37
Climate Precipitation	4052	6.6569	1.0161	3.0680	8.1985	2328	6.6383	.89414	2.5953	8.2094
Temperature Deviation from Climate	4052	0.315	0.765	-2.322	4.122	2328	0.419	1.019	-3.48	4.356
Precipitation Deviation from Climate	4052	-2.248	161.848	-724.7	898.37	2328	3.359	165.50	-919.58	1340.1
Change in Temperature	4052	0.017	0.847	-4.32	3.6	2328	0.024	1.165	-5.4	5.22
Change in Precipitation	4052	0.265	214.39	-1186.3	1089.5	2328	-0.409	234.44	-1864.2	1745.2
Growth Rate of Temperature	4052	0.038	1.536	-13.79	17.425	2328	0.085	2.744	-20.866	26.017
Growth Rate of Precipitation	4052	2.622	24.816	-73.2	300.453	2328	3.686	33.243	-82.572	471.37
Humidex Index	4052	26.1561	9.8258	-10.58	40.5764	2328	16.015	12.453	-11.689	39.249
Crop Production Index	4020	72.32	30.929	7.61	235.67	2291	89.768	63.566	1.35	962.57
Soil Quality	4052	12.66	9.344	0.154	48.1481	2154	13.02	8.768	0	55.073
Latitude	4052	0.219	0.149	0.011	0.667	2328	0.387	0.196	0.014	0.711
Tropical Area	4052	48.353	43.365	0	100	2245	21.733	36.126	0	100
Tropical Region	4052	0.6508	0.4768	0	1	2328	0.279	0.448	0	1
Malaria	4052	49.673	43.679	0	100	2245	17.589	34.570	0	100
Oil exporter	4052	0.212	0.409	0	1	2328	0.100	0.300	0	1
Military Personnel	1893	1.697	0.785	0	4.386	1134	1.820	0.7	0.248	4.146