

# Robustness of climate as an instrumental variable to estimate effect of GDP change on political change in Africa

Preliminary, comments appreciated  
Please do not cite this version  
Draft: January 15, 2012

Michael Kevane  
Department of Economics  
Santa Clara University  
Santa Clara, CA 95053  
[mkevane@scu.edu](mailto:mkevane@scu.edu)

Rahul Hirani  
Investment Banking Analyst  
Arbor Advisors, LLC  
Palo Alto, CA  
[rhhirani@gmail.com](mailto:rhhirani@gmail.com)

***Abstract:*** A continuing debate in African studies is over the characterization of causes of civil conflict and political change as primarily economic versus political or social. Advocates for the importance of underlying economic factors point to evidence from cross-country regressions that show large effects of economic change on political outcomes, from outbreak of civil conflict to protest movements to regime change. We examine the robustness of recent influential papers by Miguel, Satyanath, and Sergenti (2004), Burke and Leigh (2010) and Bruckner and Ciccone (2011) that identify causal effects of economic decline on political change in sub-Saharan African countries by using climate measures as instrumental variables for GDP shocks. We use a number of different measures of rainfall and temperature from a variety of sources and concentrate on presenting the *range* of estimates of coefficients and indicators of statistical significance. Our finding is that estimates are quite sensitive to specification and formulation of climate measures; most estimates for quite reasonable specifications are not statistically significant. There remains considerable work to be done in using the instrumental variables method to confirm a substantial and significant causal relationship between income change and political change in sub-Saharan Africa. Meanwhile, researchers should not discount alternative hypotheses about how political and social change, as well as underlying political conditions, importantly affect civil conflict and regime change.

## **1. Introduction**

Civil conflicts and autocratic repression have devastated numerous African countries over the past four decades. Large-scale and persistent conflicts in Angola, Somalia, Liberia, Sudan, Congo, Rwanda and Burundi have caused the deaths of millions, directly in combat but mostly indirectly through displacement and disruption of vital food and health delivery systems. Persistent dictatorships like that of octogenarian Robert Mugabe in Zimbabwe have led to growth collapses as regimes resort to ever-more repressive methods of extraction in order to remain in power and enfeeble opposition movements. There is little doubt that conflicts and recalcitrant autocracies have been responsible for the overall slow economic growth and especially the growth collapses of many countries in Africa.

Understanding the triggers and underlying conditions that lead to civil conflict and democratization has been a major theme of cross-country comparative statistical research over the past several decades (Blattman and Miguel, 2010; Besley and Persson, 2008). One important stream of research has been to examine how economic factors, especially economic decline, trigger and sustain civil wars (Collier, Hoeffler and Rohner, 2009). Economic decline generates feelings of desperation, which perhaps make people more likely to initiate and follow armed rebellions. But even when emotions are controlled, economic decline may raise the likelihood of conflict and political change. Economic decline may aggravate the asymmetric information problem between the government and opposition over knowing the magnitude of government spoils. Fighting is then more likely (Dal Bó and Powell, 2009).

Empirical research has concentrated on establishing the magnitudes of the causal relationships explaining political change and especially civil conflict. This would enhance a discussion of alternative possible preventative measures and remedies. These remedies range from economic programs such as income insurance for young men to readiness preparation for military intervention.

But most estimates of the relevant magnitudes of the causal effects are implausible because of the likelihood of reverse causation. Anticipating political turmoil

and civil conflict would lead people to delay investments and purchases, and thus cause economic decline.

In a much-cited paper, Miguel, Satyanath, and Sergenti (2004) attempted to identify a causal effect of economic decline on the onset and incidence of civil conflict by using current and lagged annual rainfall growth as instrumental variables for current and lagged annual growth in GDP for a sample of 40 African countries over the period 1981-1999. They concluded that a five percentage point decline in lagged GDP growth caused an increase in the likelihood of civil conflict of twelve percentage points. The average incidence of civil conflict among the African countries in their sample over the relevant time period was approximately 25%, so this would appear to be a very important explanation of the likelihood of civil conflict. The magnitudes led Miguel (2006) to recommend the establishment of a well-funded Rapid Conflict Prevention Support fund.

The method of using climate measures to instrument for GDP shocks in for the has again been used in two recent papers examining political change. These papers used the Polity IV database that scores countries around the world according to political regime. The resulting variable POLITY is coded on a scale from -10 to +10, with low scores indicating highly autocratic regimes and positive scores indicating democratic regimes. Burke and Leigh (2010) used the dataset to construct indicator variables for the onset of democratic and autocratic transitions for countries around the world. The Polity IV dataset has an indicator variable REGTRANS that is a retrospective expert judgment that a polity is beginning to experience a regime transition. Burke and Leigh then used subsequent POLITY scores to determine whether the transition was democratic or autocratic. Burke and Leigh were primarily interested in the effects of economic change on regime transitions for the entire set of countries, but they present separate estimates for democratic transitions in sub-Saharan African countries.

Bruckner and Ciccone (2011) likewise used the Polity IV database to examine the effects of GDP on political change in sub-Saharan Africa. Their outcome variable was the following year change in POLITY2, a smoothed measure of POLITY that takes into account how regime transitions unfold over time. While the middle of a regime transition may see no improvement in the practice of politics (and may even be worse when a transitional regime rules by decree), if the regime eventually becomes

democratic it becomes clear in hindsight that the political regime was indeed becoming more democratic. POLITY2 adjusts the POLITY score for this effect.

The three papers recognized that there appeared to be no clear theoretical prediction for how economic change measured by GDP should affect political outcomes. Only statistical analysis could determine what the pattern had been and whether correlations were properly interpreted as causal. Nevertheless, the three papers have quite distinct implicit (and sometimes explicit) preferred hypotheses. For Miguel, Satyanath and Sergenti, economic decline was likely to trigger civil war and continue civil war incidence because they believed the primary effect of GDP decline in poor agrarian economies was to facilitate recruitment of rebel soldiers in the hinterlands. Burke and Leigh asserted that economic decline likely made the governed less inclined to consent to rule by autocrats, and stimulated protests and disobedience that gathered momentum and resulted in regime transitions. For Bruckner and Ciccone (2011, pp. 1-2), economic decline opened up a “democratic window of opportunity” for a similar reason, since the “opportunity cost of contesting power is temporarily low.”

Table 1 presents the heart of our results. We reproduce the main estimated coefficient for each of the three papers, using the authors’ preferred specification and rainfall measure from the climate database they use. Miguel, Satyanath and Sergenti used the GPCP 2.0 measure. Burke and Leigh used a measure from Mitchell et al. interacted with two variables (the share in 1961 of labor force in agriculture and the share of unirrigated cropland). Bruckner and Ciccone are not clear in their paper, but they appear to have used GPCP 2.0 rather than the revised GPCP 2.1. Also, Bruckner and Ciccone in their published results presented the variables included noting they were lagged one period, but in their replication Stata code and in the replication dataset it appeared that they mistakenly used the second period lag for GDP and precipitation. We preferred here to follow their specification as intended, rather than the apparent mistake. Each cell in the table presents the estimate of the same coefficient using the others’ climate databases, and we add the Matsuura-Willmott rainfall data (discussed below) as a fifth specification.

The table shows that the estimates are very sensitive to the alternative rainfall measures. For the Miguel, Satyanath and Sergenti formulation of the effects of GDP change on civil conflict, the GPCP 2.1 measure (that superseded the GPCP 2.0 dataset

used in two of the papers) generates a much smaller and non-significant estimate, while the Mitchell et al. rainfall measure (interacted and alone) used by Burke and Leigh and the Matsuura-Willmott measures of rainfall generate coefficients that are not statistically significant. The Burke and Leigh estimate for their 1963-2001 sample period is not robust with the GPCP 2.1 (1982-2001), the GPCP 2.0 (1982-1999) measures, and the Matsuura-Willmott measure (1963-2001). We use the same indicator of democratic transitions and the same Burke and Leigh GDP measure. The Bruckner and Ciccone coefficient varies widely and is not statistically significant in any specification. Bruckner and Ciccone used the 6.2 Penn World Tables, but as noted above their published specification appeared to be different from the published results, at least according to their replication files. The Bruckner and Ciccone coefficients are not significant when using the other rainfall measures where all are lagged just one period.

Note that the preferred explanatory specifications of the three papers are quite different. Miguel, Satyanath and Sergenti have current and lagged GDP growth instrumented by current and lagged rainfall growth. Burke and Leigh have lagged GDP growth (alone, and not current GDP growth) instrumented by lagged and twice-lagged rainfall growth interacted with two variables measuring agriculture in the country. Bruckner and Ciccone have lagged and logged GDP level instrumented by lagged and logged rainfall level. The three papers also use different sets of controls and interactions (with the Burke and Leigh “preferred” specifications including a host of interactions and controls while Miguel, Satyanath and Sergenti specifically note that interactions are not significant and so the results hold without them; Bruckner and Ciccone include no other controls). Miguel, Satyanath and Sergenti have fixed effects and country-specific time trends, Burke and Leigh have fixed effects and time effects, and Bruckner and Ciccone have fixed effects and country-specific time trends as well as a common time trend.

If we estimate the effects of GDP on the incidence of civil wars, the onset of democratic transition, or the change in the POLITY2 measure, using the specifications used by the other authors, the coefficients were not significant.

All three of the papers reported extensive robustness checks in the form of appendices with alternative control variables and alternative climate measures. But the papers each privileged certain specifications over others; apparently solely on the basis

of statistical significance. Their verbal summaries leave the reader with an impression of a robust finding. Table 1, and the extensive robustness analysis reported in this paper, suggests otherwise. The correlations between GDP change and political outcomes for African countries, when instrumented using climate measures, are only tenuously interpretable as causal relationships.

Given that the three papers examine the causal effects of GDP on political outcomes, that each has a different preferred specification and climate database, and that their choice of databases limits the sample sizes in various ways, the problem of whether the results are robust across these specifications and climate measures becomes salient. Moreover, the Miguel, Satyanath and Sergenti data is now almost a decade old, and has been superseded by revisions of the climate data, the civil conflict data and the GDP data. It is appropriate, therefore, to examine whether the results of these three important papers are robust across the different specifications and datasets. Just such a limited robustness exercise emerged from an exchange between Ciccone (2011) and Miguel and Satyanath (2011). The strong findings of the 2004 paper were muted with new data and alternative methods.

Given the sensitivity of the interpretation of the relationship as causal, it is appropriate to renew interest in finding measures and estimates of the relationship between political and social variables and civil conflict outcomes. As Miguel and Sergenti (2011) and Miguel and Blattman (2010) suggest, more progress in this problem is likely to be made through micro-level statistical analysis than through cross-country analysis. Recent micro analysis appears to confirm the importance of economic change, but one should be cautious about making generalizations on the basis of this evidence, because it seems clear that political and social variables are harder to measure than climate and income, at local levels, and so there may be a lag in reporting of micro-analyses that focus on other variables.

The plan of the paper is as follows. Section 2 discusses the various climate databases and some of the alternative ways that climate measures may be aggregated to the country or regional level in order to be used as instruments for GDP and change in GDP. We explore a wider variety of aggregations of climate measures than the typical country average. Many countries in Africa exhibit low correlations in rainfall across regions (especially north and south). Section 3 motivates the paper by examining the

robustness of the findings of Miguel, Satyanath and Sergenti, replicating their main estimations using the same 1981-1999 time period but with different measures of rainfall. We show that the rainfall series correlate differently across databases, and also across aggregation methods. Section 4 then moves on to the heart of the paper, presenting results of analysis for the entire 1960-2007 period for conflict, regime transitions, and political change (measured by Polity2). GDP is instrumented by various measures of rainfall, temperature, and rainfall and temperature combined. While certain specifications generate statistically significant effects, in general most specifications produce coefficients that are statistically insignificant. Section 5 reviews the correlations of rainfall across the datasets and aggregations, and presents summary charts of the first-stage regressions. Section 6 concludes.

## **2. Data sources and methods**

There are a variety of climate databases used in the social sciences to estimate effects of climate on social outcomes. The rainfall and temperature measures in these databases are not always closely correlated, since they use different methods for aggregating across spatial scales. Some rely exclusively on surface measurements while others are blended measures of surface and satellite measures.

Miguel, Satyanath, and Sergenti (2004) use data from version 2.0 of the Global Precipitation Climatology Project (GPCP) which contains data on precipitation at 2.5 degree latitude by 2.5 degree longitude resolution for the period 1979-99. The series is constructed by blending surface measures of precipitation with satellite measures of cloud cover. The authors added up rainfall across months for each node in each year, and then averaged all the nodes in a country. Version 2.1 of the GPCP data covers the period 1979-2007 and contains modifications for the period 1979-99, and so might be considered a different rainfall series for that time period. This is the rainfall series used by Bruckner and Ciccone. Burke and Leigh use the precipitation data of Mitchell et al. (2004). We include the data series they provide in the online supplemental materials for their paper.

We also use data from Global Air Temperature and Precipitation: Regridded Monthly and Annual Climatologies V. 4.01, generally known as the Matsuura and

Willmott dataset.<sup>1</sup> The data are a gridded 0.5 degree latitude by 0.5 degree longitude time series of monthly precipitation and air temperature for the global land surface based on recordings from about 50,000 weather stations drawn primarily from the Global Historical Climatology Network ([GHCN version 2](#)) and the Global Surface Summary of Day ([GSOD](#)) archives (Willmott and Matsuura, 1995; Willmott et al., 1985; and Willmott and Robeson, 1995). The Matsuura-Willmott data includes monthly air temperature, an important determinant of the soil water balance that in turn affects crop and weed growth and, as a result, income. The data have been used in studies of how global climate change affects conflict and income, such as in Dell, Jones and Olken (2011).

Miguel, Satyanath, and Sergenti note that in the GPCP data "no degree grid node fell within the national boundaries for five small African countries—Burundi, Djibouti, Gambia, Guinea-Bissau, and Rwanda—so in these cases we assigned them rainfall measures from the node nearest to their borders." In the Matsuura-Willmott data nodes are .5 x .5 so multiple nodes fall inside country borders in all cases.

We use the Matsuura and Willmott dataset to construct a number of alternative measures of rainfall and temperature to supplement the Miguel, Satyanath, and Sergenti method of averaging across all nodes for the country. Averaging across all the nodes in a country is only one of many possible ways of representing relevant rainfall and temperature in a country that is characterized by large spatial eco-zone diversity. Some authors have constructed weighted averages of rainfall and temperature.

We first construct rainfall and temperature measures that aggregate over a larger land area, specifically the rectangle defined by the extreme points of latitudes and longitudes of the country, thus encompassing rainfall in neighboring regions that might likely to affect economic activity in a country. We call this the "countrybox." African countries have notoriously porous borders and many ethnic groups overlap borders. Climate just across borders may be as relevant to economic change as national climate.

Second, we aggregate the nodes for the top third and the bottom third of the countrybox, on the north-south axis.

---

<sup>1</sup> Available through the website <http://climate.geog.udel.edu/~climate/>. See also [http://climate.geog.udel.edu/~climate/html\\_pages/Global2\\_Clim/README.global2\\_clim.html](http://climate.geog.udel.edu/~climate/html_pages/Global2_Clim/README.global2_clim.html).

Lastly, we use measures of climate from the four "corners" (NE, SE, NW, NE) of a vertically oriented rectangle that broadly delineates the country, and also the small square around the country centroid (the geographic center of the country landmass). Agricultural zones of many African countries are not distributed evenly across the country in terms of productivity and adaptability to shocks (i.e. pastoral societies may be very adaptable to climate shocks while sedentary farmers may be very vulnerable, so fluctuations in rainfall in the sedentary zones may have more effects on livelihoods than fluctuations in pastoral zones).<sup>2</sup> Figure A1 in the appendix illustrates the regions involved.

Figures 1(a) and 1(b) illustrate the levels of rainfall and temperature for four countries, for corners and centroids. Two countries (Malawi and Côte d'Ivoire) have relatively high correlations for rainfall generally above .50 and for temperature generally above .80 across corners and centroid, while two countries (Nigeria and Ethiopia) have relatively low correlations, from -.20 to .20 range for rainfall, and often in the .25 to .50 range for temperature. Note that temperature is more closely correlated across geographic space than rainfall. Rainfall in corners of many countries deviates substantially from average country-wide totals and from rainfall in the center of the country.

Rainfall and temperature also vary with the seasons over the year. Summing total rainfall for the year or averaging temperature for the year may misrepresent important change in climate. Imagine for example a sequence of three temperatures, 20, 26, 20 with an average temperature of 22. Compare that sequence with 18, 30, 18, or with 22, 22, 22. The averages are the same, but the series have very different

---

<sup>2</sup> The latitude and longitude of the geographical centroid are taken from the dataset available at Harvard University's Center for International Development ([physfact\\_rev.csv](http://www.cid.harvard.edu/ciddata/geographydata.htm#general) from <http://www.cid.harvard.edu/ciddata/geographydata.htm#general>, accessed July 2010). The corners are calculated as follows. First, we take the land area in square kilometers of the country.<sup>2</sup> The square root of this gives the length of a side of a square box that has the same area as the country. We then adjust this distance to make the north and south sides twice the length of the east and west sides to create a vertically oriented rectangle. Almost all African countries are either roughly square/circle shaped or vertically oriented, with only a handful of horizontally oriented countries (e.g. The Gambia, Central African Republic). Then we take the .50 degree squares in each corner of the rectangle and include the nodes that fall within these squares. Some countries that are located on the ocean have no nodes in one or two corners (e.g. Sierra Leone, whose coastline is a diagonal oriented from northwest to southeast has no land area in the southwest corner), and in these cases we include in the corner all nodes that fall in the quadrant that is missing the corner. Centroid boxes are generated by averaging across the node(s) within .50 latitude and .50 longitude of a country's geographical centroid.

patterns, presumably with different implications for economic activity. To reflect this seasonality, we construct a measure of the total rainfall for the peak rainfall month and temperature for the peak temperature month. For each country, we construct the aggregate climate distribution over the entire range of years and then find the peak rainfall month.<sup>3</sup> We then construct a measure of the peak rainfall or temperature in the relevant region (countrybox, corner, country border) for that peak month.

To recapitulate, with the Matsuura-Willmott data we have two measures of climate (precipitation and temperature), two ways of capturing these in terms of seasonality (annual average or total for the year or for the peak month), and a variety of spatial aggregations (country borders, countrybox, centroid, northern and southern thirds of the country, and four corners). These generate 12 measures for rainfall and 12 for temperature. For countrywide average total rainfall, we also use the GPCP 2.0 data, the GPCP 2.1 data and the Mitchell et al data for an additional 6 rainfall measures (3 growth and 3 levels).

We have 18 different rainfall measures at the country level and 12 different temperature measures. For example, we may have peak temperature for the country centroid in levels and peak temperature in growth. We may have average temperature for the countrybox, in levels and in growth.

We also have a plethora of regional measures of rainfall and temperature. For the north-south measures, we have the levels and growth for the average or total, as well as for the peak. In some regressions, we include a mix of the corners (NE and SW, SW and NW, SW and SE, for example) and the centroids, generating 28 different combinations of two separate measures of rainfall for each country. All these measures enable us to estimate from 30 to 40 separate first-stage regressions, using equally plausible measures as instruments for GDP growth.

Because of this plethora of possible measures of rainfall and temperature we present results in the form of box plots of coefficients, t-statistics, R-square, and F-statistics of the climate variables.

To cover the 1960-2007 time period, we use growth and levels of real GDP from the Penn World Tables, version 6.3. For the 1981-99 replications, we use Miguel,

---

<sup>3</sup> We also find the second peak for countries with two rainy seasons, but we do not use that second month peak in this version of the paper.

Satyanath and Sergenti's replication data on GDP growth from an earlier version of the Penn World Tables.

For conflict data, we follow Miguel, Satyanath and Sergenti and use what is now known as the UCDP/PRIO Armed Conflict dataset.<sup>4</sup> For the 1981-99 replications, we use Miguel, Satyanath and Sergenti's data which used version 2.0 PRIO data, restricting the sample of conflicts to intra-state conflicts. For the 1960-2007 replications, we used the v4-2009 dataset, again restricted to intra-state conflicts. The dataset contains variables for the onset, offset, and incidence of conflicts and wars. The more recent UNCP/PRIO v4-2009 data did not always match earlier version 2.0 PRIO data. Civil conflict variables were recoded in different versions of the PRIO data, and these recodings are documented on the PRIO website.

For political change data, we use Burke and Leigh's dataset, which the authors have generously shared on the web appendix for their paper. Since they include the POLITY2 measure, we construct the POLITY2 change measure as the difference in  $POLITY2_{t+1} - POLITY2_t$ .

Appendix Figures A2 and A3 plot the political change measures over the years. The incidence of civil conflict in Africa crept upwards from 1970 to 2000, and then dropped sharply as many previously intractable civil wars ended. A resurgence of conflict in 2006 and 2007, however, makes it impossible to determine whether there is a trend towards peace that will continue. It is very clear that there was a big increase in democratic transitions in 1991, following the collapse of the former Soviet Union. Democratic transitions continued through the 2000s (the data goes up to 2006) though the average POLITY2 score barely changed. Political scientists call these regimes "illiberal democracies."

### **3. Replicating Miguel, Satyanath, and Sergenti (2004)**

#### **(a) Using the Matsuura-Willmott rainfall data**

In order to illustrate why periodic robustness checks are in order for important preliminary findings, we first replicate the IV-2SLS estimates of Miguel, Satyanath, and Sergenti presented in their Table 4, columns 6 and 7, for the period 1981-99. They find

---

<sup>4</sup> <http://www.prio.no/CSCW>

that when GDP growth and lagged GDP growth are instrumented with rainfall growth and lagged rainfall growth measured using the GPCP data, there is a significant relationship between lagged GDP growth and the incidence of civil conflict, and a significant relationship between current GDP growth and incidence of large scale (>1000 deaths) civil conflict. Moreover, in both cases the hypothesis of joint significance of current and lagged GDP on civil conflict incidence is not rejected.

We check the robustness of the Miguel, Satyanath, and Sergenti result by running 46 regressions, using 46 different measures or combinations of measures of rainfall.<sup>5</sup> Each regression includes current and lagged measures of the 46 measures as instruments for current and lagged GDP growth in IV-2SLS regressions with incidence of civil conflict as the dependent variable. The Matsuura-Willmott measures of precipitation are used for 40 of the regressions, and the GPCP rainfall measure are used for 4 of the regressions (GPCP rainfall in growth and levels from downloaded version 2.0, and GPCP growth and levels from version 2.1) and the Mitchell et al measures for 2 regressions (growth and levels). 4 of the regressions use north-south measures and 24 of the regressions use combinations of rainfall from the country corners as instruments (i.e., rainfall in the north-west corner and the southeast corner). These are grouped separated as “regional” measures of rainfall. The GDP and conflict data are those provided by Miguel, Satyanath, and Sergenti and cover the same 1981-1999 time period.

Our estimation results are summarized in Figure 2, which presents box plots of the distribution of coefficients and associated t-statistics indicating statistical significance of the coefficient estimates. For ease of interpretation we have converted t-statistics into absolute values. The solid box denotes the range of estimates that fall between the 25<sup>th</sup> and 75<sup>th</sup> quartile. The whiskers that extend from the boxes end either at a distance of 1.5 times the interquartile range or the furthest actually observed value. If the whiskers are of unequal size, the shorter one means there are no observations beyond the whisker. Since some sets of regressions generated several extreme values of t-statistics or F-stats (i.e. F-stat of 50 when all others were below 10) we have excluded from the box plots these outliers or in some cases truncated them (indicted in the chart).

---

<sup>5</sup> Table A1 lists the different rainfall variables included in the regressions.

Figure 2 shows that the coefficients on current GDP growth and lagged GDP growth are generally not statistically significant in explaining conflict or large-scale conflict. The instrumental variables regressions only occasionally result in statistically significant coefficients. The interquartile range of the t-statistics is well away from the usual cutoff value of 2 and only a few coefficients have t-statistics exceeding the normal cutoff value. Moreover, some of the few large t-statistics are associated with positive coefficients on GDP or lagged GDP growth which contravene the hypothesis that increases in GDP lower the likelihood of civil conflict. Finally, the distributions of the coefficients for the current and lagged growth in GDP have median magnitudes around smaller in magnitude than the -1.13 and -2.25 reported by Miguel, Satyanath, and Sergenti for any conflict, and smaller in magnitude than the -1.48 and -.77 for the indicator of wars with greater than 1,000 deaths as the dependent variable reported by Miguel, Satyanath, and Sergenti. The regional measures of rainfall perform similarly to the countrywide measures, though the distribution of t-statistics is generally tighter and with smaller median value (further away from 2) and the median coefficient magnitudes are all centered on zero.

Perhaps more important than the dependent variable of incidence of civil conflict is analysis of the onset of civil conflict; presumably civil conflicts have very different dynamics and incentives once fighting has been underway. Figure 3 presents the distribution of coefficient estimates using the 46 different rainfall measures and combinations of measures as instrumental variables for GDP growth and lagged GDP growth in regressions estimating onset of civil war, both any size and wars with more than 1,000 deaths. The sample size is reduced to 555 country-years from 743 when excluding all observations of countries in years when there was a conflict in the preceding year. We use the same indicator variable for onset as used in Miguel, Satyanath, and Sergenti, Table 6. Again, the distribution of t-statistics is mostly below the cutoff value of 2. The distribution of coefficients shows that the current and lagged GDP change variables have mean magnitude smaller than the -.80 and -3.15 estimates presented by Miguel, Satyanath, and Sergenti in their Table 6.

As an example of the non-robustness of the original result, when the original result is re-estimated using GPCP version 2.1, which updated the analysis procedure for blending rainfall estimates from different sources, change in GDP is no longer

significant at the 95 percent level in explaining incidence and onset of conflict, using current and lagged rainfall growth as instrumental variables. The general finding may not be that surprising, since the Miguel, Satyanath, and Sergenti results from Tables 4 and 6 were weak to begin with; of the eight coefficients estimated only one was significant at the conventional 95 percent level.

In summary, the variety of different measures of rainfall that are constructed for the period 1981-99 generate distributions concentrated towards statistically insignificant values and smaller magnitudes for coefficients than the range of estimates of Miguel, Satyanath, and Sergenti.

### **(b) Why are the results different?**

Since the statistical significance of the rainfall measures from Matsuura-Willmott are so different, it must be that the rainfall measures diverge significantly from the rainfall measures based on the GPCP version 2.0 data. Table 2 presents the correlation of the GPCP measure with the Matsuura-Willmott measure for each country, where we average the annual total rainfall for each node over all nodes within the country border over each year from 1981-1999. For 30 of the 41 countries the correlations between the two rainfall measures over the time period are above .67. For eight of the countries the correlations are between .67 and .34, and for three of the countries the correlations are less than .34. Sierra Leone has the lowest correlation, -.13. Figures 4(a)-(d) plot the two rainfall series for a number of countries, starting with four of the high correlation countries and then covering the eleven lowest correlation countries. A clear pattern emerges for the lowest correlation countries. In the mid-1990s, the series diverge, with Matsuura-Willmott rainfall measure moving upwards while the GPCP measure moves downwards. While one may be tempted to think that there is a relationship between these low correlation countries and state failure (Sierra Leone, Liberia, and Angola are at the bottom of the correlation, but Chad has a correlation between the two series of .91, and it certainly also qualified as a failed state during the 1990s. The divergences for these low correlation countries mean, not surprisingly, that the various regression results of Miguel, Satyanath, and Sergenti will no longer hold when using the Matsuura-Willmott data.

Another diagnostic explaining the difference is presented in Figures 5a-b, which show the distribution t-statistics, F-statistics (for test of joint significance of the two rainfall measures), and R-square from the first-stage regression in the instrumental variable procedure. The dependent variable is growth in real GDP per capita, and the explanatory variables of interest are the current and lagged rainfall measures. Again, the results are for 46 regressions, as described previously.

Figures 5a-b can be compared with the results from Table 2, column 3 in Miguel, Satyanath, and Sergenti. They find strongly significant effects of lagged rainfall measures. We likewise find the current rainfall growth to be strongly correlated with current GDP growth, and lagged rainfall growth to also often be statistically significant. The chart of F-statistics for joint significance and R-square for overall explanatory power suggest, however, that rainfall in levels is generally a better fit for explaining growth in GDP than rainfall as a growth measure (see the discussion in Cicconne 2011 and Miguel and Satyanath 2011, that turns on this issue). Figure 5b shows the same regressions but now with the regional (north-south and corners) measures of rainfall. The distribution is somewhat similar, though the regional measures are generally less of a good fit than the countrywide measures.

#### **4. Instrumental variable estimates using temperature and rainfall for the various outcome indicators**

We turn now to examining the robustness of the estimates of the effects of economic change on the various outcome indicators. There are seven outcome indicators: (1) incidence of civil conflict (>25 battle deaths); (2) incidence of major conflict (>1000 deaths); (3) onset of civil conflict; (4) onset of major conflict; (5) democratic transition; (6) autocratic transition; and (7) change in POLITY2 indicator.

We run 46 regressions using rainfall as an instrumental variable (18 country-wide and 28 regional measures), 40 regressions with temperature as an instrumental variable (12 country wide measures and 28 regional measures) and 46 with rainfall and temperature as instruments (where we repeat the average countrywide temperature measure for some of the different countrywide rainfall measures). For most of the regressions the sample period is now 1960-2007. The results are presented in Figures 6-9, Figures 10-13, and Figures 14-17, respectively.

Figure 6 reports the distribution of coefficient estimates for the effects of current and lagged GDP per capita growth on the incidence of conflict, instrumented with measures of rainfall, for the sample period 1960-2007. The Matsuura-Willmott country-wide measures of precipitation are used for 12 of the regressions, and the GPCP rainfall measure are used for 4 of the regressions (country border measures of GPCP rainfall in growth and levels, from version 2.0, and GPCP growth and levels, from version 2.1) and the Mitchell et al measures are used for 2 regressions (growth and levels of rainfall). 28 of the regressions use combinations of rainfall from the north and south and country corners as instruments (i.e., rainfall in the north-west corner and the southeast corner). The conflict data are from the PRIO dataset, and the GDP growth per capita from the Penn World Tables v 6.3. For the expanded time series, the interquartile range and sometimes the “whiskers” of the distribution of t-statistics are bounded below 2 for current GDP and lagged GDP for country-wide, regional, war and civil conflict indicators. For the “any PRIO” indicator (>25 deaths), the measure of rainfall at the country centroid generates a significant t-stat for the effect of current GDP, as do three of the regional specifications. For the lagged GDP, none of the country measures (including the GPCP and Mitchell et al measures) generate significant effects, though six of the regional measures do. The significant estimates using regional measures, however, almost always generate positive coefficients. The median estimates are fairly small in magnitude, and for both the dependent variables the median estimate is more often positive for lagged GDP growth.

Figures 7, 8 and 9 show that all the interquartile ranges of the t-statistics are below 2, in IV regressions explaining civil conflict onset, political transitions and POLITY2 change.

Figure 10 reports coefficient estimates for the effects of current and lagged GDP per capita growth on the incidence of conflict, instrumented with measures of temperature, for the sample period 1960-2007. There are now 36 regressions included with the Matsuura-Willmott data, since the GPCP versions 2.0 and 2.1 and the Mitchell et al data do not include measures of temperature. The results are straightforward: the coefficient estimates have medians that are on the order of magnitude of -.50, but are rarely statistically significant. The box plot indicates the t-statistics are almost always

less than 2 in magnitude. Figures 11, 12 and 13 show that the same results hold for civil conflict onset, transitions and political change.

Finally, Figures 14 through 17 show that using rainfall and temperature jointly as instruments changes somewhat the resulting estimates of the effects of GDP change on political outcomes.<sup>6</sup> There are more statistically significant coefficients, though the interquartile range is still below 2 in most cases.

To summarize the finding, the expanded time series from 1960-2007 and the inclusion of temperature as another climate variable do not support a strong relationship between economic decline and incidence of civil conflict. While some regressions do find sizable coefficients that are statistically significant, the vast majority do not, and there is no reasonable criteria that enables one to prefer one specification to the other, and there is no consistent specification across the different outcome measures (that is, a specification or rainfall measure that is significant for political change is not significant for conflict onset or democratic transition).

Figures 18a and 18b present the results for the range of first-stage estimates, with GDP growth explained by measures of rainfall, while Figures 19a and 19b show the results with rainfall and temperature as explanatory variables. For the countrywide measures, using only rainfall, the R-square coefficients are on the order of .09 (that is much lower than for the more limited 1981-99 sample period, where R-square were more centered on .13). They are even lower for the regional measures. Adding temperature improves the fit, but not by very much. The F-statistic for the test of whether the climate variables are jointly significant in explaining the variation in GDP are generally well below 10, and are sometimes higher for the regional specifications (when climate is measured in growth terms) than for the country-wide specifications.

## **Conclusion**

Academics have been devoting increased attention to exploring the correlations between indicators of climate and outcomes, such as economic growth and war. There are two reasons for the research agenda. From an empirical standpoint, new global climate

---

<sup>6</sup> For the regional measures of climate, we pair rainfall and temperature at the same region using the same method of calculation. That is, we pair peak rainfall for the southeast corner paired with peak temperature for the southeast corner. There is of course no reason not to add other permutations but at some point coding fatigue sets in.

databases have facilitated access to measures of temperature and precipitation at very fine geographic scales for long periods of time. Given the exogeneity of climate changes for any given country, these provide excellent control variables for the usual cross-country regressions. Indeed, one is tempted to say that the thousands of cross-country analyses of the previous decades have been a mere prelude to a new generation of cross-country analysis that actually has exogenous explanatory variables.

From a policy standpoint, it is important to know what the likelihood is that short-term environmental change triggers war, in view of concerns that man-made global climate change will intensify in coming decades. Miguel and Fisman (2008), for example, suggest that because rainfall changes in sub-Saharan Africa are associated with changes in GDP, and economic downturns trigger war, international policy might begin experimenting with some kind of country insurance schemes to prevent the effects of economic downturns on civil conflict. They advocate allocating significant resources to something called a Rapid Conflict Prevention Support fund. Collier (2008) in a similar vein advocates spending resources on military interventions in conflict-prone countries.

In this paper, we cast doubt on the robustness of three important papers demonstrating the causal link between economic decline and political change. Using a variety of specifications and a different dataset, we find smaller magnitudes and little statistical significance for the relationships in general.

Our conclusion does not mean that in reality the relationships are not sizable and significant. We believe, rather, that the questions are probably not answerable with available data. The analysis shows that estimates will range dramatically according to specification and measurement of the instrumental variables. Leaving aside questions of the exclusion restriction assumption, rainfall and temperature are quite weak instruments for explaining year to year variation in GDP. A recent paper by Burke, Miguel Satyanath, Dykema and Lobell (2010) implicitly acknowledged the lack of robustness of the findings reported in the 2004 paper. The authors of the more recent paper argue for a much stronger relationship between temperature and economic growth and hence civil conflict. They present reduced form regressions explaining civil conflict and a variety of different climate measures - temperature deviations are significant, while rainfall deviations are not. Indeed, for some specifications using a

different rainfall measure, the rainfall measures alone are not significant (except for the GPCP case). The instrumental variable causal analysis of the earlier work is jettisoned to instead present evidence of strong correlations, with no pretense of sorting out specific hypotheses for the complex relationships involved. The authors do not present two-stage least squares estimates of the relationship between economic decline and civil war, even though their new instrumental variables (temperature and lagged temperature) are stronger than the earlier instrumental variables.

The three papers discussed here all present extensive robustness analysis. Our argument here is that the range of robustness analysis is limited. The reader is left with an impression of a robust finding that does not hold up when the range of robustness exercises is expanded and the results are presented as a range of estimates. Presenting estimates from robustness exercises as a range gives the same weight to each specification, and contrasts with the exposition strategy of the papers that is to present a preferred regression (with statistically significant coefficients) and then examine variations of that specification, explaining away insignificant results.

The work of this paper is still preliminary, though, in that we have not yet added estimates from other permutations (regional constructs for the GPCP series, for example, temperature and rainfall country-wide measures constructed with population or agricultural area weights, alternative specifications of country and time effects, alternative measures of political change and GDP (such as GNI or poverty measures), alternative sets of non-climate time-varying controls and interactions, and alternative estimation techniques and methods for constructing standard errors). The dozens of broad permutations that are extant in the literature, and lack of clear theoretical guidance for valid specifications, suggests the desirability of presenting results in the form of ranges, rather than precision estimates.

## References

- Besley, Timothy and Torsten Persson. 2009. "Repression or Civil War?" *American Economic Review Papers and Proceedings*, 99(2): 292–97.
- Blattman, Christopher and Edward Miguel. 2010. "Civil War" *Journal of Economic Literature*, 48:1, 3–57.
- Brückner, Markus and Antonio Ciccone, 2010. "International Commodity Prices, Growth and the Outbreak of Civil War in Sub-Saharan Africa" *Economic Journal*, vol. 120(544), pages 519-534, 05
- Brückner, Markus & Antonio Ciccone, 2011. "Rain and the Democratic Window of Opportunity" *Econometrica*, vol. 79(3), pages 923-947, 05
- Buhaug, Halvard; Nils Petter Gleditsch & Ole Magnus Theisen. 2010. "Implications of climate change for armed conflict" in Robin Mearns & Andy Norton (eds) *Social Dimensions of Climate Change: Equity and Vulnerability in a Warming World*. Washington, DC: World Bank, 75–101.
- Burke, Marshall, Edward Miguel, Shanker Satyanath, John Dykema, David Lobell "Warming increases risk of civil war in Africa" *PNAS*, 106( 49):20670-74.
- Burke, Marshall and Andrew Leigh. 2010. "Do Output Contractions Trigger Democratic Change?" *American Economic Journal: Macroeconomics* 2: 124–157
- Ciccone, Antonio. 2011. "Economic Shocks and Civil Conflict: A Comment" *American Economic Journal: Applied Economics*. Vol. 3, Issue 4.
- Collier P. 2007, *The Bottom Billion: Why the Poorest Countries are Failing and What Can be Done About It*. Oxford University Press, New York.
- Collier, Paul, Anke Hoeffler and Dominic Rohner. 2009 "Beyond greed and grievance: feasibility and civil war" *Oxford Economic Papers* 61, 1–27.
- Dal Bó, Ernesto and Powell, Robert. 2009. "A Model of Spoils Politics" *American Journal of Political Science* 53(1): 207–222.
- Dell, Melissa, Benjamin Jones, Ben Olken. 2011. "Temperature Shocks and Economic Growth: Evidence from the Last Half Century" Mimeo.
- Gleditsch, Nils Petter; Peter Wallensteen, Mikael Eriksson, Margareta Sollenberg & Håvard Strand. 2002. "Armed conflict 1946–2001: A new dataset" *Journal of Peace Research* 39(5): 615–637.

Heston, Alan, Robert Summers and Bettina Aten. 2009. "Penn World Table Version 6.3, "Center for International Comparisons of Production, Income and Prices at the University of Pennsylvania.

Jensen, Peter Sandholt, and Kristian Skrede Gleditsch. 2009. "Rain, Growth, and Civil War: The Importance of Location" *Defence and Peace Economics* 20(5): 359-372

Miguel, Edward. 2006. "Stop Conflict Before It Starts" *Business Week*  
[http://www.businessweek.com/magazine/content/06\\_38/b4001106.htm](http://www.businessweek.com/magazine/content/06_38/b4001106.htm)

Miguel, Edward and Fisman, Ray. 2008. *Economic Gangsters: Corruption, Violence and the Poverty of Nations* Princeton University Press.

Miguel, Edward, Shanker Satyanath, and Ernest Sergenti. 2004. "Economic Shocks and Civil Conflict: An Instrumental Variables Approach." *Journal of Political Economy*, 112(4), 725-753.

Miguel, Edward, and Shanker Satyanath. 2011. "Re-examining Economic Shocks and Civil Conflict" *American Economic Journal: Applied Economics*. Vol. 3, Issue 4.

Mitchell, T. D., Carter, T. R., Jones, P. D., Hulme, M., & New, M. (2004). A comprehensive set of high-resolution grids of monthly climate for Europe and the globe: The observed record (1901-2000) and 16 scenarios (2001-2100). Tyndall Centre for Climate Change Research Working Paper 55.

Schlenker W., and Lobell D.B. 2009. "Robust and potential severe impacts of climate change on African agriculture." Mimeo.

Theisen, Ole Magnus. 2008. "Blood and soil? Resource scarcity and internal armed conflict revisited" *Journal of Peace Research* 45(6): 801–818.

Willmott C.J. and Matsuura, K. 2001. "Terrestrial Air Temperature and Precipitation: Monthly and Annual Time Series (1950–1999)" Newark, DE: Center for Climatic Research, University of Delaware; 2001.

Willmott, C. J., C.M. Rowe and W.D. Philpot. 1985. "Small-scale climate maps: a sensitivity analysis of some common assumptions associated with grid-point interpolation and contouring" *American Cartographer*, 12, 5-16.

Willmott, C. J. and K. Matsuura. 1995. "Smart interpolation of annually averaged air temperature in the United States" *Journal of Applied Meteorology*, 34, 2577-2586.

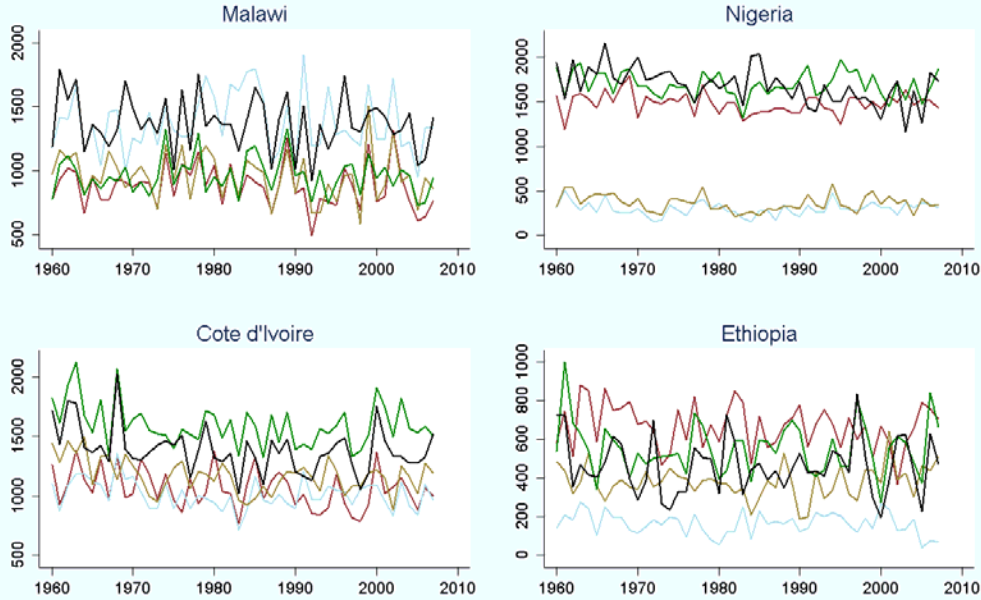
Willmott, C. J. and S.M. Robeson. 1995. "Climatologically aided interpolation (CAI) of terrestrial air temperature" *International Journal of Climatology*, 15, 221-229.



**Table 2: Correlation coefficients between rainfall measures of GPCP and Matsuura-Wilmott for 1981-1999**

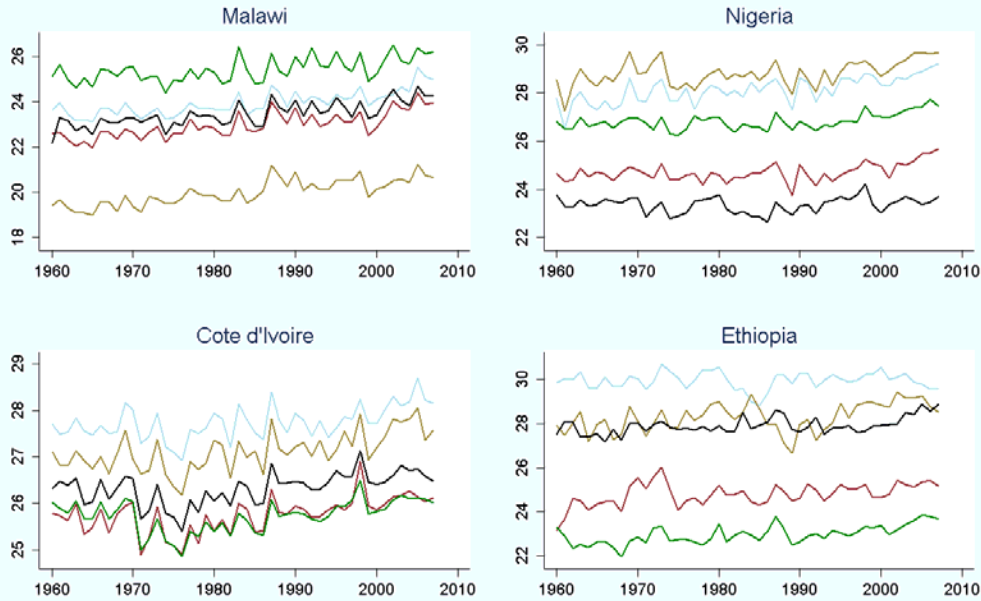
<i>Country</i>	<i>Correlation</i>	<i>Country</i>	<i>Correlation</i>
Sierra Leone	-0.13	Ethiopia	0.75
Angola	0.21	Cote D'ivoire	0.75
Liberia	0.28	Benin	0.77
Tanzania	0.34	Mauritania	0.80
Guinea	0.35	Ghana	0.80
Zambia	0.40	Togo	0.81
DRC	0.42	Burundi	0.82
Rwanda	0.45	Malawi	0.84
Djibouti	0.51	Madagascar	0.85
Uganda	0.55	Cameroon	0.86
Congo	0.57	Senegal	0.87
Guinea-Bissau	0.67	Burkina Faso	0.89
Sudan	0.68	Mozambique	0.89
Gambia	0.70	Nigeria	0.90
CAR	0.70	Chad	0.91
Kenya	0.73	Lesotho	0.93
Swaziland	0.73	Namibia	0.93
Gabon	0.74	Botswana	0.94
Somalia	0.74	South Africa	0.95
Niger	0.74	Zimbabwe	0.96
		Mali	0.96

Figure 1a: Total annual precipitation for centroid and corners for select countries



Red = centroid, light blue = northeast corner, brown = northwest, black = southeast, green = southwest.  
 Definitions of centroid and corners as in text, generated using Matsuura-Wilmott dataset.

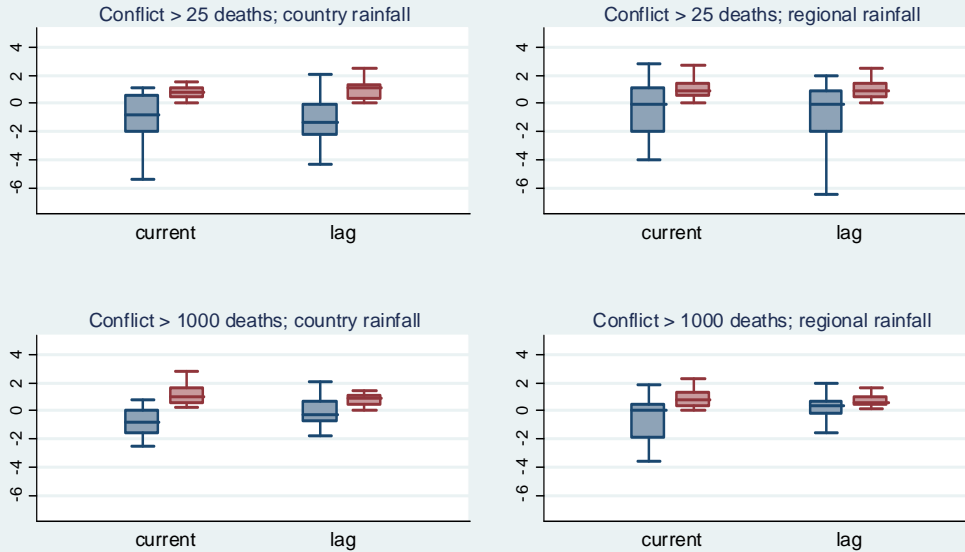
Figure 1b: Average annual temperature for centroid and corners for select countries



Red = centroid, light blue = northeast corner, brown = northwest, black = southeast, green = southwest.  
 Definitions of centroid and corners as in text, generated using Matsuura-Wilmott dataset.

Figure 2: Effects of GDP growth on incidence of civil conflict, 1981-1999

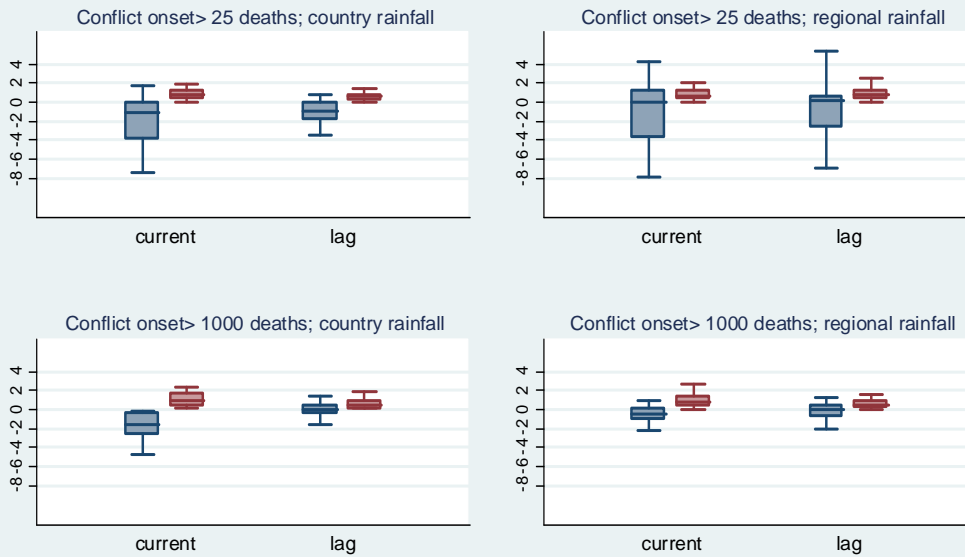
Distribution of coefficients and t-stats of replication of MSS Table 4 Columns 6 and 7



Note: Blue box plots are for estimated coefficients from 48 regressions as described in text, red for accompanying t-statistics in absolute value. Plots exclude a handful of outlier coefficients and t-statistics.

Figure 3: Effects of GDP growth on onset of civil conflict, 1981-1999

Distribution of coefficients and t-stats of replication of MSS Table 6 Columns 1 and 2



Note: Blue box plots are for estimated coefficients from 48 regressions as described in text, red for accompanying t-statistics in absolute value. Plots exclude a handful of outlier coefficients and t-statistics.

Figure 4a: Rainfall Measures for High Correlation Countries (.90 to .86)

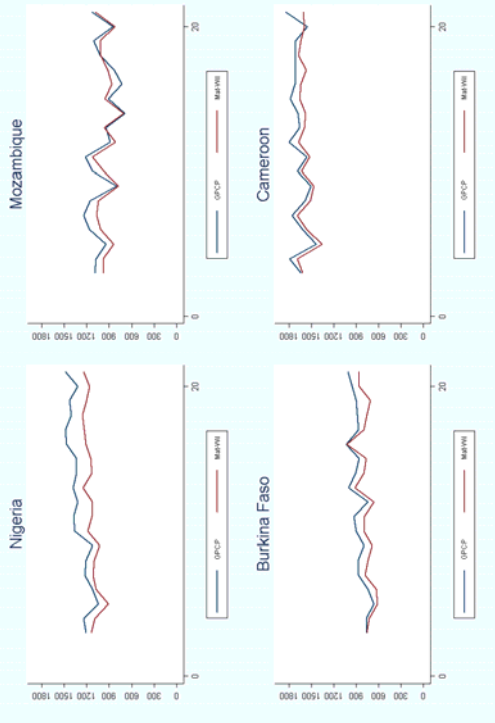


Figure 4c: Rainfall Measures for Low Correlation Countries (.42 to .34)

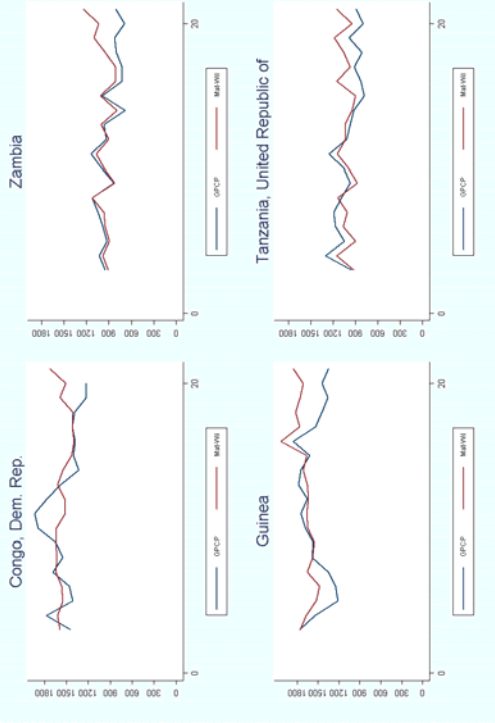


Figure 4b: Rainfall Measures for Low Correlation Countries (.57 to .45)

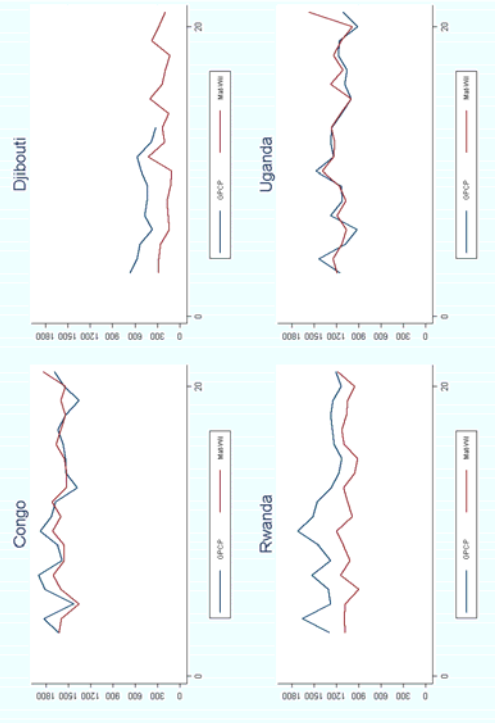
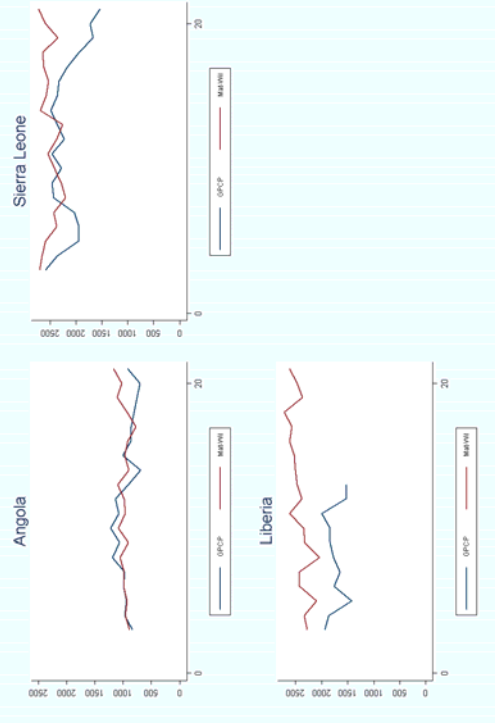
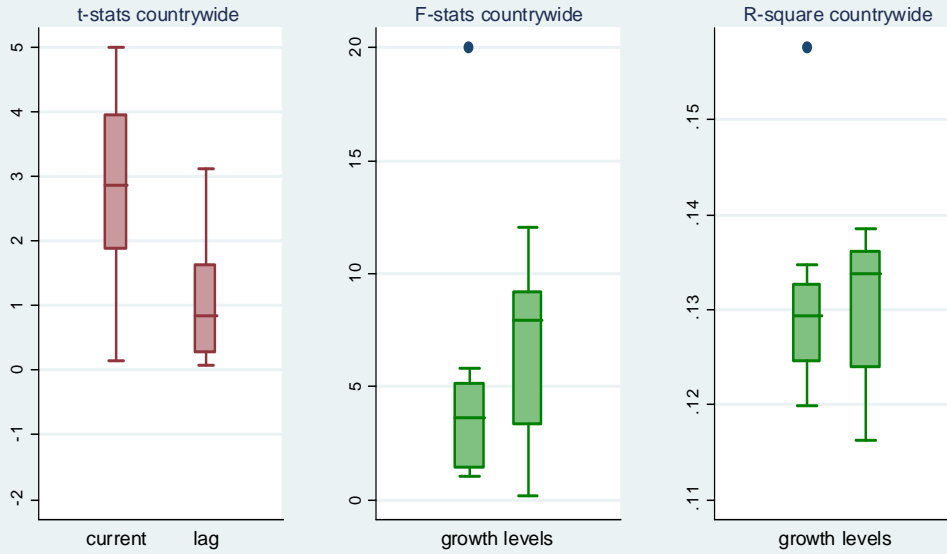


Figure 4d: Rainfall Measures for Low Correlation Countries (.28 to -.13)



**Figure 5a: Country rainfall explaining GDP growth, 1981-1999**

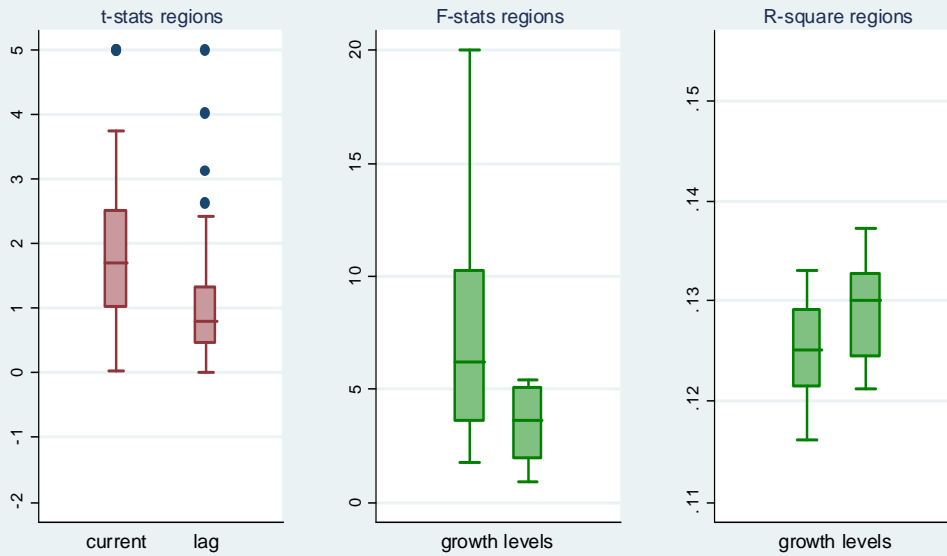
Distribution of t-stats, F-stats and R-squares of replications of MSS Table 2 Column 3



Statistics from 18 regressions. t-stats are in absolute value. Outlier F-stat capped at 20.

**Figure 5b: Regional rainfall explaining GDP growth, 1981-1999**

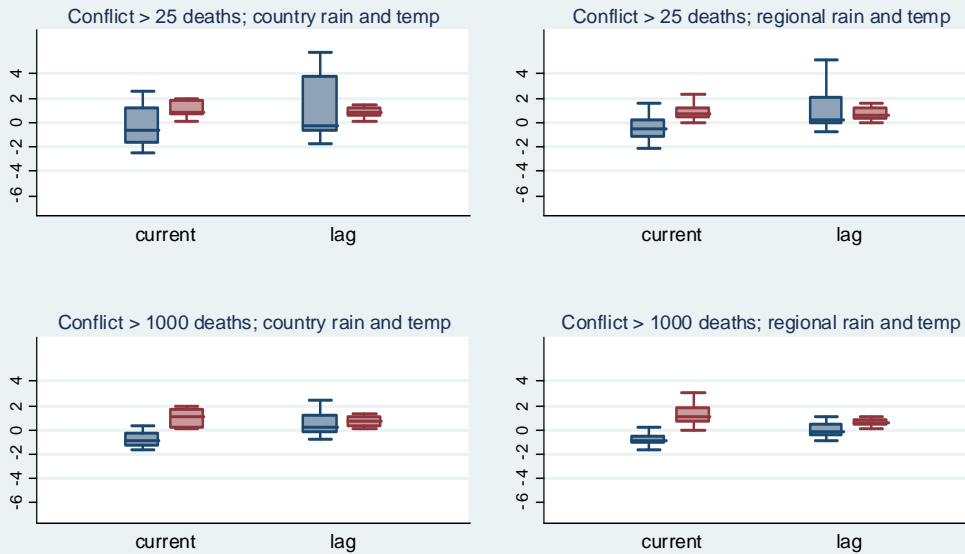
Distribution of t-stats, F-stats and R-squares of replication of MSS Table 2 Column 3



Statistics from 28 regressions. t-stats are in absolute value. Outlier F-stat capped at 20 and t-stats capped at 5.

Figure 6: Effects of GDP growth on incidence of civil conflict, 1960-2007

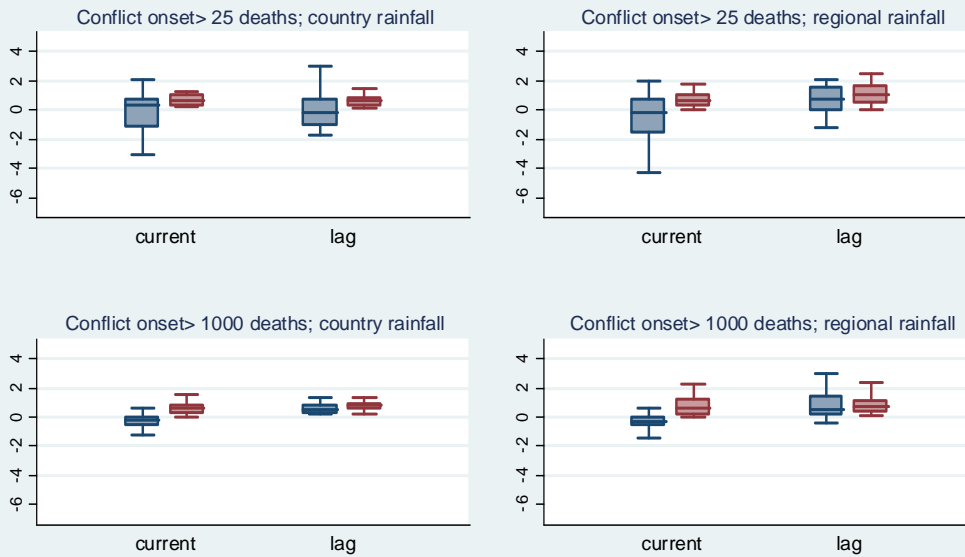
Distribution of coefficients and t-stats, rainfall variables as instruments



Note: Blue box plots are for estimated coefficients from 46 regressions as described in text, red for accompanying t-statistics in absolute value. Rainfall change and levels are instruments for GDP growth. Plots exclude a handful of outlier coefficients and t-statistics.

Figure 7: Effects of GDP growth on onset of civil conflict, 1960-2007

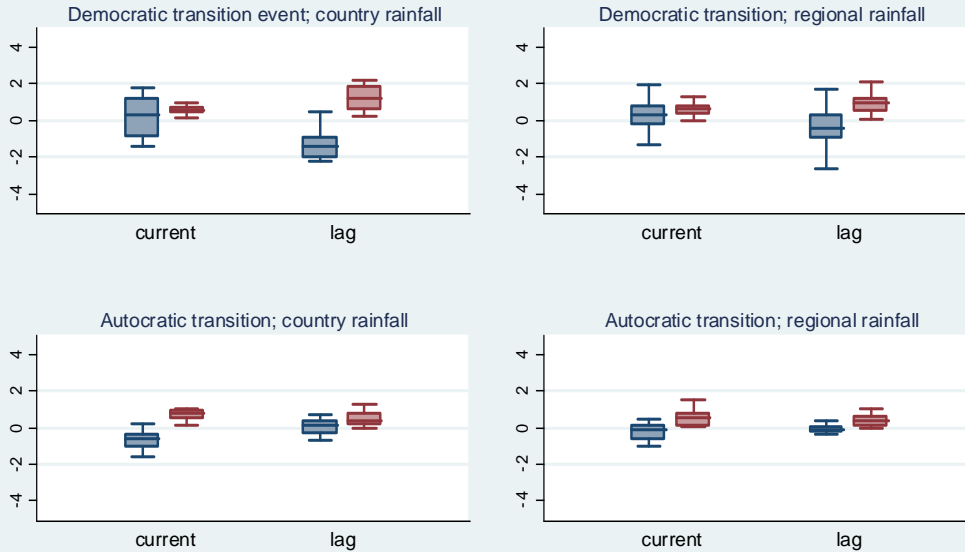
Distribution of coefficients and t-stats, rainfall variables as instruments



Note: Blue box plots are for estimated coefficients from 46 regressions as described in text, red for accompanying t-statistics in absolute value. Rainfall change and levels are instruments for GDP growth. Plots exclude a handful of outlier coefficients and t-statistics.

**Figure 8: Effects of GDP growth on political transitions, 1960-2007**

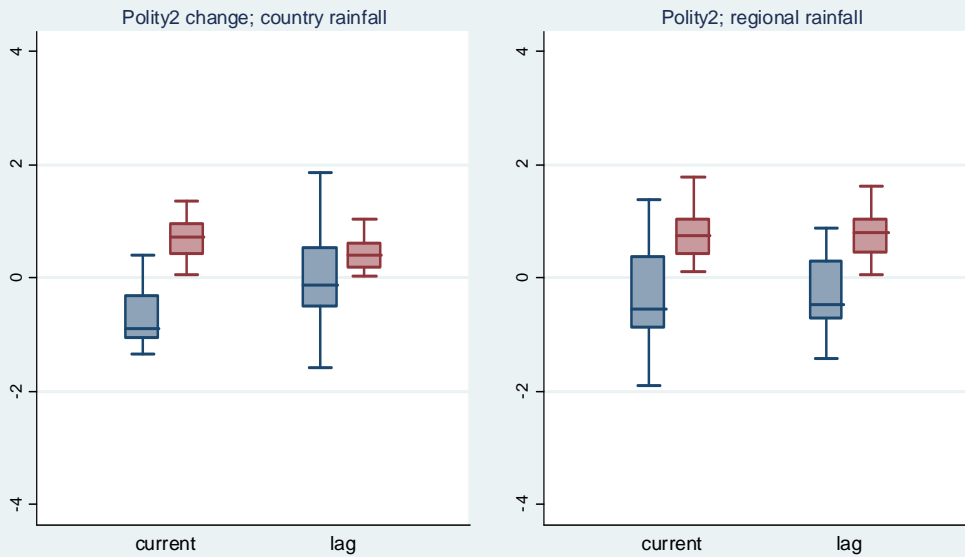
Distribution of coefficients and t-stats of semi-replication of BL Table 4 Column 3 and Table 5 column 3



Note: Blue box plots are for estimated coefficients from 46 regressions as described in text, red for accompanying t-statistics in absolute value. Rainfall change and levels are instruments for GDP growth. Plots exclude a handful of outlier coefficients and t-statistics.

**Figure 9: Effects of GDP growth on Polity2 change, 1960-2007**

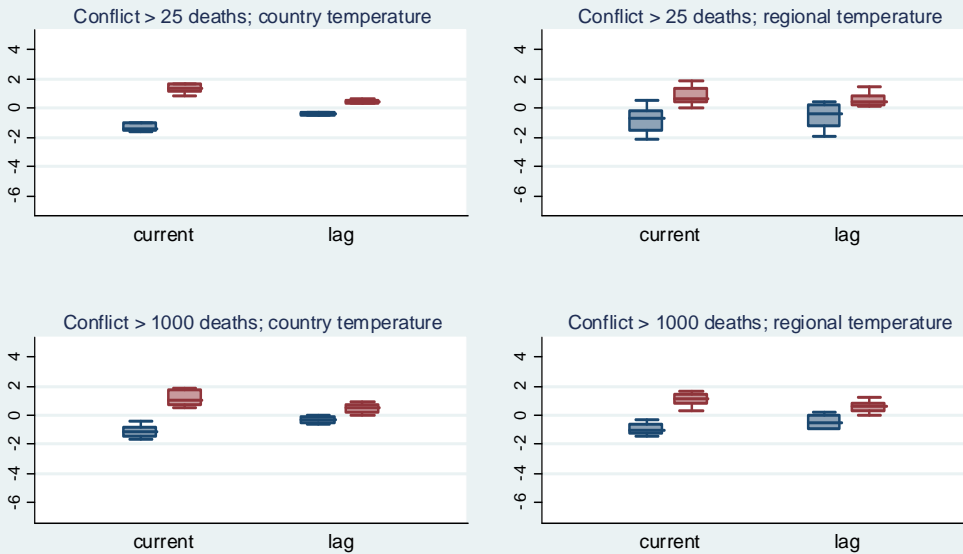
Distribution of coefficients and t-stats of semi-replication of BC Table 5 Column 1



Note: Blue box plots are for estimated coefficients from 46 regressions as described in text, red for accompanying t-statistics in absolute value. Rainfall change & levels are instruments for GDP growth. Plots exclude outlier coefficients and t-statistics. Coefficients divided by 10.

Figure 10: Effects of GDP growth on incidence of civil conflict, 1960-2007

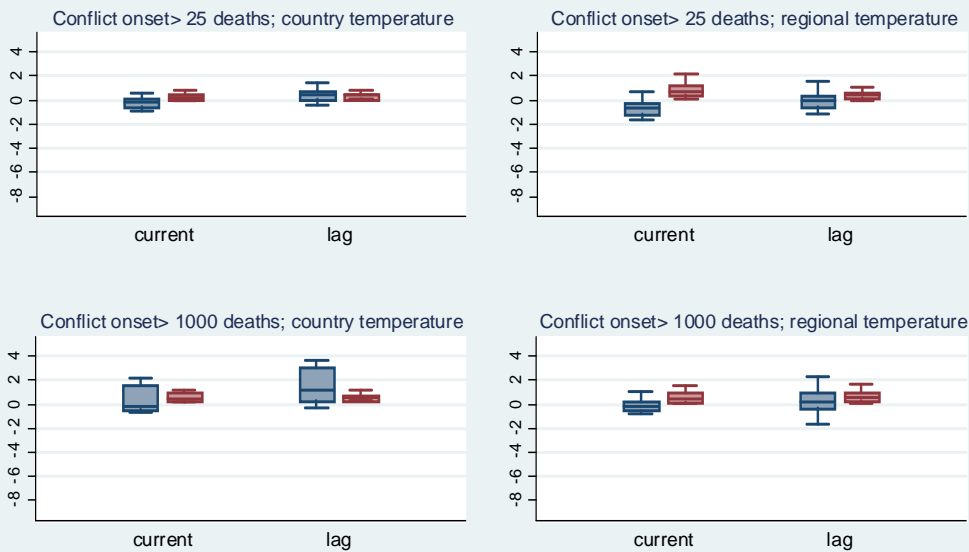
Distribution of coefficients and t-stats



Note: Blue box plots are for estimated coefficients from 40 regressions as described in text, red for accompanying t-statistics in absolute value. Temp. change is instrument for GDP growth. Plots exclude a handful of outlier coefficients and t-statistics.

Figure 11: Effects of GDP growth on onset of civil conflict, 1960-2007

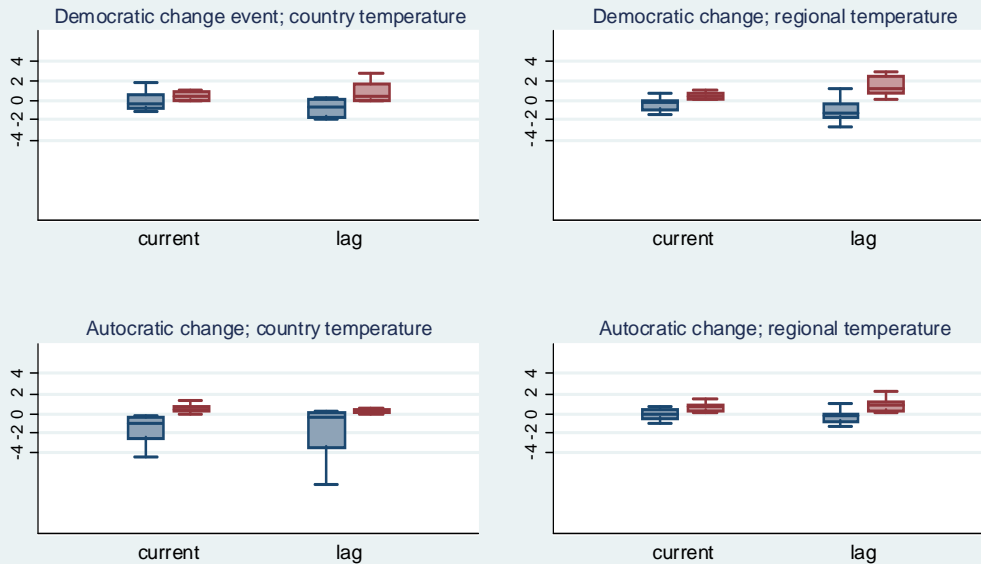
Distribution of coefficients and t-stats, temperature instruments



Note: Blue box plots are for estimated coefficients from 40 regressions as described in text, red for accompanying t-statistics in absolute value. Temp. change and levels are instruments for GDP growth. Plots exclude a handful of outlier coefficients and t-statistics.

Figure 12: Effects of GDP growth on political change, 1960-2007

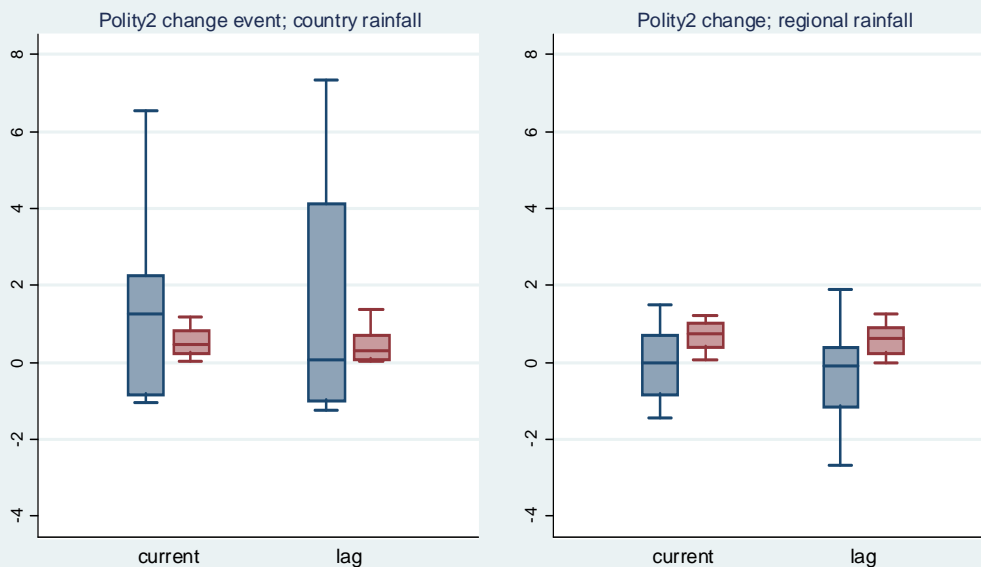
Distribution of coefficients and t-stats of semi-replication of BL Table 4 Column 3 and Table 5 column 3



Note: Blue box plots are for estimated coefficients from 40 regressions as described in text, red for accompanying t-statistics in absolute value. Temp. change and levels are instrument for GDP growth. Plots exclude a handful of outlier coefficients and t-statistics.

Figure 13: Effects of GDP growth on political change, 1960-2007

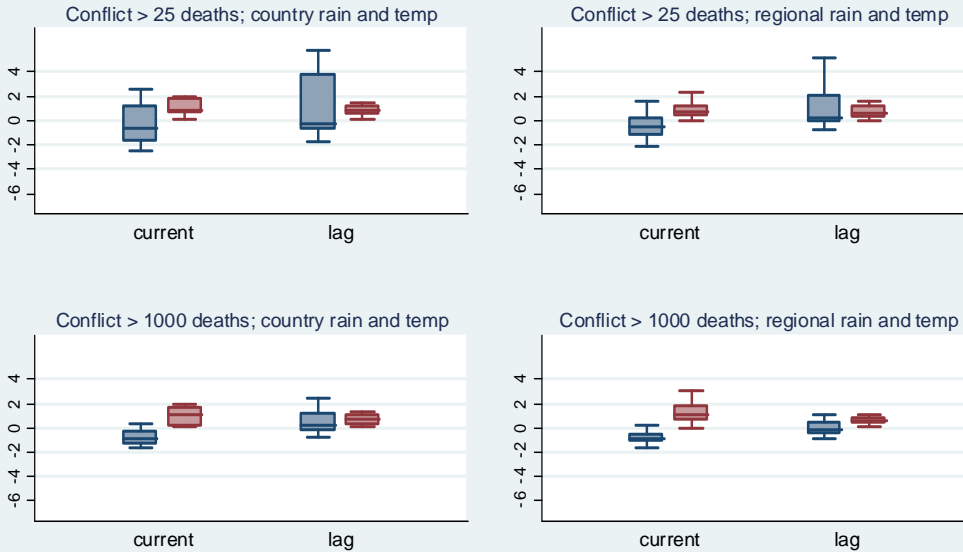
Distribution of coefficients and t-stats of semi-replication of BC Table 5 Column 1



Note: Blue box plots are for estimated coefficients from 40 regressions as described in text, red for accompanying t-statistics in absolute value. Temp. change is instrument for GDP growth. Plots exclude a handful of outlier coefficients and t-statistics. Coefficients divided by 10.

Figure 14: Effects of GDP growth on incidence of civil conflict, 1960-2007

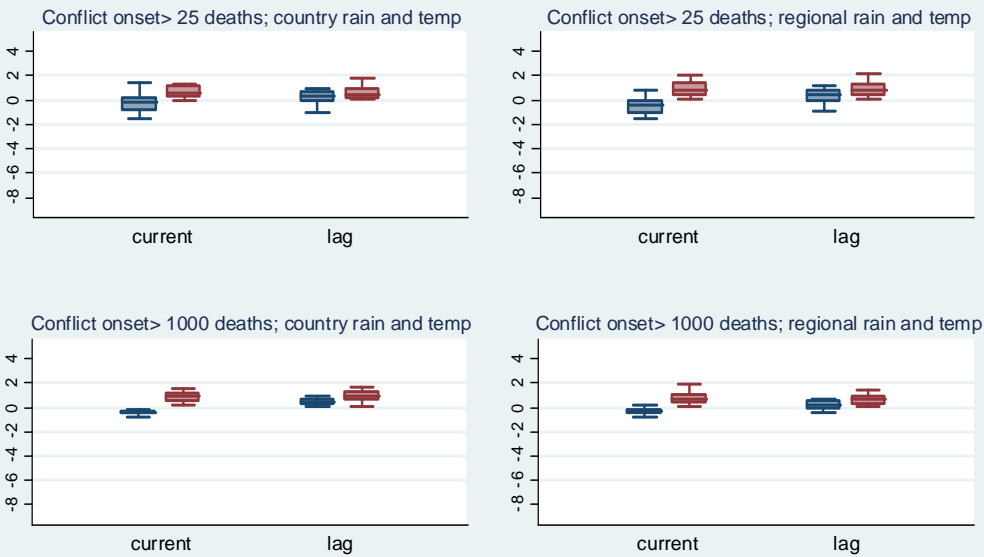
Distribution of coefficients and t-stats, multiple weather inst.



Note: Blue box plots are for estimated coefficients from 46 regressions as described in text, red for accompanying t-statistics in absolute value. Temp. and rainfall are instruments for GDP growth. Plots exclude outlier coefficients and t-statistics.

Figure 15: Effects of GDP growth on onset of civil conflict, 1960-2007

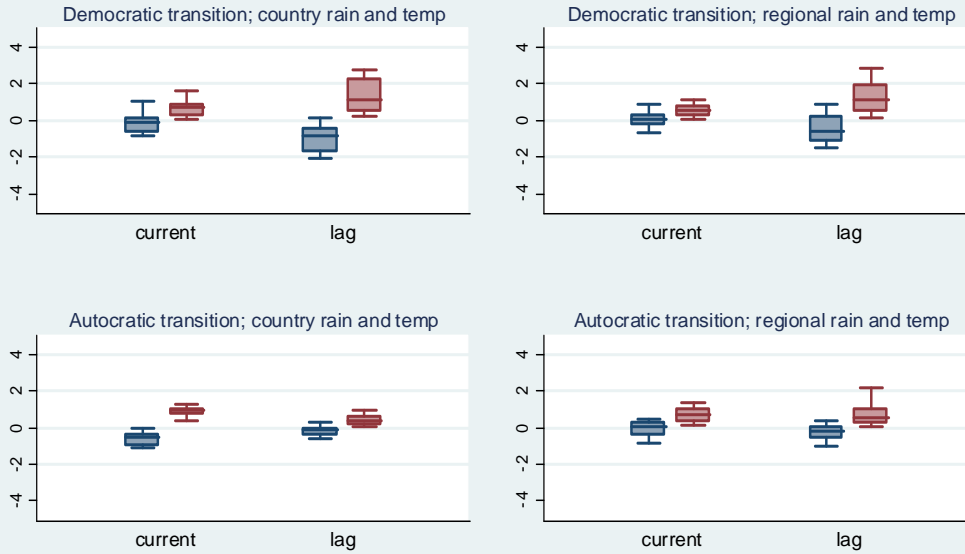
Distribution of coefficients and t-stats, multiple weather inst.



Note: Blue box plots are for estimated coefficients from 46 regressions as described in text, red for accompanying t-statistics in absolute value. Temp. and rain change are instruments for GDP growth. Plots exclude outlier coefficients and t-statistics.

Figure 16: Effects of GDP growth on political transitions, 1960-2007

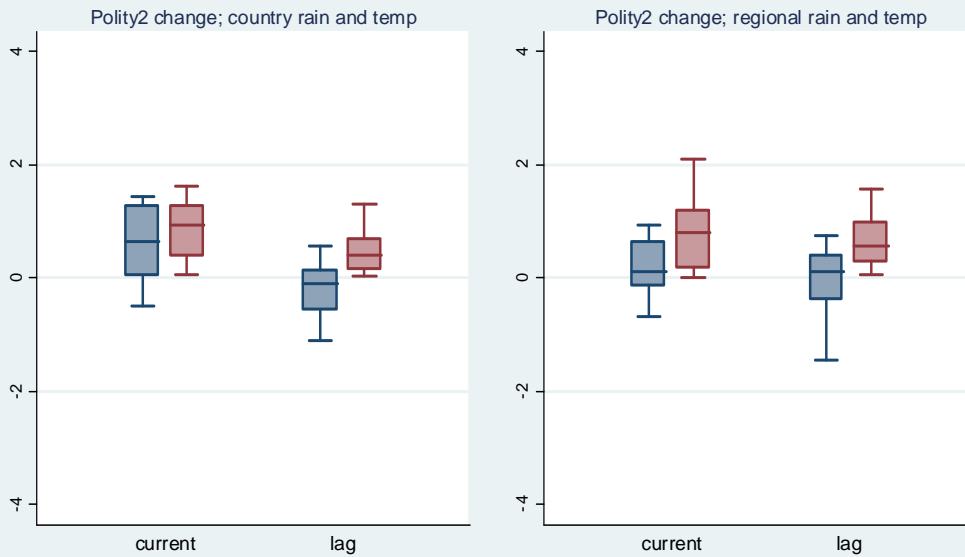
Distribution of coefficients and t-stats of semi-replication of BL Table 4 Column 3 and Table 5 column 3



Note: Blue box plots are for estimated coefficients from 46 regressions as described in text, red for accompanying t-statistics in absolute value. Temp. and rain are instruments for GDP growth. Plots exclude outlier coefficients and t-statistics.

Figure 17: Effects of GDP growth on political change, 1960-2007

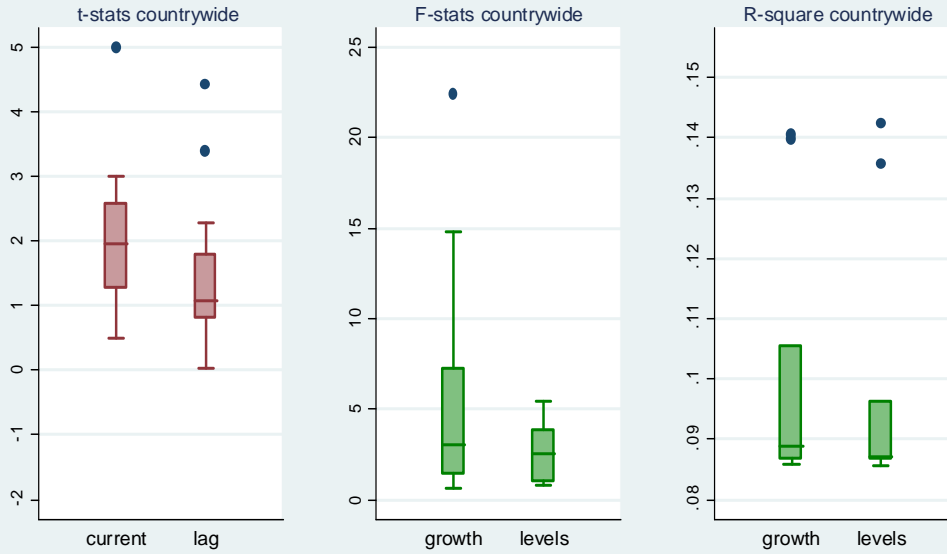
Distribution of coefficients and t-stats of semi-replication of BC Table 5 Column 1



Note: Blue box plots are for estimated coefficients from 46 regressions as described in text, red for accompanying t-statistics in absolute value. Temp. and rain are instruments for GDP growth. Plots exclude outlier coefficients and t-statistics. Coefficients divided by 10.

Figure 18a: Country rainfall explaining GDP growth, 1960-2007

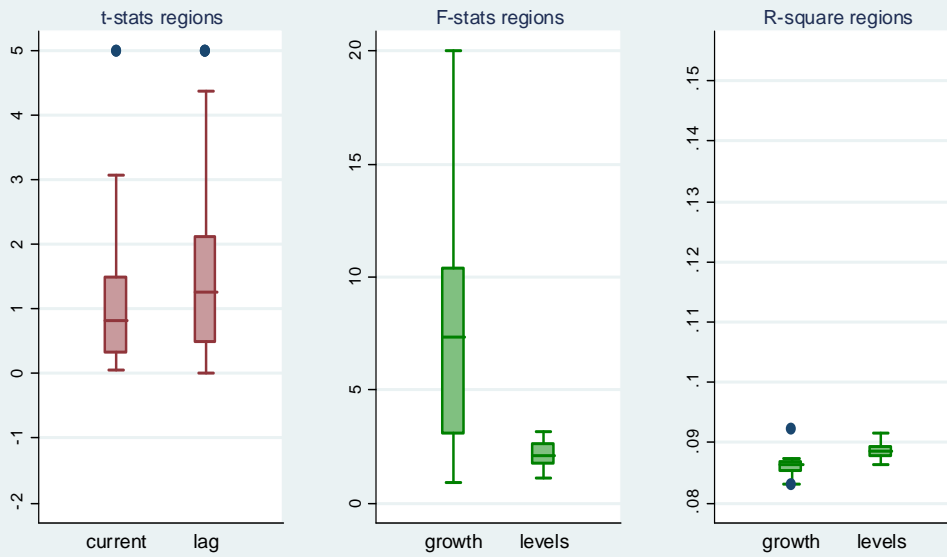
Distribution of t-stats, F-stats and R-squares



Statistics from 18 regressions. t-stats are in absolute value. Outlier F-stat capped at 20.

Figure 18b: Regional rainfall explaining GDP growth, 1960-2007

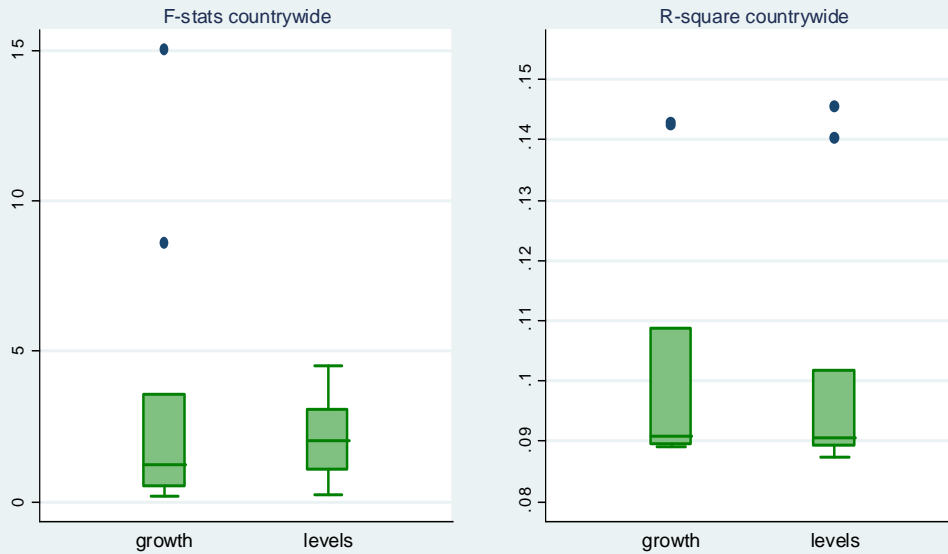
Distribution of t-stats, F-stats and R-squares



Statistics from 18 regressions. t-stats are in absolute value. Outlier F-stat capped at 20.

Figure 19a: Country rain & temp explaining GDP growth, 1960-2007

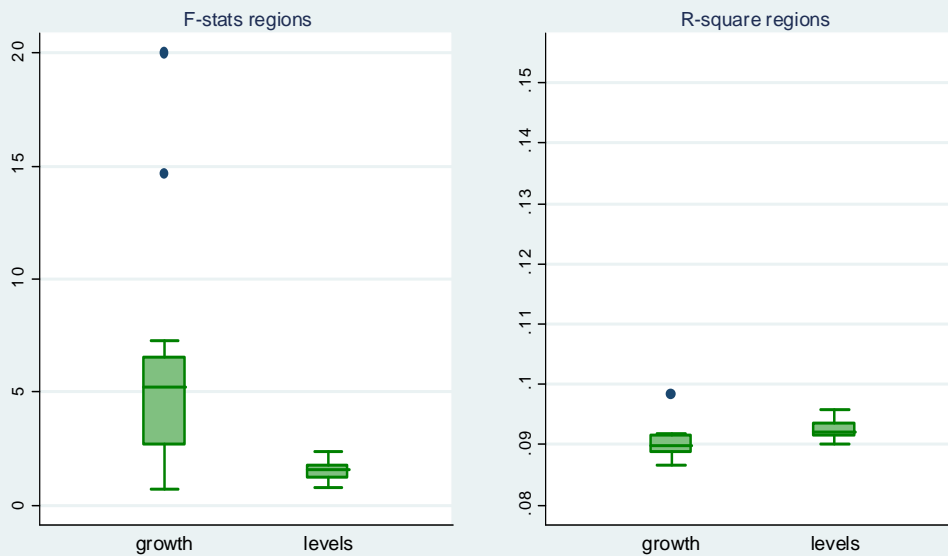
Distribution of t-stats, F-stats and R-squares



Statistics from 18 regressions.

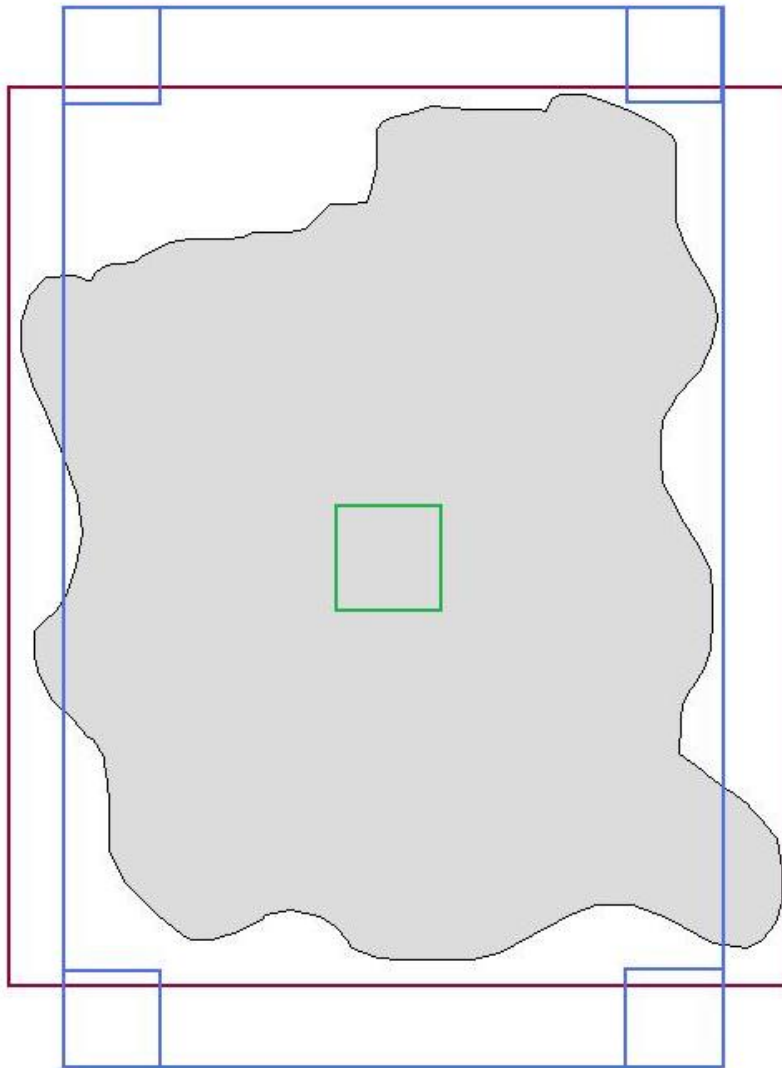
Figure 19b: Regional rain & temp explaining GDP growth, 1960-2007

Distribution of t-stats, F-stats and R-squares



Statistics from 18 regressions. Outlier F-stat capped at 20.

**Figure A1: Illustration of regions used to construct measures of rainfall**



**Note: Maroon border delineates the countrybox, gray area the country proper, delineated by its border, and the blue boxes are the corners, while the green box is the centroid. Rainfall measures average over nodes within each region; corners and centroids average over four nodes.**

Figure A2: Rainfall anomalies and civil conflict incidence, 1960-2007

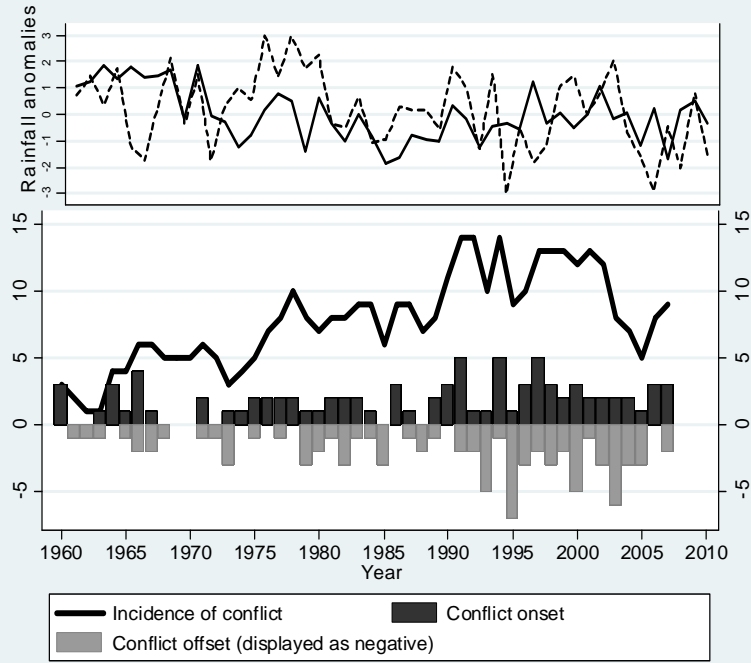
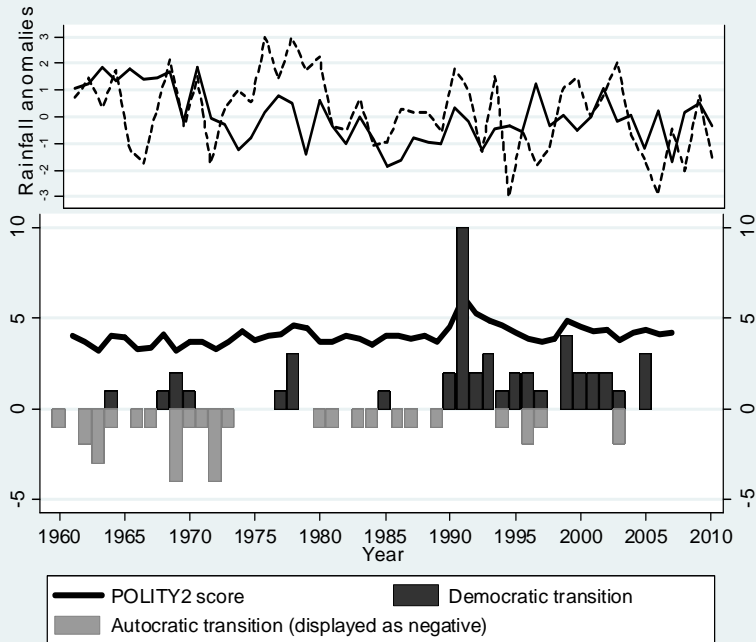


Figure A3: Rainfall anomalies and political change, 1960-2007



Note: POLITY2 scores have been shifted up by 4 units

Table A1: Variables used in first stage regression explaining per capita GDP growth

Variable 1	Variable 2		Description	
(Note: each regression uses current and lagged variables)				
1	GPCP MSS	growth	GPCP version 2.0 total annual countrywide rainfall (MSS version; 1979-99)	
2	rainfalltotcbordery	growth	MW total annual countrywide rainfall	
3	rainfalltot	growth	MW total annual country box rainfall	
4	rainfall_centroid	growth	MW total annual country centroid rainfall	
5	rainbigpeakcborder	growth	MW countrywide rainfall for rainiest month	
6	rainbigpeak	growth	MW country box rainfall for rainiest month	
7	rainiestcentroid	growth	MW country centroid rainfall for rainiest month	
8	GPCP 2.0	growth	GPCP version 2.0 total annual countrywide rainfall	
9	GPCP 2.1	growth	GPCP version 2.1 total annual countrywide rainfall	
10	precipitation	growth	Mitchell et al measure of rainfall	
11	GPCP	level	GPCP version 2.0 total annual countrywide rainfall (MSS version)	
12	rainfalltotcbordery	level	MW total annual countrywide rainfall	
13	rainfalltot	level	MW total annual country box rainfall	
14	rainfall_centroid	level	MW total annual country centroid rainfall	
15	rainbigpeakcborder	level	MW countrywide rainfall for rainiest month	
16	rainbigpeak	level	MW country box rainfall for rainiest month	
17	rainiestcentroid	level	MW country centroid rainfall for rainiest month	
18	GPCP 2.0	level	GPCP version 2.0 total annual countrywide rainfall	
19	GPCP 2.1	level	GPCP version 2.1 total annual countrywide rainfall	
20	precipitation	level	Mitchell et al measure of rainfall	
21	rainfalltotnorth	rainfalltotsouth	growth	MW total annual upper/lower third of country box rainfall
22	rainfallpeaknorth	rainfallpeaksouth	growth	MW total annual upper/lower third of country box rainfall
23	rainfalltotnorth	rainfalltotsouth	level	MW total annual upper/lower third of country box rainfall
24	rainfallpeaknorth	rainfallpeaksouth	level	MW total annual upper/lower third of country box rainfall
25	rainfalltot_ne	rainfalltot_se	growth	MW total annual rainfall for northeast and southeast country corners
26	rainfalltot_ne	rainfalltot_nw	growth	MW total annual rainfall for northeast and northwest country corners
27	rainfalltot_ne	rainfalltot_sw	growth	MW total annual rainfall for northeast and southwest country corners
28	rainfalltot_se	rainfalltot_nw	growth	MW total annual rainfall for southeast and northwest country corners
29	rainfalltot_se	rainfalltot_sw	growth	MW total annual rainfall for southeast and southwest country corners
30	rainfalltot_nw	rainfalltot_sw	growth	MW total annual rainfall for northwest and southwest country corners
31	rainbigpeak_ne	rainbigpeak_se	growth	MW rainfall for rainiest month for northeast and southeast country corners
32	rainbigpeak_ne	rainbigpeak_nw	growth	MW rainfall for rainiest month for northeast and northwest country corners
33	rainbigpeak_ne	rainbigpeak_sw	growth	MW rainfall for rainiest month for northeast and southwest country corners
34	rainbigpeak_se	rainbigpeak_nw	growth	MW rainfall for rainiest month for southeast and northwest country corners
35	rainbigpeak_se	rainbigpeak_sw	growth	MW rainfall for rainiest month for southeast and southwest country corners
36	rainbigpeak_nw	rainbigpeak_sw	growth	MW rainfall for rainiest month for northwest and southwest country corners
37	rainfalltot_ne	rainfalltot_se	level	MW total annual rainfall for northeast and southeast country corners
38	rainfalltot_ne	rainfalltot_nw	level	MW total annual rainfall for northeast and northwest country corners
39	rainfalltot_ne	rainfalltot_sw	level	MW total annual rainfall for northeast and southwest country corners
40	rainfalltot_se	rainfalltot_nw	level	MW total annual rainfall for southeast and northwest country corners
41	rainfalltot_se	rainfalltot_sw	level	MW total annual rainfall for southeast and southwest country corners
42	rainfalltot_nw	rainfalltot_sw	level	MW total annual rainfall for northwest and southwest country corners
43	rainbigpeak_ne	rainbigpeak_se	level	MW rainfall for rainiest month for northeast and southeast country corners
44	rainbigpeak_ne	rainbigpeak_nw	level	MW rainfall for rainiest month for northeast and northwest country corners
45	rainbigpeak_ne	rainbigpeak_sw	level	MW rainfall for rainiest month for northeast and southwest country corners
46	rainbigpeak_se	rainbigpeak_nw	level	MW rainfall for rainiest month for southeast and northwest country corners
47	rainbigpeak_se	rainbigpeak_sw	level	MW rainfall for rainiest month for southeast and southwest country corners
48	rainbigpeak_nw	rainbigpeak_sw	level	MW rainfall for rainiest month for northwest and southwest country corners
1	avgtemp	growth	MW average country box temperature	
2	avgtempcbordery	growth	MW average country temperature	
3	avgtempcentroid	growth	MW average country centroid temperature	
4	tempbigpeak	growth	MW temp in peak hottest month countrybox	
5	tempbigpeakcborder	growth	MW temp in peak hottest month country	
6	hottestcentroil	growth	MW temp in peak hottest month centroid	
7	avgtemp	level	MW average country box temperature	
8	avgtempcbordery	level	MW average country temperature	