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

Very preliminary, comments appreciated
Please do not cite this version
Draft: October 3, 2011

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Abstract: We examine the robustness of recent papers by Miguel, Satyanath, and Sergenti (2004), Burke and Leigh (2010) and Bruckner and Ciccone (forthcoming) that identify causal effects of economic decline on political change in sub-Saharan African countries by using climate measures as instrumental variables for GDP. We use a number of different measures of rainfall and temperature from a variety of sources and concentrate on presenting in a transparent manner the *range* of estimates of coefficients and indicators of statistical significance. Our finding is that estimates are sensitive to specification and formulation of climate measures. There remains considerable work to be done in using the instrumental variables method to confirm a substantial and significant causal relationship between GDP growth and political change in sub-Saharan Africa.

1. Introduction

Civil conflicts and resistance to democratization 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 practice cynical lifeboat ethics: "everyone overboard except us." 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 aggravates 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 permit analysis from a cost-benefit standpoint of 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 has also been used in two recent papers examining political change. These papers use 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) use the dataset to construct indicator variables for the onset of democratic transitions and autocratic transitions. 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 use subsequent POLITY scores to determine whether the transition was democratic or autocratic. Burke and Leigh are primarily interested in the effects of economic change on regime transitions for the entire set of countries, but they present separate estimates for sub-Saharan African countries.

Bruckner and Ciccone (forthcoming) likewise use the Polity IV database to examine the effects of GDP on political change in sub-Saharan Africa. Their outcome variable is the next 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 recognize that there is no clear theoretical prediction for how economic change measured by GDP should affect political outcomes. It is up to statistical analysis to determine what the pattern has been and whether correlations are properly interpreted as causal. Nevertheless, the three papers have quite distinct implicit (and sometimes explicit) preferred hypotheses. For Miguel, Satyanath and Sergenti, economic decline is likely to trigger civil war and continue civil war incidence because the primary effect of GDP decline in poor agrarian economies is to facilitate recruitment of rebel soldiers in the hinterlands. Burke and Leigh assert that economic decline makes the governed less inclined to consent to rule by autocrats, and stimulates protests and disobedience that gather momentum and result in regime transitions. For Bruckner and Ciccone (forthcoming, pp. 1-2), economic decline opens up a "democratic window of opportunity" for a similar reason, since the "opportunity cost of contesting power is temporarily low."

Table 1 presents the basic problem addressed by this paper. 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 (the shaded cells). We also estimate the same coefficient using the others' climate databases, and add the Matsuura-Willmott rainfall data (discussed below) as a fourth specification. The table shows that the Miguel, Satyanath and Sergenti estimates are not robust to the alternative rainfall measures. The GPCP 2.1 measure (that superseded the GPCP 2.0 dataset they used) generates a smaller and less significant estimate, while the Mitchell et al. rainfall measure used by Burke and Leigh and the Matsuura-Willmott measures of rainfall generate coefficients that are not statistically significant. The four estimates use the same sample period (1981-99), the same GDP numbers, and the same measure of incidence of civil conflict.

The Burke and Leigh estimate for their 1963-2001 sample period is robust with the GPCP 2.1 (1980-2001) and the GPCP 2.0 (1980-1999) measures, but not with the Matsuura-Willmott (1963-2001). We use the same indicator of democratic transitions and the 6.3 Penn World Tables for the GDP measure.

The Bruckner and Ciccone coefficient is estimated to be the same magnitude with the GPCP 2.1 climate data that they use, for the period 1980-2004, but is not statistically significant. Bruckner and Ciccone use the 6.2 Penn World Tables and we use the 6.3

Penn World Tables for the GDP measures, and this is why the results are different. The Bruckner and Ciccone coefficients are not significant when using the other rainfall measures.

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. 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 Burke and Leigh "preferred" specifications including a host of interactions while Miguel, Satyanath and Sergenti specifically note that interactions are not significant and so the results hold without them). 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 are almost never significant.

Thus while all three of the papers report extensive robustness checks in the form of appendices with alternative control variables and alternative climate measures, the papers each privilege certain specifications over others, and their verbal summaries leave the reader with an impression of a robust finding.

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.

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 differ 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.[1] 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

[1] 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.

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.

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). [3] 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

[3] 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 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.[3] 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.

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 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.[4] 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

[4] 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.

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, 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.[5] 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 $\text{POLITY2}_{t+1} - \text{POLITY2}_{t}$.

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 200, 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

[5] http://www.prio.no/CSCW

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 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.[6] 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-

[6] Table A1 lists the different rainfall variables included in the regressions.

statistics into absolute values. The solid box denotes the range of estimates that fall between the 25th and 75th 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).

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 el 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.[7] 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

[7] 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.

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 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.

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Table 1: Comparing when effects of GDP are statistically significant in affecting political change

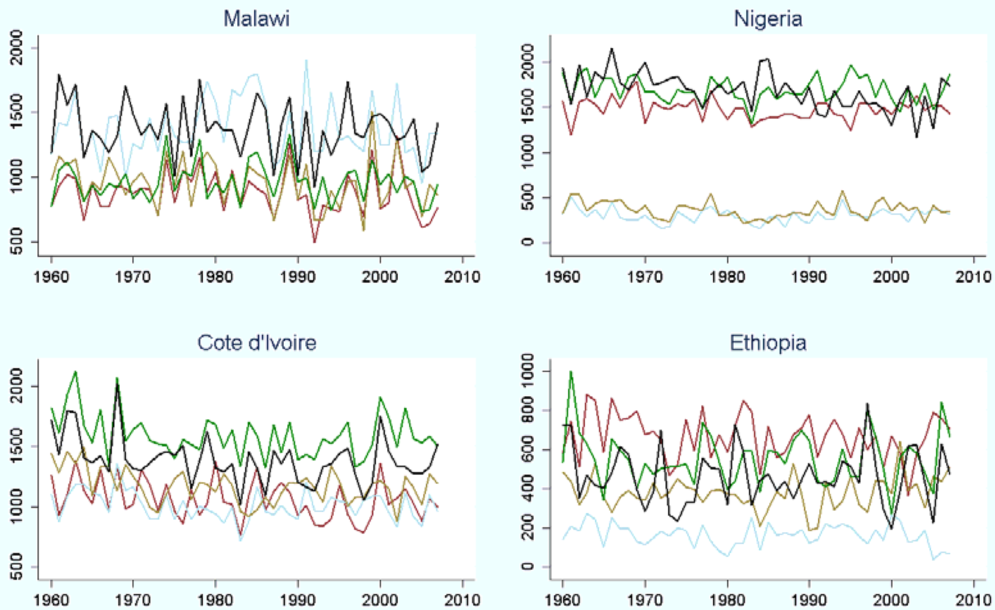
						estimates of relevant coefficients				
	Outcome	Relevant explanatory variable	Include current and lag GDP?	Controls	Instrumental variable(s)	GPCP 2.0	GPCP 2.1	Mitchell et al (2004)	Matsurra-Wilmott	Original paper time period
Miguel, Satyanath and Sergenti (2004)	incidence of civil conflict >25 deaths in year t	lag GDP change*	yes	Country, country*year	change in rainfall, year t and year t-1	-2.55**	-1.90*	-1.49	-3.04	1981-1999
Burke and Leigh (2010)	Democratic transition REGTRANS in year t followed by 3 pt improvement	lag GDP change*	no	Country, country*year	change in rainfall, year t-1 and year t-2	-2.30***	-1.55**	-1.23***	-0.80	1963-2001
Bruckner and Ciccone (2011	Change in Polity2 score year t+1 - year t	ln(lag GDP level)	no	Country, country*year, year	ln(lag rainfall level)	-13.27	-19.71	-81.55	30.11	1980-2004

Notes: Shaded cells are authors' estimations (or close to them); *None of the coefficients for current GDP change are statistically significant.

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

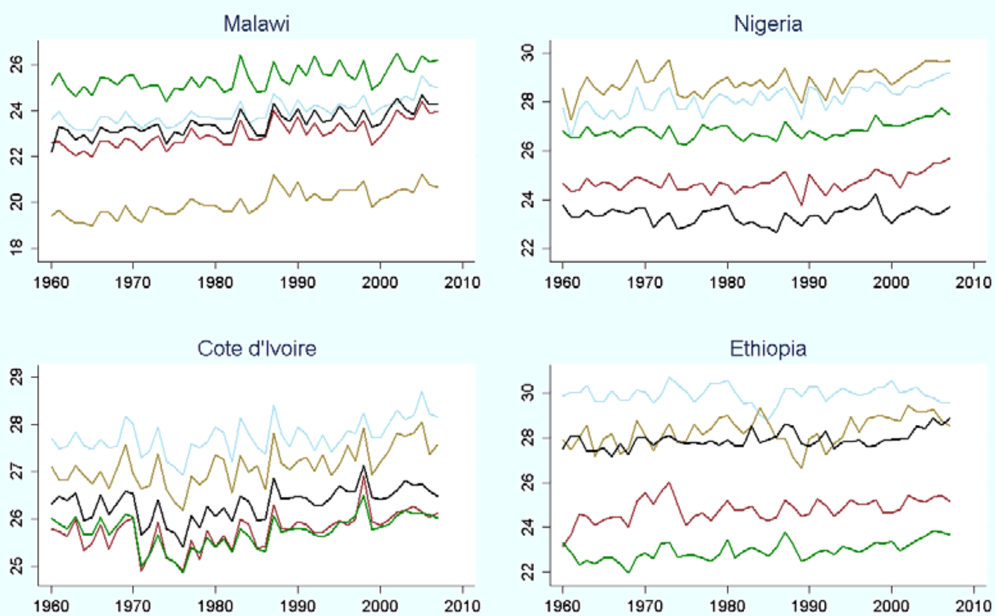
Country	*Correlation*		*Country*	*Correlation*
Sierra Leone	-0.13		Ethiopia	0.75
Angola	0.21		Cote D'ivoire	0.75
Liberia	0.28		Benin	0.77
Tanzania	0.34		Mauritania	0.80
Guinea	0.35		Ghana	0.80
Zambia	0.40		Togo	0.81
DRC	0.42		Burundi	0.82
Rwanda	0.45		Malawi	0.84
Djibouti	0.51		Madagascar	0.85
Uganda	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.

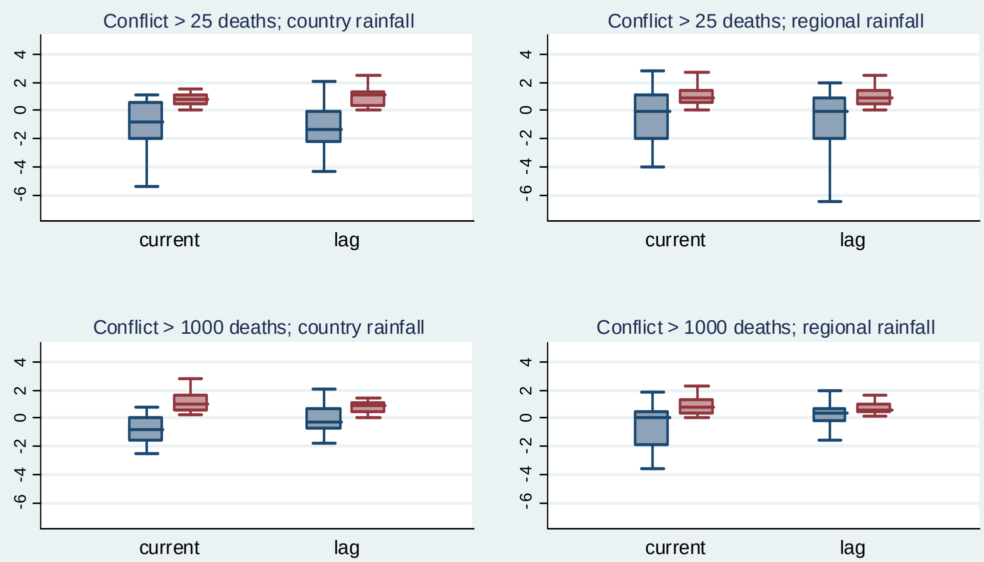
Figure 1b: Average annual temperature for centroid and corners for select countries



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

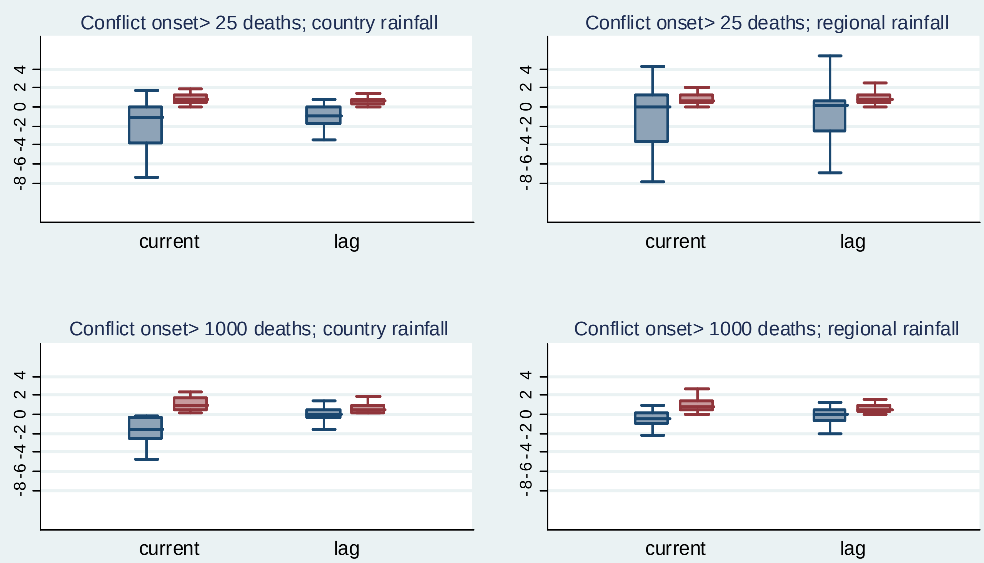
Distribution of coefficients and t-stats of replication of MSS Table 4 Columns 6 and 7



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)

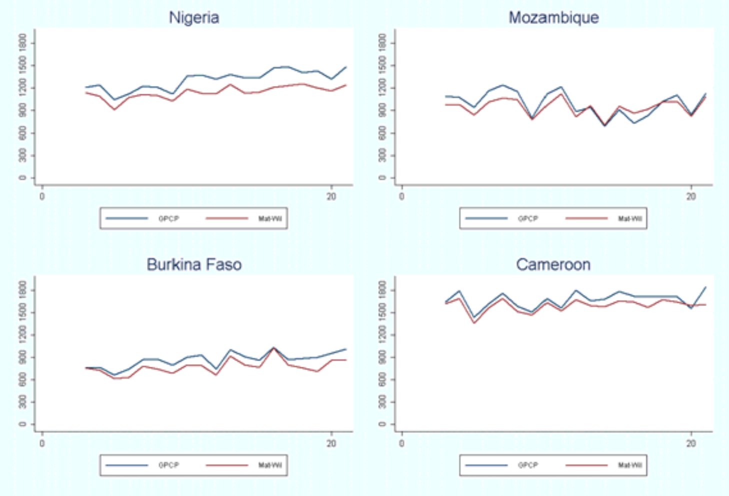


Figure 4b: Rainfall Measures for Low Correlation Countries (.57 to .45)

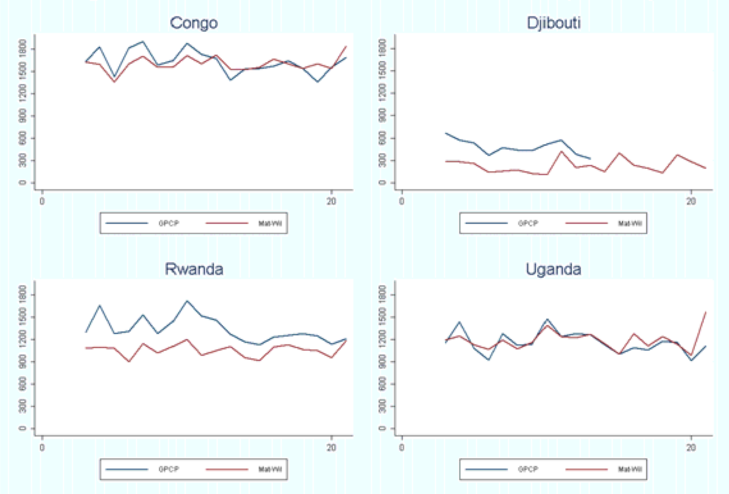


Figure 4c: Rainfall Measures for Low Correlation Countries (.42 to .34)

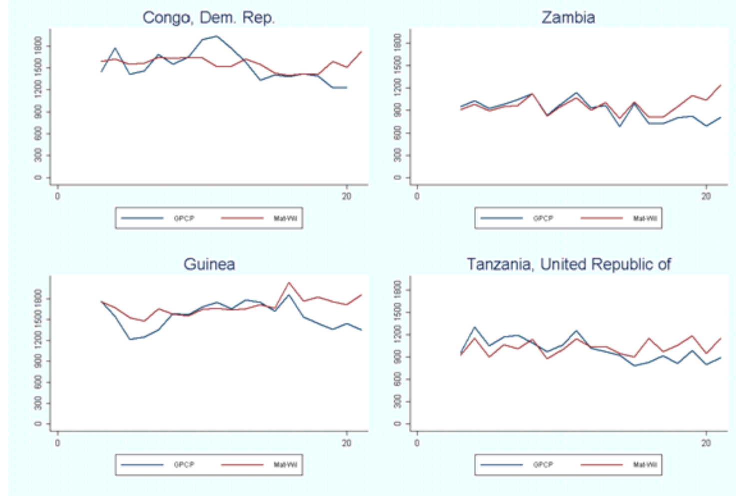
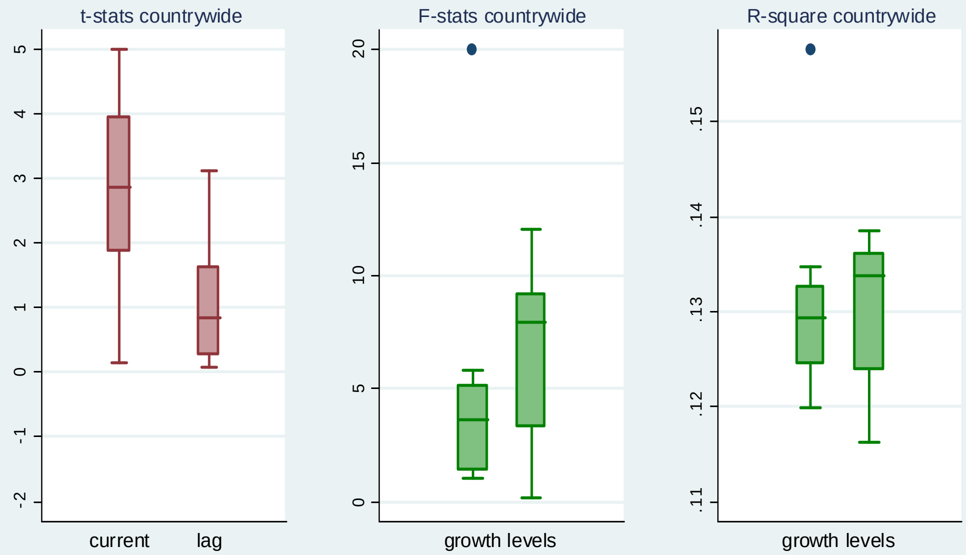


Figure 4d: Rainfall Measures for Low Correlation Countries (.28 to -.13)

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

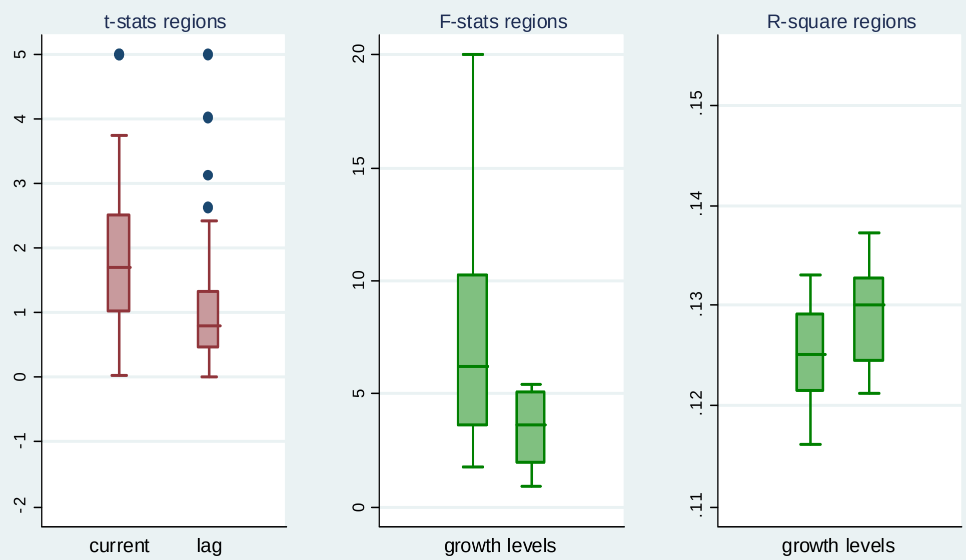
Distribution of t-stats, F-stats and R-squares of replications of MSS Table 2 Column 3



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.

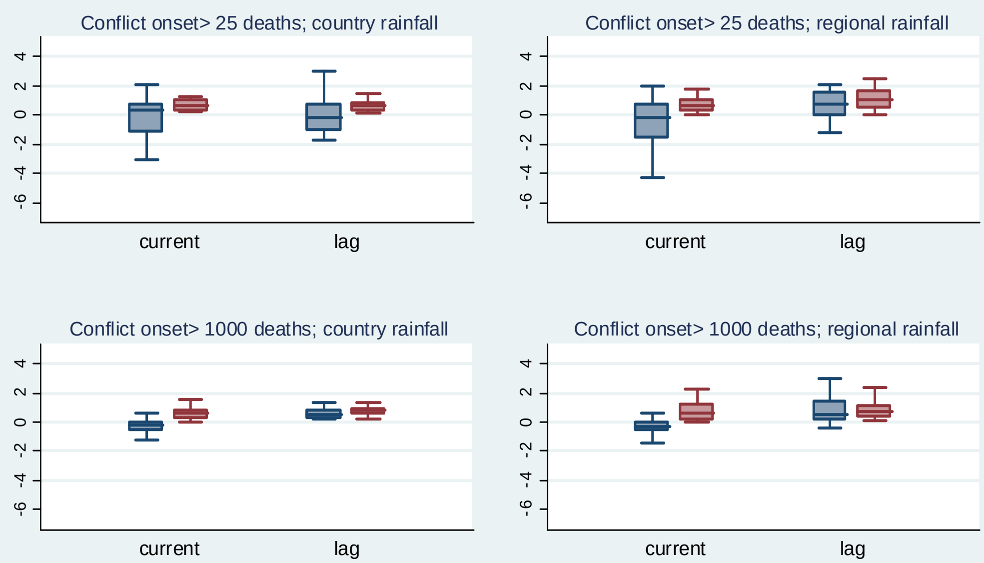
Figure 6: Effects of GDP growth on incidence of civil conflict, 1960-2007

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

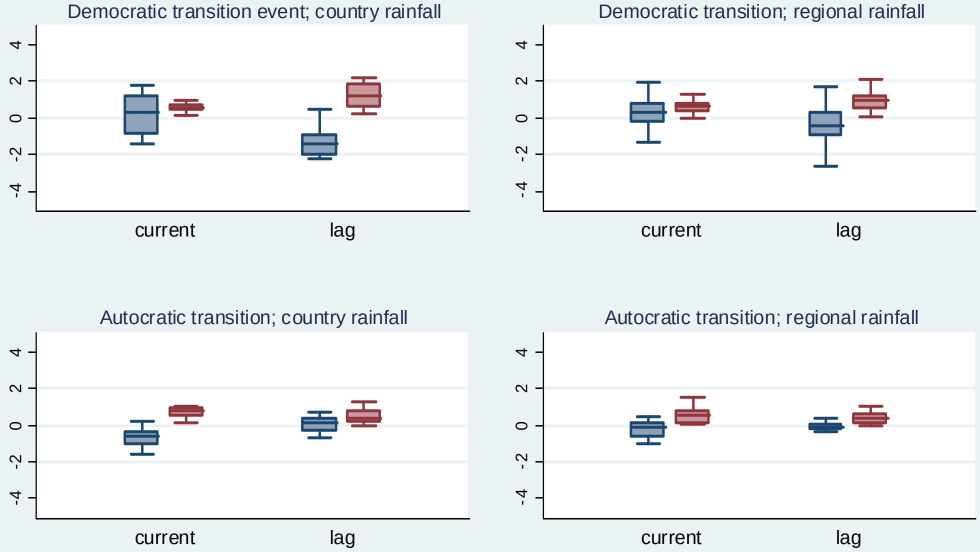
Distribution of coefficients and t-stats, rainfall variables as instruments



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

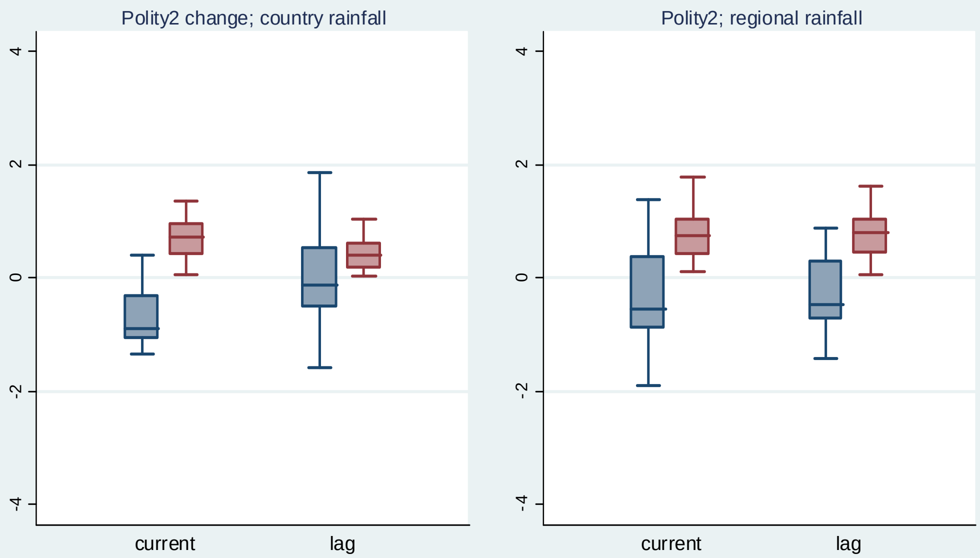
Distribution of coefficients and t-stats of semi-replication of BL Table 4 Column 3 and Table 5 column 3



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

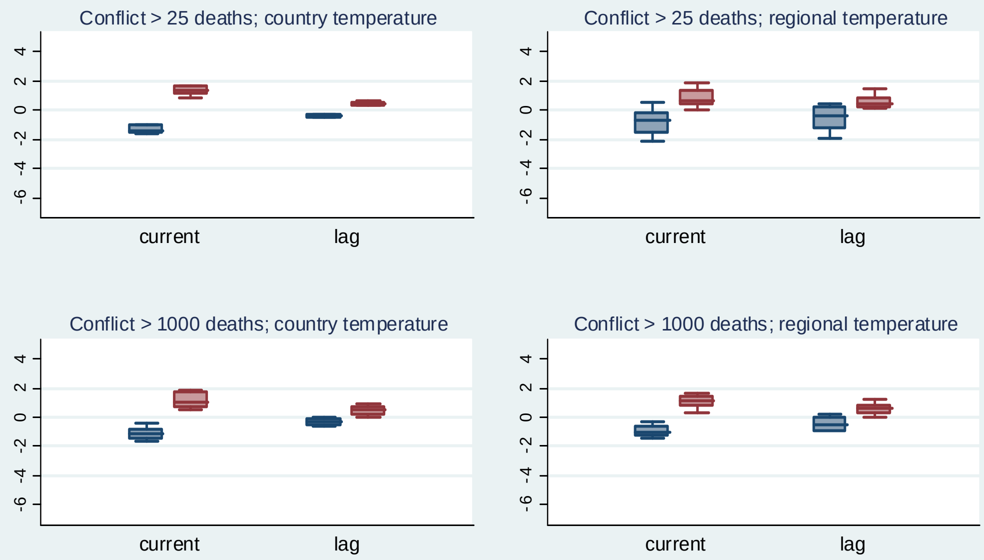
Distribution of coefficients and t-stats of semi-replication of BC Table 5 Column 1



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

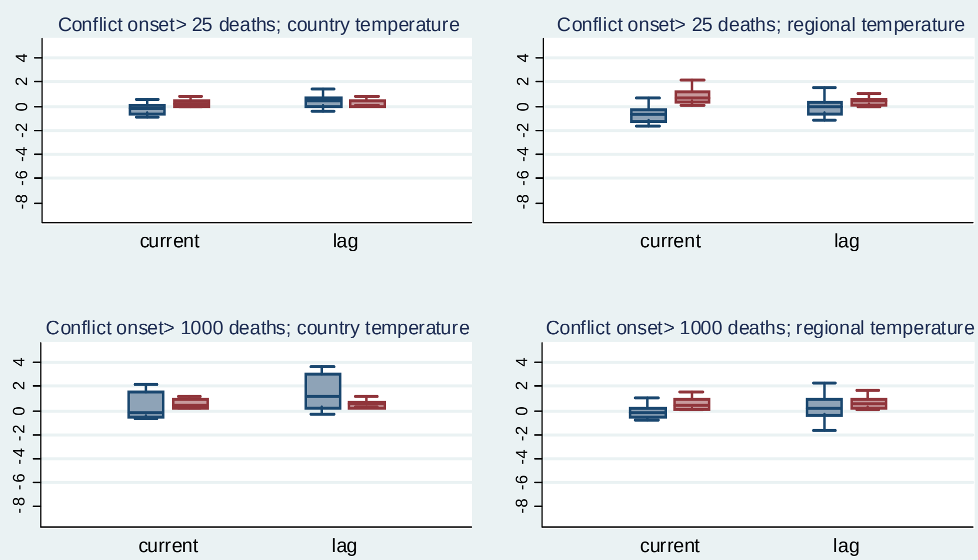
Distribution of coefficients and t-stats



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

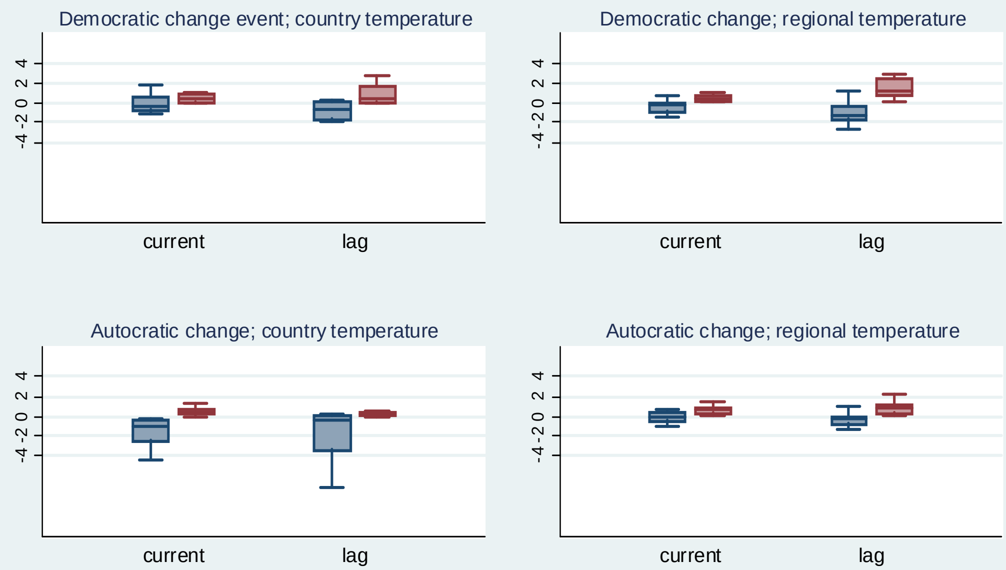
Distribution of coefficients and t-stats, temperature instruments



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

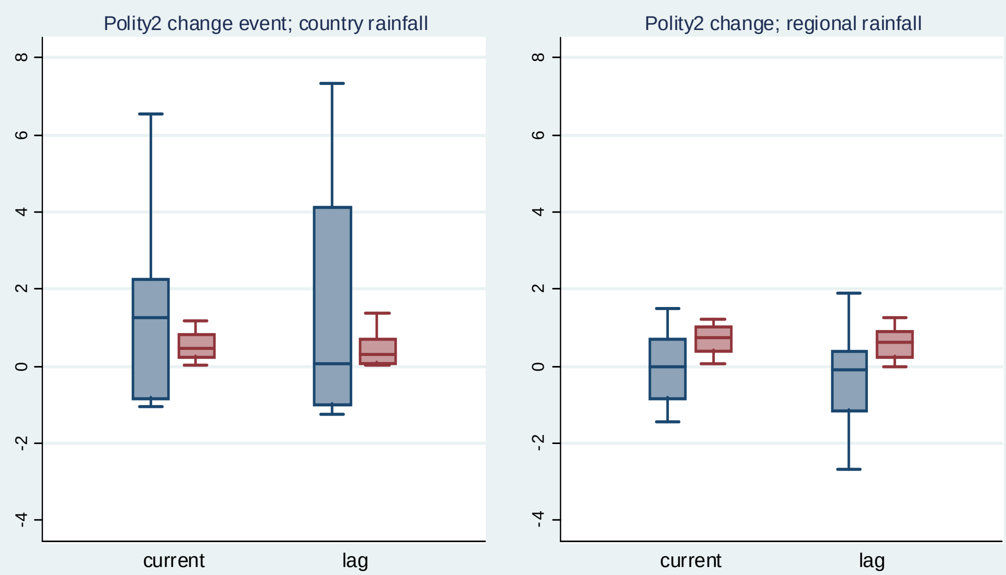
Distribution of coefficients and t-stats of semi-replication of BL Table 4 Column 3 and Table 5 column 3



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

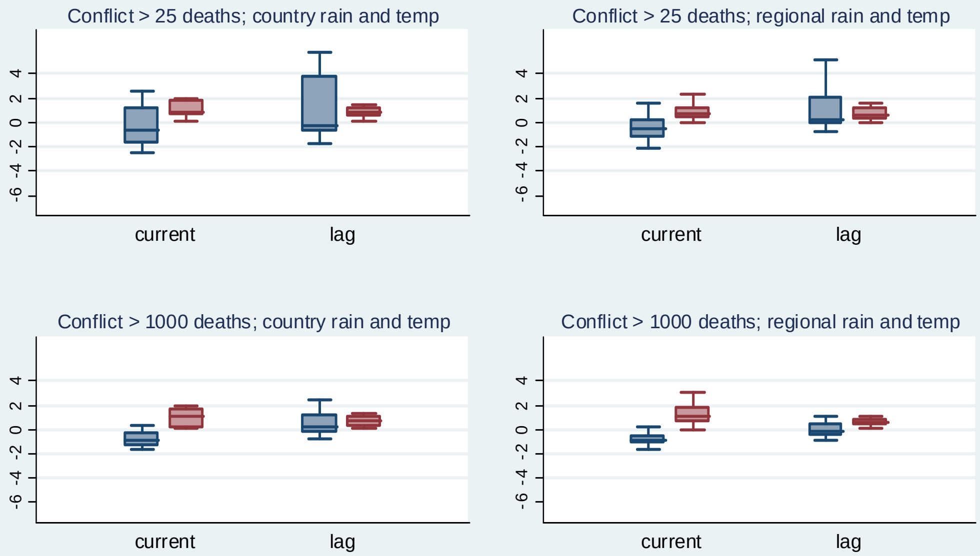
Distribution of coefficients and t-stats of semi-replication of BC Table 5 Column 1



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

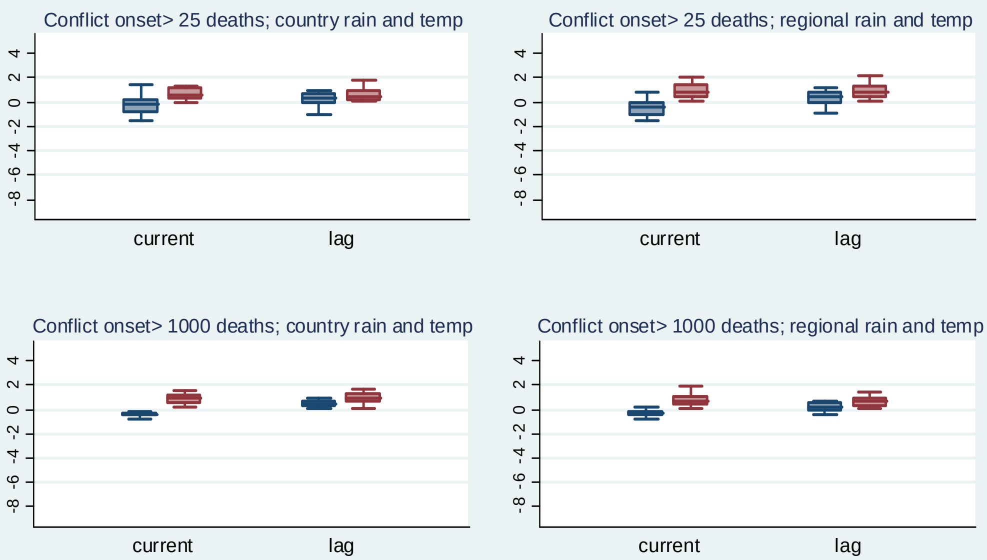
Distribution of coefficients and t-stats, multiple weather inst.



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

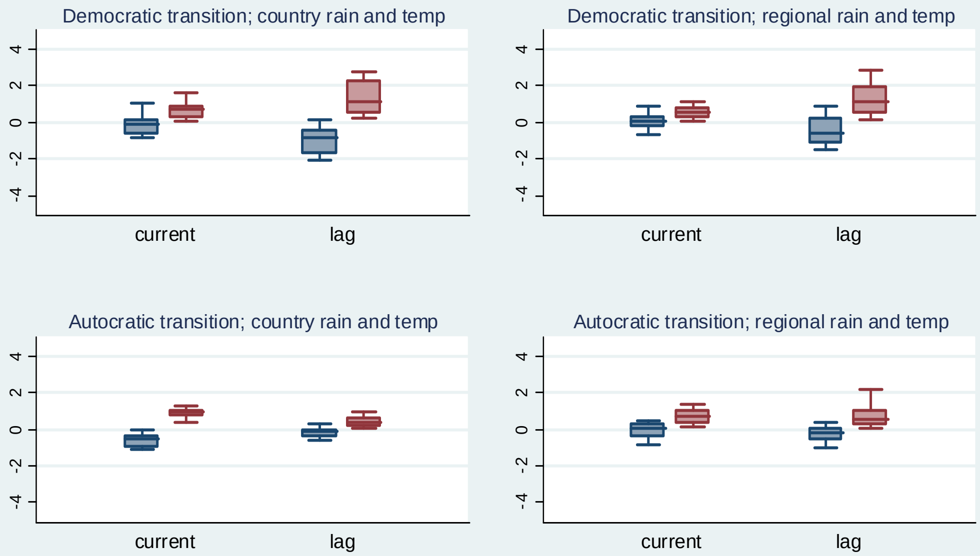
Distribution of coefficients and t-stats, multiple weather inst.



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

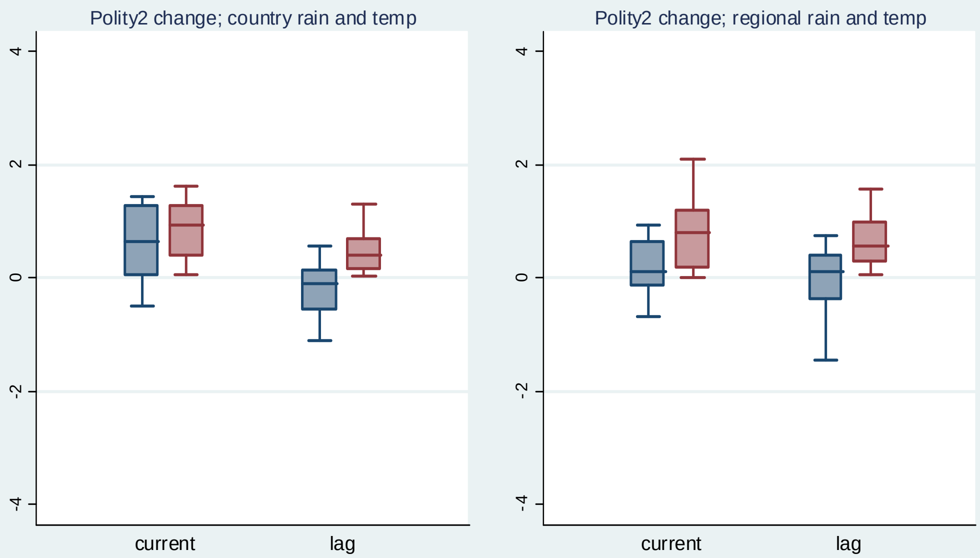
Distribution of coefficients and t-stats of semi-replication of BL Table 4 Column 3 and Table 5 column 3



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

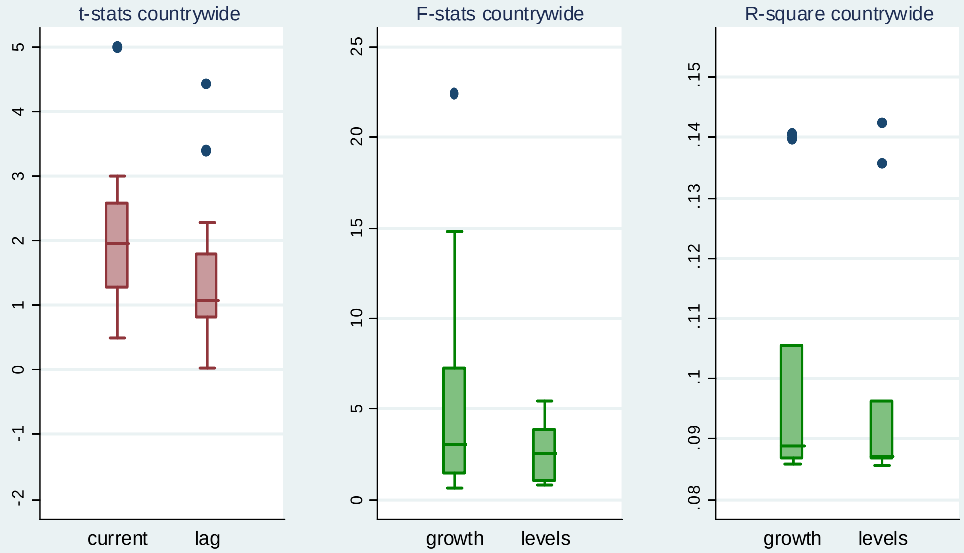
Distribution of coefficients and t-stats of semi-replication of BC Table 5 Column 1



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

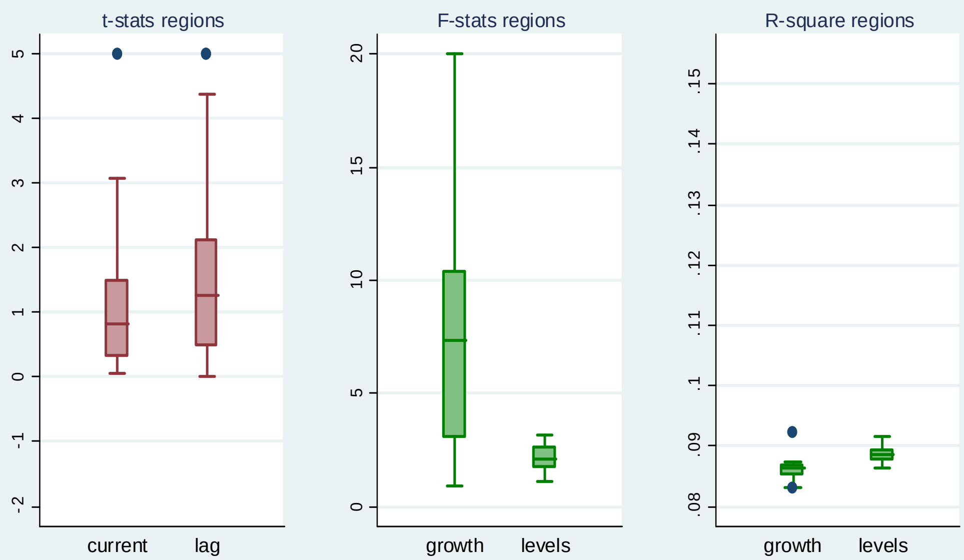
Distribution of t-stats, F-stats and R-squares



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

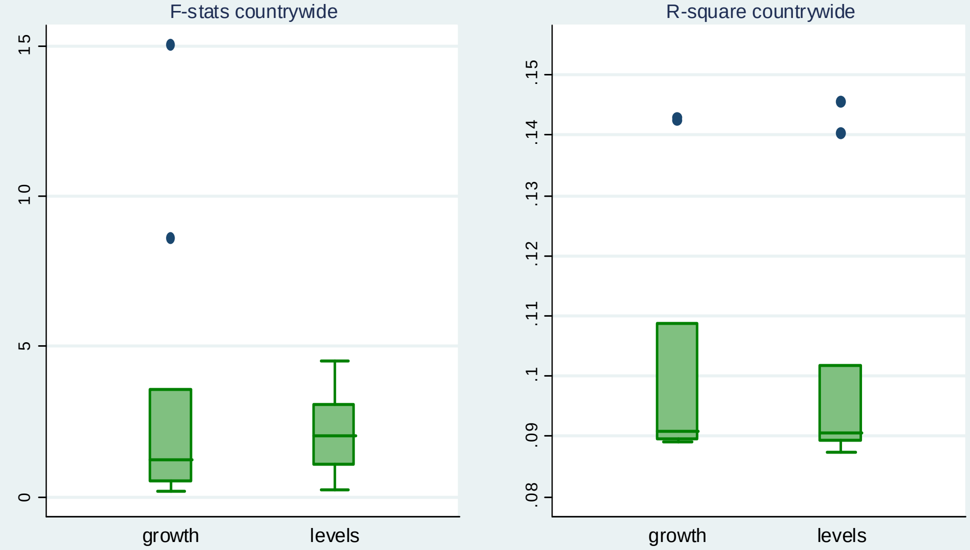
Distribution of t-stats, F-stats and R-squares



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

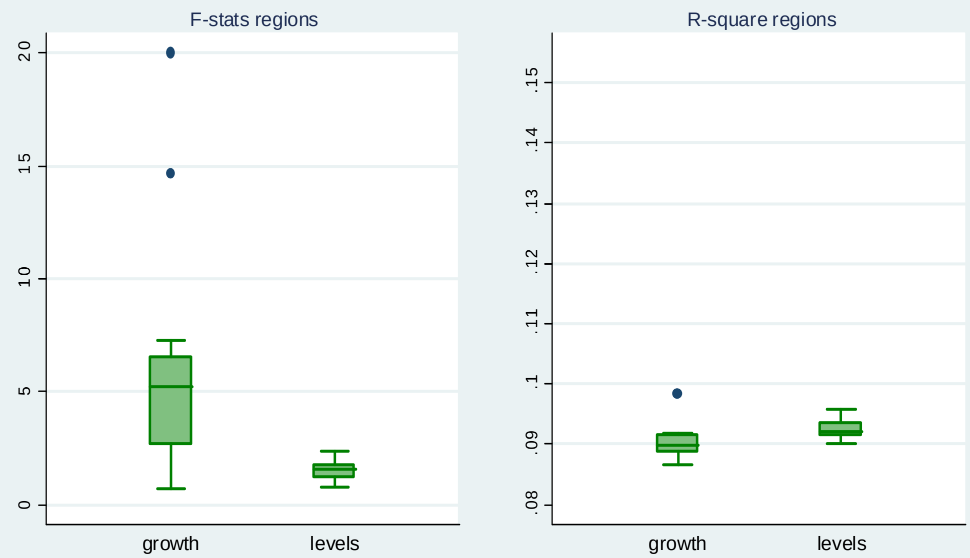
Distribution of t-stats, F-stats and R-squares



Statistics from 18 regressions.

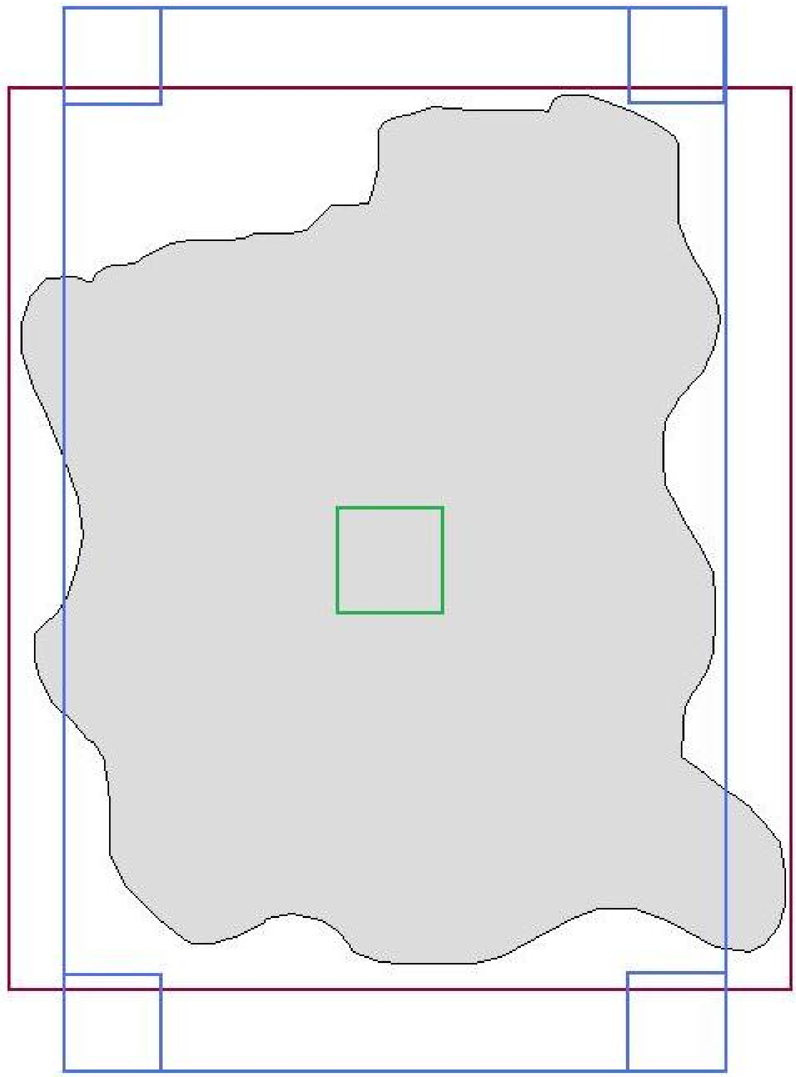
Figure 19b: Regional rain & temp explaining GDP growth, 1960-2007

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

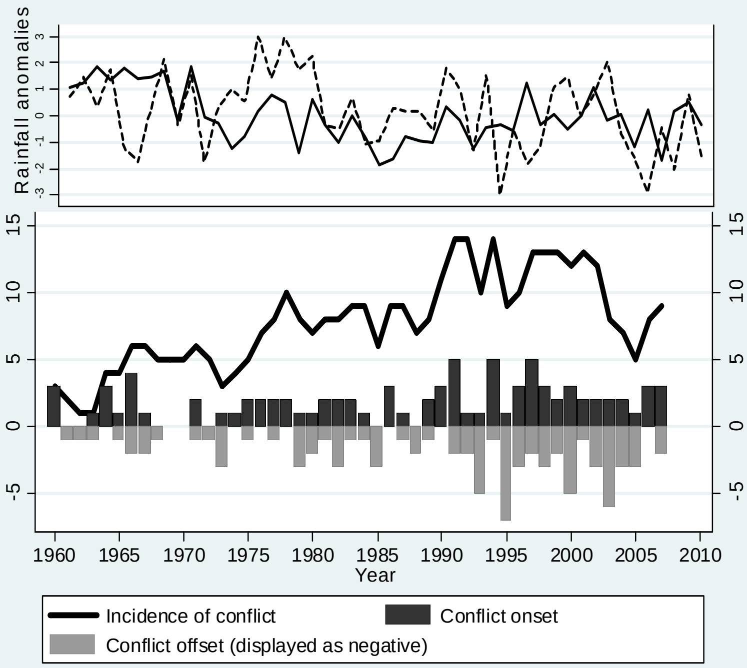
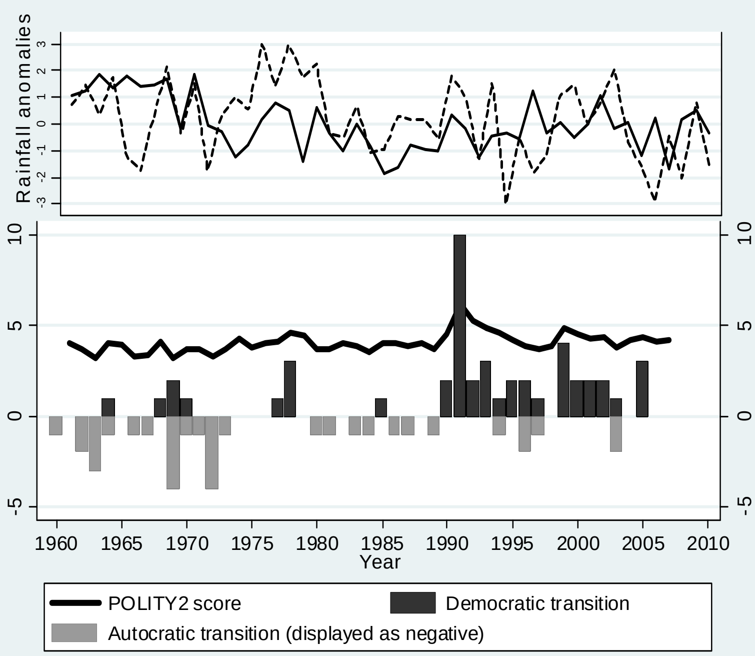


Figure A3: Rainfall anomalies and political change, 1960-2007



Note: POLITY2 scores have been shifted up by 4 units

Table A1: Variables used in first stage regression explaning 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