Transitory Economic Shocks and Civil Conflict

by

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Abstract

I examine whether civil conflict is triggered by transitory negative economic shocks. My approach follows Miguel, Satyanath, and Sergenti (2004) in using rainfall as an exogenous source of economic shocks in Sub-Saharan African countries. The main difference is that my empirical specifications take into account that rainfall shocks are transitory. Failure to do so may lead to the conclusion that civil conflict is more likely to break out following droughts when the opposite is true.

Key words: Transitory shocks, mean reversion, rainfall, conflict

JEL codes: O0, P0, Q0

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1. Introduction

Is civil conflict triggered by transitory economic downturns? Answering this question is complicated by many difficult-to-measure economic, social, political, and institutional factors that may affect both income and the likelihood of civil conflict. In addition, economic downturns may partly be driven by the expectation of future civil conflict. Miguel, Satyanath, and Sergenti (2004) show how both these issues can be addressed. Using a panel-data setup to control for unobservables, they show that civil conflict in Sub-Saharan Africa is more likely to start following years of low rainfall growth and that low rainfall growth is also associated with low income growth. Based on their instrumental-variables estimation results, Miguel, Satyanath, and Sergenti conclude that negative (rainfall-driven) income shocks trigger civil conflict. This is in line with Collier and Hoeffler (1998, 2002, 2004) and Fearon and Laitin (2003), who have argued that economic variables are often more important determinants of civil conflict than political or social grievances.

Estimating the effect of transitory economic shocks on civil conflict involves an interesting issue that has not been analyzed so far. Consider Miguel, Satyanath, and Sergenti's finding that civil conflict is more likely to start in year *t*, the lower rainfall growth between *t*-1 and *t*-2 (reproduced in Table 2, Panel B, column (7)). This result is consistent with conflict outbreak being most likely when a drought year at *t*-1 (a negative rainfall shock) follows an average rainfall year at *t*-2. But the result is also consistent with the view that conflict at *t* is most likely to start when exceptionally good rainfall conditions at *t*-2 (a positive rainfall shock) are followed by an average rainfall year at *t*-

1.[1] The general point is that because rainfall shocks are transitory, low interannual rainfall growth between t and t-1 could be due to a negative rainfall shock at t or due to mean reversion following a positive shock at t-1.[2] The finding that civil conflict is more likely when rainfall growth is negative is therefore consistent with conflict being more or conflict being less likely following droughts.

It is important to understand whether civil conflict starts following positive or negative economic shocks. If civil conflict follows negative transitory shocks, conflict onset may be related to the temporarily low opportunity cost of fighting during transitory economic downturns. This explanation of the effect of income on civil conflict was suggested by Collier and Hoeffler (1998) and is also put forward by Miguel, Satyanath, and Sergenti (for a theory of the link between transitory shocks and civil conflict, see Chassang and Padró i Miquel, 2006 and 2007[3]). But rent-seeking explanations of civil conflicts appear more plausible than opportunity-cost explanations if conflict is more likely following positive economic shocks.

It turns out to be straightforward to analyze whether civil conflict is triggered by negative or by positive (transitory) rainfall shocks. It only requires relating the probability of civil conflict to rainfall levels instead of growth rates. If conflict is triggered by transitory economic downturns, civil conflict onset should be more likely following years of low rainfall. On the other hand, if conflict is most likely when

[1] The empirical evidence indicates that Miguel, Satyanath, and Sergenti's finding appears to be driven by civil conflict onset being more likely following exceptionally good rainfall conditions at t-2 rather than low rainfall at t-1, see Table 1, Panel A, column (7).

[2] If rainfall shocks were permanent (no mean reversion) this ambiguity would disappear.

[3] A key element of their theory is that transitory negative economic shocks lower the (opportunity) costs of fighting relative to the value of assets under dispute.

economies revert to mean rainfall levels after exceptionally good years, civil conflict onset should be more probable following years of high rainfall.

The transitory nature of rainfall shocks implies another disadvantage when analyzing the relationship between civil conflict onset and rainfall using a growth specification. Suppose that using a growth specification we find that the probability of civil conflict onset at *t*, P_t, is related to rainfall growth in log points between *t* and *t*-1 by $P_t = P - 0.1(\log Rain_t - \log Rain_{t-1})$ where *P* is the probability of conflict outbreak when rainfall levels are constant. Now consider the case of a transitory positive shock that raises log rainfall levels σ points above its mean *a* at time *t*. In this case the rainfall sequence becomes $\log Rain_{t-1} = a$, $\log Rain_t = a + \sigma$, $\log Rain_{t+1} = a$, $\log Rain_{t+2} = a$, and so on. What are the consequences of the transitory positive shock for the probability of civil conflict? It turns out to lead to an oscillation that reduces the probability of conflict below *P* on impact but raises it above *P* in the next year. Note that rainfall growth at time *t* is $\log Rain_t - \log Rain_{t-1} = \sigma$ and the probability of conflict is therefore $P_t = P - 0.1\sigma$. But, because the shock is transitory, rainfall growth between *t*+1 and *t* is negative, $\log Rain_{t+1} - \log Rain_t = -\sigma$, and the probability of conflict onset at *t*+1 is above *P*, $P_{t+1} = P + 0.1\sigma$. The growth specification therefore implies that transitory positive (rainfall) shocks reduce the probability of conflict on impact but have an offsetting effect a year later due to mean reversion.[4] A simple way to avoid imposing such offsetting effects is to relate conflict onset to rainfall levels using $P_t = \lambda + \alpha \log Rain_t + \beta \log Rain_{t-1} + u_t$ where *u* is a regression residual. This regression equation contains the growth specification as a special case, but also allows for positive rainfall shocks to reduce the likelihood of civil conflict onset on impact and not increase it in the immediate future ($\alpha < 0$; $\beta = 0$).

[4] If shocks were permanent there would not be an offsetting effect in *t*+1.

In the remainder of the paper, I estimate the effect of rainfall levels on civil conflict in Sub-Saharan Africa and contrast these results with the effect of rainfall growth. My main results control for unobservable time-varying factors affecting the likelihood of civil conflict throughout Sub-Saharan Africa (e.g. effects of the end of the Cold War, see Fearon and Laitin, 2003) by including common time effects in the regression analysis. For comparison with Miguel, Satyanath, and Sergenti, I also present results that do not account for common time effects however. My empirical analysis yields robust evidence that civil conflict is more likely to start following years with low rainfall levels. Negative rainfall shocks raise the likelihood of civil conflict onset in the following year and do not have a subsequent offsetting effect. The same relationship holds between civil conflict onset and (rainfall-driven) income shocks but only when shocks affecting civil conflict throughout Sub-Saharan Africa are accounted for. Results for civil conflict incidence are similar. On the other hand, there is no robust evidence of a negative effect of rainfall growth on the onset or incidence of civil conflict.

2. Estimation Framework and Data

My main estimating equation relates civil conflict to rainfall levels, country-specific time-invariant unobservable risk factors (α_c), country-specific time trends ($\beta_c Year_t$), and common time-varying unobservable risk factors (δ_t),

$$(1)\ conflict_{c,t} = \alpha_c + \beta_c Year_t + \delta_t + \gamma_1 \log Rain_{c,t} + \gamma_2 \log Rain_{c,t-1} + \gamma_3 \log Rain_{c,t-2} + \varepsilon_{c,t}$$

where $\alpha, \beta, \delta, \gamma$ denote parameters to be estimated and ε a disturbance term. The *conflict* variable is either conflict onset or conflict incidence. Conflict incidence is captured by an indicator variable that takes the value of 1 in a country-year with civil conflict and 0 otherwise. Conflict onset is an indicator variable that is 1 in a country-year with civil conflict if there was no conflict in the previous year; the onset indicator is 0 if there is no conflict in a country-year and there was no conflict in the previous year. Conflict onset is the appropriate variable to examine whether rainfall shocks contribute to the outbreak of civil conflict. I also estimate (1) with income per capita levels on the right hand side and rain levels as instruments.[5]

The specification to estimate the effect of rainfall growth on conflict follows Miguel, Satyanath, and Sergenti (2004),

$$(2) \qquad conflict_{c,t} = \alpha_c + \beta_c Year_t + \delta_t + \gamma_1 RainGrowth_{c,t} + \gamma_2 RainGrowth_{c,t-1} + \varepsilon_{c,t}$$

where $RainGrowth_{c,t}$ ($RainGrowth_{c,t-1}$) is the growth rate of rainfall levels between *t* and *t*-1 (*t*-1 and *t*-2). The main difference with Miguel, Satyanath, and Sergenti is that I add controls for common time-varying risk factors (δ_t) in some specifications. I estimate (1) and (2) for two time periods, 1981-2006, and also the period of estimation of Miguel, Satyanath, and Sergenti, which is 1981-1999. For the 1981-1999 period, I provide results with the conflict data employed by Miguel, Satyanath, and Sergenti and with the latest version of the same conflict dataset.

The data on civil conflict comes from the UCDP/PRIO Armed Conflicts 2007 Dataset of the International Peace Research Institute's (PRIO) Centre for the Study of Civil War and the Uppsala Conflict Data Program.[6] This is the latest version of the conflict data used by Miguel, Satyanath, and Sergenti. Rainfall data for the period 1981-2001 come from Miguel, Satyanath, and Sergenti and their data website; the original data source is

[5] The main estimation method is IV-2SLS, which is usually preferred in case with a dichotomous explanatory variable as alternative estimation approaches require strong specification assumptions (Angrist and Krueger, 2001; Wooldridge, 2002).
[6] The dataset is available at http://new.prio.no/CSCW-Datasets/Data-on-Armed-Conflict.

the NASA GPCP (NASA Global Precipitation Climatology Project).[7] I extend the GPCP rainfall database to 2006 using the same methodology and data source (NASA Global Precipitation Climatology Project, Version 2).[8] The income per capita data are taken from the Penn World Tables 6.2 and are available until 2003.[9]

3. Transitory Shocks, Rainfall Growth, and Civil Conflict: A Monte Carlo Analysis

Before turning to the regression analysis, it is interesting to explore in more detail what to expect from the rainfall growth regression in (2) if civil conflict is more likely following years with low rainfall levels. Given the transitory nature of rainfall shocks, one would think that the most likely outcome is a negative effect of $RainGrowth_{t-1}$ on civil conflict at t and a positive effect of $RainGrowth_t$. The following Monte Carlo exercise is useful for examining this intuition. The setup is the following.

1) I generate $\log Rain_t$ for t = 1,…,5000 by taking 5000 independent draws from a uniform distribution on the interval [0,20/3].
2) For each of the 5000 draws, I generate a dummy variable $conflict_t$ that is equal to 1 (civil conflict) with probability $1-(3/20)\log Rain_{t-1} \in [0,1]$ and equal to 0 (no civil conflict) with probability $(3/20)\log Rain_{t-1}$. This formulation implies that less rainfall at t-1 translates into a greater probability of civil conflict at t. The coefficient (3/20=0.15) is based on empirical result I obtain for civil conflict onset (see Table 1, Panel A, column (3)).
3) I then use the generated data to estimate the least-squares regressions in (1) and (2) without country and time effects. This yields point estimates and standard errors for the coefficients on: (i) $\log Rain_t$, $\log Rain_{t-1}$, $\log Rain_{t-2}$ for the rainfall level regression in (1); (ii) $RainGrowth_t$ and $RainGrowth_{t-1}$ for the rainfall growth regression in (2) ($RainGrowth_t$ is calculated as $(Rain_t - Rain_{t-1})/Rain_{t-1}$).

[7] The data are available at http://elsa.berkeley.edu/~emiguel/data.shtml.
[8] See Adler et al. (2003). The data are available at http://precip.gsfc.nasa.gov.
[9] The dataset is available at http://pwt.econ.upenn.edu.

4) Repeat the steps above 5000 times.

The results for the rainfall level regression in (1) are quickly summarized. Of the 5000 coefficients (corresponding to 5000 regressions) on $\log Rain_t$ and $\log Rain_{t-2}$, 95.2% and 95.4% respectively have an absolute *t*-statistic smaller than 2 (i.e. are statistically insignificant at the 96% confidence level). Of the 5000 coefficients on $\log Rain_{t-1}$, 97% are negative with an absolute *t*-statistic above 2; the average coefficient is -0.15. Hence, unsurprisingly, the rainfall level regression reflects the true model.

The results for the rainfall growth regression in (2) are in line with expectations given the transitory nature of shocks. 97% of the 5000 coefficients on $RainGrowth_t$ are positive (the average is equal to 0.05) and 41% have *t*-statistics larger than 2 (the remaining 59% are statistically insignificant at the 96% confidence level). 95% of the 5000 coefficients on $RainGrowth_{t-1}$ are negative (the average equals -0.05) and 40% have *t*-statistics smaller than -2 (now 60% of the estimates are statistically insignificant at the 96% confidence level). A further interesting finding is that in 93% of the regressions, the coefficient on $RainGrowth_t$ is positive and the coefficient on $RainGrowth_{t-1}$ negative. The case of a significantly positive effect of $RainGrowth_t$ (*t*-statistic larger than 2) and insignificant effect of $RainGrowth_{t-1}$ is about as frequent as the case of a significantly negative effect of $RainGrowth_{t-1}$ (*t*-statistic smaller than -2) and insignificant effect of $RainGrowth_t$ (there is a statistically positive effect of $RainGrowth_t$ and a statistically negative effect of $RainGrowth_{t-1}$ in 8% of the cases).[10]

[10] These findings are illustrated in supplementary figures available at www.antoniociccone.eu.

Hence, the Monte Carlo analysis indicates that, if civil conflict is more likely following years with low rainfall levels, the most likely outcome of the rainfall growth regression is a positive coefficient on $RainGrowth_t$ and a negative coefficient on $RainGrowth_{t-1}$. It also suggests that a statistically significant positive effect of contemporaneous rainfall growth and negative but insignificant effect of lagged rainfall growth is about as likely as a statistically significant negative effect of lagged rainfall growth and positive but insignificant effect of contemporaneous rainfall growth. This turns out to be in line with the results of the regression analysis.

4. Empirical Results

I start by estimating the effect of rainfall on civil conflict onset and then turn to civil conflict incidence. The main result is that there is a robust negative and statistically significant effect of *t*-1 rainfall levels on the probability of civil conflict onset and incidence at *t* according to the latest PRIO conflict data. The rainfall growth specifications on the other hand do not yield robust results. Another interesting result concerns Miguel, Satyanath, and Sergenti's finding of a negative effect of rainfall growth between *t*-1 and *t*-2 on conflict onset and incidence at *t* using an earlier PRIO conflict dataset. The rainfall level specification with the same data yields that this effect is driven by positive shocks at *t*-2 (exceptionally high rainfall levels) rather than negative rainfall shocks at *t*-1.

Rainfall and conflict onset Table 1, Panel A shows the effect of rainfall levels on the probability of civil conflict onset for three different samples. The results for the longest possible sample are in columns (1)-(3). Column (1) includes country fixed effects and country-specific time trends but not common time effects. The log rainfall level at *t*-1 enters negatively and significantly at the 97% confidence level. According to the point estimate, each 10% drop in rainfall levels raises the probability of civil conflict by 1.1 percentage points. Column (2) includes a dummy variable for the period after 1990 to capture effects due to the end of the Cold War (e.g. Fearon and Laitin, 2003). The estimate indicates that after the end of the Cold War, civil conflict outbreak was 11 percentage points more likely than before. Allowing for a different probability of civil conflict onset after the end of the Cold War does not change the effect of rainfall levels. Column (3) includes common time effects to capture time-varying factors that affect civil conflict outbreak in all Sub-Saharan African countries. The common time effects are jointly significant at the 99.99% confidence value (p-values are reported in the time effects row). Controlling for common time effects increases the effect of rainfall on civil conflict outbreak. Now a 10% drop in the rainfall level at *t*-1 raises the probability of civil conflict onset at *t* by 1.4 percentage points and the effect is statistically significant at the 98% confidence level.

Columns (4)-(6) contain the empirical results using the 2007 PRIO data but only until 1999. The time period and sample correspond to that of Miguel, Satyanath, and Sergenti but I am using the 2007 version of their conflict dataset. The results are in line with those for the longest possible period in the previous columns.

Results are quite different when using the PRIO conflict data employed by Miguel, Satyanath, and Sergenti in columns (7)-(9). In the specification without common time effects in column (7), civil conflict outbreak at *t* is more likely following high rainfall a *t*-2, and the effect is statistically significant at the 96% confidence level. This will play an important role when interpreting the results of the rainfall growth specifications of Miguel, Satyanath, and Sergenti. In the specification with common time effects in column (9), there is no statistically significant effect of rainfall levels on civil conflict onset (the common time effects are highly statistically significant, see the p-value in the table).

Table 1, Panel B, estimates the effect of rainfall growth on the probability of civil conflict onset. The rainfall growth results for the longest possible sample are in columns (1)-(3). Column (1) shows a statistically significant, negative effect of lagged rainfall growth on civil conflict onset, but the effect becomes insignificant in column (2) where I allow for a different probability of civil conflict after the end of the Cold War. The post Cold War dummy is statistically significant and shows a 11 percentage points increase in the probability of civil conflict onset after 1990. Accounting for common time effects in column (3) actually yields a positive effect of rainfall growth on civil conflict (the common time effects are highly statistically significant, see the p-value in the table). Now civil conflict onset at *t* is more likely the higher rainfall growth between *t* and *t*-1. This result can be reconciled with the key finding of the corresponding rainfall level specification in column (3) of Panel A (where I found that civil conflict is more likely to start following low-rainfall years) as the transitory nature of rainfall shocks implies that high rainfall growth between *t* and *t*-1 is most likely following low rainfall at *t*-1. In any case, the results in columns (1)-(3) indicate that the effect of rainfall growth on civil conflict onset depends on whether and how shocks affecting civil conflict outbreak throughout Sub-Saharan Africa are accounted for.

For the 1981-1999 period of Miguel, Satyanath, and Sergenti, there is no statistically significant effect of rainfall growth on civil conflict onset with the PRIO 2007 data, see column (4). This continues to be the case when I allow for a change in the probability of civil conflict after the end of the Cold War in column (5). In column (6), which includes common time effects in the estimating equation, civil conflict at *t* is again more likely to break out following high rainfall growth between *t* and *t*-1.

The 1981-1999 results with the PRIO conflict data of Miguel, Satyanath, and Sergenti in columns (7)-(9) are somewhat different. In the baseline in column (7), higher rainfall growth between *t*-1 and *t*-2 reduces the probability of civil conflict onset. But the interpretation of this finding is not as straightforward as it may seem at first. The corresponding rainfall level specification in column (7) of Panel A shows that it is high rainfall at *t*-2 that makes conflict more likely at *t* in the data of Miguel, Satyanath, and Sergenti (rainfall levels at *t* and *t*-1 are insignificant statistically). Hence, conflict follows low rainfall growth because high rainfall at *t*-2 tends to be followed by more conflict at *t* and, due to mean reversion, by low rainfall growth between *t*-1 and *t*-2. In any case, the effect of rainfall growth in column (7) becomes statistically insignificant in column (8) where I allow for a different likelihood of civil conflict outbreak after the end of the Cold War. The post Cold War dummy is statistically significant and shows a 12 percentage points increase in the probability of civil conflict onset after 1990. Finally, column (9) shows no statistically significant link between rainfall growth and civil conflict onset once common time effects are included (the common time effects are highly statistically significant).[11]

When interpreting the results in Table 1, it should be kept in mind that the rainfall growth specifications have quite different implications for the response of conflict onset to rainfall shocks than the level specifications. Consider for example the results for the

[11] Miguel, Satyanath, and Sergenti (2004) also analyze the effect of rainfall on civil conflicts with more than 1000 annual battle deaths. According to the 2007 PRIO conflict data, there is no statistically significant link between the outbreak of such civil conflicts and rainfall levels whether I include time effects in the empirical analysis or not.

longest possible sample in Panel B, column (1). The statistically significant point estimate on *t*-1 rainfall growth implies that a positive (transitory) rainfall shock will lower the probability of conflict onset compared to scenario without shocks after one year, but will raise it significantly above the no-shocks scenario after two years. This is because a positive shock implies that rainfall growth is positive in the first year, but negative in the second year when rainfall levels revert to the mean. Hence, rainfall shocks give rise to an oscillation of the conflict onset probability relative to the scenario without shocks (it would be an oversimplification to say that rainfall shocks reduce or increase the likelihood of conflict outbreak). The rainfall level specification in Panel A, column (1), on the other hand, implies that the probability of conflict outbreak is below the scenario without shocks in the year following a positive rainfall shock and equal to the no-shocks scenario thereafter.

Civil conflict incidence Although the factors determining the outbreak of civil conflict are best examined using the civil conflict onset variable, it is interesting to consider results using civil conflict incidence as the variable to be explained. In Table 2, Panel A, I find that the empirical results for civil conflict incidence tend to mirror those for onset when using the rainfall level specification. The results with the 2007 PRIO data in columns (1)-(6) all yield that civil conflict is more likely following years of low rainfall. This also holds with the PRIO dataset used by Miguel, Satyanath, and Sergenti once common time effects are included in the specification. The rainfall level specification without common time effects using Miguel, Satyanath, and Sergenti's data in column (7) yields statistically insignificant effects of rainfall shocks on civil conflict incidence.

Table 2, Panel B, shows the civil conflict incidence results for the rainfall growth specifications. For the longest possible sample in column (1) there is a negative effect of rainfall growth between *t*-1 and *t*-2 on civil conflict incidence at *t*. But this effect becomes statistically insignificant in column (2) where I allow for a different likelihood of civil conflict after 1990 (civil conflict is significantly more likely after the end of the Cold War). Accounting for common time effects in column (3) yields that civil conflict at *t* is more likely following high rainfall growth between *t* and *t*-1 (the common time effects are highly statistically significant). These results indicate that, just as in the case of civil conflict onset, the link between rainfall growth and conflict incidence depends on whether and how shocks affecting civil conflict throughout Sub-Saharan Africa are accounted for.

The 1981-1999 results with the PRIO conflict data of Miguel, Satyanath, and Sergenti are in columns (7)-(9). Note that *t*-1 rainfall growth enters negatively in column (7) although there is no statistically significant effect of *t*-1 rainfall in Panel A, column (7). Accounting for common shocks to conflict incidence throughout Sub-Saharan Africa yields the opposite pattern of results. The rainfall growth variables enter statistically insignificantly in Panel B, column (9). But the level specification in Panel A, column (9) indicates that negative rainfall shocks at *t*-1 are associated with a statistically significant increase in conflict incidence.

Income shocks and civil conflict Table 3 contains the results for the effect of income per capita on civil conflict onset and incidence. The estimation method is IV-2SLS with (log) rainfall at *t* and *t*-1 as instruments for (log) income per capita at *t* and *t*-1. The sample period is 1981-2003 as there is no PWT income data after 2003. The table also contains results of first-stage regressions of log income per capita on log rainfall levels.

The first-stage regression of log income per capita at *t* on country fixed effects, country-specific time trends, and log rainfall levels at *t* and *t*-1 in column (1) yields a highly significant positive effect of rain at *t* (t-statistic=2.79). This effect becomes stronger (t-statistic=2.93) in column (2) where I include common time effects to account for shocks affecting the incomes of all Sub-Saharan African countries (the common time effects are significant at the 99.99% confidence level).

The second-stage results for civil conflict onset are in columns (3)-(4) and for civil conflict incidence in column (5)-(6). In the onset specification without common time effects in column (3), *t*-1 income enters negatively but is statistically insignificant. The effect becomes significant at the 94% confidence level once common time effects are included in the specification. Hence, negative income shocks lead to a statistically significant increase in the likelihood of civil conflict onset when shocks affecting civil conflict throughout Sub-Saharan Africa are accounted for. The effect of income shocks on civil conflict onset is quite large. According to the significant point estimate (-3.008), a 1% drop in income raises the probability of civil conflict onset by 3 percentage points. The civil conflict incidence results in columns (5)-(6) are in line with the findings for onset. The effect of *t*-1 income on conflict incidence is negative but statistically insignificant when common time effects are not accounted for. But once I control for common time effects, the effect of *t*-1 income shocks becomes statistically significant at the 96% confidence level. Hence, to reveal the link between income shocks and civil conflict, it continues to be critical to control for common shocks affecting civil conflict in Sub-Saharan Africa. The magnitude of the effect is somewhat smaller than for onset. Now a 1% drop in income is estimated to increase the probability of civil conflict by 2.5 percentage points.

For comparison, the Appendix Table, Panel A presents second-stage regression results on the link between income shocks and civil conflict incidence using the Miguel, Satyanath, and Sergenti data. In column (1) it can be seen that civil conflict incidence is more likely following positive income shocks at *t*-2, and that this effect is statistically significant at the 95% confidence level. The main result of Miguel, Satyanath, and Sergenti, reproduced in Panel B, column (1), is a negative and statistically significant link between civil conflict incidence and rainfall-driven income growth between *t*-1 and *t*-2. The results in Panel A indicate that their finding is driven by positive income shocks at *t*-2, not by negative shocks at *t*-1;[12] see also the results in Panel A, columns (2)-(4), which again fail to produce a statistically significant, negative effect of *t*-1 income. Hence, Miguel, Satyanath, and Sergenti's data does not yield support for the view that civil conflict incidence is significantly more likely after a short-term drop in the opportunity cost of fighting when common shocks to conflict in Sub-Saharan Africa are unaccounted for. Note however that the second-stage results in the Appendix, Panel A are more in line with this interpretation once common shocks to civil conflict in Sub-Saharan Africa are accounted for, see columns (5)-(8). [13] Hence, Miguel, Satyanath, and Sergenti's data are suggestive of negative economic shocks raising the likelihood of conflict incidence when rainfall-driven income shocks are treated as transitory and shocks affecting conflict

[12] Put differently, conflict incidence is increasing in income at *t*-2 rather than decreasing in income at *t*-1. These results must be treated cautiously however as rainfall is statistically insignificant in the corresponding reduced-form regressions (see Table 2, Panel A, column (7)).

[13] The income growth specifications with common shocks to conflict incidence yield either insignificant effects or a significant, positive effect of income growth on conflict incidence, see the Appendix, Panel B, columns (4)-(6).

throughout Sub-Saharan Africa are accounted for (see also Table 2, Panel A, column (9)).[14]

5. Conclusion

If civil conflict onset is partly driven by the opportunity cost of revolt, conflict outbreak in Sub-Saharan Africa should be more likely following droughts. I find this to be the case. My estimates indicate that a 50% drop in rainfall levels raises the probability of civil conflict onset in the following year by 7 percentage points. On the other hand, there is little evidence of a robust negative effect of rainfall growth on the onset of civil conflict. This is not that surprising. The transitory nature of rainfall shocks implies that if conflict is more likely to break out following years of low rainfall, the effect of rainfall growth on conflict onset can be absent, significantly positive, or significantly negative.

[14] I do not find statistically significant effects of income shocks on conflict onset with Miguel, Satyanath, and Sergenti's data when common time effects are not accounted for. With common time effects, there is some evidence of conflict onset being more likely following negative t-1 income shocks, but second-stage results must be treated cautiously in this case as rainfall is statistically insignificant in the corresponding reduced-form regressions.

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Table 1: Rainfall and Civil Conflict Onset

Panel A: Rainfall Level

	PRIO 2007 (1981-2006)			PRIO 2007 (1981-1999)			Miguel et al. (1981-1999)		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Log Rainfall, t	0.025 (0.46)	0.055 (1.00)	0.072 (1.21)	-0.010 (-0.14)	0.036 (0.49)	0.066 (0.85)	-0.073 (-0.92)	-0.022 (-0.27)	0.015 (0.18)
Log Rainfall, t-1	-0.108** (-2.22)	-0.109** (-2.16)	-0.142** (-2.57)	-0.088* (-1.75)	-0.082 (-1.56)	-0.114** (-1.99)	-0.026 (-0.34)	-0.020 (-0.26)	-0.112 (-1.23)
Log Rainfall, t-2	0.064 (1.61)	0.041 (1.15)	0.033 (0.86)	0.070 (1.25)	0.041 (0.81)	0.051 (0.72)	0.156** (2.11)	0.123* (1.83)	0.082 (0.92)
Post Cold War Dummy		0.109** (2.05)			0.108** (2.09)			0.121** (1.97)	
Country FE+ Trend	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time Effects, p-value	No	No	0.0000	No	No	0.0000	No	No	0.0000
No Observations	802	802	802	576	576	576	555	555	555

Panel B: Rainfall Growth

	PRIO 2007 (1981-2006)			PRIO 2007 (1981-1999)			Miguel et al. (1981-1999)		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Rainfall Growth, t	0.030 (0.67)	0.053 (1.19)	0.077* (1.69)	0.011 (0.30)	0.041 (1.04)	0.069* (1.72)	-0.063 (-1.31)	-0.028 (-0.56)	0.043 (0.86)
Rainfall Growth, t-1	-0.070* (-1.77)	-0.048 (-1.30)	-0.049 (-1.44)	-0.067 (-1.31)	-0.037 (-0.78)	-0.42 (-0.86)	-0.120* (-1.76)	-0.085 (-1.39)	-0.071 (-1.01)
Post Cold War Dummy		0.108** (2.04)			0.109** (2.13)			0.123** (2.02)	
Country FE+ Trend	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time Effects, p-value	No	No	0.0000	No	No	0.0000	No	No	0.0000
No Observations	802	802	802	576	576	576	555	555	555

Note: Method of estimation is least squares with Huber robust standard errors clustered at the country level; t-values in brackets. Columns (1)-(3) use the PRIO 2007 civil conflict data for the period 1981-2006; columns (4)-(6) use the PRIO 2007 civil conflict data for the period of the Miguel, Satyanath, and Sergenti (2004) sample; columns (7)-(9) use the Miguel, Satyanath, and Sergenti (2004) data on civil conflict, which is based on an earlier version of the PRIO civil conflict database. All regressions include country fixed effects and country specific time trends. The regressions of columns (3), (6), and (9) include also common time effects. The dependent variable is civil conflict onset. *Significantly different from zero at 90 percent confidence, ** 95 percent confidence, *** 99 percent confidence.

Table 2: Rainfall and Civil Conflict Incidence

Panel A: Rainfall Level

	PRIO 2007 (1981-2006)			PRIO 2007 (1981-1999)			Miguel et al. (1981-1999)		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Log Rainfall, t	-0.025 (-0.55)	0.010 (0.21)	0.020 (0.41)	-0.028 (-0.48)	-0.016 (-0.26)	0.023 (0.39)	-0.076 (-1.18)	-0.063 (-0.90)	-0.032 (-0.42)
Log Rainfall, t-1	-0.139*** (-2.78)	-0.141*** (-2.75)	-0.174*** (-3.16)	-0.104* (-1.95)	-0.103* (-1.92)	-0.133** (-2.14)	-0.115 (-1.51)	-0.114 (-1.49)	-0.183** (-2.00)
Log Rainfall, t-2	0.008 (0.13)	-0.022 (-0.36)	-0.037 (-0.49)	0.059 (0.88)	0.051 (0.79)	0.023 (0.29)	0.110 (1.39)	0.100 (1.37)	0.001 (0.01)
Post Cold War Dummy		0.136* (1.89)			0.028 (0.50)			0.032 (0.44)	
Country FE+ Trend	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time Effects, p-value	No	No	0.0000	No	No	0.0000	No	No	0.0000
No Observations	1049	1049	1049	743	743	743	743	743	743

Panel B: Rainfall Growth

	PRIO 2007 (1981-2006)			PRIO 2007 (1981-1999)			Miguel et al. (1981-1999)		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Rainfall Growth, t	0.016 (0.43)	0.045 (1.29)	0.063** (1.98)	0.006 (0.15)	0.015 (0.38)	0.059 (1.58)	-0.024 (-0.55)	-0.012 (-0.28)	0.066 (1.38)
Rainfall Growth, t-1	-0.074** (-2.08)	-0.047 (-1.45)	-0.048 (-1.41)	-0.077* (-1.84)	-0.069* (-1.71)	-0.046 (-1.07)	-0.122** (-2.35)	-0.111** (-2.38)	-0.052 (-0.95)
Post Cold War Dummy		0.134* (1.89)			0.030 (0.55)			0.038 (0.53)	
Country FE+ Trend	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time Effects, p-value	No	No	0.0000	No	No	0.0000	No	No	0.0000
No Observations	1049	1049	1049	743	743	743	743	743	743

Note: Method of estimation is least squares with Huber robust standard errors clustered at the country level; t-values in brackets. Columns (1)-(3) use the PRIO 2007 civil conflict data for the period 1981-2006; columns (4)-(6) use the PRIO 2007 civil conflict data for the period of the Miguel, Satyanath, and Sergenti (2004) sample; columns (7)-(9) use the Miguel, Satyanath, and Sergenti (2004) data on civil conflict, which is based on an earlier version of the PRIO civil conflict database. All regressions include country fixed effects and country specific time trends. The regressions of columns (3), (6), and (9) include also common time effects. The dependent variable is civil conflict incidence. *Significantly different from zero at 90 percent confidence, ** 95 percent confidence, *** 99 percent confidence.

Table 3: Income and Civil Conflict (PRIO 2007, longest possible sample)

	Per Capita GDP		Conflict Onset		Conflict Incidence	
	(1)	(2)	(3)	(4)	(5)	(6)
Log Rainfall, t	0.061*** (2.79)	0.064*** (2.93)				
Log Rainfall, t-1	0.047* (1.65)	0.046 (1.56)				
Log GDP, t			0.016 (0.15)	0.514 (0.30)	-0.649 (-0.59)	-0.023 (-0.02)
Log GDP, t-1			-1.801 (-1.60)	-3.008* (-1.95)	-1.355 (-1.45)	-2.504** (-2.21)
Country FE+ Trend	Yes	Yes	Yes	Yes	Yes	Yes
Time Effects, p-value	No	0.0000	No	0.0037	No	0.0015
No Observations	866	866	669	669	866	866

Note: Method of estimation in columns (1) and (2) is least squares and columns (3)-(6) two stage least squares. Huber robust standard errors are clustered at the country level with t-values in brackets. The excluded instruments in columns (3)-(6) are current and lagged rainfall. All regressions include country fixed effects and country specific time trends. The regressions of columns (2), (4), and (6) include also common time effects. The dependent variable in columns (1) and (2) is real per capita GDP. The dependent variable in columns (3) and (4) is civil conflict onset and in columns (5) and (6) civil conflict incidence. *Significantly different from zero at 90 percent confidence, ** 95 percent confidence, *** 99 percent confidence.

Appendix Table: Income and Civil Conflict Incidence (Miguel et al. (1981-1999))

Panel A: Income Level

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Log GDP, t	-0.854 (-0.87)		-0.927 (-0.99)		0.529 (0.27)		1.117 (0.64)	
Log GDP, t-1	-0.880 (-0.67)	-1.668 (-1.55)	-0.387 (-0.39)	-1.196 (-1.52)	-3.506 (-1.55)	-3.096** (-2.15)	-2.706** (-2.06)	-1.979* (-1.90)
Log GDP, t-2	2.303** (2.06)	2.551** (2.14)			2.450 (1.14)	2.314 (1.17)		
Country FE+ Trend	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time Effects, p-value	No	No	No	No	0.0000	0.0000	0.0001	0.0000
No Observations	743	743	743	743	743	743	743	743

Panel B: Income Growth

	(1)	(2)	(3)	(4)	(5)	(6)
GDP Growth, t	-1.130 (-0.81)		0.801 (0.93)	1.726 (0.95)		2.921** (2.00)
GDP Growth, t-1	-2.550** (-2.31)	-2.730** (-1.98)		-2.339 (-1.16)	-2.329 (-1.47)	
Country FE+ Trend	Yes	Yes	Yes	Yes	Yes	Yes
Time Effects, p-value	No	No	No	0.0000	0.0000	0.0000
No Observations	743	743	743	743	743	743

Note: Method of estimation is two stage least squares. Huber robust standard errors are clustered at the country level with t-values in brackets. The instruments are log rainfall levels in Panel A and rainfall growth in Panel B. All regressions include country fixed effects and country specific time trends. Columns (5)-(8) in Panel A and columns (4)-(6) in Panel B also include common time effects. *Significantly different from zero at 90 percent confidence, ** 95 percent confidence, *** 99 percent confidence.