Estimating the Effect of Transitory Economic Shocks on Civil Conflict

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This note tries to clarify some remaining issues in the debate on the effect of income shocks on civil conflict. Section 1 discusses the discrepant findings on the effect of rainfall shocks on civil conflict in Miguel and Satyanath (2010, 2011) and Ciccone (2011). Section 2 develops an instrumental variables approach to estimate the effect of transitory (rainfall-driven) income shocks on civil conflict and contrasts the conclusions with those of Miguel, Satyanath, and Sergenti (2004) and Miguel and Satyanath (2010, 2011). Throughout, the note uses the data of Miguel, Satyanath, and Sergenti to focus on the methodological issues at the core of the debate (for results using the latest data see Ciccone, 2011).

1. Rainfall and Civil Conflict

Miguel, Satyanath, and Sergenti (2004), MSS from now on, argue that low rainfall levels and negative rainfall shocks caused civil conflict in Sub-Saharan African countries 1979-1999. Their conclusion is based on the following regression of conflict indicators on year-on-year rainfall growth rates,

(1) $$Conflict_{c,t} = \alpha_c + \gamma_c t + b_0 RGr_{c,t} + b_1 RGr_{c,t-1} + u_{c,t},$$

where $Conflict_{c,t}$ is an indicator variable for conflict in country c at time t; $\alpha_c + \gamma_c t$ is a country fixed effect plus a country-specific linear time trend; and $u_{c,t}$ a regression residual. RGr_t is the rainfall growth rate between year t and t-1, which MSS use to proxy rainfall shocks. The civil conflict indicators used are civil conflict onset which captures the outbreak of civil conflict, and civil conflict incidence which pools new and continuing civil conflicts. MSS's least-squares estimates of equation (1) yield an insignificant effect of rainfall growth at t but a statistically significant, negative effect of rainfall growth at t-1. MSS interpret this as evidence that lower rainfall levels and negative rainfall shocks raise conflict risk.

Year-on-year rainfall growth can be approximated by the log difference in rainfall levels between adjacent years, $RGr_{c,t} = \log R_{c,t} - \log R_{c,t-1}$. Hence, equation (1) can be rewritten as

(2) $$Conflict_t = \alpha_c + \gamma_c t + \beta_0 \log R_t + \beta_1 \log R_{c,t-1} + \beta_2 \log R_{c,t-2} + u_{c,t} .$$

Ciccone (2011) observes that if MSS's interpretation of the significantly negative effect on lagged rainfall growth in equation (1) is correct and lower rainfall levels raise conflict risk, then there should be some significant negative β when estimating (2) with MSS's data. But the least-squares estimates of equation (2) in Table 1 (conflict onset) and Table 2 (conflict incidence) at the end of this note show that rainfall levels are statistically insignificant except for t-2 rainfall levels which enter positively. Hence, somewhat counterintuitively, lower rainfall levels are associated with significantly less civil conflict onset and incidence (with a lag) in MSS's data.

The stochastic process of log rainfall levels can be modeled as $\log R_{c,t} = r_c + \rho \log R_{c,t-1} + \varepsilon_{c,t}$ where ρ captures the persistence of rainfall and ε_t rainfall shocks. In MSS's data, rainfall levels are strongly mean reverting: ρ is 0.17 when country fixed effects are accounted for and 0.04 when both country fixed effects and linear country trends are taken into account (further rainfall lags are statistically insignificant). Hence, most of the variation in rainfall levels over time corresponds to rainfall shocks. Strong mean reversion of rainfall levels also implies that year-on-year rainfall growth rates are predictable: rainfall growth tends to be high following negative rainfall shocks and low following positive rainfall shocks. Ciccone therefore argues that it is unclear whether MSS's finding of a negative effect of lagged year-on-year rainfall growth on conflict risk should be interpreted as conflict being more likely following negative rainfall shocks. In fact, the estimates of equation (2) in Tables 1 and 2 suggest the contrary: civil conflict is more likely following positive rainfall shocks.

Just like Ciccone, Miguel and Satyanath (2011) find that there is no statistically significant effect of t and t-1 rainfall levels on civil conflict, see their results in Table 1, Panel C, column (2) which I am reproducing in Table 3, column (2) for convenience. But in contrast to Ciccone, they also find t-2 rainfall levels to be a statistically insignificant determinant of civil conflict. What explains the discrepancy between Miguel and Satyanath's and Ciccone's findings? First, Miguel and Satyanath do not consider civil conflict onset, which is the variable in MSS that captures the outbreak of civil conflicts. Second, when Miguel and Satyanath examine the effect of rainfall on civil conflict incidence, they do not control for lagged conflict incidence. This imposes that civil conflict is equally likely whether or not there was a civil conflict in the previous year. Ciccone controls for lagged conflict incidence and finds that the likelihood of civil conflict is significantly greater if there was a conflict in the previous year. Once the persistence of civil conflict is taken into account, lower t-2 rainfall levels and rainfall shocks are associated with significantly less civil conflict incidence.

Miguel and Satyanath (2011) argue that the results of the rainfall growth specification show that civil conflict risk is significantly higher following falling year-on-year rainfall levels. They see this result as consistent with behavioral economic theories where individuals are sensitive to recent rainfall changes relative to a status quo (defined as last year's rainfall level). However, the rainfall level results in Table 1 and 2 show that conflict risk is not significantly higher when rainfall levels fall year-on-year because an average rainfall year is followed by a negative rainfall shock. Civil conflict risk in MSS's data is only significantly higher when rainfall levels fall year-on-year because a positive rainfall shock is followed by an average rainfall year.

Miguel and Satyanath (2011) also argue that the (unrestricted) rainfall level specification lends some support to MSS's (restricted) rainfall growth specification. To see their argument, note that a rainfall growth specification where only the lagged rainfall growth rate matters for conflict implies that the coefficient on t-2 rainfall levels is equal to the negative of the coefficient on t-1 rainfall levels. As Miguel and Satyanath's rainfall level results reproduced in Table 3 do not reject this hypothesis, they see some support for this rainfall growth specification. However, two further implications of this rainfall growth specification for the rainfall level specification would be that rainfall levels at t-1 are significantly negative and that rainfall levels at t-2 are significantly positive. Both implications are rejected by Miguel and Satyanath's results reproduced in Table 3 (my results reported in Table 1 and 2 only reject the first of the two implications).

Another interesting issue in the debate is the following. Ignore for a moment that the t-2 rainfall level in Miguel and Satyanath's (2011) specification reproduced in Table 3 only enters insignificantly because the persistence of civil conflict is not accounted for. How can the insignificant effect of rainfall levels in column (2) be reconciled with the statistically significant, negative effect of t-1 rainfall growth in column (1)? To understand this, it is useful to return to the stochastic process for log rainfall levels $\log R_{c,t} = r_c + \rho \log R_{c,t-1} + \varepsilon_{c,t}$ and take

$\rho = 0$ for simplicity (we have already seen that ρ is small in MSS's data). In this case, the year-on-year rainfall growth rate can be approximated by $\log R_{c,t} - \log R_{c,t-1} = \varepsilon_{c,t} - \varepsilon_{c,t-1}$ and the rainfall growth rate may therefore be low because (i) there is a negative rainfall shock at t, $\varepsilon_{c,t} < 0$; (ii) there is a positive rainfall shock at t-1, $\varepsilon_{c,t-1} > 0$; (iii) a positive rainfall shock at t-1 is followed by a negative rainfall shock at t. The rainfall growth specification in Table 3, column (1) does not allow to distinguish between these cases. The rainfall level specification does and the results in Table 3, column (2) indicate that rainfall shocks in any one year do not appear to be causing civil conflict. But what about the hypothesis that conflict risk is significantly higher when a t-2 positive rainfall shock is followed by a t-1 negative rainfall shock? The effect of this particular sequence of rainfall shocks on conflict risk is given by the coefficient on t-2 rainfall minus the coefficient on t-1 rainfall in Table 3, column (2). Hence, this particular sequence of shocks will be associated with significantly greater conflict risk if the coefficient on t-2 rainfall is significantly greater than the coefficient on t-1 rainfall. A test of this hypothesis using the estimates in Table 3 indicates that it cannot be rejected at the 98% confidence level. Hence, the rainfall level results in column (2) indicate that the rainfall growth results in column (1) can be interpreted as the effect on conflict risk of a t-2 positive rainfall shock followed by a t-1 negative rainfall shock. More generally, Ciccone (2011) shows that the coefficients of the rainfall growth specification reflect the effects of particular sequences of shocks. Which sequence exactly depends on the rainfall growth lags included in the specification.

It is also interesting to note that due to mean reverting rainfall levels, rainfall growth rates in adjacent years are negatively correlated. Hence, the results of rainfall growth specifications may depend on which rainfall growth lags are included. Table 4, columns (1)-(4) illustrate this for civil conflict onset in MSS's data. As can be seen in column (2), when only t-1 rainfall growth is included in the specification, the effect of rainfall growth drops by about 25% in absolute value compared to column (1) and—although more precisely estimated than in column (1)—becomes statistically insignificant using the standard error preferred by Miguel and Satyanath (2011, 2011). Moreover, when t-2 rainfall growth is included in columns (3) and (4), the effect of rainfall growth at t-1 again drops in absolute value and becomes statistically insignificant. On the other hand, Table 4, columns (5)-(8) show that the statistically significant positive effect of t-2 rainfall levels on conflict onset is robust to the lag structure. This is because the correlation between rainfall levels in adjacent years is weak.

2. Income Shocks and Civil Conflict

To determine the effect of income shocks on civil conflict, MSS estimate

$$Conflict_{c,t} = \alpha_c + \gamma_c t + b_0 IncomeGr_{c,t} + b_1 IncomeGr_{c,t-1} + u_{c,t}\,, \tag{3}$$

where $IncomeGr_{c,t}$ is the growth rate of income per capita between year t and t-1. MSS take this income growth rate to be a proxy of income shocks. As income growth is endogenous, MSS use rainfall growth or rainfall levels as instruments (for more details on the rainfall level results, see Miguel and Satyanath, 2011). They find that civil conflict onset is significantly more likely following low income growth at t and that civil conflict incidence is significantly more likely following low income growth at t-1. MSS's interpretation of this finding is that civil conflict is more likely following *negative economic shocks* or *negative growth shocks*.

If rainfall shocks had a permanent effect on income, the approach of MSS would be appropriate as low year-on-year income growth rates would be a valid proxy of negative income shocks. However, rainfall-driven income shocks are transitory and MSS's approach can therefore lead to misleading conclusions. The reason is the following. Clearly, income growth may be low because current income is reduced by a *negative* rainfall shock. But income growth may also be low because *positive* rainfall shocks led to higher incomes in past years and rainfall and income levels are now reverting to the mean. This is supported by Miguel and Satyanath's (2011) empirical finding that income growth between t and t-1 is significantly lower the greater rainfall levels at t-2 (their Table 1, Panel B, column (2); see also the results reported in equation (6) below). Hence, low income growth rates reflect a mixture of negative current rainfall (income) shocks and positive past rainfall (income) shocks.

Because low income growth rates reflect a mixture of negative current rainfall shocks and positive past rainfall shocks, MSS's instrumental variables approach to equation (3) cannot be used to examine whether civil conflict is driven by positive or negative income shocks. I therefore describe an alternative approach, illustrate it using MSS's data, and contrast the results with Miguel, Satyanath, and Sergenti's (2004) and Miguel and Satyanath's (2010, 2011) conclusions.

2.A. Do Rainfall Shocks have Transitory or Permanent Effects on Income?

In principle, rainfall-driven income shocks could be transitory or permanent (even if rainfall shocks themselves are transitory). Generally speaking, income dynamics may reflect a stochastic or deterministic trend π or transitory shocks τ,

$$\ln y_{c,t} = \pi_{c,t} + \tau_{c,t}. \tag{4}$$

Rainfall shocks could affect income through τ or through π and therefore have transitory or permanent income effects. The effect of rainfall shocks on income is transitory if rainfall shocks affect short-run but not long-run income. Following Dell, Jones, and Olken (2008), the short-run and long-run effect can be estimated by regressing income growth on current and lagged rainfall. Suppose this yields

$$\text{(5)} \qquad \ln \hat{y}_{c,t} - \ln \hat{y}_{c,t-1} = \hat{\alpha}_c + \sum_{i=0}^{I} \hat{\alpha}_i \log Rain_{c,t-i} \,,$$

where hats denote estimated values. Then a 1-percent year-*t* rainfall shock raises income after *j* periods by $\hat{\alpha}_0 + \hat{\alpha}_1 + ... + \hat{\alpha}_j$ percentage points. Least-squares estimation of (5) using MSS's data yields

$$\text{(6)} \qquad \ln \hat{y}_{c,t} - \ln \hat{y}_{c,t-1} = \hat{\alpha}_c + \underset{(3.4)}{0.06} \log Rain_{c,t} - \underset{(-1.1)}{0.021} \log Rain_{c,t-1} - \underset{(-2.5)}{0.041} \log Rain_{c,t-2}$$

where $\hat{\alpha}_c$ denotes country c fixed effects, and the numbers in brackets are t-statistics.[1] Hence, a 1-percent rainfall shock at t leads to a statistically significant increase in income at t of 0.06 percentage points. But income at t+1 is predicted to increase by only 0.039 (0.06-0.021) percentage points and income at t+2 by only -0.002 (0.06-0.021-0.041) percentage points. The hypothesis that rainfall shocks do not affect income after two periods cannot be rejected at any conventional confidence level. Hence, the effect of rainfall shocks on income is transitory and rainfall cannot serve as an instrument for permanent income shocks.[2] But as rainfall has a significant contemporaneous income effect, they can be used as an instrument for transitory income shocks (assuming that the relevant exclusion restriction can be taken to be satisfied).

For a different perspective on the results in (6), suppose that the transitory component of income in (4) depends on current and past rainfall levels, $\ln y_{c,t} = \pi_{c,t} + \lambda_0 \ln R_{c,t} + \lambda_1 \ln R_{c,t-1}$. In

[1] Results are similar when, following MSS, I also control for country-specific linear time trends. In this case the rainfall coefficients (t-statistics) are 0.058 (3.1); -0.019 (-0.9); and -0.035 (-2.1).

[2] Dell, Jones, and Olken (2008) also find that the income effect of rainfall shocks is transitory (for Sub-Saharan African countries as well as a larger sample of countries).

this case, year-on-year income growth is given by $\ln y_{c,t} - \ln y_{c,t-1} = (\pi_{c,t} - \pi_{c,t-1}) + \lambda_0 \ln R_{c,t} - (\lambda_0 - \lambda_1)\ln R_{c,t-1} - \lambda_1 \ln R_{c,t-2}$. Hence, if current rainfall levels have a stronger (positive) effect on income than past rainfall levels, $\lambda_0 > \lambda_1$, year-on-year growth should depend positively on current rainfall levels and negatively on past rainfall levels. This is consistent with the results in (6) and Miguel and Satyanath's (2011) Table 1, Panel B, column (2).

2.B. Rainfall, Transitory Income Shocks, and Civil Conflict

Estimating the effect of rainfall-driven income shocks on civil conflict requires a model of income dynamics in (4). A standard approach is to model income dynamics as stationary fluctuations around a country-specific linear time trend. This model can be tested against the alternative of non-stationarity for at least one country using the Hadri (2000) panel test, which yields that stationarity around a country-specific linear time trend cannot be rejected at any conventional confidence level. Using this approach to income dynamics yields strong effects of rainfall on income fluctuations. Regressing log income on country-specific linear time trends and contemporaneous log rainfall yields a coefficient on rainfall of 0.086 with a t-statistic of 4.48.

Table 5 uses MSS's data to estimate the effect of rainfall-driven income shocks on civil conflict when income dynamics are characterized by stationary fluctuations around a country-specific linear time trend. The main regressors of interest are log income per capita levels at t, t-1, and t-2 instrumented by log rainfall levels. As the specifications also include country-specific linear time trends, the coefficient on log income levels can be interpreted as the effect of rainfall-driven income shocks. The results in column (1) indicate a significantly positive effect of t-2 income shocks on conflict. This effect becomes stronger when I drop lagged conflict incidence in column (2). Column (3) consider conflict onset as the dependent variable and finds no evidence of a statistically significant link between income shocks and conflict onset.[3] Hence, there is no evidence that negative income shocks increase the probability of civil conflict. If anything, the evidence goes in the opposite direction as negative income shocks lower the likelihood of civil conflict incidence.

An alternative way of estimating the effect of rainfall-driven income shocks on civil conflict is to follow modern macroeconomic practice and use the Hodrick-Prescott filter to decompose income dynamics into a trend and a cycle and then examine whether civil conflict is linked to the rainfall-driven cyclical income component. This approach requires two steps. The first step implements the Hodrick-Prescott filter separately for each Sub-Saharan African country following Ravn and Uhlig (2002). The second step uses the cyclical component as a measure of income shocks and runs an instrumental variables regression of civil conflict on the current and lagged cyclical income components instrumented by log rainfall levels. Even though the regressors of interest are generated, this approach yields consistent point estimates and standard errors that are valid for testing the null hypothesis of no effect (see Wooldridge, 2002, Section 6.1.2). The empirical results using MSS's data are in Table 6. The first column shows that the cyclical income component, denoted by GDP HP, is strongly positively related to rainfall. Columns (2)-(4) use log rainfall levels as an instrument to estimate the effects of cyclical income fluctuations on civil conflict incidence and onset. The results show that conflict is less likely following negative t-2 income shocks.

[3] Recall that for civil conflict onset, MSS find a significantly negative effect of income growth at t. The results in Table 5, column (3) indicate a negative effect of income shocks at t and a positive effect of income shocks at t-1. Hence, it is natural to wonder whether MSS's results reflect the effect of a positive income shock at t-1 followed by a negative income shock at t. A formal test rejects that civil conflict onset is more likely following this particular sequence of shocks at the 90% confidence level.

3. Conclusions

The discrepancies between Miguel and Satyanath's (2011) and Ciccone's (2011) findings regarding the effect of rainfall shocks on civil conflict in the data of Miguel, Satyanath, and Sergenti (2004) arise for two reasons. First, Miguel and Satyanath do not examine the effect of rainfall on civil conflict onset (outbreak). Civil conflict onset is less likely following low rainfall levels and negative rainfall shocks. Second, when Miguel and Satyanath examine the effect of rainfall on civil conflict incidence—which pools conflict onset and continuation—they do not account for civil conflict being more likely when there was a civil conflict in the previous year. Once the persistence of civil conflict is accounted for, civil conflict incidence is less likely following low rainfall levels and negative rainfall shocks.

Estimating the effect of rainfall-driven (transitory) economic shocks on civil conflict is trickier than currently understood in the literature. For example, Miguel, Satyanath, and Sergenti's (2004) instrumental variables approach cannot be used to examine whether civil conflict is more likely following positive or negative rainfall-driven economic shocks. I therefore propose an alternative approach and implement it using the data of Miguel, Satyanath, and Sergenti. My results indicate that civil conflict onset was not driven by income shocks. Civil conflict incidence was less likely following negative income shocks. This conclusion stands in contrast with that of Miguel, Satyanath, and Sergenti and Miguel and Satyanath (2010, 2011), who argue that civil conflict was more likely following negative income shocks.

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Tables

Table 1. Rainfall and civil conflict onset

	MSS (2004) data	
	(1)	(2)
Rainfall Growth, t	-0.063 (0.044) [0.048]	
Rainfall Growth, t-1	-0.120* (0.062) [0.068]	
Log Rainfall, t		-0.073 (0.078) [0.086]
Log Rainfall, t-1		-0.026 (0.069) [0.075]
Log Rainfall, t-2		0.156** (0.068) [0.074]
Country FE and Trend	Yes	Yes
Observations	555	555

Note: The left-hand-side variable is an indicator variable capturing civil conflict onset. The method of estimation is least squares. Standard errors in parentheses are robust for arbitrary heteroskedasticity and clustered at the country level. Standard errors in square brackets also apply the STATA small-sample adjustment preferred by Miguel and Satyanath (2010, 2011). The statistical theory behind hypothesis tests using the small-sample-adjusted standard errors assumes normally distributed and homoskedastic residuals (e.g. Greene, 1990, page 161). Both the normality assumption and the homoskedasticity assumption are violated in linear probability models, where the left-hand-side variable is either 0 or 1 as in the case of civil conflict onset and incidence (e.g. Wooldridge, 2002, page 454). I report standard errors incorporating the small-sample adjustment to facilitate comparison with Miguel and Satyanath (2010, 2011). *Significantly different from zero at 90 percent confidence, ** 95 percent confidence, *** 99 percent confidence. When the asterisks are next to the least-squares point estimate, the confidence level applies no matter which of the two standard errors is employed. When the asterisks are next to the standard error, the confidence level applies to that standard error only.

Table 2. Rainfall and civil conflict incidence

	MSS (2004) data			
	(1)	(2)	(3)	(4)
	LS	GMM	LS	GMM
Rainfall Growth, t	-0.025 (0.040) [0.043]	-0.017 (0.043)		
Rainfall Growth, t-1	-0.129** (0.048) [0.051]	-0.123** (0.049)		
Log Rainfall, t			-0.053 (0.060) [0.065]	-0.033 (0.063)
Log Rainfall, t-1			-0.102 (0.069) [0.074]	-0.094 (0.066)
Log Rainfall, t-2			0.128* (0.067) [0.072]	0.125* (0.064)
Lagged Incidence	0.277*** (0.077) [0.083]	0.282*** (0.077)	0.274*** (0.078) [0.084]	0.280*** (0.078)
Country FE and Trend	Yes	Yes	Yes	Yes
Observations	743	743	743	743

Note: The left-hand-side variable is an indicator variable capturing civil conflict incidence. The method of estimation is least squares or system-GMM. Standard errors in parentheses are robust for arbitrary heteroskedasticity and clustered at the country level. Standard errors in square brackets also apply the STATA small-sample adjustment preferred by Miguel and Satyanath (2010, 2011). The statistical theory behind hypothesis tests using the small-sample-adjusted standard errors assumes normally distributed and homoskedastic residuals (e.g. Greene, 1990, page 161). Both the normality assumption and the homoskedasticity assumption are violated in linear probability models, where the left-hand-side variable is either 0 or 1 as in the case of civil conflict onset and incidence (e.g. Wooldridge, 2002, page 454). I report standard errors incorporating the small-sample adjustment to facilitate comparison with Miguel and Satyanath (2010, 2011). *Significantly different from zero at 90 percent confidence, ** 95 percent confidence, *** 99 percent confidence.

Table 3. Rainfall and civil conflict incidence, Miguel and Satyanath (2011)

	MSS (2004) data	
	(1)	(2)
	LS	LS
Rainfall Growth, t	-0.024 [0.043]	
Rainfall Growth, t-1	-0.122** [0.052]	
Log Rainfall, t		-0.0762 [0.065]
Log Rainfall, t-1		-0.115 [0.076]
Log Rainfall, t-2		0.110 [0.079]
Country FE and Trend	Yes	Yes
Observations	743	743

Note: The left-hand-side variable is an indicator variable capturing civil conflict incidence. The method of estimation is least squares. Standard errors in square brackets are robust for arbitrary heteroskedasticity and clustered at the country level and also apply the STATA small-sample adjustment. *Significantly different from zero at 90 percent confidence, ** 95 percent confidence, *** 99 percent confidence.

Table 4. Rainfall and civil conflict onset

	MSS (2004) data							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Rainfall Growth, t	-0.062 (0.044) [0.048]			-0.061 (0.052) [0.058]				
Rainfall Growth, t-1	-0.120* (0.062) [0.068]	-0.094 (0.054)* [0.060]	-0.039 (0.047) [0.051]	-0.076 (0.063) [0.070]				
Rainfall Growth, t-2			0.087 (0.051)* [0.056]	0.063 (0.057) [0.063]				
Log Rainfall, t-1					-0.029 (0.072) [0.079]			-0.002 (0.069) [0.076]
Log Rainfall, t-2					0.162** (0.068) [0.075]	0.161** (0.067) [0.074]	0.169** (0.070) [0.077]	0.169** (0.070) [0.078]
Log Rainfall, t-3							-0.046 (0.057) [0.061]	-0.046 (0.056) [0.062]
Country FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country Trend	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	555	555	521	521	555	555	521	521

Note: The left-hand-side variable is an indicator variable capturing civil conflict onset. The method of estimation is least squares. The method of estimation is least squares or system-GMM. Standard errors in parentheses are robust for arbitrary heteroskedasticity and clustered at the country level. Standard errors in square brackets also apply the STATA small-sample adjustment preferred by Miguel and Satyanath (2010, 2011). The statistical theory behind hypothesis tests using the small-sample-adjusted standard errors assumes normally distributed and homoskedastic residuals (e.g. Greene, 1990, page 161). Both the normality assumption and the homoskedasticity assumption are violated in linear probability models, where the left-hand-side variable is either 0 or 1 as in the case of civil conflict onset and incidence (e.g. Wooldridge, 2002, page 454). I report standard errors incorporating the small-sample adjustment to facilitate comparison with Miguel and Satyanath (2010, 2011). When the asterisks are next to the least-squares point estimate, the confidence level applies no matter which of the two standard errors is employed. When the asterisks are next to the standard error, the confidence level applies to that standard error only. *Significantly different from zero at 90 percent confidence, ** 95 percent confidence, *** 99 percent confidence.

Table 5. GDP Growth, GDP, and Civil Conflict

	MSS (2004) data		
	Civil Conflict Incidence		Civil Conflict Onset
	(1)	(2)	(3)
Log GDP, t	-0.678 (1.202)	-0.845 (0.915)	-1.276 (1.270)
Log GDP, t-1	-0.590 (1.579)	-0.886 (1.214)	1.598 (1.530)
Log GDP, t-2	2.105* (1.250)	2.308** (1.038)	1.703 (1.242)
Lagged Incidence	0.213** (0.105)		
Country FE	Yes	Yes	Yes
Country Trend	Yes	Yes	Yes
Observations	702	743	555

Note: The method of estimation is two-stage least squares. Standard errors in parentheses are robust for arbitrary heteroskedasticity and clustered at the country level. *Significantly different from zero at 90 percent confidence, ** 95 percent confidence, *** 99 percent confidence.

Table 6. Economic Fluctuations and Civil Conflict

	MSS (2004) data			
	GDP HP	Civil Conflict Incidence		Civil Conflict Onset
	(1)	(2)	(3)	(4)
Log Rainfall, t	0.033*** (0.011)			
Log Rainfall, t-1	0.034*** (0.013)			
GDP HP, t		0.351 (2.248)	0.010 (2.120)	0.794 (2.356)
GDP HP, t-1		-0.190 (1.690)	-0.562 (1.355)	1.929 (1.578)
GDP HP, t-2		3.072* (1.756)	3.256* (1.756)	3.109* (1.702)
Lagged Incidence		0.218** (0.096)		
Country FE	Yes	Yes	Yes	Yes
Country Trend	Yes	Yes	Yes	Yes
Observations	743	702	743	555

Note: The method of estimation in column (1) is least squares; in columns (2)-(4) two-stage least squares. Standard errors in parentheses are robust for arbitrary heteroskedasticity and clustered at the country level. *Significantly different from zero at 90 percent confidence, ** 95 percent confidence, *** 99 percent confidence.