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Lecture 15

There is a strong scientific consensus that the Earth is getting warmer over time.

It is reasonable to imagine that a side effect of global warming could be an increase in armed conflict over time.

Here are some *possible* channels that could run from warming to conflict:

1. A warmer climate is bad for agriculture in many parts of the world (maybe not in Canada). When agricultural crops fail then some people in these areas might start fighting over a dwindling food supply.

2. Water supplies could dry up in some parts of the world which could lead to armed conflict over water.

3. Sea level changes could force some people off their land, possibly putting them in conflict with other people whose land is better protected from the sea.

Burke et al. address these issues using a cross country regression approach.

Their left-hand-side variable is civil war incidence, a variable that is set to “0” if there is no war in a particular country in a particular year and to “1” otherwise.

“Civil war” is given the usual meaning, requiring 1,000 battle deaths with a government fighting against a non-state group.

Burke et al. use a linear probability model rather than a logistic model. As discussed earlier in the course, the linear probability model is not the generally preferred model but it does have the advantage that their regression coefficients are easier to interpret than they would be if they had used logistic regression.

Table 1 gives the main results of the Burke et al. paper.

Table 1. Regression coefficients on climate variables, with civil war as a dependent variable

Variable	Model 1		Model 2		Model 3	
	Coefficient	SE	Coefficient	SE	Coefficient	SE
Temperature	0.0447**	(0.0218)	0.0430*	(0.0217)	0.0489*	(0.0275)
Temperature lagged 1 year	0.00873	(0.0210)	0.0132	(0.0233)	0.0206	(0.0298)
Precipitation			−0.0230	(0.0519)	0.0165	(0.0848)
Precipitation lagged 1 year			0.0250	(0.0489)	0.0278	(0.0811)
Per capita income lagged 1 year					−0.0266	(0.0258)
Political regime type lagged 1 year					−0.000538	(0.00576)
Constant	−1.514	(0.923)	−1.581*	(0.854)	−1.872	(1.254)
Observations	889		889		815	
R^2	0.657		0.657		0.389	
RMSE	0.193		0.193		0.241	

Coefficients represent effect of temperature (°C) and precipitation (m) on civil war in Africa, 1981–2002. All regressions include country fixed effects to control for time-invariant country characteristics; Models 1 and 2 include country time trends to control for time-varying country characteristics. Model 3 includes lagged income ($1,000) and political regime type [score from least democratic (−10) to most democratic (+10)] as controls, and includes a common time trend. Standard errors are robust and clustered at the country level. Asterisks indicate coefficient significance level (2-tailed): ***, $P < .01$; **, $P < .05$; *, $P < .10$.

Source: Burke et al. paper

Focus on the significant coefficient in column 1.

The interpretation of this coefficient is that an increase of 1 degree centigrade for a particular country in a particular year is associated with a 0.0447 increase in the probability of there being an ongoing civil war at that particular time and place.

The other models yield similar results on the temperature variable, although the significance level drops from 5% to 10%. In other words, rejection of the hypothesis that the temperature variable equals 0 is less strong in the other models than it is in the column-1 model.

The next table combines models 1 and 2 from table 1 (slide 4) with climate change models for Sub-Saharan Africa. The idea is to implement a two-step procedure:

1. Predict the path of temperature over time

2. Use the estimated coefficients from table 1 to predict the impact of climate change on conflict.

While the climate models generally predict rising temperatures, they disagree about the speed with which temperatures will rise.

This is why Burke et al. give three sets of models below in table 2 (A1B, A2 and B1).

In addition, both the temperature models and the conflict models do not try to predict temperatures deterministically. Each has a lot of randomness built in.

So the calculations below are based on random simulations similar to those presented in Lecture 7.

Here is the table of conflict predictions.

Table 2. Projected changes in African civil war incidence to 2030, by emissions scenario

	Median % change	% Increase in civil war relative to baseline	5th–95th percentile observations of projected % increase	% of observations < 0
A1B				
Model 1	5.9	53.7	6.2–119.4	3.0
Model 2	6.1	55.8	2.7–128.8	4.1
A2				
Model 1	5.2	47.4	5.4–101.8	3.0
Model 2	5.4	49.2	2.3–109.8	4.2
B1				
Model 1	4.8	43.4	5.0–99.4	3.0
Model 2	5.0	45.1	2.0–107.1	4.2

Projections are for all of sub-Saharan Africa for 3 emissions scenarios, based on 10,000-run bootstrap of models 1 and 2 in Table 1, which combine uncertainty in climate model projections and in the responsiveness of conflict to climate. Eleven percent of the country-years in the 1981–2002 baseline experienced civil war.

Source: Burke et al.

Here is how we can interpret the numbers in Table 2.

Let's focus on the upper-left number, which is 5.9. This number comes from climate model A1B and Model 1 of Table 1 in the following way:

1. Burke et al. randomly generate 10,000 civil war predictions combining models 1 and A1B.

2. The 10,000 civil war predictions are placed in order from smallest to largest with, for example, the median prediction in position 5,000.

3. They take the amount of civil war at the median and subtract off the average amount of civil war for their sample period, 1981 – 2002 which turns out to be 5.9. We can think of this number as "median excess civil war" caused by warming.

Similarly, we can calculate the excess amount of civil war at other percentiles.

For the 1981-2002 sample, 11% of the country years are coded as civil war ones.

The medians of the projected ranges for the different models range between 4.8% and 6.1% above 11% (see column 1).

This means that Burke et al. predict that 15.8-17.1% of the countries in Sub-Saharan Africa in 2030 will suffer from big civil wars rather than the 11% that would occur without the warming climate.

What about column 2 in Table 2 which contains percentages in the 40’s and 50’s. How did the numbers suddenly get that high?

The answer lies in the important but underappreciated distinction between percentages and percentage points.

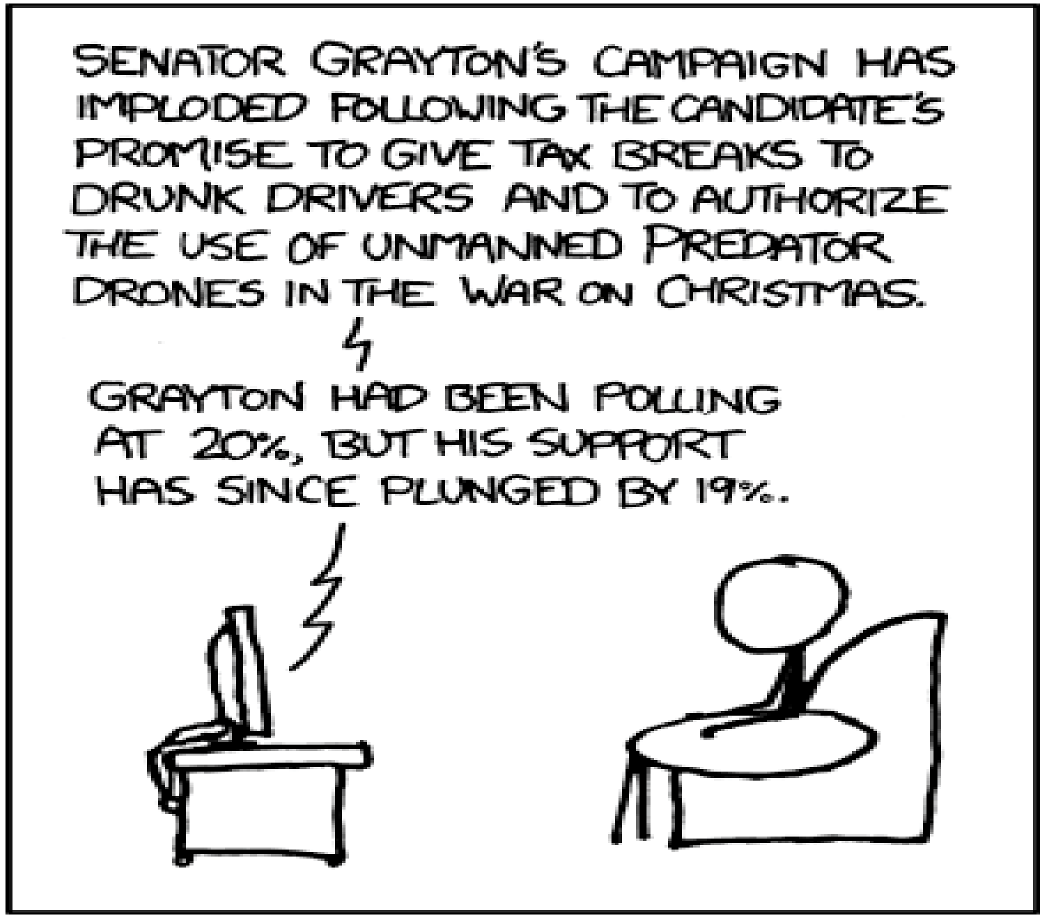
We encountered this distinction earlier in the course but the next two slides give you a quick reminder.

Take an example.

The political party UKIP was getting around 5% support in UK opinion polls in late 2011. Between then and the end of 2012 UKIP support went up by about 100%.

Does that mean UKIP support rose to 10% or to 105%? Obviously, support could not be 105% so the answer must be 10%.

A better way to express this change is to say that UKIP's support went up by 5 *percentage points*. This is very clear to people who are used to this terminology and probably clear even to people who are not. However, it is also true to say that UKIP's support went up by 100% (from 5% to 10%).



I HATE THE AMBIGUITY CREATED WHEN PEOPLE DON'T DISTINGUISH BETWEEN PERCENTAGES AND PERCENTAGE POINTS.

Senator Grayton could be at 1% or he could be at 16.2%.

Once you know this trick you will find plenty of people exploiting the ambiguity between percentage change and percentage points changed to try to manipulate peoples' impressions.

To be honest, this is what I think is happening with column 2 of Table 2. 53.7% sounds a lot bigger than 5.9% percentage points.

Burke et al. go on to predict 393,000 excess battle deaths caused by climate change. We can (almost) derive this figure as follows.

Over 28 years (2003-2030) conflict risk rises from 0.11 to 0.169. Assume these risks rise linearly. In other words, assume that conflict risk rises by 0.059/28 each year.

Assume, further, that the average size of future conflicts is the same as the average conflict size over the 1981-2002 period. (Note that this assumption is almost certainly wrong and biases the calculation upwards since battle deaths per year have declined over the 1981-2002 period but let's just go with the flow on this.)

During the period 1981 – 2002 there were 39,455 battle deaths per year.

Here are the ideas behind a calculation like the one Burke et al. describe:

1. Based on the averages for 1981 – 2002, we should expect to see 39,455 battles deaths in Sub-Saharan Africa when 11% of the countries in that zone are in conflict.

2. Assume that total battle deaths are proportional to the percentage of countries in conflict. Thus, if the percentage of countries in conflict doubles, for example, to 22% in some year then the number of battle deaths will also double to 78,910.

3. We calculate *excess battle deaths* relative to a baseline of 39,455. So if, for example, 13% of Sub-Sahara African countries are in conflict in a given year then the number of excess battle deaths will be $\frac{13-11}{11}x39,455=7,174$. (Total battle deaths in that year will be 39,455 + 7,171 = 46,626.)

4. We assume that the percentage of countries in conflict in Sub-Saharan Africa increases in equal increments of $\frac{5.9}{28}\approx.21$ for 28 years starting at 11 and ending at 16.9.

We get the following excess battle death estimates (note that there is some rounding in the figures so they may not add up to precisely what you think they should add up to):

2003 - $39{,}455x\frac{.21}{11}=753$

2004 - $39{,}455x\frac{.42}{11}=1506$

2030 - $39{,}455x\frac{5.9}{11}=21{,}162$

I get 306,852 when I add the numbers up carefully . This number is sort of like Burke et al.'s 393,000 but lower. At the moment I can't explain the difference between the two.

In any case, 306,852 is still be a big number. However, the number would be substantially smaller if one projected forward the existing trend for battle deaths rather than a flat 39,355, 39,355,….etc.

Predictive Power of the Burke et al. Model

Stijn van Weezel, who was the TA in this course two years ago, has an interesting paper studying the performance of the Burke et al. model in prediction.

Burke et al. cover the period 1981–2002. Van Weezel takes this model and uses it to make predictions for the period 2003-2013.

Table 1: Actual versus predicted wars out-of-sample for 2003-2013

	$\hat{p} \leq 0.5$	$\hat{p} > 0.5$
No war	403 obs.	Angola (2003-2005) Burundi (2003-2013) DRC (2003-2012) Rwanda (2013) Sudan (2005, 2007-2009, 2013)
War	Chad (2006) Liberia (2003) Nigeria (2013) Rwanda (2009) Somalia (2007-2012) Uganda (2004)	DRC (2013) Sudan (2003, 2004, 2006, 2010-2012)

The table on slide 18 takes 0.5 as the threshold for predicting war. This means that the left column covers the predictions of “no war” while the right column covers the predictions of “war”.

There are 414 “no war” predictions (note that Somalia counts 6 times). A war actually happens in 11 out of these 414 cases.

There are 37 predictions of “war”. War actually happens in 7 out of these 37 cases.

The Burke et al. model seems to be of some use in predicting wars although it seems to have a general tendency to predict war too often.

Van Weezel then asks how important the temperature variable is for making these predictions. For this purpose he takes the temperature variable out of the model and winds up with the following table.

Table B1: Actual versus predicted wars out-of-sample for 2003-2013
(Model with country fixed effects and country-specific time trends only)

	$\hat{p} \leq 0.5$	$\hat{p} > 0.5$
No war	398 obs.	Angola (2003-2007) Burundi (2003-2013) DRC (2003-2012) Rwanda (2010-2013) Sudan (2005, 2007-2009, 2013)
War	Chad (2006) Liberia (2003) Nigeria (2013) Rwanda (2009) Somalia (2007-2012) Uganda (2004)	DRC (2013) Sudan (2003, 2004, 2006, 2010-2012)

Rather surprisingly, this table is almost identical to the table on slide 18.

The only thing that is worse in the new table that ignores the impact of temperature is that we add in 5 false positives, i.e, predictions of wars that do not happen. These extra false positives are Angola (2006-2007) and Rwanda (2010-2012).

These findings are really a problem for Burke et al. all. They mean that temperature is not very useful for predicting civil war. In other words, you can do almost as well in your predictions by forgetting about temperature and just looking at which countries have tended to go to war in recent years (slide 20) as you can do be integrating temperature into your model (slide 18).

Going Below the Country Level

So far we have conducted our temperature analysis at the country level but this type of cross-country analysis hides a lot of local variation.

O'Loughlin et al. address this shortcoming by dividing their sample in East Africa up into a grid with components that are about 100 kilometres by 100 kilometres in size.

O'Loughlin et al. also innovate by making their dependent variable (left-hand-side) into a count of the number of violent incidents rather than being just a 0-1 variable (i.e., "no war" or "war").

These event counts come from something called the ACLED database.

Burke et al. focus only on the temperature but O'Loughlin et al. use two climate variables – temperature and precipitation. They call the precipitation variable "SPI6" and the temperature variable "TI6".

Sometimes O'Loughlin et al. do transform the temperature and precipitation variables into 0-1 forms. In these cases they set these variables equal to 1 for extreme deviations from normal levels and equal to 0 for values close to normal levels.

O'Loughlin et al. use something called a "negative binomial model." This is a commonly used model for count data, i.e., data that can take on values 0, 1, 2, 3, …..

The next slide gives the main table of the O'Loughlin paper.

Table 1. Negative binomial regression models for total number of violent events per grid cell, 1991–2009

	a) GLM socioeconomic, physical, and climate		b) SPI6 binary dry (≤−1 σ)		c) SPI6 binary wet (≥1 σ)		d) TI6 binary hot (≥1 σ)		e) TI6 binary cold (≤−1 σ)		f) GAM splines	
	Estimate	*z* value	Estimate	*z* value	Estimate	*z* value	Estimate	*z* value	Estimate	*z* value	Estimate	*z* value
Intercept	−8.196	−5.995*	−8.173	−5.982*	−8.235	−6.017*	−8.216	−6.011*	−8.228	−6.031*	−8.292	−6.029*
Space–time lag	0.524	14.917*	0.525	14.993*	0.526	14.961*	0.530	14.857*	0.532	14.822*	0.512	14.789*
Precipitation (SPI6)	−0.048	−1.558					−0.053	−1.730	−0.057	−1.832		
SPI6 dry			−0.044	−0.566								
SPI6 wet					−0.205	−2.231†						
Spline (SPI6)											*P* value	0.000*
Temperature (TI6)	0.078	1.545	0.089	1.779	0.081	1.613						
TI6 hot							0.061	0.873				
TI6 cold									0.021	0.113		
Spline (TI6)											*P* value	0.000*
Ethnic leadership	−0.334	−1.583	−0.340	−1.604	−0.337	−1.599	−0.323	−1.541	−0.314	−1.492	−0.332	−1.572
Distance to border (ln)	−0.420	−4.906*	−0.419	−4.888*	−0.419	−4.880*	−0.422	−4.923*	−0.424	−4.938*	−0.417	−4.843*
Capital city grid cell	1.636	5.666*	1.634	5.652*	1.627	5.651*	1.635	5.676*	1.632	5.672*	1.625	5.655*
Population (ln)	0.495	7.457*	0.498	7.490*	0.499	7.509*	0.494	7.453*	0.494	7.448*	0.502	7.551*
Wellbeing (IMR lag)	0.010	1.604	0.010	1.554	0.010	1.568	0.010	1.647	0.010	1.670	0.010	1.600
Political rights (lag)	0.087	1.766	0.085	1.731	0.091	1.858	0.089	1.810	0.090	1.833	0.092	1.896
Presidential election buffer	0.303	2.541†	0.287	2.414†	0.306	2.560†	0.308	2.619*	0.310	2.653*	0.325	2.715*
Grassland (%)	0.020	4.131*	0.020	4.126*	0.020	4.112*	0.020	4.148*	0.020	4.157*	0.020	4.088*
Distance to road (ln)	−0.400	−3.151*	−0.400	−3.146*	−0.400	−3.141*	−0.401	−3.150*	−0.401	−3.156*	−0.388	−3.084*
Crop production index (pct. Δ)	−0.004	−1.447	−0.004	−1.551	−0.004	−1.507	−0.004	−1.476	−0.004	−1.473	−0.004	−1.601
VCI (lag)	−0.002	−0.956	−0.002	−0.971	−0.001	−0.909	−0.001	−0.893	−0.001	−0.877	−0.002	−0.955
Log-likelihood	−25,150.6		−25,153.0		−25,146.1		−25,153.9		−25,155.0		−25,112.0	
AIC	50,395.1		50,399.9		50,386.3		50,401.9		50,404.0		50,331.7	
AUC	0.849		0.849		0.849		0.849		0.849		0.850	

Number of observations for all models is 91,656 grid months. Binary models b–d use precipitation and temperature anomalies of beyond 1 SD (σ) of the long-term mean to define binary variable. All models are estimated with year and country fixed effects (not shown). AIC, Akaike information criterion; IMR, infant mortality rate; VCI, vegetation condition index.

*$P < 0.01$ using grid-clustered SEs.

†$P < 0.05$ using grid-clustered SEs.

Here are the main points we can extract from the table.

1. Model a. Neither temperature nor precipitation have a statistically significant effect on the number of violent events.

2. Model b. There is a variable coded as 1 for conditions that are strongly drier than normal conditions. This variable does not have a statistically significant effect on the number of violent events.

3. Model c. There is a variable coded as 1 for conditions that are strongly wetter than normal conditions. This variable does have a statistically significant negative effect on the number of violent events.

4. Model d. There is a variable coded as 1 for conditions that are strongly hotter than normal conditions. This variable does not have a statistically significant effect on the number of violent events.

5. Model e. In this one there is a variable coded as 1 for conditions that are strongly cooler than normal conditions. This variable does not have a statistically significant effect on the number of violent events.

If we stopped here we would have to say that O'Loughlin et al. provides no evidence that high temperatures are associated with greater armed conflict.

However, there is the rather mysterious model f in Table 1. Models b – e considered deviations from normal conditions by one standard deviation or more.

Now O'Loughlin et al. now estimate the impact of a whole range of different sized deviations and then fit a smoothed curve to these estimates.

The following figure displays their results.

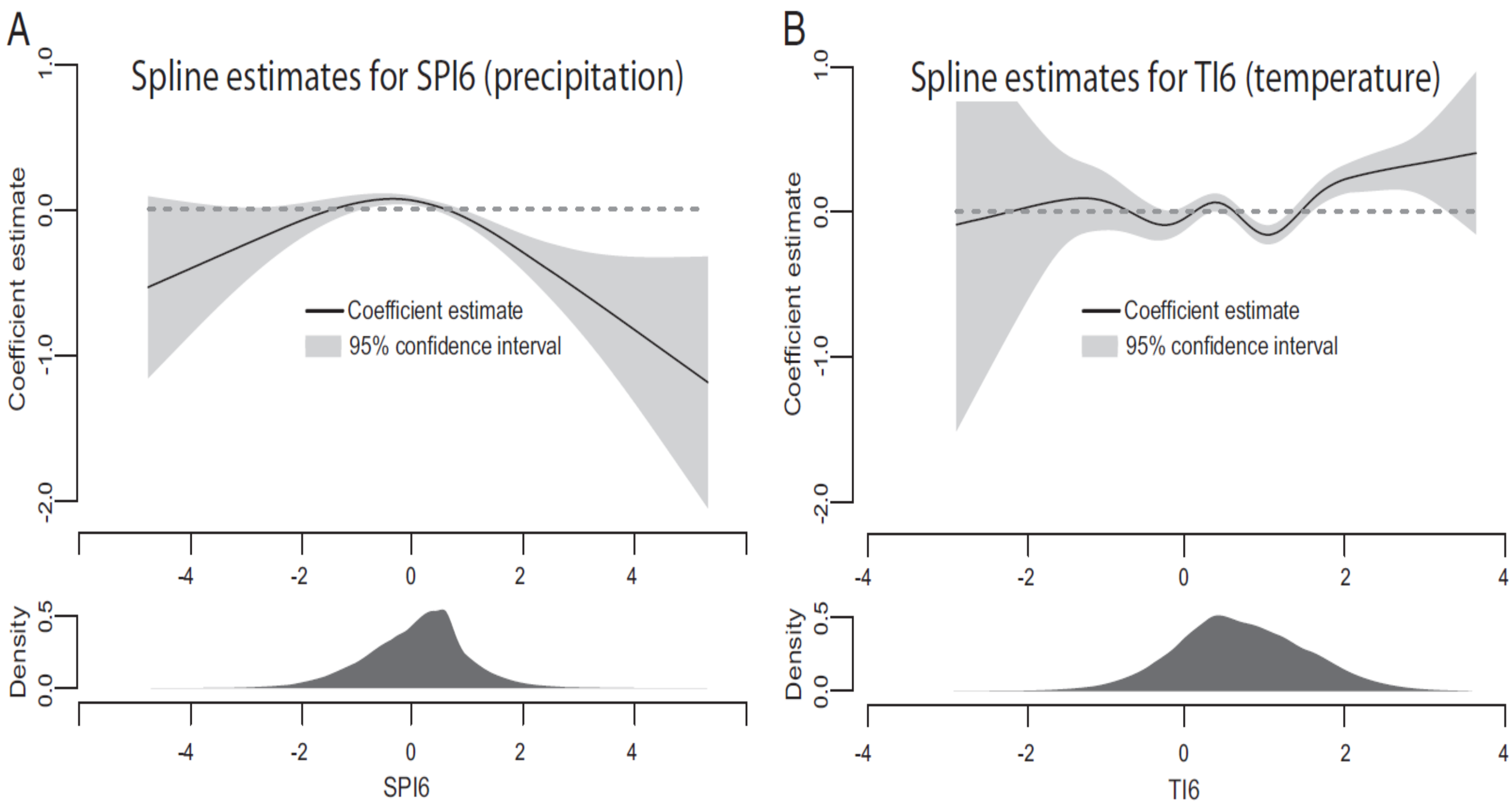


Fig. 1. These plots show the coefficient estimate and 95% confidence interval over the range of SPI6 (*A*) and TI6 (*B*) for the model in Table 1, column f. Nonoverlap between the confidence interval and dashed zero line indicates a statistically significant effect. The lower dark gray plots show the density distributions of the variable—both SPI6 and TI6 are centered right of zero, indicating that our study period is wetter and warmer than the 60-y comparison period.

Panel A shows evidence that wet deviations are associated with lower numbers of violent incidents.

Panel B of Figure 1 suggests that large, warm deviations from normal temperatures are associated with higher numbers of violent incidents.

So the O'Loughlin et al. do give some evidence that unusually warm years may also be unusually violent years in East Africa.