**Supplementary Appendix**

**Farming Then Fighting: agricultural idle time and armed conflict**

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In this appendix, we describe several of our robustness tests:

1. Logistic and count models
2. Example of a crop calendar
3. Models Excluding Deserts
4. Conditional Relationship across the percentage of cultivated land
5. Models with spatial weights
6. References
7. **Logit models and count models**

In the main manuscript, we estimate the effect of our idle index on armed conflict using a linear probability model (LPM). While it is often advised to use a logistic model for a binary dependent variable, the LPM has advantages in allowing for multiple sets of fixed effects and ease of interpretation. The LPM is particularly problematic when predicted observations fall outside the 0,1 bounds. In our primary models, no predictions fall outside this range. Moreover, the LPM model can generate bias under certain circumstances. In Table A1, we present the results of logistic regression that addresses the shortcoming of the LPM. The results of the logistic regression closely mirror the findings of our LPM. The effect of the idle index is positive and significant, as expected, under various specifications controlling for temporal dependence, temperature and rainfall, and country, unit, and monthly sources of variation. Note that we omitted observations without variation on the dependent variable to ease the estimation of the model given the inclusion of fixed effects. Table A2 shows the result of the count model. In this count model, we use a LPM model with a count dependent variable. We use this particular count model because of the very left skewed distribution of events. The results can be found in Table A2. Generally, the results remain robust: idle time is positively related to political conflict event. However, the result of SCAD are not statistically significant this is mainly due to the fact that this particular dataset records a lot of small events.

Table A1. Logit models

|  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- |
|  | (1) | (2) | (3) | (4) | (5) | (6) |
|  | SCAD | SCAD | ACLED | ACLED | UCDP | UCDP |
| Idle Index | 0.227\*\*\* | 0.198\*\* | 0.149\*\*\* | 0.123\*\* | 0.114\*\* | 0.083[[1]](#footnote-1) |
|  | (0. 065) | (0.075) | (0. 038) | (0.043) | (0.044) | (0.051) |
| Observations | 143,136 | 142,128 | 151,704 | 150,444 | 139,776 | 138,768 |
|  |  |  |  |  |  |  |
| Location FE | X | x | x | x | x | X |
| Year FE |  | x |  | x |  | x |
| Temp & Precipitation |  | x |  | x |  | x |
| Peace Months |  | x |  | x |  | x |

Standard errors in parentheses; \* p<0.05, \*\* p<0.01, \*\*\* p<0.001

Table A2. Estimations results for count dependent variables

|  |  |  |  |
| --- | --- | --- | --- |
|  | (1) | (2) | (3) |
|  | SCAD | ACLED | UCDP |
| Idle Index | 0.0024 | 0.0243\* | 0.0093\* |
|  | (0.002) | (0.011) | (0.005) |
| Observations | 241,248 | 180,936 | 241,248 |
|  |  |  |  |
| Location FE | x | x | x |
| Year FE | x | x | x |
| Temp & Precipitation | x | x | x |
| Peace Months | x | x | x |

Standard errors in parentheses; \* p<0.05, \*\* p<0.01, \*\*\* p<0.001

1. **Example crop calendar**

Our idle index is based on so-called crop calendars. Figure 1A shows an example of such a crop calendar chart for the Central African Republic. Charts for other countries can be found at <https://ipad.fas.usda.gov/rssiws/al/crop_calendar/wafrica.aspx> (accessed January 11, 2021).

|  |
| --- |
| Chart, bar chart  Description automatically generated |
| Example of a crop calendar chart from the United States Department of Agriculture website. |
| Figure A1. Crop Calendar Central African Republic |

1. **Models Excluding Deserts**

Not all areas under examination are crop-producing. For instance, large parts of the Sahara Desert are characterized by almost no production of crops. We control for this non-production by including location and year fixed effects. However, to make sure that our models are not biased due to artificial zero inflation, we estimated our SCAD models excluding areas with no variation in crop calendars. Table A2 shows the result, which remains robust.

Table A3. SCAD outcomes excluding desserts (areas without crops).

|  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- |
| SCAD Outcome | | | | | | |
|  | (1) | (2) | (3) | (4) | (5) | (6) |
| Idle index | 0.0032\*\*\* | 0.0032\*\*\* | 0.0032\*\*\* | 0.0035\*\*\* | 0.0028\*\* | 0.0028\*\*\* |
| S.E. | 0.0009 | 0.0008 | 0.0008 | 0.0008 | 0.0009 | 0.0008 |
| Per. change | 20.8 | 20.8 | 20.8 | 22.9 | 18.4 | 18.7 |
| Observations | 226,128 | 226,128 | 226,128 | 226,128 | 225,120 | 226,128 |
| R-squared | 0.08 | 0.32 | 0.32 | 0.32 | 0.33 | 0.33 |
| Specification Parameters | | | | | | |
| Location FE | x |  | x | x | x | x |
| Location-year FE |  | x | x | x | x | x |
| Calendar month FE |  |  |  | x | x | x |
| Temp & precipitation |  |  |  |  | x |  |
| Cubic polynomial |  |  |  |  |  | x |
| \* p<0.05, \*\* p<0.01, \*\*\* p<0.001 | | | | | | |

1. **Conditional relationship across the percentage of cultivated land**

Figure 3 in the main manuscript presented the marginal effects of idleness across the percentage of cultivated land. We showed that idle time has a larger impact on conflict when a greater proportion of the land is cultivated. This serves as a placebo test to demonstrate that the effect is present in agricultural areas and not in those locations in which agriculture is not a large proportion of labor. Table A4 presents the coefficients of Figure 3.

Table A4. Conditional Relationship across the log of % of cultivated land

|  |  |  |  |
| --- | --- | --- | --- |
|  | (1) | (2) | (3) |
| Idle Index | -0.002 | -0.003 | -0.003 |
|  | (0.003) | (0.004) | (0.003) |
| idle X log of % Cultivated Land | 0.002 | 0.002 | 0.002 |
|  | (0.001) | (0.001) | (0.001) |
| Observations | 242,928 | 241,248 | 242,928 |
| R-squared | 0.33 | 0.33 | 0.34 |
| Location FE | x | x | x |
| Location-Year FE | x | x | x |
| Calendar Month FE | x | x | x |
| Temp & Precipitation |  | x |  |
| Peace Months |  |  | x |

\* p<0.05, \*\* p<0.01, \*\*\* p<0.001; Standard errors in parentheses.

1. **Spatially weighted lagged dependent variables**

One can argue that our units of analysis are not independent of each other and that conflict might spill over from other areas to the unit of study (Ward and Gleditsch, 2011). To account for the spatial dependence, we calculate a spatial weight matrix based on the distance between the centroid of the first administration. This spatial weight matrix is then multiplied by the lag of dependent variables. Table A5 shows the results in which we control for the spatial correlations. As the table shows, the results remain robust.

Table A5. Agricultural idle time and armed conflict

|  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- |
| SCAD | | | | | | |
|  | (1) | (2) | (3) | (4) | (5) | (6) |
| Idle index | 0.0025\*\*\* | 0.0030\*\*\* | 0.0030\*\*\* | 0.0033\*\*\* | 0.0028\*\* | 0.0027\*\*\* |
| S.E. | 0.0009 | 0.0008 | 0.0008 | 0.0008 | 0.0009 | 0.0008 |
| Per. change | 16.1% | 19.7% | 19.7% | 21.9% | 18.2% | 17.9% |
| Observations | 242,928 | 242,928 | 242,928 | 242,928 | 241,248 | 242,928 |
| R-squared | 0.10 | 0.33 | 0.33 | 0.33 | 0.33 | 0.34 |
| ACLED | | | | | | |
|  | (7) | (8) | (9) | (10) | (11) | (12) |
| Idle index | 0.0066\*\* | 0.0078\*\*\* | 0.0078\*\*\* | 0.0092\*\*\* | 0.0075\*\*\* | 0.0092\*\*\* |
| S.E. | (0.0021) | (0.0018) | (0.0018) | (0.0018) | (0.0021) | (0.0018) |
| Per. change | 7.9% | 9.3% | 9.3% | 11.0% | 8.9% | 11.3% |
| Observations | 182,196 | 182,196 | 182,196 | 182,196 | 182,196 | 182,196 |
| R-squared | 0.26 | 0.47 | 0.47 | 0.47 | 0.47 | 0.48 |
| UCDP GED | | | | | | |
|  | (13) | (14) | (15) | (16) | (17) | (18) |
| Idle index | 0.0033\*\* | 0.0034\*\* | 0.0034\*\* | 0.0035\*\* | 0.0031\* | 0.0035\* |
| S.E. | (0.0013) | (0.0011) | (0.0011) | (0.0012) | (0.0013) | (0.0012) |
| Per. change | 7.9% | 8.1% | 8.1% | 8.4% | 7.3% | 8.3% |
| Observations | 242,928 | 242,928 | 242,928 | 242,928 | 241,248 | 242,928 |
| R-squared | 0.19 | 0.45 | 0.45 | 0.45 | 0.45 | 0.46 |
| Specification Parameters | | | | | | |
| Location FE | x |  | x | x | x | x |
| Location-year FE |  | x | x | x | x | x |
| Calendar month FE |  |  |  | x | x | x |
| Temp & precipitation |  |  |  |  | x |  |
| Time since conflict |  |  |  |  |  | x |
| Spatially weighted lagged DV | x | x | x | x | x | x |
| \* p<0.05, \*\* p<0.01, \*\*\* p<0.001; Standard errors in parentheses. | | | | | | |

1. **References**

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1. [↑](#footnote-ref-1)