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RESEARCH NOTE

Farming then fighting: agricultural idle time and armed conflict

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Abstract
Policymakers and scholars have long proposed that willingness to participate in armed conflict is influenced by citizens' income-earning opportunities. Testing this opportunity cost mechanism has led to mixed results. One reason for this might be the fact that current proxies can also serve as indicators to test grievance-based theories. In this study, we construct a more suitable measure. We use crop calendars and crop location data to build an index of agricultural idle time for first administration units on the African continent from 1990 to 2017. We test the explanatory power of this measure by examining its relationship with armed conflict. Our results show that agricultural idle time increases the probability of observing armed conflict by more than 20 percent.

Keywords: data collection; models for panel data

Opportunity costs play a central role in academic debates about the onset of political unrest, violence, and crime (e.g., Becker, 1968; Grossman, 1991). Grievances are considered by many to be regrettably common in many societies, and political unrest might then also be largely attributed to the viability of, or opportunity for, rebellion. The central claim of those examining opportunity costs is that an individual with a low pay-off for productive work—because of low ability or limited opportunities, for example—is more likely to engage in predatory behavior, such as rebellion, than an individual with a higher pay-off to productive work. While this idea is straightforward, finding solid evidence that low opportunity costs motivate political conflict has proven more challenging.

Although some studies find evidence in favor of an opportunity mechanism (e.g., Miguel *et al.*, 2004; Fjelde, 2014), others find no effect or an opposite one (e.g., Berman *et al.*, 2011; Bazzi and Blattman, 2014). One important factor causing these contradicting findings might be the validity of the existing measures of opportunity costs, such as commodity price shocks (e.g., Dube and Vargas, 2013), climate shocks (e.g., Miguel *et al.*, 2004), and unemployment (e.g., Berman *et al.*, 2011). While these measures do capture the cost of participation in rebellion, they might also capture unexpected changes in income, thereby also measuring individual grievances (e.g., Miguel *et al.*, 2004; Chassang and Padró i Miquel, 2009; Ciccone, 2013; Vestby, 2019). For example, weather shocks can not only decrease an individual's income, thereby decreasing the opportunity cost for rebellion, but it also might exacerbate grievances, (perceived) inequalities between ethnic groups, and grievances against the state, especially when the shock is persistent (e.g., Harari and La Ferrara, 2018).

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In this research note, we propose an alternative cross-national measure for opportunity costs that we think, allows for a better test: agricultural idle time. Historical and anecdotal evidence suggests that rebellion and other contentious political activities are seasonal, depending on the agricultural demand for labor. For instance, Koven (2020) explains the Taliban's annual spring offensive by referring to the opium poppy cultivation cycles: in spring, the harvest season ends, freeing up farmers and workers who are then able to (re-)join the insurgents. The seasonal variation in the demand for agricultural labor is determined by geographic and climatic factors, which dictate in which months necessary agricultural work must be carried out and during which times labor exhibits less urgency. During these agricultural idle times, the opportunity costs for taking part in political conflicts are relatively low as it removes the employment constraints. These idle times, however, are not unexpected. Rather, they are anticipated and of temporary duration. As made clear by Chassang and Padro-i-Miquel (2009), Ciccone (2013), and Guardado and Pennings (2020), this is important because it is especially unanticipated persistent shocks that give rise to grievances and increase the prize of winning. In contrast, changes in the seasonal demand for agricultural labor often do not require a significant change in household behavior to smoothen the income shocks (Jappelli and Pistaferri, 2010) and are therefore useful when exploring the opportunity costs of politically violent behavior. The measure of idle time is also useful because it shows the opportunity costs are relevant even when actors have employment to return to later in the year.

Our index of idle time based on agricultural labor demand is not only an improvement of existing opportunity cost measures, but it also resonates with several studies pointing to the salience of the rural dimension and the agricultural sector for many conflicts (e.g., Fjelde, 2014). Most importantly, we extend the work of Guardado and Pennings (2020), who provide evidence for an association between agricultural labor demand for wheat production and insurgency activity in Iraq, Pakistan, and Afghanistan. By extending the spatial coverage to all African countries, some of which were troubled by political conflict, while others were not, our study provides greater external validity. Moreover, we employ data on the geographic location of crop production and crop schedules for a basket of economically important crops, besides wheat. This is important, as agricultural producers have the incentive to minimize the risk of crop failure by crop diversification and by exploiting unused labor by growing crops on different harvest schedules (FAO, 2015). As such, measuring the demand for labor based on a single crop may bias the estimation or more strongly correlate with weather patterns. Further, we also consider the labor that is required outside the harvest and planting season, by including information on crop maintenance in our agricultural idle index.

1. Methods and data

To examine the potential positive relationship between agricultural idle time and political conflict, we use information on political violence and agricultural labor in Africa. More precisely, our unit of analysis is the first administrative unit-month observations of violence and agricultural activity on this continent between 1990 and 2017. Today, some 54 percent of Africa's working force relies on the agricultural sector for livelihoods, income, and employment, which is more than in any other continent (FAO, 2020).

1.1 Dependent variables

We use three different outcome variables to test our hypothesis to demonstrate the robustness of our results. As our central outcome, we use a binary variable indicating the onset of violent political conflict based on the Social Conflict Analysis Database (SCAD version 3.3; Salehyan *et al.*, 2012) that records monthly violent events initiated by non-state groups against governmental authorities (anti-governmental violence) or members of oppositional groups (extra-government violence).[1] This is important since it has been argued that agricultural workers are an essential human resource of non-state armed groups (e.g., Fjelde, 2014). We also use the onset of conflict events (battles and remote violence) from the Armed Conflict Location Event Dataset (ACLED 2019; Raleigh *et al.*, 2010). This dataset covers more political dissident events than just simply battles. We also use data on state-based and non-state conflict from the Uppsala Conflict Data Program-Georeferenced Event Dataset (UCDP-GED 20.1; Sundberg and Melander, 2013). UCDP-GED defines an event as an incident where armed force was by an organized actor against another organized actor, or against civilians, resulting in at least one direct death. These different measures will help to demonstrate the robustness of our findings to various levels of conflict.

1.2 Independent variables

We use several data sources to create an index that captures the degree to which agricultural labor is demanded in each first administrative unit-month. We argue that this demand for labor is contingent on two factors. First, it depends on the type of crop; some crops need more labor than others. To identify locally grown crops that are, we rely on data collected by EarthStat (Monfreda *et al.*, 2008). This dataset combines national, state, and county-level census statistics to produce a global grid of crop coverage of many different crops. The dataset also allows for the possibility that the same piece of land can be used for multiple crops in a year. Although research has shown that crop location changes little on a decadal timescale (Monfreda *et al.*, 2008), it might be the case that crop coverage is influenced by political conflict, that is, conflict might destroy cropland but can also expand it (Eklund *et al.*, 2017; Linke and Ruether, 2021). Although we cannot entirely rule out this possibility, our measure of crop coverage represents estimated crop coverage around the year 2000 and is consequently time-invariant. This allows us to alleviate concerns about endogeneity by analyzing the effect of idleness on a post-2000 sample.[2]

Second, labor demand also depends on whether the crop requires attention in a particular month. To identify these months, we rely on Crop Calendar Charts from the United States Department of Agriculture's International Production Assessment Division.[3] Each crop in each country has its calendar, which can be divided into planting, growing, maintaining (mid-season), and harvesting seasons. Based on these charts, we code whether a crop is idle if labor is necessary (this means during the planting, mid-season maintenance, or harvest time) (coded as 1), or not (coded as 0). Just as crop location might be endogenous, agricultural activity might respond to ongoing conflict and thus present the potential for endogeneity. However, these crop calendars provide information on the *ideal* harvest and maintenance time for each crop in each country. As such, armed conflict does not influence the observed harvest schedule. Further, if conflict or migration affects actual agricultural schedules, it will cause a measurement error in our idle index, making it more difficult to find evidence.

In our analysis, we focus on 17 crops that represent most of the agricultural production in Africa: barley, buckwheat, cereals, cotton, groundnut, maize, millet, mixed grain, oats, potato, rapeseed, rice, rye, sorghum, soybean, sunflower, and wheat. We then aggregate the coverage dataset and the crop calendar to the first administrative unit with the following index:

$$IDLE_{it} = 1 - \sum_{k=1}^{K} (C_{tk} \cdot L_{ik})$$

[1]For our temporal aggregation, we use the start date of the violent event.

[2]Our time-invariant option might, however, create some measurement error in cases where particular crops are strategically chosen in order to avoid being targeted. However, this will likely bias our coefficients downward as unmeasured and strategically chosen crops will reduce the probability of conflict.

[3]See the Appendix for an example (Figure A1).

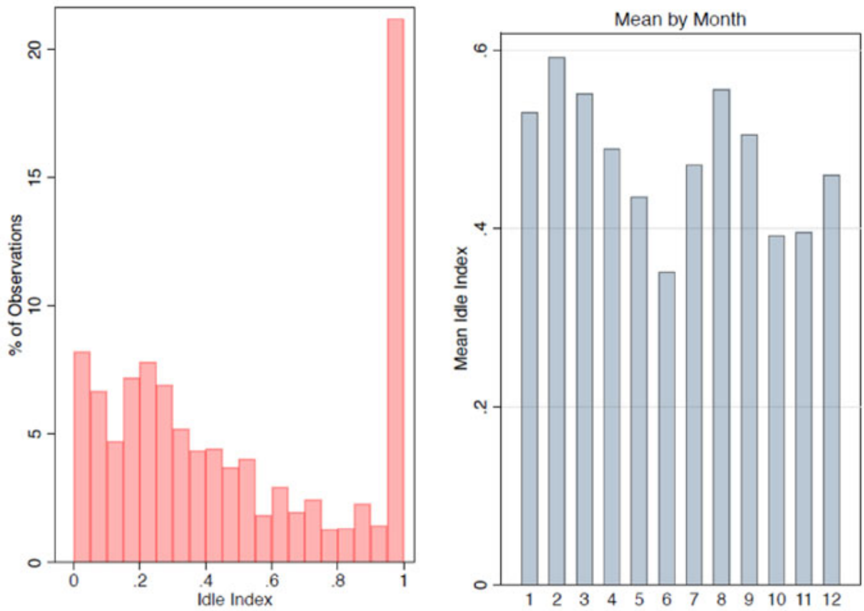

Figure 1. Distribution of idle index.

where C_{tk} represents the coverage share of each crop (k) (as a percentage of total crop area) in each month t and L_{ik} is a binary indicator of whether that crop (k) requires labor in a particular month within a particular administrative district i.

Figure 1 shows the distribution of our agricultural idle index (left panel) and the mean of the idle index for each month across Africa (right panel). Two things are worth noting. First, many localities—such as those in desert areas—do not grow any crops.[4] These observations are excluded from our analysis via the included location fixed effects. Second, the prominence of 1's in our idle index indicates that in some months, no crops require attention in localities. As Figures 1 and 2 demonstrate, however, our idle index varies substantially across time and location. Consequently, using a monthly indicator of seasonality without considering variation based on crop type or location would be misleading.[5]

1.3 Fixed effects and other covariates

In our analyses, we include additional covariates and fixed effects. First, agricultural work and crop coverage might be correlated with the weather, which may have an independent effect on political conflict beyond shocks (Eklund *et al.*, 2017). For instance, weather changes can not only influence the harvest but also the logistics of rebellion and conflict intensity (e.g., Raleigh and Kniveton, 2012; Maystadt and Ecker, 2014). To control for this, we include measures for temperature and precipitation using data from the Climate Research Unit at the University of East Anglia (Harris *et al.*, 2014). We spatially aggregate these daily data to the first administration level and then calculate their monthly average for our analysis. Second, we also control for the effect of previous conflict by including the log of the number of months (*Peace months*) since the last conflict event was observed.

[4]We have also estimated the models without desert areas (Table A2 in the Appendix).

[5]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. To account for this, we have also calculated the models with a spatial weight matrix (Table A5 in the Appendix).

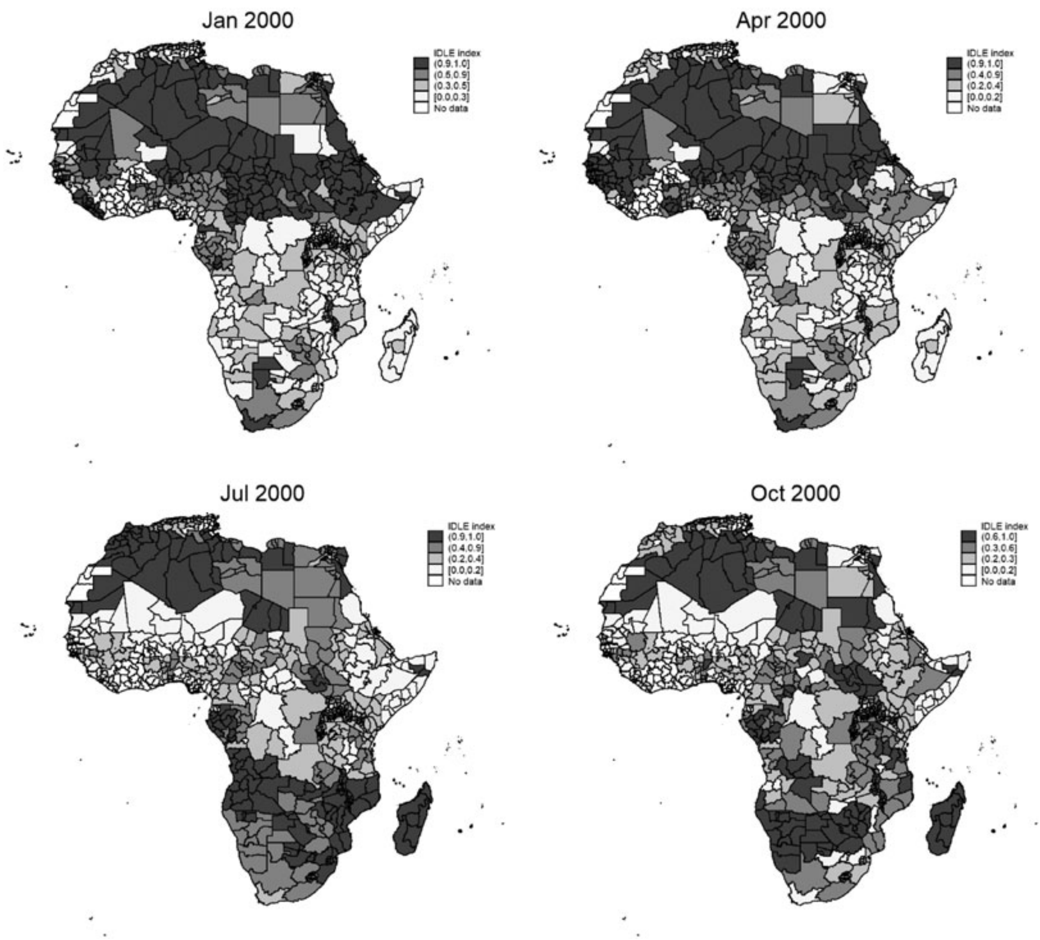

Figure 2. Spatial and temporal variation of the idle index.

In addition to these control variables, we include several sets of fixed effects. First, we include location-fixed effects for the first administrative unit to address the fact that differences in our agricultural idle index are potentially driven by cross-locational factors. Second, we include location-year fixed effects to address effects that might influence the occurrence of conflict. Notably, this ensures that we are picking up within unit-year variation in the dependent variable. Lastly, we include calendar-month fixed effects to address confounding with other reoccurring events, such as holidays, that may correlate with agricultural calendars.

2. Results

We estimate the effect of our agricultural idle index on a binary indicator of conflict using linear probability models (LPMs). LPMs allow for multiple sets of fixed effects and ease of interpretation.[6] Table 1 shows the result of our analysis.

In the top panel of Table 1, using the SCAD outcome, the dependent variable's mean is 0.015. Consequently, a change from a 0 to 1 on the idle index (the maximum change) increases the

[6]The results of the logistic regression models and the count models are presented in the Appendix (Table A1).

Table 1. Agricultural idle time and armed conflict

SCAD						
	(1)	(2)	(3)	(4)	(5)	(6)
Idle index	0.0032***	0.0032***	0.0032***	0.0035***	0.0028**	0.0029***
SE	(0.0009)	(0.0008)	(0.0008)	(0.0008)	(0.0009)	(0.0008)
Per. change	20.8	20.8	20.8	22.9	18.6	18.8
Observations	242,928	242,928	242,928	242,928	241,248	242,928
R^2	0.08	0.33	0.33	0.33	0.33	0.34
ACLED						
	(7)	(8)	(9)	(10)	(11)	(12)
Idle index	0.0083**	0.0083**	0.0083**	0.0101***	0.0081***	0.0101***
SE	(0.0021)	(0.0018)	(0.0018)	(0.0018)	(0.0021)	(0.0018)
Per. change	9.9	9.9	9.9	12.1	9.6	12.1
Observations	182,196	182,196	182,196	182,196	182,196	182,196
R^2	0.22	0.47	0.47	0.47	0.47	0.47
UCDP-GED						
	(13)	(14)	(15)	(16)	(17)	(18)
Idle index	0.0035**	0.0035**	0.0035**	0.0037**	0.0032*	0.0037*
SE	(0.0014)	(0.0011)	(0.0011)	(0.0012)	(0.0013)	(0.0012)
Per. change	8.3	8.3	8.3	8.7	7.5	8.7
Observations	242,928	242,928	242,928	242,928	241,248	242,928
R^2	0.17	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. and precipitation					x	
Time since conflict						x

*p < 0.05, **p < 0.01, ***p < 0.001.

Table 2. Idle index post-2000

	(1)	(2)	(3)	(4)	(5)	(6)
Idle index	0.0037**	0.0037**	0.0037**	0.0043***	0.0038**	0.0035**
	(0.0013)	(0.0012)	(0.0012)	(0.0012)	(0.0013)	(0.0012)
Per. change	17.8	17.8	17.8	20.9	18.3	17.1
Observations	147,492	147,492	147,492	147,492	146,472	147,492
R^2	0.12	0.34	0.34	0.34	0.34	0.35
Location FE	x		x	x	x	x
Location-year FE		x	x	x	x	x
Calendar-month FE				x	x	x
Temp. and precipitation					x	
Time since conflict						x

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

probability of political conflict by ~20.8 percent.[7] This result demonstrates a strong substantive influence of our opportunity costs measure. The remaining models show that our analyses are robust to the inclusion of additional fixed effects and control variables. Across each specification, the substantive effect remains between 18.6 and 22.9 percent. We can then also conclude that the agricultural idle index is associated with incidences of violent political conflict. The results using the ACLED and UCDP data outcomes are consistent with the SCAD models. However, the substantive effect is lower, ranging from 7.0 to 9.6 percent.

Our measure has, however, three limitations. First, if landholders have strategically planted crops in such a way that there are no gaps in labor, our index will indicate idleness where none exists. This will, however, make it more difficult to find evidence for a positive relationship. Second, excess labor may leave the geographically defined unit in search of employment outside the area. If this is the case, this would weaken the explanatory power of our index. Further, it would mean that temporarily unemployed workers would migrate to urban areas with less crop coverage and potentially increase the risk of conflict, via the opportunity cost mechanism, outside our measurement area. Again, however, if this process was playing out it would reduce a possible association between our idle index and conflict. Lastly, our measure of agricultural idle time also fails to consider the amount of labor necessary per agricultural activity and crop. Planting may be more time-consuming than harvesting for one crop, but the reverse may be true for another crop. Currently, however, we lack systematic data on the amount of labor necessary per crop.

3. Robustness tests

To further test the robustness of our index, we ran several additional tests. First, the crop data are collected around the year 2000. This raises the concern that, for at least part of our sample, conflict might be endogenous to crop location. We directly address this by restricting our sample to 2001–2017, the period after the collection of the crop location data. The results of this post-2000 analysis with the SCAD data can be found in Table 2. The table shows that even within this smaller post-2000 sample, agricultural idle time is positively and significantly associated with political conflict. To explore this in even more detail, we show in Figure 3 that the effect persists even when we consecutively limit the sample in separate models from 1990 to 2010. For example, the coefficient above 1995 indicates the effect of an estimation on 1995–2017. Figure 3 demonstrates that it is unlikely that the endogeneity between political conflict in the observation year and the location of crop data collected in the year 2000 is driving our findings.

[7]Alternatively, based on the estimates of model 1, a one standard deviation change in the idle index results in a 7.4 percent increase in the probability of conflict.

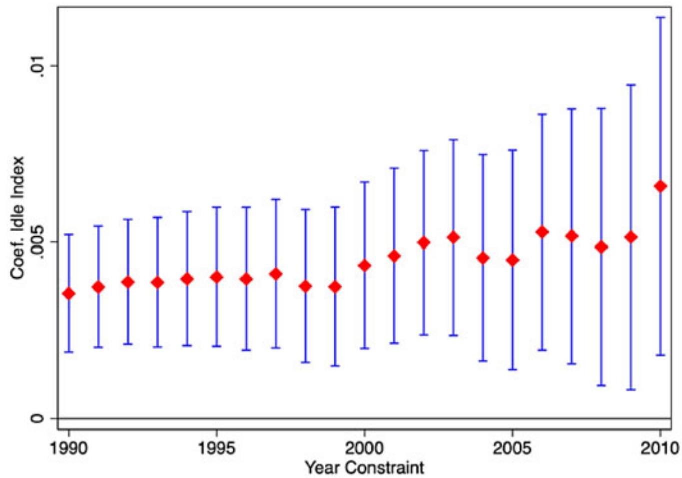

Figure 3. Constrained sample by year.
Note: Each diamond and spike indicates the coefficient and 95 percent confidence interval for each separate model. In each model, we limit the estimated sample to years equal to or greater than the year on the x-axis. Each model includes location-year and calendar-month fixed effects.

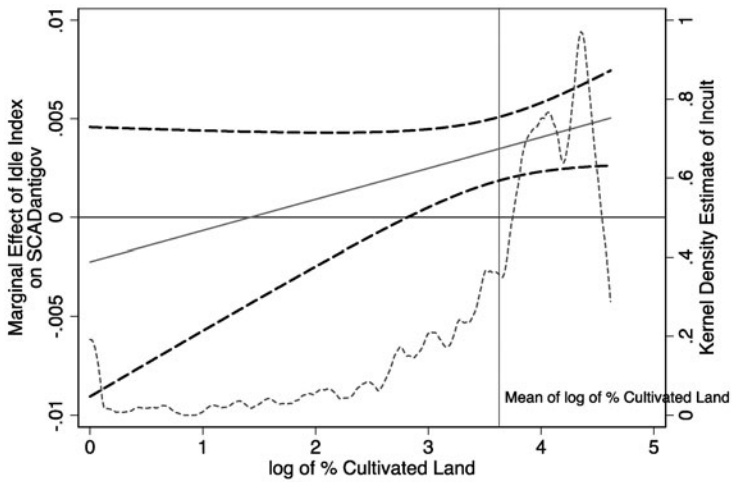

Figure 4. Marginal effect of idleness across the log of the percentage of cultivated land.
Note: Thick dashed line shows the 95 percent confidence interval. The thin dashed line is a kernel density estimate of the natural logarithm of our cultivated land variable.

Second, idle time should have the largest effect on conflict in areas in which agricultural production takes place. To further demonstrate the validity of the measure, we examine the interaction between the idle time index with the natural logarithm of the percentage of cultivated land in each administrative unit. Figure 4 presents the marginal effect (see also Table A4 in the Appendix). The figure shows that our agricultural idle time index is indeed significant in areas with high levels of cultivated land but insignificant in areas with lower levels of cultivated land in which agriculture is not a large proportion of labor. This strengthens our confidence that the idle time index is not a proxy for other mechanisms.

4. Conclusion

Although prominent in the academic literature and often used by the international policy community, evidence for the existence of an opportunity costs mechanism for political conflict behavior is ambiguous and mixed to say at least. One important problem troubling this research is the fact that most proxies used to measure this mechanism are linked with grievances. To overcome this problem, we look at the influence of anticipated agricultural idle time on political conflict events in Africa. Our analysis shows that during agricultural idle times, the likelihood of political conflict is between 7 and 23 percent higher depending on the specification.

These results give rise to many new directions that can be explored in future research. First, although we have argued that having time-invariant information on crop coverage and using the *ideal* harvest time in our idle index does not pose a major problem for our analysis, future research can expand on this project using time variant data, or integrate these calendars into time varying frameworks. Second, our measure can potentially serve as an instrument for other research agendas that examine the impact of income changes on political change and state development. This can be done when examining individual African countries, but one can also think about extending this research to other continents. Third, quantitative country case studies are needed to examine the existence of this mechanism in a more disaggregated fashion. These studies can, for instance, examine how the amount of labor per agricultural activity or the production value per crop affects idle time or how different types of crops (cash versus non-cash crops) might influence this mechanism.

In terms of policy implications, our results provide strong evidence for the existence of the opportunity costs mechanism. One way of increasing the opportunity cost for agriculture laborers to participate in political conflict is by promoting the agricultural development process on the continent. Crop variation might, for instance, decrease idle time, thereby increasing the opportunity costs for participation. Moreover, employment programs or employment subsidies might decrease the opportunity to join.

Supplementary material. The supplementary material for this article can be found at https://doi.org/10.1017/psrm.2024.6. To obtain replication material for this article, please visit Replication Link https://doi.org/10.7910/DVN/8XOFBS.

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