**Agricultural Shocks and Social Unrest in Southeast Asia[[1]](#footnote-1)**

Justin Hastings[[2]](#footnote-2) David Ubilava[[3]](#footnote-3)

*This Draft: 8 November 2022*

**Abstract**

**1. Introduction**

In low–income economies, a small change in people’s wellbeing may exacerbate a whole range of unlawful or violent activities. Where institutions are relatively weak, social unrest—whether it is relatively peaceful and contained or more violent and somewhat out of control—has been linked to changes in people’s real income (e.g., Smith, 2014; Hendrix and Haggard, 2015). Such effect is expected in cities, which not only are populous areas but also places where the state administration—the key target of protesters—resides. Political violence is, by no means, just an urban phenomenon. In rural areas, which often constitute the larger share of states’ territories where the state capacity is limited, civil conflict is common. Motives and modes of conflict vary and may depend on several factors. In regions with high agricultural dependence, which is the focus of the present study, conflict can be linked with harvest-time windfalls. Indeed, empirical evidence points to a strong linkage between crop yields and conflict (Wischnath & Buhaug, 2014; Buhaug et al., 2015; Koren, 2018; Vestby, 2019), and, somewhat less unequivocally, between commodity price shocks and conflict (Dube and Vargas, 2013; Maystadt & Ecker, 2014; Raleigh, Choi, & Kniveton, 2015; Berman and Couttenier, 2015; Crost and Felter, 2020).

The mechanism by which agricultural shocks might lead to civil conflict or social unrest can be reduced to several theories. First is the so-called *opportunity cost mechanism*, which suggests that an individual has an option to farm or to fight, whereby income from the former is an opportunity cost of the latter. The opportunity cost of fighting is seen as an increasing function of income—a negative income shock leading to more violence (Collier and Hoeffler, 1998; Fjelde, 2015). The individual will opt to keep on farming if expected benefits outweigh the costs, otherwise (e.g., after a bad crop year, or the unfavorable change in commodity prices) the individual may consider the less peaceful ways of generating income, should such opportunity present itself. Second is the *rapacity mechanism*, which suggests that perpetrators are more likely to engage in conflict when there is more at stake (e.g., after a good harvest season, or when the commodity prices are high). That is, an increase in farm income increases the value of spoils to be appropriated, which can amplify violence (Koren and Bagozzi, 2017; McGuirk and Burke, 2020). These two mechanisms are apparently offsetting in their impact on conflict incidence, thus leading to an ambiguous net effect of income shocks on conflict in agricultural sector, as illustrated by a large body of literature on the topic, as summarized by Blair et al., (2021).

A careful examination of the data, including the timing of the conflict relative to the within-year income flows and seasonal employment—both likely features of agricultural sector—as well as the forms of conflict and the types of the perpetrators involved, can help disentangle the unique forces that facilitate each of the two mechanisms. Recent studies have showcased the benefits of examining the income-conflict nexus using geographically disaggregated grid cell–level data. Using such approach, McGuirk and Burke (2020) find a positive and statistically significant relationship between cereal crop prices and conflict. More specifically, they define two broad categories of conflict, *factor conflict* and *output conflict*, based on actors’ motivations. Factor conflict, which tends to be long lasting, involves actors engaging in battles for control of a territory to seize its discounted expected returns. The aim of output conflict is to appropriate surplus, and to that end, such conflict is more transitory. To the extent that agricultural output is a readily available source of food and feed, conflict that can be linked with farm income is likely to fall into the output conflict category, as seasonal windfalls can attract perpetrators that are attempting to extract resources without controlling territory (e.g., Koren and Bagozzi, 2017).

At the heart of the question of the link between agricultural production and conflict is not only the mechanism, but also the form of conflict. The foregoing discussion primarily relates to political violence aimed at civilians, and as alluded above, such conflict can be linked to the harvest-time positive income shocks, and the relationship is expected to be positive. On the other hand, protests and related riots are often triggered by grievance associated with negative income shocks, and thus they are unlikely to be connected with agricultural harvest, or if they are, the relationship should be negative, for at least two reasons. First, when people—potential protesters—are busy harvesting, they are unlikely to take part in protests as the opportunity cost of this type of conflict is high. Second, if there is a short period of time, during the calendar year, when people in rural areas are relatively better off, compared to other times of the year or to people in urban areas, it is during or shortly after the harvest season, when the years’ worth of income has been realized. Finally, incidents linked to larger scale conflicts, such as battles between incumbents and insurgents to take control of a territory, for example, are unlikely to be driven by or related to agricultural employment income. And even if they were, the causal mechanism may very well go in the opposite direction, that is, in times of a civil war, for example, people willingly or unwillingly may be involved in the process, in expense of their usual employment, which in rural societies, often is agricultural production.

The foregoing discussion points to the benefit of a careful analysis of granular data. We do so by focusing on countries in the Southeast Asian region. This region is suitable for the present analysis for several reasons. First, most of the countries in the region fall into the lower-middle-income economies, with a considerable proportion of people living at or below the national poverty line (World Bank, 2022a, 2022b). Second, agriculture is a crucial sector for employment and income generation, across much of the region (World Bank, 2022c). Finally, civil conflict and social unrest have been defining features of the region’s politics (e.g., Crost and Felter, 2020; Crost, et al., 2020; Gatti, et al., 2021) **[perhaps some anecdotes here, e.g., insurgency in the Southern Thailand, Myanmar Civil War 2021--, etc.]**.

**2. Data**

*2.1. Conflict*

For social unrest we use the Armed Conflict Location & Event Data (ACLED) compiled by Raleigh et al. (2010) and available at <https://acleddata.com/>. This dataset is highly granular in the sense that: (i) it features any reported conflict regardless of whether the altercation resulted in any casualty; (ii) it groups incidents into six categories, which include *battles*, *strategic developments*, and *explosions/remote violence* that feature two parties, typically the state or state-affiliated militias and the rebels, that dispute the control of a territory, it also includes *violence against civilians* perpetrated by any of the paramilitary groups, as well as *protests* and *riots* that feature different manifestations of public disorder of some sort. The main caveat of this dataset is that it covers a relatively short period of time, from 2010 onward for most Southeast Asian countries except for Indonesia (from 2015 onward), Philippines (from 2016 onward), and Malaysia (from 2018 onward). Moreover, there are very few incidents observed in Brunei, Laos, Singapore, and Timor-Leste, and we omit these countries, which leaves Cambodia, Indonesia, Malaysia, Myanmar, Philippines, Thailand, and Vietnam, for the analysis

The study period, which ranges from 2010 to 2021, covers a total of nearly 60 thousand incidents observed across seven countries. This excludes incidents with the geo-precision code 3 in the database (approximately 2.5 percent of the data), as the exact locations of such incidents are unknown and they are arbitrarily attributed to the nearest known site, typically a provincial capital. Figure 1 illustrates the geographical distribution of these incidents aggregated at the one-degree cell level. Together with the conflict incidents, the figure also features a selected set of large cities in the region. The data on cities were obtained from the World Cities Database available at <https://simplemaps.com/data/world-cities>. From this map, it becomes apparent that: (i) conflict, broadly defined, occurs across much of the Southeast Asian region; (ii) within the region, some countries are more conflict-prone than others; (iii) there is a fair bit of spatial dependence in the prevalence of conflict; and (iv) conflict, while generally more prevalent in cities, where most people reside, is not necessarily and exclusively a city phenomenon.

Map

Description automatically generated with medium confidence

**Figure 1: Geographic distribution of incidents (2010 – 2021) and the major cities**

Note: The conflict data are for Cambodia, Indonesia (2015 – 2021), Malaysia (2018 – 2021), Myanmar, Philippines (2016 – 2021), Thailand, and Vietnam. The size of the dots is proportional to the incidents in a cell, ranging from 1 to 5605 (the southernmost cell of Thailand). The presented cities are the largest, in terms of population, of those with geographic centroid within a one-degree cell. When multiple cities fall within a cell, the largest of these cities is presented. Specifically, featured are the cities with population of more than 0.5 million that fall in the grid cell with aggregated city population of more than 2 million. This rule is arbitrary, and is only used for illustrative purposes, that is, to ensure that a manageable number of cities are presented on the map.

*2.2. Production*

We source the data on cropland cover and harvest months from Sacks et al. (2010) and Monfreda et al. (2008), available at <https://sage.nelson.wisc.edu/data-and-models/datasets/>. We consider two key cereal grains produced across Southeast Asia: rice and maize. While rice is, by far, the most dominant cereal—both in terms of production as well as consumption—in a select few locations, maize is the more cultivated crop. We obtain the fraction of the cropland dedicated to the major crop—i.e., that occupying the larger fraction of the cropland—within a grid cell. The harvest may extend multiple months. We define the midpoint of the harvest season as the *harvest month*. In instances where a crop is grown over two seasons, we use the main season to identify the crop year (however we also record the harvest month for the second season). Within a cell, the fraction of cropland and the month of the harvest remain fixed over the study period.

A picture containing outdoor object

Description automatically generated

**Figure 2: Geographic distribution of rice main season harvest months**

Note: The data are for Cambodia, Indonesia, Malaysia, Myanmar, Philippines, Thailand, and Vietnam. The size of the dots is proportional to the cropland area fraction of a cell, ranging from 0.01 (those with smaller values are set to zero for graphing purposes) to 0.58; the radial bars indicate the count of cells that fall within a given harvest month. Filled bars denote the count of cells with at least 0.01 cropland area fraction.

*2.3. Descriptive Statistics*

In Table 1 we summarize some of the key features of the data. Violence against civilians and protests represent the two most prevalent types of violent events. Incidentally, these two types of conflict typically involve civilians who either are directly targeted (e.g., violent attacks or abduction) or become targets (e.g., intervention against protesters).

**Table 1: Descriptive Statistics**

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
|  | Unit count | Mean | S.D. | Min | Max |
|  | *Unit of observation: cell-year-month (2010 – 2021)* | | | | |
| All conflict incidents | 37764 | 1.581 | 7.916 | 0 | 417 |
| Battles | 37764 | 0.297 | 1.827 | 0 | 63 |
| Explosions/Remote violence | 37764 | 0.179 | 1.837 | 0 | 87 |
| Violence against civilians | 37764 | 0.344 | 2.880 | 0 | 164 |
| Protests | 37764 | 0.541 | 3.641 | 0 | 268 |
| Riots | 37764 | 0.049 | 0.444 | 0 | 42 |
| Strategic developments | 37764 | 0.171 | 1.469 | 0 | 67 |
|  | *Unit of observation: cell* | | | | |
| Cropland area fraction | 359 | 0.062 | 0.087 | 0 | 0.584 |
| Rice | 326 | 0.062 | 0.087 | 0 | 0.584 |
| Maize | 33 | 0.053 | 0.085 | 0 | 0.310 |

Note: the data are for Cambodia, Indonesia (2015 – 2021), Malaysia (2018 – 2021), Myanmar, Philippines (2016 – 2021), Thailand, and Vietnam.

**3. Estimation Strategy**

We denote *location*, which is a one-degree cell, with subscript *i*, and *period*, which is a year–month, with subscript *t*. The units of analysis, thus, are location-period covering 378 unique grid cells across Southeast Asia between January 2010 and December 2020. Because we apply monthly rather than yearly data, we opt for the relatively crude level of spatial aggregation—one-degree cells that measure approximately 110×110 km near the equator—as opposed to finer level of spatial aggregation, e.g., 0.5-degree cells, as used by other studies, to ensure there are sufficient number of units with conflict incidents. The current level of aggregation is granular enough to not sabotage the within-country variation in conflict incidents.

Our main econometric specification is as follows:

(1)

where depicts the number of incidents in cell *i* in period *t*; is the time-invariant cropland area fraction in cell *i*; and is the cell-specific seasonal dummy variable that take the value of one when the period of observation is the months of harvest, and zero otherwise. is a cell fixed effect, and is a year–month fixed effect. is the error term.

The estimated coefficient  reflects the effect of harvest on incidents of social unrest or civil conflict in a hypothetical location with 100 percent cropland. A positive value of the coefficient implies that in the harvest month there is an increase in violence in agricultural cells relative to nonagricultural cells, and that this effect is more pronounced in cells with a higher fraction of cropland. While no cell has the cropland area fraction of 1, there are cells with nearly half or more of the area devoted to crop (namely rice) production. Nonetheless, we scale the estimated coefficient by the expected cropland area fraction when we present the magnitude of the impact.

**4. Results and Discussion**

In Table 2 we summarize the main results of the study.

Increase in violence against civilians and strategic developments

Decrease in protests and riots

Results not sensitive to omitting years prior to 2016

Results are sensitive to omitting Indonesia, Malaysia, and Philippines, mostly as the size of the effects becomes smaller, although the signs of the estimated effects remain unchanged, so the results are statistically weaker but qualitatively comparable to the main results.

**Table 2: Regression results**

|  | **Conflict** | **Battle** | **Explosion** | **Violence** | **Protests** | **Riots** | **Strategic** |
| --- | --- | --- | --- | --- | --- | --- | --- |
| ***Unbalanced panel: all countries, all years*** | | | | | | | |
| Copland × Harvest | −0.017 | 0.014 | 0.022 | 0.098\*\*\* | −0.195\*\*\* | −0.013\* | 0.057\*\*\* |
|  | (0.084) | (0.027) | (0.024) | (0.031) | (0.052) | (0.007) | (0.019) |
| Obs. | 37,764 | 37,764 | 37,764 | 37,764 | 37,764 | 37,764 | 37,764 |
| R2 | 0.399 | 0.34 | 0.329 | 0.411 | 0.256 | 0.124 | 0.33 |
| *Magnitude of the effect:* | | | | | | | |
| Effect (%) | -0.9 | 4.0 | 10.0 | 22.2\*\*\* | -29.1\*\*\* | -22.5\* | 28.3\*\*\* |
|  | (4.4) | (8.0) | (10.8) | (7.1) | (7.8) | (12.6) | (9.5) |
| ***Balanced panel: countries excluding Malaysia, years 2016 onward*** | | | | | | | |
| Copland × Harvest | −0.426 | 0.445 | 0.162 | 0.893\*\* | −2.134\*\* | −0.213\* | 0.421\*\* |
|  | (0.900) | (0.305) | (0.140) | (0.392) | (0.899) | (0.115) | (0.178) |
| Obs. | 23,688 | 23,688 | 23,688 | 23,688 | 23,688 | 23,688 | 23,688 |
| R2 | 0.293 | 0.315 | 0.169 | 0.377 | 0.225 | 0.124 | 0.171 |
| *Magnitude of the effect:* | | | | | | | |
| Effect (%) | -1.4 | 8.3 | 5.2 | 11.8\*\* | -20.3\*\* | -24.5\* | 12.9\*\* |
|  | (2.9) | (5.7) | (4.5) | (5.2) | (8.5) | (13.2) | (5.4) |
| ***Balanced panel: countries excluding Indonesia, Malaysia, and Philippines, all years*** | | | | | | | |
| Copland × Harvest | −0.454 | −0.016 | −0.022 | 0.231 | −0.782 | −0.056 | 0.192 |
|  | (0.517) | (0.158) | (0.141) | (0.192) | (0.584) | (0.078) | (0.149) |
| Obs. | 21,600 | 21,600 | 21,600 | 21,600 | 21,600 | 21,600 | 21,600 |
| R2 | 0.284 | 0.305 | 0.295 | 0.257 | 0.216 | 0.075 | 0.247 |
| *Magnitude of the effect:* | | | | | | | |
| Effect (%) | -1.9 | -0.3 | -0.6 | 8.0 | -9.4 | -11.8 | 5.6 |
|  | (2.1) | (3.1) | (3.5) | (6.7) | (7.0) | (16.4) | (4.3) |

Note: the outcome variable is a count variable that depicts the number of incidents in a cell during a year-month; the treatment variable is the cropland area fraction in the cell interacted with the harvest-month binary variable; the column headed by ‘Conflict’ combines all event types, the other six columns represent the separate event types; all regressions include cell and year-month fixed effects; the values in parentheses are standard errors adjusted to clustering at the level of a cell; \*\*\*, \*\*, and \* denote 0.01, 0.05, and 0.10 statistical significance levels. The magnitudes of the effect, presented in percentage terms, are calculated as:  , where is the parameter estimate, is the average cropland area fraction across all cells with at least some cropland, and is the baseline expectation of incidents, which is the monthly average incidents in cells with at least some cropland.

**5. Conclusion**

**References**

Monfreda, C., N. Ramankutty, and J. A. Foley (2008), Farming the Planet: 2. Geographic Distribution of Crop Areas, Yields, Physiological Types, and Net Primary Production in the Year 2000, *Global Biogeochemical Cycles 22*, GB1022

Raleigh, C., A. Linke, H. Hegre, and J. Karlsen (2010). Introducing ACLED: An Armed Conflict Location and Event Dataset: Special Data Feature. *Journal of Peace Research 47(5)*, 651–660.

Sacks, W.J., D. Deryng, J.A. Foley, and N. Ramankutty (2010). Crop Planting Dates: An Analysis of Global Patterns. *Global Ecology and Biogeography 19*, 607-620

World Bank (2022a). World Bank Country and Lending Groups. The World Bank Group. https://datahelpdesk.worldbank.org/knowledgebase/articles/906519-world-bank-country-and-lending-groups. Accessed 10 Nov 2022.

World Bank (2022b). World Development Indicators. Poverty headcount ratio at national poverty lines (% of population) [Data file]. https://data.worldbank.org/indicator/SI.POV.NAHC

World Bank (2022c). World Development Indicators. Employment in agriculture (% of total employment) [Data file]. https://data.worldbank.org/indicator/SL.AGR.EMPL.ZS

1. Preliminary and incomplete. [↑](#footnote-ref-1)
2. Department of Government and International Relations, University of Sydney [↑](#footnote-ref-2)
3. School of Economics, University of Sydney [↑](#footnote-ref-3)