

Aiding Peace or Conflict?

The impact of USAID cuts on violence

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Abstract: *Less than a week after its inauguration, the second Trump administration issued a blanket stop-work order for USAID, the largest national humanitarian donor. The social and political effects of abrupt aid withdrawal are poorly understood, especially in fragile states where relief is a key safety net. We provide quasi-experimental evidence on the shutdown's impact on subnational conflict across Africa. Leveraging historical exposure to USAID programs, we show that conflict increased sharply after the shutdown in areas that previously received the most support. The increase spans incidence and severity, including armed clashes, protests, and riots. The effects appear immediately and persist for months. Inclusive local institutions substantially mitigate these harms, underscoring vulnerability under weak governance and the capacity of institutions to buffer humanitarian and economic shocks.*

The United States Agency for International Development (USAID) was established by executive order in 1961. As John F. Kennedy noted in a special message to Congress, USAID would serve as a beacon of American commitment to the world, demonstrating that “economic growth and political democracy can develop hand in hand.” (1). Over the next half century, USAID became one of the world’s largest national aid provider, working in more than 100 countries, and focusing on a broad and varied range of humanitarian and development concerns, including micro-business, health, agriculture, biodiversity, education, democracy and governance, economic infrastructure, energy, financial markets, trade capacity, human trafficking, disaster relief, and water (2). The sudden, severe cuts to US aid in early 2025 represent a major policy shift that came for most observers as a surprise, both in terms of scope and speed of implementation. In the aftermath of the shutdown order, coverage of administrative challenges and on-the-ground effects quickly spread. USAID staff were given hours to exit their foreign posts and return to the United States, local contractors were left scrambling to clarify whether and when they would receive payment for services rendered and goods delivered prior to the shutdown, and medical supply and food shortages garnered global attention. Cutting-edge medical research has already highlighted very severe medical impacts of the current foreign aid cuts, resulting in millions of additional deaths (3). Yet the consequences on conflict still need empirical investigation.

Whether foreign aid reduces or fuels conflict and political violence has been a matter for considerable debate over the past fifteen years (4). Moreover, the consequences of large-scale cuts in foreign assistance also remain unclear. Therefore, we ask the following research questions:

RQ1: Were incidents of conflict after the withdrawal of USAID higher in subnational regions of Africa that received higher financial support per capita from US aid before?

RQ2: Was the impact of the USAID withdrawal on some forms of conflict—such as battles, protests and riots, and violence against civilians—more pronounced than for others?

This study presents, to the best of our knowledge, the earliest evidence of the impact of US aid cuts on the incidence of violent events. The analysis contributes to the empirical literature that has reported ambiguous effects of foreign aid and development programs on political violence (see 5, 6, 7 for surveys.) In particular, several studies find that foreign aid and internationally funded development programs—if anything—increase the risk of armed conflict, both at the

national level ([8](#), [9](#), [10](#)), as well as at the subnational level ([11](#), [12](#), [13](#)). Recent work at the subnational level that draws on the same aid data as our study finds that foreign aid is associated with higher levels of targeted political violence against local authorities and politicians, in particular during elections and in the presence of weak institutions ([14](#)). Other work reports, by contrast, a negative association between aid and conflict in some contexts. This includes findings that foreign aid may prevent civil wars from breaking out in the wake of negative economic shocks ([15](#)), that health aid may prevent conflict outbreaks in the context of epidemics ([16](#), [17](#)), and, if conflicts do emerge, aid may shorten the lifespan of violence ([18](#)). At a more granular geographic level, results of a randomized controlled trial in the Philippines, in which households received cash assistance conditional on child vaccination and school attendance, suggest that aid reduced conflict exposure and intensity ([19](#)).

Studies on the consequences of drastic aid withdrawals are rare. Existing evidence at the country level suggests that such aid shocks in the form of reductions in aid increase the incidence of armed conflict ([20](#)). To the best of our knowledge, ours is the only investigation of negative aid shocks at the subnational level and the first study of a sudden large withdrawal of aid. Since USAID was one of the largest organizations responsible for providing aid, examining the impact of such a large withdrawal has not been done before.

Conceptually, there are at least two major countervailing forces that link aid shocks to conflict, the opportunity cost effect (i.e., aid affects earnings and thereby alters the opportunity cost of fighting) versus the rapacity effect (i.e., aid is appropriable and may motivate rent-seeking). As discussed in depth in the Supplementary Materials (SM), the size of these countervailing forces depends on the speed and scale of the shock. Abrupt large-scale aid withdrawals that represent an adverse economic shock that reduces the opportunity cost of conflict are likely to lead to more violent events, whereas the reduction of appropriable rents as a consequence of an aid withdrawal might lead to a reduction in violent events. Which of the effects dominates is primarily an empirical question that we address below.

Method

Study design and measures

The empirical analysis investigates the effect of US aid cuts on conflict using a sample of all countries in Africa for a window of 10 months before and after the reference period for the USAID withdrawal (January 2025), thus covering a 21-month period from March 2024 until November 2025.

The analysis is based on two merged datasets: one tracked US aid disbursements, activities, and donations, while the other dataset tracked violent conflicts. First, with respect to USAID, we draw on a fine-grained, geographically-linked (geocoded) aid dataset that has become available only recently, the *Geocoded Official Development Assistance Dataset* (GODAD, version 1.0, see [21](#)). This dataset contains geocoded information on aid projects from the United States, European donors, China, India, and the World Bank. Various types of aid are distinguished. Information about USAID activities—the focal point of our current study—is available for the 1973-2020 period. To investigate the effect of the USAID withdrawal, we focus on variation in the intensity of USAID activities during the latest four-year window prior to withdrawal (i.e., from 2017 to 2020).

Second, we combine the aforementioned aid dataset with other data on violent conflict from the *Armed Conflict Location and Event Data* (ACLED, see [22](#)), which contains information about the location and date of violent events, the actors involved, as well as the type of event. The ACLED data are based on a wide array of local, national, and international news and data sources in over 75 languages. ACLED draws on an expert team of researchers that verifies and harmonizes the various pieces of information, establishing the best possible geo-referenced records for events.

In addition to an overall conflict measure that captures all ACLED events, we also examine several particular forms of conflict potentially impacted by US aid cuts: battles, protests and riots, and violence against civilians. Specifically, battles represent events involving sustained armed combat between organized armed groups, including engagements with government forces. Protests are public demonstrations where the demonstrators are typically peaceful, while riots are public demonstrations by one or more spontaneously organized groups that typically use violence during the event. Lastly, violence against civilians refers to deliberate acts of violence by organized

armed actors against non-combatants. Robustness checks also make use of other conflict data from the Global Database of Events, Language, and Tone (GDELT), which we detail in SM.

The impact of US aid cuts on conflict is estimated for a sample of 870 subnational regions (“admin1” regions, henceforth, ADM1) covering most of Africa over the period from March 2024 to November 2025. The strategy for estimating the effect of interest is based on different versions of a difference-in-differences design that compares the incidence of conflict during the period of USAID dismantlement (from February 2025 onward, after the blanket stop-work order after the last week of January) relative to the period before the cuts, across locations with varying exposure to the USAID withdrawal. The estimates we present, therefore, leverage the variation in conflict activity before and after the cut across regions with varying degrees of historical US aid exposure. Throughout the analysis, the statistical framework accounts for systematic variation in conflict incidence at the level of each country-month and at the subnational region level by controlling for the respective fixed effects. This specification therefore accounts for a large number of potential sources of bias. Specifically, the empirical model allows for systematic country-wide fluctuations in conflict in a given month (related to, e.g., national elections, epidemics, political events), as well as for time-invariant factors that influence conflict activity across subnational regions in the observation period (e.g., sea access, latitude, altitude, historical factors, or ethnic composition). Addressing concerns about reporting bias in ACLED, the region fixed effects also filter out any time-invariant reporting differences between various regions [as suggested by previous work, e.g., [23](#), [24](#)], while the country-month fixed effects can account for sudden changes in media focus on countries impacted by the withdrawal of USAID support. Standard errors are clustered at the level of ADM1 regions (the level at which we measure aid exposure). See SM section 4 for details.

In addition, event study designs will provide support for the parallel trends assumption and allow for dynamic impacts on conflict (see SM section 5 for details).

Results

The estimates are consistent with the notion that the removal of USAID led to an increase in conflict (Figure 1). The estimation results show the effect of the withdrawal of USAID for different conflict outcomes: for all conflict events (Panel A), battles (Panel B), protests and riots (Panel C), and violence against civilians (Panel D). Each panel contains three sets of estimates, corresponding to three different specifications of the respective conflict variable: a binary measure reflecting the observation of an event of the respective type of conflict, a count of events of the respective conflict type, and a count of the conflict-related casualties (deaths) as a measure of conflict intensity. For each specification, the coefficient estimates as well as the corresponding confidence intervals are displayed. All estimated coefficients are positive. The withdrawal of USAID led to a significant increase in the incidence of any conflict as well as of riots and protests. It led to significant increases in the number of any conflict events, the number of battles, and the number of protests and riots (p-values below 5%). Results for conflict intensity, as measured by casualties, show a significant increase for battle deaths (p-value below 5%). Violence against civilians also experienced increases, but these effects are imprecisely estimated. We conclude that the US aid cuts are associated with increased conflict across a range of different measures.

To help benchmark the magnitude of these estimated effects (which are based on a continuous measure of US aid per capita), one can consider moving from 0 to the 75th percentile of US aid per capita. A shift of this magnitude is consistent with the event study methodology below as well. According to GODAD data for 2017–2020, this corresponds to comparing Kibale (\$0 per 1,000) to Kayunga (\$251 per 1,000) in Uganda. After January 2025, this difference implies an approximate increase of 3.1 percentage points in the probability of conflict (Panel A), which represents roughly a 6.5% increase relative to the sample mean of 0.46. Breaking this down by conflict type, the same quantification suggests a 3.1 percentage point increase in the incidence of protests and riots, or a proportional increase of about 10% in the probability of protests and riots (Panel C). For conflict counts, moving from 0 to the 75th percentile of the US aid per capita implies a 10.6% increase in the total number of events, a 6.9% increase in battle events, and a 5.6% increase in protests or riots. Regarding

fatalities, the effects are generally less conclusive, except for battle-related deaths. After the US aid cut, moving from 0 to the 75th percentile in US aid per capita is associated with a 9.3% increase in battle-related fatalities.

Figure 2 presents estimates of the dynamics of the effect based on an event study methodology. These results rely on a binary indicator of US aid exposure, depending on whether regions are above or below the 75th percentile of the US aid per capita distribution, which corresponds to around 254.2 USD per 1,000 of the population. The event study reveals no statistically significant differences in the number of conflict events between regions with different levels of US aid exposure in the 11 months prior to the announcement of the US aid cuts (see also the temporal placebo tests in the SM section 5.4). After the removal of US aid, regions that benefited relatively more from US aid in the 2017-2020 period immediately experienced a higher frequency of conflict compared to regions that benefited relatively less from US aid. The magnitudes are comparable to the quantification of the results based on Figure 1. Areas that relied heavily on US aid saw an increase in the number of conflict events (of all types) of approximately 12.3%, an increase in the number of battles of around 7.3%, and an increase in protests and riots of around 6.8%. These event study results complement the estimates in Figure 1, by documenting the absence of potential pre-trends in conflict that could bias the difference-in-differences estimates. In addition, the event study sheds light on the evolution of impacts after the aid cut. Whereas protests and riots respond immediately to aid cuts, the effects on battles and violence against civilians intensify over time.

The SM presents a wide range of robustness checks. These additional statistical exercises include: excluding capital cities (SM section 5.1); alternative clustering approaches (SM section 5.2); and, alternative estimates using lower levels of subnational administrative units (“admin2” regions, henceforth, ADM2) as unit of analysis (SM section 5.3). They also present placebo tests for alternative timings of the aid cut and for other donors, as well as results that control for aid disbursed by other donors (SM section 5.4). To investigate external validity, an additional analysis was conducted for alternative data on conflict events from the Global Database of Events, Language, and Tone (GDELT, SM section 5.5), with similar results for protests and riots. Sensitivity checks regarding the precise measurement of aid exposure (in terms of baseline years for measuring exposure to US aid, different measures

and transformations of aid and aid amounts) also deliver comparable estimates (SM section 5.6). Additional results for effect heterogeneity document that the results are consistent across different specifications of the empirical model and reveal additional insights regarding mechanisms. In particular, a break-down of effects by different aid classes (SM section 6.1) shows that our findings are not driven by one particular aid sector. However, there is evidence of heterogeneous impacts depending on the strength of national institutions: The impact of the US aid reduction is stronger in countries that have weaker executive constraints (SM section 6.2). Finally, there is no evidence that exposure to Chinese aid significantly mitigates the impact of the US aid reduction (SM section 6.3).

Discussion

The evidence presented in the current contribution suggests that the radical cuts to US aid in 2025 led to an increase in conflict in the regions that received most US aid. In these regions, conflicts, especially battles as well as protests and riots, have become more frequent. The findings shown here resonate with the statements of some observers who warned of dire humanitarian consequences and rising social tensions following the radical US aid removal ([25](#)).

These results contribute to the previous literature that has reported mixed findings regarding the nexus between foreign aid and conflict. This evidence has been based mostly on variation in local programs, while the consequences of large-scale transnational variation in aid due to the abrupt shutdown of a major aid program, such as USAID, have not been investigated previously to the best of our knowledge.

The empirical results are consistent with earlier evidence that foreign aid makes societies richer, thereby potentially taming armed conflict and political violence ([26](#), [27](#)). A number of studies report that development aid programs reduce conflict locally ([19](#), [28](#)) or at the country-level ([15](#)). On the other hand, some voices, including in this journal, have argued that cutting aid and reducing dependencies might ultimately be required to foster self-reliance ([29](#)). This argument is based on the view that foreign aid does not help create an environment of sustained prosperity and peace by increasing the opportunity costs of conflict, but instead facilitates corruption and conflict by injecting rents to fight for – not dissimilar to natural resource rents resulting in a “resource curse” ([30](#), [24](#)). As highlighted in the introduction, a substantial body of evidence finds indeed that aid increases the risk of armed conflict ([8](#), [9](#), [10](#), [11](#), [12](#), [13](#), [14](#)).

The novel findings of the current contribution can be readily reconciled with the mixed results of the previous literature. In particular, existing work typically examines the impact of aid surges, and more generally the effects of marginal or gradual variation in aid, whereas the analysis of the current article investigates the consequences of a substantial and sudden drop in aid that is historically unprecedented. Thus, conceptually, the findings here do not contradict earlier findings of aid contributing to recurrent conflict. One existing study that focuses on negative aid shocks to specific countries finds that reductions in aid increased conflict risk at the country level between 1981 and 2005 (20). This work is consistent with our findings, but causal identification is more challenging in the context of country-specific aid adjustments, as these can be endogenous to conflict processes. In contrast, the present study investigates an exogenous and unanticipated shock of unprecedented scale that affected all recipients at the same time, and we focus on the subnational impacts of this aid shock.

The empirical findings on the link between the withdrawal of USAID and conflict can be rationalized by the theory-grounded forces reflected in canonical conflict models (a detailed discussion of a theoretical framework and previous results in the literature is contained in SM section A). In particular, aid may affect conflict through two major countervailing forces, the opportunity cost effect and the rapacity effect. Aid inflows, by improving local economic conditions and earnings, are associated with higher opportunity cost of conflict and thereby contribute to a reduction of conflict. However, by creating rents that can be appropriated by groups of the population, aid inflows could also induce an increase in conflict by inducing parties to fight over the distribution of these rents. This rapacity effect is often alluded to by proponents of aid withdrawal.

Importantly, the withdrawal of aid may not necessarily have a symmetrically opposite impact on conflict compared to a rise in aid inflows. A key factor is the speed and magnitude of a change in aid. In the context of a large and abrupt drop in aid, the effect might operate mostly through a sudden and massive decrease in the opportunity costs, while the rents of conflict may remain relatively unaffected in the short run — for example because these rents include capital and infrastructure that past aid flows have helped to create. In such a scenario, a sudden collapse in aid would be associated with a surge in conflict, consistent with the empirical results on the consequences of the demise of USAID.

A potential moderator of the impact of the USAID withdrawal on conflict is the quality of institutions. In countries with strong institutions, the aid cuts are expected to have smaller impacts on conflict than in countries where institutions are weak. This hypothesis is informed by earlier work that has found that strong institutions weaken the relationship between aid and conflict ([10](#)). Additional analysis in the SM investigates this hypothesis in the context of the USAID withdrawal based on a measure of executive constraints from the Polity V data ([31](#)). This evidence supports the hypothesis that stronger institutions mitigate the impact of the US aid cuts on conflict.

The empirical analysis in this article has a number of limitations that need to be kept in mind when interpreting the results. First, the identification relies on historical exposure to US aid in combination with the timing of the sudden withdrawal, not on direct measurements of cuts. Thus, while informative about the overall effects of the withdrawal on conflict, the results remain limited regarding the precise mechanisms that lead to the outbreak of specific violent events. In particular, the US aid cuts are likely to have had pronounced effects on economic conditions, which are difficult to measure as systematically and quickly as conflict outcomes. More work is needed to document these economic mechanisms precisely.

Second, our study focuses on a sample of all African countries, in line with existing work on the economic drivers of conflict ([24](#), [27](#)). This setting reduces the heterogeneity between regions in terms of income levels, institutions, colonial legacy, and baseline conflict dynamics, improving the validity of statistical comparisons between areas with and without direct exposure to the sudden shutdown of USAID ([32](#)). In addition, Sub-Saharan Africa has received a large share of American humanitarian and development assistance, with aid portfolios more heavily weighted toward civilian health, food security, and basic service delivery than in other regions ([33](#)). As a result, this region offers a setting with comparable intensity of treatment and relatively direct pathways from aid shocks to welfare and stability outcomes ([34](#)). It is also a study context that is likely to yield valuable insights for humanitarian policy debates ([35](#)), particularly given the concentration of fragile states and ongoing conflict settings where aid shocks may amplify violence or governance breakdowns ([36](#)). However, it is possible that the aid cuts in this paper had differing effects in other regions, where US aid was more closely tied to military objectives or drug enforcement.

Third, the evidence of the current contribution does not imply a statement about the (multidimensional) efficiency or welfare effects of US aid over past decades. The global impact of aid cuts may evolve in the near future as well. In particular, in the wake of the USAID shutdown, other countries announced plans to reduce their aid contributions (though the reductions were smaller in magnitude and designed to phase-in over the next few years). Hence, the estimated effect on conflict of US aid cuts may constitute a lower bound to the overall, long-term effect that sets in once other organizations and aid donors lower their aid contributions in the near term. Methodologically, it is much harder to estimate these effects than the effect of the unexpected, sudden, and drastic withdrawal of USAID. Additional work on this point is needed, drawing on more months of data.

Finally, in the very long run, one may typically expect adaptation. This could attenuate the estimated effect some years down the road. Thus, it is clear that even if we document sustained increases in conflict after the US aid cuts, we cannot speak to longer-term impacts. We leave this question for future research, but it is worth keeping in mind that surges in conflict today do not bode well for the future, given the evidence that recent conflict is the most powerful predictor of future conflict ([37](#)) and the risk of entering “conflict traps” ([38](#)).

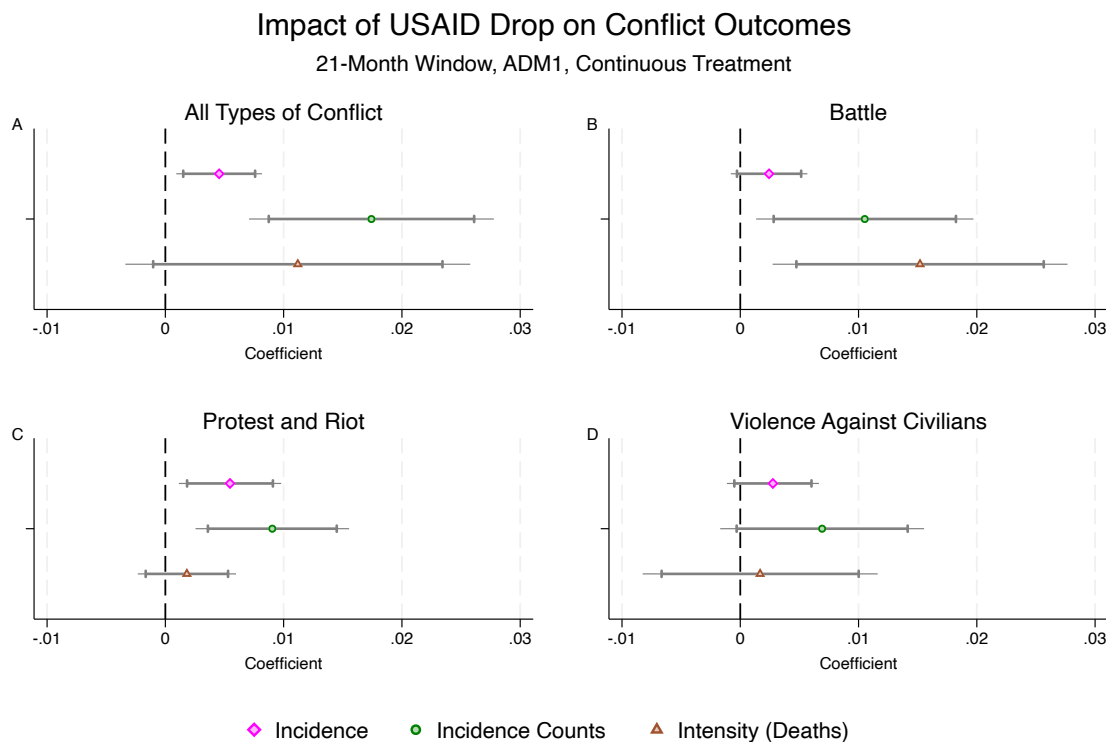


Figure 1: The USAID withdrawal led to an increase in conflict in the most affected regions. The figure plots coefficient estimates of a difference-in-differences design that compares conflict outcomes before and after the 2025 shutdown of USAID, between subnational regions with varying levels of US aid exposure. The unit of observation is a subnational region by month. The sample includes 870 subnational regions across Africa, tracking conflict outcomes from March 2024 to November 2025. US aid exposure is measured using a continuous variable of disbursements per capita during 2017-2020 (scaled by 1,000 inhabitants and inverse hyperbolic sine-transformed). The empirical model includes country-month fixed effects and subnational region fixed effects. Outcomes include: (A): all types of conflict events; (B): battles; (C): protests and riots; (D): violence against civilians. (A-D): Markers indicate different outcome margins: pink diamonds for incidence (binary outcomes), green circles for incidence counts (inverse hyperbolic sine-transformed counts), and brown triangles for intensity (inverse hyperbolic sine-transformed fatalities). The whiskers show the 95% confidence intervals around the point estimate, while the lines represent the 90% confidence intervals.

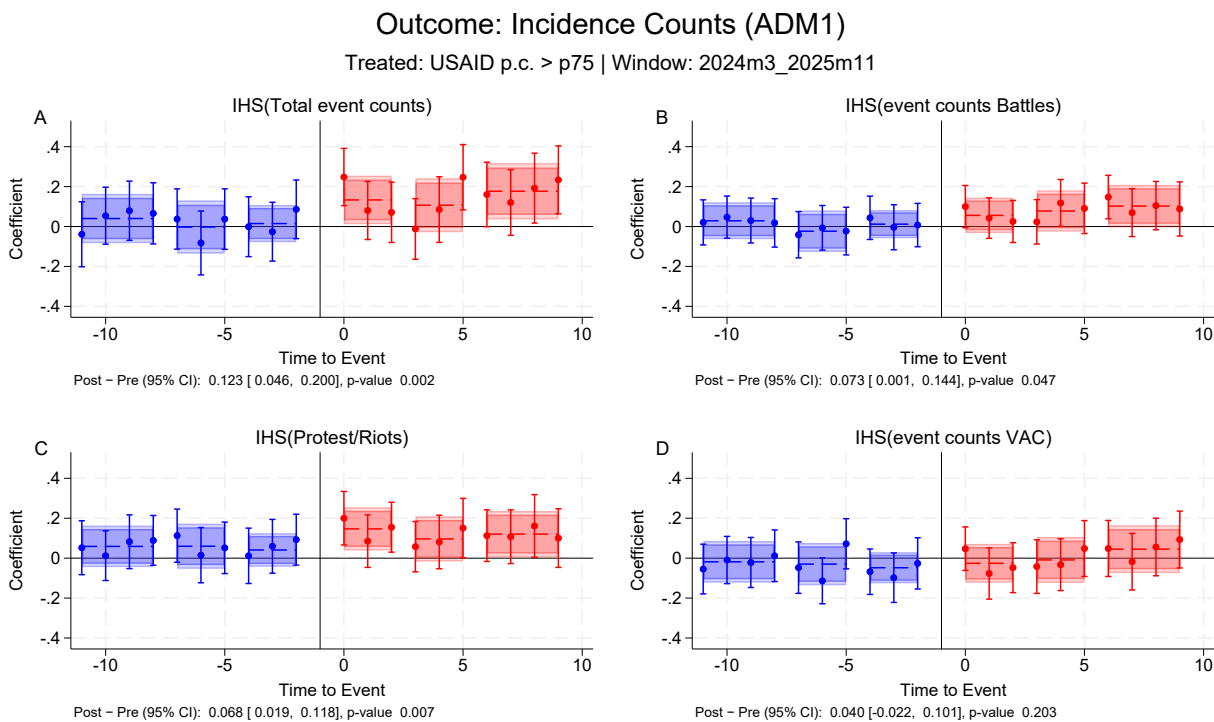


Figure 2: Time pattern of conflict around the USAID withdrawal indicates an immediate increase. The figure plots the results of an event-study for subnational regions. The outcome variable is conflict incidence counts (inverse hyperbolic sine transformed). Treated subnational regions are defined as those that received US aid disbursements above the 75th percentile of the distribution across all subnational regions between 2017 and 2020 and are therefore most likely to be affected by the USAID cut-off. The unit of observation is a subnational region by month. The sample includes 870 subnational regions across Africa, tracking conflict outcomes from March 2024 to November 2025. The horizontal axis is centered at February 2025 ($t = 0$), with the preceding month (January 2025, $t = -1$) normalized as the reference period. The empirical model includes country-month fixed effects and subnational region fixed effects. Coefficients are plotted with their 95% confidence intervals. Block averages are shown with dashed lines indicating the block means. The darker shaded areas represent 90% confidence intervals, and the lighter shaded areas indicate the corresponding blocks' 95% confidence intervals.

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Supplementary materials

Supplementary Text

Figures S1 to S6

Tables S1 to S25

References (39)-(55)

Supplementary Materials for

“Aiding Peace or Conflict? The impact of USAID cuts on political violence”

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Supplementary Text

Figures S1 to S6

Tables S1 to S25

References (39) – (55)

1 Conceptual background in light of conflict theory

In what follows, we briefly discuss our empirical results in the light of the existing theoretical conflict literature. This discussion is meant as a rationalization of the empirical findings in light of theoretical mechanisms that have been emphasized in the conflict literature, and not as a formulation of hypotheses for testing a specific model or mechanism. This discussion is illustrative but not exhaustive, and from a theoretical perspective, various alternative mechanisms could give rise to similar countervailing forces and rationalize the empirical results as well.

One way to make sense of the empirical results is with reference to the canonical workhorse model of the strand of the literature on armed conflicts that formalizes conflicts as rent-seeking activities [for surveys, see (7, 39).] It turns out that many model features and policy relevant predictions of such canonical rent-seeking settings can be similar in models of conflict as bargaining failure (6, 40).

Consider two groups in a region, i and j , where group i is in power and represents the government. The groups could reflect ethnic or political divisions. The opposition group j can engage in a series of potential types of conflict, ranging from peaceful protests to full-scale armed battles. Here we will think of the types of conflict that are feasible in a given place and time as either driven by exogenous shocks or as not mutually exclusive, which allows us to abstract from any trade-offs between selecting different conflict types. In a more elaborated setting one could think of different conflict types as inter-linked, but the qualitative arguments made below would remain equivalent.

Both the government i and opposition j fight over the appropriation of some rents R . These can include, for example, natural resource windfalls, spoils from appropriating foreign aid money, or non-monetary stakes including civic rights or the expression of grievances. The overall incentive for appropriation of rents and spoils has been referred to in the literature as *rapacity effect*.

The canonical conflict models typically contain a conflict success function that maps fighting efforts (labeled f_i, f_j) into the probability p of group i winning the conflict. We focus on the simple ratio form, with $p = \frac{f_i}{f_i + f_j}$. There is also a time constraint of total working and fighting time adding up to 1, which reflects

an *opportunity cost* of lost earnings from productive activities (or any type of income that requires time or

effort), captured by wages w .

Putting these elements together, the expected payoffs for each group are given by

$$\pi_i = \frac{f_i}{f_i + f_j} R + (1 - f_i)w$$

$$\pi_j = \frac{f_j}{f_i + f_j} R + (1 - f_j)w$$

When solving this simultaneous one-shot game, the unique interior Nash equilibrium is characterized by

$$f_i^* = f_j^* = \frac{R}{4w}.$$

In this model environment, foreign aid can entail greater appropriable rents R (the *rapacity effect*), as well as higher wages w (the *opportunity cost effect*). In contrast, aid removal reduces R and w . For the equilibrium fighting levels $f_i^* = f_j^* = \frac{R}{4w}$, the impact of a simultaneous drop in w and in R is a priori ambiguous, yet—to the extent that earnings may adjust particularly rapidly—one would (at least in the short run) typically think of the lost (wage) earnings (*opportunity effect*) to be much more substantial than the lost appropriation potential (*rapacity effect*). If that is the case, the denominator of the above expression would be reduced more than the numerator, and overall conflict (protest, riots, battle fighting) would surge.

Further, when it comes to violence against civilians, a substantial part of it may reflect government repression by standing policy and army forces. For this type of violence the opportunity cost effect of reduced wages may play less of a role, and hence we would typically expect less of an impact of aid withdrawal on this type of violence.

Importantly, the impact of positive and negative aid shocks may not be symmetrically opposite. One key element of the setting is that the relative size of the opportunity cost effect and of the rapacity effect may well depend on how sudden and large-scale changes are. In some contexts it may well be that a gradual, marginal increase in foreign aid may have stronger effects on R than on w (for example, if people's economic activity only slowly embraces new opportunities created by financial inflows), leading to an overall increase in fighting, as found in several papers in the literature. In contrast, very sudden large-scale collapses in foreign aid may result in large negative economic shocks, reducing very drastically the opportunity cost of conflict (but not so much R), and hence also leading to a surge in conflict.

Put differently, to the extent that the speed and magnitude of aid in- and out-flows is different, we would typically not expect the impact of outflows to be the mirror image of inflows. In principle, the magnitude of inflows and outflows could differ by type of aid. In particular, one could expect social and humanitarian aid to have a more direct impact on opportunity cost.

In this framework, institutions may play a moderating role, as has been found in the literature ([10](#)). In particular, strong institutions could limit the extent to which rents are appropriable by force, thus reducing R . In equilibrium, this lowers fighting efforts and limits the extent to which the lost economic opportunities push people into conflict.

Even if the above canonical conflict model can account for the findings of the current article and the previous literature, this of course does not preclude the validity of other conceptual frameworks. As mentioned above, models of conflict as bargaining failure ([6](#), [40](#))—stressing commitment problems and asymmetric information—may account for the observed empirical patterns as well. For example, in settings featuring commitment problems during averse aid shocks, rebels may gain bargaining strength relative to the government ([20](#)). To appease them, the government must promise future resource transfers, but has no incentive to continue its promised transfers if the aid shock proves to be temporary. With the government unable to credibly commit to future resource transfers, violence can break out in the face of sudden drops in aid.

2 Comparable foreign aid disruptions

The sudden and largely unexpected withdrawal of USAID, one of the world's largest donors, is exceptional. As discussed in the introduction, this provides a unique methodological opportunity to investigate the relationship between aid and conflict. First, in the past 5–10 years, numerous donors have announced to reduce their aid contributions or already substantially cut aid. However, these reductions have been gradual and stretched over an extended period of time, and occurred in different steps (e.g., [41](#), for Germany). In contrast, the withdrawal of USAID arrived with un-precedented speed and extent, enabling a difference-in-difference identification strategy to isolate its effect on conflict outcomes. However, from a more general perspective, the estimates might constitute a lower bound for the global increase in conflict

due to the reduction in aid by other donors.

Examples of earlier drastic cuts in aid include a 4 billion USD drop in Japanese aid in 2001, and [Table S1](#) provides an overview of other large-scale cuts in aid at the donor country level. As these donors are smaller in size, we expect the impact of these cuts to be smaller and/or more localized than the recent US aid cuts, which makes it challenging to estimate the impact of these historical cuts on conflict dynamics. Focusing on particular recipient countries, examples of large shocks include the abrupt cuts of French aid after coups in the Sahel. However, in contrast to the withdrawal of USAID, these instances do not provide similarly ideal settings to evaluate the effect of sudden aid stops on conflict, as the coups are likely to have affected conflict dynamics directly. Another relevant dimension to keep in mind is that much of the literature has focused on rapid up-scaling of aid and found conflict-inducing effects. However, as explained in the theoretical framework, one would not necessarily expect symmetric effects in this context.

3 Data Description

3.1 Geocoded USAID Data

The main data source for measuring the subnational region is the Geocoded Official Development Assistance Dataset (GODAD) ([21](#)). GODAD geocodes aid projects for the United States and 18 European bilateral donors using raw project data from the OECD's Creditor Reporting System (CRS), covering the period up to 2020. Geographic locations are inferred from project titles and descriptions in the CRS, which provide detailed textual information. In addition to project-level data, GODAD also includes aggregated datasets at the subnational level.

Since aid projects may generate spillover effects beyond a single point defined by latitude and longitude, we use first-order subnational regions ("admin 1", henceforth ADM1) as our unit of analysis. First-order regions are one level below the national government and include units such as provinces, states, oblasts, governorates, or emirates, depending on the country ([42](#)). To measure the average US aid support for a subnational region from 2017 to 2020, we rely on yearly disbursements in constant 2014 US dollars. Disbursements are preferred over commitments because they capture the funds actually transferred, not merely those pledged. We also consider aid from other donors, namely from the World Bank, China, and

major European donors. These data provide a measure of the exposure of regions to other donors, which is used for additional robustness analysis. We note, however, that China does not report or define official development assistance (ODA) in a way comparable to the Western definition. The data on Chinese aid commitments included in the GODAD data are drawn from the “Banking on Beijing” project, which compiles information from open sources ([21](#), [55](#)).

3.2 Political Violence Data

We identify political violence events and associated fatalities using the Armed Conflict Location and Event Data (ACLED) ([49](#)). For the most recent 12 months, publicly-available data are aggregated at the subnational ADM1 region and weekly level (and not at the level of disaggregated events). We obtain data in this format for a window of 10 months before and after our reference period of January 2025, so ranging from March 2024 until November 2025. We aggregate these weekly observations for each ADM1 region at the monthly level. In addition, researchers may request access to the most recent disaggregated events data from ACLED on a case-by-case basis. We requested and obtained this type of dataset to perform robustness checks at a finer spatial unit (ADM2, one subnational level below ADM1). Each political violence event is categorized into broad types, including battles, strategic developments, protests, riots, remote violence/improvised explosive devices, and violence against civilians. In terms of specific conflict types, we focus on battles, protests and riots, and violence against civilians, as these are the outcomes most likely to be affected by the US aid drop. Specifically, battles represent events that involve sustained armed combat between organized armed groups. Protest is a public demonstration where the demonstrators are peaceful, while riot is a public demonstration by a spontaneously organized group that uses violence. Additionally, violence against civilians (VAC) refers to deliberate acts of violence by organized armed actors against non-combatants. As the distribution of the number of conflict events (as well as the number of fatalities) is skewed and has extreme values, we rely on inverse hyperbolic sine (IHS) transformations for our main results.

3.3 Additional Data

Subnational population estimates. We obtain population estimates from WorldPop ([43](#)), which provides

high-resolution gridded population data derived from remote sensing methods. These data are useful for subnational analysis in contexts where census information is scarce or outdated. Using the gridded population layers, we aggregate population counts to the ADM1 level. We then normalize average US aid disbursements by 2020 population and scale the resulting measure per 1,000 inhabitants. This normalization facilitates meaningful comparisons across subnational regions of different sizes.

Climatic shocks. We also derive climate shock measures from ERA5 (44). ERA5 provides high-resolution reanalysis data on temperature and precipitation, allowing us to identify extreme weather events at the subnational level.

Political institutions. We construct a measure of cohesive political institutions using Polity V (31). Polity V reports annual indicators of political institutions. We construct the cohesive political institution measure using executive constraints variable from Polity V. The executive constraints variable measures “the extent of institutionalized constraints on the decision-making powers of chief executives” (45). We adapt the approach to contemporary African settings by defining cohesion as the share of years between 2000 and 2018 in which a country’s executive constraint score is above the continent’s median during this period (10).

3.4 Summary Statistics

Table S2 presents summary statistics. The dataset includes 870 African subnational (ADM1) regions observed during 21 months. Regarding conflict-related measures, the median of these variables is zero, reflecting that at least half of the ADM1 regions did not experience any conflict events during the study period, although the standard deviations are high. Among conflict types, battle events are less frequent than protests/riots or violence against civilians, but they are the deadliest. In contrast, protests and riots occur more frequently, but tend to be the least deadly type of conflict during the study period.

US aid per capita (scaled per 1,000 inhabitants) has a mean of 857.64 USD (constant 2014 US dollars) and a median of 11.46 USD. We also report summary statistics for IHS-transformed US aid per capita, disaggregated by sector and aid type, along with comparable summaries for other major donors.

Relative to US aid disbursements, aid flows from other donors more frequently target sparsely populated regions, which explains the comparatively high means observed for these variables in the summary statistics. All additional variables included in the regression analysis are reported as well, and their definitions are provided in [Table S3](#).

4 Additional Results

4.1 Tabulated Results

In this section, we report the tabulated results corresponding to Figure 1. The regression follows the specification

$$Conflict_{ict} = \alpha + \beta (USaid_i \times Post_t) + \gamma_{ct} + \delta_i + \varepsilon_{ict}$$

where a continuous measure of US aid exposure (per capita USAID received prior to the cut), $USaid_i$ is interacted with a binary indicator, $Post$, that takes value 1 for all months following the US aid reduction (February 2025 onwards). The US aid per 1000 capita variable is transformed using the inverse hyperbolic sine (IHS) function to accommodate zero values and substantial variation in magnitude. When the dependent variable is binary, the coefficients can be interpreted as the percentage-point change in the probability of conflict occurrence. When the dependent variables represent event counts or fatalities, they are also adjusted using the IHS transformation.

We include ADM1 region fixed effects to account for unobserved, time-invariant characteristics that may influence the level of pre-cut US aid. By including country-month fixed effects, we focus on within-country, within-month variation. A positive and statistically significant coefficient would indicate that regions receiving a relatively high amount of US aid experienced a significant increase in conflict-related outcomes, with larger pre-cut levels of US aid associated with a greater increase in conflict.

[Table S4](#) tabulates the coefficients shown in Figure 1. The results indicate that regions receiving US aid experienced a higher likelihood of conflict incidence. To provide a sense of magnitude: a one standard deviation change in the aid per capita variable (before the IHS transformation) corresponds to a change of

9 in the IHS-transformed variable; moving from 0 to the 75th percentile of the aid exposure distribution corresponds to a 6.23 increase in the IHS-transformed variable; the IHS-transformed variable has a standard deviation of 3.34. These values represent “typical shocks” that can be used to quantify the estimated impacts. Focusing on a 6.23 increase and applying the estimated coefficient (so moving from 0 to the 75th percentile), this change is associated with an approximate rise of 3.1 percentage points in the probability of conflict, which represents roughly a 6.5% increase relative to the sample mean of 0.46. Breaking this down by conflict type, the same quantification suggests a 3.1 percentage point increase in the incidence of protests and riots (about a 10% increase in overall protest/riot likelihood).

For conflict counts, moving from 0 to the 75th percentile of the US aid per capita, implies approximately a 10.6% increase in the total number of events (0.017×6.23), a 6.9% increase in battle events, and a 5.6% increase in protests or riots. Regarding fatalities, the effects are generally less conclusive, except for battle-related deaths. After the US aid cut, moving from 0 to the 75th percentile in US aid per capita is associated with an approximate 9.3% increase in battle-related fatalities (0.015×6.23).

Even among regions that received some US aid, the effects are substantial: comparing Iganga (\$49 per 1,000) to Kitgum (\$1,393 per 1,000), both in Uganda, implies approximately a 5.7% increase in total events, a 3.7% increase in battles, a 3.0% increase in protests and riots, and a 5.0% increase in battle-related fatalities.

4.2 Event Study

In this section, we present additional event study results. These results rely on a binary indicator of US aid exposure, depending on whether regions are above or below the 75th percentile of the US aid per capita distribution, which corresponds to around 254.2 USD per 1,000 of the population. Figures S1 and S2 present results for different margins of conflict outcomes: incidence and intensity (measured by fatalities). Both figures use the same specification as in the main event study in the article. [Figure S1](#) shows that the probability of any type of conflict and the occurrence of protests and riots are significantly higher, while the probability of battles does not increase significantly. For conflict-related fatalities, [Figure S2](#) displays a less

conclusive pattern in general, but still shows significant increases in the number of battle-related fatalities when comparing the pre- and post-treatment period. In [Figure S3](#), we implement an alternative definition of treated and control regions, classifying a region as treated if it received any US aid disbursements between 2017 and 2020, rather than using the 75th percentile threshold. This approach allows us to assess the robustness of our main event study to an alternative treatment definition.

5 Robustness

5.1 Excluding Capital Cities

Capital regions frequently appear to receive more aid, in part due to project reporting conventions that attribute nationally scoped initiatives to the capital. Additionally, because of their political and economic significance, capital regions are more likely to experience political violence compared to other areas. Given their specific status, robustness checks replicate the baseline results in [Table S4](#) for samples excluding regions of the capital city. To identify capital cities and regions, we cross-reference the GADM 3.6 dataset ([46](#)), which provides subnational administrative boundaries, with the World Cities database ([47](#)), which includes geocoordinates of major cities, including national capitals.

The corresponding results are shown in [Table S5](#). Across different outcomes, the baseline results remain robust and are statistically similar. Excluding capital regions increases both the magnitude and precision of the estimated impact of US aid cuts on protest and riot incidence counts. This aligns with the motivation for this robustness exercise: capital regions in most countries are treated and may be recorded as receiving disproportionately large aid due to reporting practices, but they also tend to experience protests and riots regardless of US aid cuts. Including them may therefore underestimate and add noise to the measured impact of US aid reductions on protest and riot incidence counts. The results confirm that our findings are not driven by capital cities.

5.2 Alternative Clusters of Standard Errors

To account for potential correlation in unobserved shocks within regions over time, standard errors are

clustered at the subnational (ADM1) level in the baseline analysis. This is the natural level of clustering, given that the USAID data varies at the ADM1 level and our empirical design only exploits within-country variation. Still, as a robustness check, additional analysis was conducted with clustering at the country (ADM0) level as an alternative to the baseline specification. Clustering at the higher country level allows for arbitrary correlation of the error term across regions within a country, addressing concerns that regional shocks may be spatially correlated due to shared national factors, such as political instability, policy changes, or reporting practices. The corresponding results are reported in [Table S6](#). Our results remain broadly consistent when standard errors are clustered at the country level. Among the coefficients that are statistically significant in the baseline (ADM1-clustered) specification, those for protests and riots as well as for overall conflict retain their significance (at 10%). For battles, the coefficients of interest become marginally insignificant. However, the effect on battles intensifies over time, and in [Table S7](#) we still find significant effects on battles in the last four months of our post-treatment period.

In [Section 5.4](#) below, we also develop a placebo test in which we randomly reshuffle all time-stamps as blocks, thereby preserving the cross-sectional structure of the data. This exercise provides an alternative inference approach that accounts for higher-level clustering. The resulting p-values (see [Figure S5](#)) are consistent with the main results in [Table S4](#).

Overall, we conclude that our findings are robust to more conservative inference assumptions.

5.3 Alternative Spatial Units

Our main analysis is conducted at the level of ADM1 units. In principle, both ACLED and GODAD data can be analyzed at a more granular level. Nevertheless, the GODAD dataset explicitly suggests that the precision of the data is not sufficient for gridcell level analysis ([21](#)). As a robustness check, we conducted the analysis at the ADM2 level. During the sample period, 36% of the USAID projects could not be precisely coded at ADM2 level based on GODAD's criteria. We also perform a consistency check evaluating whether the ADM1 disbursements equal the sum of constituent ADM2 disbursements. 44% of ADM2 regions do not satisfy the consistency check. In addition, measuring conflict outcomes at the ADM2 level requires proprietary, disaggregated ACLED event data with most recent updates (for which researchers can request access). In

spite of these limitations, [Table S8](#) confirms that our main findings continue to hold at the ADM2 level, in that the drop of US aid leads to an increase in conflict after January 2025. As only a small share of ADM2 units is reported to have received any aid in this dataset, we rely on a binary aid indicator for any aid in this analysis. The corresponding ADM1 results for any aid can be found in [Table S19](#).

5.4 Placebo tests

We implemented a range of placebo tests to support our empirical design. First of all, we implemented a formal test for pretreatment effects in our main event study (Figure 2). In [Table S9](#), we compare the different pre-treatment time blocks with each other (in the shaded rows). [Figure S4](#) visualizes these comparisons. The pre-treatment placebo effects are small and insignificant (with the exception of one comparison at 10%).

Then, we develop an alternative temporal placebo test for our main findings ([Table S4](#)). We randomly reshuffle all time-stamps in our data, in such a way that every observation in the same month in the real data is assigned to the same placebo month. Hence, the placebo datasets preserve the cross-sectional structure of the real data. Relying on our main specification, we then compare how exceptional our coefficients are compared to the effects estimated in the placebo datasets. The corresponding effects are small and consistent with the p-values of the estimates in [Table S4](#).

We then turn to placebo tests related to our aid measures. The test we implement assesses whether, after accounting for the true shock caused by the USAID shutdown, any other spurious effects stem from patterns in aid provided by other major donors. In particular, we look at effects for Chinese aid, World Bank aid, and aid by the three major European donors, controlling for the effect of US aid. These alternative aid exposure measures are weakly correlated with US aid. The results of the placebo tests are presented in [Table S10](#). We see that Chinese aid and World Bank aid are not associated with any changes in conflict. China and the World Bank did not reduce aid funding around February 2025, so these placebo results rule out that we are capturing a response of conflict to any form of aid exposure. However, there is a positive (and largely insignificant) effect for aid by the major European donors. This is also consistent with our findings. All major European donors reduced aid funding significantly in the last few years, and some

reductions were announced around the time of the US aid drop (48). However, none of these European countries reduced aid as sharply and implemented these changes as abruptly as the US, meaning that European aid does not lend itself as well to the empirical evaluation strategy we develop in our paper. This also implies that these European countries are less than ideal as placebos.

With this in mind, we also implemented a robustness check for the main results of the paper, accounting for any residual effects of pooled aid flows from the larger set of donors (i.e., China, the World Bank, and major European donors). These results are presented in [Table S11](#) and demonstrate that the main effects are unaffected. It is worth noting that, however, China does not report or define official development assistance (ODA) in a way comparable to the Western definition, as explained in [SM Section 3.1](#).

Finally, we also estimate the effect of US aid exposure after January 2025 on extreme weather events, which should obviously not be affected by this shock. [Table S12](#) considers as outcomes extreme heat, rain, or cold (defined as a binary indicator equal to 1 if monthly rainfall is more than two standard deviations below or above the region-specific monthly mean, calculated over the 1991-2020 baseline period). US aid exposure is not linked to an increased probability of facing droughts, floods, or cold spells after January 2025 ([Table S12](#)). However, we do pick up an effect for heatwaves that we consider to be a chance effect. To check for robustness, we show in [Table S13](#) that the main results are unaffected when heatwaves are included as a control in the main specification.

5.5 Alternative Conflict Data

The main analysis is based on the ACLED dataset because of its recent coverage, rigorous quality control measures, high spatial and temporal granularity, and comprehensive inclusion of conflict events (49). In addition, we examined the effects of US aid cuts on conflict using the Global Database of Events, Language, and Tone (GDELT). The GDELT project monitors global news media and classifies reports into standardized event categories and geographic locations (50). Specific events can be retrieved using CAMEO (Conflict and Mediation Event Observations) codes. We focus on protests, demonstrations, and rallies (root codes 14 and 15), as well as battles and fights (root code 19).

However, automatic coding during the GDELT data collection process is susceptible to media and attention bias, particularly toward large-scale violence (51). An event may be described as “massacres” or “mass killings” in source reportage and recorded as such by GDELT, while substantial variation across reportage raises questions whether such events actually occurred (52). In addition, although GDELT applies a deduplication process “based on the (event) attribute fields,” this process is fully machine-generated, in contrast to ACLED, which uses human evaluators to code events (53). For example, in May 2024, GDELT reported 4,334 events in the Sinai region of Egypt alone, which is a high figure that likely reflects intense media attention. Another limitation of GDELT is the absence of fatality records, whereas ACLED provides estimates of conflict-related deaths.

Table S15 summarizes GDELT variables and their corresponding ACLED measures after excluding the Sinai anomaly. We find that GDELT is broadly comparable to ACLED for protests, demonstrations, and rallies, but reports substantially more battle events. We therefore interpret the results from the GDELT outcomes with caution. Table S14 shows that results based on GDELT protest, demonstration, and rally measures are consistent with those obtained using ACLED protest and riot data but less comparable in terms of battles.

5.6 Alternative treatment measures

Our main aid exposure variable can be defined in a variety of ways. In this subsection we document the robustness of our findings to different coding choices.

First of all, our main results rely on a 4-year window (between 2017 and 2020) to measure aid exposure. For each of the 12 coefficients presented in Figure 1, Figure S6 shows how the coefficient changes for alternative aid exposure windows. The main coefficients of interest are robust across different exposure windows, even if the ones for protests and riots lose significance when we use 2020 only. We do not put much weight on these results, because an exposure measure based on one year cannot account for seasonality, and could be underpowered. In addition, in the specific case of 2020, focusing on this year only risks putting a lot of weight on aid patterns that are specific to the Covid-19 period. Overall, we conclude from Figure S6 that our findings are robust to changing the exposure window.

Second, we present results for a range of alternative aid treatment measures. We address potential bias arising from extreme values in aid dependence by winsorizing the US aid per capita variable at the 99th percentile. Our main results remain robust, as shown in [Table S16](#). In [Table S17](#) we rely on a $\log(x+1)$ transformation of the per capita aid amount rather than the inverse hyperbolic sine transformation. These results are qualitatively and quantitatively close to our main findings. In [Table S18](#), we present results for the inverse hyperbolic sine transformation of levels of aid (i.e., without per capita adjustment). Again, the results are in line with our main findings. If anything, the results regarding violence against civilians are more pronounced. In Panel B, we show results for a binary treatment indicator based on the 75th percentile of the US aid per capita distribution.

In what follows, we further focus on binary measures, as displayed in [Table S19](#). As the event studies (including Figure 2) rely on the same binary treatment, the results in Panel A of [Table S19](#) are identical to the pre-post treatment difference estimated in the corresponding event studies. As an alternative that addresses sensitivity to the per capita adjustment, we create a dummy treatment using the 75th percentile of the distribution of the level of aid (which is different from the distribution of the per capita distribution). These results are reported in Panel B and are consistent with our main findings. In Panel C, we also report findings for a binary indicator of any aid. Here we see strong results for battles, but relatively weaker results for protests and riots.

Finally, we report results using US aid per person instead of US aid per 1,000 of the population (before applying the IHS transformation), as in our main results. These results are qualitatively similar ([Table S20](#)).

6 Mechanisms

In this section, we present a set of results that shed light on the mechanisms through which the impact of aid cuts on conflict could operate.

6.1 Aid classification

To explore which type of aid explains our result, we first use the standard project classifications in GODAD

to distinguish four mutually exclusive US aid sectors: economic, social, productive, and other aid. We decompose our main specification by interacting the post-US aid drop indicator with the inverse hyperbolic sine-transformed constant-dollar per capita disbursements, averaged over 2017 to 2020, at the sector level. These sector-level aid effects are much less precisely estimated, but the pattern that emerges is that most types of aid are associated with an increase in conflict ([Table S21](#)). Social and productive aid appear to lead most consistently to increased violence across categories. The patterns for economic aid are less clear-cut, with sizable and positive (but imprecisely estimated) effects for some outcomes.

We also classify aid projects in an alternative way, distinguishing between economic development, humanitarian aid, and governance interventions. [Table S22](#) shows again no clear difference across aid categories. The theoretical framework of [section 1](#) offers further interpretation of these findings of how aid cuts in different sectors can affect conflict.

6.2 Institutions

We also examine whether strong institutions at the country level moderate the aid shock. Consistent with ([10](#)), we construct a measure of inclusive institutions based on Polity V data ([31](#)). Effects on conflict are generally stronger when institutions are weak, and they are statistically different from those in countries with stronger institutions for a range of outcomes including battle counts and violence against civilians. These results are presented in [Table S24](#). In the theoretical framework, strong institutions could limit the extent to which rents are appropriable (through violence), and therefore prevent reductions in economic opportunities (due to aid cuts) from translating into violence.

6.3 Chinese aid

The fungibility of aid across multiple donors may cushion the impact of US aid cuts ([54](#)). We test this hypothesis by splitting regions according to their average exposure to Chinese aid, which was not subject to cuts during our study period, and interacting this measure with our main US aid exposure variable. The results, presented in [Table S25](#), generally show stronger effects of the US aid cut shock in regions that rely less on Chinese aid. However, the estimated differential effects between regions with high and low exposure to Chinese aid are statistically insignificant. As noted before in SM [Section 3.1](#), China does not

report or categorize official development assistance (ODA) comparable to the Western definition ([21](#), [55](#)).

7 Figures and Tables

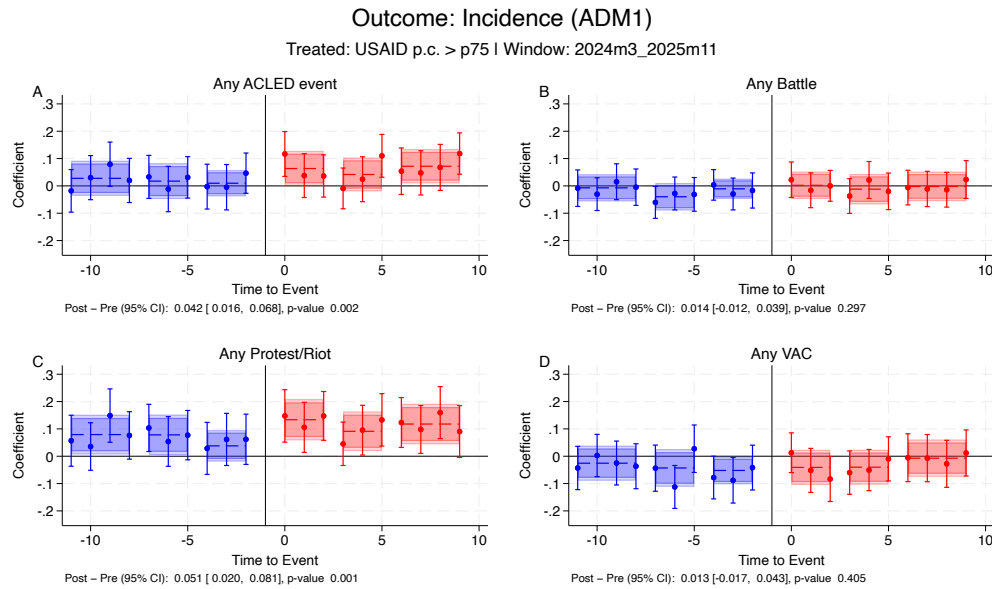


Figure S1: Time pattern of the likelihood of conflict incidence around the freeze of USAID cut-off. The figure shows event-study estimates for a binary indicator equal to one if at least one conflict event occurs in an ADM1-month. (A) includes all events, (B) battles, (C) protests and riots, and (D) violence against civilians (VAC). Treated ADM1 are those above the 75th percentile of per capita US aid disbursements (2017–2020). Event time is centered on February 2025 ($t = 0$), with $t = -1$ as the reference period. Coefficients are plotted with their 95% confidence intervals. Block averages are shown with dashed lines indicating the block means. The darker shaded areas represent 90% confidence intervals, and the lighter shaded areas indicate the corresponding blocks' 95% confidence intervals.

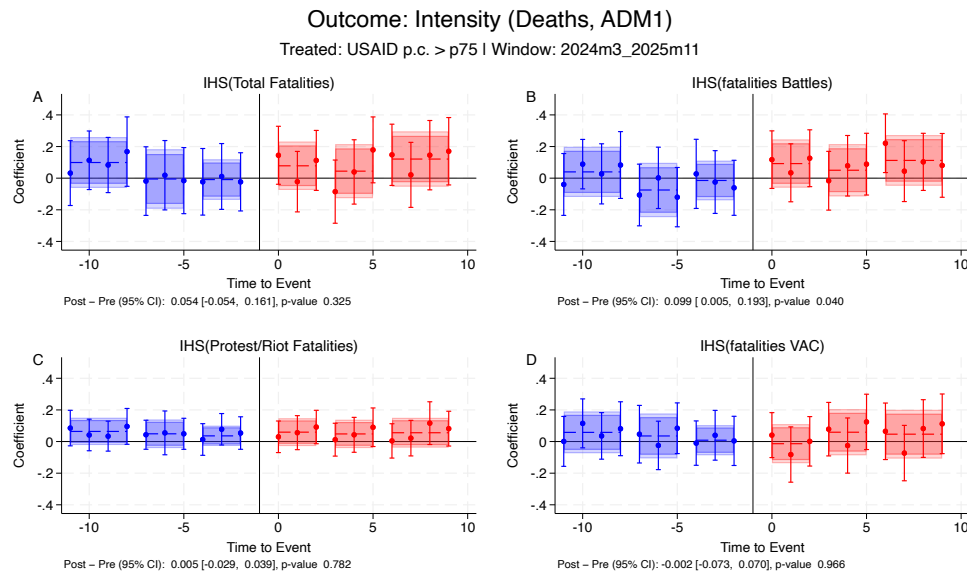


Figure S2: Time pattern of conflict intensity (measured by fatalities) around the USAID cut-off. The figure plots the event study where the outcome variable is the inverse hyperbolic sine (IHS)-transformed count of conflict-related fatalities. (A) includes all events, (B) battles, (C) protests and riots, and (D) violence against civilians (VAC). Treated ADM1 are those above the 75th percentile of per capita US aid disbursements (2017–2020). Event time is centered on February 2025 ($t = 0$), with $t = -1$ as the reference period. Coefficients are plotted with their 95% confidence intervals. Block averages are shown with dashed lines indicating the block means. The darker shaded areas represent 90% confidence intervals, and the lighter shaded areas indicate the corresponding blocks' 95% confidence intervals.

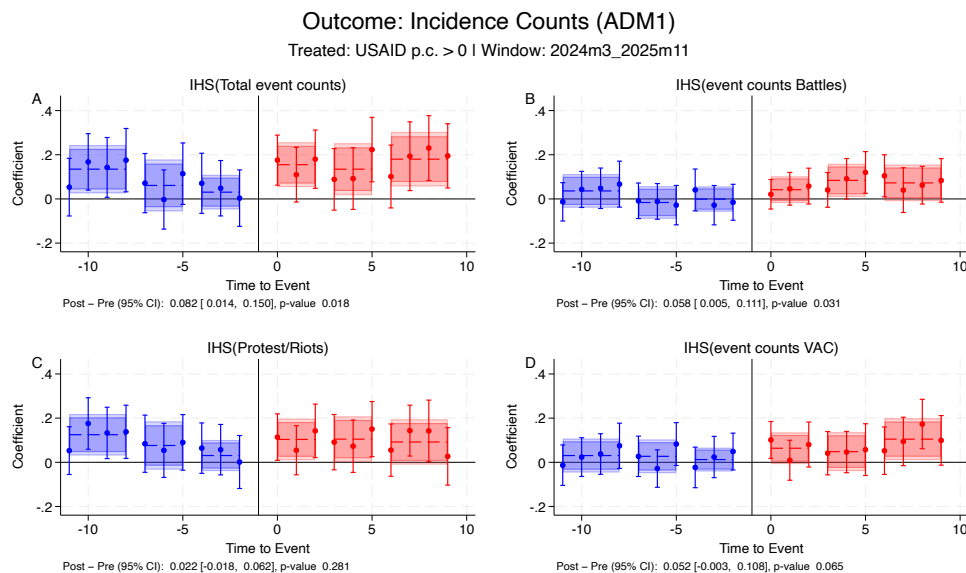


Figure S3: Time Pattern of Conflict Incidence Counts Around the USAID Cut-Off. The figure plots the event study where the outcome variable is the inverse hyperbolic sine (IHS)-transformed count of conflict-related outcomes. (A) includes all events, (B) battles, (C) protests and riots, and (D) violence against civilians (VAC). Treated ADM1 received non-zero amount of US aid disbursements per capita between 2017 and 2020. Event time is centered on February 2025 ($t = 0$), with $t = -1$ as the reference period. Coefficients are plotted with their 95% confidence intervals. Block averages are shown with dashed lines indicating the block means. The darker shaded areas represent 90% confidence intervals, and the lighter shaded areas indicate the corresponding blocks' 95% confidence intervals.

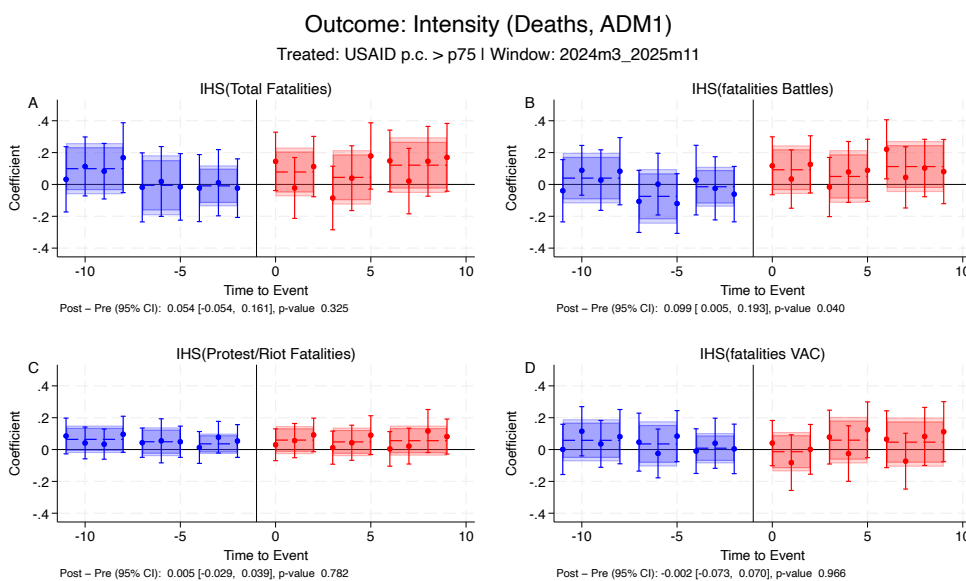


Figure S4: Main Event Study with Numbered Blocks. The figure replicates the main event-study specification in the paper and includes annotated numbered blocks used for the comparisons in Table S9. It reports IHS-transformed conflict counts for four outcomes: (A) all events, (B) battles, (C) protests and riots, and (D) violence against civilians (VAC). Treated ADM1 are those above the 75th percentile of per capita US aid disbursements (2017–2020). Block B3 includes $t = -1$, the reference period, which is normalized to zero. Coefficients are plotted with their 95% confidence intervals. Block averages are shown with dashed lines indicating the block means. The darker shaded areas represent 90% confidence intervals, and the lighter shaded areas indicate the corresponding blocks' 95% confidence intervals.

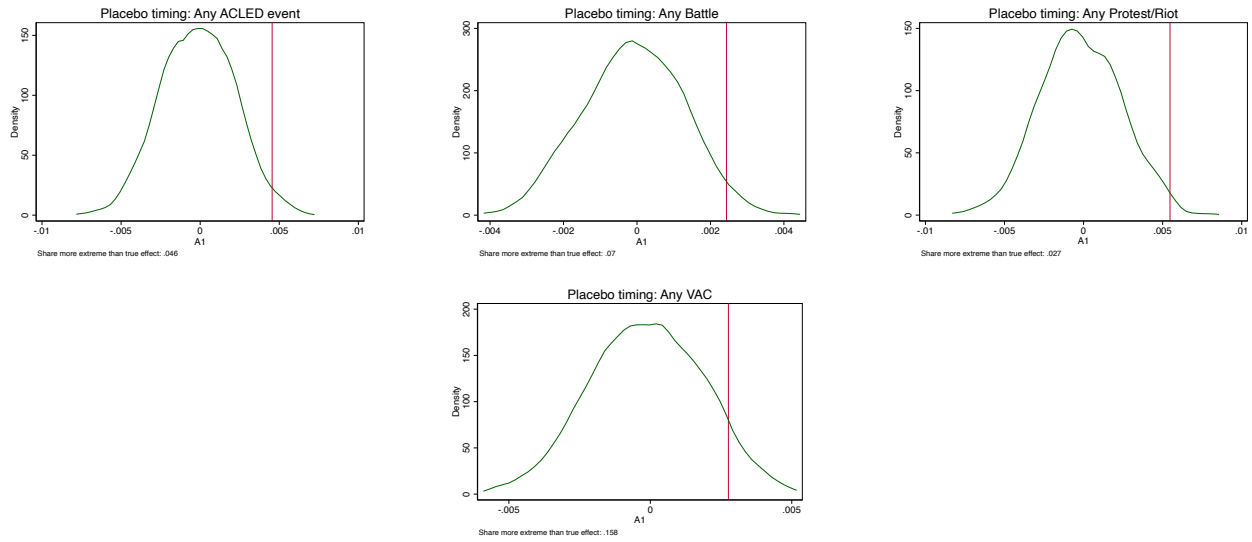


Figure S5: Placebo Treatment Timing. (A) Incidence. Each panel shows the distribution of placebo treatment effects obtained by randomly shuffling treatment timing across months. The vertical line indicates the estimate from the main result reported in [Table S4](#). Outcomes are ordered from top to bottom and left to right as: all events, battles, protests/riots, and violence against civilians (VAC).

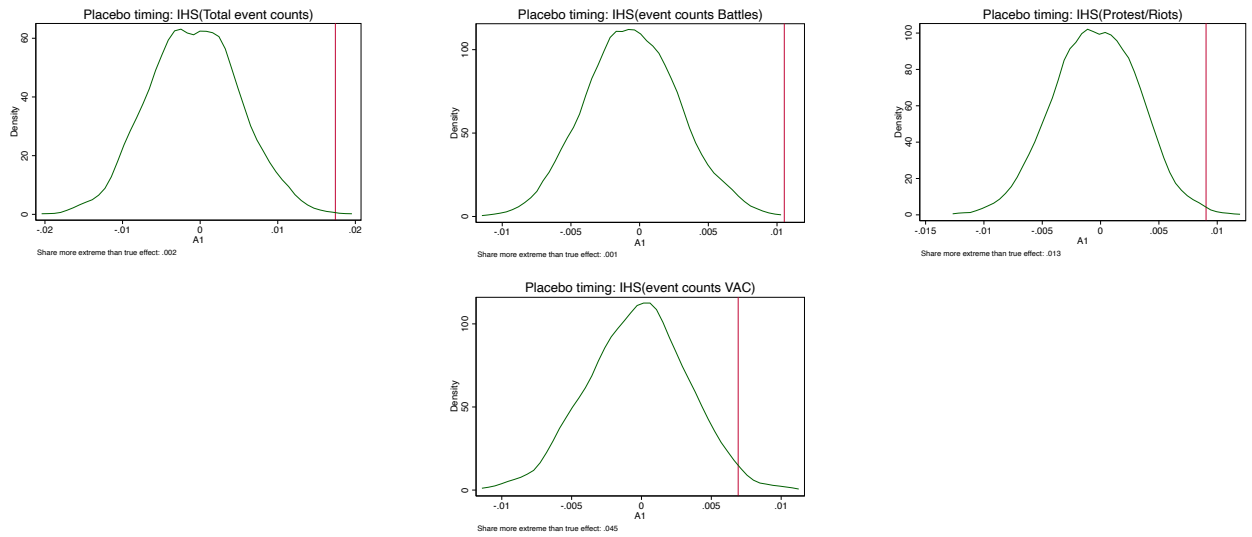


Figure S5: Placebo Treatment Timing (continued). (B) Incidence counts.

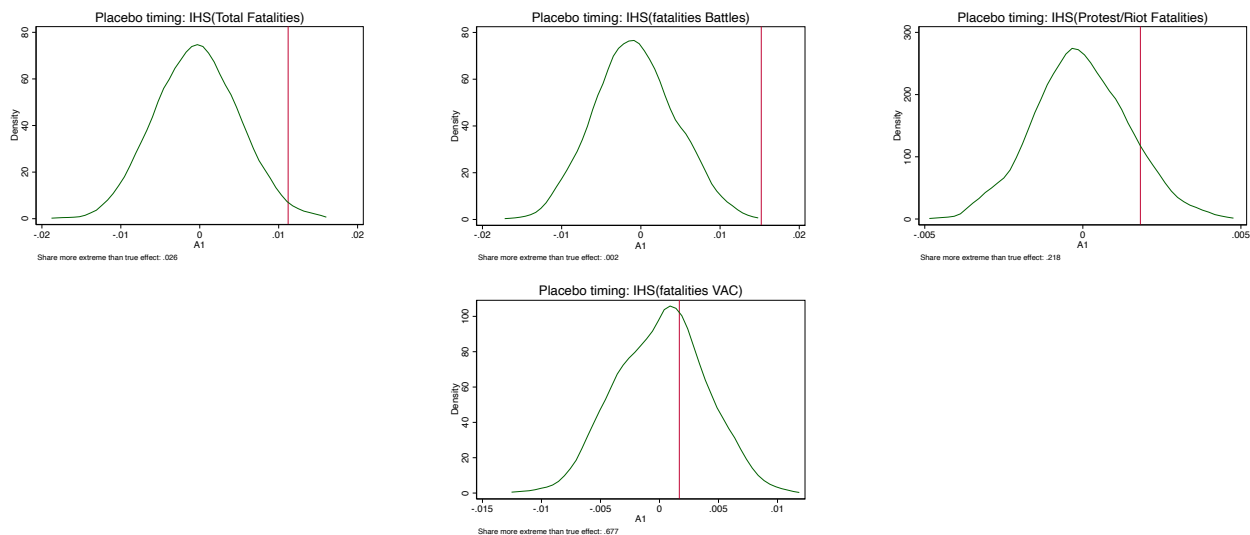


Figure S5: Placebo Treatment Timing (continued). (C) Intensity (deaths).

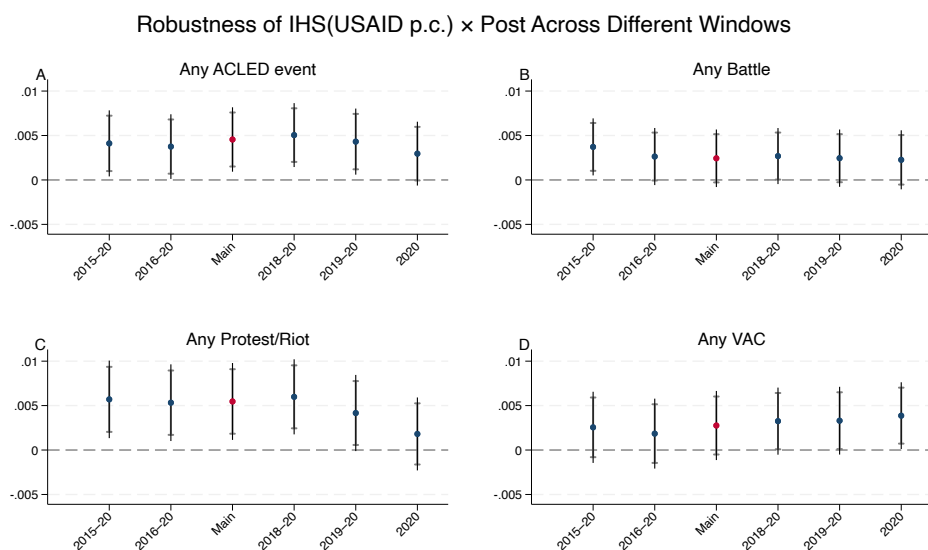


Figure S6: Robustness to Alternative Definition of US Aid Dependency: (A) Incidence. This figure presents a robustness check using alternative definitions of US aid dependency. In the baseline specification, dependency is constructed using average disbursements over 2017-2020 (main). Here, we alternatively use averages over 2015-2020, 2016-2020, 2018-2020, 2019-2020, and 2020 only (from left to right on the x-axis). All specifications replicate the baseline model. We report results for three outcome margins: incidence, incidence counts, and intensity (deaths). Within each margin, sub-panels (A)-(D), ordered from top to bottom and left to right, correspond to total events, battles, protests and riots, and violence against civilians, respectively. The whiskers show the 95% confidence intervals around the point estimate, while the lines represent the 90% confidence intervals.

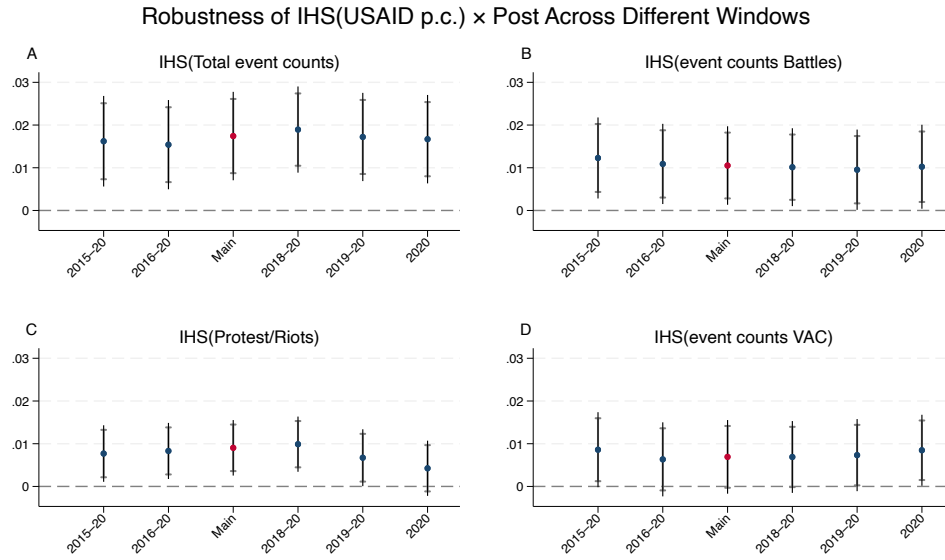


Figure S6: Robustness to Alternative Definition of US Aid Dependency (continued). (B) Incidence Counts.

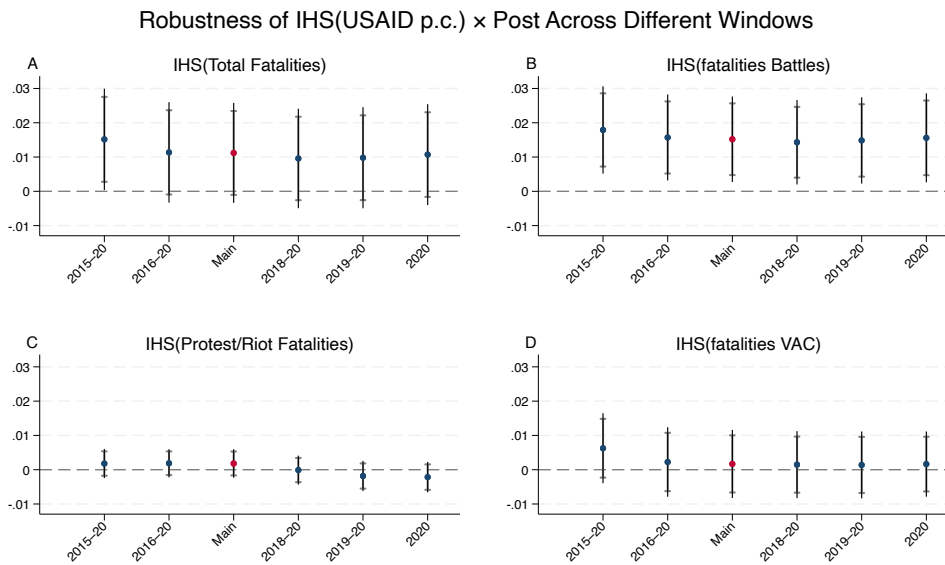


Figure S6: Robustness to Alternative Definition of US Aid Dependency (continued). (C) Intensity (Deaths).

Table S1: Comparable Foreign Aid Disruptions. The USAID termination event represented a .10% shock (cut / GDP). The values of the cuts are approximate and harmonized to USD using contemporaneous reporting in primary sources. UK figure reflects the reduction associated with the shift from 0.7% to 0.5% of GNI. Spain and Japan values are inferred from reported percentage reductions in ODA flows. Cutoff-to-GDP ratios use nominal GDP in the event year; UK ratio is reported relative to GNI, the policy benchmark used in UK aid accounting.

Donor Country	Year	Cut (USD)	Cut / GDP
United Kingdom	2021	\$4.2B	≈0.2% (of GNI)
Netherlands	2012	\$1.3B	≈0.14%
Spain	2012	\$1.9B (approx.)	≈0.14%
Finland	2016	\$0.34B	≈0.14%
Japan	2002	\$5.3B (approx.)	≈0.13%

Table S2: Summary Statistics of Main Variables. This table reports means, standard deviations, minima, medians, maxima, and sample sizes for the main variables used in the study. Variable definitions are provided in [Table S3](#).

variable	mean	sd	min	median	max	N
Total Event Counts	5.02	16.71	0.00	0.00	381.00	18270
Battle Counts	1.21	6.48	0.00	0.00	169.00	18270
Protest/Riot Counts	1.44	4.89	0.00	0.00	74.00	18270
VAC Counts	1.14	5.44	0.00	0.00	171.00	18270
Total Deaths	7.06	45.84	0.00	0.00	2298.00	18270
Battle Deaths	3.94	29.89	0.00	0.00	1104.00	18270
Protest/Riot Deaths	0.22	4.63	0.00	0.00	609.00	18270
VAC Deaths	1.89	16.05	0.00	0.00	1336.00	18270
Any ACLED Events	0.46	0.50	0.00	0.00	1.00	18270
Any Battle	0.15	0.35	0.00	0.00	1.00	18270
Any Protests/Riot	0.32	0.47	0.00	0.00	1.00	18270
Any VAC	0.20	0.40	0.00	0.00	1.00	18270
US Aid per capita	857.64	4021.79	0.00	11.46	73245.78	18270
IHS(US Aid per capita)	3.37	3.34	0.00	3.13	11.89	18270
IHS(US Aid p.c.(Eco. Sec.))	1.20	2.25	0.00	0.00	10.76	18270
IHS(US Aid p.c.(Prod. Sec.))	1.02	2.42	0.00	0.00	10.33	18270
IHS(US Aid p.c.(Soc. Sec.))	2.10	3.03	0.00	0.00	11.89	18270
IHS(US Aid p.c.(Other Sec.))	0.65	1.61	0.00	0.00	9.29	18270
IHS(US Aid p.c.(Gov. Type.))	0.84	1.80	0.00	0.00	8.87	18270
IHS(US Aid p.c.(Hum. Type.))	1.02	2.42	0.00	0.00	10.33	18270
IHS(US Aid p.c.(Eco. Dev. Type))	1.20	2.25	0.00	0.00	10.76	18270
IHS(US Aid p.c.(Other Types))	2.00	3.02	0.00	0.00	11.89	18270
IHS(WB Aid per capita)	7.24	3.95	0.00	8.83	14.64	18270
IHS(China Aid per capita)	2.82	4.21	0.00	0.00	14.34	18270
IHS(European Aid per capita)	4.77	3.50	0.00	5.61	16.98	18270
Log(1+US Aid p.c.)	2.99	3.05	0.00	2.52	11.20	18270
IHS(US Aid level)	7.56	6.53	0.00	9.90	19.72	18270
Avg. Exc. Constraint	4.21	1.55	1.00	4.32	7.00	14238
Flood	0.04	0.19	0.00	0.00	1.00	18270
Drought	0.03	0.18	0.00	0.00	1.00	18270
Heatwave	0.20	0.40	0.00	0.00	1.00	18270
Coldspell	0.00	0.07	0.00	0.00	1.00	18270

Table S3: Variable Definitions and Sources.

Variable	Source	Description
Total Event Counts	ACLED	Total number of recorded conflict events, including battles, protests, riots, strategic developments, and violence against civilians.
Battle Counts	ACLED	Total number of recorded battle events.
Protest/Riot Counts	ACLED	Total number of recorded protest and riot events.
VAC Counts	ACLED	Total number of recorded violence against civilians (VAC) events.
Total Deaths	ACLED	Total number of recorded conflict-related deaths resulting from battles, protests, riots, strategic developments, and violence against civilians.
Battle Deaths	ACLED	Total number of recorded deaths resulting from battle.
Protest/Riot Deaths	ACLED	Total number of recorded deaths resulting from protest and riot.
VAC Deaths	ACLED	Total number of recorded deaths resulting from violence against civilians.
Any ACLED Events	ACLED	Binary indicator equal to one if at least one conflict event is recorded by ACLED, zero otherwise.
Any Battle	ACLED	Binary indicator equal to one if at least one battle event is recorded by ACLED, zero otherwise.
Any Protests/Riot	ACLED	Binary indicator equal to one if at least one protest or riot event is recorded by ACLED, and zero otherwise.
Any VAC	ACLED	Binary indicator equal to one if at least one violence against civilians event is recorded by ACLED, and zero otherwise.
US Aid per capita	GODAD	Yearly average of US aid disbursements between 2017 and 2020 per 1,000 inhabitants.
US Aid p.c. (Eco. Sec.)	GODAD	Yearly average of US aid disbursements between 2017 and 2020 per 1,000 inhabitants, classified as economic, infrastructure and services sector.
US Aid p.c. (Prod. Sec.)	GODAD	Yearly average of US aid disbursements between 2017 and 2020 per 1,000 inhabitants, classified as production sector.
US Aid p.c. (Soc. Sec.)	GODAD	Yearly average of US aid disbursements between 2017 and 2020 per 1,000 inhabitants, classified as social infrastructure and services sector.
US Aid p.c. (Other Sec.)	GODAD	Yearly average of US aid disbursements between 2017 and 2020 per 1,000 inhabitants, not classified in Eco. Prod., or Soc. sectors.
US Aid p.c. (Gov. Type.)	GODAD	Yearly average of US aid disbursements between 2017 and 2020 per 1,000 inhabitants, classified as governance types.
US Aid p.c. (Hum. Type.)	GODAD	Yearly average of US aid disbursements between 2017 and 2020 per 1,000 inhabitants, classified as humanitarian types.
US Aid p.c. (Eco. Dev. Type)	GODAD	Yearly average of US aid disbursements between 2017 and 2020 per 1,000 inhabitants, classified as economic development types.
US Aid p.c. (Other Types)	GODAD	Yearly average of US aid disbursements between 2017 and 2020 per 1,000 inhabitants, not classified as governance, humanitarian, or economic development types.
WB Aid per capita	GODAD	Yearly average of World Bank aid disbursements between 2017 and 2020 per 1,000 inhabitants.
China Aid per capita	GODAD	Yearly average of Chinese aid commitments between 2017 and 2020 per 1,000 inhabitants.

Continued on next page

Variable	Source	Description
European Aid per capita	GODAD	Yearly average of combined France, UK, and Germany aid disbursements between 2017 and 2020 per 1,000 inhabitants.
Avg. Exc. Constraint	Polity V	Country-level average of the executive constraint (XCONST) score from 2000 to 2018. The original Polity V score ranges from 1 (Unlimited Authority, lowest constraint) to 7 (Executive Parity or Subordination, highest constraint).
Flood	ERA5	Binary indicator equal to one if precipitation exceeds its 1991–2020 long-term mean by more than two standard deviations.
Drought	ERA5	Binary indicator equal to one if precipitation falls below its 1991–2020 long-term mean by more than two standard deviations.
Heatwave	ERA5	Binary indicator equal to one if temperature exceeds its 1991–2020 long-term mean by more than two standard deviations.
Coldspell	ERA5	Binary indicator equal to one if temperature falls below its 1991–2020 long-term mean by more than two standard deviations.

Table S4: Tabulated Results Corresponding to Figure 1 in the Main Text. The table reports estimates for three outcome margins. Incidence refers to a binary indicator for whether any conflict event occurs. Incidence counts are IHS-transformed event counts, and Intensity (deaths) is IHS-transformed conflict-related fatalities. Column (1) covers all ACLED events, column (2) battles, column (3) protests and riots, and column (4) violence against civilians (VAC). The independent variable is the interaction between IHS-transformed US aid disbursements per 1,000 and a post-period indicator. Standard errors clustered at the ADM1-region level are reported in parentheses. Significance levels are denoted by $*p < 0.10$, $**p < 0.05$, and $***p < 0.01$.

	All Types of Conflict (1)	Battle (2)	Protest and Riot (3)	VAC (4)
Incidence				
IHS(US aid p.c.) × Post	0.005** (0.002)	0.002 (0.002)	0.005** (0.002)	0.003 (0.002)
Incidence Counts				
IHS(US aid p.c.) × Post	0.017*** (0.005)	0.011** (0.005)	0.009*** (0.003)	0.007 (0.004)
Intensity (Deaths)				
IHS(US aid p.c.) × Post	0.011 (0.007)	0.015** (0.006)	0.002 (0.002)	0.002 (0.005)
N	18270	18270	18270	18270
ADM1 FE	Yes	Yes	Yes	Yes
Country-Month FE	Yes	Yes	Yes	Yes

Table S5: The Impact of USAID Withdrawal on the Conflict Outcomes, Excluding Capitals. The table reports estimates for three outcome margins. Incidence refers to a binary indicator for whether any conflict event occurs. Incidence counts are IHS-transformed event counts, and Intensity (deaths) is IHS-transformed conflict-related fatalities. Column (1) covers all ACLED events, column (2) battles, column (3) protests and riots, and column (4) violence against civilians. The independent variable is the interaction between IHS-transformed US aid disbursements per 1,000 capita and a post-period indicator. The sample excludes 56 ADM1 regions where capitals are located. VAC stands for violence against civilians. Standard errors clustered at the ADM1-region level are reported in parentheses. Significance levels are denoted by $*p < 0.10$, $**p < 0.05$, and $***p < 0.01$.

	All Types of Conflict (1)	Battle (2)	Protest and Riot (3)	VAC (4)
Incidence				
IHS(US aid p.c.) × Post	0.004** (0.002)	0.002 (0.002)	0.006** (0.002)	0.002 (0.002)
Incidence Counts				
IHS(US aid p.c.) × Post	0.016*** (0.006)	0.009* (0.005)	0.010*** (0.003)	0.006 (0.005)
Intensity (Deaths)				
IHS(US aid p.c.) × Post	0.010 (0.008)	0.013* (0.007)	0.003 (0.002)	0.002 (0.005)
N	17073	17073	17073	17073
ADM1 FE	Yes	Yes	Yes	Yes
Country-Month FE	Yes	Yes	Yes	Yes

Table S6: The Impact of USAID Withdrawal on Conflict with Alternative SE Cluster. The table reports estimates for three outcome margins. Incidence refers to a binary indicator for whether any conflict event occurs. Incidence counts are IHS-transformed event counts, and Intensity (deaths) is IHS-transformed conflict-related fatalities. Column (1) covers all ACLED events, column (2) battles, column (3) protests and riots, and column (4) violence against civilians. The independent variable is the interaction between IHS-transformed US aid disbursements per 1,000 capita and a post-period indicator. Standard errors clustered at ADM0 (country) level are reported in parentheses. Significance levels are denoted by $*p < 0.10$, $**p < 0.05$, and $***p < 0.01$.

	All Types of Conflict (1)	Battle (2)	Protest and Riot (3)	VAC (4)
Incidence				
IHS(US aid p.c.) × Post	0.005* (0.002)	0.002 (0.002)	0.005* (0.003)	0.003 (0.002)
Incidence Counts				
IHS(US aid p.c.) × Post	0.017** (0.008)	0.011 (0.007)	0.009** (0.004)	0.007 (0.006)
Intensity (Deaths)				
IHS(US aid p.c.) × Post	0.011 (0.011)	0.015 (0.010)	0.002 (0.002)	0.002 (0.007)
N	18270	18270	18270	18270
ADM1 FE	Yes	Yes	Yes	Yes
Country-Month FE	Yes	Yes	Yes	Yes
S.E. Cluster	ADM0	ADM0	ADM0	ADM0

Table S7: The Impact of USAID Withdrawal on Conflict with Alternative SE Cluster, by Two Post Periods. This table compares the results in Table S6 by splitting the Post indicator into two periods: Post1 (February–July 2025) and Post2 (August–November 2025). All other specifications remain unchanged. Standard errors, clustered at the ADM0 (country) level, are reported in parentheses. Significance levels are denoted by $*p < 0.10$, $**p < 0.05$, and $***p < 0.01$.

	All Types of Conflict (1)	Battle (2)	Protest and Riot (3)	VAC (4)
Incidence				
IHS(US aid p.c.) × Post1	0.004 (0.003)	0.002 (0.002)	0.005 (0.004)	0.001 (0.002)
IHS(US aid p.c.) × Post2	0.006** (0.002)	0.003 (0.003)	0.006** (0.003)	0.005 (0.003)
Incidence Counts				
IHS(US aid p.c.) × Post1	0.014* (0.008)	0.008 (0.007)	0.009* (0.005)	0.004 (0.005)
IHS(US aid p.c.) × Post2	0.023** (0.009)	0.014* (0.008)	0.009** (0.004)	0.012 (0.009)
Intensity (Deaths)				
IHS(US aid p.c.) × Post1	0.007 (0.009)	0.012 (0.009)	0.002 (0.002)	-0.001 (0.005)
IHS(US aid p.c.) × Post2	0.017 (0.014)	0.020* (0.011)	0.001 (0.003)	0.005 (0.011)
N	18270	18270	18270	18270
ADM1 FE	Yes	Yes	Yes	Yes
Country-Month FE	Yes	Yes	Yes	Yes
S.E. Cluster	ADM0	ADM0	ADM0	ADM0

Table S8: Robustness to Alternative Spatial Units (ADM2-Level). This table replicates the baseline specification using ADM2 regions as the unit of observation. Sample restricted to ADM2 units whose parent ADM1 totals match the sum of constituent ADM2 disbursements (2017-2020). 56% of ADM2 regions satisfy this consistency criterion. The dependent variables measure incidence, incidence counts, and intensity (deaths) of conflict events at the ADM2–month level. The independent variable is an indicator for positive US aid disbursements per capita interacted with a post-period indicator. Share of ADM2 regions with positive US aid: 5.26%. Standard errors are clustered at the ADM1 level to account for spatial correlation and potential spillovers across neighboring ADM2 regions. Significance levels are denoted by $*p < 0.10$, $**p < 0.05$, and $***p < 0.01$.

	All Types of Conflict (1)	Battle (2)	Protest and Riot (3)	VAC (4)
Incidence				
1[US aid p.c. > 0] × Post	0.036** (0.015)	0.013 (0.008)	0.021 (0.014)	0.006 (0.008)
Incidence Counts				
1[US aid p.c. > 0] × Post	0.080*** (0.026)	0.024* (0.012)	0.048** (0.019)	0.014 (0.016)
Intensity (Deaths)				
1[US aid p.c. > 0] × Post	0.036 (0.023)	0.018 (0.016)	0.011 (0.008)	0.002 (0.013)
N	73836	73836	73836	73836
Unit FE	Yes	Yes	Yes	Yes
Country-Month FE	Yes	Yes	Yes	Yes

Table S9: Block Differences from Main Event-Study Estimates. The table reports differences between event-time blocks from the main event-study specification (see [Figure S4](#) for block definitions). Panels correspond to (A) IHS-transformed total events, (B) battles, (C) protests/riots, and (D) violence against civilians (VAC). All specifications include ADM1 and country-month fixed effects, with standard errors clustered at the ADM1 level. Column (1) reports the estimated block differences, (2) standard errors, (3) p-values, and 95% confidence intervals in column (4) and (5). Significance levels are denoted by $p < 0.10$, $**p < 0.05$, and $***p < 0.01$.

	(1) Diff	(2) SE	(3) p-value	(4) Low95	(5) High95
Panel A: Total Counts					
B2 v.s. B1	-0.043	0.043	0.322	-0.127	0.042
B3 v.s. B2	0.017	0.043	0.689	-0.068	0.103
B3 v.s. B1	-0.025	0.042	0.552	-0.109	0.058
B4 v.s. B3	0.118**	0.046	0.011	0.028	0.209
B5 v.s. B3	0.092*	0.052	0.078	-0.010	0.194
B6 v.s. B3	0.162***	0.056	0.004	0.051	0.273
Panel B: Battle Counts					
B2 v.s. B1	-0.052*	0.031	0.087	-0.112	0.008
B3 v.s. B2	0.035	0.031	0.251	-0.025	0.096
B3 v.s. B1	-0.017	0.029	0.553	-0.074	0.039
B4 v.s. B3	0.044	0.037	0.231	-0.028	0.116
B5 v.s. B3	0.066	0.043	0.125	-0.018	0.150
B6 v.s. B3	0.091*	0.047	0.054	-0.002	0.183
Panel C: Protest/Riot Counts					
B2 v.s. B1	0.001	0.034	0.983	-0.066	0.068
B3 v.s. B2	-0.019	0.037	0.607	-0.090	0.053
B3 v.s. B1	-0.018	0.031	0.558	-0.079	0.042
B4 v.s. B3	0.106***	0.037	0.004	0.034	0.178
B5 v.s. B3	0.055	0.039	0.156	-0.021	0.132
B6 v.s. B3	0.079**	0.039	0.042	0.003	0.156
Panel D: VAC Counts					
B2 v.s. B1	-0.011	0.039	0.770	-0.087	0.064
B3 v.s. B2	-0.018	0.039	0.641	-0.095	0.058
B3 v.s. B1	-0.030	0.037	0.428	-0.102	0.043
B4 v.s. B3	0.022	0.037	0.550	-0.051	0.095
B5 v.s. B3	0.039	0.045	0.388	-0.050	0.128
B6 v.s. B3	0.093**	0.045	0.039	0.005	0.181

Table S10: Placebo Test with Major International Donors. This table reports placebo tests using major international donors, including the World Bank (WB), China (CN), and major European donors (France, Germany, and the UK). Donor disbursements are constructed analogously to US aid. All specifications control for IHS-transformed US aid disbursements per 1,000 capita. Incidence refers to a binary indicator for any conflict event. Incidence counts are IHS-transformed event counts, and intensity (deaths) is IHS-transformed conflict-related fatalities. Columns (1)–(4) report results for all events, battles, protests and riots, and violence against civilians, respectively. Standard errors clustered at the ADM1 level are reported in parentheses. Significance levels are denoted by $*p < 0.10$, $**p < 0.05$, and $***p < 0.01$.

	All Types of Conflict (1)	Battle (2)	Protest and Riot (3)	VAC (4)
Incidence				
IHS(WB p.c.) × Post	0.000 (0.003)	-0.002 (0.002)	-0.004 (0.003)	-0.001 (0.002)
IHS(CN p.c.) × Post	-0.001 (0.001)	-0.000 (0.001)	0.000 (0.002)	0.000 (0.001)
IHS(European p.c.) × Post	0.003 (0.002)	0.002 (0.001)	0.002 (0.002)	0.001 (0.002)
Incidence Counts				
IHS(WB p.c.) × Post	-0.001 (0.007)	-0.003 (0.006)	-0.003 (0.004)	0.001 (0.004)
IHS(CN p.c.) × Post	-0.001 (0.003)	-0.001 (0.003)	0.001 (0.002)	0.001 (0.003)
IHS(European p.c.) × Post	0.005 (0.005)	0.002 (0.003)	0.002 (0.003)	-0.000 (0.004)
Intensity (Deaths)				
IHS(WB p.c.) × Post	-0.003 (0.010)	-0.001 (0.007)	0.004 (0.003)	0.002 (0.005)
IHS(CN p.c.) × Post	-0.006 (0.005)	-0.004 (0.004)	-0.001 (0.002)	-0.001 (0.003)
IHS(European p.c.) × Post	0.002 (0.005)	0.003 (0.004)	0.001 (0.002)	0.002 (0.004)
N	18270	18270	18270	18270
ADM1 FE	Yes	Yes	Yes	Yes
Country-Month FE	Yes	Yes	Yes	Yes

Table S11: Robustness Test with Non-US Donors. This table reports robustness tests using IHS-transformed US aid disbursements per 1,000 capita and the same measure from pooled non-US donor disbursements (World Bank, China, France, Germany, and the UK). Non-US donor disbursements are aggregated and constructed analogously to US aid. Incidence refers to a binary indicator for any conflict event. Incidence counts are IHS-transformed event counts, and intensity (deaths) is IHS-transformed conflict-related fatalities. Columns (1)–(4) report results for all events, battles, protests and riots, and violence against civilians (VAC), respectively. Standard errors clustered at the ADM1 level are reported in parentheses. Significance levels are denoted by * $p < 0.10$, ** $p < 0.05$, and *** $p < 0.01$.

	All Types of Conflict (1)	Battle (2)	Protest and Riot (3)	VAC (4)
Incidence				
IHS(US aid p.c.) × Post	0.005** (0.002)	0.002 (0.002)	0.005** (0.002)	0.003 (0.002)
IHS(non-US p.c.) × Post	0.001 (0.002)	0.001 (0.001)	-0.001 (0.002)	0.001 (0.001)
Incidence Counts				
IHS(US aid p.c.) × Post	0.017*** (0.005)	0.010** (0.005)	0.009*** (0.003)	0.007 (0.004)
IHS(non-US p.c.) × Post	0.002 (0.004)	0.001 (0.002)	-0.001 (0.003)	0.003 (0.003)
Intensity (Deaths)				
IHS(US aid p.c.) × Post	0.011 (0.007)	0.015** (0.006)	0.002 (0.002)	0.002 (0.005)
IHS(non-US p.c.) × Post	0.003 (0.004)	0.003 (0.003)	0.001 (0.002)	0.004 (0.003)
N	18270	18270	18270	18270
ADM1 FE	Yes	Yes	Yes	Yes
Country-Month FE	Yes	Yes	Yes	Yes

Table S12: Placebo Test with Extreme Weather Events. This table reports placebo tests using extreme weather outcomes from ERA5. Column (1) to (4) correspond to the dependent variables that are one if a drought, flood, heatwave, or cold spell occurs in a given ADM1 region–month, and zero otherwise. The specification is identical to the baseline model, with IHS-transformed US aid disbursements per 1,000 capita interacted with a post-treatment indicator. All specifications include ADM1 and month fixed effects. Standard errors clustered at the ADM1 level are reported in parentheses. Significance levels are denoted by * $p < 0.10$, ** $p < 0.05$, and *** $p < 0.01$.

	(1) ERA5: Drought	(2) ERA5: Flood	(3) ERA5: Heatwave	(4) ERA5: Coldspell
IHS(US aid p.c.) × Post	-0.001 (0.001)	0.001 (0.001)	-0.009*** (0.002)	0.001 (0.000)
N	18270	18270	18270	18270
ADM1 FE	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes

Table S13: Robustness Check Including Heatwave Indicator. This table reports robustness results for the baseline specification after including a heatwave indicator. Heatwave is a binary variable equal to one if an ADM1-region-month experiences temperatures more than two standard deviations above its long-term mean. The treatment variable is IHS-transformed US aid disbursements per 1,000 capita interacted with a post-treatment indicator. Incidence counts are IHS-transformed event counts, and intensity (deaths) is IHS-transformed conflict-related fatalities. Columns (1)–(4) report results for all events, battles, protests and riots, and violence against civilians (VAC), respectively. All specifications include ADM1 and country-month fixed effects. Standard errors are clustered at the ADM1 level and reported in parentheses. Significance levels are denoted by $*p < 0.10$, $**p < 0.05$, and $***p < 0.01$.

	All Types of Conflict (1)	Battle (2)	Protest and Riot (3)	VAC (4)
Incidence				
IHS(US aid p.c.) × Post	0.005** (0.002)	0.002 (0.002)	0.005** (0.002)	0.003 (0.002)
Heatwave	-0.001 (0.010)	0.006 (0.008)	0.008 (0.010)	0.012 (0.010)
Incidence Counts				
IHS(US aid p.c.) × Post	0.017*** (0.005)	0.011** (0.005)	0.009*** (0.003)	0.007 (0.004)
Heatwave	0.017 (0.019)	0.020 (0.014)	0.002 (0.016)	0.038** (0.016)
Intensity (Deaths)				
IHS(US aid p.c.) × Post	0.011 (0.007)	0.015** (0.006)	0.002 (0.002)	0.002 (0.005)
Heatwave	0.038 (0.023)	0.012 (0.022)	0.005 (0.011)	0.037* (0.019)
N	18270	18270	18270	18270
ADM1 FE	Yes	Yes	Yes	Yes
Country-Month FE	Yes	Yes	Yes	Yes

Table S14: The Impact of USAID Withdrawal using Alternative Event Data (GDELТ). This table replicates the baseline specification using alternative event data from GDELТ. Incidence refers to a binary indicator equal to one if any event of the specified type occurs in a given ADM1 region–month. Incidence counts are IHS-transformed event counts. Column (1) reports results for protest, demonstration, and rally events, and column (2) for battle events. The Sinai Peninsula (Egypt) is excluded due to an extreme concentration of battle reportage during the sample period. All specifications include ADM1 and country–month fixed effects. Standard errors clustered at the ADM1 level are reported in parentheses. Significance levels are denoted by * $p < 0.10$, ** $p < 0.05$, and *** $p < 0.01$.

	ACLED Protest/Riot (1)	ACLED Battle (2)	GDELТ Protest/Demo/Rally (3)	GDELТ Battle (4)
Incidence				
IHS(US aid p.c.) \times Post	0.005** (0.002)	0.002 (0.002)	0.004* (0.002)	0.000 (0.002)
Incidence Counts				
IHS(US aid p.c.) \times Post	0.009*** (0.003)	0.011** (0.005)	0.009** (0.004)	-0.002 (0.006)
Intensity (Deaths)				
IHS(US aid p.c.) \times Post	0.002 (0.002)	0.015** (0.006)		
N	18249	18249	18249	18249
ADM1 FE	Yes	Yes	Yes	Yes
Country-Month FE	Yes	Yes	Yes	Yes

Table S15: Summary Statistics Comparing ACLED and GDELТ. This table reports summary statistics for conflict measures constructed from ACLED and GDELТ at the ADM1 region–month level. “Any” variables indicate whether at least one event of the corresponding type occurs in a given region–month. Count variables report the total number of events. The Sinai Peninsula (Egypt) is excluded from GDELТ due to an extreme concentration of battle events reportage. Detailed variable definitions and data sources are provided in Supplementary Materials, [Section 3](#).

variable	mean	sd	min	median	max	N
ACLED: Any Battle	0.15	0.35	0.00	0	1.00	18249
ACLED: Any Protest/Riot	0.32	0.47	0.00	0	1.00	18249
ACLED: Battle Counts	1.21	6.48	0.00	0	169.00	18249
ACLED: Protest/Riot Counts	1.44	4.89	0.00	0	74.00	18249
GDELТ: Any Protest/Demo/Rally	0.37	0.48	0.00	0	1.00	18249
GDELТ: Protest/Demo/Rally Counts	5.66	24.20	0.00	0	873.00	18249
GDELТ: Any Battle	0.53	0.50	0.00	1	1.00	18249
GDELТ: Battle Counts	24.05	83.87	0.00	1	1570.00	18249

Table S16: Robustness to Outliers in US Aid Disbursements. This table replicates the baseline specification after winsorizing US aid disbursements per 1,000 capita at the 99th percentile prior to the IHS transformation. Outcome definitions, fixed effects, and estimation procedures follow the baseline specification. Incidence refers to a binary indicator for any conflict event. Incidence counts are IHS-transformed event counts, and intensity (deaths) is IHS-transformed conflict-related fatalities. Standard errors clustered at the ADM1 level are reported in parentheses. Significance levels are denoted by $*p < 0.10$, $**p < 0.05$, and $***p < 0.01$.

	All Types of Conflict (1)	Battle (2)	Protest and Riot (3)	VAC (4)
Incidence				
IHS(US aid p.c. Wins.) \times Post	0.005** (0.002)	0.002 (0.002)	0.005** (0.002)	0.003 (0.002)
Incidence Counts				
IHS(US aid p.c. Wins.) \times Post	0.018*** (0.005)	0.011** (0.005)	0.009*** (0.003)	0.007 (0.004)
Intensity (Deaths)				
IHS(US aid p.c. Wins.) \times Post	0.011 (0.008)	0.015** (0.006)	0.002 (0.002)	0.002 (0.005)
N	18270	18270	18270	18270
ADM1 FE	Yes	Yes	Yes	Yes
Country-Month FE	Yes	Yes	Yes	Yes

Table S17: Robustness to Alternative Functional Form (Log Transformation). This table replicates the baseline specification using a logarithmic transformation of US aid disbursements per 1,000 capita instead of the inverse hyperbolic sine (IHS). Specifically, the key regressor is $\log(1 + \text{US aid p.c.})$ interacted with a post-period indicator. Outcome definitions, fixed effects, and estimation procedures follow the baseline specification. Incidence refers to a binary indicator for any conflict event. Incidence counts are log-transformed event counts (plus one), and intensity (deaths) is log-transformed conflict-related fatalities (plus one). Standard errors clustered at the ADM1 level are reported in parentheses. VAC stands for violence against civilians. Significance levels are denoted by $*p < 0.10$, $**p < 0.05$, and $***p < 0.01$.

	All Types of Conflict (1)	Battle (2)	Protest and Riot (3)	VAC (4)
Incidence				
log(US aid p.c.) × Post	0.005** (0.002)	0.003 (0.002)	0.006*** (0.002)	0.003 (0.002)
Incidence Counts				
log(US aid p.c.) × Post	0.016*** (0.005)	0.009** (0.004)	0.008*** (0.003)	0.006 (0.004)
Intensity (Deaths)				
log(US aid p.c.) × Post	0.010 (0.007)	0.014** (0.006)	0.001 (0.002)	0.001 (0.005)
N	18270	18270	18270	18270
ADM1 FE	Yes	Yes	Yes	Yes
Country-Month FE	Yes	Yes	Yes	Yes

Table S18: Robustness to Alternative Treatment Scaling (US Aid Levels). This table replicates the baseline specification using the inverse hyperbolic sine (IHS) of total US aid disbursements (levels) instead of US aid disbursements per 1,000 capita, interacted with a post-period indicator. Outcome definitions, fixed effects, and estimation procedures otherwise follow the baseline specification. Incidence refers to a binary indicator for any conflict event. Incidence counts are IHS-transformed event counts, and intensity (deaths) is IHS-transformed conflict-related fatalities. VAC stands for violence against civilians. Standard errors clustered at the ADM1 level are reported in parentheses. Significance levels are denoted by $*p < 0.10$, $**p < 0.05$, and $***p < 0.01$.

	All Types of Conflict (1)	Battle (2)	Protest and Riot (3)	VAC (4)
Incidence				
IHS(US aid level) × Post	0.002* (0.001)	0.001* (0.001)	0.002 (0.001)	0.002* (0.001)
Incidence Counts				
IHS(US aid level) × Post	0.009*** (0.003)	0.006** (0.002)	0.004** (0.002)	0.005* (0.002)
Intensity (Deaths)				
IHS(US aid level) × Post	0.007* (0.004)	0.008** (0.003)	0.001 (0.001)	0.003 (0.003)
N	18270	18270	18270	18270
ADM1 FE	Yes	Yes	Yes	Yes
Country-Month FE	Yes	Yes	Yes	Yes

Table S19: Robustness to Binary Measures of US Aid Exposure. This table replicates the baseline specification using alternative binary measures of US aid exposure. In Panel A, the treatment indicator equals one if US aid disbursements per capita exceed the 75th percentile of the overall ADM1 distribution. In Panel B, the treatment indicator equals one if the level of US aid disbursements exceeds the 75th percentile of the overall ADM1 distribution. In Panel C, the treatment indicator equals one if an ADM1 region receives any positive US aid disbursement. All treatment indicators are interacted with a post-period indicator. Outcome definitions, fixed effects, and estimation procedures otherwise follow the baseline specification. Incidence refers to a binary indicator for any conflict event. Incidence counts are IHS-transformed event counts, and intensity (deaths) is IHS-transformed conflict-related fatalities. Standard errors clustered at the ADM1 level are reported in parentheses. Significance levels are denoted by $*p < 0.10$, $**p < 0.05$, and $***p < 0.01$.

	All Types of Conflict (1)	Battle (2)	Protest and Riot (3)	VAC (4)
Panel A: US Aid p.c. > p75 (cutoff = 254.2 USD) Incidence				
1[US aid p.c. > p75] × Post	0.042*** (0.013)	0.014 (0.013)	0.051*** (0.016)	0.013 (0.015)
Incidence Counts				
1[US aid p.c. > p75] × Post	0.123*** (0.039)	0.073** (0.037)	0.068*** (0.025)	0.040 (0.031)
Intensity (Deaths)				
1[US aid p.c. > p75] × Post	0.054 (0.055)	0.099** (0.048)	0.005 (0.017)	-0.002 (0.036)
Panel B: US Aid level > p75 (cutoff = 316,451 USD) Incidence				
1[US aid level > p75] × Post	0.039*** (0.014)	0.021 (0.014)	0.039** (0.016)	0.031* (0.016)
Incidence Counts				
1[US aid level > p75] × Post	0.129*** (0.043)	0.077* (0.041)	0.053** (0.027)	0.048 (0.035)
Intensity (Deaths)				
1[US aid level > p75] × Post	0.071 (0.060)	0.108** (0.053)	-0.007 (0.019)	0.006 (0.041)
Panel C: US Aid > 0				
Incidence				
1[US aid > 0] × Post	0.014 (0.013)	0.013 (0.009)	0.003 (0.015)	0.020 (0.012)
Incidence Counts				
1[US aid > 0] × Post	0.082** (0.035)	0.058** (0.027)	0.022 (0.020)	0.052* (0.028)
Intensity (Deaths)				
1[US aid > 0] × Post	0.077* (0.045)	0.072* (0.037)	0.019 (0.013)	0.039 (0.033)
N	18270	18270	18270	18270
ADM1 FE	Yes	Yes	Yes	Yes
Country-Month FE	Yes	Yes	Yes	Yes

Table S20: Robustness to Alternative Treatment Scaling (US Aid per person). This table replicates the baseline specification using the inverse hyperbolic sine (IHS) of US aid per person instead of US aid disbursements per 1,000 capita, interacted with a post-period indicator. Outcome definitions, fixed effects, and estimation procedures otherwise follow the baseline specification. Incidence refers to a binary indicator for any conflict event. Incidence counts are IHS-transformed event counts, and intensity (deaths) is IHS-transformed conflict-related fatalities. VAC stands for violence against civilians. Standard errors clustered at the ADM1 level are reported in parentheses. Significance levels are denoted by * $p < 0.10$, ** $p < 0.05$, and *** $p < 0.01$.

	All Types of Conflict (1)	Battle (2)	Protest and Riot (3)	VAC (4)
Incidence				
IHS(US aid p.p.) \times Post	0.012* (0.007)	0.010 (0.008)	0.022** (0.009)	0.006 (0.009)
Incidence Counts				
IHS(US aid p.p.) \times Post	0.041** (0.021)	0.027 (0.021)	0.025* (0.014)	0.005 (0.017)
Intensity (Deaths)				
IHS(US aid p.p.) \times Post	0.020 (0.030)	0.058** (0.028)	-0.010 (0.010)	-0.015 (0.020)
N	18270	18270	18270	18270
ADM1 FE	Yes	Yes	Yes	Yes
Country-Month FE	Yes	Yes	Yes	Yes

Table S21: Impact of US Aid Drop on Conflict-related Outcomes by Aid Sectors. This table replicates the baseline specification splitting the US aid exposure variable by which sectors the USAID provided disbursements. The classification follows GODAD's original definitions. ECO stands for Economic, Infrastructure and, Services; SOC stands for Social, Infrastructure and, Services; PROD stands for Production sector; Other includes miscellaneous un-classified aids. Outcome definitions, fixed effects, and estimation procedures otherwise follow the baseline specification. Incidence refers to a binary indicator for any conflict event. Incidence counts are IHS-transformed event counts, and intensity (deaths) is IHS-transformed conflict-related fatalities. VAC stands for violence against civilians. Standard errors clustered at the ADM1 level are reported in parentheses. Significance levels are denoted by * $p < 0.10$, ** $p < 0.05$, and *** $p < 0.01$.

	All Types of Conflict (1)	Battle (2)	Protest and Riot (3)	VAC (4)
Incidence				
IHS(US aid p.c., ECO)× Post	0.000 (0.003)	0.003 (0.002)	-0.000 (0.004)	0.002 (0.003)
IHS(US aid p.c., SOC)× Post	0.005** (0.002)	0.004** (0.002)	0.003 (0.002)	0.003 (0.002)
IHS(US aid p.c., PROD)× Post	0.001 (0.003)	-0.002 (0.003)	0.002 (0.003)	0.003 (0.003)
IHS(US aid p.c., Other)× Post	0.003 (0.004)	0.003 (0.003)	0.005 (0.004)	-0.007** (0.003)
Incidence Counts				
IHS(US aid p.c., ECO)× Post	0.005 (0.008)	0.008 (0.008)	0.002 (0.005)	-0.001 (0.005)
IHS(US aid p.c., SOC)× Post	0.014*** (0.005)	0.010** (0.004)	0.006 (0.004)	0.005 (0.004)
IHS(US aid p.c., PROD)× Post	0.014* (0.007)	0.003 (0.007)	0.007* (0.004)	0.008 (0.007)
IHS(US aid p.c., Other)× Post	0.001 (0.010)	0.008 (0.008)	0.001 (0.007)	-0.009 (0.006)
Intensity (Deaths)				
IHS(US aid p.c., ECO)× Post	0.006 (0.011)	0.009 (0.010)	0.001 (0.003)	-0.003 (0.006)
IHS(US aid p.c., SOC)× Post	0.008 (0.006)	0.009* (0.005)	-0.000 (0.003)	0.005 (0.004)
IHS(US aid p.c., PROD)× Post	0.005 (0.011)	0.009 (0.010)	0.002 (0.003)	-0.004 (0.008)
IHS(US aid p.c., Other)× Post	0.003 (0.013)	0.015 (0.011)	-0.007 (0.005)	-0.010 (0.007)
N	18270	18270	18270	18270
ADM1 FE	Yes	Yes	Yes	Yes
Country-Month FE	Yes	Yes	Yes	Yes

Table S22: Impact of US Aid Drop on Conflict-related Outcomes by Aid Types. This table replicates the baseline specification splitting the US aid exposure variable by the type of aid the USAID provided. Each sector-specific exposure variable is constructed by aggregating only the disbursements classified under that category to each ADM1 region, following the classification in [Table S23](#). All four sector exposures enter the regression simultaneously, so each coefficient captures the marginal effect of aid in that sector holding constant aid in the remaining sectors. Outcome definitions, fixed effects, and estimation procedures otherwise follow the baseline specification. Incidence refers to a binary indicator for any conflict event. Incidence counts are IHS-transformed event counts, and intensity (deaths) is IHS-transformed conflict-related fatalities. VAC stands for violence against civilians. Standard errors clustered at the ADM1 level are reported in parentheses. Significance levels are denoted by * $p < 0.10$, ** $p < 0.05$, and *** $p < 0.01$.

	All Types of Conflict (1)	Battle (2)	Protest and Riot (3)	VAC (4)
Incidence				
IHS(US aid p.c., ECODEV.)× Post	0.001 (0.003)	0.003 (0.002)	0.000 (0.004)	0.002 (0.003)
IHS(US aid p.c., GOV)× Post	0.001 (0.003)	0.005* (0.003)	-0.002 (0.004)	0.001 (0.003)
IHS(US aid p.c., HUM)× Post	0.001 (0.003)	-0.002 (0.003)	0.003 (0.003)	0.003 (0.003)
IHS(US aid p.c., Other)× Post	0.005** (0.002)	0.002 (0.002)	0.005* (0.002)	-0.002 (0.002)
Incidence Counts				
IHS(US aid p.c., ECODEV.)× Post	0.006 (0.008)	0.008 (0.008)	0.003 (0.005)	-0.001 (0.005)
IHS(US aid p.c., GOV)× Post	0.008 (0.009)	0.013 (0.009)	0.000 (0.006)	-0.000 (0.007)
IHS(US aid p.c., HUM)× Post	0.014* (0.007)	0.002 (0.007)	0.007* (0.004)	0.009 (0.007)
IHS(US aid p.c., Other)× Post	0.007 (0.005)	0.005 (0.004)	0.004 (0.004)	-0.002 (0.004)
Intensity (Deaths)				
IHS(US aid p.c., ECODEV.)× Post	0.007 (0.011)	0.010 (0.010)	0.001 (0.003)	-0.002 (0.006)
IHS(US aid p.c., GOV)× Post	0.001 (0.013)	0.013 (0.012)	-0.002 (0.004)	-0.003 (0.007)
IHS(US aid p.c., HUM)× Post	0.006 (0.011)	0.009 (0.010)	0.003 (0.003)	-0.003 (0.008)
IHS(US aid p.c., Other)× Post	0.004 (0.006)	0.006 (0.005)	-0.002 (0.003)	-0.000 (0.004)
N	18270	18270	18270	18270
ADM1 FE	Yes	Yes	Yes	Yes
Country-Month FE	Yes	Yes	Yes	Yes

Table S23: Aid Types and Shares, 2017-2020. This table breaks down the types of aid USAID provided by targeted sector, classified by grouping GODAD subcategories, as defined by the OECD, into three substantive categories: Governance, Humanitarian, and Economic Development. We classify sectors that may be related to multiple or neither of the above categories into a residual “Other” category. For each broad category and subcategory, the table reports the number of projects, total disbursements (in millions of US dollars), and each category’s share of the overall number of projects and total dollar expenditure. All figures reflect cumulative totals over the 2017–2020 period.

	Projects	Disb. (M USD)	Share Proj. (%)	Share Disb. (%)
Governance	958	146.7	10.6	3.2
I.5 Govt & Civil Society	831	125.7	9.2	2.8
I.6 Conflict, Peace & Sec.	127	20.9	1.4	0.5
Humanitarian	1,930	1,560.1	21.5	34.4
VI Food Aid	269	483.7	3.0	10.7
VIII Emergency Response	1,661	1,076.4	18.5	23.7
Econ. Development	1,609	516.5	17.9	11.4
II Economic Infrastructure	492	202.3	5.5	4.5
III Production Sectors	1,117	314.2	12.4	6.9
Other (residual)	4,499	2,311.5	50.0	51.0
I.1 Education	587	438.8	6.5	9.7
I.2 Health	909	212.3	10.1	4.7
I.3 Pop./Repro. Health	1,523	1,255.0	16.9	27.7
I.4 Water/Sanitation	369	331.5	4.1	7.3
IV Multi-Sector	1,105	72.2	12.3	1.6
IX Unallocated	6	1.6	0.1	0.0
Total	8,996	4,534.8	100.0	100.0

Table S24: Impact of US Aid Drop on Conflict-related Outcomes, by Institutions. “High executive constraints” and “Low executive constraints” are binary classifications derived from the corresponding score in the Polity V dataset. Each country’s score is calculated as the average value over the period 2000-2018. Countries with an average score above the median are categorized as “High,” while those at or below the median are classified as “Low”. Countries missing more than half of their Polity values during this period are excluded from the sample. The p-value from a Wald test of equality between the two coefficients is reported. Outcome definitions, fixed effects, and estimation procedures otherwise follow the baseline specification. VAC stands for violence against civilians. Standard errors clustered at the ADM1 level are reported in parentheses. Significance levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

	All Types of Conflict (1)	Battle (2)	Protest and Riot (3)	VAC (4)
Incidence				
IHS(US aid p.c.) × Post (High executive constraints)	0.004* (0.002)	-0.001 (0.003)	0.003 (0.003)	-0.002 (0.004)
IHS(US aid p.c.) × Post (Low executive constraints)	0.001 (0.003)	0.005* (0.003)	0.007* (0.004)	0.006** (0.003)
High = Low (p-val)	0.440	0.108	0.345	0.071
Incidence Counts				
IHS(US aid p.c.) × Post (High executive constraints)	-0.000 (0.007)	-0.005 (0.006)	0.004 (0.005)	-0.006 (0.007)
IHS(US aid p.c.) × Post (Low executive constraints)	0.025*** (0.009)	0.016** (0.007)	0.012** (0.005)	0.016** (0.007)
High = Low (p-val)	0.030	0.024	0.228	0.033
Intensity (Deaths)				
IHS(US aid p.c.) × Post (High executive constraints)	-0.009 (0.009)	0.000 (0.007)	-0.001 (0.004)	-0.009 (0.008)
IHS(US aid p.c.) × Post (Low executive constraints)	0.022* (0.013)	0.017 (0.011)	0.005* (0.003)	0.010 (0.009)
High = Low (p-val)	0.053	0.187	0.194	0.116
N	14238	14238	14238	14238
ADM1 FE	Yes	Yes	Yes	Yes
Country-Month FE	Yes	Yes	Yes	Yes

Table S25: Impact of US Aid Drop on Conflict Depending on Chinese Aid. This table estimates heterogeneous effects of US aid exposure depending on the presence of Chinese development finance. We measure Chinese aid using average annual per-capita commitments over 2017–2020 from the GODAD database (46), and classify regions as *High* or *Low* based on whether Chinese commitments per capita exceed the sample mean. Commitments rather than disbursements are used because China does not provide official disbursements data, as explained by GODAD. The continuous US aid exposure variable receives a separate coefficient for each group. The *p*-value from a Wald test of equality between the two coefficients is reported. Outcome definitions, fixed effects, and estimation procedures otherwise follow the baseline specification. Standard errors clustered at the ADM1 level are reported in parentheses. Significance levels: **p* < 0.10, ***p* < 0.05, ****p* < 0.01.

	All Types of Conflict (1)	Battle (2)	Protest and Riot (3)	VAC (4)
Incidence				
IHS(US aid p.c.) × Post (High China p.c.)	0.005 (0.004)	0.001 (0.004)	0.007* (0.004)	0.005 (0.004)
IHS(US aid p.c.) × Post (Low China p.c.)	0.005** (0.002)	0.003 (0.002)	0.005** (0.002)	0.002 (0.002)
High = Low (p-val)	0.990	0.607	0.619	0.522
Incidence Counts				
IHS(US aid p.c.) × Post (High China p.c.)	0.017** (0.008)	0.005 (0.006)	0.010* (0.006)	0.008 (0.008)
IHS(US aid p.c.) × Post (Low China p.c.)	0.017*** (0.005)	0.011** (0.005)	0.009*** (0.003)	0.007 (0.004)
High = Low (p-val)	0.949	0.289	0.853	0.829
Intensity (Deaths)				
IHS(US aid p.c.) × Post (High China p.c.)	0.013 (0.010)	0.008 (0.009)	0.003 (0.005)	0.006 (0.007)
IHS(US aid p.c.) × Post (Low China p.c.)	0.011 (0.008)	0.016** (0.007)	0.002 (0.002)	0.001 (0.005)
High = Low (p-val)	0.775	0.284	0.748	0.399
N	18270	18270	18270	18270
ADM1 FE	Yes	Yes	Yes	Yes
Country-Month FE	Yes	Yes	Yes	Yes

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