Carl von Ossietzky Universität Oldenburg

Oldenburg Discussion Papers in Economics

Foreign Aid and Local Conflict Dynamics: A Monthly Grid-Cell-Level Analysis in Africa

Jürgen Bitzer

Bernhard C. Dannemann

Erkan Gören

V – 452-25

May 2025

Department of Economics
University of Oldenburg, D-26111 Oldenburg

Foreign Aid and Local Conflict Dynamics: A Monthly Grid-Cell-Level Analysis in Africa *

Jürgen Bitzer[†] Carl von Ossietzky University Oldenburg

Bernhard C. Dannemann[‡] Carl von Ossietzky University Oldenburg

Erkan Gören[§] Carl von Ossietzky University Oldenburg

This Version: May 2025

Abstract

This study investigates the relationship between foreign aid and conflict incidence at the sub-national level across Africa using an innovative, high-resolution panel dataset of monthly grid-cell observations. By combining geo-referenced World Bank aid data with conflict event data from the Armed Conflict Location and Event Data (ACLED) project, we construct a dataset comprising over 12 million grid-month observations from 1995 to 2020. Using difference-in-differences (DiD) and event study methodologies, we estimate the immediate and dynamic effects of foreign aid allocation on local conflict. Our findings indicate that foreign aid significantly increases the likelihood of conflict onset within treated grid cells, with effects that emerge immediately upon aid allocation and persist for at least five years. These results are robust across multiple conflict types – including protests, riots, battles, and violence against civilians – and actor categories, such as military forces, militias, and protesters. The use of monthly data at a 0.25×0.25 decimal degrees spatial resolution enables precise temporal alignment of aid delivery and conflict, allowing us to capture both static and dynamic treatment effects. This paper contributes novel empirical evidence to the aid-conflict literature and raises important considerations for the spatial and temporal targeting of development assistance.

Keywords: Geo-Referenced Aid Projects, Geo-Referenced Conflicts, Africa, Sub-Annual Analysis, Grid-Cell Analysis, GIS Data, ACLED, World Bank

JEL Classification Numbers: C23, D74, F35, F52, O19, O55

*We would like to thank seminar participants at the University of Bremen 2024 for helpful comments and suggestions. This research was supported by the German Research Foundation (DFG) as part of the project "The Localized Geography of Development Assistance: A Disaggregated Grid Cell Analysis" under grant number 424612440. All remaining errors are our own.

[†]Carl von Ossietzky Universität Oldenburg, School of Computing Science, Business Administration, Economics, and Law (Faculty II), Institute of Economics, Building A5, 26111 Oldenburg, Germany, Tel.: +49 441 798 4217, e-mail: jbitzer@uol.de.

[‡]Carl von Ossietzky Universität Oldenburg, School of Computing Science, Business Administration, Economics, and Law (Faculty II), Institute of Economics, Building A5, 26111 Oldenburg, Germany, Tel.: +49 441 798 4006, e-mail: bernhard.dannemann@uol.de.

[§]Corresponding author: Carl von Ossietzky Universität Oldenburg, School of Computing Science, Business Administration, Economics, and Law (Faculty II), Institute of Economics, Building A5, 26111 Oldenburg, Germany, Tel.: +49 441 798 4292, e-mail: erkan.goeren@uol.de.

1 Introduction

One of the main objectives of foreign aid is to foster economic development; in addition, it is often intended to reduce conflict in recipient countries. By improving the living conditions of the population, aid is expected to contribute to the stabilization of the recipient country and thereby lower the likelihood of conflict. However, empirical evidence on the relationship between foreign aid and conflict is mixed, with studies showing positive, negative, or no effects (Balcells and Stanton, 2021; Zürcher, 2017, 2019). Unfortunately, the findings of these studies are rarely comparable due to differences in country coverage, time periods analyzed, levels of data aggregation, econometric methods employed, types of aid examined, and the forms of conflict studied.

There is a large body of literature at the country level, which provides important insights into the average effect of foreign aid on conflict across countries and over time (e.g., Adam and Tsarsitalidou, 2022; Ahmed and Werker, 2015; Bluhm et al., 2020; Collier and Hoeffler, 2002; Nunn and Qian, 2014; Christian and Barrett, 2024; Chu et al., 2016; de Ree and Nillesen, 2009; Mousseau, 2020; Szabó, 2022; Mary and Mishra, 2020). These country-level studies include a large number of countries – for example, Adam and Tsarsitalidou (2022) include 198 countries in their sample – and cover a time period ranging from the 1960s to the late 2010s. Thus, these studies provide results that offer a general understanding of the relationship between foreign aid and conflict, although at a highly aggregated level.

Another substantial branch of the literature comprises country-specific studies at the sub-national level, which can provide deep insights into the effect of foreign aid on conflict within the respective countries (e.g., Böhnke and Zürcher, 2013; Child, 2014, 2019; Chou, 2012; Lyall et al., 2020; Sexton, 2016; Dasgupta et al., 2017; Hoelscher et al., 2012; Khanna and Zimmermann, 2014; Berman et al., 2011a, 2013; Dube and Naidu, 2015; Weintraub, 2016; Crost et al., 2014; De Juan, 2019; Premand and Rohner, 2023). However, the findings of these country-specific studies at the sub-national level can only be transferred to other contexts to a limited extent.

Furthermore, there is a small body of literature that uses sub-national data across a large number of countries, thereby combining the insights of country-level studies and country-specific studies at the sub-national level. To the best of the authors' knowledge, only five studies – Findley et al. (2023), Gehring et al. (2022), Wood and Molfino (2016), Wood and Sullivan (2015), and Zhang and Dorussen (2025) – conduct sub-national analyses across a broader set of countries.

Despite the differences among the studies mentioned above, they share one common feature: all use annual data to analyze the relationship between foreign aid and conflict. As a result, no study to date has addressed the sub-annual dynamics of this relationship. However, since conflicts can occur at various times throughout the year – and different types of conflicts exhibit varying durations and dynamics – this remains an important aspect that has not yet been considered in the literature.

As our main contribution, we address this gap in the literature by using monthly data at the grid-cell level. This enables us to precisely align the timing of conflict incidents with the start dates of foreign aid projects. This prevents events that do not coincide in time from being incorrectly perceived as causally connected. Moreover, the use of monthly data allows us to include a greater number of conflict and treatment events in our difference-in-differences (DiD) approach. Additionally, and also novel in the literature, the monthly resolution enables us to investigate the dynamic treatment effect of foreign aid on conflict incidence. To this end, we conduct event studies that capture the dynamic treatment effect over a period of 60 months following the start of a foreign aid project.

Furthermore, the monthly data also enable us to investigate the dynamic treatment effect of foreign aid on short-term conflict events. To this end, we further differentiate our DiD estimations and event studies by various types of conflict. With the exception of Gehring et al. (2017), most studies include only a limited number of conflict types. In contrast, we contribute to the literature by incorporating a broader range of conflict types – namely, battles, explosive/remote violence, violence against civilians, protests, riots, and strategic developments. In addition, we provide evidence on conflicts involving different actors, such as military forces, rebel groups, political and identity militias, as well as rioters, protesters, and other non-state actors. Finally, we also estimate the effects of aid on violence against unarmed civilians.

To ensure that the advantages of our temporal disaggregation to monthly data are not offset by a high level of spatial aggregation, we further reduce the spatial resolution to 0.25×0.25 decimal degrees. This represents an additional contribution to the literature, as the finest spatial resolution used previously is 0.5×0.5 decimal degrees, as in Wood and Sullivan (2015) and Zhang and Dorussen (2025).

More precisely, we investigate the effect of aid allocation by the World Bank on the incidence of conflict at the sub-national level, using a grid-cell-level dataset of monthly data on aid projects and conflict events in Africa. Owing to the low temporal and spatial aggregation, our dataset comprises 12,633,372 grid-month observations covering the period from January 1995 to December 2020 across all African countries. We combine geo-referenced aid project data from the AidData database with conflict data from the Armed Conflict Location and Event Data (ACLED) project to construct this grid-cell-level dataset.

We begin our analysis by using a DiD approach to estimate the effect of aid on conflict onset. Our main results, based on an aggregate measure of general conflict onset, indicate that the allocation of aid to a grid cell significantly increases the likelihood of conflict onset in that same grid cell. This finding is robust across various fixed effects specifications, mitigating concerns about local and time-invariant unobserved heterogeneity within grid cells. In addition, we conduct an event study analysis to investigate the role of timing in determining the impact of foreign aid allocation on the likelihood of conflict. The results reveal that the effect of aid on conflict onset is both immediate and persistent, with the impact still observable up to 60 months after the aid project begins. In contrast, no pre-treatment trends are evident, suggesting that there is no anticipation effect related to aid allocation in the data.

The aggregate measure of any type of conflict is then further disaggregated into specific conflict types to uncover heterogeneity in the relationship between aid and conflict. To this end, we repeat the DiD and event study analyses for different categories of conflict: battles, explosions and remote violence, violence against civilians, protests, riots, and strategic developments. For all categories, the DiD analysis reveals a significant positive effect of aid on conflict onset, with the strongest effects observed for protests and riots. This finding is supported by the event study analysis, which shows that the effect of aid on the onset of protests and riots is immediate and persistent, whereas the effects on other conflict types tend to be delayed or display inconclusive patterns. These results can be interpreted as suggesting that aid may trigger protests and riots related to the distribution of aid resources, without necessarily escalating into more violent forms of conflict.

Accordingly, we further investigate the effect of aid on conflict onset through a disaggregated analysis based on the actors involved in the conflict. In the first step, we differentiate between conflicts involving the military, rebel groups, political and identity militias, and rioters, protesters, or other forces. The DiD results once again confirm a positive effect of aid on conflict onset for all categories, with the exception of conflicts involving rebel groups. The event study analysis shows a pronounced effect of aid on conflict onset for conflicts involving rioters, protesters, or other forces, with the effect beginning immediately after the allocation of aid and persisting for up to 60 months. Next, we analyze conflicts characterized as violence against unarmed civilians perpetrated by the military, rebel groups, political and identity militias, or rioters, protesters, and other forces. This fine-grained analysis reveals that the effect of aid on conflict onset is most evident in violence against civilians committed by rioters, protesters, or other forces. This leads to the conclusion that aid is more likely to increase violence against civilians than to trigger two-sided violence.

To assess the robustness of our results to alternative specifications of both the conflict and aid data, we conduct a series of robustness checks. We employ alternative definitions of conflict incidence by using the number of conflict events and the number of conflict-related fatalities as dependent variables. Similarly, we use alternative measures of aid by considering the number of aid projects and the total amount of aid allocated to a grid cell as independent variables. None of these alternative specifications alters the main findings of the analysis.

The remainder of the paper is structured as follows. Section 2 reviews the related literature on the effect of aid on conflict. Section 3 describes the data, and Section 4 outlines the econometric specification and estimation approach used in the analysis. Section 5 presents the main results and discusses their robustness. Section 6 provides a discussion of the key findings and situates them within the existing literature. Finally, Section 7 concludes.

2 Review of the Relevant Literature

The existing literature on the relationship between conflict and foreign aid is characterized by heterogeneous findings. Unfortunately, the results of different studies are rarely comparable, as they vary in terms of country coverage, time periods analyzed, levels of aggregation, econometric methods employed, types of aid considered, and types of conflict examined. However, the level of aggregation offers an opportunity to identify characteristics that are consistent across studies operating at the same scale. The chosen level of aggregation largely determines the kinds of results a study can produce (Balcells and Stanton, 2021), and, consequently, which issues must be addressed by research conducted at other levels of aggregation.

A large number of studies on the effect of foreign aid on conflict are based on country-level data at an annual frequency.[1] These country-level studies include a large number of countries – for instance, Adam and Tsarsitalidou (2022) include 198 countries in their sample – and therefore provide insights into the average impact of foreign aid on conflict across countries and over time. For a general understanding of the relationship between foreign aid and conflict, this represents an important contribution. The country coverage in this branch of the literature includes virtually all developing countries worldwide (e.g., Adam and Tsarsitalidou, 2022; Ahmed and Werker, 2015; Bluhm et al., 2020; Collier and Hoeffler, 2002; Nunn and Qian, 2014; Christian and Barrett, 2024; Chu et al., 2016; de Ree and Nillesen, 2009), and the time periods studied range from the 1960s (e.g., Collier and Hoeffler, 2002; Ahmed and Werker, 2015; Mousseau, 2020) to the late 2010s (e.g., Szabó, 2022; Mary and Mishra, 2020).

Despite the extensive body of research at the country level, no clear consensus has emerged regarding the effect of foreign aid on conflict. While several studies find a conflict-reducing effect of foreign aid (de Ree and Nillesen, 2009; Metzger, 2024; Narang, 2014; Nielsen et al., 2011; Savun and Tirone, 2017; Young and Findley, 2011; Mary and Mishra, 2020), others report that foreign aid increases the likelihood of conflict (Mousseau, 2020; Narang, 2015). Moreover, some studies arrive at mixed results, suggesting that foreign aid can have both conflict-reducing and conflict-enhancing effects, depending on the context (Adam and Tsarsitalidou, 2022; Ahmed and Werker, 2015; Bluhm et al., 2020; Nourou, 2019; Nunn and Qian, 2014). Additionally, Strange et al. (2015) and Szabó (2022) find that a reduction in foreign aid can lead to an increase in conflict.

While the heterogeneity in findings mentioned above may be partially explained by differences in samples and econometric methods, there is a more fundamental reason underlying these discrepancies. As widely discussed in the aid effectiveness literature, estimates based on aggregated data are subject to aggregation bias, resulting from the aggregation of local events to the country level (Bitzer and Gören, 2024). More specifically, a foreign aid project may be implemented in a region entirely different from where a conflict event occurs. Given the large geographic size of many developing countries, there may be considerable distance between the location of the aid project and the conflict event, with no direct connection between the two. When data are aggregated to the country level, information about spatial distribution is lost, and the resulting estimates may be biased.

In addition, several studies (Schraeder et al., 1998; Alesina and Dollar, 2000; Kuziemko and Werker, 2006; Dreher et al., 2009; Brech and Potrafke, 2014) show that donors often pursue strategic political, economic, and ideological interests in the allocation of foreign aid. This unobserved heterogeneity in donor motivations, combined with the tendency to allocate aid to poorer countries, poses a significant challenge to identifying the true effect of foreign aid on conflict. Unfortunately, at the country level, it is not possible to control for this heterogeneity through the use of country-by-year fixed effects.

Studies at the sub-national level can mitigate the problem of spatial aggregation bias and, in addition, allow for the control of unobserved heterogeneity by introducing country-by-year fixed effects. However, most

[1] See, for example, Adam and Tsarsitalidou (2022); Bluhm et al. (2020); Mary and Mishra (2020); Mousseau (2020); Szabó (2022) for a few recent examples.

existing sub-national studies focus on a single country.[2]

These studies provide deep insights into the effect of foreign aid on conflict within the respective countries and are not subject to the spatial aggregation bias discussed above. However, the foreign aid examined in these analyses is often highly specific to the country in question. For example, Berman et al. (2011a, 2013) analyze U.S. Army reconstruction spending in Iraq; Crost et al. (2014) examine the Philippines' large community-driven program KALAHI-CIDSS; Sexton (2016) studies the U.S. Army's Commanders Emergency Response Program (CERP) in Afghanistan; and Hoelscher et al. (2012) include India's National Rural Employment Guarantee Act (NREGA) program. As a result, the findings of these studies cannot be generalized to other countries, limiting their external validity. Furthermore, because these studies focus on a single country, they are unable to control for unobserved heterogeneity in donor interests and the allocation of foreign aid across countries.

However, there is a small body of literature that uses sub-national data across a large number of countries, thereby combining the advantages of cross-country studies at the national level with those of country-specific studies at the sub-national level. To the best of the authors' knowledge, only five studies – Findley et al. (2023), Gehring et al. (2022), Wood and Molfino (2016), Wood and Sullivan (2015), and Zhang and Dorussen (2025) – conduct sub-national analyses across multiple countries. Although all of these studies perform cross-country sub-national analyses, they exhibit considerable heterogeneity. They differ in terms of sub-national aggregation levels, country samples, and particularly in the types of conflict analyzed. Only the timing and time periods used are relatively similar across studies.

With respect to the heterogeneity in sub-national aggregation levels, Gehring et al. (2022) and Wood and Molfino (2016) use ADM1 as the aggregation level, while Findley et al. (2023) employ the finer ADM2 level. The studies by Wood and Sullivan (2015) and Zhang and Dorussen (2025) go further by using grid-cell-level data. Both of the latter studies use grid cells with a resolution of 0.5×0.5 decimal degrees latitude and longitude, which corresponds to a square with dimensions of approximately 55 km $\times$ 55 km at the equator.

Regarding country coverage, the studies mentioned focus exclusively on African countries. However, they differ considerably in terms of the specific countries analyzed. While Findley et al. (2023) (18 countries), Wood and Molfino (2016) (20 countries), and Wood and Sullivan (2015) (22 countries) concentrate on sub-Saharan Africa, the sample in Zhang and Dorussen (2025) includes only seven African countries, six of which are in sub-Saharan Africa, along with Sudan. The broadest coverage is provided by Gehring et al. (2022), who analyze all African countries with populations exceeding one million.

There is also considerable heterogeneity in the types of conflict analyzed across these studies. Findley et al. (2023) examine military and civilian fatalities occurring within one year of the causative event. Gehring et al. (2022) analyze conflicts involving at least five battle-related deaths (BRD) per year. In addition, they

[2] See, for example, Böhnke and Zürcher (2013); Child (2014, 2019); Chou (2012); Lyall et al. (2020); Sexton (2016) for Afghanistan; Dasgupta et al. (2017); Hoelscher et al. (2012); Khanna and Zimmermann (2014) for India; Berman et al. (2011a, 2013) for Iraq; Dube and Naidu (2015); Weintraub (2016) for Colombia; Crost et al. (2014) for the Philippines; De Juan (2019) for Nepal; and Premand and Rohner (2023) for Niger.

distinguish between various conflict types: government-related groups versus non-state actors, non-state actors versus other organized non-state actors, government-related groups versus civilians, and non-state actors versus civilians. They also address categories such as “Riots, Demonstrations, and Strikes” and “Non-lethal Government Repression”. Wood and Molfino (2016) study the number of battles in a given district within one year between rebel and government forces. Wood and Sullivan (2015) focus on attacks on civilian targets by either insurgent or government forces within a grid cell over the course of a year. Finally, Zhang and Dorussen (2025) analyze one-sided violence against unarmed civilians resulting in at least 25 deaths. All of the aforementioned studies use annual data and cover largely overlapping time periods. Findley et al. (2023) cover the years 1989-2008, Gehring et al. (2022) analyze the period 1995-2012, Wood and Molfino (2016) focus on 1990–2008, Wood and Sullivan (2015) examine 1989-2008, and Zhang and Dorussen (2025) study the years 1989-2007.

A characteristic shared by all studies – regardless of their level of aggregation – is their reliance on annual data for analysis. This raises concerns about potential temporal aggregation bias, as conflicts and foreign aid projects occurring months apart may be incorrectly associated when using yearly data. This issue is especially relevant for short-duration conflicts, which may not align temporally with the aid interventions being studied. For example, using annual data, a riot occurring in January could be erroneously linked to a foreign aid project that began in December of the same year. The problem is exacerbated when lag structures are applied; with a one-year lag, the time gap between the conflict event and the aid project could extend to nearly two years. Furthermore, annual data prevent the analysis of the dynamics of the relationship between foreign aid projects and short-term, sub-annual conflicts. It is reasonable to assume that there is a temporal evolution between the initiation of foreign aid projects and the occurrence of conflict.

All classical theoretical mechanisms discussed in the literature – such as rent-seeking, looting of aid, “hearts and minds”, and redistribution – require that foreign aid is already in place for it to influence conflict incidence (Findley, 2018). This raises an important but underexplored question: how do the impacts of foreign aid on conflict unfold over time? To date, this has not been adequately addressed in the literature.

A major contribution of our paper is to directly address this temporal aggregation bias and to investigate the dynamics of the relationship between foreign aid projects and conflict. For this purpose, we use data from the ACLED project for conflict events and aid data from the AidData international development research lab, which enables us to work with sub-annual, geo-referenced data at the grid-cell level. We reduce both temporal and spatial aggregation by using monthly data in grid cells of 0.25×0.25 decimal degrees, which further mitigates the risks of temporal and spatial aggregation bias.

The use of monthly data reduces the maximum potential mismatch between the start of a foreign aid project and a conflict event to just two months. Moreover, this temporal structure enables us to investigate the dynamics of aid-conflict interactions by conducting an event study analysis. This allows us to examine how conflict incidence evolves in the months following the initiation of a foreign aid project. This is particularly important, as the existing literature provides no insights into the dynamic relationship between foreign aid and conflict.[3]

[3]The only studies addressing the dynamics of the aid-conflict relationship are Metzger (2024), Narang (2014), and Narang (2015), who use Cox proportional hazard models to estimate the duration of peace or conflict periods based on foreign aid flows. However,

We also further reduce the spatial aggregation level by using grid cells of 0.25 $\times$ 0.25 decimal degrees. This is a finer resolution than in Gehring et al. (2022) and Wood and Molfino (2016), who use ADM1, and Findley et al. (2023), who use ADM2. Even compared to Wood and Sullivan (2015) and Zhang and Dorussen (2025), who use grid cells of 0.5 $\times$ 0.5 decimal degrees, our approach offers a substantial improvement in spatial granularity. A 0.5 $\times$ 0.5 grid cell corresponds to an area of approximately 55 km $\times$ 55 km, or 3,078 km^2 at the equator, whereas a 0.25 $\times$ 0.25 grid cell is roughly 27 km $\times$ 27 km, or 768 km^2.

Finally, the low temporal and spatial aggregation levels enable us to investigate both the static and dynamic relationships between foreign aid and various types of conflict, including those of short duration (e.g., riots and demonstrations). We include the following conflict types in our analysis: battles, explosive/remote violence, violence against civilians, protests, riots, and strategic developments.

Moreover, we assess whether the impact of foreign aid on conflict incidence varies depending on the actors involved. To this end, we differentiate our estimations by actor type: military, rebel groups, political and identity militias, and rioters, protesters, and other forces. Finally, we also provide estimates of violence against unarmed civilians, disaggregated by the same actor categories.

3 Data and Variables

We utilize a highly disaggregated spatial and temporal framework to examine the relationship between foreign aid allocation and conflict incidence across Africa. The unit of analysis consists of uniformly sized grid cells measuring 0.25 decimal degrees in both latitude and longitude, resulting in a total of 40,664 grid cells covering the African continent. This grid size is chosen deliberately to balance spatial resolution with measurement precision: it is fine-grained enough to mitigate concerns about unobserved heterogeneity at the local level, while also being large enough to correct for typical geocoding inaccuracies in aid and conflict event data (Jedwab et al., 2022; Alpino and Hammersmark, 2020).

The conflict data are sourced from the ACLED project, which provides detailed, geo-referenced records of conflict incidents. These events are aggregated to the grid-cell level on a monthly basis, generating a binary indicator that equals one if at least one conflict event occurs in a given cell-month, and zero otherwise. This high-frequency temporal resolution allows us to capture short-term fluctuations and dynamic responses to aid interventions, which are often obscured in studies using annual data or more spatially aggregated units.

The foreign aid data come from the AidData international research lab at William & Mary, which provides geo-coded information on World Bank-funded development projects under the IBRD and IDA lending portfolios (AidData, 2017). The original dataset spans the period from 1995 to 2014 and includes 5,684 projects across 61,243 location entries. Each project location is tagged with geographic coordinates (latitude and longitude) and a precision code indicating the spatial accuracy of the location.

We match these geo-referenced aid locations to the corresponding grid cells based on their spatial coor-

these analyses are conducted at the country level and thus share the limitations discussed above.

dinates and construct a time-varying treatment variable using the official start date of each aid project. This high-resolution temporal alignment enables us to study not only whether aid is associated with conflict, but also when and how conflict patterns respond to aid disbursements.

In addition to conflict and aid data, we compute several control variables at the grid-cell level, including climate indicators (e.g., precipitation and temperature), population estimates from the Gridded Population of the World (GPW) dataset, and proxies for local economic activity using nighttime lights intensity. These controls help account for confounding factors that may influence both aid allocation and the likelihood of conflict.

The combined use of monthly data and 0.25×0.25 decimal degree grid cells allows for a nuanced examination of both static and dynamic treatment effects. This structure facilitates causal identification through difference-in-differences and event study models, addressing spatial and temporal aggregation biases that have constrained prior research using annual data or more aggregated spatial units (e.g., country-level or sub-national analysis). Finally, the use of grid cells as the unit of analysis enables us to effectively control for unobserved heterogeneity at the local level through the inclusion of various fixed effects specifications.

We employ a high-frequency time structure, incorporating both year and month, to construct a treatment status variable that enables analysis of the impact of foreign aid projects on conflict events. This approach offers several advantages: (i) the monthly granularity of our data allows for precise tracking of foreign aid interventions, facilitating the observation of short-term fluctuations and immediate responses to aid initiatives. This temporal resolution is critical for understanding the nuanced effects of foreign aid on conflict dynamics; (ii) the high-frequency structure enables us to assess how the timing and intensity of multiple foreign aid projects interact over time, providing insights into their cumulative impact on the incidence and severity of conflict events; (iii) using high-frequency data helps mitigate potential confounding factors that may arise in annual-level analyses. By observing monthly changes, we can more accurately attribute fluctuations in conflict to specific aid interventions, enhancing the robustness of our empirical findings; and (iv) the monthly resolution allows us to explore whether conflict events respond rapidly to foreign aid initiatives. This capability is crucial for distinguishing immediate consequences from long-term effects, offering a clearer picture of the aid-conflict relationship.

3.1 Conflict Measures

We use data from the ACLED project to measure conflict events across space and time.[4] ACLED provides detailed information for tracking and analyzing political violence, protests, and other politically significant developments worldwide.[5] It collects information on various event types, locations, dates, and actors involved, including governments, rebel groups, militias, and civilians. The database focuses on capturing incidents of

[4] The data are available at https://acleddata.com/.

[5] See the ACLED codebook for a detailed description of the data structure and coding rules at https://acleddata.com/acleddatanew/wp-content/uploads/dlm_uploads/2023/06/ACLED_Codebook_2023.pdf.

political violence – such as battles, attacks, and violence against civilians – as well as demonstrations, including both peaceful protests and violent riots. In addition, it tracks strategic developments, which are non-violent but politically significant actions such as peace talks, high-level arrests, or territorial changes.

ACLED data are coded in real time by researchers and are made publicly available on a weekly basis. This real-time approach is particularly valuable for measuring conflict dynamics in African countries, where ACLED offers a unique depth of coverage dating back to January 1997. By maintaining and updating historical data alongside ongoing events, ACLED enables users to measure long-term trends and conflict patterns across the African continent with high temporal accuracy.

ACLED categorizes conflict events into several key event types, each representing distinct forms of violence or politically significant activity. These event types are divided into subcategories, allowing for detailed tracking and analysis of global conflict dynamics. We follow this categorization and focus on the following event types: battles, protests, riots, explosions/remote violence, violence against civilians, and strategic developments. These event types are aggregated to the grid-cell level by counting the number of events in each grid cell and month.

The main dependent variable in our analysis is a binary indicator that equals one if at least one conflict event occurs in a given grid cell in a given month, and zero otherwise.[6]

Since foreign aid is primarily intended to improve the living conditions of the population, we also focus on two-sided conflict events that directly affect civilians. Specifically, we construct binary indicators for different conflict actors (e.g., military, rebels, and political militias) involved in violence against civilians. These indicators enable us to explore key theoretical mechanisms linking foreign aid to conflict, such as the *hearts and minds* hypothesis (Berman et al., 2011b).

3.2 Geo-Referenced Aid Data

This study utilizes geocoded World Bank foreign aid data spanning the period 1995–2014, systematically processed and distributed by the AidData international development research lab hosted at William & Mary (AidData, 2017). The dataset includes 5,684 projects funded under the World Bank's International Bank for Reconstruction and Development (IBRD) and International Development Association (IDA) lending lines, geocoded to 61,243 distinct point locations. Each project location is accompanied by geographic coordinates (latitude and longitude) and a precision code indicating the spatial accuracy and specificity of the location data.

To ensure high spatial resolution and analytical precision, we restrict our analysis to project locations with geocoded precision codes ranging from 1 to 3. Precision code 1 corresponds to exact locations, offering the highest level of spatial accuracy. Code 2 indicates that the project is located "near" a known point, typically within a 25-kilometer radius, while code 3 refers to locations situated within second-order administrative divi-

[6]We also consider alternative dependent variables that capture the intensity of conflict events in a grid cell, such as the number of conflict events or the number of conflict-related fatalities. These allow us to investigate the relationship between aid and conflict intensity, which may differ from the relationship between aid and the likelihood of conflict occurrence.

sions (ADM2), such as counties or districts. We exclude locations with lower spatial accuracy – i.e., precision codes 4 through 8 – to ensure the robustness of our geo-spatial analysis. Specifically, code 4 refers to first-order administrative divisions (ADM1), code 5 to estimated or multi-location projects, and codes 6 through 8 to regional, national, or ambiguous spatial references.

AidData's geocoding approach aligns with the International Aid Transparency Initiative (IATI) classification system, which distinguishes between different types of geographic locations – such as administrative regions, populated places, structures, and topographical features.[7] These classifications are paired with assessments of coordinate accuracy (exact or approximate) to assign a precision code ranging from 1 (exact) to 8 (national or ambiguous).[8] The methodology for assigning these codes is documented in AidData's geocoding methodology guide (Strandow et al., 2011).

Applying this spatial precision filter to the African continent yields a working dataset of 818 projects and 10,668 uniquely geocoded locations. Focusing on these higher-precision records enhances the reliability of spatial identification and improves the robustness of our estimates of localized aid effects on conflict outcomes.

For the empirical analysis, we use the recorded start month and year of each aid project to construct a treatment variable coded as 1 for the month in which a grid cell receives any foreign aid project, and 0 otherwise. Grid cells receiving multiple projects in the same month are treated as having received a single treatment.[9] The treatment variable can increase incrementally with additional projects initiated in the same cell and month, allowing us to capture the cumulative intensity and overlapping nature of aid exposure.

In contrast to the traditional binary staggered adoption approach often used in DiD models, our dynamic treatment coding enables a more granular analysis of how repeated or clustered foreign aid interventions influence conflict incidence over time.

3.3 Additional Geo-Spatial Data

We complement the empirical analysis with a set of control variables that capture various factors potentially influencing the relationship between foreign aid and conflict events. These control variables include biogeographic, climate, demographic, and economic characteristics.

Night-Time Lights. We use night-time lights time-series data from the National Oceanic and Atmospheric Administration (NOAA) National Geophysical Data Center (NGDC) to proxy for local economic activity (NOAA-NGDC, 2015). Night-time light emissions have been shown to strongly correlate with country-level GDP and are widely used as a reliable indicator of economic activity (Henderson et al., 2012).

The original night-time lights data are available at a 30 arc-second resolution (approximately 1 km at the equator) for the period from 1992 to 2013, collected via different satellite missions under the U.S. Air Force

[7] See the IATI geographic location classification at https://iatistandard.org/en/iati-standard/203/codelists/geographiclocationclass/.

[8] See the IATI precision scale at https://iatistandard.org/en/iati-standard/203/codelists/geographicalprecision/.

[9] As a robustness check, we also construct alternative treatment variables accounting for the cumulative number of aid projects per grid cell and month.

Defense Meteorological Satellite Program (DMSP) Operational Linescan System (OLS). We use a recently released extended version of the dataset, which provides observations up to 2021 (Ghosh et al., 2021).[10]

The night-time lights values range from 0 to 63, with higher values indicating greater brightness. However, values are not directly comparable across satellite missions due to differences in calibration and sensor degradation (Elvidge et al., 2014). To ensure consistency, we apply an inter-annual calibration procedure that adjusts brightness values across satellite-years to a common reference: satellite F12 in the year 1999, using Los Angeles as the calibration benchmark (Elvidge et al., 2009, 2014; Hsu et al., 2015).[11] We use the calibrated data to calculate the average annual brightness of each grid cell.

Population Size. We obtain population estimates from the Gridded Population of the World (GPW), Versions 3 and 4, datasets provided by the Center for International Earth Science Information Network (CIESIN) (CIESIN, 2017). These datasets offer gridded population data at 5 arc-minute resolution for the years 1990, 1995, 2000, 2005, 2010, 2015, and 2020.[12]

Climate Data. To account for the potential influence of climatic conditions on conflict (Burke et al., 2015), we use monthly gridded climate data from the Climate Research Unit (CRU) of the University of East Anglia (Harris et al., 2020). The CRU TS v4.05 dataset provides monthly precipitation and temperature data at a 0.5 degree resolution from 1901 to 2020.[13]

Micro-Geographic Variables. To further control for local geographic characteristics potentially influencing conflict, we include several time-invariant micro-geographic variables. Although these are absorbed by grid-cell fixed effects in the baseline model, we interact them with time trends to account for differential pre-trends across treated and control grid cells.

These variables include absolute latitude and longitude, distance to the nearest international border, coastline, river, road, railway, power transmission line, larger settlements (i.e., cities with at least 100,000 inhabitants), and capital city.[14]

[10]The extended night-time lights data are available from the Earth Observation Group (EOG), Payne Institute for Earth Observations, Colorado School of Mines: https://eogdata.mines.edu/products/dmsp/.

[11]The calibration assumes constant brightness in Los Angeles over time, attributing observed differences to technical variation across satellite missions.

[12]Available from NASA's Socioeconomic Data and Applications Center (SEDAC): https://www.earthdata.nasa.gov/centers/sedac-daac.

[13]The dataset is available at: https://crudata.uea.ac.uk/cru/data/hrg/.

[14]Settlement data are obtained from the Global Rural-Urban Mapping Project (GRUMP), Version 1, available at https://www.earthdata.nasa.gov/data/catalog/sedac-ciesin-sedac-grumpv1-stlmnt-1.00. Capital city coordinates are taken from the CIA's *The World Factbook*, available at https://www.cia.gov/the-world-factbook/. Rivers and lakes data are sourced from the Global Self-consistent, Hierarchical, High-resolution Geography Database (GSHHG), available at https://www.ncei.noaa.gov/products/shoreline-coastline-resources. Remaining infrastructure data are from the *Seamless Digital Chart of the World* (SDCW) Base Map Version 10.5, available at https://worldgeodatasets.com/basemaps/index.html.

We also include variables capturing land cover characteristics: the share of cropland,[15] the mean and standard deviation of elevation,[16] and a binary indicator for whether the grid cell is classified as arid, based on the Köppen climate classification (Peel et al., 2007).[17]

Finally, we control for the presence of diamond and gemstone deposits, which may act as conflict drivers in some regions (Berman et al., 2017).[18]

3.4 Summary Statistics

Summary statistics for the main regression variables are presented in Table C1. Panel A shows that approximately 0.75% of grid-cell-month observations record at least one conflict event. When disaggregating by conflict type, the data indicate that the majority of events involve violence against civilians (0.28%), followed by battles (0.25%) and protests (0.19%).[19]

For completeness, we also report summary statistics for the full set of climatic and socioeconomic control variables. Panel B provides descriptive statistics for the time-invariant grid-cell-level controls, which are employed in robustness checks to account for pre-trend differences between treated and control units arising from specific geographic characteristics.[20]

Regarding the foreign aid treatment variable, 754,018 observations – equivalent to 5.97% of the full sample of 12,633,372 grid-cell-months – are classified as treated, meaning that at least one foreign aid project was initiated in the grid cell during that month. A closer look at the treatment distribution shows that 3,634 grid cells (8.93%) received at least one aid intervention over the sample period (see Table C3). Among these, 1,862 grid cells (51.24%) were treated only once, while 1,772 grid cells (48.76%) received multiple treatments. Notably, 3,311 of the treated grid cells (91.11%) received up to five treatments over the entire sample period. The maximum number of treatment months observed in a single grid cell is 29.

The spatial distribution of conflict events and foreign aid projects is visualized in Figure B1. Aside from the Sahara Desert, the map reveals that much of the African continent experiences a high frequency of conflict events, driven by factors such as poverty, political instability, and historical legacies. Similarly, World Bank-funded foreign aid projects are predominantly concentrated in Sub-Saharan Africa, while other regions receive relatively fewer interventions. This distribution reflects broader aid allocation patterns shaped by humanitarian

[15] Derived from EarthStat: http://www.earthstat.org/. Values range from 0 (no cropland) to 1 (entire grid cell covered).

[16] Elevation data are from the NASA Shuttle Radar Topography Mission (SRTM v2.1), available from the U.S. Geological Survey (USGS): https://earthexplorer.usgs.gov/.

[17] Köppen climate data can be downloaded from the supplementary materials of Peel et al. (2007): https://doi.org/10.5194/hess-11-1633-2007.

[18] Data on diamond and gemstone deposits are provided by the Peace Research Institute Oslo (PRIO): https://www.prio.org/data.

[19] These relatively low figures are due to the high temporal and spatial resolution of our data structure. We use monthly grid-cell-level data, which is substantially more granular than the annual data employed in most previous studies. Additionally, conflict events are rare occurrences, leading to a low average frequency per observation unit.

[20] Correlation coefficients between the main variables of interest are reported in Table C2.

need, strategic interests, and donor preferences.

While there is a notable spatial overlap between the occurrence of conflict events and the location of foreign aid projects, this correlation should not be interpreted as causal. Foreign aid may be strategically targeted toward regions with existing or elevated conflict risk. The following section outlines our empirical strategy to identify the causal impact of foreign aid interventions on conflict incidence in Africa.

4 Econometric Specification and Estimation Approach

The relationship between foreign aid and conflict is subject to endogeneity concerns, which may bias estimation results. One key source of endogeneity is self-selection: regions experiencing higher levels of conflict may be more likely to receive foreign aid due to urgent humanitarian or stabilization needs. Conversely, reverse causality may also be present. Specifically: (i) conflict-affected areas may receive less aid due to security concerns or logistical constraints, and (ii) formerly conflict-affected regions may receive more aid as part of peacebuilding or prevention strategies.

To address these endogeneity concerns, we analyze the relationship between foreign aid and conflict likelihood at the level of small, equally sized grid cells. This disaggregated approach offers several advantages. First, by narrowing the unit of analysis to a fine spatial scale, we are able to establish a more direct link between aid allocation and conflict locations while controlling for time-invariant unobserved heterogeneity using fixed effects. Second, we leverage monthly data on conflict events, rather than the more common annual data, to better capture the temporal dynamics of the aid-conflict relationship. This allows us to investigate whether aid disbursed in a particular month affects the probability of conflict in subsequent months. Third, we employ a DiD framework to estimate the causal effect of foreign aid on conflict likelihood. This approach compares the change in conflict incidence over time between treated and untreated grid cells, controlling for both spatial and temporal fixed effects. In addition, we extend the DiD model with an event study specification that includes leads and lags of the foreign aid treatment variable relative to the timing of aid disbursement. This allows us to further explore the dynamic effects of aid on conflict and to test the parallel trends assumption underlying the validity of the DiD identification strategy.

Thus, the baseline econometric specification is given by the following equation:

$$C_{gt} = \alpha + \beta Foreign\ Aid_{gt} + X'_{gt}\Pi + S'_{gt}\Gamma + \lambda_g + \lambda_{c(g)t} + \varepsilon_{gt}, \tag{1}$$

where C_{gt} is a binary variable that takes a value of 100 if a conflict event occurs in grid cell g and time t, and zero otherwise. $Foreign\ Aid_{gt}$ is a treatment status variable that takes the value of one in any month in which a foreign aid project occurs in grid cell g, and zero otherwise. It increases by one unit for each additional month in which grid cell g receives at least one foreign aid project. This definition aligns with the approach of Schmidheiny and Siegloch (2023), who propose a similar framework where treatment units may receive multiple interventions over the study period. This cumulative treatment specification allows us to capture the compounding effects of repeated foreign aid disbursements on conflict likelihood within the same grid cell.

The vector X_{gt} includes a baseline set of time-varying climate controls at the grid-cell level, specifically mean monthly precipitation and mean monthly temperature. The vector S_{gt} contains time-varying socio-economic controls, including the log of population size and the log of night-time lights intensity, both measured at the grid-cell level for each year.

Our specification includes grid cell fixed effects, λ_g, and country-by-time fixed effects, $\lambda_{c(g)t}$, where grid cell g is nested within country c. Estimation is conducted using Ordinary Least Squares (OLS) with standard errors clustered two ways: at the grid cell level and at the region-by-year level. This two-way clustering accounts for both serial correlation over time and spatial autocorrelation across grid cells within broader administrative (i.e., ADM1) regions. The region-by-year clustering is particularly important in our context, as it allows for the possibility that unobserved shocks may affect multiple grid cells within the same region at the same time.

The inclusion of grid cell fixed effects λ_g controls for time-invariant unobserved heterogeneity across space, such as geographical or historical factors, that may affect the likelihood of conflict in a given grid cell. Meanwhile, the country-by-time fixed effects $\lambda_{c(g)t}$ control for unobserved heterogeneity that varies across countries and over time – such as differences in institutional quality, macroeconomic conditions, or national aid allocation policies.

We implement two versions of time fixed effects: (i) country-by-year fixed effects, which control for country-specific shocks or trends at the annual level, and (ii) country-by-year-by-month fixed effects, which capture seasonal variation and more granular time-specific unobservables at the monthly level. The latter specification is particularly useful for addressing potential seasonality in conflict patterns that could be correlated with the timing of foreign aid disbursement.

For the event study specification, we estimate the following regression model:

$$C_{gt} = \alpha + \sum_{j=-2}^{-J} \beta_j D_{gt}^j + \sum_{k=0}^{K} \gamma_k D_{gt}^k + X'_{gt}\Pi + S'_{gt}\Gamma + \lambda_g + \lambda_{c(g)t} + \varepsilon_{gt}. \tag{2}$$

The lead terms, denoted as D_{gt}^j for $j \in \{-2, \dots, -(J-1)\}$, represent binary variables for the pre-treatment periods. They indicate whether a foreign aid project is exactly j periods away for a specific grid cell g at time t. These lead terms capture the anticipation of the foreign aid project before it actually occurs. Similarly, the lag terms, denoted as D_{gt}^k for $k \in \{0, \dots, K-1\}$, represent binary variables for the post-treatment periods. They indicate whether the foreign aid project has been passed exactly k periods relative to the foreign aid event date. These lag terms capture the effects of the foreign aid project after it has occurred. It's important to note that the first lead term, D_{gt}^{-1}, is excluded from the event study specification. This means that the coefficient $\beta-1$ is set to zero in the month prior to the foreign aid event. This normalization allows us to interpret the estimated leads and lags regression coefficients relative to this baseline period. In the standard event study specification, the values of J and K refer to binned endpoints that accumulate leads and lags effects beyond the event window. In this case, J is set to 36, representing 36 leads (or 3 years) for the pre-treatment period, and K is set to 60, representing 60 lags (or 5 years) for the post-treatment period. These values are chosen to examine the dynamic treatment effects of aid allocation on conflict likelihood relative to the reference month. Overall, the event study specification helps us understand the short-term and long-term effects of aid allocation on conflict likelihood. It also allows us to investigate the parallel trends assumption, which is important for the validity of the DiD approach.[21]

5 Empirical Results

We begin by presenting the results from the DiD analysis, which estimates the average treatment effect of the foreign aid intervention on conflict likelihood. The DiD model shows a statistically significant impact on various conflict measures, indicating that the intervention led to a meaningful change in the outcome variable relative to the control group. While this provides a clear indication of the overall effect, it does not reveal how the treatment effect may have varied over time.

To examine these time dynamics more closely, we turn to the event study analysis. The event study provides a more detailed look at how the treatment effect evolves before and after the intervention. In the pre-intervention period, the coefficients are small and statistically not significant, supporting the assumption that the treatment and control groups followed similar trends before the foreign aid intervention. After the intervention, the treatment effect begins to emerge, with statistically significant increases observed just after the aid intervention takes effect.

5.1 Foreign Aid Allocation and Overall Conflict Likelihood

Difference-in-Differences Estimates. We begin the empirical analysis by examining the relationship between foreign aid allocation and conflict likelihood, conditioning on various fixed effects specifications and control variables. Our goal is to present a step-by-step analysis that demonstrates the robustness of the relationship to potential omitted variable bias. The corresponding estimates are reported in Table A1. We start with a parsimonious specification and incrementally introduce additional controls and fixed effects.

In column (1), we estimate the baseline relationship without any control variables. The results indicate a positive and statistically significant association between foreign aid allocation and conflict likelihood at the 1% level. The coefficient suggests that the presence of any foreign aid project in a given grid cell and month increases the likelihood of conflict events by approximately 2.0288 percentage points per month. This is a substantial effect, given that the average conflict likelihood in the sample is approximately 0.7517 percentage points per month.

In column (2), we introduce grid cell fixed effects, which control for time-invariant, grid-cell-specific characteristics potentially correlated with both aid allocation and conflict risk. The coefficient estimate remains virtually unchanged and statistically significant at the 1% level. This finding suggests that using small grid cells as the unit of analysis effectively mitigates concerns related to unobserved, time-invariant heterogeneity at the local level.

[21] We do not consider statistically significant pre-treatment coefficients in close proximity to the event date as evidence against the parallel trends assumption. Rather, we interpret them as evidence of the presence of short-term anticipation effects.

Column (3) adds country-by-year fixed effects to the model, thereby accounting for country-specific, time-varying factors such as macroeconomic conditions, political stability, and institutional quality. This specification exploits within-country, within-year variation in aid allocation and conflict incidence. The coefficient on the foreign aid variable remains robust and significant at the 1% level.

In columns (4) and (5), we sequentially include exogenous climatic controls (e.g., monthly precipitation and temperature) and socio-economic controls (e.g., population size and night-time lights). The coefficient estimate for foreign aid declines slightly in magnitude but remains statistically significant at the 1% level. The estimates in column (5) indicate that foreign aid is associated with an average increase of 1.8746 percentage points in the monthly likelihood of conflict events in treated grid cells compared to untreated ones.

Columns (6) through (8) incorporate an even more exhaustive set of fixed effects. Specifically, we include country-by-year-by-month fixed effects, which allow us to control for time-varying, country-specific shocks at a monthly resolution. This approach enables us to exploit variation in aid allocation and conflict incidence within countries, years, and months. The coefficient estimates for the foreign aid treatment variable remain highly robust and statistically significant at the 1% level.

Taken together, these results suggest that the use of country-by-year fixed effects is sufficient to account for time-varying, country-level unobserved heterogeneity, and that the positive relationship between foreign aid and conflict is not driven by omitted variable bias.

Event Study Estimates. Figure B2 presents the event study estimates of the dynamic treatment effects of foreign aid on conflict likelihood, allowing us to explore the evolution of the outcome variable both before and after the aid intervention.

The pre-treatment coefficients for periods $t < 0$ are close to zero and statistically insignificant at conventional levels. This suggests that, prior to the intervention, treated and control grid cells followed parallel trends – supporting the key identification assumption of the DiD framework. In particular, the absence of significant pre-treatment effects indicates that outcome trajectories were stable in the periods leading up to treatment, with no evidence of anticipatory effects or divergent trends that might compromise causal interpretation.

Turning to the post-intervention period, we observe a steady increase in the estimated treatment effect over time. Beginning at period $t = 8$, the coefficient becomes positive and statistically significant, with the probability of conflict rising by approximately 1 percentage point after 24 months relative to untreated grid cells. As time progresses, the effect continues to grow, indicating a gradual adjustment process. By $t + 36$ months, the estimated effect reaches roughly 1.5 percentage points, and by $t + 60$ months, the impact peaks at nearly 2 percentage points. This pattern suggests a cumulative and intensifying effect of foreign aid interventions over time.

The persistence of the positive and increasing treatment effects underscores the lasting influence of aid on conflict dynamics. Even at the furthest horizon considered ($t + 60$ months), the treatment effect remains substantial, highlighting that the consequences of aid allocation continue to accumulate well after the initial disbursement. The observed trajectory suggests that the full impact of aid takes time to materialize.

The 90% confidence intervals, depicted by capped spikes above and below the point estimates in Figure B2, provide further insight into the statistical precision of the estimates. These intervals are relatively narrow in the early post-treatment periods, indicating high precision and strong statistical significance.

These event study results align closely with the DiD estimates reported earlier. While the DiD model captures the average post-treatment effect – estimated at approximately 1.8746 percentage points (cf. Table A1, column 5) – the event study framework reveals how this effect evolves over time. Specifically, the DiD estimate reflects a weighted average of all post-treatment periods, potentially masking important dynamic heterogeneity. In contrast, the event study illustrates that the treatment effect builds gradually, reaching levels consistent with the DiD average only after several years.

In sum, the event study analysis provides compelling evidence that foreign aid interventions led to a positive and sustained increase in conflict likelihood. The absence of significant pre-treatment effects strengthens the validity of the parallel trends assumption, while the significant and growing post-treatment effects illustrate the enduring impact of aid on conflict outcomes. Moreover, the dynamic perspective offered by the event study adds valuable information on the timing and progression of the treatment effect – insights that static DiD models alone cannot capture. These findings underscore the importance of considering temporal dynamics when evaluating the consequences of foreign aid on conflict likelihood.

5.2 Different Types of Conflict Events

The conflict events in the ACLED database can be systematically categorized along a conflict intensity dimension, which varies based on the severity, scale, and directness of the violence involved.

High-intensity conflict events – such as battles and explosions/remote violence – represent the most severe forms of violence. Battles involve direct armed confrontations between organized groups, often resulting in significant casualties and territorial changes. Explosions and remote violence, including bombings and airstrikes, entail the use of destructive weaponry, leading to widespread damage and fatalities. Violence against civilians also qualifies as high-intensity conflict, though it differs in its asymmetric nature; in such events, armed actors target unarmed civilians through killings, abductions, or sexual violence.

Moderate-intensity conflict includes riots, which typically involve spontaneous violent or destructive acts by mobs. These events tend to be localized and less organized. Protests vary in intensity, ranging from peaceful demonstrations (low intensity) to confrontational or repressive incidents (moderate intensity), depending on escalation and responses from authorities.

Strategic developments, while generally non-violent, encompass politically significant actions such as peace agreements, arrests of high-profile figures, or territorial changes. These are categorized as low-intensity events but can be pivotal in shaping future conflict dynamics.

This categorization enables us to assess whether foreign aid interventions influence the likelihood of specific types of conflict events along this intensity spectrum.

Difference-in-Differences Estimates. Table A2 presents the results of the DiD analysis disaggregated by conflict event type. Each column reports the estimated treatment effect of foreign aid intervention on a specific conflict event category, using our preferred specification with the full set of fixed effects and control variables. For comparison, column (1) replicates the overall average treatment effect previously reported (cf. column 5 of Table A1).

The results indicate that foreign aid interventions significantly influence multiple conflict event types. For high-intensity events, including battles (cf. column 2) and explosions/remote violence (cf.column 3), the treatment effects are positive and statistically significant at the 1% level. The estimated increases in conflict likelihood are 0.2270 and 0.0795 percentage points per month, respectively. These results suggest that aid is associated with an escalation in severe forms of violence.

Similarly, for moderate- and low-intensity conflict types, the treatment effects remain positive and highly significant. The likelihood of violence against civilians (cf. column 4) increases by 0.5335 percentage points, riots by 0.7968 points (cf. column 6), and protests by 1.2955 points (cf. column 5). These results imply that foreign aid interventions are also associated with higher frequencies of less organized or more diffuse conflict events.

The estimated effect on strategic developments is likewise positive and statistically significant at the 1% level, with an increase of 0.3302 percentage points per month. This suggests that foreign aid may also trigger or coincide with politically significant, though non-violent, developments.

Event Study Estimates. Figure B3 presents the event study estimates of the dynamic treatment effects of foreign aid on each conflict event type. Pre-treatment coefficients for periods $t < 0$ are close to zero and statistically not significant for all event types, supporting the parallel trends assumption and reinforcing the validity of our DiD identification strategy.

For battles, post-treatment effects become positive and statistically significant in months $t+8$, $t+21$, $t+42$, and $t+51$, suggesting a wave-like response pattern following aid allocation. The treatment effect remains significant at $t+60$ and beyond, indicating persistent impacts. In contrast, the coefficients for explosions/remote violence fluctuate without a clear pattern and are statistically insignificant across most post-treatment periods, suggesting a weaker or more context-dependent effect for this conflict type. For violence against civilians, the post-treatment effects are consistently positive and statistically significant across short-, medium-, and long-term horizons, including at $t+60$ months. This again suggests a lasting relationship between foreign aid and civilian-targeted violence. Protests and riots exhibit a steadily increasing treatment effect over time, with the largest impacts observed in the long term. This pattern suggests a cumulative mobilization effect possibly linked to the redistribution or visibility of aid. Strategic developments also exhibit a wave-like post-treatment pattern, with significant effects emerging primarily in the long run, consistent with the delayed institutional or political reactions to aid flows.

Together, the event study results highlight the temporal dynamics and heterogeneity of conflict responses to foreign aid. They reinforce the DiD estimates while adding crucial insight into the evolution, timing, and persistence of these effects. The findings suggest that the impact of aid is not uniform across conflict types, but instead unfolds differently depending on the nature and intensity of the event.

5.3 Type of Conflict Actors Involved

Conflicts often involve a diverse array of actors, including state forces, rebel groups, political militias, and civilians, each with distinct roles and motivations. These actors directly impact the humanitarian landscape, influencing where and how aid can be delivered. For instance, rebel groups may control territory where civilians are most in need, yet these areas might be inaccessible due to ongoing hostilities or political constraints. Furthermore, the strategic behavior and influence of these actors in the wake of aid interventions can shape conflict dynamics, potentially leading to unintended consequences (e.g., sabotage of aid efforts, diversion of resources, or exploitation of aid for political gain). Understanding how different conflict actors respond to foreign aid interventions is thus crucial for assessing the policy's overall impact on conflict outcomes.[22]

Difference-in-Differences Estimates. Table A3 presents the DiD estimates of the impact of foreign aid intervention on different conflict actors. The results indicate that foreign aid intervention leads to a significant increase in military violence, militia violence, riots, and protests. Specifically, the coefficient estimates for military and militia violence are positive and statistically significant at the 1% significance level, suggesting that foreign aid intervention is associated with a higher likelihood of violent actions by state forces and organized armed groups. Similarly, the treatment effects for riots and protests are also positive and statistically significant, indicating that foreign aid intervention correlates with an increased incidence of civil unrest and public demonstrations. These findings highlight the complex and multifaceted nature of conflict dynamics, where foreign aid can inadvertently exacerbate tensions and lead to various forms of violence involving different actors.

Event Study Estimates. Figure B4 illustrates the event study estimates of the dynamic treatment effects of foreign aid on different conflict actors. The pre-treatment coefficients for periods $t < 0$ are, once again, close to zero and statistically not significant, indicating parallel trends between treatment and control groups before the intervention. In the post-intervention period, the treatment effects gradually rise over time, becoming positive and statistically significant. This upward trend suggests that the impact of foreign aid on conflict actors intensifies as time progresses. For instance, the likelihood of military and militia violence increases steadily, reflecting a growing response to the aid intervention. Similarly, the treatment effects for riots and protests also show a gradual rise, indicating that civil unrest and public demonstrations become more frequent over time. These findings underscore the dynamic nature of the treatment effects, highlighting that the influence of foreign aid on conflict actors becomes more pronounced as the post-intervention period extends.

5.4 Violence against Civilians

Violence against civilians is a critical factor in shaping foreign aid targeting, as it directly impacts both the need for humanitarian assistance and the challenges of delivering it. Foreign aid organizations must carefully assess

[22] A detailed analysis of the various theoretical mechanisms through which foreign aid might shape the behavior of different conflict actors is beyond the scope of this paper and is left for future research.

the patterns of violence against civilians to ensure that assistance reaches those most in need while minimizing the risk of aid diversion or manipulation by violent actors. Understanding the dynamics of violence against civilians, where both state and non-state actors target unarmed populations, is thus essential for effective aid allocation and conflict mitigation.

Difference-in-Differences Estimates. Table A4 presents the DiD estimates of the impact of foreign aid intervention on violence against civilians. The results show that foreign aid intervention leads to a significant increase in violence against civilians, with a positive and statistically significant treatment effect with the exception of violence against civilian by rebel groups. This finding suggests that foreign aid allocation is associated with a higher likelihood of violence against civilians by both state and non-state actors. The results underscore the complex and multifaceted nature of violence against civilians, where foreign aid can inadvertently exacerbate tensions and lead to increased harm to unarmed populations.

Event Study Estimates. Figure B5 shows how foreign aid affects violence against civilians over time. Before the aid projects began (periods $t < 0$), there are no noticeable differences between areas that received aid and those that did not. This supports the idea that both groups followed similar trends before the intervention.

After aid is introduced, we see a steady and lasting increase in violence against civilians carried out by military forces, militias, rioters, and protesters. These effects grow stronger over time and are statistically significant, meaning they are unlikely to be due to random chance. For rebel groups, the increase in violence against civilians is less consistent – positive and significant only in a few periods – which suggests that the link between aid and rebel violence is weaker.

Overall, the results indicate that foreign aid is followed by a long-term rise in violence against civilians. This highlights a concerning unintended consequence of foreign aid programs: rather than reducing conflict, they may contribute to increased harm to civilian populations.

5.5 Sensitivity Analysis

In the following, we consider various sensitivity checks of the baseline findings, including alternative definitions of the conflict variables, foreign aid measures, and fixed effects specifications. We apply this sensitivity analysis to the types of conflict events (cf. Table A2) to assess the stability of the treatment effects and the validity of the identification strategy. The results of the sensitivity analysis are presented in Table A5.

In Panels A and B, we consider the log number of conflict events and fatalities, respectively, as alternative conflict measures that capture the intensity of conflict events. In both specifications, the treatment effect of foreign aid on conflict intensity is positive and statistically significant at the 1% level. This finding suggests that foreign aid intervention leads to a higher incidence of high-intensity conflict events, reflecting an escalation in conflict severity.

In Panel C, we retain the original conflict incidence measure but consider the log number of foreign aid projects as an alternative treatment variable. The main results remain qualitatively unchanged, with the treatment effect of foreign aid on conflict likelihood staying positive and statistically significant at the 1% level.

In Panel D, we include interactions between grid-cell-specific biogeographic characteristics (e.g., terrain ruggedness, distance to rivers, and land cover) and polynomial time trends up to the third order. This specification accounts for time-varying non-linear changes in conflict likelihood that are correlated with grid-cell-specific biogeographic features observed before the start of the foreign aid project. Although unit-specific time trends aim to control for omitted variables that trend over time, they might be correlated with our treatment variable, thus potentially over-controlling for time-varying treatment effects (Miller, 2023; Goodman-Bacon, 2021).

Summarizing the results, we find that the treatment effect of foreign aid on conflict likelihood produces coefficient estimates that are smaller in magnitude but remain statistically significant at the 1% level, except in the specification for strategic developments.

6 Discussion

Our estimation results show that including grid-cell and country-by-year fixed effects, along with socioeconomic control variables, tends to reduce the estimated coefficients of the foreign aid variable. This finding is consistent with Gehring et al. (2022), who similarly report smaller coefficients after accounting for country-by-year fixed effects. In contrast, the inclusion of climate controls does not substantially affect the results. The same holds when using country-by-year-by-month instead of country-by-year fixed effects. These patterns suggest that unobserved heterogeneity in the strategic, political, economic, or ideological motivations of donor countries may play an important role in shaping how foreign aid influences conflict outcomes. While Gehring et al. (2022) provide some evidence in this regard – showing, for example, that Chinese foreign aid does not appear to increase conflict – this topic requires further investigation and is beyond the scope of this study.

Overall, our estimations indicate that foreign aid is positively and significantly associated with conflict incidence in 13 out of 15 model specifications, including those that differentiate by conflict type, actor involvement, and violence against civilians. However, we find no statistically significant effect in cases involving rebel groups – either in general or specifically in relation to violence perpetrated by rebels against civilians.

Unfortunately, many of our results cannot be directly compared with previous studies due to differences in data structure and design. As discussed in Section 2, much of the existing work relies either on country-level data or on sub-national data limited to individual countries, which restricts comparability. Our study, by contrast, joins a smaller set of sub-national analyses with cross-country coverage.[23]

Our findings of a positive and significant association between battles and foreign aid (see Table A2, column 2) complement those of Wood and Molfino (2016), who also found a positive association between battles and foreign aid. However, they used humanitarian aid as an independent variable and had yearly data on the ADM1

[23] For example, the study by Findley et al. (2023) investigates the relationship between conflict and the spatial concentration of foreign, and is therefore not directly comparable to our analysis.

level for twenty sub-Saharan African countries between 1990 and 2008. In contrast, Gehring et al. (2022) found that World Bank foreign aid projects had a negative effect on conflicts involving at least five battle-related deaths. However, although their data contains all African countries, as in our study, their analysis is based on annual ADM1-level data for the period 1995–2012.

With regard to our findings on violence against civilians perpetrated by rebel groups, for which our estimations yield insignificant coefficients (see Table A3, column 2 and Table A4, column 3), these align with the results of Zhang and Dorussen (2025), who also found no significant direct influence of humanitarian foreign aid. However, they provide evidence that humanitarian foreign aid may reduce violence against civilians by rebel groups when combined with peacekeeping activities. However, their analysis is based only on seven African countries for the period 1989–2007, and on humanitarian aid at grid-cell level. In contrast, Wood and Sullivan (2015) find persistent significant and positive effects in all their specifications. However, they only consider humanitarian foreign aid, using yearly data from 22 sub-Saharan African countries and a time period from 1989 to 2008. They also use grid-cell level data, albeit at a 0.5 decimal degrees level, as opposed to our study's 0.25 decimal degrees level. In contrast, Gehring et al. (2022) find a negative association between violence by non-state actors against civilians and foreign aid.

Our results show that foreign aid is positively associated with military violence against civilians (see Table A4, column 2). This is partly in line with Wood and Sullivan (2015), who also found such a positive association between humanitarian aid and governmental violence against civilians in one of three of their specification. The other two specifications in Wood and Sullivan (2015) receive only insignificant coefficients. Gehring et al. (2022) also found no significant association between state violence against civilians and foreign aid. In contrast, Zhang and Dorussen (2025) found a negative association between government violence against civilians and foreign aid.

Finally, our findings on violence against civilians, regardless of the perpetrator, indicate a positive and significant association with foreign aid (cf. Table A4, column 1). These results are partly in line with those reported by Zhang and Dorussen (2025), who find a similar association in their reduced-form model specification. However, once additional controls are included, the association in their analysis becomes statistically insignificant.

7 Conclusion

This paper has investigated the relationship between the allocation of foreign aid and conflict likelihood in sub-national grid cells of recipient countries in Africa on monthly basis. We analyzed this relationship empirically by using geo-referenced data on foreign aid projects and conflict events in a difference-in-differences framework, as well as by employing an event study approach.

Our central results based on difference-in-differences suggest that foreign aid allocation is associated in general with a higher likelihood of conflict incidence in recipient grid cells. A closer inspection of event study results indicates that this effect of foreign aid on conflict likelihood is on the one hand immediate, manifesting already in the month of project implementation, and on the other hand persistent, lasting for more than 60 months after project start. These results are robust to alternative specifications splitting the sample by conflict type and actors involved. While the DiD results confirm the conflict-inducing effect of foreign aid across the different samples, the event study results suggest that the effect is particularly pronounced and immediate for non-state conflicts, such as riots and protests, as well as for conflicts involving non-state actors, such as rioters and protesters.

The results of this study can be interpreted as a warning signal for policy makers and donors that foreign aid may not only fail to prevent conflict but may even exacerbate it. A possible reason for this could be that foreign aid allocation to a specific grid-cell may inadvertently fuel grievances and competition over the newly introduced resources among the different groups in the project's vicinity. Therefore, a limitation of our study is that we do not differentiate between different types of aid, such as humanitarian, development, or military aid. These are likely to have different effects on conflict likelihood, as discussed in the literature on aid fungibility. Thus, future research should investigate the local conditions and underlying mechanisms through which certain types of foreign aid projects affect conflict likelihood. In conclusion, our study contributes to the literature on the relationship between foreign aid and conflict by providing sub-national evidence on a fine-grained temporal and spatial scale, which allows for a more nuanced understanding of the complex relationship between foreign aid and conflict likelihood.

References

Adam, A. and Tsarsitalidou, S. (2022). The effect of international development association's (ida) aid on conflict. a fuzzy regression discontinuity approach. *European Journal of Political Economy*, 74:102162.

Ahmed, F. Z. and Werker, E. D. (2015). Aid and the rise and fall of conflict in the muslim world. *Quarterly Journal of Political Science*, 10(2):155–186.

AidData (2017). World_Bank_GeocodedResearchRelease_Level1_v1.4.2 geocoded dataset.

Alesina, A. and Dollar, D. (2000). Who Gives Foreign Aid to Whom and Why? *Journal of Economic Growth*, 5:33–63.

Alpino, M. and Hammersmark, E. M. (2020). The role of historical christian missions in the location of world bank aid in africa. *The World Bank Economic Review*, 35(1):207–233.

Balcells, L. and Stanton, J. A. (2021). Violence against civilians during armed conflict: Moving beyond the macro- and micro-level divide. *Annual Review of Political Science*, 24(1):45–69.

Berman, E., Callen, M., Felter, J. H., and Shapiro, J. N. (2011a). Do working men rebel? insurgency and unemployment in afghanistan, iraq, and the philippines. *Journal of Conflict Resolution*, 55(4):496–528.

Berman, E., Felter, J. H., Shapiro, J. N., and Troland, E. (2013). Modest, secure, and informed: Successful development in conflict zones. *American Economic Review*, 103(3):512–517.

Berman, E., Shapiro, J. N., and Felter, J. H. (2011b). Can hearts and minds be bought? the economics of counterinsurgency in iraq. *Journal of Political Economy*, 119(4):766–819.

Berman, N., Couttenier, M., Rohner, D., and Thoenig, M. (2017). This mine is mine! how minerals fuel conflicts in africa. *American Economic Review*, 107(6):1564–1610.

Bitzer, J. and Gören, E. (2024). The impact of foreign aid on local development: A grid cell analysis. *The Journal of Development Studies*, 60(10):1557–1591.

Bluhm, R., Gassebner, M., Langlotz, S., and Schaudt, P. (2020). Fueling conflict? (de)escalation and bilateral aid. *Journal of Applied Econometrics*, 36(2):244–261.

Brech, V. and Potrafke, N. (2014). Donor Ideology and Types of Foreign Aid. *Journal of Comparative Economics*, 42:61–75.

Burke, M., Hsiang, S. M., and Miguel, E. (2015). Climate and conflict. *Annual Review of Economics*, 7(1):577–617.

Böhnke, J. R. and Zürcher, C. (2013). Aid, minds and hearts: The impact of aid in conflict zones. *Conflict Management and Peace Science*, 30(5):411–432.

Child, T. B. (2014). Hearts and minds cannot be bought: Ineffective reconstruction in afghanistan. *The Economics of Peace and Security Journal*, 9(2).

Child, T. B. (2019). Conflict and counterinsurgency aid: Drawing sectoral distinctions. *Journal of Development Economics*, 141:102245.

Chou, T. (2012). Does development assistance reduce violence? evidence from afghanistan. *The Economics of Peace and Security Journal*, 7(2).

Christian, P. and Barrett, C. B. (2024). Spurious regressions and panel iv estimation: Revisiting the causes of conflict. *The Economic Journal*, 134(659):1069–1099.

Chu, C., Henderson, D. J., and Wang, L. (2016). The robust relationship between us food aid and civil conflict. *Journal of Applied Econometrics*, 32(5):1027–1032.

CIESIN (2017). Center for International Earth Science Information Network - CIESIN - Columbia University. Gridded Population of the World, Version 4 (GPWv4): Population density, revision 11.

Collier, P. and Hoeffler, A. (2002). Aid, policy and peace: Reducing the risks of civil conflict. *Defence and Peace Economics*, 13(6):435–450.

Crost, B., Felter, J., and Johnston, P. (2014). Aid under fire: Development projects and civil conflict. *American Economic Review*, 104(6):1833–1856.

Dasgupta, A., Gawande, K., and Kapur, D. (2017). (when) do antipoverty programs reduce violence? india's rural employment guarantee and maoist conflict. *International Organization*, 71(3):605–632.

De Juan, A. (2019). Heterogeneous effects of development aid on violent unrest in postwar countries: Village-level evidence from nepal. *International Studies Quarterly*, 64(1):168–182.

de Ree, J. and Nillesen, E. (2009). Aiding violence or peace? the impact of foreign aid on the risk of civil conflict in sub-saharan africa. *Journal of Development Economics*, 88(2):301–313.

Dreher, A., Sturm, J.-E., and Vreeland, J. R. (2009). Development Aid and International Politics: Does Membership on the UN Security Council Influence World Bank Decisions? *Journal of Development Economics*, 88:1–18.

Dube, O. and Naidu, S. (2015). Bases, bullets, and ballots: The effect of us military aid on political conflict in colombia. *The Journal of Politics*, 77(1):249–267.

Elvidge, C. D., Hsu, F.-C., Baugh, K. E., and Ghosh, T. (2014). National Trends in Satellite-Observed Lighting: 1992-2012. In Weng, Q., editor, *Global Urban Monitoring and Assessment through Earth Observation*, pages 97–118. CRC Press.

Elvidge, C. D., Ziskin, D., Baugh, K. E., Tuttle, B. T., Ghosh, T., Pack, D. W., Erwin, E. H., and Zhizhin, M. (2009). A Fifteen Year Record of Global Natural Gas Flaring Derived from Satellite Data. *Energies*, 2:595–622.

Findley, M., Young, J. K., Strandow, D., and Cat, O. (2023). Aiding war: Foreign aid and the intensity of violent armed conflict. *International Studies Quarterly*, 67(3).

Findley, M. G. (2018). Does foreign aid build peace? *Annual Review of Political Science*, 21(1):359–384.

Gehring, K., Kaplan, L. C., and Wong, M. H. (2022). China and the world bank—how contrasting development approaches affect the stability of african states. *Journal of Development Economics*, 158:102902.

Gehring, K., Michaelowa, K., Dreher, A., and Spörri, F. (2017). Aid fragmentation and effectiveness: What do we really know? *World Development*, 99:320–334.

Ghosh, T., Baugh, K. E., Elvidge, C. D., Zhizhin, M., Poyda, A., and Hsu, F.-C. (2021). Extending the dmsp nighttime lights time series beyond 2013. *Remote Sensing*, 13(24):5004.

Goodman-Bacon, A. (2021). Difference-in-differences with variation in treatment timing. *Journal of Econometrics*, 225(2):254–277.

Harris, I., Osborn, T. J., Jones, P., and Lister, D. (2020). Version 4 of the cru ts monthly high-resolution gridded multivariate climate dataset. *Scientific Data*, 7(1).

Henderson, V., Storeygard, A., and Weil, D. N. (2012). Measuring Economic Growth from Outer Space. *The American Economic Review*, 102:994–1028.

Hoelscher, K., Miklian, J., and Vadlamannati, K. C. (2012). Hearts and mines: A district-level analysis of the maoist conflict in india. *International Area Studies Review*, 15(2):141–160.

Hsu, F.-C., Baugh, K. E., Ghosh, T., Zhizhin, M., and Elvidge, C. D. (2015). DMSP-OLS Radiance Calibrated Nighttime Lights Time Series with Intercalibration. *Remote Sensing*, 7:1855–1876.

Jedwab, R., Meier zu Selhausen, F., and Moradi, A. (2022). The economics of missionary expansion: evidence from africa and implications for development. *Journal of Economic Growth*, 27(2):149–192.

Khanna, G. and Zimmermann, L. (2014). Fighting maoist violence with promises: Evidence from india's employment guarantee scheme. *The Economics of Peace and Security Journal*, 9(1).

Kuziemko, I. and Werker, E. (2006). How Much Is a Seat on the Security Council Worth? Foreign Aid and Bribery at the United Nations. *Journal of Political Economy*, 114:905–930.

Lyall, J., Zhou, Y.-Y., and Imai, K. (2020). Can economic assistance shape combatant support in wartime? experimental evidence from afghanistan. *American Political Science Review*, 114(1):126–143.

Mary, S. and Mishra, A. K. (2020). Humanitarian food aid and civil conflict. *World Development*, 126:104713.

Metzger, S. K. (2024). Calendar versus analysis time: Reanalyzing the relationship between humanitarian aid and civil conflict duration. *International Studies Quarterly*, 68(3).

Miller, D. L. (2023). An introductory guide to event study models. *Journal of Economic Perspectives*, 37(2):203–230.

Mousseau, D. Y. (2020). Does foreign development aid trigger ethnic war in developing states? *Armed Forces & Society*, 47(4):750–769.

Narang, N. (2014). Humanitarian assistance and the duration of peace after civil war. *The Journal of Politics*, 76(2):446–460.

Narang, N. (2015). Assisting uncertainty: How humanitarian aid can inadvertently prolong civil war. *International Studies Quarterly*, 59(1):184–195.

Nielsen, R. A., Findley, M. G., Davis, Z. S., Candland, T., and Nielson, D. L. (2011). Foreign aid shocks as a cause of violent armed conflict: Aid shocks and conflict. *American Journal of Political Science*, 55(2):219–232.

NOAA-NGDC (2015). National Oceanic and Atmospheric Administration (NOAA) National Geophysical Data Centre (NGDC). Defense Meteorological Satellite Program (DMSP) Data Collected by US Air Force Weather Agency.

Nourou, M. (2019). Foreign aid and development: The civil conflict channel reexamined. *International Economic Journal*, 34(1):1–15.

Nunn, N. and Qian, N. (2014). US Food Aid and Civil Conflict. *American Economic Review*, 104(6):1630–1666.

Peel, M. C., Finlayson, B. L., and McMahon, T. A. (2007). Updated world map of the köppen-geiger climate classification. *Hydrology and Earth System Sciences*, 11(5):1633–1644.

Premand, P. and Rohner, D. (2023). Cash and conflict: Large-scale experimental evidence from niger. *SSRN Electronic Journal*.

Savun, B. and Tirone, D. C. (2017). Foreign aid as a counterterrorism tool: More liberty, less terror? *Journal of Conflict Resolution*, 62(8):1607–1635.

Schmidheiny, K. and Siegloch, S. (2023). On event studies and distributed-lags in two-way fixed effects models: Identification, equivalence, and generalization. *Journal of Applied Econometrics*, 38(5):695–713.

Schraeder, P. J., Hook, S. W., and Taylor, B. (1998). Clarifying the Foreign Aid Puzzle: A Comparison of American, Japanese, French, and Swedish Aid Flows. *World Politics*, 50:294–323.

Sexton, R. (2016). Aid as a tool against insurgency: Evidence from contested and controlled territory in afghanistan. *American Political Science Review*, 110(4):731–749.

Strandow, D., Findley, M. G., Nielson, D., and Powell, J. (2011). The UCDP and AidData Codebook on Georeferencing Aid Version 1.1. *Uppsala Conflict Data Program, Paper No. 4*.

Strange, A. M., Dreher, A., Fuchs, A., Parks, B., and Tierney, M. J. (2015). Tracking underreported financial flows: China's development finance and the aid–conflict nexus revisited. *Journal of Conflict Resolution*, 61(5):935–963.

Szabó, K. (2022). Smoothing the way or stirring the pot: The impact of foreign aid shocks on conflict in recipient countries. *The Journal of Development Studies*, 58(8):1501–1515.

Weintraub, M. (2016). Do all good things go together? development assistance and insurgent violence in civil war. *The Journal of Politics*, 78(4):989–1002.

Wood, R. M. and Molfino, E. (2016). Aiding victims, abetting violence: The influence of humanitarian aid on violence patterns during civil conflict. *Journal of Global Security Studies*, 1(3):186–203.

Wood, R. M. and Sullivan, C. (2015). Doing harm by doing good? the negative externalities of humanitarian aid provision during civil conflict. *The Journal of Politics*, 77(3):736–748.

Young, J. K. and Findley, M. G. (2011). Can peace be purchased? a sectoral-level analysis of aid's influence on transnational terrorism. *Public Choice*, 149(3–4):365–381.

Zhang, S. and Dorussen, H. (2025). Does peacekeeping mitigate the impact of aid on conflict? peacekeeping, humanitarian aid and violence against civilians. *Journal of Conflict Resolution*.

Zürcher, C. (2017). What do we (not) know about development aid and violence? a systematic review. *World Development*, 98:506–522.

Zürcher, C. (2019). The folly of "aid for stabilisation". *Third World Quarterly*, 40(5):839–854.

Appendix

A Regression Tables

Table A1: Difference-in-Differences Estimates of Foreign Aid on Conflict Likelihood

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
			Fixed Effects Specification					
			Country-by-Year FE			Country-by-Year-by-Month FE		
	No Controls	Grid Cell FE	Grid Cell FE	Climatic Controls	Socioeconomic Controls	Grid Cell FE	Climatic Controls	Socioeconomic Controls
	Dependent Variable: Conflict Likelihood (from 0 to 100)							
Foreign Aid	2.0288***	2.0114***	1.9169***	1.9173***	1.8746***	1.9190***	1.9192***	1.8765***
	(0.1050)	(0.0990)	(0.1045)	(0.1045)	(0.1039)	(0.1046)	(0.1046)	(0.1040)
Number of Cells	40701	40701	40701	40701	40701	40701	40701	40701
Number of Treated Cells	3634	3634	3634	3634	3634	3634	3634	3634
Mean of Dependent Variable	0.752	0.752	0.752	0.752	0.752	0.752	0.752	0.752
Observations	12,633,372	12,633,372	12,633,372	12,633,372	12,633,372	12,633,372	12,633,372	12,633,372
Adjusted $R-squared$	0.026	0.160	0.184	0.184	0.184	0.188	0.188	0.188
Grid Cell FE	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country × Year FE	No	No	Yes	Yes	Yes	No	No	No
Country × Year × Month FE	No	No	No	No	No	Yes	Yes	Yes
Climatic Controls	No	No	No	Yes	Yes	No	Yes	Yes
Socioeconomic Controls	No	No	No	No	Yes	No	No	Yes

Notes: Unless otherwise stated, the spatial unit of analysis is a grid cell measuring 0.25 decimal degrees in latitude and longitude. The dependent variable equals 100 if a conflict event occurred in a given grid cell and time period, and 0 otherwise. *Foreign Aid* is a dichotomous treatment status variable that increments by one unit with the initiation of any foreign aid project in a given cell and month. *Climatic Controls* include the mean of total monthly precipitation (in millimeters per month) and mean monthly temperature (in degrees Celsius). *Socioeconomic Controls* include the logarithm of population size and the logarithm of night-time light intensity. A constant term is included in all regressions but not reported. Clustered standard errors – robust to serial correlation within grid cells and spatial correlation across grid cells within ADM1 region-years – are reported in parentheses.
* Significant at the 10% level. ** Significant at the 5% level. *** Significant at the 1% level.

Table A2: Difference-in-Differences Estimates of Foreign Aid on Conflict Likelihood – Type of Conflicts

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Type of Conflict						
	Any Conflicts	Battles	Explosions/Remote Violence	Violence against Civilians	Protests	Riots	Strategic Developments
	Dependent Variable: Conflict Likelihood (from 0 to 100)						
Foreign Aid	1.8746***	0.2270***	0.0795***	0.5335***	1.2955***	0.7968***	0.3302***
	(0.1039)	(0.0389)	(0.0213)	(0.0525)	(0.0980)	(0.0585)	(0.0466)
Number of Cells	40701	40701	40701	40701	40701	40701	40701
Number of Treated Cells	3634	3634	3634	3634	3634	3634	3634
Mean of Dependent Variable	0.752	0.253	0.0661	0.276	0.192	0.122	0.0884
Observations	12,633,372	12,633,372	12,633,372	12,633,372	12,633,372	12,633,372	12,633,372
Adjusted $R-squared$	0.184	0.100	0.0944	0.119	0.145	0.0840	0.0738
Grid Cell FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country × Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Climatic Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Socioeconomic Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: Unless otherwise stated, the spatial unit of analysis is a grid cell measuring 0.25 decimal degrees in latitude and longitude. The dependent variable equals 100 if a specific conflict event occurred in a given grid cell and time period, and 0 otherwise. *Foreign Aid* is a dichotomous treatment status variable that increments by one unit with the initiation of any foreign aid project in a given cell and month. *Climatic Controls* include the mean of total monthly precipitation (in millimeters per month) and the mean annual temperature (in degrees Celsius). *Socioeconomic Controls* include the logarithm of population size and the logarithm of night-time light emissions. A constant term is included in all regressions but not reported. Clustered standard errors – robust to serial correlation within grid cells and spatial correlation across grid cells by ADM1 region-year – are reported in parentheses.
* Significant at the 10% level. ** Significant at the 5% level. *** Significant at the 1% level.

Table A3: Difference-in-Differences Estimates of Foreign Aid on Conflict Likelihood – Type of Actors Involved

	(1)	(2)	(3)	(4)
	Dependent Variable - Conflict Likelihood (from 0 to 100)			
	Military	Rebel Groups	Political and Identity Militias	Rioters, Protesters and other Forces
Foreign Aid	1.0299***	0.0201	0.5812***	1.6413***
	(0.0829)	(0.0471)	(0.0498)	(0.0972)
Number of Cells	40701	40701	40701	40701
Number of Treated Cells	3634	3634	3634	3634
Mean of Dependent Variable	0.329	0.204	0.291	0.320
Observations	12,633,372	12,633,372	12,633,372	12,633,372
Adjusted $R-squared$	0.125	0.116	0.126	0.155
Grid Cell FE	Yes	Yes	Yes	Yes
Country $\times$ Year FE	Yes	Yes	Yes	Yes
Climatic Controls	Yes	Yes	Yes	Yes
Socioeconomic Controls	Yes	Yes	Yes	Yes

Notes: Unless otherwise stated, the spatial unit of analysis is a grid cell measuring 0.25 decimal degrees in latitude and longitude. The dependent variable takes a value of 100 if a specific conflict event occurred in a given grid cell and time period, and 0 otherwise. *Foreign Aid* is a dichotomous treatment status variable that increases by one unit with the initiation of any foreign aid project in a given cell and time. *Climatic Controls* include the mean of total monthly precipitation (in millimeters per month) and the mean annual temperature (in degrees Celsius). *Socioeconomic Controls* include the logarithm of population size and the logarithm of night-time light emissions. A constant term is included in all regressions but not reported. Clustered standard errors – robust to serial correlation within grid cells and spatial correlation across grid cells by ADM1 region-year – are reported in parentheses.

* Significant at the 10% level. ** Significant at the 5% level. *** Significant at the 1% level.

Table A4: Difference-in-Differences Estimates of Foreign Aid on Conflict Likelihood – Violence against Civilians

	(1)	(2)	(3)	(4)	(5)
	Dependent Variable - Conflict Likelihood (from 0 to 100)				
	Violence against Civilians	Military against Civilians	Rebel Groups against Civilians	Political and Identity Militias against Civilians	Rioters, Protestors, and other Forces against Civilians
Foreign Aid	0.7936***	0.3561***	-0.0108	0.3874***	0.2637***
	(0.0640)	(0.0440)	(0.0301)	(0.0344)	(0.0257)
Number of Cells	40701	40701	40701	40701	40701
Number of Treated Cells	3634	3634	3634	3634	3634
Mean of Dependent Variable	0.338	0.0724	0.0737	0.192	0.0395
Observations	12,633,372	12,633,372	12,633,372	12,633,372	12,633,372
Adjusted $R-squared$	0.128	0.0785	0.0726	0.112	0.0290
Grid Cell FE	Yes	Yes	Yes	Yes	Yes
Country $\times$ Year FE	Yes	Yes	Yes	Yes	Yes
Climatic Controls	Yes	Yes	Yes	Yes	Yes
Socioeconomic Controls	Yes	Yes	Yes	Yes	Yes

Notes: Unless otherwise stated, the spatial unit of analysis is a grid cell measuring 0.25 decimal degrees in latitude and longitude. The dependent variable takes a value of 100 if a specific conflict event occurred in a given grid cell and time period, and 0 otherwise. *Foreign Aid* is a dichotomous treatment status variable that increases by one unit with the initiation of any foreign aid project in a given cell and time. *Climatic Controls* include the mean of total monthly precipitation (in millimeters per month) and the mean annual temperature (in degrees Celsius). *Socioeconomic Controls* include the logarithm of population size and the logarithm of night-time light emissions. A constant term is included in all regressions but not reported. Clustered standard errors – robust to serial correlation within grid cells and spatial correlation across grid cells by ADM1 region-year – are reported in parentheses.
* Significant at the 10% level. ** Significant at the 5% level. *** Significant at the 1% level.

Table A5: Difference-in-Differences Estimates of Foreign Aid on Conflict Likelihood – Type of Conflicts (Robustness Checks)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
				Type of Conflict			
	Any Conflicts	Battles	Explosions/Remote Violence	Violence against Civilians	Protests	Riots	Strategic Developments
	Panel A: Conflict Intensity Measure (Log Number of Conflict Events + 0.01)						
Foreign Aid	0.1012***	0.0105***	0.0040***	0.0264***	0.0673***	0.0397***	0.0160***
	(0.0062)	(0.0021)	(0.0011)	(0.0027)	(0.0056)	(0.0031)	(0.0023)
	Panel B: Conflict Intensity Measure (Log Number of Fatalities + 0.01)						
Foreign Aid	0.0298***	0.0094***	0.0018**	0.0123***	0.0017***	0.0113***	0.0002***
	(0.0032)	(0.0020)	(0.0008)	(0.0018)	(0.0003)	(0.0011)	(0.0001)
	Panel C: Foreign Aid Measure (Project Counts)						
Foreign Aid	1.2419***	0.1525***	0.0508**	0.3728***	0.9259***	0.5794***	0.2556***
	(0.0785)	(0.0279)	(0.0212)	(0.0372)	(0.0645)	(0.0385)	(0.0364)
	Panel D: Baseline Results + Biogeographic Controls × Grid Cell Specific Time Trends						
Foreign Aid	0.6896***	0.2602***	0.1175***	0.2496***	0.2591***	0.2646***	0.0625
	(0.1396)	(0.0765)	(0.0412)	(0.0815)	(0.0967)	(0.0716)	(0.0621)
Observations	12,633,372	12,633,372	12,633,372	12,633,372	12,633,372	12,633,372	12,633,372
Number of Cells	40701	40701	40701	40701	40701	40701	40701
Number of Treated Cells	3634	3634	3634	3634	3634	3634	3634
Grid Cell FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country × Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Climatic Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Socioeconomic Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: The spatial unit of analysis is a grid cell measuring 0.25 decimal degrees in latitude and longitude. The dependent variable in Panels A and B is defined as the logarithm of the number of conflict events and conflict fatalities, respectively, plus 0.01, observed in a given grid cell and time period. In Panels C and D, the dependent variable equals 100 if a specific conflict event occurred in a given grid cell and time period, and 0 otherwise.

Foreign Aid in Panels A, B, and C is a dichotomous treatment status variable that increases by one unit with the initiation of any foreign aid project in a given grid cell and time period. In Panel C, an alternative specification uses a count treatment variable indicating the number of foreign aid project starts per cell and time. In Panel D, grid-cell-specific third-order polynomial time trends interacted with biogeographic controls are added to the baseline specification to account for differential time trends in conflict likelihood.

Climatic Controls include the mean of total monthly precipitation (in millimeters per month) and the mean annual temperature (in degrees Celsius). *Socioeconomic Controls* include the logarithm of population size and the logarithm of night-time light emissions. A constant term is included in all regressions but not reported. Clustered standard errors – robust to serial correlation within grid cells and spatial correlation across grid cells by ADM1 region-year – are reported in parentheses.

* Significant at the 10% level. ** Significant at the 5% level. *** Significant at the 1% level.

B Figures

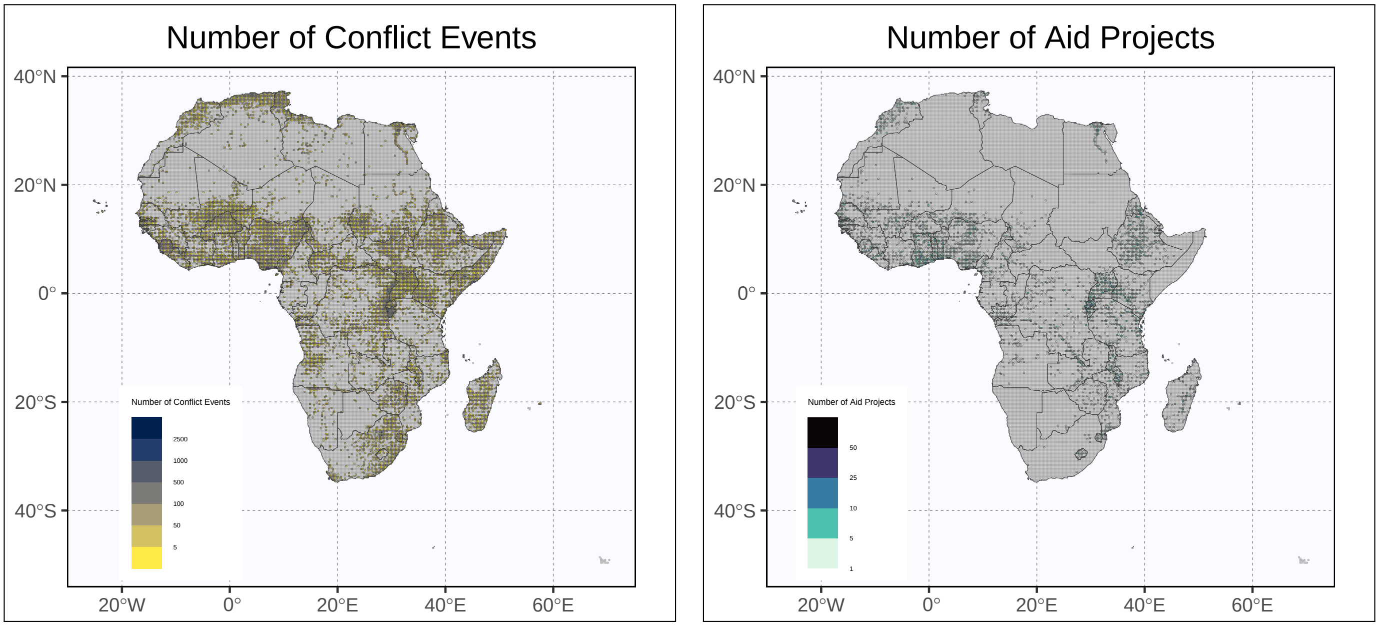

Figure B1: Geographic Distribution of Conflict Locations and Aid Projects Across Grid Cells in Africa

Notes: This figure displays the spatial distribution of conflict events and foreign aid projects across Africa. The spatial unit of analysis is a grid cell measuring 0.25 decimal degrees in latitude and longitude. Color intensity indicates the number of conflict events or foreign aid projects initiated within each grid cell over time. The data are sourced from the ACLED and AidData databases.

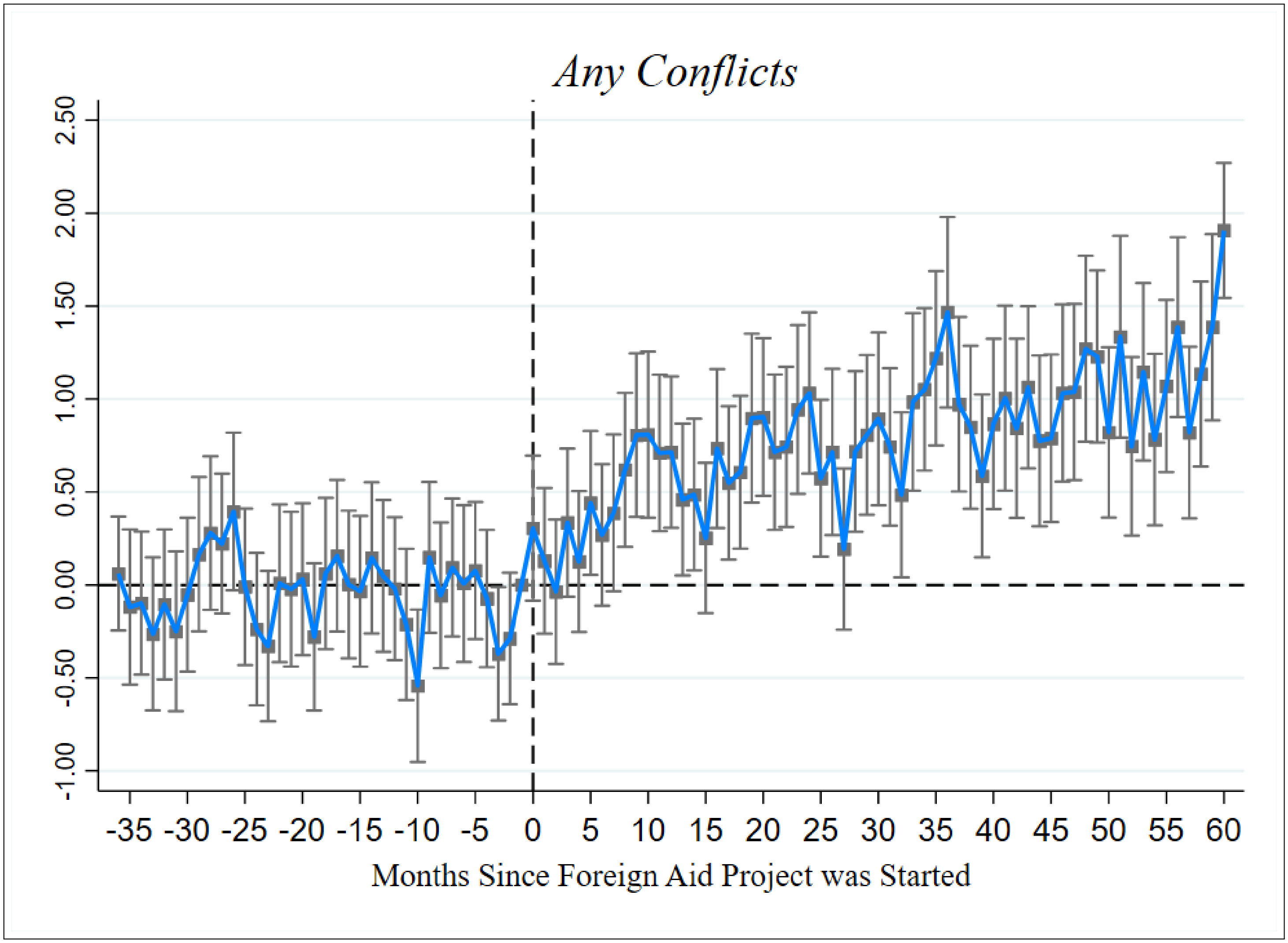

Figure B2: Event Study Estimates of Conflict Likelihood

Notes: This figure displays OLS coefficient estimates and corresponding 90% confidence intervals from the event study specification described in Equation 2. The dependent variable is the likelihood of conflict in grid cell g at time t, coded as 100 if a conflict event occurs and 0 otherwise. The treatment indicator equals one when any foreign aid project is initiated in grid cell g at time t. Control variables include climatic conditions, population, night-time lights activity, as well as grid cell and country-by-year fixed effects. The specification accounts for multiple foreign aid treatments within the same grid cell. Binned endpoints are used, assuming that dynamic treatment effects remain constant beyond the event window. The dataset covers the period from January 1995 to January 2018 and includes 11,290,048 grid-by-year-by-month observations.

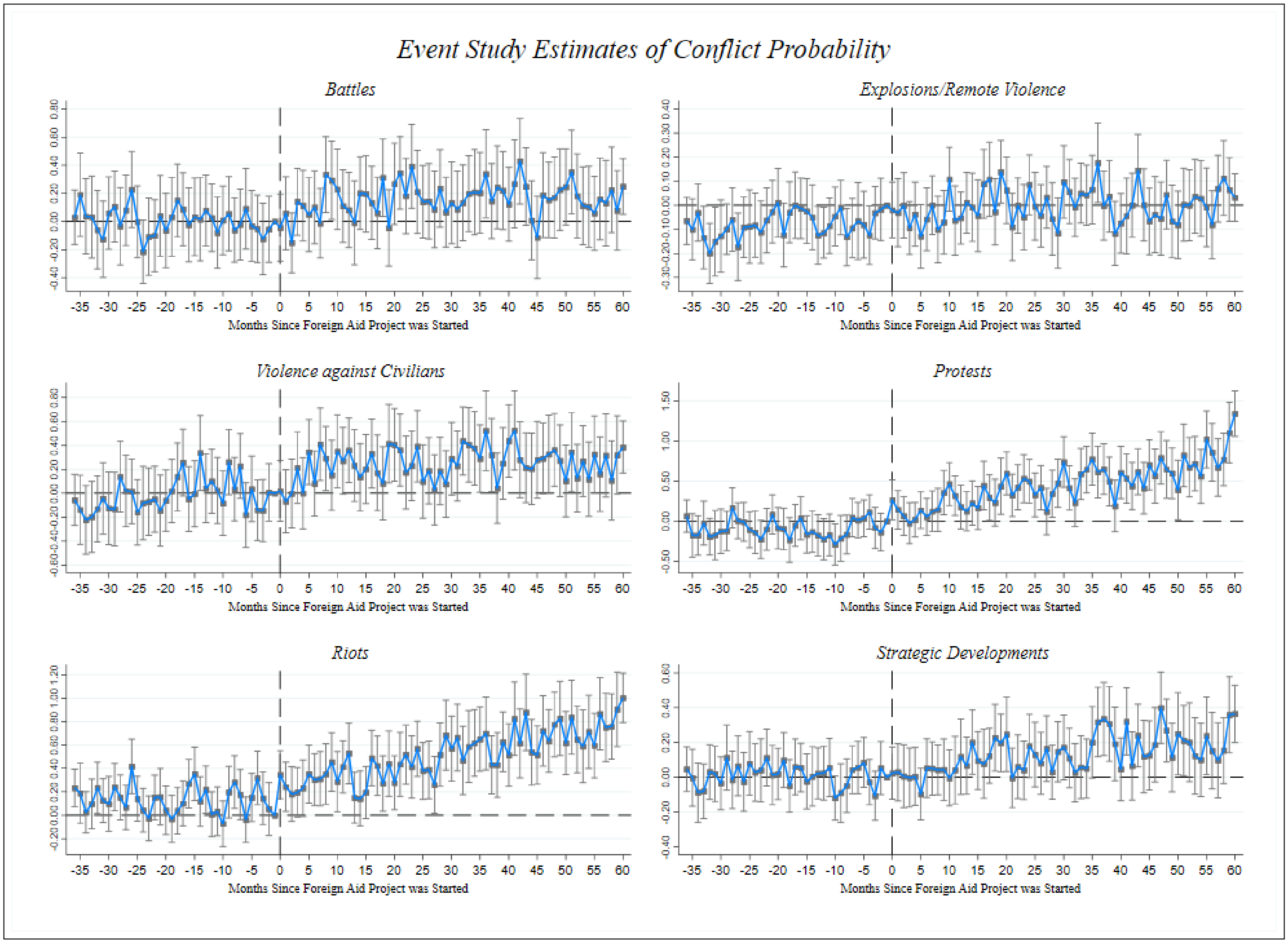

Figure B3: Event Study Estimates of Conflict Likelihood – Type of Conflicts

Notes: This figure plots OLS coefficient estimates and corresponding 90% confidence intervals from the event study specification in Equation 2. The dependent variable is the likelihood of conflict in grid cell g at time t, coded as 100 if a conflict event occurs and 0 otherwise. The treatment indicator captures the initiation of any foreign aid project in grid cell g at time t. Control variables include climatic factors, population size, night-time lights activity, as well as grid cell and country-by-year fixed effects. The specification accounts for multiple foreign aid treatments within the same grid cell. Binned endpoints are used, meaning that dynamic treatment effects are assumed to remain constant beyond the effect window. The data cover the period from January 1995 to January 2018, comprising 11,290,048 grid-by-year-by-month observations.

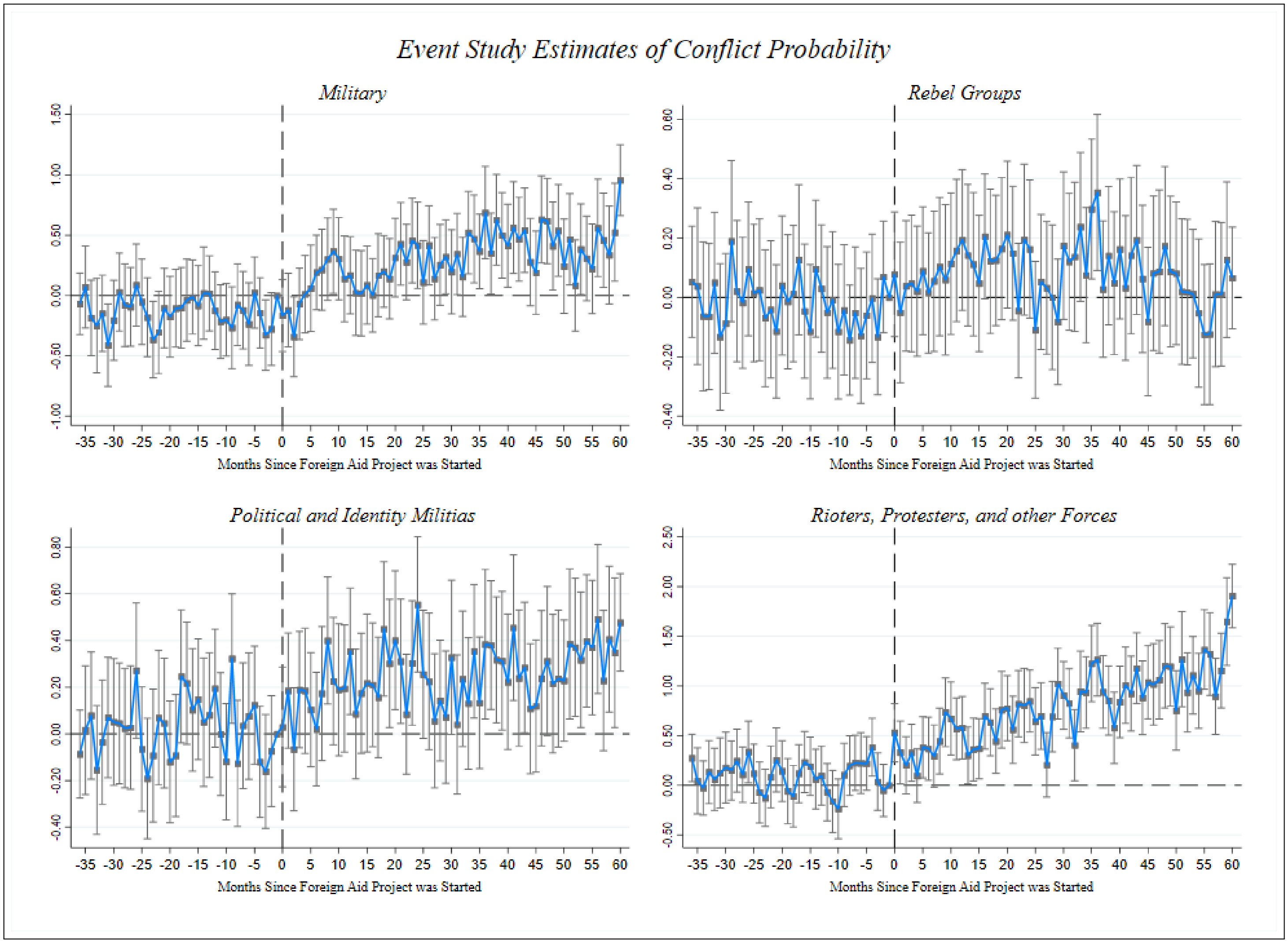

Figure B4: Event Study Estimates of Conflict Likelihood – Type of Actors Involved

Notes: This figure displays OLS coefficient estimates and corresponding 90% confidence intervals from the event study specification in Equation 2. The dependent variable is the likelihood of conflict in grid cell g at time t, coded as 100 if a conflict event occurs and 0 otherwise. The treatment indicator captures the initiation of any foreign aid project in grid cell g at time t. Control variables include climatic conditions, population size, night-time lights intensity, as well as grid cell and country-by-year fixed effects. The specification accounts for multiple foreign aid treatments. Binned endpoints are used, implying that dynamic treatment effects are assumed constant beyond the event window. The data cover the period from January 1995 to January 2018 and include 11,290,048 grid-by-year-by-month observations.

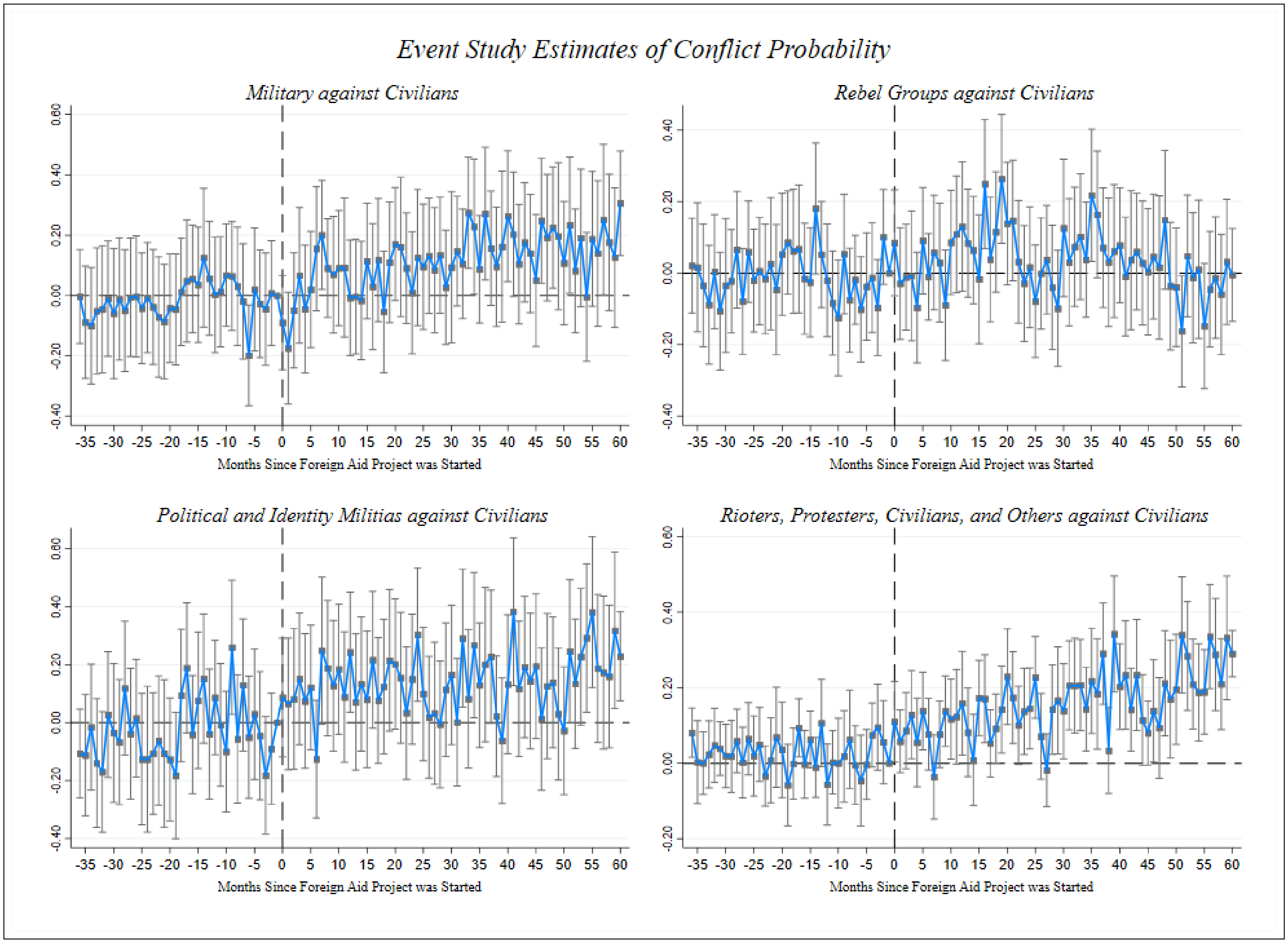

Figure B5: Event Study Estimates of Conflict Likelihood – Two-Sided Violence Against Civilians

Notes: This figure presents OLS coefficient estimates and corresponding 90% confidence intervals from the event study specification in Equation 2. The dependent variable measures the likelihood of conflict in grid cell g at time t, coded as 100 if a conflict event occurs and 0 otherwise. The treatment indicator captures the initiation of any foreign aid project in grid cell g at time t. Control variables include climatic conditions, population size, night-time lights activity, as well as grid cell and country-by-year fixed effects. The specification accounts for multiple foreign aid treatments. Binned endpoints are used, assuming that dynamic treatment effects remain constant outside the effect window. The data cover the period from January 1995 to January 2018, comprising 11,290,048 grid-by-year-by-month observations.

C Descriptive Statistics

Table C1: Summary Statistics for the Main Regression Variables

Variable	N	Mean	SD	Minimum	Maximum
Panel A: Descriptive Statistics for the Baseline Sample During the Period 1995m1 to 2020m12 across 40,701 Grid Cells Cells					
Conflict Incidence Measures (in %): Type of Conflicts					
Any Conflicts	12,633,372	0.7517	8.6376	0	100
Battles	12,633,372	0.2527	5.0210	0	100
Explosion/Remote Violence	12,633,372	0.0661	2.5702	0	100
Violence against Civilians	12,633,372	0.2763	5.2489	0	100
Protests	12,633,372	0.1917	4.3740	0	100
Riots	12,633,372	0.1217	3.4861	0	100
Strategic Developments	12,633,372	0.0884	2.9724	0	100
Conflict Incidence Measures (%): Type of Actors Involved					
Military	12,633,372	0.3287	5.7236	0	100
Rebel Groups	12,633,372	0.2043	4.5158	0	100
Political and Identity Militias	12,633,372	0.2914	5.3902	0	100
Rioters, Protesters and other Forces	12,633,372	0.3205	5.6519	0	100
Conflict Incidence Measures (%): Two-Sided Violence against *Civilians*					
Violence *against* Civilians	12,633,372	0.3379	5.8035	0	100
Military *against* Civilians	12,633,372	0.0724	2.6904	0	100
Rebel Groups *against* Civilians	12,633,372	0.0737	2.7137	0	100
Political and Identity Militias *against* Civilians	12,633,372	0.1925	4.3827	0	100
Rioters, Protesters, Civilians and other Forces *against* Civilians	12,633,372	0.0395	1.9860	0	100
Foreign Aid Measure					
Treatment Status Variable: $Foreign\ Aid_{gt}$	12,633,372	0.1229	0.6836	0	29
Climate Measures					
Annual Mean Precipitation Rate (mm/month)	12,633,372	56.3395	83.4190	0	2229.4000
Annual Mean Temperature (degree Celsius)	12,633,372	25.1475	5.4365	-0.3000	38.2000
Socioeconomic Measures: Yearly Averages					
ln Population Size: $\ln(0.01 + Pouplulation_{gt})$	12,633,372	7.9152	2.9903	-4.6052	16.1560
ln Light Emissions: $\ln(0.01 + Light_{gt})$	12,633,372	8.1917	0.2716	7.4292	10.9428
Panel B: Cross-Sectional Variables across 40,701 Grid Cells					
ln(0.01 + Absolute Latitude)	40,701	2.5107	0.9187	-2.0025	3.6146
ln(0.01 + Absolute Longitude)	40,701	2.7183	0.9765	-2.0025	3.9345
Cropland	40,701	0.0719	0.1451	0	1
Elevation (in meters above the sea level)	40,701	628.3852	439.2773	-113.0767	3654.368
Std Dev. of Elevation	40,701	54.0378	73.0833	0	1030.656
Koeppen Climate Zone A: Arid	40,701	0.2949	0.4560	0	1
Number of Diamond Mines	40,701	0.0137	0.1954	0	14
Number of Gemstone Deposits	40,701	0.0088	0.1098	0	4
ln(0.01 + Distance ot Border)	40,701	4.4285	1.2078	-4.4456	6.4880
ln(0.01 + Distance to Coast)	40,701	6.0795	1.1381	-3.1276	7.5035
ln(0.01 + Distance to River)	40,701	4.2142	1.8029	-4.5808	7.2037
ln(0.01 + Distance to Railroad)	40,701	4.9501	1.3919	-4.3940	7.0768
ln(0.01 + Distance to Road)	40,701	2.2970	1.6583	-4.6016	6.0594
ln(0.01 + Distance to Power Transmission Line)	40,701	5.2055	1.3618	-4.3504	7.1966
ln(0.01 + Distance to Capital)	40,701	6.2200	0.7736	0.9906	7.5831
ln(0.01 + Distance to Larger Settlement)	40,701	5.3181	0.9148	-1.2554	6.9984

Notes: This table reports basic summary statistics for the main variables used in the empirical analysis. The data cover the period from January 1995 to December 2020. The spatial unit of analysis is a grid cell measuring 0.25 decimal degrees in latitude and longitude. See the main text for further details on data construction and sources.

Table C2: Pairwise Correlations for the Main Regression Variables

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
(1) Any Conflicts	1.0000										
(2) Battles	0.5784	1.0000									
(3) Explosion/Remote Violence	0.2955	0.2060	1.0000								
(4) Violence against Civilians	0.6048	0.2550	0.1457	1.0000							
(5) Protests	0.5035	0.0839	0.0661	0.1350	1.0000						
(6) Riots	0.4011	0.0664	0.0441	0.1194	0.2374	1.0000					
(7) Strategic Developments	0.3418	0.1806	0.1366	0.1833	0.1001	0.0786	1.0000				
(8) Military	0.6598	0.6364	0.3017	0.3553	0.2616	0.3070	0.2819	1.0000			
(9) Rebel Groups	0.5199	0.5882	0.3226	0.3278	0.0459	0.0265	0.2918	0.4694	1.0000		
(10) Political and Identity Militias	0.6212	0.5488	0.2617	0.5597	0.1346	0.1206	0.2942	0.3846	0.1788	1.0000	
(11) Rioters, Protesters and other Forces	0.6515	0.1905	0.1750	0.1836	0.7729	0.6156	0.1628	0.3641	0.1517	0.1939	1.0000
(12) Violence *against* Civilians	0.6691	0.2596	0.2625	0.9039	0.1561	0.2454	0.2765	0.3801	0.3455	0.5641	0.2666
(13) Military *against* Civilians	0.3094	0.1432	0.1821	0.4423	0.1331	0.1135	0.1925	0.4688	0.1117	0.1572	0.1514
(14) Rebel Groups *against* Civilians	0.3120	0.1978	0.1935	0.4494	0.0324	0.0199	0.1955	0.1659	0.6001	0.1096	0.0662
(15) Political and Identity Militias *against* Civilians	0.5046	0.2007	0.1982	0.7642	0.1193	0.1065	0.2051	0.2015	0.1034	0.6908	0.1511
(16) Rioters, Protesters, Civilians and other Forces *against* Civilians	0.2283	0.0592	0.0764	0.1084	0.1079	0.4751	0.0606	0.0992	0.0371	0.0780	0.3503
(17) Treatment Status Variable: $Foreign\ Aid_{gt}$	0.1606	0.0519	0.0278	0.0867	0.1647	0.1330	0.0689	0.1271	0.0289	0.0859	0.1746
(18) Annual Mean Precipitation Rate (mm/month)	0.0278	0.0158	-0.0018	0.0211	0.0096	0.0117	0.0134	0.0161	0.0133	0.0186	0.0141
(19) Annual Mean Temperature (degree Celsius)	-0.0120	0.0020	0.0038	-0.0043	-0.0172	-0.0154	-0.0009	-0.0085	0.0069	-0.0055	-0.0173
(20) ln Population Size: $\ln(0.01+Pouplulation_{gt})$	0.0959	0.0479	0.0241	0.0573	0.0632	0.0510	0.0317	0.0653	0.0387	0.0580	0.0745
(21) ln Light Emissions: $\ln(0.01+Light_{gt})$	0.1327	0.0385	0.0363	0.0520	0.1520	0.1069	0.0386	0.0914	0.0177	0.0653	0.1539

Notes: This table reports basic pairwise correlations among the main variables used in the empirical analysis. The data cover the period from January 1995 to December 2020. The spatial unit of analysis is a grid cell measuring 0.25 decimal degrees in latitude and longitude. See the main text for further details on data construction and sources.

Table C2: Pairwise Correlations for the Main Regression Variables

Variables	(12)	(13)	(14)	(15)	(16)	(17)	(18)	(19)	(20)	(21)
(1) Any Conflicts										
(2) Battles										
(3) Explosion/Remote Violence										
(4) Violence against Civilians										
(5) Protests										
(6) Riots										
(7) Strategic Developments										
(8) Military										
(9) Rebel Groups										
(10) Political and Identity Militias										
(11) Rioters, Protesters and other Forces										
(12) Violence *against* Civilians	1.0000									
(13) Military *against* Civilians	0.4624	1.0000								
(14) Rebel Groups *against* Civilians	0.4664	0.0783	1.0000							
(15) Political and Identity Militias *against* Civilians	0.7541	0.1509	0.0834	1.0000						
(16) Rioters, Protesters, Civilians and other Forces *against* Civilians	0.3412	0.0709	0.0253	0.0752	1.0000					
(17) Treatment Status Variable: $Foreign\ Aid_{gt}$	0.1062	0.0860	0.0189	0.0720	0.0720	1.0000				
(18) Annual Mean Precipitation Rate (mm/month)	0.0233	0.0094	0.0124	0.0166	0.0077	0.0957	1.0000			
(19) Annual Mean Temperature (degree Celsius)	-0.0056	-0.0051	0.0037	-0.0049	-0.0070	-0.0336	-0.0253	1.0000		
(20) ln Population Size: $\ln(0.01 + Pouplulation_{gt})$	0.0644	0.0341	0.0258	0.0486	0.0278	0.2118	0.3420	-0.1174	1.0000	
(21) ln Light Emissions: $\ln(0.01 + Light_{gt})$	0.0655	0.0499	0.0103	0.0458	0.0476	0.1971	0.0807	-0.0539	0.2650	1.0000

Notes: This table reports basic pairwise correlations among the main variables used in the empirical analysis. The data cover the period from January 1995 to December 2020. The spatial unit of analysis is a grid cell measuring 0.25 decimal degrees in latitude and longitude. See the main text for further details on data construction and sources.

Table C3: Distribution of Treated Months Across Grid Cells

Number of Treated Months	Frequency	Percent	Cumulative
0	37,067	91.07	91.07
1	1,862	4.57	95.65
2	732	1.80	97.44
3	364	0.89	98.34
4	192	0.47	98.81
5	161	0.40	99.21
6	120	0.29	99.50
7	62	0.15	99.65
8	33	0.08	99.73
9	42	0.10	99.84
10	17	0.04	99.88
11	11	0.03	99.91
12	7	0.02	99.92
13	12	0.03	99.95
14	4	0.01	99.96
15	2	0.00	99.97
17	4	0.01	99.98
18	1	0.00	99.98
19	2	0.00	99.99
20	2	0.00	99.99
21	1	0.00	99.99
22	1	0.00	100.00
27	1	0.00	100.00
29	1	0.00	100.00
Total	40,701	100.00	

Notes: This table presents the distribution of the maximum months treated across grid cells. The treatment variable is coded as 1 for the month in which a foreign aid project is initiated in a grid cell and 0 otherwise. The table shows the number of treatments, frequency, percent, and cumulative percent of the maximum number of months treated by foreign aid. See the main text for further details on the treatment variable and the data sources.

Zuletzt erschienen /previous publications:

V-452-25 **Jürgen Bitzer, Bernhard C. Dannemann, Erkan Gören**, Foreign Aid and Local Conflict Dynamics: A Monthly Grid-Cell-Level Analysis in Africa
V-451-25 **Bernhard C. Dannemann, Erkan Gören**, Where Does the Money Go? Spatial Patterns in the Distribution of World Bank Foreign Aid Projects
V-450-25 **Emmanuel Asane-Otoo, Bernhard C. Dannemann, Thies Reisemann**, Spatial Distribution of EV Charging Infrastructure in Germany:An Analysis of Determinants
V-449-25 **Abigail O. Asare**, More Than Money: The Critical Role of Management in Educational Aid Effectiveness in Africa
V-448-24 **Jürgen Bitzer, Bernhard C. Dannemann, Erkan Gören**, Heterogeneous Effects of Foreign Aid on Local Economic Development
V-447-24 **Heinz Welsch**, Explaining Happiness Trends in Europe by Welfare Policies and Economic Growth: Easterlin and O'Connor Revisited
V-446-24 **Abigail Asare, Laura Schürer**, Incidence of Carbon Pricing in Tanzania: Using Revenues to Empower Low-Income Households with Renewable Energy
V-445-24 **Heinz Welsch**, Are National Climate Change Mitigation Pledges Shaped by Citizens' Climate Action Preferences? Evidence from Globally Representative Data
V-444-24 **Heinz Welsch**, Household Sector Carbon Pricing, Revenue Rebating, and Subjective Well-Being: A Dollar is not a Dollar
V-443-24 **Heinz Welsch**, Do National Well-Being Scores Capture Nations' Ecological Resilience? Evidence for 124 Countries
V-442-23 **Jürgen Bitzer, Erkan Gören, Heinz Welsch,** How the Well-Being Function Varies with Age: The Importance of Income, Health, and Social Relations over the Life Cycle
V-441-23 **Heinz Welsch,** Why is Satisfaction from Pro-Environmental Behaviors Increasing in Costs? Insights from the Rational-Choice Decision-Error Framework
V-440-23 **Abigail O. Asare, Bernhard C. Dannemann, Erkan Gören**, Locust Infestations and Individual School Dropout: Evidence from Africa
V-439-22 **Christoph Böhringer, Carolyn Fischer, Nicholas Rivers**, Intensity-Based Rebating of Emission Pricing Revenues
V-438-21 **Heinz Welsch,** What Shapes Cognitions of Climate Change in Europe? Ideology, Morality and the Role of Educational Attainment
V-437-21 **Heinz Welsch**, Do Social Norms Trump Rational Choice in Voluntary Climate Change Mitigation? Multi-Country Evidence of Social Tipping Points
V-436-21 **Emmanuel Asane-Otoo, Bernhard C. Dannemann**, Station heterogeneity and asymmetric gasoline price responses
V-435-21 **Christoph Böhringer, Thomas F. Rutherford, Jan Schneider,** The Incidence of CO_2 Emission Pricing Under Alternative International Market Responses
V-434-21 **Christoph Böhringer, Sonja Peterson, Thomas F. Rutherford, Jan Schneider, Malte Winkler,** Climate Policies after Paris: Pledge, Trade and Recycle
V-433-20 **Bernhard C. Dannemann,** Better Off On Their Own? How Peer Effects Determine International Patterns of the Mathematics Gender Achievement Gap
V-432-20 **Christoph Böhringer, Carolyn Fischer**, Kill Bill or Tax: An Analysis of Alternative CO2 Price Floor Options for EU Member States
V-431-20 **Heinz Welsch**, How Climate-Friendly Behavior Relates to Moral Identity and Identity-Protective Cognition: Evidence from the European Social Surveys
V-430-20 **Christoph Böhringer, Knut Einar Rosendahl,** Europe beyond Coal – An Economic and Climate Impact Assessment
V-429-20 **Oliver Richters**, Modeling the out-of-equilibrium dynamics of bounded rationality and economic constraints

V-428-20 **Bernhard C. Dannemann,** Peer Effects in Secondary Education: Evidence from the 2015 Trends in Mathematics and Science Study Based on Homophily

V-427-19 **Christoph Böhringer, Knut Einar Rosendahl, Halvor Briseid Storrøsten,** Smart hedging against carbon leakage

V-426-19 **Emmanuel Asane-Otoo, Bernhard Dannemann,** Rockets and Feathers Revisited: Asymmetric Retail Fuel Pricing in the Era of Market Transparency

V-425-19 **Heinz Welsch,** Moral Foundations and Voluntary Public Good Provison: The Case of Climate Change

V-424-19 **Gökçe Akın-Olçum, Christoph Böhringer, Thomas Rutherford, Andrew Schreiber,** Economic and Environmental Impacts of a Carbon Adder in New York

V-423-19 **Jasper N. Meya, Paul Neetzow,** Renewable energy policies in federal government systems

V-422-19 **Philipp Biermann, Heinz Welsch**, Changing Conditions, Persistent Mentality: An Anatomy of East German Unhappiness, 1990-2016

V-421-19 **Philipp Biermann, Jürgen Bitzer, Erkan Gören,** The Relationship between Age and Subjective Well-Being: Estimating Within and Between Effects Simultaneously

V-420-19 **Philipp Poppitz,** Multidimensional Inequality and Divergence: The Eurozone Crisis in Retrospect

V-419-19 **Heinz Welsch,** Utilitarian and Ideological Determinants of Attitudes toward Immigration: Germany before and after the "Refugee Crisis"

V-418-19 **Christoph Böhringer**, **Xaquin Garcia-Muros, Mikel González-Eguino**, Greener and Fairer: A Progressive Environmental Tax Reform for Spain

V-417-19 **Heinz Welsch, Martin Binder, Ann-Kathrin Blankenberg**, Pro-environmental norms and subjective well-being: panel evidence from the UK