Growth in the Aftermath of War: Aid Effectiveness in Post-Conflict Locations

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Abstract

I investigate if foreign aid supports subnational development in post-conflict African countries and examine heterogeneous effects of the fighting intensity a district was exposed to by introducing a novel conflict intensity index. Employing a panel of 5418 African districts over a period from 1996 to 2015, estimates indicate the overall effectiveness of aid. However, depending on the intensity of experienced fatalities, the total impact on nighttime light growth is mitigated or even negative for post-conflict districts. Nevertheless, post-conflict districts experience a rebound effect through substantial additional growth in economic activity. Further, there is evidence for within-country spillover effects.

Keywords: Economic Growth, Post-Conflict, Foreign Aid, Development, GIS data

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1 Introduction

War and conflict are an inherent state to today's society. de Groot et al. (2022) show on a global scale, if there had not been any conflicts since 1970, global GDP in 2014 would have been 12 percent higher. Their results indicate the enormous costs of conflict. However, the world is not absent of such events, as the trend of conflict outbreaks is going upward (Pettersson et al., 2021).

Lots of research has been done on the costs, consequences and what triggers conflict (Abadie & Gardeazabal, 2003; Almer & Hodler, 2015; E. Berman et al., 2013; N. Berman & Couttenier, 2015; N. Berman et al., 2017; Collier, 1999; Crost et al., 2014; de Groot et al., 2022). Less so, which policies and tools are effective as soon as peace materializes. And peace does materialize. Out of 47 African nations, 18 can be considered as having had post-conflict periods between the years 1990 to 2017.

One instrument in such a setting is foreign aid. For example, UN humanitarian assistance mostly targets conflict-prone locations (Rohner & Thoenig, 2021). Collier and Hoeffler (2004) examined aid effectiveness in post-conflict countries, showing its increased effectiveness on the aggregate level conditioned on institutional performance. There is further evidence for sectoral post-conflict aid being effective in improving social infrastructure (Donaubauer et al., 2019). However, districts are not affected by the same intensity of fighting and not all of them receive aid. Even when there is a major conflict like the current war in Ukraine, some parts of the country are more heavily affected than others (ACAPS, 2022). At the same time, pernicious effects of conflict may not only affect the immediate surroundings of battles but also spill over to other regions. Similarly, it is the case with aid. Foreign aid projects target certain subnational regions, not necessarily the country as a whole. Dreher and Lohmann (2015) establish a link between aid and growth on a subnational level and Bitzer and Gören (2018) find positive effects on a grid-cell level. However, post-conflict locations may underlie different mechanisms. In such situations, the effectiveness of aid may depend on its active involvement and the intensity of fighting a district was exposed to. Knowledge about the implications of such subnational variation is important for targeted policies.

Building on this research, this paper aims to answer three questions addressing this research gap in the context of African countries: How is a district's growth affected by its country's violent past? Are there heterogeneous effects depending on the subnational variation of conflict intensity? Is aid effective under such circumstances?

To the best of my knowledge, this paper is the first to examine aid effectiveness in a post-conflict environment on a district level following a panel of 5418 African districts over the period from 1996 to 2015. It contributes to the literature by introducing a novel index to measure the intensity of past conflict on a subnational level and further adds by creating a new methodology to categorize different stages of conflict subnationally. It further adds by estimating the spillover effects of conflicts and past conflict events within the country and on neighboring districts.

Official statistics on subnational economic activity in developing countries are either lacking or inaccurate (Henderson et al., 2012). Recent developments offer opportunities for consistent geocoded data over longer time frames. Bruederle and Hodler (2018) and Henderson et al. (2012) show that nighttime light can be a valid approximation for subnational growth and development. Hence, to approximate growth in African districts, remote sensing satellite observations of nighttime light from Li et al. (2020) are used. Li et al. (2020) are the first to globally calibrate and harmonize nighttime light images from the DMSP and VIIRS satellite systems to provide consistent data for the years 1992 to 2018. The intensity of nighttime light is extracted from yearly satellite images within ADM2 boundaries (equivalent to districts) (Runfola, 2020) and the annual growth of nighttime light is then estimated.

The panel is further constructed by combining geocoded World Bank (WB) aid disbursements from the AidData database (AidData, 2017) with geocoded conflict data for the years 1989 to 2020 from the UCDP-GED dataset (Sundberg & Melander, 2013). AidData provides information on 5,684 WB aid projects spreading over 61,234 locations for the years of 1995 to 2014 (AidData, 2017). Disbursements of projects identified on a district level are then split across the locations and years a project took place. To identify post-conflict districts, I set up a new approach. Thus, aggregated on the country level, observations are categorized depending on their sum of battle deaths to be either a district within a country at war, post-conflict, with minor conflict, post-minor conflict or at peace. An observation's categorization can change over time and smoothing averages are introduced to reflect common war periods of countries.

Part of the empirical strategy is this clear-cut categorization of the stages of conflict. Conditioned on the aggregate level, a district takes on its country's category but can be actively involved or not depending on the fatalities on the district level. In the specific case of post-conflict districts that were actively involved in a war, an index is created to account for the intensity of the fighting throughout the whole war period.

The index is designed in a way that takes into consideration the length of the war and when the most intense fighting occurred in the district. The idea is that as war evolves over time and space, districts are affected more or less intensely at different times. This is likely to impact post-conflict development and also the effectiveness of aid if e.g. heavy fighting in the district already happened seven years ago or right before the country entered the post-conflict stage. If a district was targeted heavily at the beginning of the war, this is discounted compared to if it was more exposed to violence towards the end of the war. Furthermore, the index takes into account conflict re-occurrences, meaning if the country counts as post-conflict but then war reoccurs, fatalities of the first war are still taken into consideration. Any post-conflict or past war experiences collapse to peace after ten years have passed, which is in accordance with the standard definition used by Collier and Hoeffler (2004) and Donaubauer et al. (2019).

Employing the constructed panel, the applied empirical strategy needs to consider that aid is not randomly disbursed. Results regarding the effects of aid on growth are ambiguous (Bazzi & Clemens, 2013; Burnside & Dollar, 2000; Clemens et al., 2012; Rajan & Subramanian, 2008). One of the reasons is the difficulty to find a valid instrument and different specifications for aid. Recent literature (Chauvet & Ehrhart, 2018; Dreher et al., 2021; Dreher & Langlotz, 2020) finds robust estimates by employing an instrumental variable strategy using quasi-experiments by exploiting an exogenous shock in combination with the likelihood of receiving aid.[1] Based on this methodology, I instrument aid by using the exogenous variation of holding the presidency of the United Nations Security Council (UNSC) in a specific year and interacting it with the initial amount of aid projects within a district. The idea of the instrument is based on Kuziemko and Werker (2006). Their results indicate a significant increase in aid during a country's UNSC membership.[2] This effect is quasi-random for African countries as they use a strict rotational system for the candidacy to UNSC membership (Dreher et al., 2018). Own estimations indicate that particularly holding the UNSC presidency increases aid disbursements.

[1] The discussion about these types of instruments is ongoing (Borusyak et al., 2021; Christian & Barrett, 2017; Gehring et al., 2022; Goldsmith-Pinkham et al., 2020).

[2] Berlin et al. (2023) show that subnational regions are targeted by an increase in aid projects and commitments during UNSC membership.

Whether a successful candidate holds the presidency follows the alphabetical order of the English names of members and can be considered quasi-random. A drawback of this instrument however is the likely identification of a local average treatment effect (LATE) as it mainly identifies the effect of politically motivated aid. Thus following Gehring et al. (2022), I estimate as an alternative approach a model that includes a term to control for heterogeneous trends of districts and countries and further fixed effects for the country, district and time. This strategy underlines the robustness of the results and allows us to identify the effects of politically motivated aid and aid in general.

In the model, a district's growth rate in annual nighttime light is explained by aid and the interaction of aid and a binary variable for post-conflict districts. This enables interpretations of the overall effect of aid and also investigates its effectiveness in post-conflict districts. To examine the effects of different intensity levels, the post-conflict variable is then conditioned on certain levels of the index measure. The model further employs dummies for the various conflict categories on a country and district level with peace as a baseline thus constructed to identify peace as a counterfactual to post-conflict. This allows the interpretation of the effects of any conflict stage in comparison to a peaceful setting. Using the different levels, one can identify within-country spillover effects from those that were actively involved in the war to those that were not.

Furthermore, I control for a district's remoteness, the lagged level of nighttime light, agricultural and population indicators as well as the deployment of peacekeeping troops on a district level (Cil et al., 2020) and further controls on the country level. To take care of any possible confounding factors and omitted variables, country, year and district fixed effects are applied. The results undergo a battery of robustness checks.

In accordance with recent literature (Bitzer & Gören, 2018; Chauvet & Ehrhart, 2018), there is evidence for the effectiveness of aid in any district, no matter if peaceful or post-conflict. However, aid is not necessarily more effective in improving a district's growth rate within a post-conflict environment. Depending on the intensity of fighting a district was exposed to, additional stimulation of growth through aid is lower or even negative when disbursed in a post-conflict setting. At first sight, this contrasts Collier and Hoeffler's (2004) findings of increased aid effectiveness in post-conflict environments at the country level conditional on institutional factors. For aid disbursed at a subnational level, however, there is evidence that its effectiveness depends on the active involvement and fighting intensity a district experienced. This finding could be explained by weaker administrative capacities to effectively manage and utilize the received aid in areas affected by violence. It might be further exacerbated by the displacement of skilled personnel or the destruction of local institutions. This shows the importance of considering the heterogeneity of aid effectiveness depending on the intensity of fighting a district was subjected to. Results further suggest a rebound effect for districts in post-conflict countries with significantly higher growth rates compared to those in peaceful countries.

The following section describes the data and methodology used for the estimations and explains the identification of the different variable categories. Section 3 presents the baseline estimates and discusses the robustness of the results. Section 4 further explores the mechanisms and channels and section 5 discusses policy implications and concludes the paper.

2 Data and Methodology

I use a model that allows exploring the subnational heterogeneity of aid and conflict and its effects on growth. By examining both subnational and national factors, my model provides a more nuanced understanding of the link between aid and growth in post-conflict locations.

2.1 The Empirical Model

The link between aid and growth and its effectiveness in post-conflict locations is thus investigated using the following specification:

$$\begin{aligned} \Delta ln(light_{crt}) = \alpha + \beta Aid_{crt-1} + \sigma PCDistrict_{crt} + \gamma Aid_{crt-1} * PCDistrict_{crt} + \\ \delta_{ct} + \psi_{crt} + \omega_{ct} + \mu_{crt} + \eta_r + \rho_c + \tau_t + \epsilon_{crt} \end{aligned} \tag{1}$$

with $\Delta ln(light_{crt})$ measured as the change in average annual nighttime light of district r at time t in country c. Aid_{crt-1} is the logarithmic function of WB aid disbursed to a specific district at time t-1 to allow aid to affect growth.[3] $PCDistrict_{crt}$ represents a binary variable for post-conflict districts. The interaction of Aid_{crt-1} and $PCDistrict_{crt}$ illustrates aid disbursed at time t-1 in a district that experienced conflict within the previous year and up to 10 years after the conflict ended. δ_{ct} and ψ_{crt} describe vectors for the different conflict category dummies at the country and district level, respectively. The category peace is excluded to serve as a baseline. This way, peace is interpreted as counterfactual to post-conflict, allowing us to interpret the effects in comparison to peaceful districts in peaceful countries. Further, ω_{ct} serves as a vector for country-level and μ_{crt} for district-level controls. To capture unobservable time-invariant heterogeneity, ρ_c as country and η_r as district fixed effects are included in the model. τ_t captures year fixed effects. In an altered version of this model, I include the terms $\Delta\chi_r$ and $\Delta\kappa_c$ which are linear time trends that can differ for each district and country respectively thus controlling for heterogeneous trends of districts and countries. This provides an alternative strategy to deal with any concerns of endogeneity and potential issues arriving from the utilization of a shift-share instrument.

2.2 Economic activity and nightlight

Official statistics for economic activity on a subnational level can be difficult to obtain, or if available might not be accurate, especially in the context of developing countries (Henderson et al., 2012). In such a case, other sources need to be used to approximate economic activity. One of those sources is using the intensity of light during nighttime captured by satellites. Henderson et al. (2012) are one of the first to argue that particularly in the context of developing countries, nighttime light is a valid approximation for GDP growth. Especially the changes of nightlight can be used for within-country estimations as for levels, one would need purchasing power parity (PPP) exchange rates for cross-country comparisons (Henderson et al., 2012). Bruederle and Hodler (2018) further show that variation in nighttime light reflects the variation of human development indicators and Bluhm and Krause (2018) argue nightlights are a reliable proxy at a city level.

[3] Aid_{crt-1} includes an added value of 1 to allow for districts that did not receive any aid disbursements. This approach is robust as shown in the robustness checks when aid disbursements are transformed using an inverse hyperbolic sine (ihs) transformation instead of a logarithmic function

An issue that occurs with using nighttime light is the dependency on satellite systems. So far, samples were therefore restricted to certain time periods, either being covered by the DMSP or by the VIIRS system. The images from the DMSP satellite system cover the period from 1992 to 2013 and the VIIRS system records data since 2012. Li et al. (2020) addressed the inconsistency between the DMSP and VIIRS satellite systems by calibrating and harmonizing observations from 1992 to 2018 for temporal consistency. They remove any attributes that could potentially cause noise like clouds, auroras, fires and other temporal disturbances. In the next step, they integrate DMSP and VIIRS observations to then obtain DMSP-like observations for the years that only VIIRS is available. Applying the images calibrated and harmonized by Li et al. (2020) offers the opportunity to investigate longer time frames and more recent years.[4]

Using the images from Li et al. (2020) the intensity of the light during nighttime is then further extracted following the procedure in Fischer (2022).[5] To extract the nighttime light intensity, the images get a layer of geographic boundaries (Runfola, 2020) at the ADM2 level. ADM2 describes the second administrative level and is equivalent to districts or counties (Runfola, 2020). The mean of the nighttime light is then extracted within the boundary layer. For cells that are just partly covered, a weighted value of surrounding polygons is estimated (Fischer, 2022). The mean of the nighttime light is then extracted for 5714 districts within 50 African countries[6] with values between 0 to 63. As mentioned in Martínez (2022) that use the same nightlight data, despite the harmonization process, there is a jump in the level of nightlights in 2014 which coincides with the harmonized years. Thus, following Martínez (2022) I impute the value for the change in nightlight for 2014 based on the average value in the previous two years (2012-2013) and the two years after (2015-2016).

Henderson et al. (2012) exclude some cases of top-coded observations as outliers. This is not done within this data set, as there is no country with a very high percentage of only top-coded observations. However, those coded at the bottom pose an issue for estimating growth rates. One cannot solely exclude observations with an extracted value of zero as such an observation still possesses an observational value in the sense that they state zero economic activity at a certain place, which could either mean that that district

[4]In the case of this paper it allows to extend the analysis to the years 2014 and 2015.

[5]In Fischer (2022) nighttime light is extracted at the ADM1 level.

[6]Sudan and South Sudan are in a next step excluded as their borders are not consistent over the whole time frame of the sample. Furthermore, Sao Tome and Principe is excluded from the analysis as not all control variables are available for this country.

is not populated (as could be the case for areas within a desert or within mountainous terrain) but it could also mean that the population in a bottom-coded area is too poor to have any light emissions during nighttime. In both cases, excluding such observations would cause a sample bias.

Therefore, observations with an extracted value of zero are transformed. First, the smallest non-zero value in the data is identified. Zeros are replaced by this minimal value, and growth rates are then estimated.[7]. To prevent outliers and distortion of observed values, cases that would have an estimated infinite growth rate when estimated from zero are treated as missings after the transformation.[8] The robustness of this transformation is shown in Section 3.2

2.3 Identifying post-conflict locations

For the identification of post-conflict locations, first, conflict locations need to be located. For this purpose, the UCDP-GED dataset is employed as it reports events of armed force "used by an organised actor against another organized actor, or against civilians, resulting in at least 1 direct death at a specific location and a specific date" (Högbladh, 2022, p.4). Data with global coverage is available from 1989 to 2022.

As an alternative source the ACLED, Armed Conflict Location and Event, dataset (Raleigh et al., 2010) could be used to identify conflict events on a disaggregated level.[9] Although the ACLED dataset is more accurate when it comes to conflict events related to political violence as it also includes riots and protests, this would likely distort estimations for post-conflict events, which primarily capture the district's post-war state.[10]

[7]The formula used for the growth rate is the standard estimation:

$$\Delta ln(light) = \frac{ln(light_t) - ln(light_{t-1})}{ln(light_{t-1})} \tag{2}$$

$\Delta light$ indicates the change in annual nighttime light. Values of $light_t$ and $light_{t-1}$ include a minimal value for cases of value zero as described in Section 2.2.

[8]Despite the imputation and transformation, there are some extreme outliers. Observations for the change in nightlight at the 98th and 0.5th percentile are excluded based on the dataset used for the analysis which includes any observations with complete information on all explanatory and control variables for the years 1996 to 2015.

[9]ACLED data is available for most African countries for the years 1997 to 2022. Comoros and Sao Tome and Principe are not available for that time frame.

[10]One should also note that ACLED is not always accurate when it comes to major battles, as e.g. during

Additionally, the longer time frame of the UCDP-GED dataset is preferable as it allows the identification of conflict and post-war locations for the whole period that aid data is available.[11] Therefore, the main analysis uses the UCDP-GED dataset.

2.3.1 Categorization

The standard in the conflict literature is, any country with an aggregated sum of 1000 battle deaths or more is considered to be at war. Those with at least 25 to 999 battle deaths are coded as minor conflict. Bluhm et al. (2021) introduce an ordinal measurement to better capture the dynamic nature of conflict escalation and de-escalation. However, this measurement is not applicable for the transition to post-conflict.

To also reflect a post-conflict stage, this paper employs a novel categorization to capture how the different stages from peace to post-conflict evolve over time and space within countries and locations. Countries are categorized into one of five categories in any year following a dummy encoding system. A country can be either in a state of war, post-conflict, having minor conflict, post-minor conflict or experiencing a state of peace.

For example, in 1999 on an aggregated level there are 948 conflict deaths in the Republic of Congo. When using the standard cut-off of 1000 battle deaths this would not be coded as war anymore. However, as those 948 deaths happened after having had more than 3,700 fatalities in the previous year and more than 10,000 deaths two years before that, this should still count towards being part of a period during which the country was at war. It is important to capture the war periods as accurately as possible as this could otherwise add noise particularly when further categorizing post-conflict countries. [12]

The encoding is done as follows. Countries at time t having 1000 or more fatalities or more than 300 battle deaths at time t and an average of more than 500 battle deaths over the current and past 2 years are considered to be at war. This way, common war periods are reflected well at the country level. In the next step, a country is categorized as post-conflict if within the past 1 to 10 years it was coded to be in a state of war but by the above definition, there is no active war anymore. A post-conflict period can be interrupted if there is a new war onset. The baseline for the encoding is peace. A country

the time of the Liberian civil war barely any conflict deaths are observed whereas UCDP captures the total amount of deaths well on an aggregate level.

[11] World Bank aid disbursements from the AidData dataset are available from 1995 to 2014

[12] At the same time it potentially adds noise when interacting the variable with aid. When a country is still considered to be at war by the international community, this likely affects aid disbursement decisions.

is coded to be at peace if it is neither at war nor post-conflict and has less than 25 battle deaths at time t or a 3-year rolling average of fewer than 25 fatalities. Again, a smoothing average around the minimum cut-off is used to reduce noise.

In addition to the major categories of war, post-conflict, and peace, there are also minor conflicts and post-minor conflict periods. Countries that are coded as having had minor conflict are coded as post-minor conflict for the two subsequent years that the minor conflict is over. This middle step ensures that countries at peace serve as a counterfactual, avoiding capturing effects in the peace category that may be due to past minor conflicts.

This type of categorization has the advantage, that the impact of experiencing any kind of conflict state can be compared to the state of peace at the aggregate level. In terms of subnational interpretation, it allows the identification of effects e.g. if a district that is part of a conflict country experiences adverse effects compared to a district that is part of a peaceful country.

The second step is to categorize the districts by their involvement. Meaning, are they or have they been involved in active fighting within their territory during the war periods that the country experienced or not? The same is with minor conflict, did they have any fatalities within their administrative boundaries within the year that a country experienced a minor conflict?[13] The district level is always dependent on the country level, however, showing passive or active involvement in the country's events. Figure 1 in the Appendix A shows the countries' aggregate category in 2005, whereas Figure 2 shows those districts that are coded as post-conflict in 2005 due to their active involvement. Variation in the figures indicates that not every district was actively involved in its country's war experience.

Furthermore, active involvement does not necessarily consider the intensity of fighting a district was subjected to. Likely, even for those actively involved, there is variation in the intensity of fighting they experienced.

2.3.2 Intensity Index

The index is designed in a way that takes into consideration the length of the war and when the most intense fighting occurred in the district. The idea is that as war evolves

[13] The decision tree A.2 in Appendix A shows the respective coding of the binary variables.

over time and space, districts are affected more or less intensely at different times. This is likely to impact post-conflict development and the effectiveness of aid if heavy fighting in the district happened some years ago or right before the country entered the post-conflict stage. If a district was targeted heavily at the beginning of the war, this is discounted compared to if it was more exposed to violence towards the end of the war. Furthermore, the index takes into account conflict re-occurrences, meaning if the country counts as post-conflict but then war reoccurs, fatalities of the first war are still taken into consideration. Any post-conflict or past war experiences collapse to peace after ten years have passed, which is in accordance with the standard definition used by Collier and Hoeffler (2004) and Donaubauer et al. (2019). The formula for the intensity index in post-conflict districts takes on the following form:

$$\omega_{ct} \sum_{i_t=1}^{N_t} \delta_{crt} \frac{i_t}{N_t} + \tau_{ct} \sum_{i_z=1}^{N_z} \delta_{crz} \frac{i_z}{N_z} (1 - \frac{\sigma_t}{11}) \tag{3}$$

in which $\omega \epsilon \{0,1\}$ is 1 if a district is part of a post-conflict country. δ accounts for the sum of battle deaths per district at time t and i is the year of the event during the war, whereas N accounts for the sum of total years of consecutive war. The first term of the formula considers the intensity of the most recent war period, discounting the fatalities a district experienced dependent on the length that the war lasted.[14] In some countries, post-conflict peace might not last and another war period sets on. When that war outbreak again comes to peace, any fatalities that happened during the first war should not be forgotten if this happens within a 10-year time frame. They must still be taken into account when trying to establish the intensity of fighting a district was subjected to during war times. The second term of the formula integrates situations in which war resurges. $\tau \epsilon \{0,1\}$ is 1 in case of war re-occurrence and $\sigma \epsilon [1,...,11]$ denotes the time passed since the first war ended. The subscript z states that the time for such events is in the past determined as $z = \text{t}-11+\sigma_t$.[15]

The term $(1 - \frac{\sigma_t}{11})$ denotes that for events of war re-occurrence, fatalities that were experienced during the first war period are not considered anymore in the intensity in-

[14] The discount factor follows a linear function and thus makes a strong assumption in regards of shorter war periods, as recent fatalities for short periods are more heavily discounted than such of long periods.

[15] Based on the dataset, there are restrictions posed to the starting point of possible combinations of t and σ_t.

dex after 10 years passed since the last active fighting. This follows partly the definition of Collier and Hoeffler (2004) in which post-conflict countries are only considered post-conflict for 10 years and after that countries are at peace. Similarly, fighting that a district experienced more than 10 years ago does not affect its current intensity value anymore. It further implies that fatalities from the first war are additionally discounted by each year that it lies in the past compared to the current post-conflict experience. Figure 3 in Appendix A indicates the variation of fighting intensity based on the intensity index in the year 2005. It shows that there is considerable variation in the fighting intensity districts experienced during post-war periods.

2.4 Disbursing foreign aid

Subnational data for aid disbursements is retrieved from the AidData database (AidData, 2017). AidData tracks 5,648 World Bank projects from 1995 to 2014, covering disbursements worth 390 billion US$ and 630 billion US$ in commitments spread over 61,243 locations. For each project, information about the start and end date, the total amount of disbursements during that time and the different locations that were targeted is provided. As this study concentrates on the district level, only projects that are administered and identified at the ADM2 level are included. As just the start and end date are known, the disbursed amount is evenly split across the years a project took place, thus averaging over those years. A project can target several locations, therefore, the total amount of disbursement is further evenly split across the locations in which a project took place following Fischer (2022) and Gehring et al. (2022). WB aid disbursements targeted to centralized government agencies, other state-level institutions or that can only be identified at the ADM1 level are excluded from the analysis (Dreher & Lohmann, 2015; Fischer, 2022; Strandow et al., 2011).[16]

The AidData dataset for WB projects is widely used in recent aid literature (BenYishay et al., 2022; Bitzer & Gören, 2018; Briggs, 2018; Dreher & Lohmann, 2015; Gehring et al., 2022). In terms of the generalizability of results, however, the use of this dataset limits the results' interpretation to foreign aid disbursed by the World Bank and does not reflect other donors' impact or bilateral aid.

[16]Figure 4 in Appendix A shows the distribution of aid disbursements for African countries at the ADM2 level in the year 2005.

Aid is considered to be endogenous. There is a vivid debate about methods to establish a causal link between aid and growth (Bazzi & Clemens, 2013; Clemens et al., 2012). Poor growth or conflict could induce a donor's decision to disburse more or less aid in a certain region or country. Another point is the timing of aid. Aid likely needs time to cause growth, however, lagged aid as stated in Clemens et al. (2012) might as well affect current growth, thus instruments based on lagged aid could bias the resulting coefficient. Furthermore, results based on supply-side instruments that mostly take their strength from its correlation with population size do not capture the variance of aid flows enough to correct the bias generated in an OLS estimation (Clemens et al., 2012). Clemens et al. (2012) suggest a specification without relying on instruments, giving aid a lag structure to capture the timeline from the time that aid is disbursed to causing growth and further introducing first-differencing.

The specification of this model partly follows this structure. I lag aid and control for time-invariant unobservable heterogeneity through country- and district fixed effects. I further use a large set of controls at the country and district level to control for observable heterogeneity. However, there are still some remaining concerns about endogeneity through omitted unobservables and reverse causality. This is addressed in two ways: In the first approach, aid is instrumented.[17] In the case of this specific model, the instrument needs to provide exogenous variation of multilateral aid, reflect the variation of aid disbursement on a local level and is not allowed to be correlated with the error term.

A recent strand of literature relies on instruments using an interaction between the exogenous variation of the donor's aid budget and the strength of the relationship with the recipient country or a country's probability to receive aid. For example, Nunn and Qian (2014) rely on the time variation of the US's wheat production changes and a recipient country's likelihood to receive food aid. Chauvet and Ehrhart (2018) introduce exogenous variation using the total amounts of tax revenues of donor countries in interaction with colonial ties between the donor and the recipient country to account for the strength of the bilateral relationship. Dreher and Langlotz (2020) employ an instrument that uses the government fractionalization of donor countries interacted with a country's probability to receive aid. These instruments work well for bilateral aid but are not

[17] There is a rigorous debate on the difficulty of finding valid instruments for determinants of growth. For an instrument to be valid, it is not allowed to " materially affect growth through channels other than the variable of interest" and it needs to be strong in the sense that "instruments correlate well with the variable of interest."(Bazzi & Clemens, 2013, p.152)

useful for exploring exogenous variation in multilateral aid.

Instruments used in a multilateral donor setting are employed by Dreher et al. (2021), Dreher and Lohmann (2015), and Galiani et al. (2016). Galiani et al. (2016) present the crossing of the IDA threshold as an exogenous shock for countries to receive less aid and Dreher and Lohmann (2015) combine this with a country's probability to receive aid which is then used as an instrument for WB aid disbursements. This would be a possible instrument, however, it limits the sample size of countries that can be used for the analysis as they must have a period in which they crossed the IDA threshold. Dreher et al. (2021) introduced an instrument that can be used at a subnational level, the WB's total budget proxied by the IBRD equity-to-loan ratio and IDA funding position in combination with the country's probability to receive aid.[18] This instrument is used as a robustness check and to ensure comparability of the results to other studies in the aid literature, however, it is not used as the main strategy due to concerns in regard to issues highlighted by Christian and Barrett (2017).

This paper exploits a new version of an instrument that has been well studied regarding its validity (de Mesquita & Smith, 2010; Fischer, 2022) and strength (Dreher et al., 2018; Fischer, 2022) in recent aid literature.[19] It uses the quasi-random allocation of holding the United Nations Security Council (UNSC) presidency lagged by three years interacted with the initial number of projects to gain variation at the district level.

Research has shown that donors[20] increase their aid funds towards temporary members of the United Nations Security Council (UNSC) which receive increased amounts of aid during their tenure. For African countries this additional aid inflow is quasi-random as a strict rotational rule to participate in the UNSC is enforced (Dreher et al., 2008; Dreher et al., 2009).[21]

[18] Data for this instrument is used from Dreher et al. (2021).

[19] Fischer (2022) employs a seemingly similar instrument which uses a binary variable for holding the presidency of the UNSC interacted with the number of projects a country received. As this is used for all developing countries and not exclusively for Africa, the exclusion restriction is likely violated. Moreover, the delay between UNSC membership to receiving aid disbursements is disregarded and as the projects were counted on a country level, there is no variation on the district level. Although, based on this idea, the instrument used in this paper is further refined to be strong and valid in this specific context.

[20] Kuziemko and Werker (2006) show this in the case of the US, Dreher et al. (2015) provide similar evidence for Germany and Dreher et al. (2009) for Japan and multilateral organizations. Dreher et al. (2018) give an overview.

[21] There are 5 permanent members (China, France, Russia, the UK and the US) and 10 temporary members which are voted by the UN General Assembly and which hold their seat for 2 years. The membership is not immediately renewable. The 10 temporary seats are distributed between the world regions. Latin

Own estimations indicate that the increase in aid is mainly predicted by holding the presidency of the UNSC in a certain year and less so by the membership itself.[22] The presidency introduces further exogeneity as it rotates every month and changes based on the English names of the members following the alphabet (United Nations, 2022).[23] As an increase in aid is likely not an immediate response but delayed, the UNSC presidency dummy is lagged by three years (t-3) to instrument aid at time t-1 and causing growth at time t, following a modified[24] version of the proposed timeline in Dreher et al. (2018).

The additional influx of aid for recipient countries is likely motivated by geopolitical interests. Dreher et al. (2008) demonstrate that the US buys voter compliance in the UN General Assembly through aid, while Dreher et al. (2018) indicate that politically motivated aid distributed while a recipient country was a temporary member of the UNSC is less effective. Any results should therefore be interpreted as a local average treatment effect (LATE) of politically motivated aid.

Another concern targeting the exclusion restriction is that UNSC membership itself has an impact on growth. Due to the territorial scope, this issue is partly addressed and additionally findings by de Mesquita and Smith (2010) indicate that election to the UNSC is unrelated to development concerns within the member country. As the research question targets aid to post-conflict locations, UNSC membership could make the deployment of peacekeeping troops more likely. To address this concern, peacekeeping deployment at the district level is included as a control. [25]

As this approach mainly identifies the effect of politically motivated aid and concerns based on Borusyak et al. (2021), Christian and Barrett (2017), and Goldsmith-Pinkham et al. (2020) might still apply, an alternate model is estimated using rigorous fixed effects and incorporating controls for heterogeneous trends of districts and countries to target

America and Asia hold competitive elections which is usually won by the regional power, Western Europe mixes elections with rotation and Eastern Europe has no systematic patterns (Dreher et al., 2018; Malone, 2000)

[22]Table 19 in Appendix B.6 shows the respective regression results. It indicates that UNSC presidency has adverse effects for districts with initial aid disbursements.

[23]The presidency instigates additional power as the country holding the presidency sets the agenda. At the same time, it is quasi-random if a country holds the presidency during its term at the UNSC or not.

[24]Dreher et al. (2018) use 4-year averages with shares of UNSC membership within those 4 years, which is then followed by a 4-year average for the disbursement.

[25]The results in Table 10 show no alteration of the magnitude of the baseline estimates and the instrument's strength is not affected by the inclusion of this variable. This suggests that a district's growth is not directly affected by the UNSC presidency through increased deployment of peacekeeping troops.

any remaining endogeneity.[26] Juxtaposing these two strategies has the advantage to show the effectiveness of politically motivated aid in comparison to general aid and further underlines the robustness of the results.

2.5 Controls

On a district level, various factors potentially affect its economic activity. The geoquery application from AidData (Goodman et al., 2019) provides a tool to obtain data on the ADM2 level from various sources. To control for weather conditions that potentially affect a district's agricultural output, mean precipitation (Harris et al., 2020) and temperature (Harris et al., 2020) are taken into account. The remoteness of the district could also affect growth, the conflict intensity or distribution of aid and is thus controlled by the average travel time to the next urban center (Nelson, 2008) and the mean distance to roads (CIESIN & ITOS, 2013) within a district.

As already mentioned in regard to the instrument validity, peacekeeping troops can play a role in places that are or were affected by war. Cil et al. (2020) provide a geocoded dataset offering information about the deployment of peacekeeping troops from 1994 to 2020. Based on this dataset, a binary variable detecting peacekeeping deployment in a specific year and district is created.

Further controls on the district level are population density (CIESIN, 2018) and nightlight lagged by two years to control for convergence and the level of growth. The population density addresses concerns mentioned in Clemens et al. (2012) regarding instruments that collapse when introducing population variables as they base their strength on population size. In addition to the district-level controls, continuous variables for population growth and density at the country level are obtained from the World Development Indicators (World Bank, 2022). To check the robustness of the baseline estimates, in Table 11, results are shown for estimates including potentially omitted growth determinants as e.g. FDI flows, trade and migration as covariates on the country level.

[26] A similar approach has been used in Gehring et al. (2022), employing heterogeneous trends in their preferred strategy and showing the robustness of their results via the aforementioned IV strategy using the IDA financial position in combination with a district's probability to receive aid.

3 Results

3.1 Baseline Results

Table 1 shows the regression results for different specifications of the model displaying variations of included control variables and modifications of the fixed effects and trends used. The different specifications give an overall picture of the stability and robustness of the results. Coefficients for the interaction term in the second line are jointly significant. Column (6) in Table 1 indicates the results for the preferred specification of the model, an estimation with rigorous country, district and time fixed effects, further controlling for heterogeneous trends.

It shows that in general, aid has a significant positive effect on economic growth in African districts. In terms of the effectiveness of aid in post-conflict districts[27], the magnitude of the overall effect becomes negative when aid is distributed to actively involved post-conflict districts.[28] An explanation for this could be that while post-conflict countries have increased absorptive capacities as has been shown by Collier and Hoeffler (2004), local administrative capacity might be limited to effectively utilize and manage the received aid in districts directly affected by violence. This weakened capacity could be explained by the physical destruction of local institutions as well as a lack of skilled personnel due to displacement. On a country level, the role of migration is controlled within the robustness checks, indicating no alteration of the results.

When considering column (7) in comparison, a 2SLS estimation with country, district and time fixed effects with aid instrumented by the UNSC presidency and initial aid projects, the picture looks different. In total, aid still has a positive impact on economic development, but this effect is mitigated compared to if it was distributed in a district within a country at peace.[29] The F-statistics of the first stage, the Kleibergen-Paap test for underidentification and the Kleibergen-Paap Wald F-stat give satisfactory results and confirm the instrument's validity and strength. The estimates are robust to including

[27] As a little reminder, a post-conflict district indicates a district actively involved in the war. The results as can be seen in Table 4 do not necessarily imply the same for non-involved districts.

[28] For the interpretation of the overall effect in post-conflict districts, one needs to add the value of the coefficient for ln Aid_{crt-1} to the coefficient of the interaction term.

[29] The results must be interpreted in terms of identifying the effect of politically motivated aid.

Table 1: Baseline Results

	Dependent variable: $\Delta ln(light_{crt})$							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
ln Aid_{crt-1}	0.0008***	0.0009***	0.0017***	0.0006**	0.0009***	0.0007*	0.0593***	0.0023**
	(0.0003)	(0.0003)	(0.0002)	(0.0003)	(0.0003)	(0.0004)	(0.0185)	(0.0011)
ln Aid_{crt-1} × Post-Conflict District		-0.0005	-0.0003	0.0002	-0.0012	-0.0011	-0.0004	-0.0025**
		(0.0008)	(0.0007)	(0.0009)	(0.0008)	(0.0010)	(0.0114)	(0.0010)
Post-Conflict District	0.0255***	0.0300***	0.0248***	0.0171***	0.0287***	0.0359***	0.0294	0.0297***
	(0.0055)	(0.0056)	(0.0047)	(0.0060)	(0.0056)	(0.0074)	(0.0315)	(0.0057)
Post-Conflict Country	-0.0129**	-0.0093	-0.0095*		-0.0127**	0.0158*	0.0470**	-0.0254***
	(0.0057)	(0.0057)	(0.0055)		(0.0057)	(0.0082)	(0.0222)	(0.0066)
War Country	-0.0029	0.0074	0.0061		-0.0028	0.0378***	0.0039	-0.0178**
	(0.0065)	(0.0065)	(0.0064)		(0.0065)	(0.0096)	(0.0109)	(0.0075)
Minor Conflict Country	-0.0217***	-0.0231***	-0.0209***		-0.0216***	-0.0185***	-0.0373***	-0.0095*
	(0.0044)	(0.0044)	(0.0044)		(0.0044)	(0.0048)	(0.0088)	(0.0050)
Minor Post-Conflict Country	-0.0097*	-0.0091	-0.0074		-0.0096*	-0.0128**	-0.0048	0.0007
	(0.0055)	(0.0056)	(0.0055)		(0.0055)	(0.0059)	(0.0078)	(0.0057)
Conflict district	-0.0021	-0.0012	-0.0058	0.0002	-0.0024	-0.0050	0.0106	-0.0062
	(0.0071)	(0.0072)	(0.0065)	(0.0071)	(0.0071)	(0.0078)	(0.0109)	(0.0071)
Minor Conflict District	-0.0164	-0.0142	-0.0123	-0.0074	-0.0165	-0.0149	0.0250	-0.0349**
	(0.0150)	(0.0150)	(0.0141)	(0.0148)	(0.0150)	(0.0161)	(0.0235)	(0.0166)
Minor Post-Conflict District	-0.0167**	-0.0039	-0.1424***	0.0978***	-0.0162**	0.0444***	0.3056***	
	(0.0070)	(0.0068)	(0.0107)	(0.0259)	(0.0070)	(0.0093)	(0.1029)	
Observations	101482	101482	101482	101482	101482	101482	101482	96314
Regions	5418	5418	5418	5418	5418	5418	5418	5418
Country FE	YES	YES	YES	NO	YES	YES	YES	YES
Region FE	YES	YES	NO	YES	YES	YES	YES	YES
Time FE	YES	YES	YES	NO	YES	YES	YES	YES
Country-Year FE	NO	NO	NO	YES	NO	NO	NO	NO
Heterog. Time Trends	NO	NO	NO	NO	NO	YES	NO	NO
District Controls	YES	NO	YES	YES	YES	YES	YES	NO
Country Controls	YES	NO	YES	NO	YES	YES	YES	NO
R2	0.105	0.101	0.032	0.157	0.105	0.159		
First-Stage F-Stat							18.060	184.290
First-Stage F-Stat Int							30.340	1500.930
Kleibergen-Paap rk LM stat							0.000	0.000
Kleibergen-Paap rk Wald F stat							8.313	187.735

Standard errors in the parentheses are clustered at the district level. Columns (1)-(6) show OLS estimates with variations of fixed effects, trends and controls as indicated in the bottom half of the table. Column (7) shows 2SLS estimates with ln Aid_{crt-1} instrumented by $SCPresidency_{ct-3} \times AidProjects_{cr1995}$ and column (8) shows 2SLS estimates based on the instrument of Dreher et al. (2021) using the IBRD equity-to-loan and IDA financial position interacted with a districts probability to receive aid. Underidentification is tested by the Kleibergen-Paap rk LM statistics, which is indicated by its p-value. Weak identification is indicated by the Kleibergen-Paap rk Wald F statistics. Stock and Yogo weak ID test critical value at 10 percent level is 7.03 for column (7) and 16.87 for column (8). * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

controls for the population density at the district and country level, indicating that the instrument is valid and does not take its strength from a country's population, which could be the case if UNSC membership and henceforth presidency are partly determined by that.

Based on how the model is specified, further implications can be drawn regarding growth patterns during different stages between conflict and peace. Post-conflict districts experience a so-called rebound effect. It shows that districts that are part of a post-conflict country have on average a higher growth rate compared to their peaceful counterparts. This is especially true for those districts that were actively involved in the fighting during the country's war period experiencing in total an average increased growth rate of approximately 5.2 percentage points. This additional growth experience has been described by Hoeffler (2012) as the "peace dividend". One potential explanation is that funds formerly directed to the military during the war period are diverted to more productive sectors and reconstruction efforts during the post-conflict period. A further explanation is an increase in economic activity after wartime as businesses and investors are more likely to invest when the risk of violence is reduced.

It further shows in column (6) that especially minor conflicts have adverse effects on economic activity, decreasing an actively involved district's nightlight growth by on average 3.3 percentage points in comparison to the baseline. However, it also shows that those districts that were actively involved in the minor conflict experience increased changes in nighttime light within the 2 years that this minor conflict is peacefully settled again.

A more conservative estimation using country-year and district fixed effects is shown in column (4). It is the only estimation showing a positive coefficient for the interaction term, however, this more conservative estimation undermines the specification for the different conflict-to-peace categories and thus does not allow a straightforward interpretation of the effects in post-conflict countries and districts.

To make results more comparable to the general aid literature, column (1) shows the results for the same baseline model as in equation 1 while excluding the interaction term from the model. When comparing the aid coefficient in column (1) to the same coefficient for other model specifications and estimators, the same conclusion can be drawn for the overall effectiveness of aid. Further attention should be drawn to the estimates in column 7, using a version of the instrument established in Dreher et al.

(2021) and utilized in Cruzatti et al. (2023) and Gehring et al. (2022). While the coefficient for aid in the first line of column (9) is slightly higher than in the preferred specification of column (7), the overall effectiveness for post-conflict districts is marginally the same and both coefficients are significant. This indicates that the preferred specification is a lower-bound and more conservative estimation.

3.2 Robustness Checks

3.2.1 Instrument Validity

One of the main concerns when instrumenting determinants of growth is that the employed instrument violates the exclusion restriction (Bazzi & Clemens, 2013; Clemens et al., 2012). Clemens et al. (2012) showed for example for the studies of Boone (1996) and Rajan and Subramanian (2008) that when including a control for population, their instruments collapse. Table 1 shows that the instrument used for aid in this study is robust to including controls for population on the district and country level.

One specific concern to my setting is the deployment of peacekeeping in post-conflict districts. Peacekeeping deployment has the potential to affect growth in post-conflict districts as well as it could affect the instrument. UNSC presidency might not solely cause growth through increased aid, but also growth through increased peacekeeping deployment. Table 10 in Appendix B.1 shows estimation results including different peacekeeping specifications. The results indicate peacekeeping does not invalidate the instrument as the coefficient for aid in the main specification shown in column (2) of Table 10 is not altered in its magnitude or strength. If peacekeeping distorts the instrument, this would especially show in the case of aid effectiveness in post-conflict districts. As the coefficient of the interaction term merely changes, the exclusion restriction holds in terms of peacekeeping deployment. The Kleibergen-Paap tests for underidentification and weak identification demonstrate as well the robustness of the instrument against the inclusion of a dummy for peacekeeping deployment. To further strengthen the validity of the baseline results, I estimate a specification that includes the peacekeeping variable and, additionally, an interaction term of peacekeeping and initial aid projects, which can be interpreted as districts with more aid projects in 1995 receiving more peacekeeping deployment. This interaction term is insignificant and does not alter the coefficient for aid or its interaction with the post-conflict dummy.

A further concern regarding a potential violation of the exclusion restriction is omitted growth determinants as stated by Bazzi and Clemens (2013). I, therefore, include potential determinants of growth on the country level like FDI flows, trade and, likely important in the case of developing and especially post-conflict countries, migration. Tables 11 and 12 in Appendix B.1 show the results when including those variables. The results indicate that the inclusion of those controls does not alter the magnitude or significance of the aid coefficient and its interaction. In terms of the 2SLS estimations in Table 11 the Kleibergen-Paap tests show similar results as well, thus the instrument and results prove to be robust to other growth determinants. In light of the discussion in regards of shift-share instruments (Borusyak et al., 2021; Christian & Barrett, 2017; Goldsmith-Pinkham et al., 2020), Figure 5 shows trends of districts whose countries held UNSC presidency and those that received aid projects in the initial year of 1995 in regards of the main dependent variable, the change in nighttime light.

3.2.2 Sample Dependence

Any further robustness checks are based on the preferred specification (6) in Table 1. Clemens et al. (2012) show that results of some of the most impactful studies (Boone, 1996; Burnside & Dollar, 2000; Rajan & Subramanian, 2008) in the aid literature are dependent on their sample period or sample of countries. In the case of this study, this issue is less of a concern as there is subnational variation and it is not a cross-country study. However, results might still have issues of sample dependence if districts in major aid-receiving countries are differently affected.

Therefore, the sample is modified, dropping various combinations of potentially impactful countries and each country at once. Table 13 in Appendix B.2 shows the results when dropping the five African countries with the highest GDP, namely, Egypt, Nigeria, South Africa, Algeria and Morocco.[30] This coincides with a drop of approximately 1/3 of observations. The coefficient for aid effectiveness stays at the same level as the baseline. At the same time, the magnitude of the interaction term increases. Interpreting it jointly, the overall effect of aid in actively-involved post-conflict districts becomes increasingly

[30] Ranking of the highest overall GDP in PPP INT$ based on World Bank data from 2021. https://worldpopulationreview.com/country-rankings/richest-african-countries

negative.[31]

When dropping all North African countries from the sample, thus dropping Egypt, Morocco, Tunisia and Algeria at the same time, which makes up for 1/4 of the observations, coefficients are similar to those in column (2). This is not further surprising as there is a big overlap between the overall richest and North African countries. Column (4) indicates a smaller decrease in observations, dropping the five richest countries when considering GDP per capita.[32] In this estimation observations of districts within Egypt, South Africa, Equatorial Guinea, Botswana and Gabon are dropped. Those countries account for only 1/10 of the observations of the full sample. The magnitude of the coefficients and tests for instrument validity change only marginally in comparison to results based on the full sample. Similarly, when dropping each country at once the effect is negligible and results are robust.

3.2.3 Further checks

One further concern is the transformation of the variables as explained in Section 2.2. The transformation of growth [33] could potentially change the findings. Therefore, Table 14 in Appendix B.3 shows in column (5) the coefficients for the sample without the transformation. In those estimations, any observations where no nightlight is observed are excluded from the sample. This could potentially bias the outcome as regions with little economic activity are excluded from the dataset. For better comparison, column (4) shows the regression results for the same sample but with the transformation. In terms of those transformations, the magnitude of the coefficient changes marginally but aid becomes insignificant. Testing for joint significance, the coefficients for aid and its interaction term are jointly significant. Estimating the same specifications without controlling for heterogeneous trends, coefficients and significance levels do not alter. [34]

[31] Coefficients are interpreted jointly as joint significance tests are significant.

[32] Ranking of the five countries within the sample with the highest GDP per capita in current$ based on World Bank data from 2021. https://worldpopulationreview.com/country-rankings/richest-african-countries

[33] As stated in Section 2.2 I added the smallest observed value to make the computation of growth possible for most observations that would otherwise be excluded due to consecutive zero nightlight observations.

[34] For the baseline estimations, outliers are excluded using a 2 percent cut-off at the maximum and 0.5 percent at the minimum. To assure, that results are robust in regard to the chosen cut-off level, column (6) in Table 14 shows results when using outlier cut-offs at the 1st and 99th.

Columns (1) and (2) indicate results for different transformations of the aid variable. In column (1), as in the baseline, a logarithmic function including an added value of 1 is used whereas in column (2) aid is transformed using an inverse hyperbolic sine (ihs) transformation. Results for both versions are basically identical, thus this transformation has no influence on the estimates.

Another point regarding the sensitivity of the results is the timeline between aid disbursement and aid causing growth in economic activity. Table 16 in Appendix B.4 investigates results in this regard and if the proper timeline is chosen. The results show that the baseline should be the preferred timeline.

A further potential issue could be a distortion of growth rates in the year 2014 due to a likely error in the harmonization process of the nightlight data as mentioned in Martínez (2022).[35] Columns (4) and (5) in Table 14 show results excluding the years 2014 and 2015 and therefore any years that could be distorted by a harmonization error. Estimates are jointly significant and have the same magnitude as in the baseline, thus reassuring the validity and stability of the chosen model.

4 Mechanisms and Channels

4.1 Conflict Intensity and Timing of Aid

The baseline results indicate the overall effectiveness of aid but also show a mitigated effect for post-conflict districts. In the baseline estimations, following the main definition, a district counts as a post-conflict district if it experienced any kind of active involvement in the fighting resulting in fatalities. But likely aid's effectiveness is heterogeneous across different fighting intensities and a district's involvement in the war.

In Section 2.3.2 I introduced a novel intensity index that measures the exposure to war a district experienced in the past. In Table 2 each column depicts an estimation in which the treatment is conditioned on having the corresponding intensity index.[36] As

[35] Following Martínez (2022), I impute the value for 2014 based on the average value of change in night-time light in the previous two years (2012-2013) and the two years after (2015-2016).

[36] This means the binary variable is coded as 1 when the intensity of a district falls within the stated range.

Table 2: Regression Results considering Conflict Intensity

	Dependent variable: $\Delta ln(light_{crt})$					
Intensity:	any	$[>0,5]$	$[>0,25]$	>25	>100	>1000
ln Aid$_{crt-1}$	0.0007*	0.0006	0.0006	0.0007*	0.0007*	0.0007*
	(0.0004)	(0.0004)	(0.0004)	(0.0004)	(0.0004)	(0.0004)
ln Aid$_{crt-1}$ $\times$	-0.0011	-0.0002	0.0001	-0.0020	-0.0032*	-0.0070**
Post-Conflict District	(0.0010)	(0.0014)	(0.0013)	(0.0014)	(0.0019)	(0.0035)
Post-Conflict District	0.0359***	0.0258***	0.0327***	0.0196*	0.0367**	0.0118
	(0.0074)	(0.0090)	(0.0077)	(0.0116)	(0.0153)	(0.0303)
Post-Conflict Country	0.0158*	0.0260***	0.0210***	0.0278***	0.0284***	0.0306***
	(0.0082)	(0.0078)	(0.0079)	(0.0078)	(0.0077)	(0.0077)
Observations	101482	101482	101482	101482	101482	101482
Country, Region, Time FE	YES	YES	YES	YES	YES	YES
Country-Year FE	NO	NO	NO	NO	NO	NO
Heterog. Time Trends	YES	YES	YES	YES	YES	YES
District & Country Controls	YES	YES	YES	YES	YES	YES

Standard errors in the parentheses are clustered at the district level. Columns (1) to (6) show OLS estimates fixed effects and trends as indicated. The Post-Conflict District treatment is conditioned on the intensity as indicated in the respective column. The intensity level stems from the intensity index for conflict exposure. Post-Conflict Country accounts for districts within a post-conflict country that were not actively involved. All displayed coefficients are jointly significant for various combinations. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

a reminder, the intensity index cannot be equally interpreted as the number of fatalities but is the discounted number of fatalities depending on when those occurred during the war period. Still, a low-intensity index means lower numbers of fatalities over the whole war period or higher numbers that are heavily discounted, whereas a higher intensity index means either extremely high numbers of fatalities during the beginning, a very short war period with a smaller discounting factor or high numbers towards the end of the country's war period.

The results in Table 2 indicate that the effectiveness of aid depends on the number of fatalities a district had during the country's war period. In column (1), the post-conflict variable takes on the treatment if the intensity index for that district is above 0. Therefore, estimations are less conservative in terms of what counts as an actively involved post-conflict district as some districts could have had 10 fatalities at some point during the country's war period whereas others had more than 1000 within their administrative borders. As we are interested in the heterogeneous effects of the fighting intensity on aid's effectiveness, columns (2) and (3) show low-intensity fighting with column (2) only considering districts that had an intensity index above zero and below five and column (3) indicating a slightly higher intensity, namely above zero but below 25. Columns (4) and (5) take on treatment for only higher intensity post-conflict districts, with column (5) showing the effects for districts that had an intensity of at least 25, column (5) with at least 100 and column (6) with more than 1000.

The results in Table 2 indicate that high-intensity fighting has an adverse effect on aid effectiveness. From left to right in Table 2, it shows that post-conflict districts with intensities above 25 experience significant negative effects from aid disbursed within their administrative borders. This is not necessarily the case for districts with low-intensity fighting in the past as is shown in columns (2) and (3) of Table 2. As coefficients are jointly significant, we can conclude that for such districts, aid is still effective even if its effectiveness is mitigated. Still, the magnitude of the effect becomes lower the higher the intensity index is, which can be interpreted as the higher the intensity, the less effective is aid as the coefficients have a negative sign. For high numbers of fatalities, this means that aid in the aftermath is less effective. An explanation of this might be twofold. Areas disproportionately more affected by heavy fighting could be more likely to experience an effect called the "war ruin" hypothesis as explained in Nkurunziza (2019). It poses that especially civil wars have destructive effects on the economy and post-conflict reconstruction can be costly and cumbersome in such places, making aid less effective. Furthermore, heavily destroyed locations might have weaker institutions and administrative capacities in place to absorb aid effectively. Policies should take this into consideration, aiming for the so-called "phoenix effect" (Nkurunziza, 2019). One policy measure to benefit from the phoenix effect can be to rebuild institutions from scratch and replace them with more effective ones for which the absorptive capacity of aid is higher.

In terms of post-conflict growth itself, it shows that in any case, there is a rebound effect for districts of post-conflict countries, no matter if they were subject to violent outbreaks of the war or not. Those that were subjected to heavy fighting, still have some additional growth but less than the low-intensity districts. This is indicated when comparing the coefficients for post-conflict districts of columns (6) to columns (2) and (3).

It shows that there are underlying mechanisms in terms of experienced conflict intensity. Depending on the number of fatalities a district was subjected to during the

Table 3: Regression Results considering Conflict Intensity in early and late post-conflict years

	Dependent variable: $\Delta ln(light_{crt})$					
Intensity:	any	$[>0,5]$	$[>0,25]$	>25	>100	>1000
Years 1-5 post-conflict						
ln Aid_{crt-1}	0.0006	0.0006	0.0006	0.0006	0.0006	0.0006
	(0.0004)	(0.0004)	(0.0004)	(0.0004)	(0.0004)	(0.0004)
ln Aid_{crt-1} $\times$ Post-Conflict District	0.0001	-0.0002	0.0009	-0.0006	-0.0018	-0.0033
	(0.0011)	(0.0014)	(0.0014)	(0.0015)	(0.0019)	(0.0040)
Post-Conflict District	0.0225***	0.0227***	0.0201***	0.0169	0.0457***	0.0265
	(0.0060)	(0.0073)	(0.0061)	(0.0104)	(0.0142)	(0.0304)
Post-Conflict Country	0.0270***	0.0284***	0.0279***	0.0286***	0.0288***	0.0292***
	(0.0076)	(0.0076)	(0.0076)	(0.0076)	(0.0076)	(0.0076)
Years 6-10 post-conflict						
ln Aid_{crt-1}	0.0007	0.0006	0.0006	0.0006	0.0006	0.0006
	(0.0004)	(0.0004)	(0.0004)	(0.0004)	(0.0004)	(0.0004)
ln Aid_{crt-1} $\times$ Post-Conflict District	-0.0024**	0.0007	-0.0011	-0.0029*	-0.0018	-0.0092
	(0.0012)	(0.0022)	(0.0021)	(0.0016)	(0.0020)	(0.0059)
Post-Conflict District	0.0081	-0.0034	0.0103	0.0041	-0.0285	-0.0056
	(0.0080)	(0.0106)	(0.0095)	(0.0130)	(0.0185)	(0.0669)
Post-Conflict Country	0.0290***	0.0293***	0.0275***	0.0307***	0.0317***	0.0308***
	(0.0080)	(0.0077)	(0.0078)	(0.0078)	(0.0077)	(0.0076)
Observations	101482	101482	101482	101482	101482	101482
Country, Regions, Time FE	YES	YES	YES	YES	YES	YES
Country-Year FE	NO	NO	NO	NO	NO	NO
Heterog. Time Trends	YES	YES	YES	YES	YES	YES
District & Country Controls	YES	YES	YES	YES	YES	YES

Standard errors in the parentheses are clustered at the district level. The Post-Conflict District treatment is conditioned on the intensity as indicated in the respective column and further treatment only shows if the district is for EARLY within year 1 to 5 years post-conflict and for LATE within year 6 to 10 post-conflict. The intensity level stems from the intensity index for conflict exposure. Displayed coefficients are jointly significant. * $p<0.10$, ** $p<0.05$, *** $p<0.01$

war, aid is more or less effective during the post-conflict time. The intensity of fighting further affects the district's ability to experience extraordinary growth rates during the post-conflict period.

The rebound effect and aid effectiveness are especially strong for those districts that experienced only low-intensity fighting. This might be explained due to less destruction, wherein the economy of the district can pick up faster again, in comparison to places that experienced heavy fighting.

Collier and Hoeffler (2004) suggest that the effectiveness of aid is especially pronounced within 5 to 7 years post-conflict. I test if this applies also in a subnational context. Table 3 shows the heterogeneous effects of different intensities for the early years after the war ended and then 6 to 10 years after the last conflict event took place. It shows that for most intensities, aid is slightly more effective in the early years compared to the whole post-conflict period. Conditioned on intensity it follows similar patterns as discussed in Table 2. Interestingly, the coefficient for being part of a post-conflict country, does not change much over the two periods, and is more pronounced within the late years. However, post-conflict districts' growth rate is slightly less in magnitude for the years 6 to 10, suggesting that actively involved districts have their "phoenix" moment during the early post-conflict years, whereas districts that were not actively involved in the war benefit later from increased economic activity.

4.2 Spillover Effects

de Groot et al. (2022) explore the effects of conflicts on growth in a cross-country setting, examining different conflict types, and how much spillover effects of conflicts in neighboring countries affect a peaceful country's economic growth. It shows that those spillover effects have a small positive or negative effect depending on the type of conflict.

By construction, the baseline model as stated in Equation 1 already accounts for spillover effects from actively involved districts to non-involved districts within a country. This is reflected in the difference between the post-conflict country and post-conflict district variables. The baseline results in Table 1 in column (4) show that districts that are part of a post-conflict country experience higher growth rates than those in peaceful ones. This effect is even more pronounced for the districts that were actively involved in the fighting. So far, the heterogeneity of aid effectiveness was only investigated for post-conflict districts that experienced fighting. For such, it shows that overall aid effectiveness is mitigated. However, those that were not actively involved but are part of a post-war country might still experience heterogeneous effects. Including an additional interaction of aid and the dummy for post-conflict countries allows for an even more nuanced interpretation.

Table 4: Within-country spillovers

	Dependent variable: $\Delta ln(light_{crt})$					
	(1)	(2)	(3)	(4)	(5)	(6)
Intensity:	any	$[>0,5]$	$[>0,25]$	>25	>100	>1000
ln Aid_{crt-1}	0.0010**	0.0010**	0.0010**	0.0010**	0.0010**	0.0010**
	(0.0004)	(0.0004)	(0.0004)	(0.0004)	(0.0004)	(0.0004)
ln Aid_{crt-1} × Post-Conflict District	0.0007	0.0011	0.0017	-0.0006	-0.0019	-0.0058*
	(0.0012)	(0.0015)	(0.0014)	(0.0015)	(0.0019)	(0.0035)
ln Aid_{crt-1} × Post-Conflict Country	-0.0022***	-0.0018**	-0.0020***	-0.0017**	-0.0016**	-0.0015**
	(0.0008)	(0.0007)	(0.0007)	(0.0007)	(0.0007)	(0.0007)
Post-Conflict District	0.0314***	0.0219**	0.0281***	0.0164	0.0336**	0.0082
	(0.0077)	(0.0092)	(0.0079)	(0.0116)	(0.0154)	(0.0304)
Post-Conflict Country	0.0230***	0.0326***	0.0287***	0.0329***	0.0336***	0.0357***
	(0.0087)	(0.0083)	(0.0084)	(0.0082)	(0.0081)	(0.0081)
Observations	101482	101482	101482	101482	101482	101482
Country, Region, Time FE	YES	YES	YES	YES	YES	YES
Country-Year FE	NO	NO	NO	NO	NO	NO
Heterog. Time Trends	YES	YES	YES	YES	YES	YES
District & Country Controls	YES	YES	YES	YES	YES	YES

Standard errors in the parentheses are clustered at the district level. Columns (1) to (6) show OLS estimates fixed effects and trends as indicated. The Post-Conflict District treatment is conditioned on the intensity as indicated in the respective column. The intensity level stems from the intensity index for conflict exposure. Post-Conflict Country accounts for districts within a post-conflict country that were not actively involved. All displayed coefficients are jointly significant for various combinations. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 4 shows the results when an interaction for aid and post-conflict country is included in the specification. Although the coefficients for the interaction term indicating aid in post-conflict districts are not significant in any individual specification, joint significance tests reveal that the interaction term is highly significant when considered jointly with the aid coefficient and the post-conflict country interaction term. The results can be interpreted the following way: as always, the first line shows the average effectiveness of aid for any district, no matter if post-conflict or at peace. To interpret the effectiveness in non-actively involved districts that are part of a post-conflict country, the coefficients then have to be added to the interaction term for aid and post-conflict countries. It shows that for such districts, receiving aid might actually dampen nightlight growth. Furthermore, interpreting the effect of actively involved post-conflict districts, the first three lines have to be summed up to see the overall effect. Thus, going from the left columns to the right within the second line, one can see that for low fighting intensity, aid is still effective but becomes less effective and even negative, the higher the intensity.

The way it is constructed, the baseline model as shown in Equation 1 captures within-country spillovers of conflict and post-conflict. A modification of the baseline model allows for estimating spatial spillover effects across districts dependent on the spatial proximity of districts.[37] The alteration is to include a spillover variable that can either stand for conflict or post-conflict spillovers. The construction of the spillover variable is explained in detail in the following paragraph.

$Spill_{crt}$ can take on the conflict intensity or post-conflict intensity neighbors experienced as well as aid disbursements they got. For each neighbor, weights are estimated proportional to the inverse spherical distance. Thus the strength of their neighbor link attenuates with distance. Furthermore, weights are calculated so that neighbor links in areas with fewer neighbors get a larger value than such with many neighbors. Using this framework, a matrix is created that assigns weights to each district pair. This matrix is then used to calculate fatalities, post-conflict intensity and disbursed aid spillovers based on the weights. As one district might have several neighbors with conflicts, the mean of the weighted spillovers is used. I further condition the neighbor relationship on different distances between the affected district and the neighbor as well as buffer zones.

Table 5 displays the results for the effects of spillovers varying the distance and buffers between the district and its neighbors. For active conflict, the spillover is based on the number of fatalities. For any distance, there are no spatial spillovers of active or past conflict from neighboring districts. This does not necessarily mean that effects of conflict do not spillover to neighboring districts, but rather shows that the model already picks up any spillovers by construction. In terms of spillover effects from aid disbursements, there is no clear pattern in terms of distance. It shows that neighbors within a 100km buffer experience significant negative effects. Any other buffer shows negligible

[37] The modified model is as follows:

$$\begin{aligned}\Delta ln(light_{crt}) = \alpha + \beta Aid_{crt-1} + \sigma PCDistrict_{crt} + Spill_{crt} + \\ \delta_{ct} + \psi_{crt} + \omega_{ct} + \mu_{crt} + \eta_r + \rho_c + \tau_t + \Delta\chi_r + \Delta\kappa_c + \epsilon_{crt}\end{aligned} \tag{4}$$

Table 5: Subnational conflict spillovers

	Dependent variable: $\Delta ln(light_{crt})$						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Neighbour Dist. in km:	0 to 336	0 to 250	0 to 100	0 to 50	20 to 50	50 to 150	150 to 250
Spillovers Active Conflict							
ln Aid_{crt-1}	0.0008***	0.0007*	0.0008**	0.0006*	0.0006*	0.0008**	0.0009***
	(0.0003)	(0.0004)	(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0003)
Spillovers Conflict	0.0000	0.0000	-0.0000	-0.0000	-0.0000	-0.0001	0.0001
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Spillovers Post-Conflict Intensity							
ln Aid_{crt-1}	0.0008***	0.0007*	0.0008***	0.0006*	0.0006*	0.0008***	0.0009**
	(0.0003)	(0.0004)	(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0003)
Spillover Post-Conflict	-0.0000	-0.0000	-0.0000	-0.0000	-0.0000	-0.0000	-0.0000
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Spillovers Aid							
ln Aid_{crt-1}	0.0009***	0.0006	0.0010***	0.0007**	0.0008**	0.0009***	0.0009**
	(0.0003)	(0.0004)	(0.0003)	(0.0004)	(0.0004)	(0.0003)	(0.0004)
Spillovers ln Aid_{crt-1}	-0.0013	0.0007	-0.0014**	-0.0001	-0.0001	-0.0013	0.0002
	(0.0010)	(0.0012)	(0.0007)	(0.0006)	(0.0006)	(0.0008)	(0.0009)
Observations	101482	56613	92713	75289	74134	88888	86203
Country, Region, Time FE	YES	YES	YES	YES	YES	YES	YES
Country-Year FE	NO	NO	NO	NO	NO	NO	NO
Heterog. Time Trends	NO	NO	NO	NO	NO	NO	NO
Country & District Controls	YES	YES	YES	YES	YES	YES	YES

Standard errors in the parentheses are clustered at the district level. Distance indicates the distance or buffer zone within which neighbour pairs are linked. All estimations are OLS estimations with the indicated fixed effects and heterogeneous trends. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

and insignificant positive or negative effects.

4.3 Sectoral Aid

Aid can take on various forms and is distributed across different sectors. Likely, subnational implications of aid on growth differ depending on the sector the aid project targets. Projects in the AidData database are categorized into 11 different sector categories which can be aggregated into three main sectors namely production, social infrastructure and economic infrastructure.

Donaubauer et al. (2019) explore the effect of post-conflict aid on changes in infrastructure, showing that cross-country post-conflict aid positively affects changes in social infrastructure. It examines if sector-specific post-conflict aid can affect some sectors more than others. In this study, the question is somewhat reversed estimating if aid targeted to certain sectors is effective in enhancing changes in nighttime light. Bitzer and Gören (2018) have a similar approach in estimating the heterogeneous effects of different aid sectors on nighttime light growth on a grid-cell level, but they do not include all types of aid sectors and do not consider post-conflict locations.

Table 17 and Table 18 show the effectiveness of aid distributed to certain sectors. Projects targeting economic infrastructure are most effective in increasing the growth of economic activity. Within economic infrastructure, especially projects in transportation are effective, however not necessarily more effective in post-conflict districts. In this special environment, agricultural projects have the most adverse effects on nighttime light change. Within the production sector, the industrial sector shows even more pronounced adverse effects in a post-conflict environment. However, any conclusions should be carefully drawn as there might not be many treatment observations of sector-specific post-conflict aid disbursements. Still, there is evidence for sector-specific heterogeneous effects on a subnational level, which should be further investigated in future research.

Hoeffler (2012) argues that so far institutions hardly differentiate the targeted sectors in regard to if the aid recipient is within a post-conflict state or not. Evidence of this paper and former papers such as Donaubauer et al. (2019) indicate however that sector-specific targeting of aid is important to the effectiveness of aid in this special economic environment and should be taken into account when policy decisions are made.

5 Conclusion

I investigated the effectiveness of aid in a specific economic environment namely post-conflict locations. Collier and Hoeffler (2004) showed in their cross-country study that post-conflict districts differ when it comes to their absorptive capacity and their reaction to the influx of monetary foreign support. More importantly, within a country, districts likely experience the effects of the past war heterogeneously. This heterogeneity of post-conflict experience may affect the effectiveness of aid projects targeted to such districts.

When aid is distributed to such vulnerable areas, it is important to consider such effects.

To capture the variation of conflict intensity a district was subjected to in the past, I introduced a novel scheme of categorizing countries in their different stages between peace and war and further evolve this categorization onto the district level. This allows us to get a full picture of how a conflict evolves over time and space within a country and reflects districts that were actively involved in the war versus those that were not.

In accordance with recent literature on subnational foreign aid (Bitzer & Gören, 2018; Chauvet & Ehrhart, 2018; Dreher & Lohmann, 2015), the overall effect of foreign aid on changes in subnational economic activity is positive. However, the results indicate for districts that were actively involved in their country's violent war, the effectiveness of aid is mitigated, and for some, it even has negative effects. This diminished effectiveness of aid in post-conflict districts is particularly pronounced for those with high-intensity fighting during the country's past war. Those with low-intensity fighting, still have some positive gains from aid. By construction, the model also allows the interpretation of spillover effects between actively involved and non-actively involved districts within a post-conflict country. It shows, for those not actively involved in the fighting, aid can have adverse effects on the change in nighttime lights. Various checks indicate the robustness of those results.

What this tells us in terms of policy implications is: as far as it concerns aid, it is effective in general but as a first aid kit to post-conflict districts it should be administered with caution. If the special circumstances of a district are disregarded it can have adverse effects. Therefore, depending on the intensity of human loss, one needs to tailor policies and projects that particularly consider those circumstances. On the positive side, there is evidence that a post-conflict situation can be a place for increased economic development. This calls for further research on the underlying mechanisms in post-conflict situations on a subnational level.

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A Appendix Graphs and Figures

A.1 Descriptive Graphs

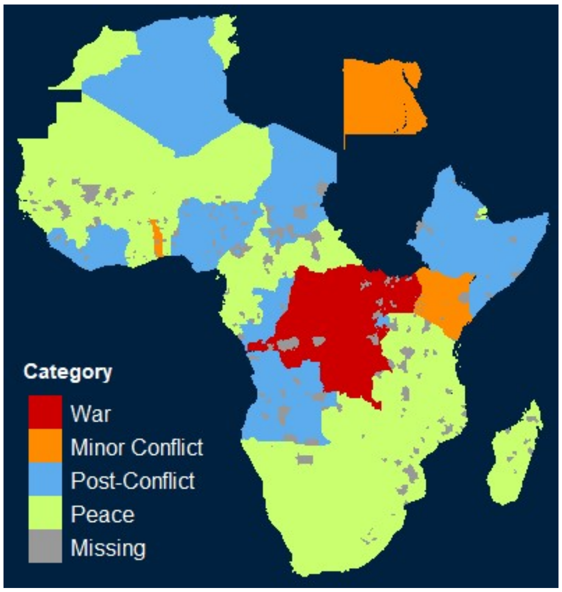


Figure 1: Aggregate categorization from war to peace in the year 2005. Source: UCDP/Author's estimations.

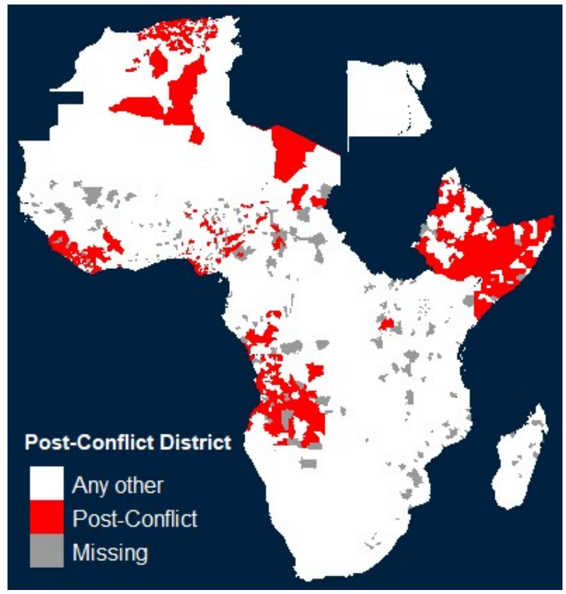


Figure 2: Post-conflict districts in the year 2005 based on active involvement during war periods. Source: UCDP/Author's estimations.

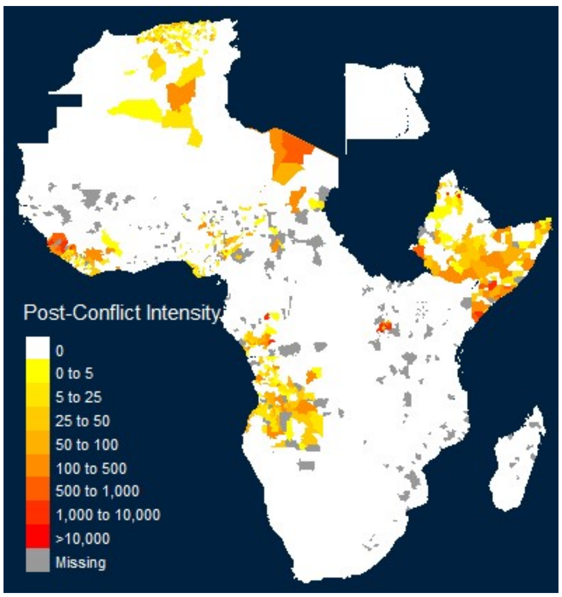


Figure 3: Post-Conflict intensity exposure in 2005 based on author's intensity index. Source: UCDP/Author's estimations.

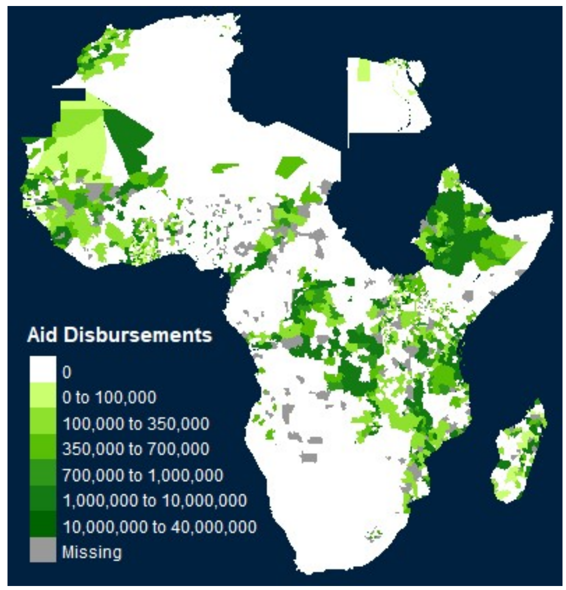


Figure 4: World Bank aid disbursements at ADM2 level in 2005. Source: Aid-Data/Author's estimation.

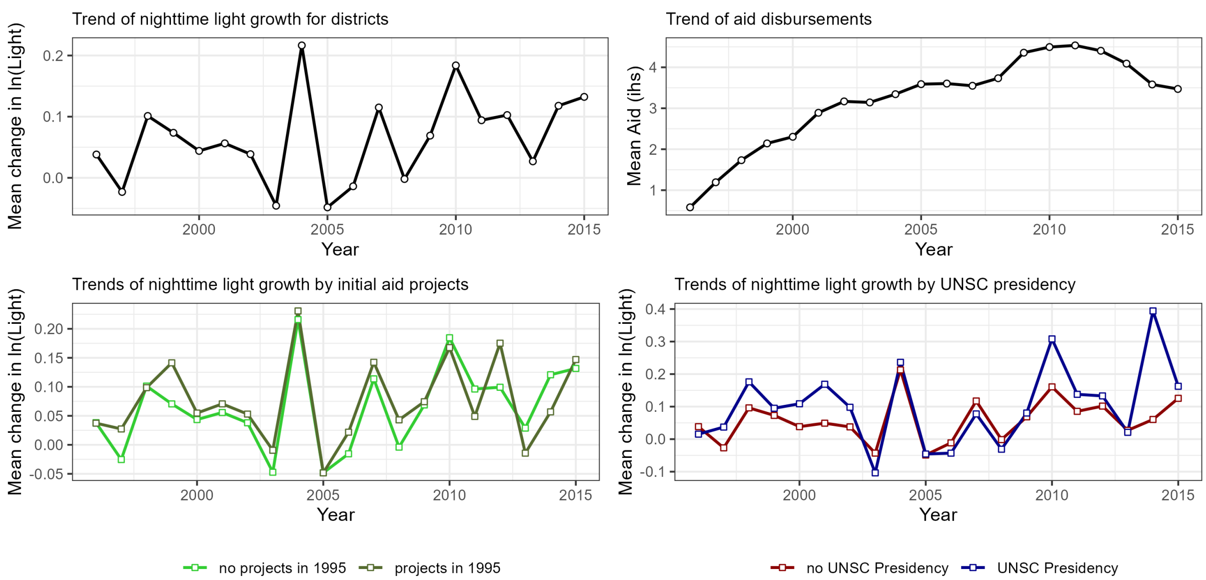
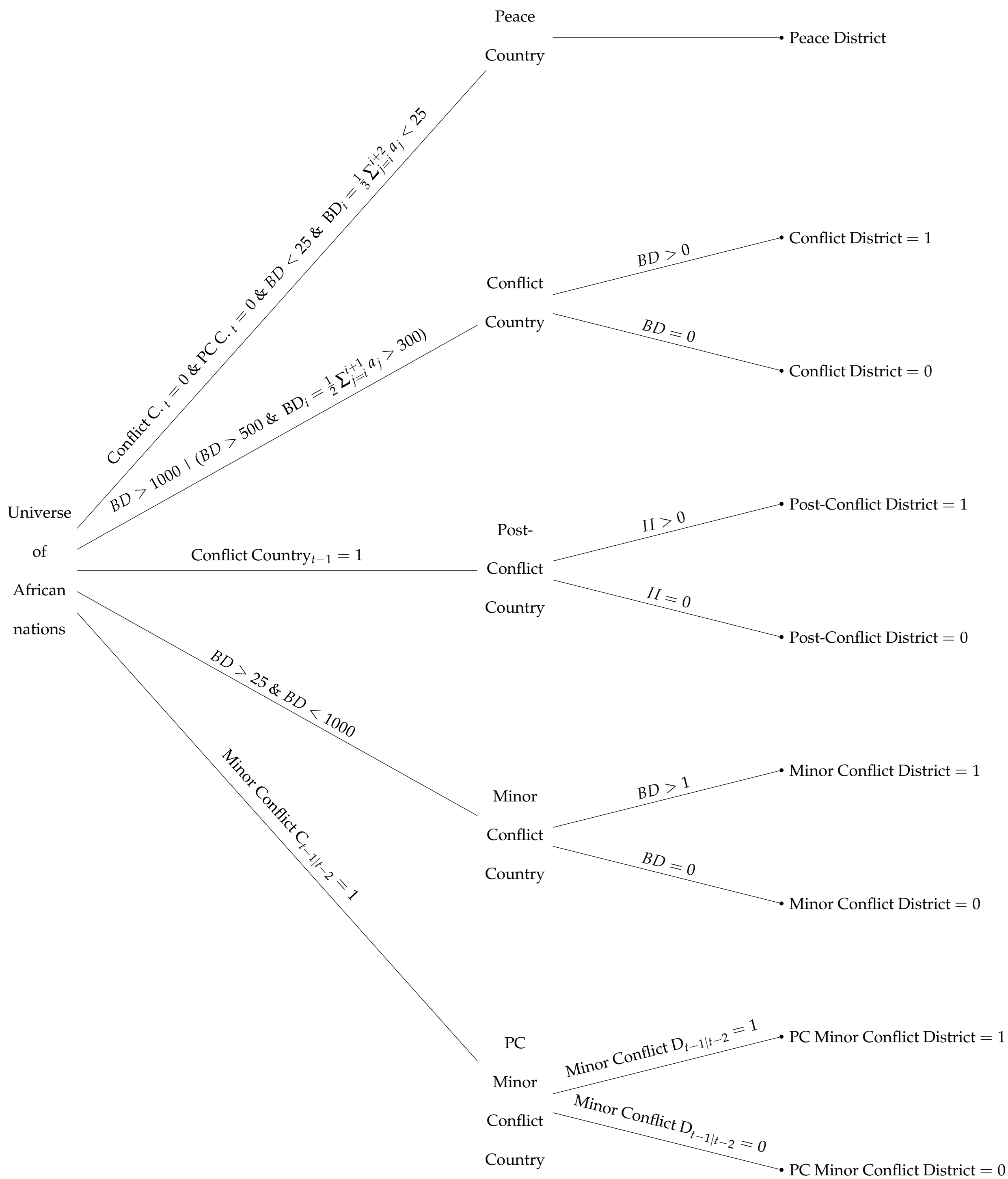


Figure 5: The top-left graph shows the trend of the average nighttime light growth for districts from 1995 to 2015. The top-right graph shows the trend for average aid disbursements transformed with IHS in districts over the same years. The bottom-left graph shows the trends of the average change in nighttime light for those districts that received aid projects in 1995 (dark green line) versus those districts that did not receive any aid projects in 1995 (light green line). The bottom-right graph shows the trends of the average change in nighttime light for those districts within countries that hold the UNSC presidency in the respective year (blue line) versus those districts in countries that do not hold it in the respective year (red line). Source: Author's estimations.

A.2 Categorization of Conflict

Graph A.2 describes a decision tree for coding the different stages between conflict and peace at the country and district levels. It shows that each district-level coding depends first on the country level at the respective time t. Dummy encoding is used, meaning if a country is at war at time t, the binary dummy for Conflict Country is 1, and 0 for each other country-stage. The same is true for the district level. In the regressions, the binary variables for peace at the country and district level are excluded as they indicate the baseline. In order for the system to be estimated correctly, every other stage must be included in the regression estimation.


Universe of African nations
Conflict C.$_t$ = 0 & PC C.$_t$ = 0 & $BD < 25$ & $BD_i = \frac{1}{3}\sum_{j=i}^{i+2} a_j < 25$
$BD > 1000$ | ($BD > 500$ & $BD_i = \frac{1}{2}\sum_{j=i}^{i+1} a_j > 300$)
Conflict Country$_{t-1} = 1$
$BD > 25$ & $BD < 1000$
Minor Conflict C$_{t-1|t-2} = 1$
Peace Country
Peace District
Conflict Country
$BD > 0$
Conflict District = 1
$BD = 0$
Conflict District = 0
Post-Conflict Country
$II > 0$
Post-Conflict District = 1
$II = 0$
Post-Conflict District = 0
Minor Conflict Country
$BD > 1$
Minor Conflict District = 1
$BD = 0$
Minor Conflict District = 0
PC Minor Conflict Country
Minor Conflict D$_{t-1|t-2} = 1$
PC Minor Conflict District = 1
Minor Conflict D$_{t-1|t-2} = 0$
PC Minor Conflict District = 0

A.3 Summary and Treatment Statistics

Table 6: Summary Statistics

Variable	N	Mean	St. Dev.	Min	Max
$\Delta ln(light_{crt})$	101,482	0.016	0.330	−1.000	1.904
ln Aid$_{t-1}$	101,482	3.033	5.413	0.000	17.726
ln Nightlight$_{t-2}$	101,482	0.922	1.284	0.000	4.159
Precipitation	101,482	79.541	52.728	0.034	305.895
Temperature	101,482	23.225	4.042	9.212	30.989
Pop. Density District	101,482	1,011	4,458	0	82,302
Pop. Density Country	101,482	70.198	66.975	2.020	460.846
Pop. Growth Country	101,482	2.393	0.874	−0.616	8.118
Trade % GDP	94,481	61.300	25.499	20.964	347.997
FDI Flows	99,808	3.585	8.037	−8.703	161.824
Debt & GDP	97,343	3.321	4.493	0.001	59.671
Migration	101,482	−114,461	202,883	−958,174	1,244,966
Peacekeeping	101,482	0.016	0.125	0	1
Conflict Fatalities	101,482	3.8	195	0	48,183
Intensity Index	101,482	28	746	0	63,183

Table 7: Treatment Statistics

Category	Treatment	0
Post Conflict District any*	9,545	91,937
PC D. 0 to 5*	3,007	98,475
PC D. 0 to 25*	5,725	95,757
PC D. min. 25*	3,811	97,671
PC D. min. 100*	1,836	99,646
PC D. min. 1000*	362	101,120
Post Conflict D. Late any*	3,642	97,840
PC D. Late 0 to 5*	1,149	100,333
PC D. Late 0 to 25*	2,258	99,224
PC D. Late min. 25*	1,380	100,102
PC D. Late min. 100*	622	100,860
Post Conflict Country	25,360	76,122
War Country	22,305	79,177
Minor Conflict Country	11,191	90,291
Post Minor Conflict Country	4,252	97,230
Peace Country	38,374	63,108
PC Districts with Aid	2,051	99,431
Districts within PC Countries with Aid	4,909	96,573

*based on Intensity Index

A.4 Data

Table 8: UN Security Council Membership and Presidency

Country	Year	Presidency
Algeria	2004	1
	2005	0
Angola	2003	1
	2004	0
	2015	0
Benin	2004	0
	2005	1
Botswana	1995	1
	1996	1
Burkina Faso	2008	1
	2009	1
Cameroon	2002	1
	2003	0
Chad	2014	1
	2015	0
Congo	2006	1
	2007	1
Egypt	1996	1
	1997	0
Gabon	1998	0
	1999	1
	2010	1
	2011	1
Gambia	1998	1
	1999	1
Ghana	2006	1
	2007	1
Guinea	2002	0
	2003	1
Guinea-Bissau	1996	1
	1997	0
Kenya	1997	1
	1998	1
Morocco	2012	1
	2013	0
Namibia	1999	1
	2000	1
Nigeria	1995	1
	2010	1
	2011	1
	2014	1
	2015	1
Rwanda	1995	0
	2013	1
	2014	1
South Africa	2007	1
	2008	1
	2011	0
	2012	1
Tanzania	2005	0
	2006	1
Togo	2012	1
	2013	1
Tunisia	2000	0
	2001	1
Uganda	2009	1
	2010	1

Table 9: Conflict-/Post-Conflict Country Periods

Country	Conflict-/Post-Conflict Periods				
Angola	War 1992-1994	Post-Conflict 1995-1997	War 1998-2002	Post-Conflict 2003-2012	Peace 2013-2017
Algeria	Minor Conflict 1992-1993	War 1994-2004	Post-Conflict 2005-2014	Minor Conflict 2015-2017	
Burundi	Minor Conflict 1992	War 1993-2005	Post-Conflict 2006-2015	Minor Conflict 2016-2017	
Central African Republic	Peace 1992-2000	Minor Conflict 2001-2002	Post Minor Conflict 2003-2004	Peace 2005	Minor Conflict 2006-2007
	Post Minor Conflict 2008	Minor Conflict 2009-2012	War 2013-2017		
Chad	War 1992-1993	Post-Conflict 1994-1999	War 2000	Post-Conflict 2001-2005	War 2006-2008
	Post-Conflict 2009-2017				
Congo	Peace 1992	Minor Conflict 1993	Post Minor Conflict 1994-1995	Peace 1996	War 1997-1999
	Post-Conflict 2000-2009	Peace 2010-2017			
Côte d'Ivoire	Peace 1992-1999	Minor Conflict 2000	Post Minor Conflict 2001	War 2002-2003	Post-Conflict 2004-2010
	War 2011	Post-Conflict 2012-2017			
DR Congo	Minor Conflict 1992	War 1993-1994	Post-Conflict 1995	War 1996-2005	Post-Conflict 2006
	War 2007-2017				
Eritrea	Post-Conflict 1992-1998	War 1999-2000	Post-Conflict 2001-2010	Peace 2011-2017	
Ethiopia	War 1992	Post-Conflict 1994-1994	War 1995	Post-Conflict 1996-1997	War 1998-2000
	Post-Conflict 2001	War 2002-2004	Post-Conflict 2005-2014	Minor Conflict 2015-2017	
Ghana	Minor Conflict 1992	Post Minor Conflict 1993	War 1994	Post-Conflict 1995-2004	Peace 2005-2017
Liberia	War 1992-1996	Post-Conflict 1997-2001	War 2002-2003	Post-Conflict 2004-2013	Peace 2014-2017
Mozambique	War 1992	Post-Conflict 1993-2002	Peace 2003-2013	Minor Conflict 2014	Post Minor Conflict 2015
	Minor Conflict 2016	Post Minor Conflict 2017			
Nigeria	Minor Conflict 1992	War 1993	Post Conflict 1994-1998	War 1999-2004	Post-Conflict 2005-2009
	War 2010-2017				
Rwanda	War 1992-1998	Post-Conflict 1999-2000	War 2001	Post-Conflict 2002-2011	Peace 2012-2017
Sierra Leone	War 1992-2000	Post-Conflict 2001-2010	Peace 2011-2017		
Somalia	War 1992-1996	Post-Conflict 1997-2001	War 2002	Post-Conflict 2003-2005	War 2006-2017
South Africa	War 1992-1994	Post-Conflict 1995-2004	Peace 2005-2017		
Uganda	Post-Conflict 1992-1995	War 1996-2000	Post-Conflict 2001	War 2002-2006	Post-Conflict 2007-2016
	Peace 2017				

B Appendix Further Regression Results

B.1 Exclusion Restrictions

Table 10: Regression results including peacekeeping deployment

	Dependent variable: $\Delta ln(light_{crt})$			
	(1)	(2)	(3)	(4)
ln Aid_t-1	0.0593***	0.0588***	0.0593***	0.0588***
	(0.0185)	(0.0183)	(0.0185)	(0.0183)
ln Aid_t-1 × Post-Conflict District	-0.0004	-0.0005	-0.0004	-0.0005
	(0.0114)	(0.0113)	(0.0114)	(0.0113)
Post-Conflict District	0.0294	0.0302	0.0293	0.0299
	(0.0315)	(0.0313)	(0.0314)	(0.0312)
Post-Conflict Country	0.0470**	0.0495**	0.0469**	0.0491**
	(0.0222)	(0.0228)	(0.0222)	(0.0228)
Peacekeeping		-0.0737**		-0.0787**
		(0.0324)		(0.0328)
Peacekeeping × Aid_projects_ADM2_initial			0.0142	0.0410
			(0.0256)	(0.0324)
First-Stage F-Stat	18.06	18.13	18.05	18.12
First-Stage F-Stat Int	30.34	30.57	30.48	30.32
Observations	101482	101482	101482	101482
Country, Region, Time FE	YES	YES	YES	YES
Heterog. Time Trends	NO	NO	NO	NO
Country-Year FE	NO	NO	NO	NO
District & Country Controls	YES	YES	YES	YES
Kleibergen-Paap rk LM stat	0.000	0.000	0.000	0.000
Kleibergen-Paap rk Wald F stat	8.313	8.416	8.316	8.411

Standard errors in the parentheses are clustered at the district level. Columns (1) to (4) show 2SLS estimates with ln Aid$_{crt-1}$ instrumented by $SCPresidency_{ct-3} \times AidProjects_{cr1995}$, fixed effects and controls are used as indicated in the second half of the table. Underidentification is tested by the Kleibergen-Paap rk LM statistics, which is indicated by its p-value. Weak identification is indicated by the Kleibergen-Paap rk Wald F statistics. Stock and Yogo weak ID test critical value at 10 percent level is 7.03 for columns(1-4). $^{*}\ p < 0.10$, $^{**}\ p < 0.05$, $^{***}\ p < 0.01$

Table 11: Country-level Controls 2SLS

	Dependent variable: $\Delta ln(light_{crt})$				
	(1)	(2)	(3)	(4)	(5)
ln Aid_{crt-1}	0.0593***	0.0612***	0.0597***	0.0571***	0.0628***
	(0.0185)	(0.0188)	(0.0186)	(0.0171)	(0.0186)
ln Aid_{crt-1} $\times$ Post-Conflict District	-0.0004	-0.0019	-0.0009	-0.0005	-0.0014
	(0.0114)	(0.0114)	(0.0114)	(0.0113)	(0.0115)
Post-Conflict District	0.0294	0.0371	0.0296	0.0288	0.0355
	(0.0315)	(0.0323)	(0.0337)	(0.0315)	(0.0326)
Post-Conflict Country	0.0470**	0.0487**	0.0474**	0.0431**	0.0569**
	(0.0222)	(0.0238)	(0.0223)	(0.0202)	(0.0239)
Trade % of GDP		-0.0000			-0.0002
		(0.0002)			(0.0002)
FDI Flows			-0.0008**		0.0017***
			(0.0003)		(0.0006)
Migration				-0.0000	0.0000
				(0.0000)	(0.0000)
First-Stage F-Stat	18.06	17.59	17.76	18.78	17.72
First-Stage F-Stat Int	30.34	29.87	30.32	31.42	30.70
Observations	98279	91356	96606	94197	98279
Regions	5382	5204	5369	5242	5382
Country FE	YES	YES	YES	YES	YES
Region FE	YES	YES	YES	YES	YES
Time FE	YES	YES	YES	YES	YES
Country-Year FE	NO	NO	NO	NO	NO
District Controls	YES	YES	YES	YES	YES
Country Controls	YES	YES	YES	YES	YES
Kleibergen-Paap rk LM stat	0.000	0.000	0.000	0.000	0.000
Kleibergen-Paap rk Wald F stat	9.834	9.989	9.866	9.804	10.623

Standard errors in the parentheses are clustered at the district level. Columns (1) to (5) show 2SLS estimates with ln Aid_{crt-1} instrumented by $SCPresidency_{ct-3} \times AidProjects_{cr1995}$, fixed effects and controls are used as indicated in the second half of the table. Underidentification is tested by the Kleibergen-Paap rk LM statistics, which is indicated by its p-value. Weak identification is indicated by the Kleibergen-Paap rk Wald F statistics. Stock and Yogo weak ID test critical value at 10 percent level is 7.03 for columns(1-5). * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 12: Country-level Controls FE

	Dependent variable: $\Delta ln(light_{crt})$					
	(1)	(2)	(3)	(4)	(5)	(6)
ln Aid_{crt-1}	0.0007*	0.0007	0.0006	0.0008*	0.0007*	0.0008*
	(0.0004)	(0.0004)	(0.0004)	(0.0004)	(0.0004)	(0.0004)
ln Aid_{crt-1} $\times$ Post-Conflict District	-0.0011	-0.0001	-0.0013	-0.0012	-0.0012	-0.0005
	(0.0010)	(0.0011)	(0.0010)	(0.0010)	(0.0010)	(0.0012)
Post-Conflict District	0.0359***	0.0291***	0.0360***	0.0375***	0.0347***	0.0355***
	(0.0074)	(0.0081)	(0.0077)	(0.0074)	(0.0074)	(0.0083)
Post-Conflict Country	0.0158*	0.0112	0.0192**	0.0201**	0.0171**	0.0233**
	(0.0082)	(0.0088)	(0.0084)	(0.0083)	(0.0082)	(0.0094)
Trade % of GDP		-0.0011***				-0.0014***
		(0.0004)				(0.0004)
FDI Flows			0.0007***			0.0301***
			(0.0003)			(0.0057)
Migration				0.0000***		0.0000***
				(0.0000)		(0.0000)
Peacekeeping					-0.0292	-0.1598
					(0.0404)	(0.1130)
Observations	101482	94473	99801	101482	101482	94473
Regions	5418	5246	5411	5418	5418	5246
Country FE	YES	YES	YES	YES	YES	YES
Region FE	YES	YES	YES	YES	YES	YES
Time FE	YES	YES	YES	YES	YES	YES
Country-Year FE	NO	NO	NO	NO	NO	NO
Exogenous Controls $\times$ Time FE	YES	YES	YES	YES	YES	YES
Heterog. Time Trends	YES	YES	YES	YES	YES	YES
District Controls	YES	YES	YES	YES	YES	YES
Country Controls	YES	YES	YES	YES	YES	YES
R2	0.159	0.169	0.163	0.162	0.160	0.173

Standard errors in the parentheses are clustered at the district level. Coefficients are jointly significant. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

B.2 Sample Dependence

Table 13: Sample Dependence - dropping influential country groups

	Dependent variable: $\Delta ln(light_{crt})$			
	(Baseline)	(richest GDP)	(North Africa)	(richest GDP pc)
ln Aid$_{crt-1}$	0.0007*	0.0009*	0.0009**	0.0008*
	(0.0004)	(0.0005)	(0.0005)	(0.0004)
ln Aid$_{crt-1}$ × Post-Conflict District	-0.0011	-0.0017	-0.0017	-0.0014
	(0.0010)	(0.0013)	(0.0011)	(0.0010)
Post-Conflict District	0.0359***	0.0289**	0.0455***	0.0393***
	(0.0074)	(0.0125)	(0.0097)	(0.0076)
Post-Conflict Country	0.0158*	0.0211**	0.0113	0.0167*
	(0.0082)	(0.0103)	(0.0098)	(0.0086)
Observations	101482	66643	76552	91331
Country, Region, Time FE	YES	YES	YES	YES
Country-Year FE	NO	NO	NO	NO
Heterog. Time Trends	YES	YES	YES	YES
District & Country Controls	YES	YES	YES	YES

Standard errors in the parentheses are clustered at the district level. All displayed variables are jointly significant. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

B.3 Variable Transformations

Table 14: Variable Transformations

	Dependent variable: $\Delta ln(light_{crt})$					
	(1) Δln(light$_{crt}$)	(2) Aid IHS	(3) Δ(light$_{crt}$)	(4) <2014 Δln(light$_{crt}$) transformed	(5) <2014 Δln(light$_{crt}$) non-transformed	(6) trimmed at 99th perc
ln Aid$_{crt-1}$	0.0007*		0.0005	0.0006	0.0004	0.0007
	(0.0004)		(0.0005)	(0.0004)	(0.0005)	(0.0005)
ln Aid$_{crt-1}$ $\times$ Post-Conflict District	-0.0011		-0.0013	-0.0011	-0.0028*	-0.0015
	(0.0010)		(0.0011)	(0.0012)	(0.0015)	(0.0012)
Post-Conflict District	0.0359***	0.0359***	0.0414***	0.0435***	0.0705***	0.0464***
	(0.0074)	(0.0074)	(0.0084)	(0.0091)	(0.0127)	(0.0091)
Post-Conflict Country	0.0158*	0.0158*	0.0224**	0.0122	0.0061	0.0043
	(0.0082)	(0.0082)	(0.0093)	(0.0124)	(0.0163)	(0.0108)
ihs Aid$_{crt-1}$		0.0007*				
		(0.0004)				
ihs Aid$_{crt-1}$ $\times$ Post-Conflict District		-0.0011				
		(0.0010)				
Observations	101482	101482	101482	91373	70333	102003
Country, Region, Time FE	YES	YES	YES	YES	YES	YES
Country-Year FE	NO	NO	NO	NO	NO	NO
Heterog. Time Trends	YES	YES	YES	YES	YES	YES
District & Country Controls	YES	YES	YES	YES	YES	YES

Standard errors in the parentheses are clustered at the district level. All displayed variables are jointly significant. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 15: Variable Transformations

	Dependent variable: $\Delta ln(light_{crt})$				
	(1) Δln(light$_{crt}$)	(2) Aid IHS	(3) Δ(light$_{crt}$)	(4) <2014 Δln(light$_{crt}$) transformed	(5) <2014 Δln(light$_{crt}$) non-transformed
ln Aid$_{crt-1}$	0.0009***		0.0008**	0.0009***	0.0010**
	(0.0003)		(0.0003)	(0.0003)	(0.0004)
ln Aid$_{crt-1}$ $\times$ Post-Conflict District	-0.0012		-0.0015*	-0.0011	-0.0016
	(0.0008)		(0.0009)	(0.0009)	(0.0012)
Post-Conflict District	0.0287***	0.0287***	0.0391***	0.0246***	0.0278***
	(0.0056)	(0.0056)	(0.0064)	(0.0059)	(0.0080)
Post-Conflict Country	-0.0127**	-0.0127**	-0.0137**	-0.0294***	-0.0422***
	(0.0057)	(0.0057)	(0.0066)	(0.0070)	(0.0088)
ihs Aid$_{crt-1}$		0.0008***			
		(0.0003)			
ihs Aid$_{crt-1}$ $\times$ Post-Conflict District		-0.0011			
		(0.0008)			
Observations	101482	101482	101482	91373	70333
Country, Region, Time FE	YES	YES	YES	YES	YES
Country-Year FE	NO	NO	NO	NO	NO
Heterog. Time Trends	NO	NO	NO	NO	NO
District & Country Controls	YES	YES	YES	YES	YES

Standard errors in the parentheses are clustered at the district level. All displayed variables are jointly significant. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

B.4 Time structure of Aid

Table 16: Time structure of Aid

	Dependent variable: $\Delta ln(light_{crt})$				
	(1)	(2)	(3)	(4)	(5)
ln Aid$_{crt}$	0.0006				
	(0.0004)				
ln Aid$_{crt}$ × Post-Conflict District	-0.0003				
	(0.0010)				
ln Aid$_{crt-1}$		0.0007*			
		(0.0004)			
ln Aid$_{crt-1}$ × Post-Conflict District		-0.0011			
		(0.0010)			
ln Aid$_{crt-2}$			0.0002		
			(0.0004)		
ln Aid$_{crt-2}$ × Post-Conflict District			-0.0021**		
			(0.0010)		
ln Aid$_{crt-3}$				-0.0009*	
				(0.0005)	
ln Aid$_{crt-3}$ × Post-Conflict District				-0.0010	
				(0.0010)	
ln Aid$_{crt-4}$					-0.0005
					(0.0005)
ln Aid$_{crt-4}$ × Post-Conflict District					-0.0026***
					(0.0010)
Post-Conflict District	0.0405***	0.0359***	0.0448***	0.0398***	0.0470***
	(0.0088)	(0.0074)	(0.0075)	(0.0075)	(0.0078)
Post-Conflict Country	0.0132	0.0158*	0.0141*	0.0175**	0.0165*
	(0.0108)	(0.0082)	(0.0085)	(0.0087)	(0.0089)
Observations	96314	101482	96361	91281	86287
Country, Region, Time FE	YES	YES	YES	YES	YES
Country-Year FE	NO	NO	NO	NO	NO
Heterog. Time Trends	YES	YES	YES	YES	YES
District & Country Controls	YES	YES	YES	YES	YES

Standard errors in the parentheses are clustered at the district level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

B.5 Sectoral Aid

Table 17: Regression Results for aid sectors

	Dependent variable: $\Delta ln(light_{crt})$		
Sector$_{t-1}$	Production	Social Infra.	Economic Infra.
ln Aid$_{crt-1}$	0.0006	0.0016	-0.0001
	(0.0005)	(0.0011)	(0.0006)
Sector$_{t-1}$	0.0018	-0.0119	0.0152**
	(0.0068)	(0.0135)	(0.0076)
ln Aid$_{crt-1}$ × Sector$_{t-1}$ × Post-Conflict District	-0.0024*	-0.0010	-0.0012
	(0.0013)	(0.0010)	(0.0011)
Post-Conflict District	0.0357***	0.0354***	0.0351***
	(0.0072)	(0.0074)	(0.0074)
Post-Conflict Country	0.0161**	0.0159*	0.0159*
	(0.0082)	(0.0082)	(0.0082)
Observations	101482	101482	101482
Country, Region, Time FE	YES	YES	YES
Country-Year FE	NO	NO	NO
Heterog. Time Trends	YES	YES	YES
District & Country Controls	YES	YES	YES

Standard errors in the parentheses are clustered at the district level. Interaction term for economic infrastructure is jointly significant. Sector$_{t-1}$ is a dummy indicating if part of the aid is disbursed in the corresponding sector. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 18: Regression Results for aid sectors - subcategories

	Dependent variable: $\Delta ln(light_{crt})$					
Sector_{t-1}:	Energy	Banking	Agriculture	Industry	Mining	
ln Aid_{crt-1}	0.0007	0.0006	0.0006	0.0005	0.0006	
	(0.0004)	(0.0004)	(0.0004)	(0.0004)	(0.0004)	
Sector_{t-1}	-0.0023	0.0043	0.0059	0.0080	-0.0216	
	(0.0096)	(0.0100)	(0.0075)	(0.0096)	(0.0161)	
ln $\text{Aid}_{crt-1} \times \text{Sector}_{t-1}$	-0.0014	-0.0007	-0.0034***	-0.0051***	0.0090	
$\times$ Post-Conflict District	(0.0014)	(0.0018)	(0.0012)	(0.0017)	(0.0098)	
	Education	Health	Water	Government	Transport	Communication
ln Aid_{crt-1}	0.0009**	0.0008*	0.0005	0.0006	-0.0002	0.0006
	(0.0004)	(0.0004)	(0.0005)	(0.0008)	(0.0005)	(0.0004)
Sector_{t-1}	-0.0123	-0.0082	0.0060	0.0012	0.0189***	-0.0064
	(0.0076)	(0.0076)	(0.0071)	(0.0108)	(0.0070)	(0.0132)
ln $\text{Aid}_{crt-1} \times \text{Sector}_{t-1}$	-0.0007	0.0005	-0.0014	-0.0012	-0.0009	-0.0015
$\times$ Post-Conflict District	(0.0012)	(0.0011)	(0.0011)	(0.0011)	(0.0011)	(0.0027)
Observations	101482	101482	101482	101482	101482	101482
Country, Region, Time FE	YES	YES	YES	YES	YES	YES
Country-Year FE	NO	NO	NO	NO	NO	NO
Heterog. Time Trends	YES	YES	YES	YES	YES	YES
District & Country Controls	YES	YES	YES	YES	YES	YES

Standard errors in the parentheses are clustered at the district level. Displayed coefficients are jointly significant for sectors Transport, Agriculture and Industry. Displayed coefficients together with dummy for post-conflict district are jointly significant for sectors Education, Health, Water, Government, Communications, Energy, Banking and Mining. Sector_{t-1} is a dummy indicating if part of the aid is disbursed in the corresponding sector. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

B.6 First Stage Analysis

Table 19: First Stage Regression Analysis

	Dependent variable: $ln\ Aid_{crt-1}$			
	(1)	(2)	(3)	(4)
Security Council Member$_{t-3}$	0.5235***		0.0125	
	(0.0580)		(0.0933)	
Security Council Presidency$_{t-3}$		0.6430***	0.6307***	
		(0.0575)	(0.0826)	
Security Council Presidency$_{t-3}$ $\times$ Aid Projects$_{1995cr}$				-0.7122***
				(0.1715)
Observations	101482	101482	101482	101482
Regions	5382	5382	5382	5382
Country FE	YES	YES	YES	YES
Region FE	YES	YES	YES	YES
Time FE	YES	YES	YES	YES
Country-Year FE	NO	NO	NO	NO
District Controls	YES	YES	YES	YES
Country Controls	YES	YES	YES	YES
Adj. R2	0.56	0.56	0.56	0.56

Standard errors in the parentheses are clustered at the district level. All specifications include country, district and year-fixed effects. All country and district-level controls are used. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$