A Spatial Analysis of the Effect of Foreign Aid in Conflict Areas

Stijn van Weezel

Abstract:

Although most aid projects are aimed at local development, research on aid and conflict mainly uses the country-year as unit of analysis. This study examines the link between aid and conflict at the sub-national level for three African countries between 1999-2008, using a unique dataset with information on local aid projects. The data shows that in general aid is allocated relatively close to the capital whereas conflicts occur in the peripheral areas. In contrast with the literature this study doesn't find a strong effect of aid on conflict as the analysis provides relatively little empirical support for a link in either positive or negative direction. Some of the results do show that non-fungible aid corresponds with decreases in conflict levels suggesting that aid increases the opportunity costs of rebellion although the magnitude of the effect is very low.

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A Spatial Analysis of the Effect of Foreign Aid in Conflict Areas

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AidData – a joint venture of the College of William and Mary, Development Gateway and Brigham Young University – is a research and innovation lab that seeks to make development finance more transparent, accountable, and effective. Users can track over $40 trillion in funding for development including remittances, foreign direct investment, aid, and most recently US private foundation flows all on a publicly accessible data portal on AidData.org. AidData's work is made possible through funding from and partnerships with USAID, the World Bank, the Asian Development Bank, the African Development Bank, the Islamic Development Bank, the Open Aid Partnership, DFATD, the Hewlett Foundation, the Gates Foundation, Humanity United, and 20+ finance and planning ministries in Asia, Africa, and Latin America.

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1. Introduction

Annually billions of dollars of foreign aid flow from developed to developing countries with the aim to reduce malnutrition, poverty, and increase stability. With regard to stability, the empirical literature on aid and conflict has produced diverging results with no consensus on the direction of the effect. This might not be surprising given the mixed results on the effectiveness of foreign aid in general, as documented by Roodman (2007), Doucouliagos and Paldam (2008, 2011) as well as Easterly and Pfutze (2008)).

In this paper I do not aim to address the whole debate on foreign aid effectiveness, but rather zero in on the aid-conflict nexus focussing on effects at the sub-national level. This nexus has been studied in the quantitative literature predominantly using the country-year as unit of analysis. Due to this level of aggregation, useful information on the dynamics of aid and conflict is potentially lost as most aid projects are targeted at local development (Findley et al., 2011; Berman et al., 2013) and conflict tends to be highly localised (Raleigh et al., 2010). It is therefore straightforward to see that a more disaggregated approach, that takes into account the local dynamics, could improve our understanding of how aid influences conflict.

There are some examples of recent research that take this approach. These include the study by Berman et al. (2013) on Iraq, , Tahir (2015) on Pakistan, and work by Arcand et al. (2011) and Crost et al. (2014) on the Philippines as well as the paper by Strandow et al. (2014) that also focuses on Africa. Most of these studies focus on particular conflicts in specific countries which makes their results hard to generalise. This study extends the current literature by providing a cross-country study in which the analysis is focussed on the sub-national level. More specifically I examine the link between foreign aid allocations and conflict intensity in three African countries (Democratic Republic of Congo, Ethiopia, and Sudan) between 1999-2008. I estimate the effect at the provincial and district level based on data from a unique dataset on local aid allocations using Bayesian estimation to produce consistent estimates in the presence of spatial autocorrelation.

This work is most similar to that of Strandow et al. (2014), the main difference is that their work focuses on the effect of aid distribution in contested areas whereas I examine the more general effect of aid allocations on conflict.

This study also adds to the growing literature on conflict intensity which includes work by O'Loughlin et al. (2012), Hendrix and Salehyan (2012), Costalli and Moro (2012), Maystadt et al. (2014), Hegre et al. (2009), and Raleigh and Kniveton (2012). Focussing on conflict intensity again allows us to get better insights in conflict dynamics as we keep the full information of the conflict data, this in contrast with the commonly used cruder binary measures.

The statistical analysis shows that there is little evidence for a particular strong link between aid and conflict. Pushing the results hard I find that at best that moving from low to high changes in aid corresponds with 0.2% decrease in conflict intensity. This negative link between aid and conflict is stronger for non-fungible aid compared to fungible aid which likely has no effect in this sample. Given the data availability on aid, which only maps commitments and not disbursements, I am however cautious with drawing too strong conclusions about the causal mechanisms.

In the model the strongest predictor for changes in conflict intensity are past changes which correspond negatively with current changes in conflict intensity. This results shows that high intensity conflict events in general are not persistent over time. Considering the spatial effects of conflict the results show that conflict tends to be highly localised and that there is a some risk of contagion across districts but not provinces.

2. Foreign Aid and Conflict

There is a large schism in the literature concerning the effect of foreign aid on conflict dynamics, specifically the direction of the effect. Theoretically the perceived positive link between aid and conflict is channelled through rent-seeking behaviour and the potential shift in the domestic power balance as a result of aid allocations.[1]

One strand of the literature argues that aid flows are beneficial and might improve stability: Aid money can be used for social spending which potentially reduces grievances the population might have versus the government. It also increases opportunity costs of conflict, making it more difficult to recruit insurgents, and additionally aid money could be diverted to increase military expenditures which provides a strong deterrent (Collier and Hoeffler, 2002, 2007). In all these cases foreign aid will bolster government capacity and reduce conflict risk, an effect for which Collier and Hoeffler (2002) offers three routes:

[1] An important concept in this regard is the issue of state capacity as described by Fearon and Laitin (2003) who argue that bureaucratically weak states have an increased risk for insurgency. See Petřík (2008) for an overview on the literature on the role of development assistance in ongoing conflicts and its influence on violent tensions during times of peace.

In the direct route aid augments the government budget and relaxes budget constrains while indirectly aid affects economic growth (although this is heavily debated) and diversifies the economy making it less dependent on primary commodities. According to Collier and Hoeffler (2002) these three factors combined make conflict less likely as a result of foreign aid flows.

de Ree and Nillesen (2009) provide empirical evidence for the direct channel, where aid relaxes the budget constraints. They find that higher levels of foreign aid are correlated with a reduction in conflict duration, possibly due to increased government capacity according to the authors.[2]

In similar vein, Savun and Tirone (2011) show that stability improves in countries during a democratic transition when receiving foreign development assistance. So called democracy aid helps reduce the commitment problems of the government that occur during this democratisation process as the authority of the central government weakens and uncertainty increases. Subsequently the likelihood of conflict decreases due to this democracy aid.

In contrast, the other strand of the literature is more negative in tone and argues that aid increases conflict risk. In a seminal paper, Grossman (1992) describes how the insurgents' objective is to capture the state for financial advantages and how more aid will make this objective more lucrative and thus increase incentives, something also echoed by Addison and Murshed (2001). The empirical proof for this hypothesis is based mainly on the uncertainty or volatility in aid flows.

For example Arcand and Chauvet (2001) find that although aid can have a stabilizing effect, the uncertainty of aid flows will actually increase conflict likelihood. Aid flow volatility leads to higher uncertainty levels which fosters instability. In turn, large negative shocks will lead to a shift in the domestic power balance which increases conflict likelihood as shown by Nielsen et al. (2011). Focussing on state capacity, Djankov et al. (2008) find that negative aid shocks can lead to a deterioration in institutional quality. They also find that the magnitude of the effect of aid rents is larger compared to that of natural resources such as oil.

Besides this volatility, there are other parallels between natural resources and foreign aid. For instance local aid allocations, like humanitarian aid, provide a lootable resource similar to natural resources. Aid can be appropriated by insurgents (Blouin and Pallage, 2008) in order to supplement their income or help support their operations, both of which will potentially increase conflict duration (Findley et al., 2011). Anecdotal

[2] They are unable to establish a causal link however.

evidence includes the theft by al-Shabaab in Southern Somalia of about $500,000 worth of humanitarian materials and supplies between late 2011 and early 2012 (Department for International Development, 2013).

Similarly Nunn and Qian (2014) find in a study on the effect of U.S food aid on conflict that increases in food aid correspond with increases in both the incidence and duration of civil conflict.[3]

There are a number of papers that have tried to disentangle the relation between aid and conflict at the local level.[4] Berman et al. (2013) look at the effect of per district development spending by the U.S. military in Iraq and find that aid potentially reduces violence. This effect mainly occurs in district with small aid projects (below $50,000) combined with high levels of troop strength, and the availability of development expertise. This paper provides an interesting insight in the effect of aid spending in a conflict situation, highlighting some of the factors required for aid to have a beneficial impact on the local community.

Two other examples focus on the effect of local development programmes in the Philippines: Arcand et al. (2011) use a rent-seeking model for conflict and show that between 2003-2006 increases in the intensity of violence around aid projects are related to the insurgents' ideology and not just an effect of the level of aid itself. Similarly Crost et al. (2014) examine the effect of a large development programme on conflict intensity between 2002-2009 and find that municipalities that are barely eligible for receiving aid from this programme experience large increases in fatalities as the authors argue the insurgents try to sabotage the project. Focussing on Pakistan, Tahir (2015) finds that aid increases conflict risk as it erodes the fiscal capacity of the state.

Most similar to this study is the work by Strandow et al. (2014) who examine the effect of aid distribution in contested areas during ongoing wars in Sub-Sahara Africa. They find that concentrated aid increases the likelihood of conflict.

From the literature the following mechanism emerges linking foreign aid and conflict (as discussed in Findley et al. (2011)) that is of interest to this study. Larger aid flows will increase the prize associated with capturing the state, an effect that provides rent-seeking opportunities which increases the risk of insurgency. However, simultaneously higher aid levels potentially decrease conflict risk as it improves state capacity. Following this

[3] This effect tends to be more pronounced in countries with a recent spell of conflict. Collier and Hoeffler (2002) argue that food aid is the only type of aid that can be appropriated by insurgents during a conflict.

[4] Böhnke and Zurcher (2013) study the impact of aid on perceived security in Afghanistan and is therefore not directly comparable with the other works discussed here or this paper in general.

mechanism, in the local context we would expect to observe more conflict in remote regions of the country. In these peripheral areas at a distance from the capital the central government has arguably less authority and is also less visible compared to regions closer to the seat of power. Considering the effect of local development projects we would expect that higher levels of regional aid allocations intensify conflict as it has the potential to weaken insurgents on the long term as local economic development increases opportunity costs and popular support for the government (Crost et al., 2014).

Additionally, since aid is a resource that can be appropriated it potentially provides incentives for conflict at the local level as well. Aid appropriation can become a key objective for local insurgents in order to supplement income and accordingly, at the local level, we would expect to observe regions where aid and conflict tends to cluster.

3. Data and Measurement

First and second level administrative divisions are used as unit of analysis as they capture the social heterogeneity that follows sub-national boundaries (Østby et al., 2009; Aas Rustad et al., 2011).[5] I use two different levels as the statistical results could be driven by the level of aggregation as a result of modifiable areal unit problem (MAUP) (Gehlke and Biehl, 1934; Openshaw, 1983; Fotheringham and Wong, 1991) and also to account for possible displacement effects (Maystadt et al., 2014).

3.1. Foreign Aid

Measurements on local foreign aid allocations are taken from the UCDP/AidData dataset constructed by Findley et al. (2011) which includes detailed information on the location of aid projects for the period 1989-2008 and is currently the most comprehensive geocoded aid dataset available.[6]

This dataset is based on AidData (Tierney et al., 2011) which contains detailed information on development finance (loans or grants) allocated to developing countries with the intend to promote economic development.

[5] Data source: GADM database of Global Administrative Areas v.2.0 (GADM, 2012). First and second level administrative divisions correspond with provinces and districts respectively.

[6] Data source: AidData (see also Strandow et al. (2011))

It includes data on finance by governments, official government aid agencies, and inter-governmental organisations but not from non-governmental organisations, the private sector or military assistance. The information in the dataset is compiled from a wide range of sources such as annual donor reports and project documents from bilateral and multilateral aid agencies as described in Tierney et al. (2011).[7]

For each region aid allocations, measured in constant U.S. dollars, are aggregated to region-year level and lagged by one year.[8] The lag is taken for two reasons.

One is to account for simultaneity bias as aid commitments could be the results of donors' reaction to violence levels (de Ree and Nillesen, 2009). Donors could decide to increase aid commitment to an area experiencing conflict to help reduce the adverse effects of violence or reduce commitments as risk mitigation. However, it is very unlikely that donors are able to anticipate conflict as there is very little known about how aid, and donors behaviours, influences conflict (Strandow et al., 2014).[9]

Second, a shortcoming of the dataset is that it only contains information on commitments and does not track disbursements.[10] To deal, at least partially, with this problem the aid commitments are lagged since there is likely a delay between commitments and the actual disbursement in the intended region. This also implies another constraint concerning the estimation of the effect of aid on conflict. Due to the absence of information on disbursements I can't account for longer delays than one year between aid commitments and disbursements or for cases where there is not a one to one relation between commitments and disbursements. This means that ultimately I rely on the assumption that aid commitments will have short term effects on conflict intensity.

Although this is the most comprehensive dataset available it is unclear, and also impossible to know, whether it includes the total number of aid projects.[11]

An inspection on data availability shows that potentially missing data might not be random in terms of temporal coverage. The number of aid projects per year in the earlier year (1989-1997) is considerably lower (only 16% of the total) compared to the later period from 1998 onwards.

[7] See AidData user guide for more detailed information.

[8] To account for scale differences, the natural log is taken.

[9] Additionally Strandow et al. (2014) argue that in the unlikely case that donors do anticipate conflict, this will probably lead to an increase in variation in aid commitments meaning that there is no systematic effect across donors and aid types that biases the results.

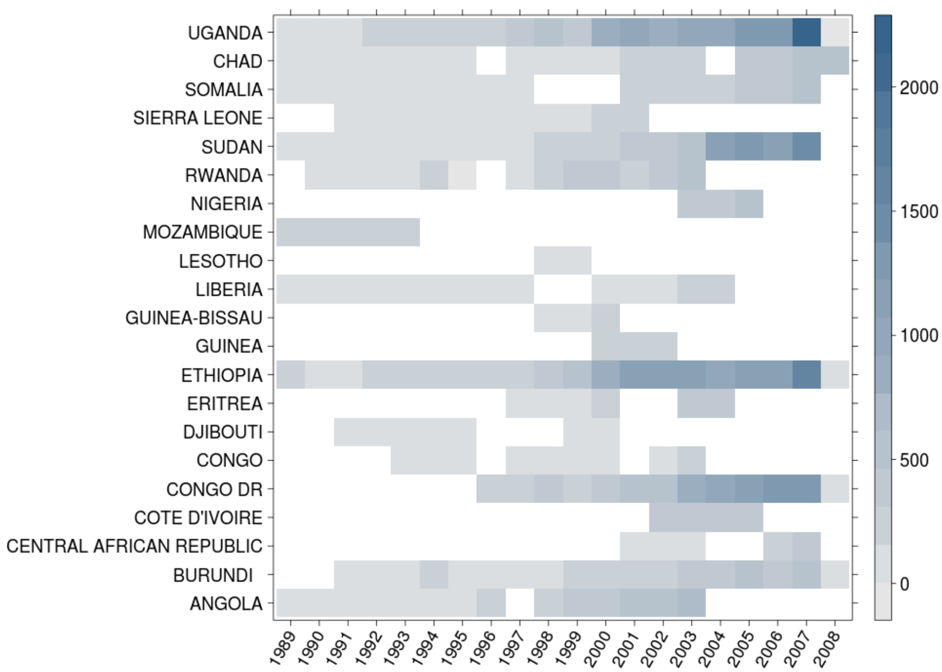
[10] This data is not available.

[11] This is also acknowledged by Strandow et al. (2014).

A more serious source of bias is the country selection. Only Sub-Saharan African countries with conflict between 1989-2008 are sampled, and predominantly conflict-years are included. This leads to gaps in data availability as shown in figure 1.

To account for these problems I focus the analysis on the period with relatively good coverage (1999-2008) and only include countries that have no gaps in their records. I therefore limit the sample to 3 countries: the Democratic Republic of the Congo (DRC), Ethiopia, and Sudan. These three are included as they are roughly comparable in size, also in terms of the sub-national administrative units, and additionally have substantial within-country variation in both conflict levels and aid allocation.[12]

Figure 1. Overview of the coverage of aid allocations per country for the period 1989-2008. Darker shades of blue indicate a higher number of aid projects included for the corresponding country-year



Sources: UCDP/AidData, Findley et al. (2011)

[12]For these reasons I do not include Uganda and Burundi as they are not comparable in size at national and sub-national level.

3.2. Civil Conflict

Data for the outcome variable is taken from the UCDP Georeferenced Event Dataset v.1.5-2011 (Sundberg et al., 2010; Sundberg, 2013).[13] This is the most accurate geocoded dataset on conflict available (Eck, 2012). An additional advantage is that it uses the same geocoding methodology as the aid dataset (Strandow et al., 2011).[14]

A conflict event is defined as "a phenomenon of lethal violence occurring at a given time and place" and each event is given as a point with longitude and latitude coordinates, time of occurrence, and the number of fatalities. This point data is aggregated to the regional level to create the conflict measure: the total number of fatalities in a year.[15]

Conflict at the local level might exhibit particular spatial patterns which leads to spatial autocorrelation in the outcome variable.[16] This means that the observed value for conflict intensity in region i could depend on conflict levels in nearby regions, rather than only the covariates in region i itself. To account for this interdependence a spatial lag of outcome variable W is included in the model. This spatial lag is a spatially weighted conflict measure based on conflict intensity in the k neighbouring regions of i. W is calculated using a binary spatial weights matrix based on first order contiguity, i.e. only including the direct neighbours of i.[17] The spatial weights matrix is not row-standardised as row-standardisation would imply that the influence of region j on i decreases when the number of neighbours increases. This would entail that the effect of conflict in neighbouring areas is larger when a region has relatively few neighbours which is not theoretically justifiable in this case.[18]

[13] Data source: UCDP GED

[14] This ensures that the precision of the two datasets is identical, in contrast with other available datasets where the precision of the geocoding is less clear, and thus facilitates accurate matching.

[15] As a robustness check the model is also estimated using a binary indicator for conflict incidence. This indicator takes value 1 if there is a conflict in region i at time t and 0 otherwise.

[16] This could mean diffusion where conflict in region i could spread uniformly to other regions in the geographic space or clustering where region i and its k neighbours have very similar levels of conflict. Spatial autocorrelation is similar to temporal autocorrelation with the main difference that spatial autocorrelation can move in either direction.

[17] Direct neighbours irrespective of national borders. Contiguity is used rather than a distance based measure because of the variability in size of the regions.

[18] Note that according to LeSage and Pace (2010) the estimates and inferences from the regression model should not be sensitive to particular specifications of the spatial weights structure.

3.3. Other Explanatory Variables

In some model specifications a number of additional explanatory variables are included to account for specific factors that could be linked to civil conflict.

I include regional total population with yearly data derived from the Gridded Population of the World v.3 dataset (CIESIN, 2004). Local income shocks are linked to conflict (Hodler and Raschky, 2014a), but since comparable income data at the sub-national level for developing countries is almost non-existent I follow Henderson et al. (2012), Michalopoulos and Papaioannou (2011), Hodler and Raschky (2014b), and (Besley and Reynal-Querol, 2014) by using satellite night light density data as a proxy for economic activity. Data is taken from the National Oceanic and Atmospheric Administration's Earth Observation Group.

Some recent studies have provided empirical evidence for a link between ethnic heterogeneity and the prevalence of conflict (Bosker and de Ree, 2014; Cederman and Girardin, 2007; Kuhn and Weidmann, 2013; Weidmann, 2009), therefore an ethnic polarisation measure (Garcia-Montalvo and Reynal-Querol, 2005) is included, data taken from the GREG dataset (Weidmann et al., 2010).

Similarly total population (Hegre and Sambanis, 2006) and lootable resources (Ross, 2004, 2006; Lujala et al., 2005) are linked to conflict. Natural resources are accounted for by a dummy indicating the presence of oil or diamonds.[19] Finally, as a proxy for government capacity the natural log of the distance from the national capital is included as peripheral areas far from the capital could be more likely to experience conflict as government power is weak in these regions.[20]

4. Estimation Framework

The effect of foreign aid on conflict is estimated using Bayesian regression which has the advantage of producing consistent estimates in the presence of spatial interdependence (LeSage, 2000). This in contrast with classic methods like OLS, used by Berman et al. (2013) and Crost et al. (2014)), which suffers from omitted variable bias if the spatial structure is not modelled, or simultaneity bias when the spatial lag is

[19]Data source: Gilmore et al. (2005) for diamonds and PRIO Petroleum Dataset v.1.2 for oil (Lujala et al., 2007)
[20]The distance is measured in kilometres from the centroid of the administrative division.

included as the errors are no longer independent.

To identify the effect of aid on conflict I use the same approach as Berman et al. (2013) and use a first-differences design. I regress changes in conflict levels on changes in lagged aid allocations controlling for changes in conflict in neighbouring areas and lagged changes in conflict as given in the following model specification (Eq.1):

$$\Delta C_{it} = \rho \Delta \sum_{k} W_{ikt} C_{kt} + \beta \Delta C_{it-1} + \gamma \Delta A_{it-1} + \theta_t \tag{1}$$

Outcome variable C_{it} is the change in the log count of the number of fatalities in region i at time t. The sign and strength of the interdependence in the outcome variable is estimated by $\rho \sum_k W_{ikt} Conflict_{kt}$, where W is the autoregressive term and ρ the spatial autoregressive parameter.[21]

The temporal lag of the outcome variable is included as in the model as this effectively captures common trends and accounts for temporal dynamics (Plúmper and Neumayer, 2010). Year indicators (θ_t) are included in the model to account for common shocks. γ represents the effect of changes in aid levels on changes in conflict intensity.

Although less informative, I also consider changes on the extensive margin using a conflict onset indicator and estimating the model with logit as a robustness check.

The conflict onset measure is a binary indicator for region i in year t which equals 1 if there is a conflict in year t but not in year $t-1$ and 0 if there is no conflict in both year t and $t-1$. If there is a conflict in year $t-1$ then the indicator is not defined for t.

To estimate the effect I use a multilevel model similar to the one used by Danneman and Ritter (2013). The advantage of using a multilevel model is the ease with which it can handle the time-series cross-sectional structure of the data and account for differences across the units of analysis (Gelman and Hill, 2006).[22] I use

[21] The inclusion of the spatial lag controls for contemporaneous correlation in the outcome variable and allows me to estimate the sign and strength of the correlation. I refer to the work by Beck et al. (2006); Plúmper and Neumayer (2010); Franzese and Hays (2007) for an extensive overview of model specification in the presence of interdependence. Annex B presents results for the Moran's I test for autocorrelation which establishes that there is spatial autocorrelation in the outcome variable.

[22] The unit of analysis, the region-year, is nested within the regions so the data has a clustered structure with two levels or hierarchies: the regional level and the time component. The multilevel models recognises the existence of this hierarchy by allowing residual components at each level in the hierarchy.

For a more extensive theoretical elaboration on the use of Bayesian multilevel models with time-series cross-sectional data I refer to the following estimation framework:

$$C_{it} = \alpha_i + \rho \sum_k W_{ikt} C_{kt} + \beta C_{it-1} + \gamma Aid_{it-1} + \theta_t \tag{2}$$

$$\alpha_i = \alpha_0 + \eta_i \tag{3}$$

Where $\eta_i \sim N(0, \sigma_i^2)$ and X is a vector with other explanatory variables. The model is estimated using a partial pooling procedure which means that intercept α_i is an outcome in the model, where α_0 represents the average intercept across the regions and η_i is the unique effect of region i on α which is assumed to be a random shock from the normal distribution (Shor et al., 2007).

The models are estimated using a Gibbs sampler, which is a Markov Chain Monte Carlo (MCMC) algorithm, in order to construct the posterior distribution for the parameters from which the coefficients and their uncertainty interval are calculated.[23] Parameters in the model, such as γ and ρ, are modelled using vague or non-informative priors with distribution $N(0, 10)$ (Gelman et al., 1995).[24] To construct the parameters I run 3 parallel MCMC chains each with 40,000 iterations with the thinning rate set at 5 in order to account for the autocorrelation in the chains. For each of the chains the first 10,000 iterations are discarded as burn-in in order to have some more certainty that the coefficient estimates are taken from the posterior distribution (Brooks and Gelman, 1998; Brooks et al., 2011). The coefficients and their uncertainty intervals are constructed as averages across the remaining iterations (18,000 in this case).

5. Results

5.1. Preliminaries: Spatial Patterns in Point Sample Data

Figure 2 shows the spatial distribution of aid allocations (aggregated to 0.5 degree grid cells, larger circles correspond with larger aid flows) and civil conflicts (individual events) for the three sampled countries covering the period 1999-2008 (the black diamond indicates the national capital). Large aid flows are concentrated

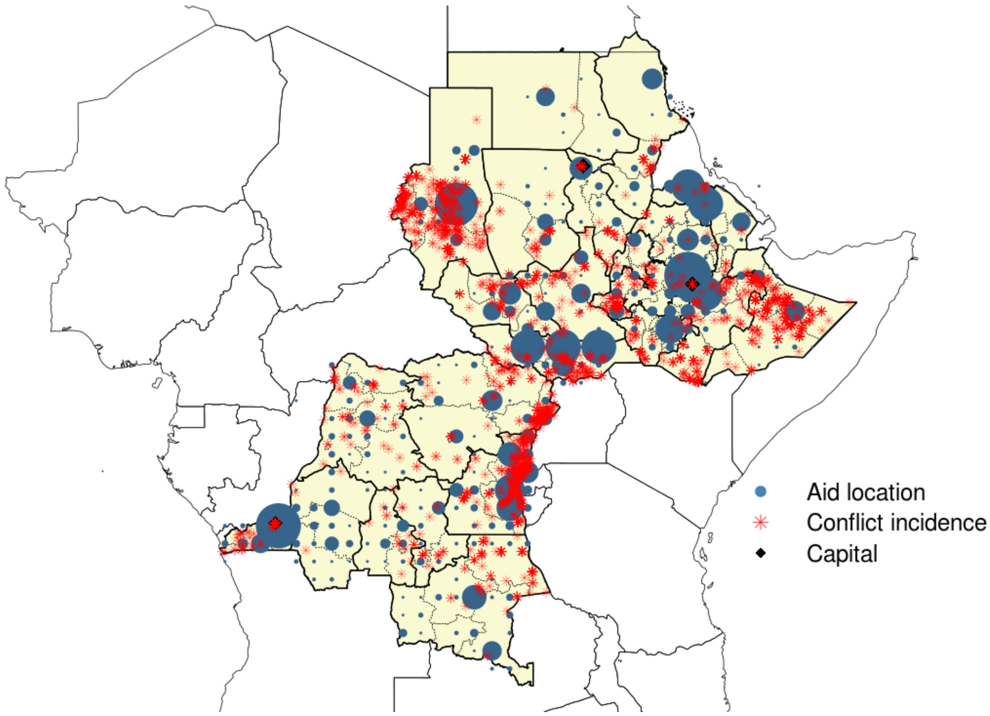
Shor et al. (2007).

[23] JAGS is used for the Gibbs sampler (Plummer, 2014).

[24] These priors should add nothing to the analysis and not influence the posterior. As a result of using non-informative priors the estimated coefficients will be similar to maximum likelihood estimation.

around the capital of DRC, Darfur and South Sudan in Sudan, and the central region of Ethiopia. In contrast, conflict tends to be highly localised in DRC's Kivu region, Somali in Ethiopia, and Darfur in Sudan. In general the data does not seem to show a high degree of overlap between aid and conflicts, save for a few regions such as Darfur and Kivu.

Figure 2. Unique observations of conflict incidence and aid locations between 1999-2008



Data Source: UCDP/AidData

As a preliminary test I examine the spatial patterns in aid and conflict using the non-aggregated data, retaining all the information there is on location. Based on the results in the literature we would expect to observe conflict at distance from the capital and close to aid sources.

Figure 3 maps the location of aid and conflict relative to the capital, where larger circles represent larger aid flows or higher conflict intensity. It illustrates that conflict tends to occur relatively far away from the capital, but aid in general is allocated closer to the capital. On average the distance between the capital and conflict is about 1000 Km (1016 Km $\pm$ 492 Km) which is relatively large. Since this number is an average across the three countries, I account for the size of each country standardizing the distance dividing it by the distance between the capital and the furthest point in the country relative to the capital.[25] I find that for both DRC and Sudan conflicts occur at large distances from the capital, with average ratios of 0.72 and 0.70 respectively. This could mean that for these two countries the central government has difficulties in controlling the peripheral areas or that the government is stronger in the central areas pushing conflict to these other areas. For Ethiopia the average ratio is considerably smaller at 0.44 which could be explained by the fact the Addis Abeba is located much more central compared to Kinshasa and Khartoum.

For foreign aid the distance ratios are smaller at 0.50 (DRC), 0.31 (Ethiopia), and 0.55 (Sudan).

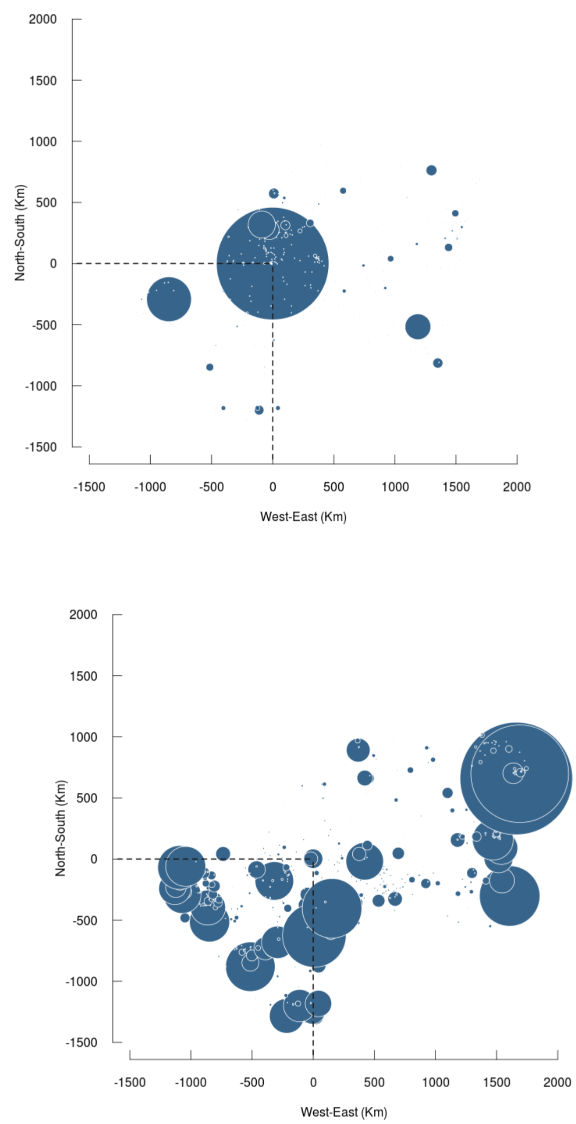
The data suggests that aid is mainly allocated in the central areas whereas conflict tends to occur in the peripheral areas. There are a number of possible explanations for this pattern. It could be, as suggested by the literature, that aid will strengthen the position of the government. Aid projects will foster local development which increases the opportunity costs of insurgency. In the peripheral areas there are less aid projects meaning that these regions lag in their economic development and are therefore more likely to harbour insurgencies. Additionally, aid donors could be risk averse and allocate money to locations where the government is relatively strong again depriving the peripheral areas from aid.

To test whether aid and conflict cluster in localised areas I examine the interdependence between observations measured by the Nearest Neighbour Distance (NND).[26] The NND is calculated as the distance between an aid project and the nearest conflict event for each year between 1999-2008, where the aid allocations are lagged by one year to account for simultaneity. The results are presented in figure 4.

[25] $\bar{D}_{capital \rightarrow conflict}/max\ D_{capital}$. $max\ D_{capital}$ is 1945 Km for DRC, 1035 Km for Ethiopia, and 1364 Km for Sudan.

[26] I also examine the intensity of the number of aid and conflict observations using the kernel density. Results for which are briefly discussed in the appendix C.

Figure 3. Spatial distribution of aid *(top)* and conflict *(bottom)* relative to the capital

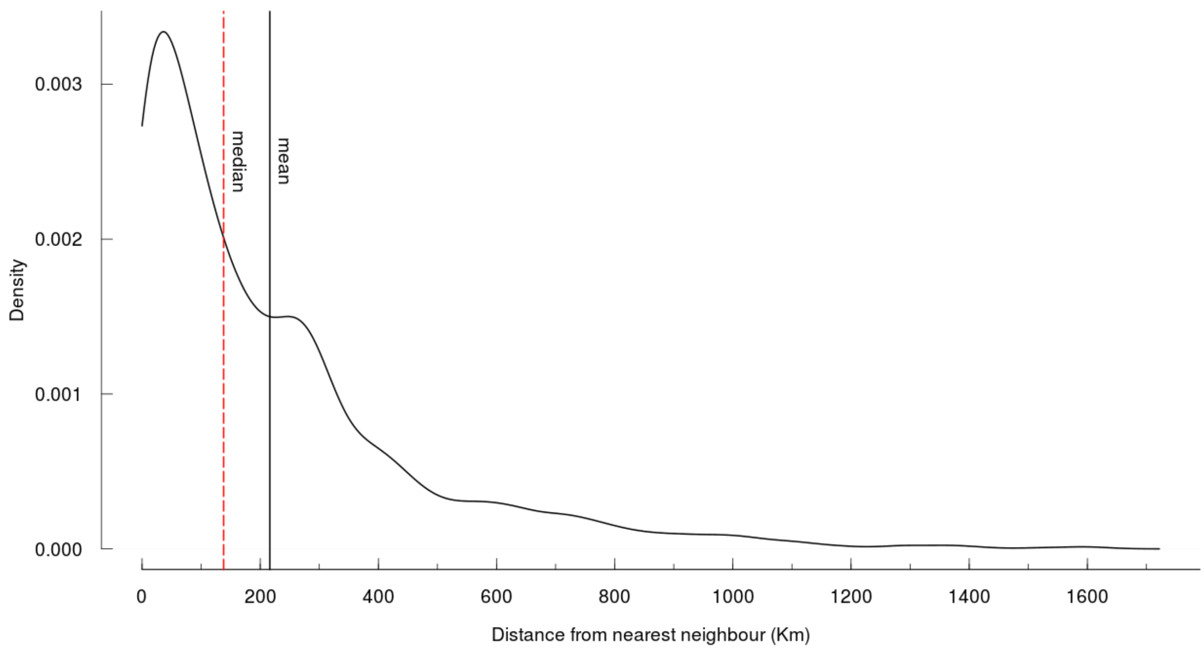


Notes: The size of the circle indicates the number of fatalities or the amount of foreign aid in U.S.$.

If aid provides incentives for conflict, because it is a prize that can be appropriated or the subject of sabotage, then we would expect that the distance between aid and conflict is small. Smaller distances correspond with stronger interdependence, but as illustrated by the figure in general there is a large spread in distances and interdependence appears to be weak. The mean NND is 218 Km and median NND is 141 Km. These are relatively large distances compared to the NND values for aid and conflict separately where the average distance between observations is around 100 Km.[27]

For 27% of the observations (435 cases out of a 1651 observations) the distance between an aid project and conflict is below 50 Km.[28] This indicates some stronger interdependence and provides some support for the notion that aid might provide incentives for conflict in some individual cases. This corresponds with some of the results found by Strandow et al. (2014) where aid distributed to areas which were contested increases the likelihood of violent armed conflict.

Figure 4. Density of nearest neighbour distance between conflict and aid



Notes: Black vertical line indicates the mean value, the red vertical dotted line indicates median value.

[27] Adjusting the sample to only include observations with the highest level of precision in geocoding does not alter these figures much: mean NND=257 Km, median NND=150 Km. The NND for the full sample is a 110 Km and 98 Km for conflict and aid respectively. See also see figure C4.

[28] 24% (275 out of 1135 observations) using the sample with higher precision levels.

5.2. Regression Results

Table 1. Predicting changes in conflict intensity

	Province level (*N=203*)			District level (*N=952*)		
Specifications	Model 1 (1)	Gov. (2)	Sector (3)	Model 1 (4)	Gov. (5)	Sector (6)
Foreign aid	−0.2 (−0.7; 0.3)	−0.2 (−0.7; 0.3)		0.01 (−0.17; 0.19)	0.01 (−0.17; 0.19)	
Foreign aid to government		0.2 (−0.4; 0.8)			−0.1 (−0.3; 0.1)	
Fungible aid			0 (−0.5; 0.5)			0.02 (−0.16; 0.20)
Non-fungible aid			−0.5 (−1.0; 0)			−0.07 (−0.25; 0.11)
Spatial lag	−0.2 (−0.7; 0.2)	−0.2 (−0.7; 0.2)	−0.2 (−0.7; 0.4)	0.12 (−0.06; 0.29)	0.13 (−0.05; 0.30)	0.11 (−0.07; 0.29)
Temporal lag	−1.4 (−1.9, −0.9)	−1.4 (−1.9, −0.9)	−1.4 (−1.9; −0.9)	−1.32 (−1.50, −1.14)	−1.32 (−1.50; −1.14)	−1.31 (-1.49; -1.14)

Notes. Table presents point estimates with their 95% intervals between parentheses. All models estimated with year indicators. Estimates are taken as the mean from 4 parallel chains with 40,000 iterations each where the first 10,000 are discarded as burn-in, thinning rate was set to 5. Priors are $N(0, 10)$.

Table 1 presents the estimated coefficients along with their 95% interval (in parentheses) at both levels of aggregation.[29] Since the input variables are all placed on a common scale centered around the mean and divided by two standard deviations, in order to facilitate easier comparison, they can be interpreted as the effect of moving from low to high values(Gelman, 2008).[30]

Model 1 is the preferred model and specified according to Eq.1. Some results in the literature (Arcand et al., 2011; Nielsen et al., 2011; Crost et al., 2014) show that larger amounts of foreign aid should increase conflict risk due to the creation of rent-seeking opportunities and possible attempts by insurgents to sabotage local development projects. At the province level I find that the estimated effect at the province level (table 1 col.1) has the opposite sign, indicating that positive changes in aid correspond with changes to lower conflict intensity levels. The magnitude of the effect is not very large: moving from low to high changes in aid levels corresponds with just a 0.2% decrease in conflict intensity.[31] Although the 95% interval shows that the effect is not statistically significant, the results indicate a negative link with about 0.82 probability.[32]

The province level results contrast with the district level (col.4) where the magnitude of the estimated effect is near 0 and the probability of a negative link is just 0.46. This large difference in probability could be due to the

[29] All models converged based on a visual inspection of the traceplots for the parameters of interest and the values for the $\hat{R}$ statistic which was below the 1.05 threshold in all cases.

[30] The dummy for natural resources was also standardised because the input was skewed.

[31] These results are robust to the inclusion of country-specific time trends.

[32] There is some variation between 0.80 to 0.83 based on the model specification.

fact that at the district level there is no link between aid and conflict. There could be a case of an ecological fallacy here, where we would assume that the relation found at one level of aggregation (provinces) would also be true at another level of aggregation (districts).[33] Although in both cases there is basically a null result based on the magnitude of the estimated effect.

The results also contrast with those of Berman et al. (2013) and Crost et al. (2014) who use a similar level of aggregation, although they only look at a conflict in one particular country.

The discrepancy could also be partially explained by attenuation bias as a result of measurement error. The use of a finer resolution means that some observations are lost due to the precision of the geocoding. For the conflict events the loss is not very large, just an 18.5% reduction in the number of observations. It is considerably larger for the included number of aid projects, reducing the sample by 53.6%.[34]

At both levels of aggregation the strongest predictor for changes in conflict intensity is the lagged outcome variable. Moving from low to high levels of intensity corresponds negatively with current changes. Potentially this is due to some kind of mean-reversion process as conflicts are relatively rare events, and even rarer are conflict events with very high fatality counts.[35]

The estimated effect of the spatial lag also differs across provinces and districts. This seems to indicate that the spillover effects of conflict are confined to the smaller administrative units. It is easier for insurgents to move from one district to another district than it is to move between larger provinces.[36] As provinces are the larger administrative units they might therefore not pick up the sub-national variation the way districts do when conflict is highly localised.

Aid that goes directly to the government could increase state capacity and reduce the probability of conflict onset and shorten conflict duration as found by de Ree and Nillesen (2009). I therefore include a variable for government aid in the model (col.2) and find that at the province level positive changes in foreign aid going to the government corresponds with an increase in conflict levels (75.6% probability). The magnitude of this effect is almost identical to the negative effect of aid at the local level, thereby offsetting each other. Again

[33] See also Maystadt et al. (2014) for an example on mining and conflict in the DRC.

[34] Number of unique events per level of aggregation, at province level there are 7,381 conflict events and 6,586 aid projects whereas the district level includes 6,008 conflict events and 3,052 aid projects.

[35] Conflicts, like other forms of human behaviour, exhibit universal patterns that approximate power-law distributions (Bohorquez et al., 2009).

[36] Katanga in the DRC for instance is about 16 times the size of Belgium.

the results show a different effect at the district level which is rather puzzling in this case given the fact that there are no changes in the measurement of the variable.

The main aid variable is agnostic about the fungibility of aid, the ease with which it can be diverted from its intended purposes. The reason for estimating the model with a pooled aid variable is that in general aid is likely to become fungible if the donor is not able to monitor the actual disbursement (Devajaran and Swaroop, 1998), which is a reasonable assumption in this case.[37] Rather than increasing net-expenditures in particular sectors it could be that aid money is actually substituting government spending. Feyzioglu et al. (1998) find that aid money is not necessarily fungible at the aggregate level but that it depends on the sector for which the aid money is destined. Development loans or grants for agriculture, education, and energy lead to a reduction in government spending in these sectors whereas money earmarked for the transport and communication sector are fully spend on the intended purposes. This entails that at the local level aid going to these fungible aid sectors might be easier to appropriate by insurgents as well Findley et al. (2011). [38] I estimate the effect of aid accounting for the potential fungibility.

Following Feyzioglu et al. (1998) and Findley et al. (2011) aid going to going to agriculture, education, energy supply and generation (as well as general budget support) are coded as fungible whereas aid going to transport and communication is coded as non-fungible.

The results show that at both the province and district level there is a likely no effect between fungible aid and conflict. Non-fungible aid is more strongly negatively linked with conflict. The magnitude of the effect for non-fungible aid is smaller at the district level which again could be due to previous mentioned reasons such as attenuation bias. The interpretation of the negative effect of non-fungible aid is that this aid type improves local welfare and therefore increases the insurgents' opportunity costs. In this case we don't see an increase in violence as a result of insurgents trying to sabotage the project as was suggested in the Crost et al. (2014) study.

In general the estimations provide very little support for a link between aid and conflict in either direction and this is consistent across a number of different robustness checks. Including additional variables to account for changes in population and economic activity (proxied by satellite night lights) doesn't alter the results.[39]

[37] There is some debate in the literature whether aid is fungible or not. See the literature review in Feridun (2014) for a synopsis.
[38] This effect is similar to what Dube and Vargas (2013) find for the capturing of rents from the oil sector in Colombia.
[39] See table D1 and D2 for results.

Rather than using inter-annual changes I estimate the model using aid shocks following Nielsen et al. (2011). Again the results provide no strong support for a link between aid and conflict in this sample.[40] The results are also not specifically driven by the estimation method as estimating the model with a more orthodox methods such as OLS produces very similar results. [41]

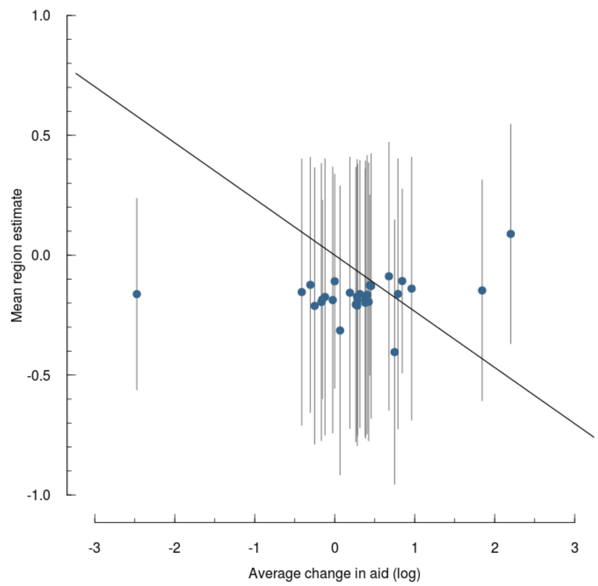
5.3. Comparing Estimates with Outcomes

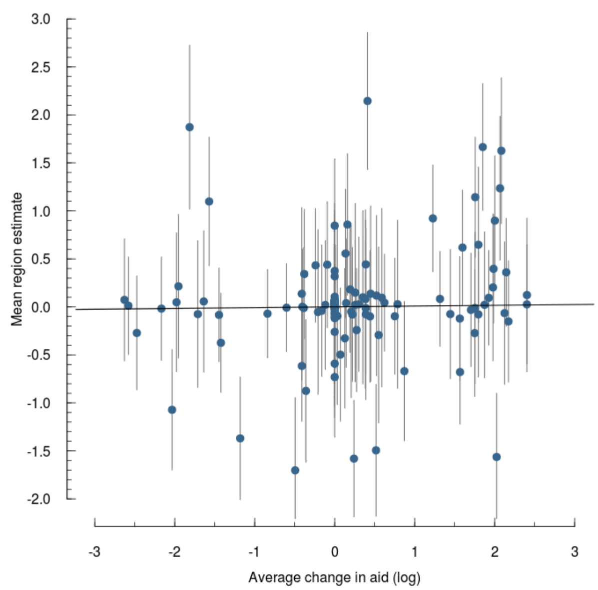
The regression results only provide some very minor evidence for a link between aid and conflict with the magnitude of the effect being very minor. The estimated coefficient in the main model is based on the assumption that the effect is homogeneous across regions. There could be the possibility that aid actually has a different impact depending on the region. The estimated effect in the main model therefore could be averaged out, missing region-specific effects. To account for this I re-estimate the model allowing separate coefficients per region, both for the aid variable as well as the variables that control for the temporal and spatial effect of conflict.

Figure 5 shows the estimated coefficients for each region and illustrates that most region-specific coefficients fall within a one standard deviation range of the estimated regression line of the main model. Only at the district level there are some district located more remotely from the main model's regression line but still within two standard deviations. The figure indicates that in general the main model seems to capture the effect of aid on conflict accurately.

[40] Shocks are defined as standardised deviations from the region mean: $(Aid_{it} - \overline{Aid_i})/\sigma Aid_i$. See table D7 for results.
[41] See table D3 and D4.

Figure 5. Estimated coefficient for each province (*left*) and district (*right*) level along the regression line from the main model

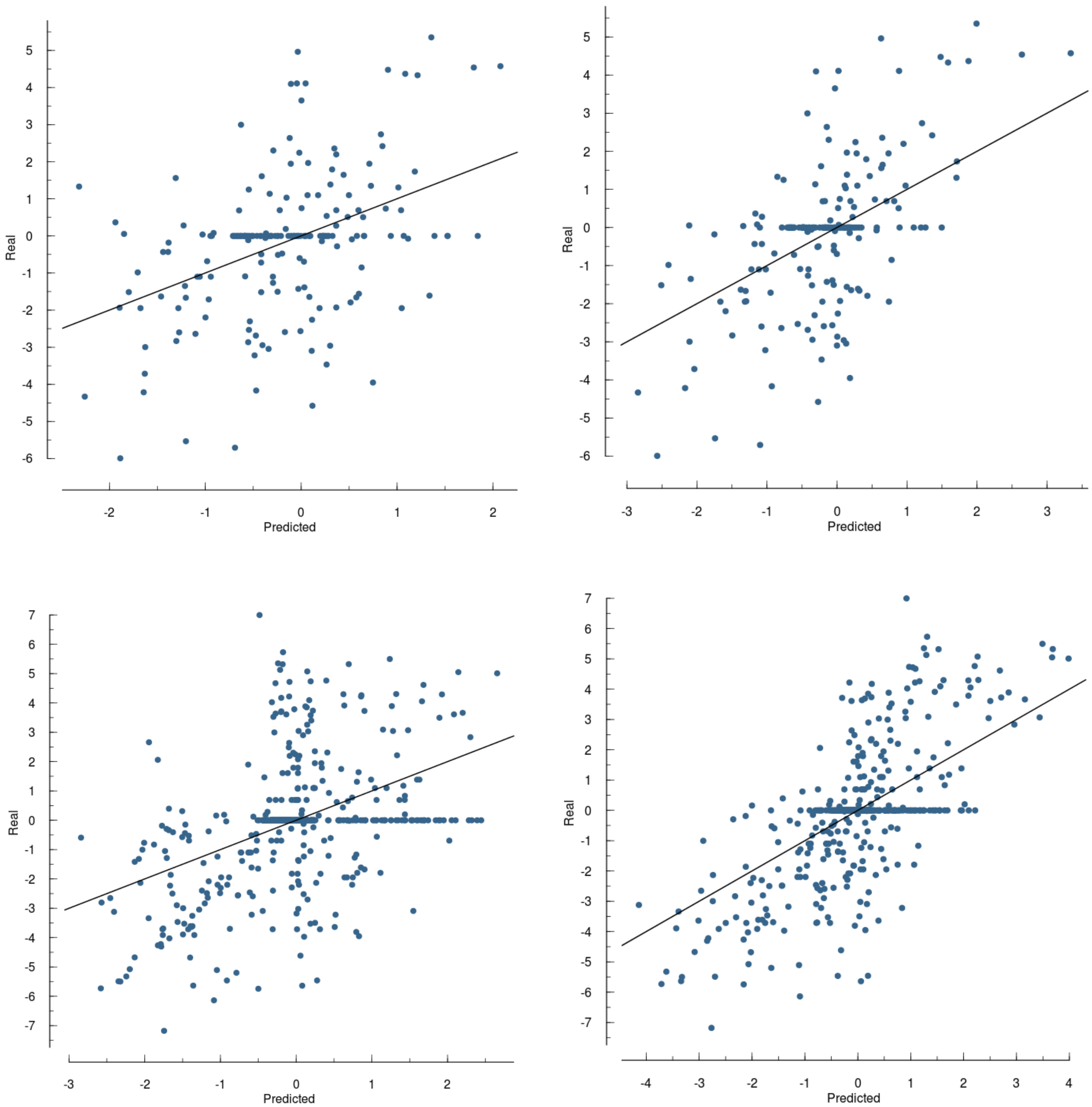




Notes: The grey lines for each coefficients indicate the standard deviation.

Figure 6 shows the actual change in conflict intensity compared to the estimated change in conflict intensity generated by the pooled and the varying slope model. There does not seem to be a systematic bias in the estimates and to some extent the model seems quite capable matching the estimated changes with corresponding actual changes. The model slightly underestimates the magnitudes of the changes in the outcome variable. Also the zeroes in the outcome variable pose difficulties as there is a lot of scatter around these observations where there are no changes in conflict intensity. Based on the difference between the estimated outcomes at the provincial and district level, the model unsurprisingly performs better with more data points as illustrated by the difference in fit. Also the varying slope model fits the data marginally better than the pooled regression model, indicating that the region-specific coefficients for the variables better capture the local conflict dynamics in contrast with the more generalised approach.

Figure 6. Actual changes in conflict intensity compared to estimated changes at province (*top*) and district (*bottom*) level using pooled regression (*left*) and a varying slope model (*right*)



5.4. Interaction Effects

Besides the direct effect of aid on conflict I also consider the effect of interactions between aid and other possible influential factors. These include the temporal and spatial lag, distance from the capital, and ethnic polarisation, results for which are summarised in figure 7.[42]

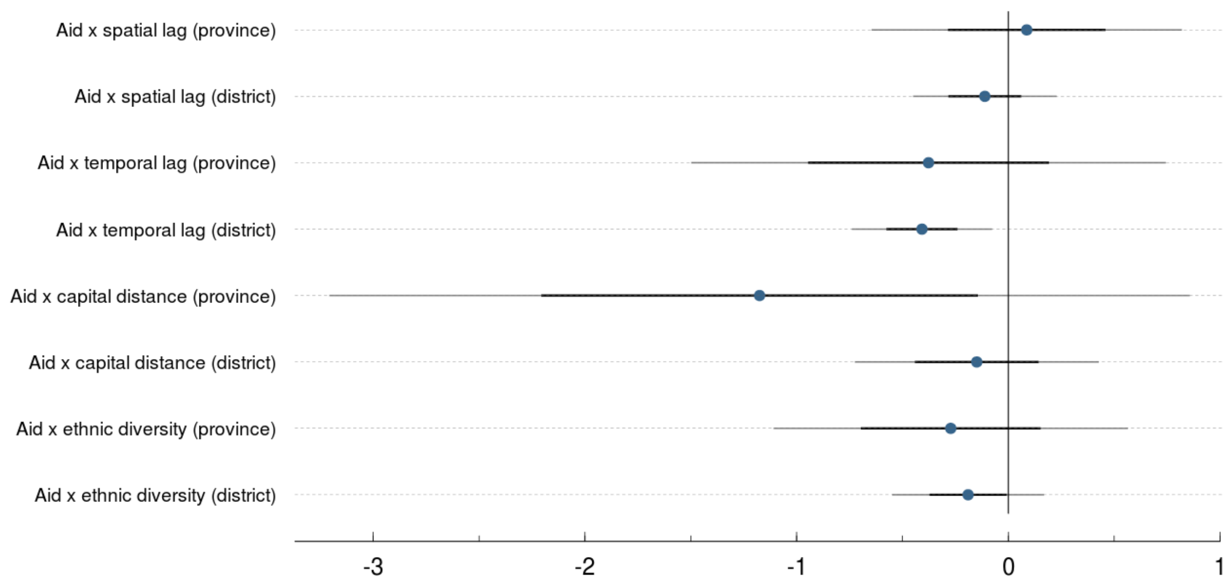
In general all the interaction terms are skewed towards negative values. Consistent with the main results the estimated effects are close to zero or have zero in their 95% interval. The only exception to this is the interaction between the temporal lag and aid at the district level. This effect is likely to be largely driven by the temporal lag. The main results showed that higher levels of past conflict correspond with a reduction in current conflict levels.

Hodler and Knight (2012) show that foreign aid is more effective in promoting economic growth in ethnic homogeneous countries. This might imply that as aid is less effective in ethnically polarised regions as opportunity costs for insurgency remain low and the aid itself provides rent-seeking opportunities. As a result these regions might experience higher levels of conflict. The estimation result do not provide support for this hypothesis as the effect of aid on conflict in regions with higher levels of ethnic polarisation is not different from the main result.

Similarly, the estimated effect of aid is also not different in regions further away from the capital and regions in conflict ridden neighbourhoods.

[42] See table D5 and table D6 for results.

Figure 7. Estimates with 68% and 95% intervals interaction effect coefficients



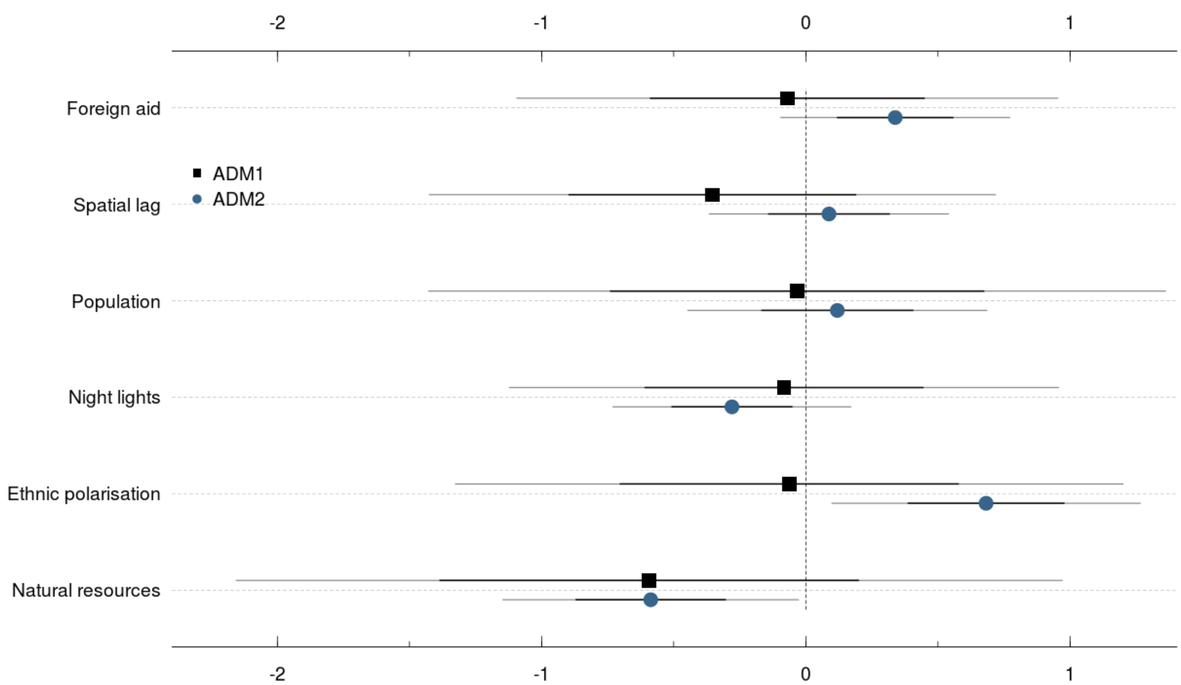
5.5. Effect of Aid on Conflict Onset

So far the estimations have focussed on the effect of changes in aid on changes in conflict intensity, i.e. looking at the intensive margin. I now consider the extensive margin examining the effect of changes in aid on conflict onset, results are summarised in figure 8.[43]

Most variables have relatively low predictive power, especially at the provincial level, and is therefore not adequate in predicting the outbreak of conflict.[44] Although at the district level there seems to be a slightly stronger relation between foreign aid and conflict onset. However, the strongest predictors for the outbreak of conflict are ethnic polarisation and the presence of natural resources which have opposite effects. Ethnic polarisation increases the probability of conflict onset which resonates with a number of other studies (Buhaug and Gleditsch, 2008; Weidmann, 2009; Bosker and de Ree, 2014). The presence of natural resources is negatively associated with conflict onset, but this could be the result of a displacement effect where conflict actually takes place in the surrounding areas as argued by Maystadt et al. (2014).

[43] This is the model specified according to Eq.2. Full results are reported in table D8.
[44] See figure D1.

Figure 8. Estimates with 68% and 95% intervals at province (ADM1) and district (ADM2) level



6. Discussion

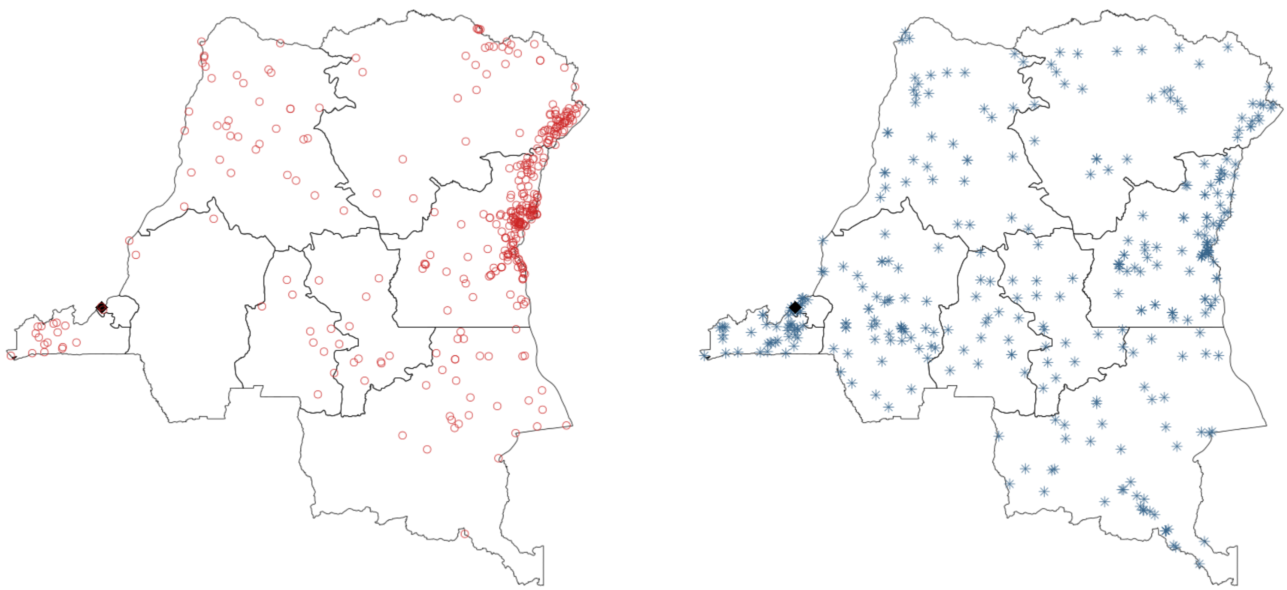
This study extends the aid-conflict literature by focussing on the link at the sub-national level across different countries. This means that the full information on local development projects and sub-national variation in conflict is retained.

In contrast with the existing work I find no strong effect of aid on conflict in either positive or negative direction. The spatial analysis shows that although both aid and conflict cluster in localised geographic areas there does not exist a strong interdependence. In the regression analysis I find no strong empirical proof for an effect of aid on conflict levels or conflict onset. I do find that non-fungible aid corresponds negatively with conflict intensity but the evidence is not very strong.

The strongest predictor for conflict levels is the change in past conflict levels where the analysis showed that current conflict levels decrease after a previous year with very high levels. This shows that high levels of intensity are relatively rare and not sustained over time. At the district level there is spillover effect of conflict where districts in violent neighbourhoods are more likely to experience violence. This effect is highly localised though as the analysis at a higher aggregation level does not produce the same results.

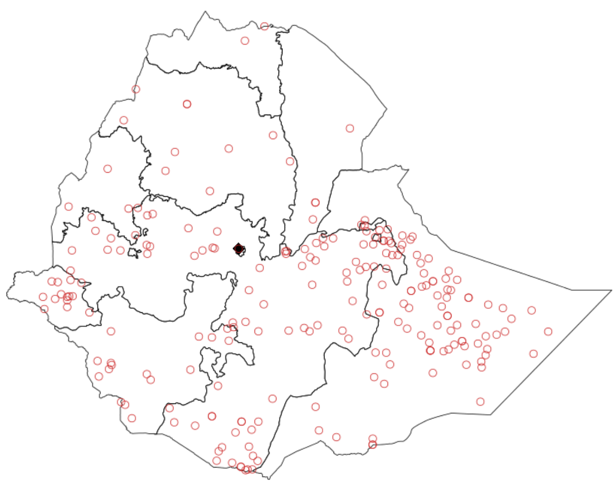
A. Appendix A. Descriptive Statistics

Figure A1. Conflict incidence *(left)* and aid locations *(right)* for the Democratic Republic of Congo, 1999-2008



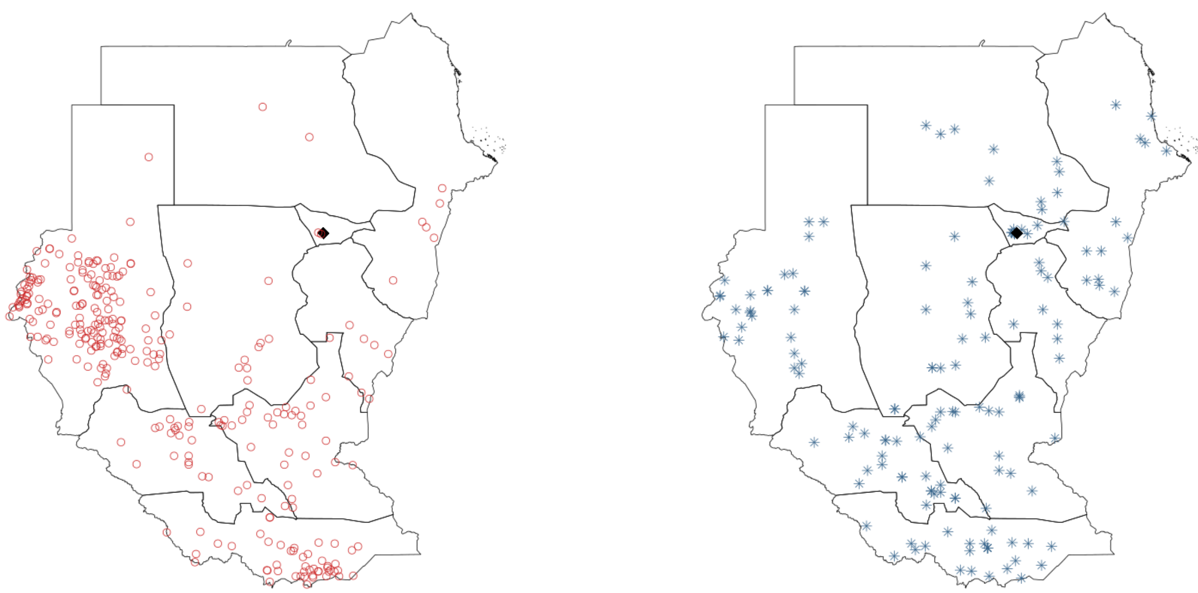
Notes: Capital indicated with black diamond

Figure A2. Conflict incidence *(left)* and aid locations *(right)* for Ethiopia, 1999-2008



Notes: Capital indicated with black diamond

Figure A3. Conflict incidence *(left)* and aid locations *(right)* for Sudan, 1999-2008



Notes: Capital indicated with black diamond

Table A1. Summary statistics

	Province level			District level		
Variable	All data (N=203)	No conflict at t (N=92)	Conflict at t (N=111)	All data (N=952)	No conflict (N=719)	Conflict (N=233)
Conflict Onset	0.11	0	0.21	0.09	0	0.36
Log Conflict intensity	5.36	0	5.97	3.67	0	5.08
Log Conflict intensity$_{t-1}$	5.49	1.91	6.08	3.79	2.03	4.35
Log Conflict intensity$_k$	6.27	6.34	6.20	4.14	4.06	5.06
Log Foreign aid$_{t-1}$	16.63	16.27	16.86	14.44	14.19	14.96
Log Fungible aid$_{t-1}$	14.60	14.72	14.49	12.63	12.43	13.06
Log Non-fungible aid$_{t-1}$	16.23	15.90	16.44	14.16	13.90	14.69

B. Appendix B. Local Moran's I Test

To correct for spatial autocorrelation in the outcome variable the spatial lag is included in the model structuring the model as a spatial autoregressive model (SAR) model.[45] This section reports the tests results of the Moran's I test for spatial autocorrelation. Moran's I statistic is a global measure of spatial autocorrelation, which means that it assumes that the spatial process is homogeneous across the different regions.

Two different measures for conflict are tested: conflict intensity which is measured by the natural log of the number of battle-related fatalities, and conflict incidence level which is the sum of all conflict years between 1999-2008. Additionally I also test foreign aid for spatial autocorrelation which is in this case measure by the natural log of the total amount of foreign aid committed to the region.

Results for the Moran's I test, done at the provincial (ADM1) and district (ADM2) level, are shown in table B1 where the odd columns report the results using the binary spatial weights matrix and even columns for the row-standardised matrix as a robustness check.[46]

Although the Moran's I test performs well in small samples (Anselin and Florax, 1995) it could be that the results are sensitive to the skewed distribution on the spatial data attributes. Since there are a relatively few number of observations as the test is done at the cross-sectional level, the Moran's I is estimated using Monte Carlo simulations.[47] Moran's I is measured on a -1 to 1 scale where 0 indicates no spatial autocorrelations, small values (approaching -1) indicate spatial diffusion and large values (approaching 1) indicate spatial clustering.

The results show that there is some variability in the extent of spatial autocorrelation with respect to conflict comparing across the levels of aggregation and the two different measures. For conflict intensity the results indicate that there is almost no spatial autocorrelation at the provincial level as the test shows no statistically significant results and are accompanied by values with very low magnitude.

For the district level on the other hand we see that there is spatial autocorrelation between the regions were

[45]The SAR model is chosen based on the assumption that the interdependence in the outcome variable is more than just a nuisance which can be corrected using a spatial error model, and thus needs an autoregressive term to correctly model the spatial pattern.

[46]Note that in this case the spatial weights matrix only includes regions in the selected countries and thus omits data attributes in regions in neighbouring countries.

[47]N 29 for the ADM1 level and N=136 for ADM2 level.

districts with similar levels of fatalities, and thus conflict intensity, tend to cluster. This result is statistically significant at the 1% level and also robust to using a different spatial weights matrix and using a cruder measure for conflict. These results are also illustrated by the local Moran's I plot shown in figure A1 for both the provincial and district level, where regions tend to cluster at the lower left for low intensity and upper right for high intensity.

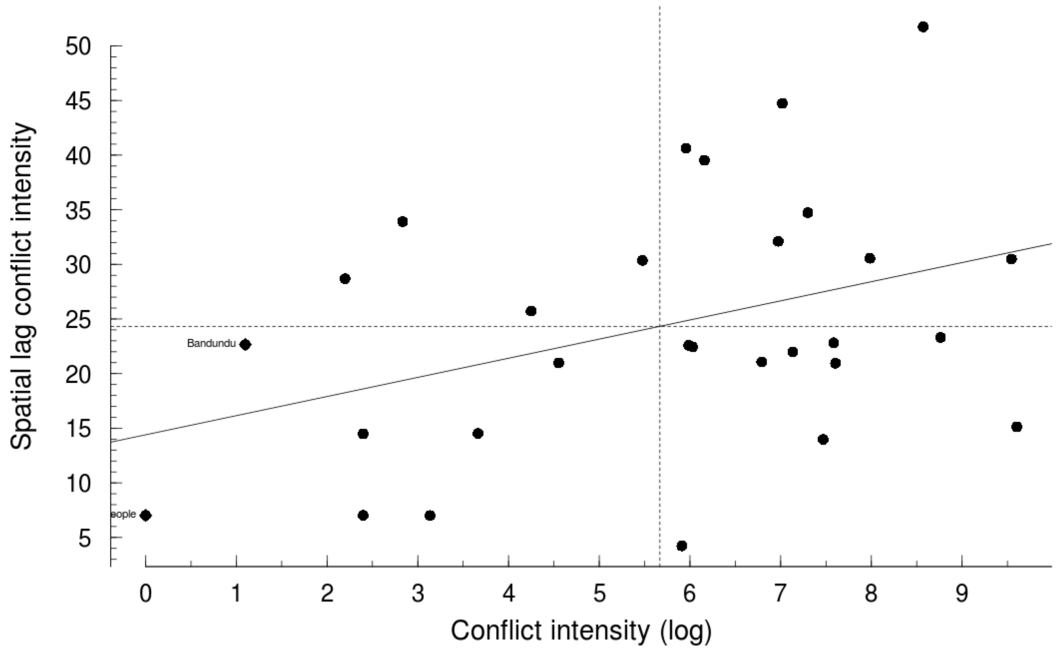
Focussing on the simple incidence measure the results do show some autocorrelation at the provincial level in this case but the magnitude is much lower compared to the district level. It is likely that the difference in results is driven by the level of aggregation and thus by the size of the administrative level in this indicating that the clusters of violence in general tend to be relatively small and highly localised. As far as foreign aid is concerned the test results rule out any strong spatial dependence between regions as all test statistics are close to zero, fail to reach statistical significance, and this result is not sensitive to the level of aggregation.

Table B1. Moran's I

	Province level *(ADM1)*		District level *(ADM2)*	
	(1)	(2)	(3)	(4)
Conflict intensity	0.07	0.03	0.47***	0.48***
Conflict incidence	0.18**	0.14*	0.41***	0.46***
Foreign aid	− 0.04	− 0.08	0.04	0.03
Row standardised	–	Yes	–	Yes

Notes. Test statistics obtained under randomisation. Number of Monte Carlo simulations under randomisation: 10,000. $N = 29$ for ADM1, and $N = 136$ for ADM2. *** p≤ 0.01, ** p≤ 0.05, * p≤ 0.1.

Figure A1. Local Moran's I measures at the provincial level *(top)* and district level *(bottom)*



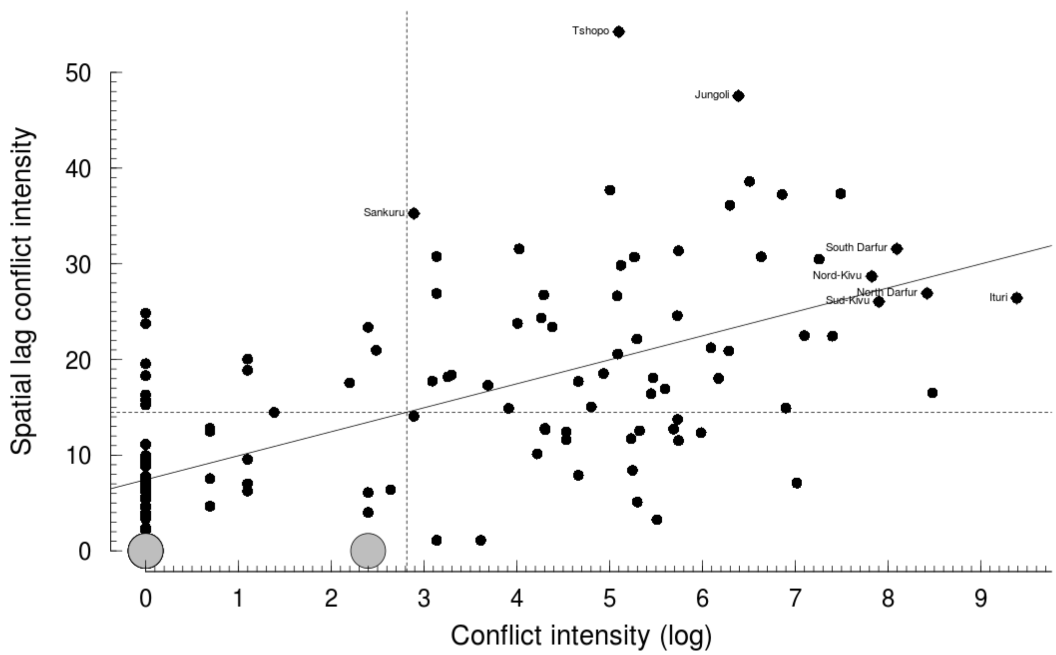
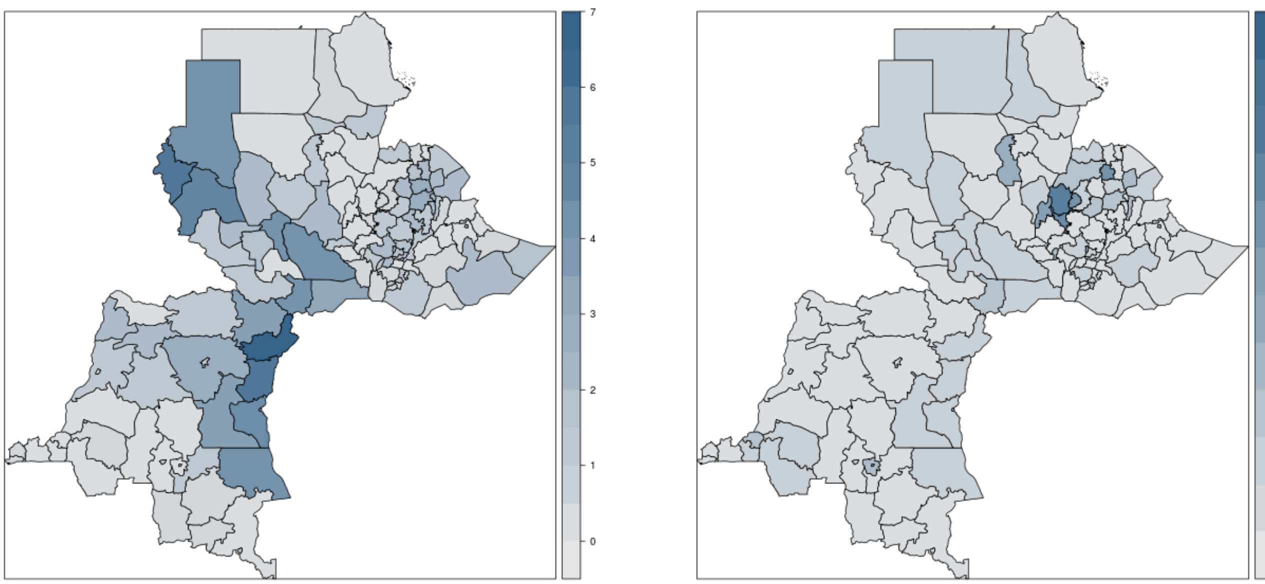


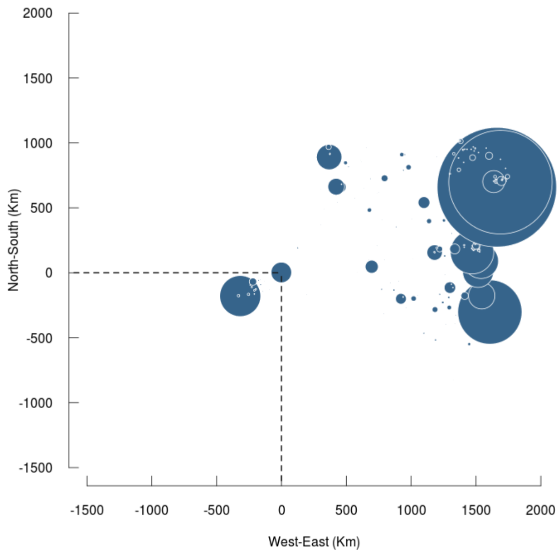
Figure A2. Local Moran's I at the provincial level (ADM1) for conflict intensity *(left)* and aid locations *(right)*

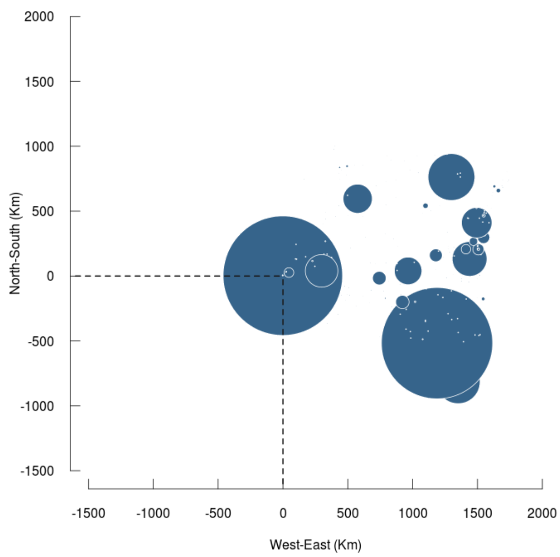
Figure A3. Local Moran's I at the district level (ADM2) for conflict intensity *(left)* and aid locations *(right)*



C. Appendix C. Preliminaries

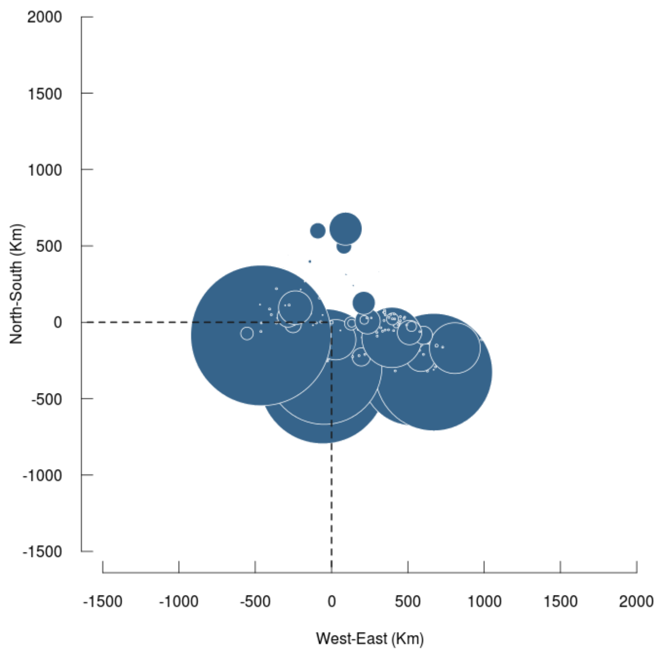
Figure C1. Spatial distribution for the Democratic Republic of the Congo of conflict *(top)* and aid *(bottom)* relative to the capital

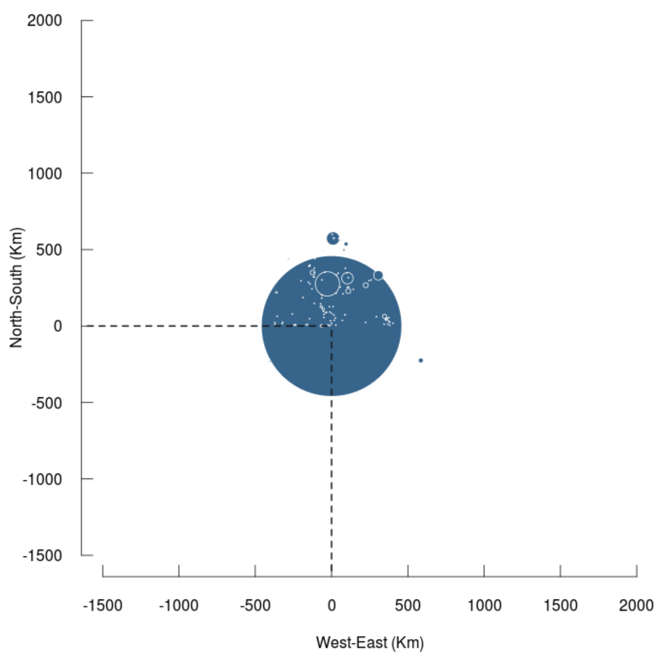




Notes: The size of the circle indicates the number of fatalities or the amount of foreign aid in U.S.$

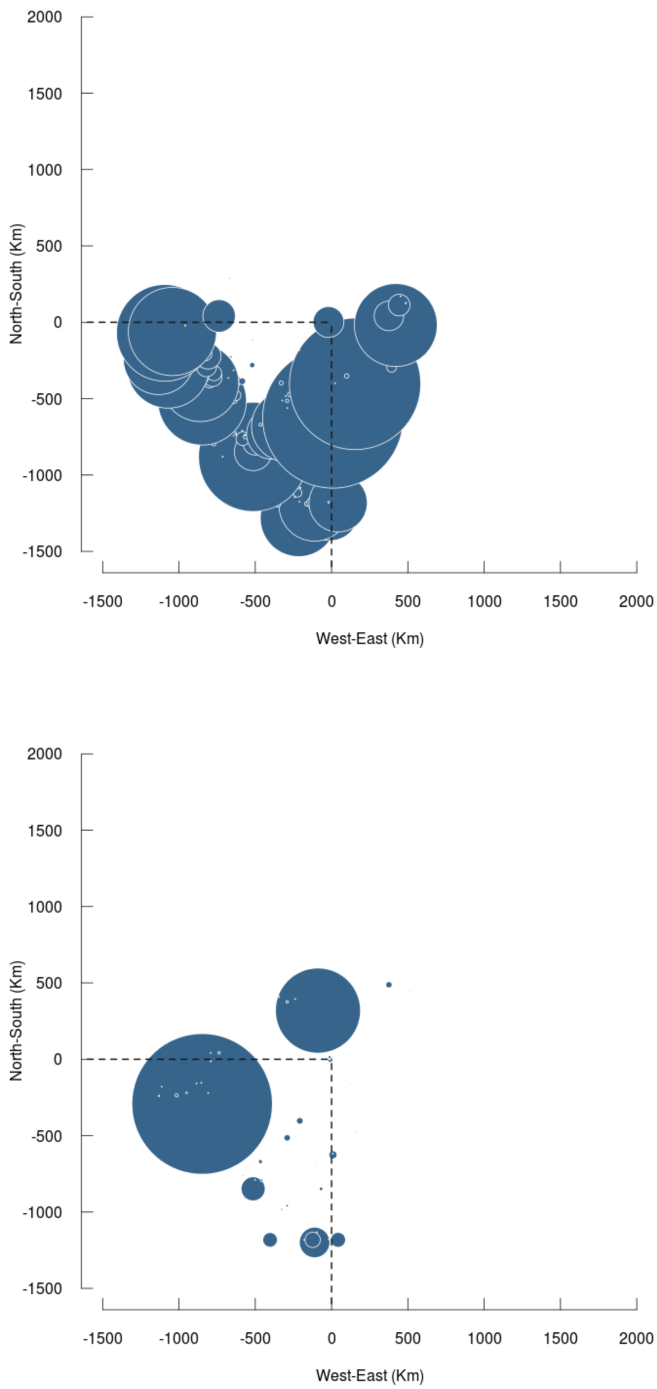
Figure C2. Spatial distribution for Ethiopia of conflict *(top)* and aid *(bottom)* relative to the capital





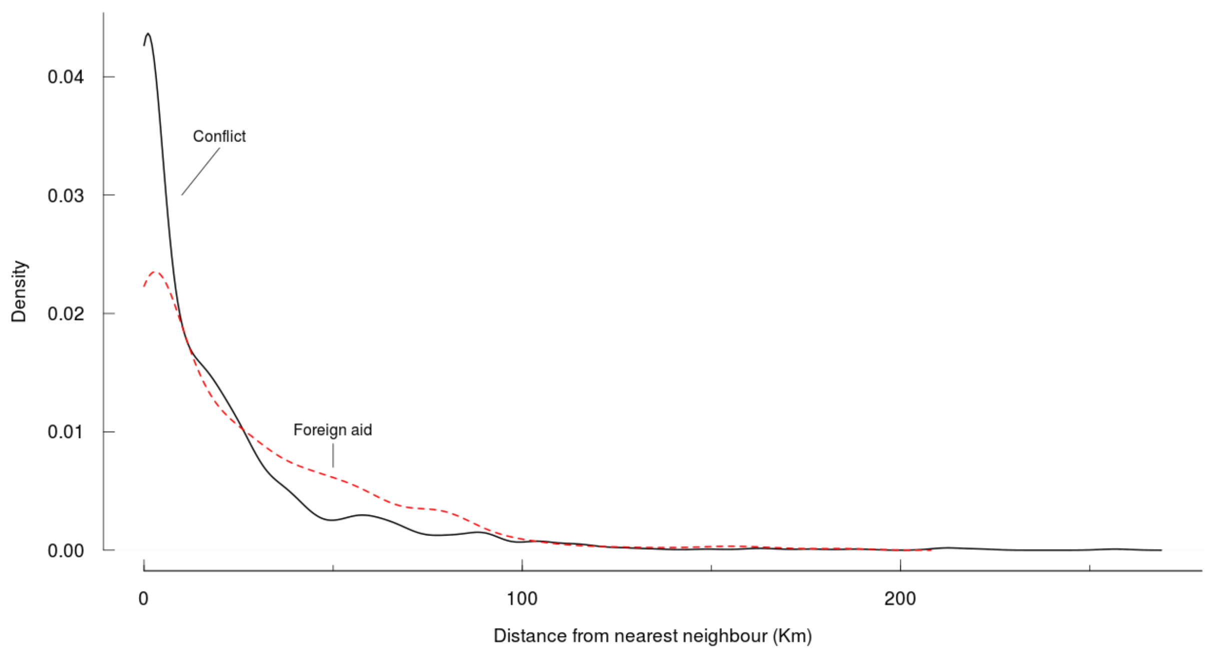
Notes: The size of the circle indicates the number of fatalities or the amount of foreign aid in U.S.$

Figure C3. Spatial distribution for Sudan of conflict *(top)* and aid *(bottom)* relative to the capital



Notes: The size of the circle indicates the number of fatalities or the amount of foreign aid in U.S.$.

Figure C4. Density of nearest neighbour distance for conflict and aid



C.1. Kernel Density Estimation

Figure C5 shows the kernel density estimation results, using the cross-sectional data on aid and conflict, where darker shaded areas indicate higher density values.[48] There is some clustering of aid and conflict in the region west of the DRC capital, the Eastern part of DRC, the Southern part of Sudan[49], and the Somali region in Ethiopia. However, these values are predominantly driven by conflict incidence and since the estimation is based on cross-sectional data it is not possible to establish the causal direction as conflict ridden areas might see an influx of aid.[50]

[48] Figure C6 shows kernel density estimations for aid and conflict separately.

[49] What is now the independent nation of South Sudan

[50] Besides a visual inspection I also used a spatial Kolmgorov-Smirnov test to estimate the goodness-of-fit of a Complete Spatial Randomness (CRS) pattern, generated by a Poisson process, with the observed values based on the distribution of the longitude coordinates of each point. For both conflict incidence and foreign aid locations I find that the null hypothesis of a random spatial pattern is rejected at the 99% level with D-statistics of 0.13 and 0.18 respectively ($N_{conflict} = 885$, $N_{aid} = 754$).

Figure C5. Kernel density estimation cross-section foreign aid projects and conflict incidence

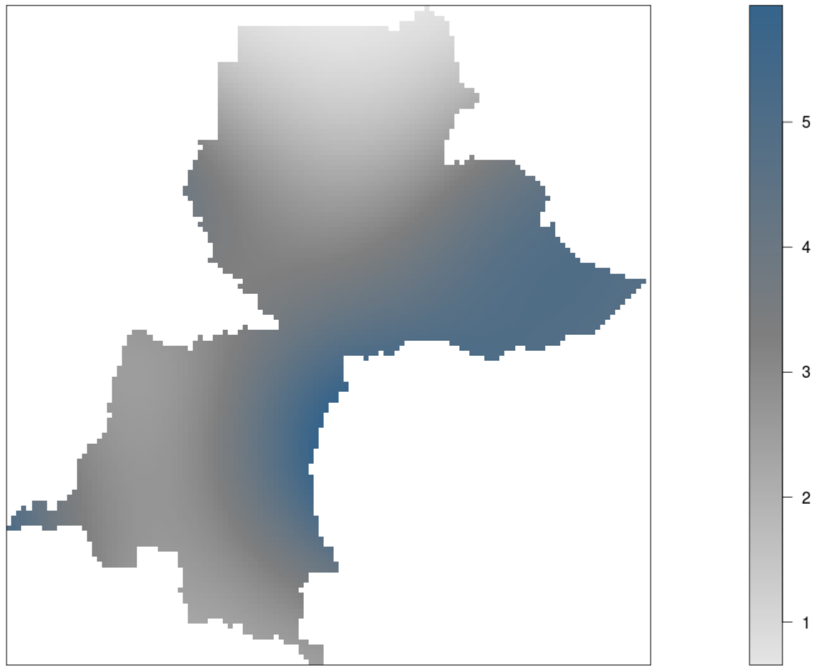
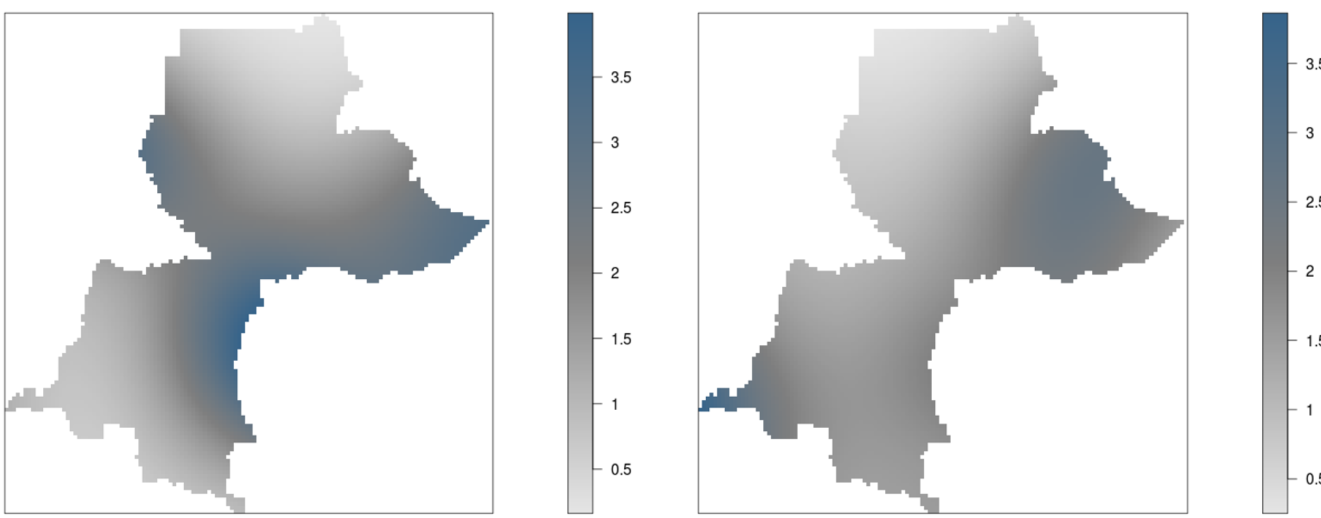


Figure C6. Kernel density estimations conflict incidence *(left)* and aid locations *(right)*



D. Appendix D. Regression Results

Table D1. Predicting changes in conflict intensity (province level)

Specifications	Parsimonious (1)	Main (2)	Gov. (3)	Extended (4)	Sector (5)
Foreign aid	−0.3 (−0.8; 0.3)	−0.2 (−0.7; 0.3)	−0.2 (−0.7; 0.3)	−0.2 (−0.7; 0.3)	
Foreign aid to government			0.2 (−0.4; 0.8)	0.2 (−0.4; 0.8)	
Fungible aid					0 (−0.5; 0.5)
Non-fungible aid					−0.5 (−1.0; 0)
Spatial lag		−0.2 (−0.7; 0.3)	−0.2 (−0.7; 0.3)	−0.2 (−0.8; 0.3)	−0.1 (−0.7; 0.4)
Temporal lag		−1.4 (−1.9, −0.9)	−1.4 (−1.9, −0.9)	−1.4 (−1.9, −0.9)	−1.4 (−1.9; −0.9)
Population				−0.2 (−0.7; 0.4)	
Night lights				−0.1 (−0.6; 0.5)	

Notes. Table presents point estimates with their 95% intervals between parentheses. All models include year indicators. Estimates are taken as the mean from 4 parallel chains with 40,000 iterations each where the first 10,000 are discarded as burn-in, thinning rate was set to 5. Priors are $N(0, 10)$. $N = 203$.

Table D2. Predicting changes in conflict intensity (district level)

Specifications	Parsimonuous (1)	Main (2)	Gov. (3)	Extended (4)	Sector (5)
Foreign aid	−0.1 (−0.3; 0.1)	0.01 (−0.17; 0.19)	0.01 (−0.17; 0.19)	0.01 (−0.17; 0.19)	
Foreign aid to government			−0.1 (−0.3; 0.1)	−0.1 (−0.3; 0.1)	
Fungible aid					0.02 (−0.15; 0.20)
Non-fungible aid					−0.06 (−0.24; 0.12)
Spatial lag		0.12 (−0.06; 0.30)	0.13 (−0.05; 0.30)	0.12 (−0.05; 0.30)	0.11 (−0.07; 0.29)
Temporal lag		−1.32 (−1.50, −1.14)	−1.32 (−1.50, −1.14)	−1.33 (−1.51, −1.14)	−1.31 (−1.49; −1.14)
Population				−0.12 (−0.31; 0.07)	
Night lights				0 (−0.19; 0.19)	

Notes. Table presents point estimates with their 95% intervals between parentheses. All models include year indicators. Estimates are taken as the mean from 4 parallel chains with 40,000 iterations each where the first 10,000 are discarded as burn-in, thinning rate was set to 5. Priors are $N(0, 10)$. $N = 952$

Table D3. OLS estimation province level

Specifications	Parsimonious (1)	Main (2)	Gov. (3)	Extended (4)	Sector (5)
Foreign aid	−0.3 (0.3)	−0.2 (0.2)	−0.2 (0.2)	−0.2 (0.2)	
Foreign aid to government			0.2 (0.3)	0.2 (0.3)	
Fungible aid					0 (0.3)
Non-fungible aid					−0.5 (0.2)**
Spatial lag		−0.2 (0.3)	−0.2 (0.3)	−0.2 (0.3)	−0.2 (0.3)
Temporal lag		−1.4 (0.3)***	−1.4 (0.3)***	−1.4 (0.3)***	−1.4 (0.3)***
Population				−0.2 (0.2)	
Night lights				−0.1 (0.2)	
adjusted R^2	0.01	0.13	0.13	0.13	0.14
AIC	841.5	815.3	816.8	820.4	814.3

Notes. $N = 203$. AIC, Akaike information criterion. Robust standard errors clustered at unit level (given in parentheses). *** p≤ 0.01, ** p≤ 0.05, *≤ 0.1

Table D4. OLS estimation district level

Specifications	Parsimonious (1)	Main (2)	Gov. (3)	Extended (4)	Sector (5)
Foreign aid	−0.1 (0.1)	0 (0.1)	0 (0.1)	0 (0.1)	
Foreign aid to government			−0.1 (0.1)	−0.1 (0.1)	
Fungible aid					0 (0.1)
Non-fungible aid					−0.06 (0.10)
Spatial lag		0.12 (0.10)	0.13 (0.10)	0.12 (0.10)	0.11 (0.1)
Temporal lag		−1.3 (0.1)***	−1.3 (0.1)***	−1.3 (0.1)***	−1.3 (0.1)***
Population				−0.12 (0.07)*	
Night lights				0 (0.05)	
adjusted R^2	0.01	0.19	0.19	0.19	0.19
AIC	3529.9	3340.5	3340.7	3343.2	3342.0

Notes. $N = 952$. AIC, Akaike information criterion. Robust standard errors clustered at unit level (given in parentheses). *** p≤ 0.01, ** p≤ 0.05, *≤ 0.1

Table D5. Interaction effects province level

Specifications	Time lag	Space lag	Distance	Ethnicity
Foreign aid	−0.2 (−0.7; 0.3)	−0.2 (−0.8; 0.3)	−0.1 (−0.7; 0.4)	−0.2 (−0.7; 0.4)
Foreign aid x time lag	−0.4 (−1.5; 0.8)			
Foreign aid x spatial lag		0.1 (−0.6; 0.8)		
Foreign aid x distance to capital			−1 (−3; 1)	
Foreign aid x ethnic polarisation				−0.3 (−1.1; 0.6)
Spatial lag	−0.2 (−0.7; 0.3)	−0.2 (−0.7; 0.3)	−0.2 (−0.7; 0.3)	−0.2 (−0.7; 0.3)
Temporal lag	−1.4 (−1.9, −0.9)	−1.4 (−1.9, −0.9)	−1.4 (−1.9, −0.9)	−1.4 (−1.9; −0.9)

Notes. Table presents point estimates with their 95% intervals between parentheses. All the estimates are taken as the mean from 4 parallel chains with 40,000 iterations each where the first 10,000 are discarded as burn-in, thinning rate was set to 5. Priors are $N(0, 10)$.

Table D6. Interaction effects district level

Specifications	Time lag	Space lag	Distance	Ethnicity
Foreign aid	0.02 (−0.16; 0.20)	0.01 (−0.17; 0.19)	0.02 (−0.16; 0.21)	0.01 (−0.17; 0.19)
Foreign aid x time lag	−0.4 (−0.7; −0.1)			
Foreign aid x spatial lag		−0.1 (−0.4; 0.2)		
Foreign aid x distance to capital			−0.1 (−0.7;0.4)	
Foreign aid x ethnic polarisation				−0.2 (−0.5; 0.2)
Spatial lag	0.11 (−0.07; 0.29)	0.12 (−0.06; 0.30)	0.12 (−0.06; 0.30)	0.12 (−0.06; 0.30)
Temporal lag	−1.30 (−1.48, −1.13)	−1.32 (−1.50, −1.14)	−1.32 (−1.49, −1.14)	−1.31 (−1.49, −1.14)

Notes. Table presents point estimates with their 95% intervals between parentheses. All the estimates are taken as the mean from 4 parallel chains with 40,000 iterations each where the first 10,000 are discarded as burn-in, thinning rate was set to 5. Priors are $N(0, 10)$.

Table D7. Predicting changes in conflict intensity: Aid shocks

Specifications	Provinces ($N = 203$) (1)	Districts ($N = 952$) (2)
σ Foreign aid	-0.2	-0.06
	(-0.7; 0.4)	(-0.24; 0.12)
Spatial lag	-0.3	0.12
	(-0.8; 0.3)	(-0.06; 0.30)
Temporal lag	-1.4	-1.31
	(-1.9, -0.9)	(-1.49; -1.13)

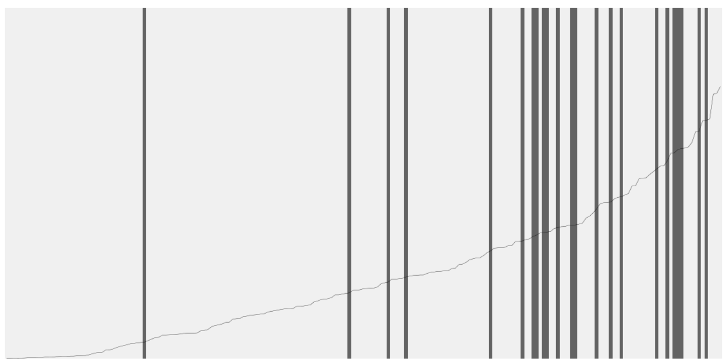
Notes. Table presents point estimates with their 95% intervals between parentheses. All models include year indicators. Estimates are taken as the mean from 4 parallel chains with 40,000 iterations each where the first 10,000 are discarded as burn-in, thinning rate was set to 5. Priors are $N(0, 10)$.

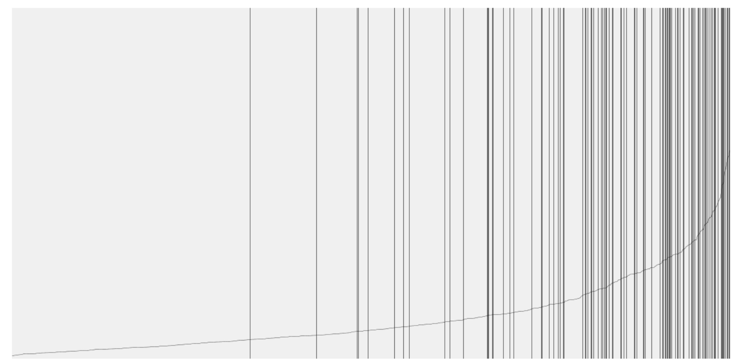
Table D8. Predicting conflict onset (logit)

Specifications	Provinces ($N = 203$) (1)	Districts ($N = 952$) (2)
Δ Foreign aid	0.4	0.4
	(-0.8; 1.7)	(-0.1;0.9)
Spatial lag	-0.6	0
	(-1.9; 0.6)	(-0.5; 0.5)
Population	-1.0	-0.4
	(-4; 1)	(-1.2; 0.3)
Night lights	0.4	0.1
	(-0.7; 1.6)	(-0.6; 0.7)
Ethnic polarisation	0.2	1.2
	(-1.6; 2.0)	(0.5; 2.0)
Natural resources	1	0.3
	(-2; 4)	(-0.4;1.0)
Mean intercept	-3	-3
	(-9; 3)	(-10; 4)

Notes. Table presents point estimates with their 95% intervals between parentheses. All models include year indicators. All the estimates are taken as the mean from 4 parallel chains with 40,000 iterations each where the first 10,000 are discarded as burn-in, thinning rate was set to 5. Priors are $N(0, 10)$.

Figure D1. Separation plot for province (*left*) and district (*right*) level





Notes: The separation plot (Greenhill et al., 2011) orders the cases from left to right according to their predicted probability. The dark grey lines indicate positive cases (conflict onset) and light grey lines negative cases.The figure illustrates that the model is marginally better at predicting the outcome at the district than at the province level.

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