Aid and conflict at the local level - Mechanisms and causality (Draft, do no circulate please)

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Abstract:
The recent literature suggests that aid might fuel conflicts in developing countries. We process and use geocoded data on worldwide aid projects by the World Bank as the most important multilateral donor, as well as by China and India as examples of emerging donors. Our results at the first and second-order administrative subnational level over the 1995-2012 period highlight how important it is to consider the actual locations of projects instead of focusing on the aggregate country level. When controlling for regional unobservables and time trends, the initially positive correlation disappears. Due to possible within-country selection effects, we exploit changes in the World Bank's liquidity as exogenous variation in the amount of aid a region receives in an instrumental variable setting. Overall, the results strongly suggests that World Bank project aid has no conflict-increasing effect. Results on Indian and Chinese aid are currently being computed.

Keywords: Development Aid, Conflict, geolocation, World Bank
JEL Codes: H77, N9

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1 Introduction

Development aid has been criticized on several grounds, e.g., for being politicized (Dreher et al., 2016) or lacking effectiveness (Doucouliagos and Paldam, 2009), but one of the most alarming concerns is the suggestion that aid fuels conflict in the receiving countries. Nunn and Qian (2014) show that US food aid, using weather shocks as exogenous variation in the supply of aid, leads to more conflict. There are two major concerns with this approach. First, food aid is a very specific type of aid, for instance because it is very volatile and rather easily lootable. Moreover, the US as a donor could differ from multilateral aid or other donors, and more targeted project aid might differ from budget aid going to the recipient government. Second, by using data and variation at the aggregate country level, it is impossible to test specific hypotheses; instead, the aid-conflict nexus is treated as a black box. Moreover, Nunn and Qian (2014)'s identification-strategy at the country level could be driven by spurious trends as a recent contribution indicates (Christian and Barrett, 2017). As donor countries spend billions of US dollar per year on development aid, we need better data and strategies to understand the relationship between aid disbursements and conflict incidence.

The literature on the relationship between aid and conflict is so far either focusing on the macro level (Nunn and Qian, 2014; Bluhm et al., 2015), very specific types of aid Berman et al. (2011); Crost et al. (2014) or on a limited subset of countries (van Weezel, 2015). Moreover, the literature has so far mostly ignored the spatial distribution of aid projects, while related studies indicate that inequality between regions or ethnic groups has significant effects (Alesina et al., 2016; Cederman et al., 2015). Our study makes three major contributions. First, we use an identification strategy combining spatial variation with temporal variation caused by fluctuations in the World Bank's liquidity to induce exogenous variation in local aid disbursements. Second, to the best of our knowledge we are the first study to cover aid projects in a broad set of developing countries around the world and assign projects to specific sub-national administrative units. Finally, we aim to take account of ethnic and regional identities and potential grievances, and propose our own measure of *aid inequality* between these entities.

It is not just a matter of detail and precision, but there is a real need to study the effect of aid on conflict at the local level. In contrast to the historical focus on the macro level, the theory underlying the proposed link between aid and conflict practically requires using sub-national data to distinguish between different channels and estimate the effect correctly. Very briefly, there are several different hypotheses put forward in the literature linking the two measures. On the one hand, the opportunity cost hypothesis claims that higher resources and the associated revenues and higher incomes make it less likely that people are fighting or joining rebel groups. On the other hand, resources can be regarded as a price of fighting, and the contest (or rapacity) theory suggests that a higher price sets an incentive for more fights (e.g., Collier and Hoeffler, 2004). Besides these prominent main theories, there are, however, several other possible channels linking aid and conflict.

If aid is to some degree fungible, it can soften the central government's budget constraint and strengthen the military via increased spending (Langlotz et al., 2016).[1] This is estimated to occur with 11.4% of foreign aid for the poorest African nations, and could contribute as much as 40% of these countries' military budgets (Collier and Hoeffler, 2006). If it deters rebels from attacking the government, this might lead to less conflict taking place. At the same time it might lead to more violence by the government against opposing groups. This is a good example how using the exact location of conflicts in combination with the conflict characteristics could help us to disentangle between different channels. Moreover, if aid leads to increased revenues for rebels, either through looting or via increasing the income in the region they control, this could amplify rebel fighting activity (Anderson, 1999). To identify this channel we aim to connect different existing databases and consider the actors and their roles in the specific conflicts. Finally, if aid would lead in contrast to its often cited ineffectiveness to more development in the regions that receive aid, we should observe less conflict in this region or violence initiated by people from that region or ethnicity.

We make use of one of the major innovations in the field of development aid research in the last years: the availability of geo-coded project level data at a local level (Strandow et al., 2011; Strange et al., 2017). Through an impressive data collection effort mostly managed by the AidData consortium we now possess detailed information about project types, disbursements numbers and their locations for important donors.

World Bank project aid is interesting for several reasons. The World Bank has a highly qualified team of country and academic experts trying to ensure that aid is spent in an effective way. Despite evidence that it is also affected by political motivations of its main shareholders, it should be less politically motivated than individual country disbursements(Dreher et al., 2009). Generally, project aid is also supposedly less political than budget aid, which usually flows directly to the national recipient government. At the same time, all aid projects provide possibilities for looting, for instance many anecdotal reports suggest that equipment in hospitals or schools was sold to raise money instead of its intended use. Accordingly, it serves as a useful test whether aid projects can be administered and allocated in a way not to foster conflict.

[1] Van de Sijpe (2012), however, suggests that fungibility is limited and takes place only partly.

Chinese and Indian development aid are the most prominent examples of development finance provided by emerging Non-OECD donors (not being on the OECD Development Assistance Committee DAC list). In contrast to World Bank aid, this type of aid is, in particular in the Western world, often characterized as ignoring conditions on human rights and good governance practices and focusing solely on the economic benefit of the donor.[2] At the same time, the importance of these two rising donors has constantly increased over time and will continue to do so in the future. Accordingly, a comparison between the different donors could also reveal how different approaches affect the relationship between aid and conflict.

We contribute to the literature on the relationship between aid and conflict, which until now was mostly focusing on the macro level and, thus, could not test these channels and hypotheses by taking the spatial dimension of these two phenomena seriously. Important studies include Nunn and Qian (2014), who combine the historical likelihood to receive aid with exogenous variation in the donor country to construct an instrument exhibiting spatial and temporal variation. Their results indicate a positive effect of US food aid and conflict incidence and duration. However, this result is only at the country level and focuses on a very specific type of aid, most notably the type of aid which is most likely to be positively related to conflict. Also at the country level, Bluhm et al. (2015) use a new instrument for aid (Dreher and Langlotz, 2015) and focus on conflict dynamics. These results complement a broader literature on positive income shocks, contributing counter-intuitively to higher conflict risk. An example in this regard, is an early study by Miguel et al. (2004), who suggest this channel for positive income shocks induced by rainfall variation across African countries.

We also connect to the emerging literature arguing that inequality in development levels between (ethnic) groups influences development (Alesina et al., 2016) and also contributes to conflict (Cederman et al., 2015). More specifically, these authors use satellite nighttime light data and survey results to compute the development level of different ethnic groups and the degree of inequality between groups. We transfer these insights to the analysis of aid and conflict. It seems immediately plausible that group inequality in aid allocation needs to be considered to take into account an important channel of the effect of aid on conflict. If neighboring administrative units or grid cells receive more aid payments, but belong to the same ethnic groups, we would not expect this to strongly fuel grievances and lead to conflict between these units. In contrast, if the neighboring unit is controlled by a different ethnic group and receives disproportionally many aid projects, we can plausibly expect this to play a role. Aid to the central government or the ethnic region of the ruling ethnicity increases the rents and attractiveness for other

[2] Even though empirical studies suggest that the difference in allocation criteria and decisions compared to Western donors might not be as large as many casual observers expect (Fuchs and Vadlamannati, 2013).

regions and groups to capture government as they want to gain these rents (Grossman, 1992). Regarding the rent seeking mechanism, Morelli and Rohner (2015) run country and ethnicity level regressions for 157 countries over the 1960-2008 period using a measure of oil inequality between regions and show how this contributes to the risk of civil (in particular secessionist) conflict.

Moreover, a related literature studies the effect of windfall gains and income shocks on conflict. Abidoye and Calì (2015), for instance, innovatively link local oil production and household surveys in Nigeria, to localize the link between oil prices and conflict. This way, they claim to be able to more precisely integrate the opportunity costs in the model. Still they find higher oil prices to fuel conflict most of the time, which is in line with Dube and Vargas (2013). Arezki et al. (2015), use income shocks related to natural resources and a novel data set on mineral discoveries, but find no consistent relationship of this type of income shock with conflict at the grid cell level in Africa. Carreri and Dube (2016) show that natural resource wealth influences which kind and quality of leaders rise to powers and Berman et al. (2017) combine information on mineral deposits with changes in world prices and find that mining is positively correlated with conflict at the local grid-cell level (0.5 x 0.5°) in Africa over the 1997-2010 period. Development aid has many features of other resources that provide windfall gains to the government or other groups. It might differ to the extent that often no aid projects can be implemented if this is strongly against the will of the national government.

Most directly, our study relates to the few studies using localized aid projects. There are also some studies focusing on individual countries. Child (2016) and Sexton (2016), for instance, find that education and civil aid would fuel conflict in Afghanistan, especially, when disbursed in contested regions. Berman et al. (2011) provide an example where aid seems to reduce violence. Reconstruction spending in Iraq is correlated with less violence against forces of the international coalition. Crost et al. (2014) examine exogenous variation in project allocation for a large development program in the Philippines. Their bargaining model shows that the peaceful equilibrium collapses if the entity receiving a project cannot ensure project success and credibly commit to the terms of the project. In these cases, they posit that development projects can foster conflict, which is also what they found in their empirical investigation. The only paper using more than one country that we are aware of is van Weezel (2015). He considers geolocalized aid projects and links them to conflict, but focuses on three select countries and employs data on aid commitments instead of disbursements. The reason for this were most likely data limitations, but it is also evident that disbursements are to be preferred over commitments when analyzing the relationship between aid and conflict. The literature usually assumes that it takes between 2 to 5 years until a commitment is finally disbursed (Dreher et al., 2016).

We build on data covering World Bank aid projects from AidData by Strandow et al. (2011) over the 1995 to 2012 period. Data on Chinese development aid in Africa, and the data on Indian development aid is from Strange et al. (2017) and from Asmus et al. (2017) respectively. These data sets became reasonably available and enable us to examine the aid conflict link on a local level for almost two decades. Using them makes it possible to take the spatial component of an aid shock into account, e.g., by examining how aid impacts the stability in neighboring regions or how conflict risk is affected if aid is allocated unequally across regions. Our analysis on the first and second administrative level enables us to link the actual location of aid projects to the location of a conflict within the country. The existing literature has mostly bundled together aid projects and conflicts, even if in an extreme case one happened far apart from the other.

Beyond that, we address a further open issue in the literature - the endogeneity of aid and conflict. Donor agencies on the one handoften want to facilitate reconstruction and reestablish peace as a prime objective. Still, if on average donors decide to give more aid to regions affected by conflict, this could mistakenly be accounted as a sign that aid induces conflict. This notion has been supported by well-thought identification strategies to identify the causal effect of US food aid (Nunn and Qian, 2014) and general official development assistance (Bluhm et al., 2015) on conflict at the macro country level. On the other hand, donor agencies might try to anticipate future conflicts and if successful direct less aid to regions with a higher conflict likelihood in the future. This could lead to a negative, but spurious correlation, suggesting that aid leads to less conflict. Looking at the country level only completely ignores the distribution of aid within countries, which is often highly unequal. The same endogeneity issues that are existing at the country level also exist at the subnational level. Ignoring them would lead to biased estimates. We thus augment existing studies by further examining the aid-conflict nexus, but at a much more micro level, which allows us to take the distribution of aid and the spatial component of conflict properly into account.

We will also code and consider different types of aid. In the long term, we also plan to include the ethnic group level (Cederman et al., 2014; Weidmann et al., 2010; Wucherpfennig et al., 2011) to carve out which type of inequality matters. Moreover, we will consider different types of aid to uncover potential heterogeneity which was suggested by prior studies.

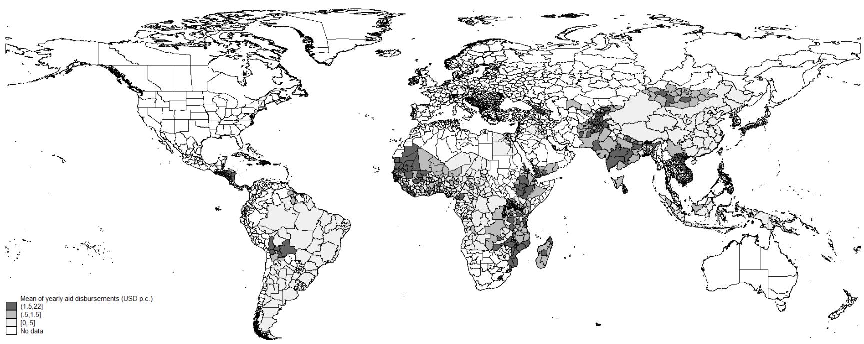
The paper proceeds as follows. Section 2 explains the data and its sources, and provides descriptive statistics and maps. Section 3 explains the specification and empirical strategy. Section 4 shows the results and Section 5 concludes.

2 Data

2.1 Aid Data

2.1.1 World Bank aid

Our treatment variable in the first part of the paper are geo-referenced World Bank aid disbursements from the AidData collaboration (Strandow et al., 2011). The data set is comprehensive both regarding time, ranging from 1995 to 2012, and regarding project scope with geo-coded disbursements worth USD 389,037,095,462 distributed over 5684 projects in 61,243 locations. This corresponds to approximately 18.5% of total bilateral and multilateral disbursements of DAC donors in the corresponding years (OECD, 2017). Additionally, it provides information on the sectoral allocation of disbursements, enabling us to distinguish potentially differential effects of different aid types on conflict probability and intensity.



Note: Yearly means of gross aid flows to ADM1 regions.

Figure 1: Sample - Aid

The aid disbursements that contain latitude and longitude were subsequently allocated to first and second order administrative regions (ADM).[3]

(i) The allocation per administrative region is based on data on subnational administrative units by Hijmans et al. (2010), where we matched project locations with administrative units. As yearly disbursement amounts are only assigned to specific projects rather than more accurately to a specific project locations, assumptions have to be made how the aid is distributed across different project locations.We use different approaches for robustness:

a) Shares per locations in region: In line with previous research by Dreher and Lohmann (2015) we assume that aid is distributed equally across locations and allocate aid proportionally to the locations per region.

[3] For some countries the underlying database does not comprise data on all administrative levels. For instance, Macedonia and Azerbaijan lack coverage on the second level of administrative units. Here, administrative units of the first level are used for the analysis for second level administrative units, resting on the assumption that first and second level administrative unit size is arbitrary.

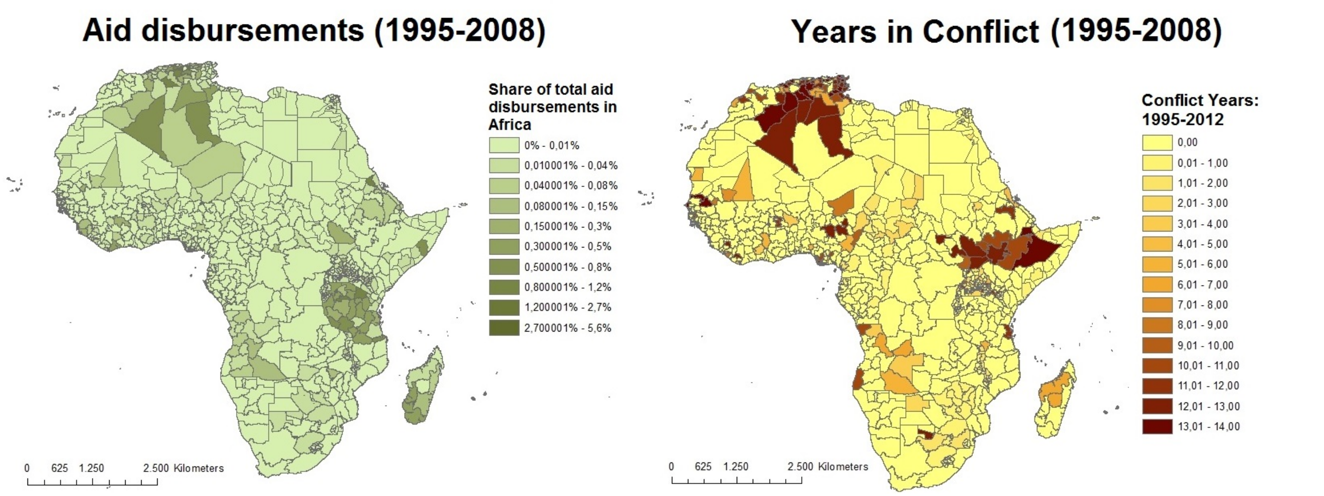


Figure 2: Aid and Conflict (1995-2008)

For instance, for a project with 10 locations, where 4 locations are in region A and 6 locations are in region B, 40% of project disbursements would be accounted in region A and 60% in region B. [4]

b) Shares per population: Here we assume that aid is allocated based on the regional population shares. For instance, if a project would have project locations in two regions of a country, where two million inhabitants would reside in region A and three million would reside in region B, 40% of project disbursements would be accounted in region A and 60% in region B. Here, the aid attribution formula would write as follows: $Aid_{pijt} = \frac{Aid_{pit}}{\int Population_{pi}} * Population_{pj}$, where again p is the project, i is the country, j is the region and t is the period for which we estimate the allocation shares.[5]

Figure 1 depicts the geographical distribution of development aid disbursements across administrative regions as well as the number of years the respective region was involved into conflict for Africa as an example. It is immediately visible that there is large variation in disbursements as well as in conflict incidents across countries, but also within countries. This is important as our analysis will distinguish between two main steps of equations. In the first set, we condition on observables and unobservables through fixed effects and time trends, but still exploit country wide variation. In the second set, we use country times year fixed effects to control for any variation in the countrywide conflict level in a particular year. In these specifications, we can rule out an effect of any spurious events at the country-year level affecting conflict and by chance coinciding with changes in disbursements. Accordingly, we can

[4] Hence, our aid attribution formula would be: $Aid_{pijt} = \frac{Aid_{pit}}{\int Locations_{pi}} * Locations_{pj}$, where p is the project, i is the country, j is the region and t is the period for which we estimate the allocation shares.

[5] Our population data builds on the gridded population data provided by for International Earth Science Information Network CIESIN Columbia University (2016). As global population censuses have to build on strong assumptions and yearly data has to be imputed, measures building on this are of course subject to a certain degree of measurement error.

see whether the within-country distribution of aid has any effect on conflict incidents. Nevertheless, these specifications might also eliminate too much variation, which is why we also consider the first set in detail.

Visually examining the overlap between average aid disbursements and years and conflict seems to suggest a positive spatial correlation in some areas. The Magreb states Algeria and Mauretania in northern Africa are both recipients of a lot of aid, and had to endure a lot of conflict. Similarly, Angola exhibits high averages on both measures, as does South Sudan. In contrast, Ethiopia seems to have received relatively little aid, and still experienced many years of conflict. Of course, it is tempting to engage in such visual analysis, but these averages tell us very little about causality. Obviously, countries that had endured conflict in the past are also more in need for post-conflict aid. Regions can be both more conflict prone and in need of aid due to a third factor like the frequency of natural disasters. The high within-country variation in aid disbursements highlights how important it is to study the local level instead of focusing at the aggregate country level. The location of a conflict and the location of aid projects might not overlap at all, but an aggregation over a country and a year would still suggest a correlation between the two.

2.1.2 Chinese Aid

Although China is perceived as a major political and economic actor, it was until recently a recipient of sizeable aid amounts. For instance, it only graduated from IDA in 1999 (Galiani et al., 2016).

Nowadays, China is a major donor itself and its extended interest in the African continent as well as its policy of “mutual benefit” earned it some reputation as a "rogue donor" (Naím, 2007). This concerns are fueled by the Chinese policy to report no information according to the DAC standards, because large disbursement amounts might lead to citizens’ discontent in Chinese regions, which are less developed.

In order to shed light on Chinese aid activities, Dreher et al. (2015) compiled data on Chinese ODA like disbursements based on media reports. We draw from these data information on Chinse disbursements in Africa for the years 2000-2012. In total these flows amount to USD 24.83 bn from 1955 projects.

Descriptive cHINA & India: usd; projekte; years; country coverage

2.1.3 Indian Aid

Slightly less prominent and also less controversially discussed is the involvement of India as another emerging donor. Nonetheless, India has become a very important donor country while still receiving development aid itself. Researchers have examined its allocation practices and found it to be comparable to some prominent Western donors in terms of considering neediness and political self-interest (Fuchs and

Vadlamannati, 2013).

Asmus et al. (2017) compiled data on 190 Indian ODA like projects from official documents of India's Ministry of External Affairs (MEA) and the Export Import (Exim) Bank of India. Although graduating from IDA even more recently in 2014, Indian commitments to African countries amount to USD 6.57 bn for the years 2006 to 2012.

2.1.4 Conflict measures

As an outcome, we code binary variables measuring conflict incidents at the regional level. They are constructed based on the Uppsala Conflict Data Program's (UCDP) georeferenced event dataset (GED) (Sundberg and Melander, 2013; Croicu and Sundberg, 2015).[6] Derived from global media and NGO reports as well as secondary sources (local, field reports or books) UCDP's GED provides the most reliable and comprehensive data on incidences of violence including the involved parties, casualties and location. In line with previous models from the cross-country literature (e.g., Bluhm et al., 2015) we use dichotomous indicators of conflict intensity based on thresholds. Nevertheless, the thresholds commonly used in the cross country literature are not applicable at the smaller scale regional level. A threshold of 1000 casualties is clearly way too high, and would lead to only a tiny share of real conflicts being identified. In contrast, a minimum threshold of more than one casualty would be too low and contain a lot of measurement error. Acknowledging the apparent trade of with which we are faced here, we chose two different thresholds minimize researchers degrees of freedom and provide a comprehensive picture. More specifically, we obtain two different intensity measures. 5 (low intensity) and 25 (medium intensity) battle related deaths.[7] One complication the analysis is that countries differ largely with regards to their size. Our units of observation are the first-and second-order subnational administrative units, which can accordingly differ a lot as well. For some very large countries, a threshold of 50 or 100 might be suitable for the adm1-level. In other countries, however, this would be too high and ignore actually existing conflicts. Still, we chose the administrative level instead of the grid-cell level as it seems more useful for the analysis. Aid allocation often involves some regional balance between administrative areas, and administrative regions can differ in terms of policies both towards the use of aid and towards conflict.

[6] An alternativ would be to use geo-localized data from the PRIO dataset, which rely on similar primary data as UCDP. However, one issue with these data is that neighboring cells in a 50km radius are also coded as conflict affected, which might lead erroneous conflict coding of neighboring administrative and ethnic regions (). Moreover, PRIO only provides dichotomous information on conflict occurence, but not on intensity, which would preclude the analysis of conflict intensity. Nonetheless, this is an important feature of conflict (Bluhm et al., 2015).

[7] UCDP GED provides assessment of its data quality (e.g., high, low, best). For the construction of these thresholds we rely on UCDP's best estimates.

Using two different thresholds and administrative areas as the unit of analysis is in our opinion the best choice to get comprehensive and reliable results.

2.1.5 Control Variables

Besides our main variables of interest, we consider several other variables, which are suggested in the literature as either determinants of aid allocation or drivers of conflict. Regarding development aid, the regional GDP level needs to be considered in order to account for poverty targeting. For our purpose, the regional GDPs are proxied by nighttime light, as sub-national income estimates are scarce, especially in low and lower middle income states (Henderson et al., 2012). What is more, we account for regional population taken from the *gridded population of the world* dataset (for International Earth Science Information Network CIESIN Columbia University, 2016). Population is both a relevant determinant of aid allocation as well as in terms of scale effects for conflict potential (Hegre and Sambanis, 2006).

As a large literature in development economics and political science stresses the role of resources as windfall gains on conflict (Dube and Vargas, 2013; Abidoye and Calì, 2015), we take into account several natural resource indicators including oil, gold, gem stones as well as narcotics provided by the PRIO GRID data (Tollefsen et al., 2012). This dataset also includes measures on temperature and precipitation, providing us with a proxy for local income shocks causing conflict (Miguel et al., 2004). Finally, we also control for ethnic exclusion, as it is suggested in the economic conflict literature as a main determinant of political violence (Esteban et al., 2012; Michalopoulos and Papaioannou, 2016).

Table 1 shows descriptive statistics for the two conflicts indicators and aid per capita, as well as the logged version of aid which we use in the analysis. Aid per capita at the ADM1 level is on average US$5.42, with the maximum for a individual region and year being much higher at US$24,000. At the ADM2 level, the numbers are a bit smaller. On average US$1.10 per capita, and the maximum being US$4510. The reason is of course not that aid is somehow reduced by switching to a smaller level, but that the amount of projects that have coordinates precise enough to allow assigning them to second order subnational units is smaller. The average incidence of small-scale conflict (five or more battle related death) at the ADM1 level is 8.72%, and four medium scale conflict (25 or more BRD) it is 5.67%. The respective numbers at the ADM2 level are 2.42% and 1.14%. Crossing a fixed threshold is of course a rarer event at smaller units with less population.

3 Empirical strategy

Our baseline empirical specification looks as follows:

$C_{irt} = A_{ir,t} + X_{ir,t-1} + \gamma_t + \lambda_r + \epsilon_{ir,t},$

where $C_{ir,t}$ is our conflict indicator of interest, $A_{ir,t}$ is the log of per capita aid disbursements and $X_{ir,t-1}$ is a vector of lagged control variables.[8] Furthermore, our baseline specification contains γ_t and λ_r, which are time and region fixed effects, as well as an error term $\epsilon_{ir,t}$.

Our baseline results are estimated via an ordinary least squares model, where we use multi-way clustering of the standard errors at the country-year and regional level (Cameron et al., 2011). This allows for arbitrary correlation within a country and year, which is important as conflicts often have a strong spatial components and tend to spillover. Also allowing for correlation within a region over time is important as conflict also tends to exhibit a strong persistence over time.

We begin our examination of the relationship between local aid disbursements and conflict incidents as the outcome with a simple specification not relying on any control variables. We will then add space and time fixed effects, as well as unit specific time trends to eliminate omitted variable bias without having to rely on other conditioning factors. In the next step, clearly exogenous controls, for instance related to climate, are added. Finally, we add lagged versions of important but potentially endogenous ("bad") controls. Country times year fixed effects are included in the last two specifications. Including them eliminates a lot of variation and asks a subtly different question: conditional on the whole country being in conflict are not in a particular year, how has the disbursement of aid payments in the last year affected the likelihood of a region to be in conflict this year.

3.1 Instrumental Variable approach

The potential endogeneity of results reported in the aid conflict literature is a serious concern for the interpretation of the results. Time-variant omitted variables, like economic or political shocks at the regional level might both trigger aid inflows as well as animosities. Additionally, donors might tend to reduce or increase aid disbursements to conflict-affected regions depending on their allocation targets. Recently, different studies offered convincing strategies to tackle these endogenity concerns. For instance, Crost et al. (2014) used regional differences in passing the eligibility thresholds of a development program in the Philippines to assess the impact of financial transfers on conflict probability in a Regression Discontinuity

[8] Lagged control variables are used in order to avoid that these are affected by our main independent variable, development aid.

Design. Of course the previously reported results might be subject to endogeneity concerns. In another influential study Nunn and Qian (2014) suggest an instrumental variable, which is based on exogenous weather shocks in the US interacted with recipient's probability to receive US food aid, to assess the impact of US food aid on conflict for a broad set of recipients. While these study address endogeneity only for one single country (Crost et al., 2014) or can only estimate impacts on an aggregate national level (Nunn and Qian, 2014) our paper analyses the effect of development aid on sub-national regions in a broad set of low income countries.

Table 1: Descriptive statistics

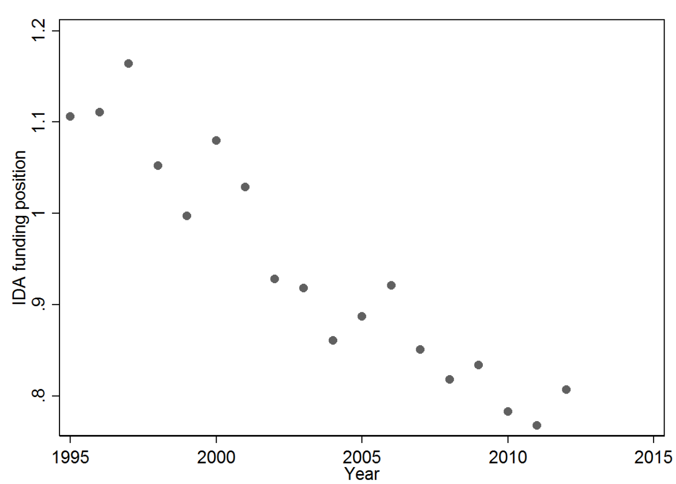
	Observations	Mean	Standard Deviation	Min	Max
Panel A: ADM1					
Conflict (BRD>5)	25,286	8.72	28.22	0.00	100.00
Conflict (BRD>25)	25,286	5.67	23.12	0.00	100.00
Aid p.c.	25,286	5.24	224.235	-0.010	23595.85
Ln (Aid)	25,286	-2.677	2.514	-10.011	10.068
Panel B: ADM2					
Conflict (BRD>5)	219,787	2.42	15.36	0.00	100.00
Conflict (BRD>25)	219,787	1.14	10.59	0.00	100.00
Aid p.c.	219,787	1.10	21.22	-0.01	4510.313
Ln (Aid)	219,787	-4.17	1.56	-9.35	8.41

Descriptive statistics for our main variables. The sample period is 1995-2012, where aid refers to IDA disbursements per capita and ln(Aid) is based on aid+0.01USD.

Our identification approach builds on a proxy exogenous variation in the yearly availability of IDA resources - IDA's funding position - which is defined by the World Bank as "the extent to which IDA can commit to new financing of loans, grants and guarantees given its financial position at any point in time and whether there are sufficient resources to meet undisbursed commitments of loans and grants" (World Bank 2015). The World Bank publicly discloses this measure on a yearly basis in its annual financial report since the year 2008. As our panel starts in 1995, we rely on a reconstructed time series by Dreher et al. (2017) who use the World Bank's own guidance on how this indicator is calculated. More specifically, based on the World Bank's reports the authors sum the "Bank's net investment portfolio and its non-negotiable, noninterest-bearing demand obligations (on account of members' subscriptions and contributions) and then divide this figure by the sum of the Bank's undisbursed commitments of development credits and grants."

We then interact this time-varying variable with $prob_{ir,t}$, the probability that a region receives aid. The latter is computed by dividing the years of positive aid receipts in the region over the past number of years in our panel. The main or constituent term which is included in the second stage of all regressions captures the probability, and we exploit only the interaction term as an instrument. This is a difference-in-difference design. It rests on the fact that the exogenous fluctuation in the IDA position affects regions differently depending on their past likelihood to have received aid. We expect that regions would have a higher likelihood in the past also profit to a larger degree from more available funds than regions, which not received any or very small amounts of development finance. Such an effect is supported by anecdotal evidence, for instance from interviews of recipient country personnel administering World Bank projects.

It is exogenous to our outcome, regional conflict incidence, as the likelihood is pre-determined and an individual region has no substantial effect on the IDA position. Regarding the timing, we have to take into account that the World Bank's fiscal year ends in June. This means that aid disbursements in t-1 are affected and correlated with the position in t, t-1 and t -2. It is also possible that there is a certain time lag between a change in the position and the receipt of aid. Accordingly, our main specification uses the interactions between the past probability and the position in t-2, t-1 and t. Using only the probability in t-1 is a viable alternative and also works well in first stage estimations. What is important in this DiD setting is the common trend assumption. As an indication of whether this is violated, we also include a lead term in one specification. The insignificant and small coefficient for the lead variable (t+1) supports our notion that one individual region cannot influence the overall IDA position and that changes are not anticipated.



Note: Yearly values of $IDA - Position_t$ based on Dreher et al. (2017).

Figure 3: Marginal Effects

4 Results

Table 2 shows the results for the first order administrative level and the two measures of conflict incidence. Column one shows that for both measures the simple correlation is strongly positive and highly significant. One percent more aid relates to a 0.68 (.43) percent higher likelihood of conflict at the 5 (25) deaths threshold. Column 2 adds country and year fixed effects. This already decreases the size of the coefficients by about one half or more. Column 3 adds country specific linear and quadratic time trends capturing conflict dynamics at the country level, and continent times year fixed effects capturing continent specific conflict dynamics in a flexible way. This increases the point estimates to some degree, but has no substantive effect on the significance of the results.

Column 4 is very important as it demonstrates the importance of controlling for regional specific characteristics. It adds region fixed effects which control for any time-invariant district specific characteristics like terrain, suitability for agriculture, or average climate. In this specification, the positive correlation suggesting that a indeed fuels conflict suddenly turns negative. It is significant only for the second conflict incidence measure, and signals that a 1% increase in aid would decrease conflict likelihood by 15 and 24%.

Column 5 and 6 then add the exogenous time-varying control variables as well as time-invariant factors like elevation or location interacted with year fixed effects. The intention here is that the former are clearly exogenous but potentially relevant for conflict, and that the latter interactions allows for instance that the location of a region could play a different role at different points in time. The effect of adding these variables is a further decrease towards a more negative and conflict-reducing point estimate. Adding linear region specific time trends strongly decreases the point estimates, which also both clearly turn insignificant.

Column 7 includes lagged values of several potentially important control variables. Development level, population, and the geo-referenced size of World Bank's IBRD loans that a region receives. IBRD loans usually include subsidized interest payments and are intended to bridge countries shifting from IDA help to borrowing money. To some extent surprisingly, this has very little effect on the point estimates. For both measures of conflict incidence the coefficients are negative but far from any conventional levels of statistical significance.

Finally, columns 8 and 9 control for country times year fixed effects. As outlined above, this controls for the fact whether a country as a whole is experiencing a conflict in a certain year. The coefficients are accordingly trying to measure the effect using only within-country variation in aid disbursements and within-country variation in conflict. In both specifications, the point estimates differ only to a very small extent compared to the estimates not using these fixed effects. Adding lagged potentially endogenous controls in column 9 also has very little effect, and the coefficients are not statistically significant in both specifications.

Table 3 turns to the second order administrative division as the unit of analysis. The pattern of specifications is exactly identical to the analysis of the first order division. The pattern of results is also to a large degree comparable. The simple correlation, and even the specification including country and year fixed effects indicate a conflict increasing effect of aid. In column 2, 10% more aid is related to 2% higher likelihood of a small-scale conflict, and 0.8% higher likelihood of a medium-scale conflict.

Again, the coefficients turn negative once we condition on the region fixed effects, which captures time-invariant region specific characteristics. The estimates become statistically insignificant and significantly smaller in magnitude once we condition on the exogenous controls and linear regional trends. Further adding country times year fixed effects only slightly affects the point estimates, which are always far above conventional levels of statistical significance. Accordingly, neither the ADM1 or ADM2 level results support a significant effect of World Bank project aid on conflict.

Table 2: ADM1 results (clustering at country-year and regional level)

Panel A: Intensity 1	b/se	b/se	b/se	b/se	b/se	b/se	b/se	b/se	b/se
$ln(aid)_{t-1}$	0.6774***	0.3691**	0.4517**	-0.1436	-0.1839	-0.0930	-0.1050	-0.1162	-0.1112
	(0.2616)	(0.1802)	(0.1878)	(0.1487)	(0.1567)	(0.1788)	(0.1746)	(0.1872)	(0.1866)
Panel B: Intensity 2	b/se	b/se	b/se	b/se	b/se	b/se	b/se	b/se	b/se
$ln(aid)_{t-1}$	0.4289**	0.1376	0.1841	-0.2377*	-0.3014**	-0.1734	-0.1797	-0.2185	-0.2177
	(0.2045)	(0.1510)	(0.1544)	(0.1259)	(0.1320)	(0.1417)	(0.1383)	(0.1485)	(0.1485)
Country FE	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time Trends	No	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Region FE	No	No	No	Yes	Yes	Yes	Yes	Yes	Yes
Exogeneous Controls	No	No	No	No	Yes	Yes	Yes	Yes	Yes
Exogeneous*Time Controls	No	No	No	No	Yes	Yes	Yes	Yes	Yes
Linear Regional Trends	No	No	No	No	No	Yes	Yes	Yes	Yes
Lagged Endogeneous Controls	No	No	No	No	No	No	Yes	No	Yes
Country-Year FE	No	No	No	No	No	No	No	Yes	Yes

The table displays regression coefficients with standard errors in parantheses. Standard errors are clustered at the level of country-year and regional unit. The sample period is 1996-2012 for a sample of developing countries around the world. Time Trends include linear and squared country specific time trend and continental and continent times time fixed effects.

Table 3: ADM2 results (clustering at country-year and regional level)

Panel A: Intensity 1	b/se	b/se	b/se	b/se	b/se	b/se	b/se	b/se	b/se
$ln(aid)_{t-1}$	0.6657***	0.1959***	0.0726	-0.1520**	-0.1815***	0.0139	0.1824	-0.0195	0.1991
	(0.1596)	(0.0739)	(0.0596)	(0.0614)	(0.0689)	(0.0697)	(0.1726)	(0.0736)	(0.1696)
Panel B: Intensity 2	b/se	b/se	b/se	b/se	b/se	b/se	b/se	b/se	b/se
$ln(aid)_{t-1}$	0.3128***	0.0758*	0.0405	-0.1169***	-0.1430***	-0.0412	0.0285	-0.0742	0.0624
	(0.0795)	(0.0390)	(0.0351)	(0.0447)	(0.0497)	(0.0556)	(0.0623)	(0.0611)	(0.0678)
Country FE	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time Trends	No	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Region FE	No	No	No	Yes	Yes	Yes	Yes	Yes	Yes
Exogeneous Controls	No	No	No	No	Yes	Yes	Yes	Yes	Yes
Exogeneous*Time Controls	No	No	No	No	Yes	Yes	Yes	Yes	Yes
Linear Regional Trends	No	No	No	No	No	Yes	Yes	Yes	Yes
Lagged Endogeneous Controls	No	No	No	No	No	No	Yes	No	Yes
Country-Year FE	No	No	No	No	No	No	No	Yes	Yes

The table displays regression coefficients with standard errors in parantheses. Standard errors are clustered at the level of country-year and regional unit. The sample period is 1996-2012 for a sample of developing countries around the world. Time Trends include linear and squared country specific time trend and continental and continent times time fixed effects.

Of course, despite the large amount of fixed effects, time trends and control variables, these estimates can still be upward or downward biased. To get a rough estimate of this, we turn to a model including lead terms of the treatment variable. The next specification shown in Table 4 (ADM1 level) and Table 5 thus includes aid disbursements in t and t+1 as well. We show results for the strictest specifications from the table above, two without and two with country-times-year fixed effects. In all specifications, the lead term is a negative and rather large in size. This could be taken as an indication that the World Bank anticipates future conflict and is less likely to disperse money to regions at the brink of conflict. The coefficients are, however, only statistically significant in the first specification. At the second order administrative unit the coefficients are small and none of the lead terms is statistically significant. Overall, there are no strong signs of selection bias, if anything our estimates could be biased a bit against finding a significant relationship as aid seems marginally less likely to flow in regions with higher conflict likelihood.

Table 4: ADM1 Pre-Trends results, (clustering at country-year and regional level)

Panel A.1: Intensity 1				
Pre-Trends	b/se	b/se	b/se	b/se
$ln(aid)_{t+1}$	-0.3419**	-0.2702	-0.2528	-0.2534
	(0.1570)	(0.1749)	(0.1814)	(0.1820)
$ln(aid)_t$	0.0328	0.0287	0.0457	0.0465
	(0.1678)	(0.1846)	(0.1851)	(0.1851)
$ln(aid)_{t-1}$	0.0062	-0.0091	-0.0022	0.0034
	(0.1793)	(0.1959)	(0.2073)	(0.2073)
Panel A.2: Intensity 2				
Pre-Trends	b/se	b/se	b/se	b/se
$ln(aid)_{t+1}$	-0.2748**	-0.2055	-0.1724	-0.1694
	(0.1305)	(0.1401)	(0.1365)	(0.1366)
$ln(aid)_t$	-0.0385	-0.0310	0.0807	0.0856
	(0.1324)	(0.1451)	(0.1540)	(0.1542)
$ln(aid)_{t-1}$	-0.0892	-0.0873	-0.1848	-0.1874
	(0.1337)	(0.1466)	(0.1623)	(0.1620)
Exogeneous Controls	No	Yes	Yes	Yes
Exogeneous*Time Controls	No	Yes	Yes	Yes
Linear Regional Trends	No	Yes	Yes	Yes
Lagged Endogeneous Controls	No	No	No	Yes
Country-Year FE	No	No	Yes	Yes

The table displays regression coefficients with standard errors in parantheses. Standard errors are clustered at the country-year and respective region level. The sample period is 1996-2012 for a sample of developing countries around the world. All regressions control for country FE, year FE, Region FE and Linear Time Trends, which include linear continental and country specific time trend and squared country specific time trend. The exogenous variables include ..., the time-invariant variables are ..., and the endogenous variables are .

Table 5: ADM2 Pre-Trends results, (clustering at country-year and regional level)

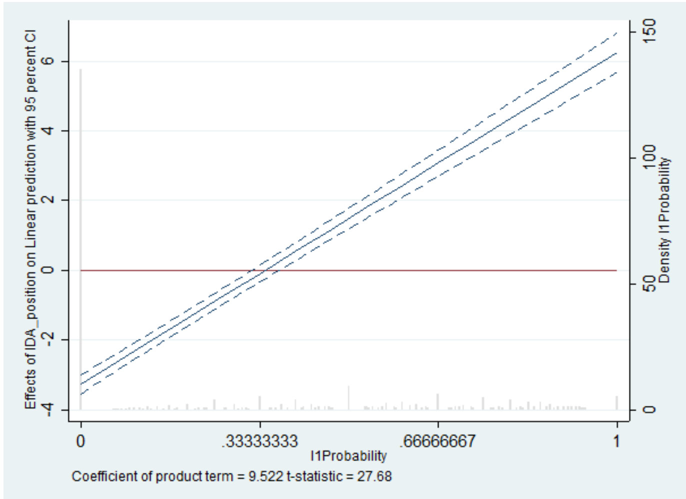
Panel A.1: Intensity 1				
Pre-Trends	b/se	b/se	b/se	b/se
$ln(aid)_{t+1}$	-0.0559	-0.0203	-0.0408	-0.0672
	(0.0856)	(0.0816)	(0.0990)	(0.1723)
$ln(aid)_{t}$	-0.0515	-0.0398	-0.0583	0.1580
	(0.1077)	(0.1265)	(0.1488)	(0.1824)
$ln(aid)_{t-1}$	-0.1063	0.0196	0.0607	0.0963
	(0.0980)	(0.1060)	(0.1215)	(0.2143)
Panel A.2: Intensity 2				
Pre-Trends	b/se	b/se	b/se	b/se
$ln(aid)_{t+1}$	-0.0575	-0.0481	-0.0494	0.0710
	(0.0591)	(0.0610)	(0.0610)	(0.1512)
$ln(aid)_{t}$	-0.0207	-0.0265	-0.0956	0.1419
	(0.0721)	(0.0802)	(0.0764)	(0.1258)
$ln(aid)_{t-1}$	-0.0966	-0.0330	0.0319	-0.0333
	(0.0639)	(0.0746)	(0.0764)	(0.1296)
Exogeneous Controls	No	Yes	Yes	Yes
Exogeneous*Time Controls	No	Yes	Yes	Yes
Linear Regional Trends	No	Yes	Yes	Yes
Lagged Endogeneous Controls	No	No	No	Yes
Country-Year FE	No	No	Yes	Yes

The table displays regression coefficients with standard errors in parantheses. Standard errors are clustered at the country-year and respective region level. The sample period is 1996-2012 for a sample of developing countries around the world. All regressions control for country FE, year FE, Region FE and Linear Time Trends, which include linear and squared country specific time trend and continental and continent times time fixed effects. The exogenous variables include ..., the time-invariant variables are ..., and the endogenous variables are .

4.1 Instrumental variable results

Nonetheless, we take this as the starting point to further examine the causal relationship between the aid disbursements and conflict using the instrumental variables strategy outlined above. Our strategy relies on fluctuations in the World Bank's IDA position, which are exogenous to any individual region in a particular year, and influence regions differently conditional on their past likelihood to receive projects.

Table 6 shows the first stage results using the three instrumental variables described above. We can see that a positive deviation in the IDA position benefits regions that ex ante had a higher probability to receive World Bank projects profit more. This is also graphically visible in Figure 5. When considering aid disbursement per capita as the dependent variable, this holds for the IDA position in t-2, as well as for the positions in the t-1, and in t. Remember that t includes the half of the fiscal year t-1, which

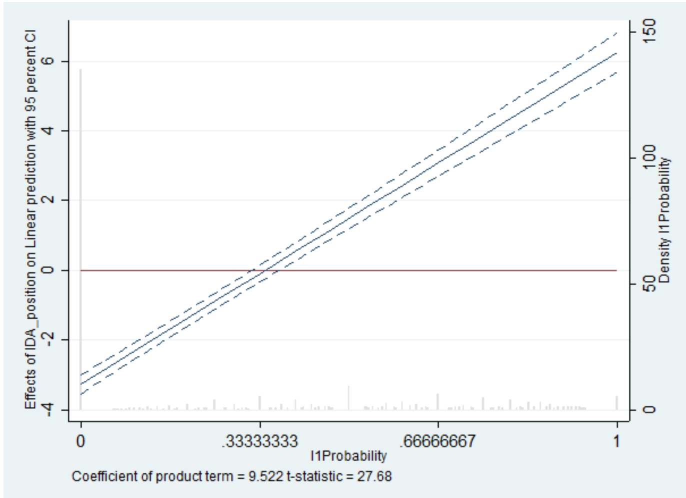


Note: Marginal effects of global $IDA - Position_t$ conditional on probability to receive IDA funds in previous years.

Figure 4: Marginal Effects

explains the positive effect on aid in t-1. The Appendix shows that a potentially problematic lead term in t+1 is insignificant. This is reassuring, and supports the visual inspection of the variation in the IDA position shown in figure 3. It becomes apparent that the fluctuations seem to be rather random in nature between consecutive years, which would enable us to identify an exogenously induced causal effect.[9]

[9] There seems to be a downward trend over time. The first stage relationship that we exploit is robust to using a de-trended version of the IDA position. The interaction term in t-1 is still positive and significant.



Note: Marginal effects of global $IDA - Position_t$ conditional on probability to receive IDA funds in previous years.

Figure 5: Marginal Effects

All interaction terms used as instruments in the first stage are not only positive but also highly significant, in almost all cases at the 1% level. The first stage also works well when including country times year fixed effects, which shows that changes in the IDA position even affect regions differently, when conditioning on within country-year variation. The instruments seem to be working well, and the Kleibergen-Paap underidentification test p-value always rejects the null hypothesis (shown in Table 8 and 9). The weak identification F-statistic is always above the rule of thumb value of 10, in almost all cases much higher with values above 30.

Accordingly, we turn to the second stage results for the first and second-order administrative level next. For the ADM1 level, the instrumented coefficient is negative and insignificant in the first specification, and turns positive and the second specification controlling for exogenous factors and linear region specific time trends. When including country times year fixed effects, the point estimates become a bit more positive, but still far away from conventional levels of statistical significance. The results look a bit different when considering the second-order administrative level. The point estimates become more negative in the second compared to the first specification. Moreover, the coefficient of aid turns significant at the 5%-level in the second specification. 10% more aid leads to 3.6% less medium scale conflict. When adding country times year fixed effects, the estimates remain negative, and again significant for medium scale conflict, now at the 1%-level. The additions of the potentially endogenous controls including IBRD loans turns the sign of the coefficient and leads to statistical insignificance. Overall, no clear pattern emerges. Some of the point estimates are negative, and some are positive, but not in a systematic way. Due to the fact that

Table 6: ADM1 IV results, First stage (clustering at country-year and regional level)

ADM1				
IV First stage: IDA Position	b/se	b/se	b/se	b/se
$IDA\_position_t \times prob_{t-2}$	9.2665***	15.6508***	14.2570***	14.2235***
	(1.5765)	(1.8905)	(2.5722)	(2.5554)
$IDA\_position_{t-1} \times prob_{t-2}$	1.8710	6.3968***	8.2904***	8.3089***
	(1.7568)	(1.7921)	(2.3531)	(2.3454)
$IDA\_position_{t-2} \times prob_{t-2}$	5.7875***	11.3579***	12.4705***	12.4521***
	(1.6288)	(1.8353)	(2.3778)	(2.3767)
Exogeneous Controls	No	Yes	Yes	Yes
Exogeneous*Time Controls	No	Yes	Yes	Yes
Linear Regional Trends	No	Yes	Yes	Yes
Lagged Endogeneous Controls	No	No	No	Yes
Country-Year FE	No	No	Yes	Yes

The table displays regression coefficients with standard errors in parantheses. Standard errors are clustered at the country-year and respective region level. The sample period is 1996-2012 for a sample of developing countries around the world. All regressions control for country FE, year FE, Region FE and Linear Time Trends, which include linear and squared country specific time trend and continental and continent times time fixed effects. The exogenous variables include ..., the time-invariant variables are ..., and the endogenous variables are . * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table 7: ADM2 IV results, First stage (clustering at country-year and regional level)

ADM2				
IV First stage: IDA Position	b/se	b/se	b/se	b/se
$IDA\_position_t \times prob_{t-2}$	7.9018***	16.8973***	17.2546***	11.3607***
	(2.0195)	(2.2362)	(2.4709)	(4.3422)
$IDA\_position_{t-1} \times prob_{t-2}$	4.8112*	11.7412***	12.1675***	4.9978
	(2.4538)	(2.4208)	(2.6944)	(3.9909)
$IDA\_position_{t-2} \times prob_{t-2}$	4.2101**	12.8125***	11.8305***	10.5840***
	(2.1096)	(2.3672)	(2.6445)	(3.1497)
Exogeneous Controls	No	Yes	Yes	Yes
Exogeneous*Time Controls	No	Yes	Yes	Yes
Linear Regional Trends	No	Yes	Yes	Yes
Lagged Endogeneous Controls	No	No	No	Yes
Country-Year FE	No	No	Yes	Yes

The table displays regression coefficients with standard errors in parantheses. Standard errors are clustered at the country-year and respective region level. The sample period is 1996-2012 for a sample of developing countries around the world. All regressions control for country FE, year FE, Region FE and Linear Time Trends, which include linear and squared country specific time trend and continental and continent times time fixed effects. The exogenous variables include ..., the time-invariant variables are ..., and the endogenous variables are . * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

the instruments work well, being individually highly significant in the first stage, and yielding convincing F-statistics, insignificant results should not be attributable to weak instruments but the absence of a significant effect. As the only two statistically significant coefficients at the second-order administrative level point towards aid lowering conflict incidence, this is strong evidence that World Bank projects are

Table 8: ADM1 IV results, second stage

Panel A.1: Intensity 1				
IV: IDA Position	b/se	b/se	b/se	b/se
$ln(aid)_{t-1}$	-0.0257	0.3229	0.4699	0.4518
	(0.7046)	(0.7100)	(0.6712)	(0.6729)
Kleibergen-Paap underidentification test p-value	0.000	0.000	0.000	0.000
Kleibergen-Paap weak identification F-statistic	45.976	47.680	36.479	36.301
Panel A.2: Intensity 2				
IV: IDA Position	b/se	b/se	b/se	b/se
$ln(aid)_{t-1}$	-0.1995	0.1387	0.1450	0.1510
	(0.5800)	(0.5557)	(0.5271)	(0.5247)
Exogeneous Controls	No	Yes	Yes	Yes
Exogeneous*Time Controls	No	Yes	Yes	Yes
Linear Regional Trends	No	Yes	Yes	Yes
Lagged Endogeneous Controls	No	No	No	Yes
Country-Year FE	No	No	Yes	Yes
Kleibergen-Paap underidentification test p-value	0.000	0.000	0.000	0.000
Kleibergen-Paap weak identification F-statistic	45.976	47.680	36.479	36.301

The table displays regression coefficients with standard errors in parantheses. Standard errors are clustered at the country-year and respective region level. All regressions control for country FE, year FE, Region Fe and Linear Time Trends, which include linear and squared country specific time trend and continental and continent times time fixed effects. The exogenous variables include ..., the time-invariant variables are ..., and the endogenous variables are . * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table 9: ADM2 IV results, Second stage

Panel A.1: Intensity 1				
IV: IDA Position	b/se	b/se	b/se	b/se
$ln(aid)_{t-1}$	0.2780	-0.2026	-0.3002	0.6777
	(0.3070)	(0.2618)	(0.2763)	(0.8166)
Kleibergen-Paap underidentification test p-value	0.000	0.000	0.000	0.000
Kleibergen-Paap weak identification F-statistic	44.347	46.710	44.798	11.469
Panel A.2: Intensity 2				
IV: IDA Position	b/se	b/se	b/se	b/se
$ln(aid)_{t-1}$	-0.0051	-0.3646**	-0.4472***	0.4242
	(0.1860)	(0.1653)	(0.1732)	(0.3774)
Exogeneous Controls	No	Yes	Yes	Yes
Exogeneous*Time Controls	No	Yes	Yes	Yes
Linear Regional Trends	No	Yes	Yes	Yes
Lagged Endogeneous Controls	No	No	No	Yes
Country-Year FE	No	No	Yes	Yes
Kleibergen-Paap underidentification test p-value	0.000	0.000	0.000	0.000
Kleibergen-Paap weak identification F-statistic	44.347	46.710	44.798	11.469

The table displays regression coefficients with standard errors in parantheses. Standard errors are clustered at the country-year and respective region level. All regression control for country FE, year FE, Region FE and Linear Time Trends, which include linear and squared country specific time trend and continental and continent times time fixed effects. The exogenous variables include ..., the time-invariant variables are ..., and the endogenous variables are . * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

not fueling aid in the average recipient country.

5 Conclusion and further steps

Our paper uses geocoded data on aid projects and disbursements by three major donors to reassess the relationship between development aid and conflict incidence. With the help of the recently collected and digitized data on World Bank, Chinese and Indian projects we are able to compute disbursements at the first and second-order sub-national administrative level. Combining these data with local conflict measures from UCDP GED, we open up the black box relating to aid and conflict in most existing studies. This is important from both a scientific and political perspective today more than ever. Generally, billions of dollars are spent on development aid per year. In times of the refugee crisis in Europe politicians across countries call for even more development aid to fight poverty as the source of migratory movements (even though the relationship is more complex than usually assumed by politicians). Although some share of this is driven by political motivations (Dreher and Kreibaum, 2016), a large share also pursues the aim to improve the situation in receiving countries. Although the empirical analysis has concentrated on US food aid, Nunn and Qian (2014)'s contribution has raised serious concerns about conflict as an unexpected negative consequence of aid.

Conceptually, our results highlight how important it is to consider the distribution and local disbursements of development aid. Region specific unobserved variation seems to be crucial in explaining the relationship between aid and conflict. Similarly, properly accounting for different time trends and in some specifications country times year fixed effects helps us to eliminate omitted variable bias. Using specifications with a pre-trend suggest that the World Bank as a donor might anticipate future conflict risk and disburse less aid to those regions being more exposed. As this could potentially lead to a biased estimation, we also exploit exogenous fluctuations in the World Bank's IDA position, which benefit regions differently depending on the past likelihood to receive projects. Using this interaction term as an instrumental variable also yields no signs of a systematic conflict-fueling effect of aid. If anything, some specifications suggest a negative conflict-de-escalating effect.

With the current level of results, this is already a strong sign that the result in Nunn and Qian (2014) might be quite specific to US food aid and the particular assumptions in the identification strategy. At the moment, we are running the same estimations using data on China and India as the two most important bilateral emerging donors. This will further help to shed light on the aid-conflict relationship. Moreover, we will analyze different types of conflict, continents separately, inequality in aid distribution, as well as the role of ethnic groups and ethnic aid inequality.

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Appendix

A Data Appendix

To do: Add information on controls; Write some words on general background of data sources. E.g., coding rules

ADM regions

For our administrative boundaries, we build on the GADM dataset constructed by Hijmans et al. (2012). One difficulty with these data is that for some countries including several small island states like Cape Verde, but also mor populous nations like Armenia more fine grained administrative distinctions are missing. As the size of administrative regions is not fixed by size across countries, we assume in this cases that our ADM1 regions would be ADM2 regions.

We use only data with precision codes 1-4, but drop observations, which are only attributed to regions larger than ADM1. These comprise USD 35 bn, which approximately equals one third of the USD 112 bn. disbursed by IDA during the years 1995-2012.

Development Aid data

For our analysis we draw on the "World Bank IBRD-IDA, Level 1, Version 1.4.1" provided by the AidData consortium, which covers all approved loans under the IBRD-IDA lending line between 1995 and 2014. These data correspond to project aid disbursed from 5684 projects in 61243 locations. The data build on information provided by the World Bank, including the disbursement dates, project sectors and disbursed values. These values were deflated to 2011 values. In an effort to allow for more fine-grained analysis of aid projects, AidData's coders filtered the location names from aid project documentation and assigned these to specific locations including latitude and longitude. However, for some projects, which had a more policy or regulation oriented purpose, it was only possible to assign an administrative level (e.g., ADM1 or ADM2 regions). One challenge arises due to this multitude of locations, where it was not possible to derive a distinct value of disbursements. In this regard, we suggest four solutions.

First, we allocate disbursements by the number of locations. In line with previous research by Dreher and Lohmann (2015) we assume that aid is distributed equally across locations and allocate aid proportionally to the locations per region (ADM, ethnic regions or grid cell). For instance, for a project with 10 locations, where 4 locations are in region A and 6 locations are in region B, 40% of project disbursements would be accounted in region A and 60% in region B.

Second, we calculate population weighted disbursements.ere we assume that aid is allocated based on the regional population shares. For instance, if a project would have project locations in two regions of a country, where two million inhabitants would reside in region A and three million would reside in region B, 40% of project disbursements would be accounted in region A and 60% in region B. Here, the aid attribution formula would write as follows: $Aid_{pijt} = \frac{Aid_{pit}}{\int Population_{pi}} * Population_{pj}$, where again p is the project, i is the country, j is the region and t is the period for which we estimate the allocation shares. *Third*, as a robustness check we only focus on the aid projects, which had disbursements in one specific region, e.g., we drop the projects with disbursements in multiple regions. This way we can put more confidence in the exact amount of the disbursements in a given region, at the cost of leaving a lot of variation in aid flows unexplained.

Fourth, aid projects are usually not disbursed within one singly payment, but are rather split across longer periods. The World Bank provides for each project data on the date of disbursements. We make use of this feature and construct instead of the monetary disbursements a count variable of all positive aid disbursements over all projects in a given region. We assume that all locations are part of a disbursement and do not apply further location or population based weighting.

In addition to this different geographic allocation mechanisms, we also make use of the information provided on sectoral distribution of project disbursements by the World Bank. Here we assume constant sectors shares accross all locations of a project. These sectors range from "Agriculture, fishing, and forestry" over "Health and other social services" to "Industry and Trade”.

Finally, our dataset comprises development finance from IBRD and IDA. However, only IDA disbursements can be classified as Official Development Assistance. What is more, our identification strategy of passing the IDA eligibility threshold is only relevant for IDA disbursements, but not IBRD disbursements. For this purpose, we use additional data by the World Bank, which provides information on the financier for each disbursement for each project. Based on these information disbursements were disentangled into IDA and IBRD disbursements.

Conflict data

As Aid data and UCDP use the same coding framework, we can make use of similar coding rules and use likewise only observations, which are coded at least at the ADM2 level (precision code 1,2,3,4).

Again for the more precise data (precision code 1 and 2), we use a point to polygon analysis on the ADM level and a nearest polygon analysis for the ethnic group level. As one conflict event is always coded in one discernible location (Program, 2015), we do not need to make additional distributional assumptions by location number or population size for conflict data, because we do not face issues of multiple project locations, which we had in the aid data. Yet, for conflict observations on the ADM1 level (precision code 4), we distribute battle related deaths by population weights and round the number of casualties. Again, we use population and area shares to allocate observations from administrative entities to ethnic homelands.

Analoguously, to the disbursement count indicator, we construct a count variable for the incidences / conflict events.

What is more, for our measure of ethnic conflicts, we rely on ACD2EPR data by (Cederman, Vogt?), who classify a group as ethnically supported by three dimesions: (i) the group claims to fight one specific ethnic group, (ii) it recruits from one specific ethnic group and (iii) has support from one specific ethnic group. If one group has all these three characteristics, we classify it as enjoying ethnic support. We make use of this classification to code conflict episodes with an ethnic dimension, when at least one of the involved conflict parties fulfills these three dimensions.

Controls from PRIO Grid

One great feature is the availability of control variables on various geo located dimensions by the PRIO grid. As its name indicates data is only available on a geographic grid level. In order to transform these observations to regional aggregates, we use averages of the grid cells by regional entities.

For instance, five grid cells would have their centroid within an ADM1 region. If now two of these five grid were characterised by ethnic exclusion, we would code this region as a 0.4.

2017-08-03: Test output

Table 10: ADM1 results (clustering at regional level)

Panel A: Intensity 1	b/se	b/se	b/se	b/se	b/se	b/se	b/se	b/se	b/se
$ln(aid)_{t-1}$	0.6774***	0.3691**	0.4517**	-0.1436	-0.1839	-0.0930	-0.1050	-0.1162	-0.1112
	(0.1614)	(0.1552)	(0.1803)	(0.1331)	(0.1400)	(0.1535)	(0.1505)	(0.1670)	(0.1667)
Panel B: Intensity 2	b/se	b/se	b/se	b/se	b/se	b/se	b/se	b/se	b/se
$ln(aid)_{t-1}$	0.4289***	0.1376	0.1841	-0.2377**	-0.3014**	-0.1734	-0.1797	-0.2185	-0.2177
	(0.1291)	(0.1324)	(0.1529)	(0.1150)	(0.1222)	(0.1227)	(0.1213)	(0.1342)	(0.1343)
Country FE	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time Trends	No	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Region FE	No	No	No	Yes	Yes	Yes	Yes	Yes	Yes
Exogeneous Controls	No	No	No	No	Yes	Yes	Yes	Yes	Yes
Exogeneous*Time Controls	No	No	No	No	Yes	Yes	Yes	Yes	Yes
Linear Regional Trends	No	No	No	No	No	Yes	Yes	Yes	Yes
Lagged Endogeneous Controls	No	No	No	No	No	No	Yes	No	Yes
Country-Year FE	No	No	No	No	No	No	No	Yes	Yes

The table displays regression coefficients with standard errors in parantheses. Standard errors are clustered at the level of the respective cross-sectional unit. Linear Time Trends include: Linear continetal and country specific time trend and squared country specific time trend.

Table 11: ADM2 results (clustering at regional level)

Panel A: Intensity 1	b/se	b/se	b/se	b/se	b/se	b/se	b/se	b/se	b/se
$ln(aid)_{t-1}$	0.6657***	0.1959***	0.0726	-0.1520***	-0.1815***	0.0139	0.1824	-0.0195	0.1991
	(0.0559)	(0.0472)	(0.0466)	(0.0462)	(0.0530)	(0.0598)	(0.1637)	(0.0595)	(0.1646)
Panel B: Intensity 2	b/se	b/se	b/se	b/se	b/se	b/se	b/se	b/se	b/se
$ln(aid)_{t-1}$	0.3128***	0.0758**	0.0405	-0.1169***	-0.1430***	-0.0412	0.0285	-0.0742	0.0624
	(0.0345)	(0.0305)	(0.0297)	(0.0342)	(0.0392)	(0.0455)	(0.0587)	(0.0454)	(0.0631)
Country FE	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time Trends	No	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Region FE	No	No	No	Yes	Yes	Yes	Yes	Yes	Yes
Exogeneous Controls	No	No	No	No	Yes	Yes	Yes	Yes	Yes
Exogeneous*Time Controls	No	No	No	No	Yes	Yes	Yes	Yes	Yes
Linear Regional Trends	No	No	No	No	No	Yes	Yes	Yes	Yes
Lagged Endogeneous Controls	No	No	No	No	No	No	Yes	No	Yes
Country-Year FE	No	No	No	No	No	No	No	Yes	Yes

The table displays regression coefficients with standard errors in parantheses. Standard errors are clustered at the level of the respective cross-sectional unit. Linear Time Trends include: Linear continetal and country specific time trend and squared country specific time trend.

Table 12: ADM1 Reduced Form results, (clustering at country-year and regional level)

Panel A.1: Intensity 1				
Reduced Form: IDA Position	b/se	b/se	b/se	b/se
$IDA\_position_t \times prob_{t-2}$	3.0051	4.3615	-7.3776	-7.3561
	(14.0533)	(16.8472)	(17.7336)	(17.8081)
$IDA\_position_{t-1} \times prob_{t-2}$	-7.2004	-4.4244	20.7893	20.5571
	(15.8049)	(16.4594)	(18.3539)	(18.3116)
$IDA\_position_{t-2} \times prob_{t-2}$	2.6421	8.1954	0.1065	-0.3483
	(15.4990)	(18.1641)	(15.9780)	(16.0281)
Panel A.2: Intensity 2				
Reduced Form: IDA Position	b/se	b/se	b/se	b/se
$IDA\_position_t \times prob_{t-2}$	0.9200	2.3495	-16.0531	-16.1816
	(10.5710)	(12.3286)	(13.6113)	(13.6377)
$IDA\_position_{t-1} \times prob_{t-2}$	-8.0011	-1.2667	22.4094	22.6555
	(13.0197)	(13.6662)	(14.8941)	(14.8728)
$IDA\_position_{t-2} \times prob_{t-2}$	3.1975	2.9406	-2.8661	-2.7990
	(11.2459)	(12.9051)	(11.5042)	(11.5498)
Exogeneous Controls	No	Yes	Yes	Yes
Exogeneous*Time Controls	No	Yes	Yes	Yes
Linear Regional Trends	No	Yes	Yes	Yes
Lagged Endogeneous Controls	No	No	No	Yes
Country-Year FE	No	No	Yes	Yes

The table displays regression coefficients with standard errors in parantheses. Standard errors are clustered at the level of the respective cross-sectional unit. All regression control for country FE, year Fe, Region Fe and Linear Time Trends, which include linear contineNtal and country specific time trend and squared country specific time trend. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table 13: ADM2 Reduced Form results, (clustering at country-year and regional level)

Panel A.1: Intensity 1				
Reduced Form: IDA Position	b/se	b/se	b/se	b/se
$IDA\_position_t \times prob_{t-2}$	6.8591	3.0898	-3.0649	19.9306
	(7.1523)	(7.8797)	(7.7920)	(20.5377)
$IDA\_position_{t-1} \times prob_{t-2}$	-5.7089	-8.5542	-2.0098	-4.7280
	(7.3473)	(8.1925)	(8.0658)	(16.2519)
$IDA\_position_{t-2} \times prob_{t-2}$	3.2431	-2.9542	-8.1273	2.0273
	(6.2619)	(7.1142)	(7.0701)	(14.1749)
Panel A.2: Intensity 2				
Reduced Form: IDA Position	b/se	b/se	b/se	b/se
$IDA\_position_t \times prob_{t-2}$	0.5589	-4.9697	-5.1212	0.1532
	(4.6677)	(5.6553)	(5.6505)	(4.0221)
$IDA\_position_{t-1} \times prob_{t-2}$	-11.5676**	-14.5629***	-11.3509***	2.1444
	(4.7805)	(5.4296)	(4.2466)	(2.7577)
$IDA\_position_{t-2} \times prob_{t-2}$	11.2176**	5.3014	-1.4405	8.5025
	(4.4601)	(5.1470)	(4.7400)	(7.5293)
Exogeneous Controls	No	Yes	Yes	Yes
Exogeneous*Time Controls	No	Yes	Yes	Yes
Linear Regional Trends	No	Yes	Yes	Yes
Lagged Endogeneous Controls	No	No	No	Yes
Country-Year FE	No	No	Yes	Yes

The table displays regression coefficients with standard errors in parantheses. Standard errors are clustered at the level of the respective cross-sectional unit. All regression control for country FE, year Fe, Region Fe and Linear Time Trends, which include linear contineNtal and country specific time trend and squared country specific time trend. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table 14: ADM1 Pre-Trends results, (clustering at regional level)

Panel A.1: Intensity 1				
Pre-Trends	b/se	b/se	b/se	b/se
$ln(aid)_{t+1}$	-0.3419***	-0.2702*	-0.2528	-0.2534
	(0.1221)	(0.1402)	(0.1688)	(0.1691)
$ln(aid)_t$	0.0328	0.0287	0.0457	0.0465
	(0.1302)	(0.1472)	(0.1747)	(0.1747)
L.(aid)	0.0062	-0.0091	-0.0022	0.0034
	(0.1422)	(0.1575)	(0.1754)	(0.1758)
Panel A.2: Intensity 2				
Pre-Trends	b/se	b/se	b/se	b/se
$ln(aid)_{t+1}$	-0.2748***	-0.2055*	-0.1724	-0.1694
	(0.1047)	(0.1158)	(0.1292)	(0.1291)
$ln(aid)_t$	-0.0385	-0.0310	0.0807	0.0856
	(0.1028)	(0.1156)	(0.1477)	(0.1480)
$ln(aid)_{t-1}$	-0.0892	-0.0873	-0.1848	-0.1874
	(0.1152)	(0.1238)	(0.1367)	(0.1370)
Exogeneous Controls	No	Yes	Yes	Yes
Exogeneous*Time Controls	No	Yes	Yes	Yes
Linear Regional Trends	No	Yes	Yes	Yes
Lagged Endogeneous Controls	No	No	No	Yes
Country-Year FE	No	No	Yes	Yes

The table displays regression coefficients with standard errors in parantheses. Standard errors are clustered at the level of the respective cross-sectional unit. All regression control for country FE, year Fe, Region Fe and Linear Time Trends, which include linear contineNtal and country specific time trend and squared country specific time trend.

Table 15: ADM2 Pre-Trends results, (clustering at regional level)

Panel A.1: Intensity 1				
Pre-Trends	b/se	b/se	b/se	b/se
$ln(aid)_{t+1}$	-0.0559	-0.0203	-0.0408	-0.0672
	(0.0550)	(0.0666)	(0.0668)	(0.1352)
$ln(aid)_t$	-0.0515	-0.0398	-0.0583	0.1580
	(0.0692)	(0.0817)	(0.0825)	(0.2463)
$ln(aid)_{t-1}$	-0.1063*	0.0196	0.0607	0.0963
	(0.0638)	(0.0747)	(0.0780)	(0.2271)
Panel A.2: Intensity 2				
Pre-Trends	b/se	b/se	b/se	b/se
$ln(aid)_{t+1}$	-0.0575	-0.0481	-0.0494	0.0710
	(0.0383)	(0.0466)	(0.0507)	(0.1359)
$ln(aid)_t$	-0.0207	-0.0265	-0.0956*	0.1419
	(0.0467)	(0.0540)	(0.0557)	(0.1086)
$ln(aid)_{t-1}$	-0.0966**	-0.0330	0.0319	-0.0333
	(0.0462)	(0.0542)	(0.0574)	(0.1231)
Exogeneous Controls	No	Yes	Yes	Yes
Exogeneous*Time Controls	No	Yes	Yes	Yes
Linear Regional Trends	No	Yes	Yes	Yes
Lagged Endogeneous Controls	No	No	No	Yes
Country-Year FE	No	No	Yes	Yes

The table displays regression coefficients with standard errors in parantheses. Standard errors are clustered at the level of the respective cross-sectional unit. All regression control for country FE, year Fe, Region Fe and Linear Time Trends, which include linear contineNtal and country specific time trend and squared country specific time trend.

Table 16: ADM1 Reduced Form results, (clustering at regional level)

Panel A.1: Intensity 1				
Reduced Form: IDA Position	b/se	b/se	b/se	b/se
$IDA\_position_t \times prob_{t-2}$	3.0051	4.3615	-7.3776	-7.3096
	(11.6203)	(14.8037)	(19.4236)	(19.4366)
$IDA\_position_{t-1} \times prob_{t-2}$	-7.2004	-4.4244	20.7893	22.7209
	(10.8321)	(12.2857)	(17.2728)	(18.6147)
$IDA\_position_{t-2} \times prob_{t-2}$	2.6421	8.1954	0.1065	-0.4430
	(10.5031)	(13.4941)	(14.8229)	(14.9107)
Panel A.2: Intensity 2				
Reduced Form: IDA Position	b/se	b/se	b/se	b/se
$IDA\_position_t \times prob_{t-2}$	1.2479	2.2555	-16.0531	-16.1816
	(9.7292)	(11.7424)	(15.8383)	(15.8693)
$IDA\_position_{t-1} \times prob_{t-2}$	-7.6059	-1.4078	22.4094	22.6555
	(10.4249)	(11.6500)	(15.4504)	(15.4338)
$IDA\_position_{t-2} \times prob_{t-2}$	3.3352	2.9292	-2.8661	-2.7990
	(8.3100)	(10.5027)	(12.3174)	(12.3671)
Exogeneous Controls	No	Yes	Yes	Yes
Exogeneous*Time Controls	No	Yes	Yes	Yes
Linear Regional Trends	No	Yes	Yes	Yes
Lagged Endogeneous Controls	No	No	No	Yes
Country-Year FE	No	No	Yes	Yes

The table displays regression coefficients with standard errors in parantheses. Standard errors are clustered at the level of the respective cross-sectional unit. All regression control for country FE, year Fe, Region Fe and Linear Time Trends, which include linear contineNtal and country specific time trend and squared country specific time trend. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table 17: ADM2 Reduced Form results, (clustering at regional level)

Panel A.1: Intensity 1				
Reduced Form: IDA Position	b/se	b/se	b/se	b/se
$IDA\_position_t \times prob_{t-2}$	6.8591	3.0898	-3.0649	20.0533
	(5.5197)	(6.3046)	(6.8429)	(19.5780)
$IDA\_position_{t-1} \times prob_{t-2}$	-5.7089	-8.5542	-2.0098	-8.4029
	(4.5574)	(5.7107)	(6.4440)	(15.4436)
$IDA\_position_{t-2} \times prob_{t-2}$	3.2431	-2.9542	-8.1273	1.9139
	(4.2132)	(5.1777)	(5.7593)	(12.3950)
Panel A.2: Intensity 2				
Reduced Form: IDA Position	b/se	b/se	b/se	b/se
$IDA\_position_t \times prob_{t-2}$	0.8691	-4.9791	-5.1212	0.1532
	(3.7299)	(5.0202)	(5.7249)	(5.7037)
$IDA\_position_{t-1} \times prob_{t-2}$	-11.0178***	-14.5868***	-11.3509**	2.1444
	(3.5874)	(4.2421)	(4.5555)	(6.1423)
$IDA\_position_{t-2} \times prob_{t-2}$	11.3468***	5.2942	-1.4405	8.5025
	(3.2688)	(4.0561)	(4.4991)	(8.1869)
Exogeneous Controls	No	Yes	Yes	Yes
Exogeneous*Time Controls	No	Yes	Yes	Yes
Linear Regional Trends	No	Yes	Yes	Yes
Lagged Endogeneous Controls	No	No	No	Yes
Country-Year FE	No	No	Yes	Yes

The table displays regression coefficients with standard errors in parantheses. Standard errors are clustered at the level of the respective cross-sectional unit. All regression control for country FE, year Fe, Region Fe and Linear Time Trends, which include linear contineNtal and country specific time trend and squared country specific time trend. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table 18: ADM1 IV results, First stage (clustering at regional level)

ADM1				
IV First stage: IDA Position	b/se	b/se	b/se	b/se
$IDA\_position_t \times prob_{t-2}$	9.2665***	15.6508***	14.2570***	14.2235***
	(0.7236)	(0.9169)	(1.3071)	(1.3038)
$IDA\_position_{t-1} \times prob_{t-2}$	1.8710***	6.3968***	8.2904***	8.3089***
	(0.6027)	(0.6868)	(0.8887)	(0.8887)
$IDA\_position_{t-2} \times prob_{t-2}$	5.7875***	11.3579***	12.4705***	12.4521***
	(0.6389)	(0.8565)	(1.0469)	(1.0482)
Exogeneous Controls	No	Yes	Yes	Yes
Exogeneous*Time Controls	No	Yes	Yes	Yes
Linear Regional Trends	No	Yes	Yes	Yes
Lagged Endogeneous Controls	No	No	No	Yes
Country-Year FE	No	No	Yes	Yes

The table displays regression coefficients with standard errors in parantheses. Standard errors are clustered at the level of the respective cross-sectional unit. All regressions control for country FE, year Fe, Region Fe and Linear Time Trends, which include linear continetal and country specific time trend and squared country specific time trend. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table 19: ADM1 IV results, Second stage (clustering at regional level)

Panel A.1: Intensity 1				
IV: IDA Position	b/se	b/se	b/se	b/se
$ln(aid)_{t-1}$	-0.0257	0.3229	0.4699	0.4518
	(0.6481)	(0.6301)	(0.6915)	(0.6934)
Kleibergen-Paap underidentification test p-value	0.000	0.000	0.000	0.000
Kleibergen-Paap weak identification F-statistic	84.704	137.150	91.052	90.183
Panel A.2: Intensity 2				
IV: IDA Position	b/se	b/se	b/se	b/se
$ln(aid)_{t-1}$	-0.1995	0.1387	0.1450	0.1510
	(0.5346)	(0.5015)	(0.5434)	(0.5429)
Exogeneous Controls	No	Yes	Yes	Yes
Exogeneous*Time Controls	No	Yes	Yes	Yes
Linear Regional Trends	No	Yes	Yes	Yes
Lagged Endogeneous Controls	No	No	No	Yes
Country-Year FE	No	No	Yes	Yes
Kleibergen-Paap underidentification test p-value	0.000	0.000	0.000	0.000
Kleibergen-Paap weak identification F-statistic	84.704	137.150	91.052	90.183

The table displays regression coefficients with standard errors in parantheses. Standard errors are clustered at the level of the respective cross-sectional unit. All regressions control for country FE, year Fe, Region Fe and Linear Time Trends, which include linear continetal and country specific time trend and squared country specific time trend. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table 20: ADM2 IV results, First stage (clustering at regional level)

ADM2				
IV First stage: IDA Position	b/se	b/se	b/se	b/se
$IDA\_position_t \times prob_{t-2}$	7.9018***	16.8973***	17.2546***	11.3607***
	(0.5380)	(0.6501)	(0.6991)	(1.9138)
$IDA\_position_{t-1} \times prob_{t-2}$	4.8112***	11.7412***	12.1675***	4.9978***
	(0.5036)	(0.5388)	(0.5447)	(1.2155)
$IDA\_position_{t-2} \times prob_{t-2}$	4.2101***	12.8125***	11.8305***	10.5840***
	(0.5482)	(0.6911)	(0.7306)	(1.3243)
Exogeneous Controls	No	Yes	Yes	Yes
Exogeneous*Time Controls	No	Yes	Yes	Yes
Linear Regional Trends	No	Yes	Yes	Yes
Lagged Endogeneous Controls	No	No	No	Yes
Country-Year FE	No	No	Yes	Yes

The table displays regression coefficients with standard errors in parantheses. Standard errors are clustered at the level of the respective cross-sectional unit. All regressions control for country FE, year Fe, Region Fe and Linear Time Trends, which include linear continetal and country specific time trend and squared country specific time trend. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table 21: ADM2 IV results, Second stage (clustering at regional level)

Panel A.1: Intensity 1				
IV: IDA Position	b/se	b/se	b/se	b/se
$ln(aid)_{t-1}$	0.2780	-0.2026	-0.3002	0.6777
	(0.2794)	(0.1990)	(0.2124)	(0.8166)
Kleibergen-Paap underidentification test p-value	0.000	0.000	0.000	0.000
Kleibergen-Paap weak identification F-statistic	160.593	354.986	345.362	28.413
Panel A.2: Intensity 2				
IV: IDA Position	b/se	b/se	b/se	b/se
$ln(aid)_{t-1}$	-0.0051	-0.3646**	-0.4472***	0.4242
	(0.1792)	(0.1489)	(0.1605)	(0.4371)
Exogeneous Controls	No	Yes	Yes	Yes
Exogeneous*Time Controls	No	Yes	Yes	Yes
Linear Regional Trends	No	Yes	Yes	Yes
Lagged Endogeneous Controls	No	No	No	Yes
Country-Year FE	No	No	Yes	Yes
Kleibergen-Paap underidentification test p-value	0.000	0.000	0.000	0.000
Kleibergen-Paap weak identification F-statistic	160.593	354.986	345.362	28.413

The table displays regression coefficients with standard errors in parantheses. Standard errors are clustered at the level of the respective cross-sectional unit. All regressions control for country FE, year Fe, Region Fe and Linear Time Trends, which include linear continetal and country specific time trend and squared country specific time trend. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table 22: ADM2 IV results, First stage (clustering at country-year and regional level)

Panel A.1:

-Position_t+1	b/se	b/se	b/se	b/se
$IDA\_position_{t+1} \times prob_{t-2}$	3.2588	4.9643*	5.6921	5.6996
	(2.4875)	(2.7121)	(3.8464)	(3.8413)
$IDA\_position_{t} \times prob_{t-2}$	6.9852***	14.6045***	14.0657***	14.0312***
	(2.0190)	(2.2995)	(3.2901)	(3.2800)
$IDA\_position_{t-1} \times prob_{t-2}$	3.2900*	7.2429***	8.9338***	8.9559***
	(1.9695)	(2.0734)	(2.8703)	(2.8614)
$IDA\_position_{t-2} \times prob_{t-2}$	4.3988*	8.9261***	9.9988***	9.9627***
	(2.3531)	(2.4396)	(3.4173)	(3.4180)
T-Test:	(0.0000)	(0.0000)	(0.0000)	(0.0000)

The table displays regression coefficients with standard errors in parantheses. Standard errors are clustered at the level of the respective cross-sectional unit. All regressions control for country FE, year Fe, Region Fe and Linear Time Trends, which include linear continetal and country specific time trend and squared country specific time trend. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. The T-Test in the bottom row displays the p-value for the joint-significance of $IDA - Position_{t,\,t-1,\,t-2}$