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Aid and conflict at the subnational level – Evidence from World Bank and Chinese development projects in Africa

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Abstract:
Using geo-referenced data on development projects by the World Bank and China, we provide a comprehensive analysis of the effect of aid on conflict using fixed effects and instrumental variables strategies. The results show that aid projects seem to reduce rather than fuel conflict, on average. Our analysis suggests that this is driven by projects in the transport and financial sectors, and through less lethal violence by governments against civilians. There are no clear differences based on ethnic fractionalization and government affiliation of a region, but some indications of spill-overs to other regions. We also find no increased likelihood of demonstrations, strikes or riots, but a higher likelihood of non-lethal government repression in areas where China is active.

Keywords: Development Aid, Conflict, Repression, Geolocation, World Bank, China, Africa
JEL Codes: H77, N9

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1 Introduction

According to UNHCR, an unprecedented 65.3 million people are displaced from their homes by war, internal conflicts, natural disasters or poverty. Africa is the continent most affected by this, and while other African countries bear the majority of the burden, developed countries like those in the European Union increasingly feel the impact of instability and conflict through migratory flows. The common reaction to an increased inflow of refugees, besides tougher border controls, is to call for more development aid to reduce poverty and conflicts as the root causes of displacement. While the literature on aid converges towards a small, but mostly positive effect on development outcomes (Dreher et al., 2018; Galiani et al., 2017; Clemens et al., 2011), other studies have raised the question whether in some cases aid might actually fuel instead of pacify conflict (Nunn and Qian, 2014; Child, 2018; Crost et al., 2014, 2016).

Nunn and Qian (2014), for instance, show that US food aid seems to lead to more conflict. Berman et al. (2011) use subnational data to document that only specific types of development projects succeed in reducing conflict in Iraq. Crost et al. (2014) and Crost et al. (2016) show that development projects in the Philippines and Iraq can lead to an increase in conflict. Generally, the existing literature on the relationship between aid and conflict is mostly focusing on the macro country level (Bluhm et al., 2016; Nielsen et al., 2011; Nunn and Qian, 2014) or on specific types of aid in individual countries (Berman et al., 2011; Child, 2018; Crost et al., 2016; Sexton, 2016). Our paper aims to combine the strengths of these existing approaches. We consider a large set of countries in Africa to draw broader implications, but use subnational geo-referenced data to link aid projects and conflict events more precisely. In a situation where fragile, conflict-prone states are described as the "new frontier of development" and many important donors, plan to increase their activities in those countries, this seems a relevant question.[1]

We make three major contributions. First, we cover aid projects in a broad set of developing countries in all of Africa and are able to assign projects locations to specific subnational administrative units (based on Strandow et al., 2011; Strange et al., 2017). This degree of precision in our dataset allows us to flexibly control for a wide range of potentially distorting factors through fixed effects, time trends, and observable region-specific factors. To further reduce endogeneity concerns, we also propose an instrumental variable (IV) strategy that combines spatial variation in the regions' pre-determined likelihood to receive projects with donor-specific temporal variation that is exogenous to conflict in individual regions.

Second, we consider two donors that represent contrasting types of projects and approaches to development. The WB is a multilateral donor that emphasizes scientific expertise, frequently imposes human-right and sustainability conditions, and aims not only at growth but also at social

[1] See The Economist (2017), last accessed 14.06.2018.

and political improvements in destination countries. China, in contrast, is not a member of the OECD's Development Assistance Committee (DAC) and often portrayed as a "rogue" donor (Naím, 2007). It propagates a policy of "non-interference" in the internal affairs of recipient countries and emphasizes economic "mutual benefits." In addition, Chinese economic targets such as securing resource supply are a central part of their aid strategy. Many observers would expect that WB-like aid is less likely to cause conflict, whereas Chinese engagement is often seen more critically and accused of fueling conflict and repression (Raleigh et al., 2010). Being able to thus compare what can be thought of as two extreme ends of the spectrum of aid policies strengthens the external validity of our approach.

Third, we can distinguish between aid projects in various sectors, and between different conflict types and the actors involved. In addition, we can exactly identify the regions within countries where development projects are implemented, and contrast that with the locations where conflicts take place. We match ethnic groups' homelands with administrative regions and combine this with data about the group's status as belonging to the governing coalition or not. This allows us, for instance, to measure whether more aid to regions controlled by the government increases the likelihood of conflict in non-governing coalition regions. Combining spatial data on development projects and conflict actors, thus, allows us to also better test specific mechanisms.

Using subnational data is, hence, not just a matter of more detail and precision, but opens up the opportunity to better understand and distinguish between different theories. There are, generally, two main mechanisms emphasized in the literature linking aid to conflict. On the one hand, the opportunity cost hypothesis claims that higher resources and the associated revenues, as well as higher incomes, make it less likely that people join rebel groups or engage in a conflict (Collier and Hoeffler, 2004; McGuirk and Burke, 2017). On the other hand, resources may be regarded as a price of winning control, and the contest (or rapacity) theory suggests that a higher price sets an incentive to engage into combat (e.g., Grossman, 1992). Still, there are several other possible channels besides these prominent main theories that we describe in more detail below.

To test for a potential effect of aid projects on conflict, we use georeferenced project level data for the WB and China, available due to the efforts of various scholars (see Strandow et al., 2011; Strange et al., 2017; Dreher et al., 2016) associated with AidData. With US$ 13.4 bn disbursed in 2014, the WB's foreign aid arm – the International Development Association (IDA) – is arguably the most important multilateral donor organization in the World (World Bank, 2017). At the same time, China is also continually expanding its development and investment activities. Recently, the "One Belt, One Road" initiative was prominently and controversially discussed, but China's engagement in Africa has already started to expand considerably in the late 1990s.

In order to establish causality, our identification strategy combines pre-determined cross-sectional variation interacted with a conditionally exogenous time series (as in Gehring and Lang, 2018 and Lang, 2016). Similar to Nunn and Qian (2014) and Bluhm et al. (2018), we create this cross-sectional variation by computing the probability that a region receives aid from a donor. Based on Dreher et al. (2017), we use official information on the WB's funding position and Chinese steel (over-)production (World Steel Association, 2014) as temporal variation that is arguably exogenous to conflict in individual region-years when conditioning on regional and country-year fixed effects. The assumptions for this type of instrument are comparable to Bartik and shift-share instruments. They essentially emulate a difference-in-difference approach in the first stage, where we compare the effect of donors' budget expansion on regions with differing pre-determined probabilities.

Our results provide several important insights. Most importantly, the OLS and IV specifications provide no indication that aid fuels conflict on average. For the WB, a 10% increase in aid even seems to reduce the likelihood of a conflict by up to two percentage points. This result becomes insignificant when using an IV specification, however. More surprisingly, there is also no conflict fueling relationship for Chinese aid on average. The point estimates are mostly negative, but close to zero and in almost all cases statistically insignificant with OLS and IV.

Starting from these results, we then investigate heterogeneous effects and examine some hypotheses in more detail. Regarding projects in different sectors, we find a significant negative relationship between projects in the finance sector (WB only), as well as in the transportation sector (WB and China). Aid in no sector is related to significantly more conflict. When considering conflict actors, we find that both WB and Chinese engagement seems to lead to a *reduction* in lethal violence by governments against civilians in the respective regions and years. We also find no evidence of a conflict-fueling effect when considering different levels of aggregation, setting a higher threshold of battle-related deaths for our conflict indicator, or when using the continuous number of deaths instead. Additional specifications related to, among others, spill-overs, the clustering of standard errors, and taking account of ethnic groups expand upon these main results.

Following the main results, we also examine types of conflicts that might remain overlooked with our main outcome variable based on the number of battle-related deaths. Specifically, we consider lower-level types of conflict like demonstrations, riots, and strikes, as well as repression used by governments against the population (from the SCAD dataset). For both donors, we find no positive effect on any of the first three measures. We do, however, find that an increased Chinese engagement leads to an increase in non-lethal government repression.

The paper proceeds as follows. Section 2 summarizes the existing literature and outlines proposed theories linking development finance to conflict. Section 3 explains the data and the corresponding sources and provides descriptive statistics. Section 4 presents the specification and empirical strategy. Section 5 shows and discusses the results, and Section 6 concludes.

2 Existing Literature and theoretical considerations

2.1 Literature and theories

Many papers have linked development aid to conflict in different ways. The underlying theories, if spelled out explicitly, however often make diverse and contradictory predictions. Generally, aid can be considered as a type of windfall income shock, linking this literature to the larger research field on (resource-related) income shocks and conflict (e.g., Berman et al., 2017; Berman and Couttenier, 2015; Caselli et al., 2015; Morelli and Rohner, 2015). The literature then proposes two main mechanisms on how aid affects conflict. The opportunity costs mechanism (e.g., Grossman 1991; McGuirk and Burke 2017) and the contest model (e.g., Hirshleifer 1989, 1995). The first theory hypothesizes that with a rise in income the opportunity costs of fighting increase (McGuirk and Burke, 2017), leading to less conflict on average. Similarly, if aid commitments are withdrawn, e.g., negative aid shocks occur, recipient governments' ability to make credible commitments is weakened and citizens' opportunity costs of engaging into conflict are reduced (Nielsen et al., 2011; Strange et al., 2017). The contest model, or rapacity effect, in contrast, predicts that with higher income the potential gains from fighting increase. This makes fighting more attractive, both for groups as the payoff to "winning" control increases and for individuals, who are offered higher wages for fighting in expectation of higher gains (Collier and Hoeffler, 2004). Considering aid projects and conflict in the same unit of observation can reflect both those channels. This is the main approach of our analysis, resembling Figure 1 a.).

As suggested above, the distributional dimension is important as conflict in many African countries is often best characterized as conflict between opposing groups and coalitions, less often between individuals (Cederman et al., 2009). In many cases, existing tensions between ethnic groups can be amplified or dampened by foreign aid projects. Still, the incentives can be very different in regions controlled by the government or by ethnic groups that are part of the governing coalition, than in other regions. To examine a potential contest effect, where groups "fight" for the prize of holding the government, more accurately, we distinguish between different groups of regions. More specifically, we distinguish between (i) regions controlled by the government, (ii) those being composed of ethnic groups that are not part of the governing coalition, and (iii) mixed or contested regions.

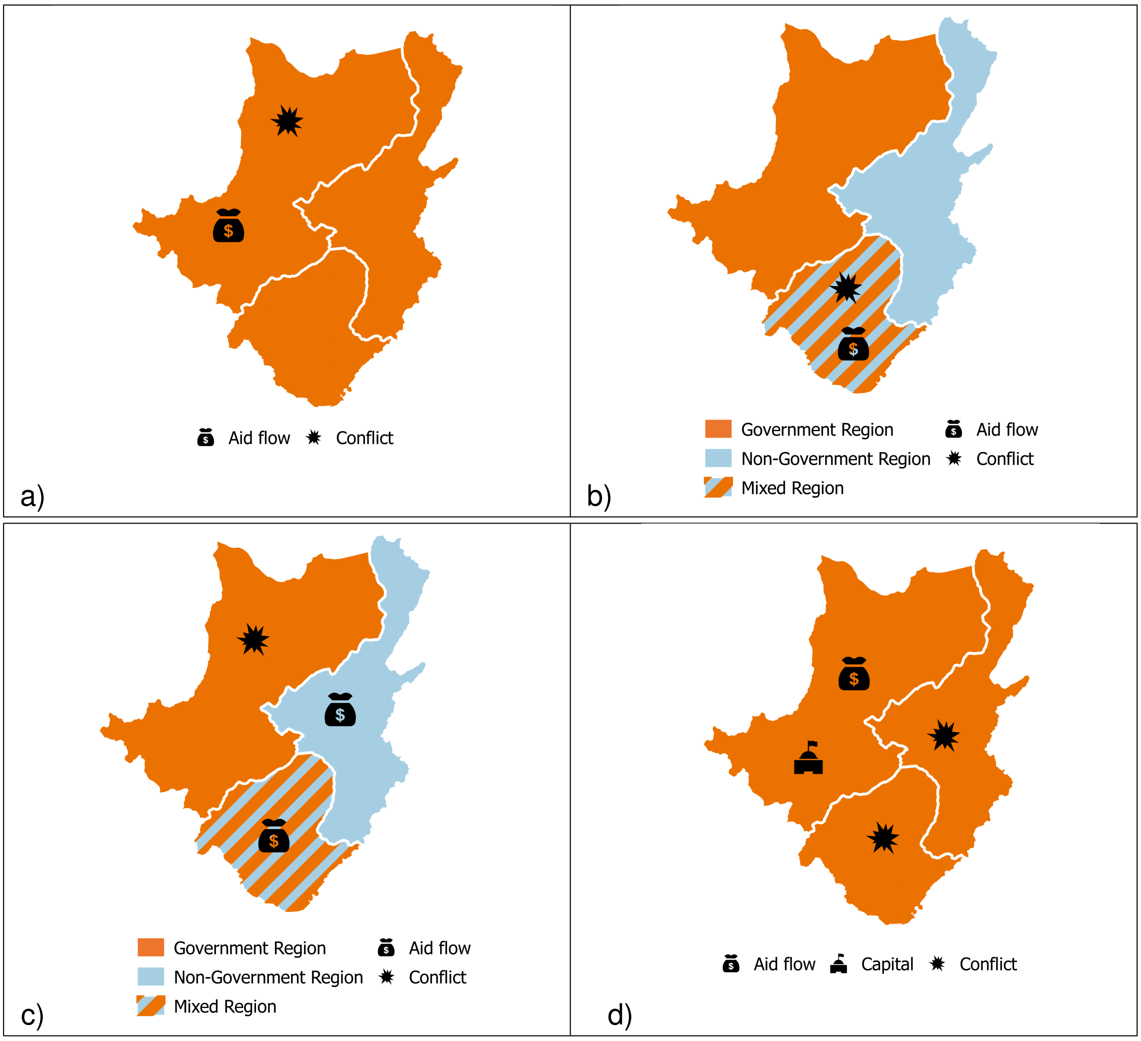


Figure 1: Scenarios linking aid to conflict

Aid is usually controlled by the government and can help to undermine the political power of opposing groups and increase support for the government (Beath et al., 2017). Crost et al. (2014) suggest that rebel groups sabotaged a large community-driven development program in the Philippines anticipating that it might be successful and weaken support for the rebels. Sexton (2016) shows that aid is associated with increases in insurgent violence in contested districts. Figure 1 b.) shows an example of a specification focusing on regions, which are home to ethnic groups with differing power status and, hence, more likely to be contested. Similarly, we can instead also restrict our analysis to government-controlled regions, as Berman et al. (2013) postulate that communities profit from aid projects only in areas controlled by the government.

Nonetheless, our data also allow us to distinguish more nuanced theories and test them empirically. For instance, when considering development aid as a potential price for opposing groups, this would not apply equally to all types of aid. We can distinguish between different aid types, some of them with output that is hard to loot (e.g., a street or bridge) and others making looting more likely (e.g., expensive health equipment in hospitals). The prior literature has also pointed towards an interesting incentive aid can set for recipient governments. In order not to lose aid, they might be more reluctant to engage in conflict actions that appear unnecessary or overly violent to reduce the risk of being shamed at the international stage (Lebovic and Voeten, 2009). We test both hypotheses by considering aid flows specifically to the capital region or regions associated with the governing coalition, and relating those to higher or lower conflict in other regions of the same country (e.g., Figure 1 d.).

Another large strand of the literature revolves around equity questions of local revenues from resources (Morelli and Rohner, 2015). In this regard, the importance of inter-group grievances is stressed, which would particularly play a role in the ethnically diverse sub-Saharan African region (Cederman et al., 2011; Michalopoulos and Papaioannou, 2016; Østby, 2008). To explore this, we test whether the relationship between development projects and conflict differs between highly fractionalized and more homogeneous regions.

Moreover, intra-country spill-over effects are typically not considered. Aid payments in one region might not fuel conflict in the region itself, but increase it in other regions. Again, existing theories provide hypotheses about such a relationship that we can put to an empirical test. For instance, other research emphasized that aid payments are largely fungible. This means that governments that receive health aid might cut their own health expenditures, and use the free funds to bolster military spending. Kishi and Raleigh (2015) suggest that if a country receives Chinese aid, its military increases its violence against civilians (including bombing them).[2] Moreover, the government might use developmental funds to increase its control over minorities' homelands, which could induce backlash effects by the "sons of the soil" (Fearon and Laitin, 2011). The same holds for aid to regions controlled by rebel groups. A higher military capacity by one conflict party can be used to attack regions controlled by rival groups or mixed regions that feature both government-related and other groups. At the same time, a more capable military might make it less likely that the respective other parties dare to attack (see a similar argument in Collier and Hoeffler (2007)). The direction of the net effect is again theoretically unclear. Figure 1 c.) depicts this case for the example of aid flowing mainly to non-coalition regions (and potential rebel groups) and measuring conflict in regions that are part of the governing coalition. Figure 1 d.) depicts this case for the example of aid flowing mainly to the capital and measuring conflict in regions outside the capital.[3]

Returning to the main theories, whether aid succeeds in raising average incomes and, thus, increases opportunity costs is fiercely discussed in the aid effectiveness literature. The results

[2] This is in line with Azam and Hoeffler (2002), who suggest that foreign funds might increase violence against civilians. However, these predictions hold only for aid to war-affected countries, while we consider both peaceful and contested regions.

[3] Further work on the country level also stresses the context specificity of aid (e.g., resource endowments or institutions) as well as its role for conflict dynamics (De Ree and Nillesen, 2009; Bluhm et al., 2016; Strange et al., 2017). We leave those aspectsfor further research on the local level .

converge towards a null on average (Doucouliagos and Paldam, 2009) or only small positive effects (Galiani et al., 2017). This effect, however, depends on whether aid was politically motivated or had a clear development focus (Dreher et al., 2018). Accordingly, whether and to what extent aid projects raise income at the regional level is most likely quite heterogeneous, comprising both negative and positive effects. In that regard, it is interesting to observe differences between China and the WB. The WB is at least perceived by many to have a rather strong development focus.

When comparing the impact of aid projects to the gains from resource-related income shocks (Berman et al., 2017; Gehring and Langlotz, 2018), it becomes clear that in both cases the distribution of gains is also important. Dube and Vargas (2013) show that in the case of Colombia, higher resource prices lowered conflict if the resource was more labor-intensive. However, fueled conflict if it was more capital intensive and the gains most likely accrued only to a small elite. Similarly, there will be groups or people that profit from aid (the money must always go somewhere), but whether these gains are used for short-term consumption, invested in fostering development or ending up in the foreign bank accounts of government officials is unclear.

One aspect where aid differs from other shocks, prominently featured in the literature, is that donors can to some extent impose which conditions and procedures need to be respected during the implementation. Minasyan et al. (2017), for example, demonstrate the importance of donor quality for aid effectiveness and Berman et al. (2013) hypothesize that projects are more successful in reducing violence if they require the integration of development experts. Aid can also be earmarked for certain projects or sectors, for instance generally for infrastructure or specifically for building a particular school or hospital, which is a second conceptual difference compared to other windfall income gains. Berman et al.'s (2011) analysis of development projects in Iraq, for instance, suggests that only a small share and specific types of projects have a conflict-reducing effect.

Considering donors that reflect the different ends of the distribution along those dimensions, can crucially contribute to evaluating the effect of aid on conflict more systematically than the existing literature. The next section explains shortly why the WB and China differ consistently with regard to (i.) the use of conditionality, (ii.) the use of development expert knowledge, and (iii.) the focus of their projects.

2.2 Two types of donors: China vs. the WB

The WB mostly reflects a model of conditional aid integrating expert knowledge with a clear focus on development, whereas China specifically highlights non-interference, mutual economic benefits, and room to maneuver for the recipient governments. This is visible along three dimensions. First, conditionality is very common and used intensively by the WB. Projects often have a large variety of conditions attached ranging from human rights and democratic procedures to gender equality. Second, the WB employs a large team of academics and country experts with the aim to ensure that aid is spent effectively. Third, WB projects have a rather clear focus on development and supporting particular democratic institutions and civil organizations. Although there is also some political influence on WB decisions (Dreher et al., 2018), their projects are less politically motivated than other types of aid (e.g., Dreher et al., 2009).

The WB's aid arm provided 16.8% of funding of traditional Western donors between 1995 and 2012. This makes IDA the second largest donor after the EU institutions (18.7%) and before UN agencies (6.4%) (OECD, 2017). As mentioned above, there are concrete plans to intensify and scale-up its involvement in conflict-prone regions. For instance, the WB has spent up to 500 million in the Central African Republic, approximately a third of its GDP, to prevent the fragile state from sliding back into civil war. The Kecamatan Development program, which was directed by the WB in cooperation with the Indonesian government, attempts to reduce conflict probability via a transparent and participatory approach (Gibson and Woolcock, 2005; Barron et al., 2011). Nevertheless, WB projects have also been linked to increases in civil unrest and conflict. The construction of the Pak Mun hydroelectric dam in the rural north-east of Thailand, for instance, sparked widespread protests due to complaints that it displaced families, destroyed local fish stocks and wrecked irrigation systems.[4]

China, in contrast, is the most prominent example of an emerging "rogue" donor (Naím, 2007), that is not a member of the OECD's traditional Development Assistance Committee (DAC). It is constantly expanding its activities in Africa, and during the 2000-2012 period, its official development aid (ODA) commitments equaled 17.8% of US' aid commitments (based on OECD, 2017; Strange et al., 2017). When considering ODA and other official finance (OOF) activities USAID and Chinese aid are en par.[5] The latter country is often characterized as ignoring conditions on human rights and good governance practices, in particular by the Western world and media. One example is Ethiopia, where large energy projects allegedly ignored the needs and demands of the local population. As another case in point, China's president has visited and himself welcomed Zimbabwe's former president Mugabe, contrasting efforts of Western donors to sanction the country for electoral fraud and human rights abuses.[6] At another instance, Uganda turned to China to increase its engagement, after Western donors protested against strict "anti-gay" laws in the country.[7] Regarding conditions and focus, the Chinese perspective is to run a policy of

[4] See The Economist, "Rural unrest," last accessed 14.06.2018.

[5] Strange et al. (2017) as cited in Reuters, "New database focuses on China's secretive aid to Africa," last accessed 08.10.2018.

[6] Washington Post, "When China gives aid to African governments, they become more violent," last accessed 26.07.2018.

[7] See The Diplomat, "Uganda Looks to China," last accessed 26.07.2018.

"non-interference" in the internal affairs of recipients, where projects are supposedly often directly offered to state leaders and regimes focusing on economic "mutual benefit." [8] In this regard, Dreher et al. (2016) find that Chinese projects in Africa are more likely to benefit the birth regions of the respective leader, i.e., seem to be allocated less on a need-base. The implementation is in most cases left to a larger degree to the respective partner governments, but at the same time, some projects are reported to be mostly implemented by China and Chinese workers. Labor intensity can crucially influence whether external shocks dampen or fuel conflict, as it is linked to how evenly the gains are distributed (Dube and Vargas, 2013; Gehring and Langlotz, 2018)

In contrast, Western development projects have also been criticized for a lack of "ownership" and missing use of local knowledge in recipient countries. Hence, the Chinese approach can have an upside, which several African countries have also welcomed along with the larger focus on developing common business interests.[9]

Empirically, Dreher et al. (2018) and Fuchs and Vadlamannati (2013) suggest that the degree to which the Chinese government considers demand-side humanitarian and socioeconomic needs is comparable to Western donors. Even though China puts less emphasis on strict human rights conditions, China's increasing focus on humanitarian issues becomes evident in its growing role in UN peacekeeping missions over time and its official aim to "play a constructive role of settling conflicts and hot issues and maintaining peace and security in Africa."[10] What is more, with its expanding activities and larger presence of Chinese employees in Africa, it also has a rising interest in avoiding conflicts that threaten the value of its investments or the life of its citizens.

To sum up, when considering the mechanisms highlighted above, it becomes apparent that almost all of them work at the subnational level, whereas most of the literature operates with national level data. When aggregating both aid and conflict data at the national level most of the postulated conflict theories are indistinguishable from each other. To analyze channels in more detail with the help of subnational data, we differentiate between (i.) different types of aid, (ii.) different actors, (iii.) regional attributes (e.g., fractionalization and power status), (iv.) different spatial aggregations and (v.) spatial spill-overs. We will compare two donors. The WB with its strong use of conditionality and expert knowledge, as well as its clear development focus should theoretically have a low likelihood of leading to conflict. China, in contrast, is the donor that most observers would deem much more likely to fuel conflicts due to the lack of human rights conditions, more leeway for local politicians and a stronger focus on business interests.

[8] David Shinn on Chinausfocus, "Africa Test's China's Non-interference Policy," last accessed 26.07.2018.

[9] Anthony Germain on CBC, "China in Africa: No strings attached," last accessed 12.09.2018.

[10] The Guardian, for instance, postulates that "Chinese aid to Africa is going to come with all sorts of strings attached, despite the "no-conditionality" rhetoric." The Guardian: "The west has no right to criticise the China-Africa relationship". Also reflected in saferworld.org.uk, "China's growing role in African peace and security" and The Guardian, "New report discusses China's role in Africa's conflicts," all last accessed 26.07.2018.

3 Data

3.1 Aid Data

Our unit of observation is the country-region-year, and the unit of analysis is the first level of subnational administrative regions, henceforth ADM1 or regions (data from Hijmans et al., 2010). The names of ADM1 regions vary by country but are commonly known as "provinces" or "states." We choose this as the main unit over lower level administrative regions (ADM2), ethnic groups, or grid-cells. Figure 2 shows that georeferenced projects alone, those that contain latitude and longitude coordinates, comprise only less than 50% of overall projects. Taking projects assigned to ADM2 and ADM1 regions also into account ensures that a reasonable share of total aid is covered.[11] For both China and the WB, this allows us to exploit variation covering over 90% of the overall spending.[12] Note that we capture a lower fraction of projects for China, but these are mostly smaller projects. The first order administrative level is also highly relevant for aid allocation, as many projects are assigned to specific regions, and the regional government can decide how or where to spend the money, which is relevant for conflict outcomes.

Precisely georeferenced projects and projects where we possess information about the ADM2 regions are assigned to the respective ADM1 region. In most cases, projects also have several locations. When processing the project level data, we assume that aid is distributed equally across locations and allocate aid proportionally to the locations per region, which is in line with previous research (Dreher and Lohmann, 2015). For instance, for a project with 10 locations, where four locations are in region A and six locations are in region B, 40% of project volume would be accounted in region A and 60% in region B.[13]

The data appendix provides more details. The remainder with less precise locations is mostly non-geocoded aid accruing directly to the government, which we assign to the capital region in a robustness test when considering potential spill-overs. We show results using the ADM2 regions as a robustness test in the appendix, and incorporate ethnic group homelands by intersecting those with the regions.

[11] The WB officially releases information on its *disbursements*. In contrast, the only opportunity to compile information on Chinese projects is the open source data collection on *commitments*. In line with Dreher et al. (2017), who show that "project duration amounts to 664 days" on average, we take this into account by assuming a two year lag until which Chinese aid projects would become effective.

[12] Figure 6 provides a complimentary overview about the precision coding of locations.

[13] Hence, our aid attribution formula is: $Aid_{pijt} = \frac{Aid_{pit}}{\int Locations_{pi}} * Locations_{pj}$, 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. For robustness, Tables A 51 and 50 also display the main results using population weights. For instance, if a project has project locations in two regions of a country, and two million inhabitants reside in region A and three million in region B, 40% of project funds are allocated to region A and 60% to region B. Here, the aid attribution formula is $Aid_{pijt} = \frac{Aid_{pit}}{\int Population_{pi}} * Population_{pj}$. Our population data build on the gridded population data provided by the Center for International Earth Science Information Network (CIESIN) Columbia University (2016). As global population censuses have to build on strong assumptions and yearly data have to be imputed, this is of course subject to a certain degree of measurement error.

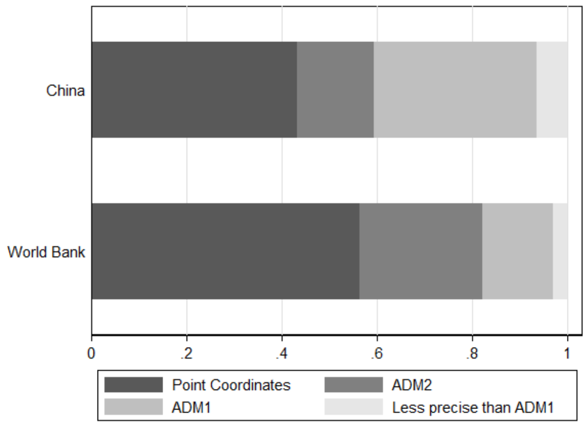


Figure 2: Disbursement/Commitment Amounts by Precision Codes

Table 1 shows a comparison of the two donors in some important dimensions. While information for aid disbursements by WB's IDA is available from 1995 to 2012, information on Chinese aid commitments in Africa is constrained to the years 2000 to 2012.[14] Over the sample period, the WB still outspends China with USD 29.4 bn compared to USD 13.2 bn.[15]

Table 1: Donor Comparison: WB vs. China

	WB Aid	Chinese Aid
Total Disbursements/Commitments (USD):	29.4bn	13.2bn
Active in no. of Countries:	35	41
Number of projects:	1,472	333
Number of locations:	25,041	1,308
Mean number of locations per project	17	4
Mean per project (USD):	19.97m	39.63m
Mean per location (USD):	1.17m	10.09m

Notes: Aid is measured in constant 2011 USD.

Both are active in most African countries, 35 for the WB and 41 for China. They are, thus, mostly active in the same set of countries (Humphrey and Michaelowa, 2018), which adds to the comparability of donors. One interesting difference is that the WB finances a larger number of projects which then also have more locations across countries on average. China finances fewer but larger projects. Accordingly, China spends nearly twice as much per project and nearly ten times as much per project location.

[14] This analysis focuses on Official Development Aid (ODA) flows in contrast to other official finance (OOF). OOF also plays a large role in China's finance portfolio, but has a less development oriented focus. The WB also augments its ODA with the International Bank for Reconstruction and Development (IBRD), which provides development finance in the form of loans with interest rates closer to market rates. However, we expect a clearer relationship between aid and conflict than with less concessionary development finance. One reason is that the domestic government's role in distributing concessionary development aid might increase the risk of distributive conflicts. Moreover, as development finance is acquired on a loan basis, the respective government has to pay it back and, hence, has larger incentives to invest it in a sustainable way.

[15] The WB outspends China also for the shorter 2000 to 2012 period (USD 27.9 bn).

We focus our analysis on the African continent and on countries with more than 1 million inhabitants and include all countries, which were on the OECD's DAC recipient list in the initial year of 1995. The remaining sample comprises 728 ADM1 regions in 45 countries. Table 2 provides summary statistics of our most important analytical variables at the country-region-year level. With regard to the main treatment variables WB and Chinese Aid, it becomes visible that the WB provides higher levels of aid on average (e.g., USD 2.2 million versus USD 1.4 million per region-year). However, the large standard deviation indicates that Chinese aid has a higher degree of variation, with the maximum Chinese spending per region-year being USD 900 million; nearly twice as large as the highest value for the WB. The high project values indicate China's large involvement in mega-projects to fund infrastructure including dams and power plants.

Table 2: Descriptive statistics - ADM1 Region

	Mean	SD	Min	Max
World Bank Aid (USD million)	2.240	8.992	0	488.643
ln(WB Aid)	6	9	-5	20
Chinese Aid (USD million)	1.391	22.843	0	900.000
ln(Chinese Aid)	-4	4	-5	21
Battle Related Deaths	21	342	0	33,417
Conflict Incidence in Percent	12	32	0	100

Notes: Descriptive statistics for our main variables. ln(Aid) is based on aid +0.01USD. The sample period is 1995-2012 for WB IDA and 2000-2012 for Chinese Aid. For Chinese Aid 41 and for the WB Aid 35 recipients are considered respectively.

3.1.1 WB Aid

The dataset from AidData (Strandow et al., 2011) about WB aid disbursements is comprehensive both regarding time, ranging from 1995 to 2012, and regarding project scope. Geocoded disbursements sum up to US$ 29.4 bn. distributed over 1,472 projects in 25,041 locations in Africa. Additionally, AidData provides information on the sectoral allocation of disbursements, enabling us to distinguish potentially differential effects of different aid types on conflict probability and intensity. We focus on disbursements by the WB's IDA, the WB's arm for development aid.

3.1.2 Chinese Aid

Although China is perceived as a major political and economic actor, it was also a recipient of sizeable amounts of development aid until recently. For instance, China only graduated from IDA in 1999 (Galiani et al., 2017). Since the 2000s, China has become a major donor itself and extended its activities especially in Africa, and during the 2000-2012 period, its official development aid

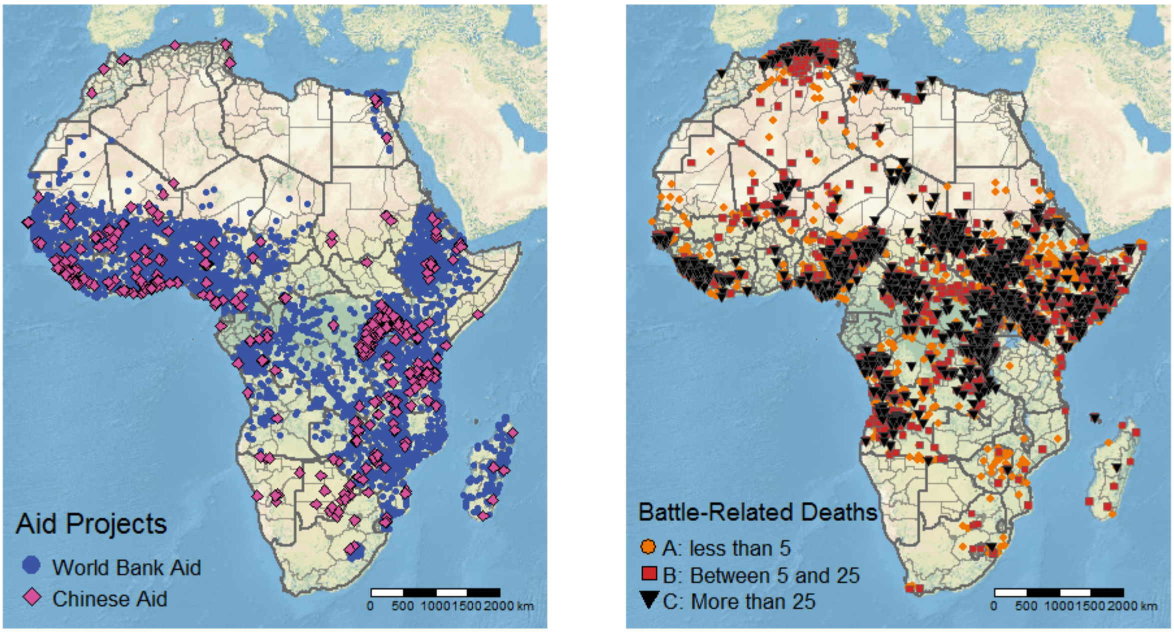
(ODA) and other official finance (OOF) activities were comparable to that of USAID (Strange et al., 2017). However, China does not provide official disaggregated information on aid flows according to the DAC standards. We build on the impressive data collection and geo-localization efforts by Strange et al. (2017) and Dreher et al. (2016), associated with AidData. Those authors compile data on Chinese ODA-like commitments for the years 2000-2012 based on a variety of sources, mostly media reports. In total, these flows amount to USD 13.2 bn from 333 projects in 1308 locations.

3.2 Conflict measures

For our main specification, we rely on the number of battle-related deaths at the regional level based on the Uppsala Conflict Data Program's (UCDP) georeferenced event dataset (GED) (Sundberg and Melander, 2013; Croicu and Sundberg, 2015). Derived from media and NGO reports, as well as secondary sources (e.g., field reports or books), GED provides the most reliable and comprehensive data on incidences of violence including the involved parties, casualties, and location.[16] Table 2 shows that the range of battle-related deaths per region-year varies between 0 and 33,417. The thresholds commonly used in the cross-country literature to identify conflict are not applicable at the smaller regional level. A threshold of 1,000 casualties is too high, but a minimum threshold of just one casualty would be too low and create too much measurement error. Acknowledging the apparent trade-off, we chose 5 (low intensity) as the threshold for our main specifications. We use 25 (medium intensity) as well as the log of battle-related deaths for robustness tests. We use a similar measure from the Social Conflict Analysis Database (SCAD) to evaluate smaller-scale conflict events like demonstrations, strikes or riots and non-lethal government repression (Salehyan et al., 2012).

We depict the geographical distribution of development aid locations for the WB and for China in Figure 3a, as well as the number of experienced conflict years in Figure 3b. Visually examining the overlap between average aid disbursements/commitments and conflict years in these maps is not very informative, as they do not display the temporal order of events. Moreover, we cannot distinguish selection into conflict-prone regions from an effect of aid, as well as account for particular regions being different in unobservable factors that cause them to be large aid recipients and conflict-prone at the same time. Countries that had endured conflict in the past are also more in need of post-conflict aid. WB's IDA, for instance, disbursed 19% of its funds to regions recently suffering from conflict, and China commits about 10% of its project volume to such regions.

[16] An alternative would be the ACLED and PRIO Gridded datasets, which rely on similar primary data as UCDP. One issue with PRIO Gridded data is that neighboring cells in a 50km radius are also coded as conflict-affected, which might lead to erroneous conflict coding of neighboring administrative and ethnic regions (Tollefsen et al., 2012). ACLED is broader in coverage than UCDP data, but is criticized for its ambiguous inclusion criteria and vague geo-coding (Eck, 2012).



(a) (b)

Figure 3: a.) Chinese (2000-2012) and WB (1995-2012) development aid. Authors' depiction based on AidData (2017) and Dreher et al. (2016).
Figure 3 b.) Conflict 1996-2014. Authors' depiction based on Croicu and Sundberg (2015).
Category 1 (binary) = B+C, Category 2 (binary) = C, Category 3 (continuous) = {A, B, C}
Notes: Depicted borders refer to countries (thick line) and first administrative divisions (thin line).

Generally, conflict is widespread and often overlaps with the presence of the two donors. 52% of the WB's IDA resources and 31% of Chinese ODA-like finance are spent in regions that also experience conflict at some point during our observation period.

Overall, there is a lot of variation in aid from both donors, as well as in conflict across and within countries. This variation is crucial for our analysis, which distinguishes between two main types of equations. In the first set, we condition on observables and unobservables through various fixed effects and time trends. For instance, region-fixed effects eliminate within-country differences related to the likelihood of receiving aid and experiencing conflict, which gets lost when aggregating at the national level. For example, Angola appears to receive relatively more aid projects in specific regions, which at the same time experience more conflict. Of course, this is merely one correlation that might be affected by unobserved region-specific factors that make both conflict and receiving aid projects more likely. The second set goes one step further and uses country times year (from now on country-year) fixed effects to rule out an effect of any spurious events at the country-year level affecting conflict and by chance coinciding with changes in aid allocation (e.g., a change in political regime).

3.3 Control Variables

Besides our main variables of interest, we consider several other variables, which are suggested in the literature as determinants of aid allocation or drivers of conflict. Regarding the targeting of development aid, it is interesting to account for the initial regional development. GDP is proxied using nighttime light, as subnational income estimates are scarce and of poor quality in low and lower-middle income states (Henderson et al., 2012). Although lights already capture parts of population density, as indicated by Henderson et al. (2017), we account for regional population taken from the *gridded population of the world* dataset (Center for International Earth Science Information Network (CIESIN) Columbia University, 2016). Population is both a relevant variable in terms of aid allocation as well as in terms of a scale effect for conflict potential (Hegre and Sambanis, 2006).

As a large literature stresses the potentially conflict-inducing effects of windfall gains related to certain resources (e.g., Berman et al., 2017), we control for several natural resource indicators including oil, gold, gemstones as well as narcotics. For this purpose, we use information from the PRIO Gridded data (Tollefsen et al., 2012) and intersect them with the administrative boundaries. This dataset also includes measures on temperature and precipitation, providing us with proxy variables for local income shocks causing conflict (Miguel et al., 2004). To match the gridded data to the respective regional units of observation, we intersect the PRIO-Grid with the countries' regional dimension and calculate area-weighted averages for each region. Finally, we use data from Cederman et al. (2014) and Wucherpfennig et al. (2011) to control for the distribution of ethnic groups, which are often linked to conflict in the literature (Esteban et al., 2012; Michalopoulos and Papaioannou, 2016).

4 Empirical strategy

Aid projects are not randomly allocated. This potential endogeneity of aid project allocation is the concern when studying the relationship between development finance and conflict. Time-varying omitted variables, like economic or political shocks at the regional level can affect both aid inflows and conflict. Additionally, donors might tend to reduce or increase aid targeting to conflict-affected regions depending on their allocation targets, raising issues of reverse causality. We pursue two different empirical strategies. First, we use OLS regressions with varying sets of fixed effects, time trends, and control variables, which allow a transparent examination of the underlying relationship when exploiting different variation in the data. Our detailed subnational dataset exhibits enough variation to allow the use of very restrictive sets of fixed effects and time trends that rule out many concerns raised in the existing literature. Second, we will pursue IV strategies for both donors

4.1 Linear models with fixed effects, time trends and control variables

Our baseline empirical specification is

$$C_{i,c,t} = A_{i,c,t-1/t-2} + \lambda_c + \tau_t + \delta_i + \lambda_c T + \lambda_c T^2 + X^{Ex}_{i,c,t} + \delta_i T + X^{En}_{i,c,t-2} + \kappa_{c,t} + \epsilon_{i,c,t}, \tag{1}$$

where $C_{i,c,t}$ is our conflict indicator of interest in region i, in country c and year t. $A_{i,c,t-1/t-2}$ are the log of per capita aid disbursements/commitments. With regard to the timing, we consider the WB disbursements from the previous year and follow the literature (Dreher et al., 2016, 2017) in using a two year lag for Chinese commitment data.

We will add fixed effects, time trends, and control variables step by step to transparently show how the relationship between conflict and aid changes when eliminating further variation. Fixed effects include λ_c, τ_t, δ_i, which are country, time, and region fixed effects, respectively. Furthermore, we in a first step add country-specific linear $\lambda_c T$ and quadratic time trends $\lambda_c T^2$, and later also regional linear time trends $\delta_i T$, which control for any differing linear conflict trends across regions. Country-year fixed effects $\kappa_{c,t}$ need to be considered carefully, as they eliminate many potentially critical omitted variable problems, but also a lot of variation in the data. In essence, including them asks a subtly different question: conditional on the whole country being in conflict or not in a particular year, how have previous aid payments affected the likelihood of a particular region to be in conflict. For that reason, we will always consider specifications with and without country-year fixed effects.

Regarding control variables, we distinguish between three types of controls. First, controls such as climatic shocks are exogenous and not affected by our treatment variable. Second, we account flexibly for the effect of time-invariant controls like elevation or ruggedness by interacting them with year dummies. These first two sets are contained in $X^{Ex}_{i,c,t}$, as they are not at risk of being bad controls. Third, we lag potential "bad controls" like nighttime light (as a proxy for economic activity) or population, which can be affected directly by aid projects, by two periods. Using "predetermined" values solves the bad control issue if we assume sequential exogeneity. This might be a strong assumption, which is why we show specifications including $X^{En}_{i,c,t-2}$, but do not include those variables in our baseline equations. The error term is denoted as $\epsilon_{ir,t}$.

We cluster 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 component and tend to spill-over. Also allowing for correlation within a region over time is important as conflict also tends to exhibit strong persistence over time. Other potential clustering options are shown in Tables A 49 and 48.

4.2 Instrumental Variable approach

Our IV strategies exploit the heterogenous impact of a plausibly exogenous time-series interacted with a (pre-determined or fixed) cross-sectional difference.[17] The identifying assumption is that in absence of a change in the time series there would be common trends in aid allocation in low and high aid probability recipient regions. As in any Difference-in-Difference (DiD) setup, the first and second stage control for the main constituting terms forming the interaction and only the interaction term is used as the conditionally exogenous instrument. For both the WB and China, we use a cumulative (initial or pre-determined) probability over the whole sample period. This is computed by dividing the number of years a region i had received aid in the past by the number of years passed until period t.[18] Beyond the donor-specific probability, identification strategies for the WB aid and Chinese Aid, hence, differ only in the time-varying factor T_t used to induce variation in project allocations over time.

4.2.1 Instrumenting WB Aid

For the WB, we use exogenous yearly variation in the availability of free IDA resources. This funding position is defined 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" (World Bank, 2015).[19] Starting in 2008, we use the measure publicly disclosed in the annual financial reports. From 1995 to 2008 we rely on the reconstructed time series by Dreher et al. (2017). Thus, the first stage equation has the following form:

$$Aid_{i,c,t-1} = \alpha_1 p_{i,c,t-2} + \alpha_2 IDA_{t-1} + \alpha_3 p_{i,c,t-2} IDA_{t-1} + \epsilon_{i,c,t-1} \tag{2}$$

Figure 4 shows the fluctuations in the indicator. The variation can be caused by internal adjustments, the timing of payments by the shareholders, as well as repayments by large borrowers like India. Conflict in any individual African region cannot plausibly affect the measure to a significant degree. Overall, there is a downward trend, partly caused by some major shareholders failing to

[17] This builds on Nunn and Qian (2014), who exploit temporal variation in US wheat production, which they then interact with the aid recipient's probability to receive US food aid. In essence, this strategy is similar to Bartik instruments used, e.g., in the labor economics literature (Autor et al., 2013) or the shift-share instruments common in the migration literature (Altonji and Card, 1991). In contrast to most Bartik and shift-share instruments, where cross-sectional units differ in many dimensions, e.g., different industry shares or immigrant enclave sizes, the units in our approach differ only along one dimension, the probability to receive aid.

[18] If our sample begins in 1995, and a region received aid in three out of five years, the value of the probability in 1999 would be 0.6. If aid receipts stop in 1999, the probability would decline to 0.5 in 2000 as the country would have received aid in three out of six years. The constant probability used in Nunn and Qian (2014) or Bluhm et al. (2018) relies on all observed treatment values per unit, i.e., the term for region i in year t also depends on the values in $t+1, t+2, \ldots$. These future values can themselves be a function of conflict. Nizalova and Murtazashvili (2016) show that under certain assumptions the interaction of an exogenous variable with an endogenous variable can be interpreted as exogenous when controlling for the endogenous factor (in this case the constant probability). Nonetheless, using initial or pre-determined values minimizes endogeneity concerns.

[19] The idea is based on Lang (2016) and Gehring and Lang (2018), who employ such a supply-push identification approach using variation in the IMF's liquidity.

deliver on payments promised before. However, despite the general decline, the indicator also fluctuates strongly between the years. For instance, it initially increases between 1996 and 1997, before it falls sharply in the following years.

We then interact this time-varying variable with $p_{i,c,t}$, the probability of a region receiving aid. Regions with a higher likelihood to receive aid in the past seem to profit more if there are additional funds available.[20] Thus, we expect a positive interaction term in the first stage.[21]

4.2.2 Instrumenting Chinese Aid

There is no exact equivalent to the IDA's funding position for Chinese aid. Instead, $T_{i,c,t}$ is a time series on production in the country's over-sized steel sector (World Steel Association, 2009, 2014). The production level was shown to affect the overall amount of Chinese aid as China would commit to more aid projects to clear markets and protect domestic companies from potential losses (Dreher et al., 2016). These projects are often large-scale infrastructure projects (Bräutigam, 2011), but Bluhm et al. (2018) show that steel production also induces variation in other sectors (social, education or health) beyond roads and railways. China is also generally known as engaging in "mega-deals" (Strange et al., 2017), which are generally larger than WB projects. Thus, the local average treatment effect based on the variation induced by the IV is rather representative of China's aid activities. The time series itself is hardly influenced by any individual region in Africa, and we control for the main effect in the second stage. Our instrument is, as for the WB, the interaction with the region-specific prior (or initial) cumulative probability to receive Chinese aid. Based on the existing literature, We expect that (over-)production benefits regions with a low prior probability more, as China apparently expands its activities to new regions. The first stage equation for Chinese aid has the following form:

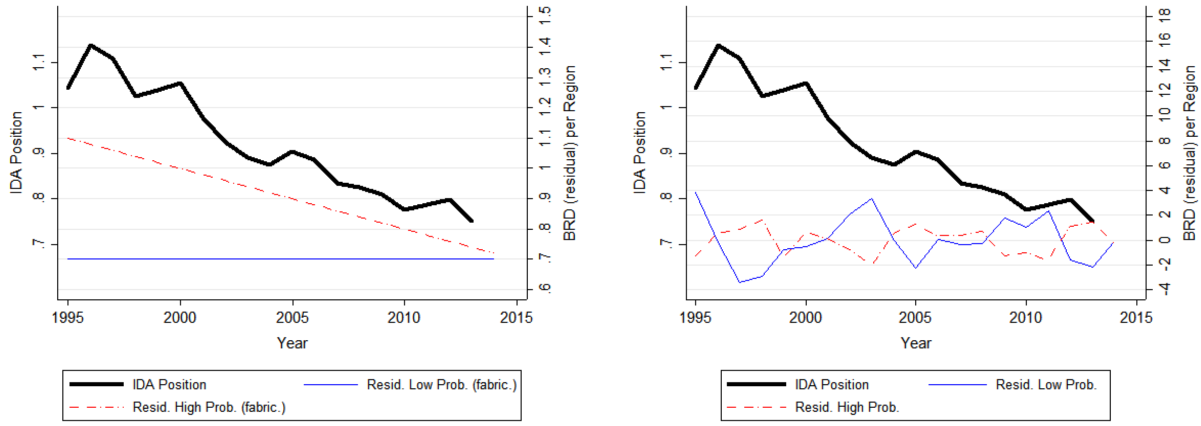
$$Aid_{i,c,t-2} = \alpha_1 p_{i,c,t-3} + \alpha_2 Steel_{t-3} + \alpha_3 p_{i,c,t-3} Steel_{t-3} + \epsilon_{i,c,t-2} \tag{3}$$

One potential issue is a long-term upward trend in Chinese steel (over-)production and the fact that there is less year-on-year variation than in the WB funding position. This linear trend increases the risk of picking up trends in other variables that differ between high and low probability regions and overlap with the conflict trends, one of the concerns raised by Christian and Barrett (2017). For that reason, we de-trend the time series for our main specification. We show results without de-trending in a robustness test; in practice, this transformation makes little difference.

[20] This was confirmed in informal talks with WB and recipient country staff.

[21] Because the WB's fiscal year ends in June, the reported position in the fiscal years t and t-1 can both affects disbursements in t-1. Using only the position in t-1 is a viable alternative and also works well in first stage estimations, which is demonstrated in Table A20. Using both fiscal years t and t-1 to compute the funding position appears more coherent and is applied subsequently.

4.2.3 Examining the first stages



(a) Mean BRD: Problematic trends

(b) Mean BRD: Actual trends

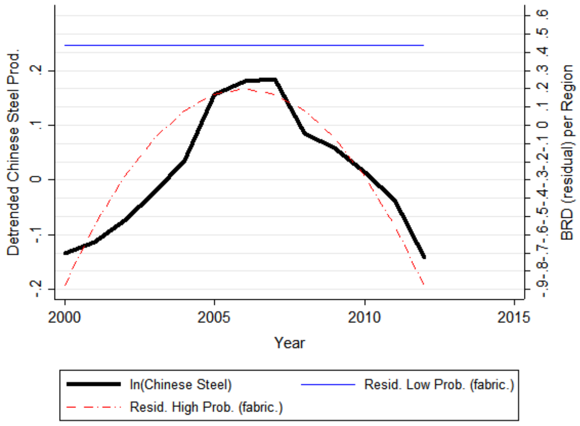
Figure 4: WB: IDA funding position and Battle-Related Deaths for low and high probability regions.

Note: Figure 4 (a) displays the running average of the IDA Funding Position (thick line), fabricated trends in the mean battle-related deaths per low probability recipient regions (thin line) and in the mean battle-related deaths per high probability recipient regions (dashed line). Figure 4 (b) displays the IDA Funding Position (thick line), the mean residual of the battle-related deaths per low probability recipient regions (thin line) and the mean residual of the battle-related deaths per high probability recipient regions (dashed line). The residuals refer to the underlying variation used in our preferred specification from column (4) in Table 3.

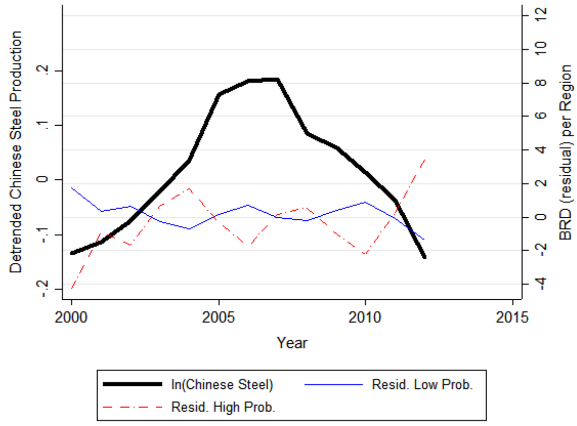
In order to illustrate potentially problematic variation causing biased estimates of aid on conflict as suggested by Christian and Barrett (2017), the left-hand side of Figures 4 and 5 shows the time series that we use, along with manually fabricated trends in conflict in low and high probability regions. This illustrates a potentially problematic case as the trends for high probability regions overlap with the long-term trends of the IDA funding position or the detrended steel production. On the right-hand side, we show the actual residual variation net of fixed effects and time trends in the outcome and the instrumental variables that we exploit in our estimations. There is no clear overlap between long-term trends in the time series variables and outcomes in either low or high probability regions, in particular when considering the residual variation used in our subsequent analysis.[22]

Goldsmith-Pinkham et al. (2018) describe the potential risks and caveats of similar IV strategies and highlighted the importance of considering differences in the cross-sectional units and emphasize the need to consider whether the first stage is driven by only a few observations or outliers. Christian and Barrett (2017) emphasize potential problems with trends that differ between high and low probability countries (regions) both in the treatment and in the outcome variable. The various robustness tests we explain below suggest no such problem, but we also highlight that we regard the IV approach as complementary to the more transparent OLS specifications.

[22] To allow the reader to assess the trends in the treatment variables, Figure A 13 depicts the time series for the means of logged WB and Chinese aid per high and low exposure regions.



(a) Mean BRD: Problematic trends



(b) Mean BRD: Actual trends

Figure 5: China: Deviations from trend in Chinese steel production and Battle-Related Deaths for low and high probability regions.

Notes: Figure 5 (a) displays the log of the detrended Chinese Steel Production (thick line), fabricated trends in the mean battle-related deaths per low probability recipient regions (thin line) and in the mean battle-related deaths per high probability recipient regions (dashed line). Figure 5 (b) displays the log of Chinese Steel Production (thick line), the mean residual of the battle-related deaths per low probability recipient regions (thin line) and the mean residual of the battle-related deaths per high probability recipient regions (dashed line). The residuals refer to the underlying variation used in our preferred specification from column (4) in Table 3.

5 Results

5.1 OLS, fixed effects and time trends

Ruling out potential sources of omitted variables bias in cross-country studies through fixed effects and time trends comes at the costs of losing useful variation. Even though we normally try to minimize false discoveries, a plausible prior in our case is to assume that aid fuels conflict (e.g., based on studies like Nunn and Qian, 2014 and Crost et al., 2014). Thus, focusing on conservative specifications which eliminate much variation creates the risk of over-looking such an effect. To allow readers to evaluate the trade-off for themselves, we begin by showing simple correlations and then step-by-step add fixed effects, time trends and different categories of control variables.[23]

Beginning with WB aid in Table 3, we find that the raw correlation with conflict incidence is negative. The coefficient of -0.19 suggests that 10% more WB aid is correlated with a conflict likelihood that is about 1.9 percentage points lower. Adding country and year fixed effects shift the coefficient upward (column 2), adding country-specific linear and quadratic trends to capture country-specific conflict dynamics moves it again slightly downward to -0.05 (column 3). When adding region fixed effects, which capture region-specific time-invariant attributes that can explain

[23] A second trade-off is between showing both donors over the same period. The advantage is that it would increase comparability. The disadvantage is that we would lose five years for the WB (1996-2001). Moreover, when doing this for IV specifications the F-statistics for the WB are much smaller, giving rise to potential weak instrument concerns. Hence, we exploit the full range of available data for the main specification, and show the results for both donors combined in Table A54 with OLS and in Table A52 with IV.

heterogeneity within countries, the point estimates nearly quadruple in size (-0.21) and become statistically significant at the 1%-level (column 4).

Adding exogenous controls and time-invariant region characteristics, interacted with year dummies to capture their potentially time-varying influence (column 5), as well as adding region-specific linear time trends changes the coefficient only slightly (column 6). Column 8 goes one step further by controlling for country-year fixed effects. The remaining variation is then only due to differences in aid across regions within country-years, conditional on the country as a whole being in conflict or not. Despite the strict specification, the robust negative relationship between WB aid and conflict does not disappear and remains significant at the 5%-level. It becomes insignificant when controlling for lagged values of factors that are potentially endogenous controls (columns 7 and 9), but remains negative. Although these are only conditional correlations, the fact that 8 out of 9 coefficients are negative suggests that there is no conflict-fueling effect of WB aid on average.

Turning to China, our prior is that a positive relationship with conflict is more likely. Chinese aid is by some observers deemed as "rogue aid," which promotes authoritarian and violent elites and leaders. Nonetheless, the raw correlation with conflict is also negative. The coefficient drops drastically in size when adding country and time fixed effects, as well as country-specific quadratic time trends (columns 2 and 3), but loses significance. Overall, the coefficients are much smaller and closer to zero than for the WB. Remarkably, however, there is not a single positive coefficient, also suggesting no signs of a conflict-inducing effect of Chinese aid. Our preferred specifications in columns 6 and 8 indicate that 10% more Chinese aid corresponds with a 0.65 and 0.35 percentage points decrease in conflict incidence.

These results need to be put into perspective. Table 3 reveals that researches have many degrees of freedom, especially at the subnational level. What we find reassuring is that throughout all these different specifications there is no sign of a conflict-inducing effect for either WB or Chinese development finance projects. Relating to the ideas in Altonji et al. (2005) and Oster (2018), we also see that the effect of adding additional FE, trends, and covariates neither suggests a clear upward nor a downward bias. Certainly, a zero, as well as negative effects, could be a part of the true confidence interval. Still, it seems unlikely that unobserved factors would push the average effect towards a positive and significant coefficient. We continue examining a potentially remaining selection bias with our IV estimations, focusing on the specifications in columns 6 and 8.

Table 3: OLS results: Aid and conflict at the ADM1 level

Panel A: WB Aid	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
ln(World Bank Aid $_{t-1}$)	-0.1918*	0.0010	-0.0496	-0.2129***	-0.2057***	-0.1608**	-0.0419	-0.1772**	-0.1420
	(0.0989)	(0.0776)	(0.0683)	(0.0659)	(0.0701)	(0.0782)	(0.0849)	(0.0847)	(0.1048)
N	13104	13104	13104	13104	13050	13050	11017	13050	11017
Panel B: Chinese Aid									
ln(Chinese Aid $_{t-2}$)	-0.1753**	-0.0233	-0.0026	-0.1090*	-0.0663	-0.0654	-0.0641	-0.0347	-0.0369
	(0.0865)	(0.0705)	(0.0642)	(0.0572)	(0.0783)	(0.0827)	(0.0877)	(0.1015)	(0.0916)
N	9464	9464	9464	9464	8700	8700	8261	8700	8261
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 Controls $\times$ Year FE	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 $\times$ Year FE	No	No	No	No	No	No	No	Yes	Yes

Notes: Dependent variable: Category 1 binary conflict indicator (100 if BRD$\geq$5, 0 if BRD<5). Standard errors in parentheses, two-way clustered at the country-year and regional level. The sample includes African countries for the sampling period of 1995-2012 for the WB and 2000-2012 for Chinese Aid. Conflicts are considered for the WB from 1996 to 2013 and for Chinese aid from 2002 to 2014 due to the lag structure. Time Trends include linear and squared country-specific time trends. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

5.2 IV

Table 4 shows the IV results for our preferred specifications. The first stages for both donors work well. The interaction term between the prior probability to receive aid and the IDA position (Chinese steel, respectively) is highly significant in both specifications, with and without country-year fixed effects. On average, the first stage works better for the WB (F= 99/86) than for China (F=22/16), but all F-statistics are well above the critical value of 10. In addition to being relevant, the signs of the coefficients are also plausible. Regions with a higher initial probability profit more from a higher WB liquidity. Table A15 and A16 illustrate that the mechanism seems to work through both the extensive and intensive margin. High probability regions receive more projects, but the size of projects also increases. China shows a reverse pattern. In years where excess steel production is higher, China expands its activities with new projects in regions with an initially lower likelihood of receiving a project.

The second stage results largely confirm the OLS results. Both specifications yield a negative coefficient for the WB and China. The coefficients for the WB are somehow smaller (larger) in the specification without (with) country-year FE, and become statistically insignificant. The coefficients for China become much more negative but remain insignificant. There is again no evidence for a conflict-fueling effect of aid projects. This is noteworthy, as despite estimating a rich set of specifications, we could not find for any of the two extremely different donors an average effect, which would link aid to conflict.

Examining those results with more scrutiny raises the question to what degree they represent a local average treatment effect (LATE) that might be different from the average effect. By definition, the IV estimate is identified using a particular kind of variation in the variable of interest. Nonetheless, comparing the IV point estimates with OLS shows some differences in size but no difference with regard to the direction of the effects.

We can check whether the direction of the changes when moving from OLS to IV estimations is plausible by running OLS specifications using leads and lags of our variable of interest (Table A14). More specifically, we include three lags, the contemporaneous value, and a lead term. For the WB, there are no clear indications of a pre-trend that would signal selection bias. For China, however, the lead terms are positive in both cases. This indicates that China selects regions that are more likely to experience a conflict in the following years. Maybe this is due to China being less worried about violent regimes, or attempts to fill up the space left by other donors who are more hesitant to enter that type of region.[24] This suggests an upward bias in the OLS coefficients, which is in line with the IV coefficients for China being more negative. For the WB, without apparent

[24] In this regard, Strange et al. (2017) demonstrate that after withdrawal of Western aid Chinese commitments fill gaps and, hence, can reduce conflict risk.

pre-trends, IV and OLS results are very similar.

Despite signaling a null or slightly negative effect on average, the rather large standard errors suggest that this average effect hides considerable heterogeneity. Thus, we continue by examining different types of aid, the actors involved in conflict, and potential heterogeneity related to ethnic fractionalization and governing coalition membership.

Table 4: IV results: Aid and conflict at the ADM1 level

Panel A: WB Aid	(1)	(2)
IV Second stage: IDA Position		
ln(World Bank Aid $_{t-1}$)	-0.1014	-0.2252
	(0.3752)	(0.4192)
Kleibergen-Paap underidentification test p-value	0.000	0.000
Kleibergen-Paap weak identification F-statistic	99.639	86.724
IV First stage: IDA Position		
IDA Position $_{t-1}$ × Cum. Prob $_{t-2}$	70.9363***	80.8832***
	(7.1065)	(8.6854)
N	12325	12325
Panel B: Chinese Aid	**(1)**	**(2)**
IV Second Stage: Chinese Steel		
ln(Chinese Aid $_{t-2}$)	-0.4509	-0.4276
	(0.6168)	(0.8068)
Kleibergen-Paap underidentification test p-value	0.000	0.000
Kleibergen-Paap weak identification F-statistic	22.468	16.456
IV First stage: Chinese Steel		
Steel Prod detrend $_{t-3}$ × Cum. Prob $_{t-3}$	-70.8763***	-60.6567***
	(14.9526)	(14.9524)
N	7975	7975
Country-Year FE	No	Yes

Notes: Dependent variable: Category 1 binary conflict indicator (100 if BRD≥5, 0 if BRD<5). Standard errors in parentheses, two-way clustered at the country-year and regional level. The sample includes African countries for the sampling period of 1995-2012 for the WB and 2000-2012 for Chinese Aid. Both regressions include exogenous (time-varying) controls. Year and region fixed effects as well as time trends are included in all regressions. Time Trends include linear and squared country-specific time trends and a linear regional trend. The constituent term of the probability is depicted in Table A17. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

5.3 Channels - Aid Subtypes

Theoretically, different types of aid should be more or less likely to fuel or calm down a conflict. Investments in education and communication infrastructure are often highlighted as those with particularly high long-term benefits, but most likely also require more time to have an effect. To the extent that projects in particular areas stimulate economic development in the short run, we would expect that they increase the opportunity costs of fighting and could, thus, lead to less conflict. At the same time, some development projects like hospitals, and to lesser extent schools, provide more potential for looting due to, for instance, expensive machines that can be sold on the black market. Other areas, like infrastructure projects, are notoriously known for being prone to corruption.

We assign aid projects to eight subcategories and consider them as a treatment in our two favorite specifications with and without country-year FE. For the WB, the IV strategy works well, using sector-specific probabilities. For China, the IV does not work sufficiently well, because there are only a few observations in some sectors. Thus, we show those results using OLS. Interesting differences emerge, suggesting that different types of aid indeed can have a different relationship to subsequent conflict. Note that in almost all cases, the country-year FE only affect the coefficients' sizes, not their signs.

In some categories, there is a positive coefficient of WB (Chinese) aid, but it never becomes statistically significant. Based on significance, the negative coefficient we found for the WB seems to be driven by projects in the area "finance" and "transportation" on average. Those coefficients remain significant both in the less and more restrictive specification with country-year FE. In the latter specification, a 10% increase in WB spending on transportation (finance) is related to a 6.7 (16) percentage points reduction in the likelihood of conflict. Transportation comprises both a large scope of projects and funds, compared to financial development, which is rather small in terms of dollars spent. Despite the limited amount of disbursements, the financial sector is important and comprises overall 1,361 projects. The negative effect for transportation, often infrastructure projects, is particularly interesting when considering the potential for corruption and cronyism in this sector. It suggests that existing constraints on movement or high transportation costs were a significant obstacle for development before.[25] Moreover, transportation is the only sector where we consistently find negative and significant effects on conflict likelihood for both the WB and China.

Putting these sector-specific results into perspective, Table 5 suggests heterogeneities across aid categories which help to explain the large confidence interval when estimating the mostly negative coefficient on overall aid. It is important to note that we find no significant conflict-fueling effect for any type of aid and any of the two donors. It is reassuring that the overall negative relationship is not masking strong conflict-fueling effects in some sectors.[26]

[25] The high conflict reducing effect of aid in the "transportation" sector also corresponds to other related studies, which indicate the salience of transport costs for economic growth across African countries (Berman and Couttenier, 2015; Storeygard, 2016; Bluhm et al., 2018)

[26] Table A47 presents the regressions for the WB with OLS and China with IV. The OLS results differ in some cases, but again there is no significant positive coefficient for any sector.

Table 5: ADM1 - Aid Subtypes

WB Aid Subtypes - IV	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Panel A: No Country-Year FE	AX	BX	CX	EX	FX	JX	LX	TX	WX	YX
ln(World Bank Aid $_{t-1}$)	0.2179	-0.2102	0.3423	0.5525	-1.6744**	0.2773	-0.1658	-0.7843**	0.5021	-0.4463
	(0.3572)	(0.4195)	(0.3016)	(0.4572)	(0.7877)	(0.4321)	(0.2858)	(0.3323)	(0.5593)	(0.3647)
Kleibergen-Paap underidentification test p-value	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Kleibergen-Paap weak identification F-statistic	58.309	80.342	39.353	50.568	16.781	73.307	33.666	64.555	40.026	31.887
Panel B: Country-Year FE										
ln(World Bank Aid $_{t-1}$)	0.4793	-0.4087	0.2652	0.2253	-1.5963*	0.2952	-0.1206	-0.6667*	-0.2726	-0.3717
	(0.3152)	(0.4445)	(0.2709)	(0.4771)	(0.9361)	(0.4020)	(0.2764)	(0.3570)	(0.6850)	(0.3299)
N	12325	12325	12325	12325	12325	12325	12325	12325	12325	12325
Kleibergen-Paap underidentification test p-value	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Kleibergen-Paap weak identification F-statistic	59.949	61.188	56.632	31.111	12.238	73.686	36.219	28.587	23.180	33.957
Chinese Aid Subtypes - OLS										
Panel C: No Country-Year FE	AX	BX	CX	EX	FX	JX	LX	TX	WX	YX
ln(Chinese Aid $_{t-2}$)	-0.3165	-0.2123	0.1770	-0.0830	N.A.	-0.0168	0.3516	-0.2780*	-0.2974	0.8388
	(0.2007)	(0.1391)	(0.1325)	(0.1637)	(N.A.)	(0.1448)	(0.2661)	(0.1611)	(0.1935)	(0.8093)
Panel D: Country-Year FE										
ln(Chinese Aid $_{t-2}$)	-0.1946	-0.1881	0.1281	-0.0484	N.A.	0.0287	0.3241	-0.3378*	0.0377	0.7787
	(0.2239)	(0.1434)	(0.1329)	(0.1703)	(N.A.)	(0.1561)	(0.2848)	(0.2018)	(0.2138)	(0.7893)
N	8700	8700	8700	8700	8700	8700	8700	8700	8700	8700

Notes: The dependent variable is a binary conflict indicator (100 if BRD≥5, 0 if BRD<5). The sample includes African countries for the sampling period of 1995-2012 for the WB and 2000-2012 for Chinese Aid. Conflicts are considered for the WB from 1996 to 2013 and for Chinese aid from 2002 to 2014 due to the lag structure. Regressions account for (time-varying) exogenous controls and time trends. Time Trends include linear and squared country-specific time trends as well as a linear regional trend. AX - "Agriculture, fishing, and forestry" BX - "Public Administration, Law, and Justice" CX - "Information and communications" EX - "Education" FX - "Finance" JX - "Health and other social services" LX - "Energy and mining" TX - "Transportation" WX - "Water, sanitation and flood protection" YX - "Industry and Trade" Standard errors in parentheses, two-way clustered at the country-year and regional level:
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

5.4 Actors

Many claims about a conflict-fueling or alleviating effect make implicit assumptions about involved actors. For donors, it is a crucial difference whether the government is fighting against rebel groups, rebel groups are fighting each other, or uninvolved third parties (i.e., civilians) are attacked. War actions against rebel groups might be accepted or even encouraged by donors. In contrast, attacks on civilians are often condemned by donors, even if happening during an existing conflict, and might be a reason to withhold aid or reduce future payments.[27] We can distinguish between state- and rebel violence, and actions by those two groups against civilians not directly involved in the conflict. The UCDP Codebook describes one-sided violence as "[...] the use of armed force by the government of a state or by a formally organized group against civilians [...]" (Eck and Hultman, 2007).

Table 25 shows the results for both the WB and China with and without country-year FE. State-based violence decreases with additional WB aid but increases with additional Chinese aid. The coefficients are not statistically significant but of an economically meaningful magnitude. Both for the WB and China, we find positive coefficients on violence by actors like rebel groups, which are larger for China but never statistically significant. The picture looks very different when considering violence against civilians. In a region that receives either more WB or Chinese aid, there are fewer attacks and assaults that kill civilians. This holds for both violence by non-government and state actors, but the effect is more nuanced for state violence. 10% more WB aid leads to a between 3.6 and 2.9 percentage points lower likelihood of lethal violence against civilians (columns 5 and 6), and 10% more Chinese aid even to a between 7.9 and 8.9 percentage points reduction (columns 5 and 6). Both coefficients are remarkably stable to the addition of country-year fixed effects, suggesting that this effect is not driven by unobservable time-varying factors at the country level. Even within a country that is already in conflict, administrative regions with aid projects are less likely to experience violence against civilians.

A plausible and underappreciated channel is the threat of losing out on future payments and projects (Lebovic and Voeten, 2009). Even for recipient politicians that are not solely concerned with public goods, the withdrawal of aid can be a viable threat to regions or governments. This conflict-reducing effect is even stronger for Chinese projects. Even without officially imposing conditions about human rights violations, governments in Africa seem to abstain from lethal actions against civilians when China supports a project in a particular region. Besides business interests, the presence of Chinese workers might be another reason to lobby recipient governments to abstain from engaging in actions that could cause severe conflicts.

[27] Analogously donors might also accept or encourage rebels to fight an opposed regime as in the case of covert aid to Angolan UNITA under president Reagan (Lagon, 1992). Our data cover almost exclusively projects implemented in accordance with the government, so this latter aspect should be of lesser importance.

Table 6: ADM1 - Actors (clustering at country-year and regional level)

Panel A: WB Aid - IV	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
IV: IDA Position - Actors	State vs N-State		N-State vs N-State		State vs Civilans		N-State vs Civilians	
ln(World Bank Aid $_{t-1}$)	-0.4177	-0.4319	0.1252	0.1488	-0.3579*	-0.2939*	-0.0961	-0.1417
	(0.3174)	(0.2630)	(0.2096)	(0.2447)	(0.1885)	(0.1739)	(0.2072)	(0.2704)
N	12325	12325	12325	12325	12325	12325	12325	12325
Kleibergen-Paap underidentification test p-value	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Kleibergen-Paap weak identification F-statistic	99.639	86.724	99.639	86.724	99.639	86.724	99.639	86.724
Panel B: Chinese Aid - IV								
IV: Chinese Steel - Actors	State vs N-State		N-State vs N-State		State vs Civilans		N-State vs Civilians	
ln(Chinese Aid $_{t-2}$)	0.4519	0.4148	0.3811	0.5800	-0.7980**	-0.8882*	-0.3983	-0.4488
	(0.2851)	(0.3421)	(0.2967)	(0.4270)	(0.3463)	(0.4776)	(0.3361)	(0.4218)
N	7975	7975	7975	7975	7975	7975	7975	7975
Kleibergen-Paap underidentification test p-value	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Kleibergen-Paap weak identification F-statistic	22.468	16.456	22.468	16.456	22.468	16.456	22.468	16.456
Country-Year FE	No	Yes	No	Yes	No	Yes	No	Yes

Notes: The dependent variable is a binary conflict indicator (100 if BRD$\geq$5, 0 if BRD<5). The sample includes African countries for the sampling period of 1995-2012 for the WB and 2000-2012 for Chinese Aid. Conflicts are considered for the WB from 1996 to 2013 and for Chinese aid from 2002 to 2014 due to the lag structure. Exogenous (time-varying) controls are included in all regressions. Time Trends included, consist of linear and squared country-specific time trends as well as linear regional time trends. "State vs N-State" refers to state-based violence against non-government actors, "N-State vs N-State" refers to non-government violence against the other organized non-state groups, and "State vs Civilians" refers to one-sided violence versus civilians by the government and "N-State vs. Civilians" refers to one-sided violence versus civilians by non-government (NG) actors. The categories are mutually exclusive. Standard errors in parentheses, two-way clustered at the country-year and regional level: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

5.5 Types of Violence

Kishi and Raleigh emphasize "dire consequences" of Chinese aid, and state that "political violence rates involving state forces also increase" (Raleigh et al., 2010). Should we conclude that these fears are unwarranted? Not necessarily. Our analysis has focused on violent conflict that involves battle-related deaths, but the authors highlight that states "use this aid to finance their hold on power by repressing political competitors." It seems plausible that China is interested to avoid outright battles, but using government repression to ensure stability is in line with its domestic approach and ideology. In that regard, some observers claim that Chinese aid purposefully supports building up recipient countries' surveillance capacities to repress elements of civil society.[28]

To evaluate this hypothesis, we rely on the Social Conflict Analysis Database (SCAD) (Salehyan et al., 2012). The particular strength of this database is that it covers types of social and political disorder that are usually overlooked in other conflict datasets, with georeferenced data available from 1990-2016. We are in particular interested in two types of variables. We code binary variables that take on the value one if there was at least one riot, strike, or demonstration in a district to measure potential civil unrest or protests against projects related to China. Second, we code whether there was at least one event recorded as repression by the government, focusing on non-lethal repression to distinguish these regressions from our prior results.

Table 7 begins with regressions running our two main specifications, but now replacing the outcome variable with an indicator measuring whether at least one demonstration, riot, or strike took place.[29] For the WB, all specifications yield a negative or very small positive coefficient but remain statistically insignificant. Regarding China, we observe positive coefficients for demonstrations and riots, but although they are rather large (10% more aid increase the likelihood of riots by 5.3%) they remain statistically insignificant. Accordingly, despite reports indicating increasing protests against Chinese projects, we find no clear evidence of this over our sample period.[30]

Recipient governments might achieve this absence of protests and outright conflict by intensifying non-lethal repression. Table 8 tests whether more reports relate non-lethal government repression to aid. The results indicate neither a positive nor significantly negative relationship for the WB. The results for China contrast our prior findings and confirm that repression intensifies in regions where China is present. A 10% increase in Chinese aid increases the likelihood of experiencing repression by about 13%.[31]

[28] Washington Post, last accessed 26.07.2018.

[29] Table 26 depicts corresponding OLS results. Tables A28, 29 and 30 show OLS regressions separately for demonstrations, riots and strikes.

[30] See, for instance, The Telegraph, last accessed 09.10.2018.

[31] Table 32 reports results for a count variable of non-lethal pro-government violence events, which are robust to this change in the outcome variable. Table 31 verifies that this is driven by events recorded in SCAD that are distinct from the UCDP events, by coding only those region-years as a one that did not experience lethal government violence against civilians according to UCDP.

Table 7: ADM1 IV (Riots, Demonstrations & Strikes [SCAD])

Panel A: WB Aid	(1)	(2)	(3)	(4)	(5)	(6)
IV Second stage: IDA Position						
	Demonstr.	Demonstr.	Riots	Riots	Strikes	Strikes
ln(World Bank Aid $_{t-1}$)	-0.2232	-0.1458	0.0106	-0.1950	0.0289	-0.0184
	(0.2514)	(0.2808)	(0.2543)	(0.2294)	(0.1793)	(0.1463)
N	12325	12325	12325	12325	12325	12325
Kleibergen-Paap underidentification test p-value	0.000	0.000	0.000	0.000	0.000	0.000
Kleibergen-Paap weak identification F-statistic	99.639	86.724	99.639	86.724	99.639	86.724
Panel B: Chinese Aid						
IV Second stage: Chinese Steel						
	Demonstr.	Demonstr.	Riots	Riots	Strikes	Strikes
ln(Chinese Aid $_{t-1}$)	0.1891	0.2717	0.1300	0.1922	-0.1806	-0.1203
	(0.5720)	(0.6863)	(0.5144)	(0.6737)	(0.5557)	(0.7172)
N	7975	7975	7975	7975	7975	7975
Kleibergen-Paap underidentification test p-value	0.000	0.000	0.000	0.000	0.000	0.000
Kleibergen-Paap weak identification F-statistic	22.468	16.456	22.468	16.456	22.468	16.456
Country-Year FE	No	Yes	No	Yes	No	Yes

Notes: The table displays regression coefficients for any violence of these three types as dependent variable. Standard errors in parentheses, two-way clustered at the country-year and regional level. The sample includes African countries for the sampling period of 1995-2012 for the WB and 2000-2012 for Chinese Aid. Both regressions include year and region fixed effects as well as time trends. Time Trends include linear and squared country-specific time trends. OLS results are depicted in the appendix. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 8: Non-lethal pro-government Violence [SCAD]

Panel A: WB Aid	(1)	(2)
IV Second stage: IDA Position		
ln(World Bank Aid $_{t-1}$)	0.1543	0.0885
	(0.1042)	(0.1177)
N	12325	12325
Kleibergen-Paap underidentification test p-value	0.000	0.000
Kleibergen-Paap weak identification F-statistic	99.639	86.724
Panel B: Chinese Aid		
IV Second Stage: Chinese Steel		
ln(Chinese Aid $_{t-1}$)	0.9798***	1.3059***
	(0.3663)	(0.5025)
N	7975	7975
Kleibergen-Paap underidentification test p-value	0.000	0.000
Kleibergen-Paap weak identification F-statistic	22.468	16.456
Country-Year FE	No	Yes

Notes: The table displays regression coefficients for a binary indicator of non-lethal pro-government violence as dependent variable. Standard errors in parentheses, two-way clustered at the country-year and regional level. The sample includes African countries for the sampling period of 1995-2012 for the WB and 2000-2012 for Chinese Aid. Both regressions include year and region fixed effects as well as time trends. Time Trends include linear and squared country-specific time trends.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

5.6 Spatial spill-overs

Moving beyond studying aid and conflict in the same region we account for potential spatial spill-over effects. This is important for two reasons. First, some existing theories can only be tested by considering the effect of aid in location *i* on conflict in a particular location *j*. The "price" theory postulating government as a price for rebels would predict that more aid to capital regions or the capital itself leads to a higher likelihood of conflict in that location. Other theories, however, predict that aid payments to one region affect the likelihood of conflict in another region. Kishi and Raleigh (2015) suggest that as aid is fungible, governments can shift expenditures towards strengthening their military. Improved military forces could then be used to strike down on rebel groups and other areas of the country.

In line with our prior results, aid projects to outsider regions might strengthen those regions and reduce conflict there but also enable rebel groups to contest the government and attack regions that belong to the governing coalition. To test this, we code binary variables indicating (i) whether a region is the capital region or not, and (ii) whether a region features only groups that are part of the governing coalition, has no coalition groups or is mixed. Second, even if actors are similarly concerned about losing aid revenues, we would expect that fighting continues in other regions if underlying tensions are not resolved.

For these tests, we proceed in the following way. Within each country and year, we aggregate all aid projects and conflicts at the categorical level of these variables. For instance, we aggregate the overall amount of aid spent in regions (A) that belong to a country's governing coalition, and the overall amount spent in all other regions (B). We apply the same procedure to get an aggregate of the conflict incidence variable. In the following, we then test whether aid receipts in area A lead to a higher likelihood of conflict in A but also in area B. Table 9 presents the results using OLS regressions and clustering standard errors at the country level.

Table 9: Spill-Overs from coalition to non-coalition regions - OLS

Panel A: World Bank			
Conflict in region belonging to...	Non-Coalition	Coalition	Mixed
ln(WB Aid non-coalition $_{t-1}$)	-1.7092***	0.4046**	-0.0432
	(0.5116)	(0.1942)	(0.4648)
ln(WB Aid coalition $_{t-1}$)	1.3437**	-1.4479***	-0.0482
	(0.5493)	(0.3317)	(0.6200)
ln(WB Aid mixed $_{t-1}$)	-0.6811	0.6578**	0.1513
	(0.4946)	(0.2806)	(0.6715)
N	703	703	703
Panel B: China			
Conflict in region belonging to...	Non-Coalition	Coalition	Mixed
ln(Chinese Aid non-coalition $_{t-2}$)	-0.2931	-0.2897	-0.8032***
	(0.4996)	(0.3274)	(0.2367)
ln(Chinese Aid coalition $_{t-2}$)	-0.1080	-0.1373	-0.1501
	(0.1816)	(0.1482)	(0.1673)
ln(Chinese Aid mixed $_{t-2}$)	0.2577	-0.0313	0.1550
	(0.3071)	(0.1773)	(0.2523)
N	666	666	666
Country FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes

Notes: Dependent variable: Category 2 binary conflict indicator (100 if BRD25, 0 if BRD<25). Standard errors in parentheses are clustered at the level of country unit. The sample includes African countries for the sampling period of 1995-2012 for the WB and 2000-2012 for Chinese Aid. Conflicts are considered for the WB from 1996 to 2013 and for Chinese aid from 2002 to 2014 due to the lag structure. Both regressions include year and country fixed effects as well as time trends. Time Trends include a linear country-specific time trend. Column (1) refer to all regions without members of the governing coalition, whereas column (2) to regions that contain groups exclusively from the coalition and column (3) to mixed regions with some groups in and out of the coalition.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

For China, there are no signs of any conflict-inducing spill-over effects. For the WB, aid disbursements in coalition regions as well as to non-coalition regions strongly and significantly reduce conflict in the same respective regions, conditional on aid to the other parts of the country. For mixed, and, hence, more likely contested regions, the coefficient is close to 0 and insignificant. This is in line with the prior results, and mostly similar to the results for China.

Still, there is also some evidence of positive spill-overs for the WB. More aid to non-coalition and to mixed regions increases the likelihood of violent conflict in coalition regions. This effect is considerably large in size. 10% more WB aid to non-coalition regions increases the likelihood of conflict with at least five casualties by 4 percentage points. 10% more aid to mixed regions even by 6.5%.[32] This would be in line with a strengthening of non-government groups, which increases their capacity and willingness to engage. Of course, causality is even harder to establish in such a setting.

5.7 Sensitivity

We conduct various sensitivity tests, which we describe in short here grouped by issue. All accompanying tables and figures can be found in the Online Appendix.

Modifiable area unit problem - different aggregation levels: We show results both at a more aggregated and a less aggregated level. First, we aggregate at the country level. This allows us to see whether our prior analyses of spill-overs hide important patterns that we might see in the aggregation, and makes our results comparable to studies at the country level. We show results with the WB and China in the same regression, with and without controlling for aid projects that could not be assigned to a particular region. This is to a large extent projects where money flows directly to the central government. Coefficients are in both specifications and for both donors negative. When controlling for non-geocoded aid the coefficient for WB aid becomes more negative, though insignificant, while the coefficient for China remains virtually unchanged. Thus, our results at the local level do not seem to be driven by choosing a particular spatial unit.[33]

In Table A43 (A42), we move towards OLS (IV) regressions at a lower level of aggregation, the ADM2 level. Note that we are capturing a smaller share of all projects at this level due to the precision level in the georeferencing. The OLS results for the WB and China are both similar to the ones at the ADM1 level, with the majority of coefficients being negative. The patterns of statistical significance are also similar with OLS; five out of nine coefficients are significantly negative for the WB, and none for China. The IV point estimates differ somehow, but never turn statistically significant.

Choice of conflict indicator: As we discuss in the data section, there is no "correct" coding of the dependent variable, just more and less plausible choices. Table A35 (A36) presents alternative regression results with a higher conflict threshold of at least 25 BRD per region year using the OLS (IV) specifications. Table A33 (Table A34) considers the log of battle-related deaths (+0.01) as a continuous measure of conflict intensity instead of looking at a binary indicator of conflict incidence

[32] Table A44 runs a similar analysis, but instead of regions that according to EPR are part of the governing coalition, it focuses on capital vs. other regions.

[33] Point estimates for the less precisely coded aid can be found in Table A45. Although the coefficient for non-geocoded WB aid is positive it remains insignificant, suggesting also a null effect at the country level.

using OLS (IV). We find largely negative OLS coefficients for the WB and slightly positive ones for China, but with IV both coefficients turn negative in line with prior results.

Table 10: Aggregate - Cross-country Analysis - OLS

	(1)	(2)
$ln(WB\,Aid_{\text{t-1}})$	-0.2035	-0.3419
	(0.2492)	(0.4410)
$ln(Chinese\,Aid_{\text{t-2}})$	-0.2061*	-0.2081*
	(0.1043)	(0.1158)
R^2	0.317	0.318
N	792	792
Non-geocoded aid as control:	No	Yes

Notes: Dependent variable: Category 2 binary conflict indicator (100 if BRD$\geq$25, 0 if BRD<25). Estimates refer to the country level, where aid and battle-related deaths were aggregated at the country level. Columns (1) and (2) depict coefficient for geocoded aid aggregated at the country level. Column (2) controls for non-geocoded aid, which is aid coded less precise than the ADM1 level (refer to Figure 2). The sample includes African countries for the sampling period of 1995-2012 for the WB and 2000-2012 for Chinese Aid. Conflicts are considered for the WB from 1996 to 2013 and for Chinese aid from 2002 to 2014 due to the lag structure. All regressions include year and country fixed effects as well as time trends. Regressions include country and year fixed effects as well as a linear county-trend. Standard errors in parentheses are clustered at the level of the country. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Instrumental variable: We conduct the majority of robustness tests regarding our IV strategy. As outlined above, we detrended the Chinese steel production time series because it is dominated by a long-term trend, but not the WB liquidity where there is enough year-to-year variation.[34] Table 23 shows that our first stages also work when using the detrended IDA position or the unadjusted Chinese steel excess production. This suggests that the long-term trends in steel production do not overlap with a problematic trend in conflict that differs between low and high probability regions.

The second component of the IV, the probability term, can also be computed in different ways. We test various plausible options. Using the cumulative probability is advantageous as it only uses pre-determined values, but could create problems if the probability in the first year(s) is not as informative. Table A22 drops the first year of the respective panel (start at 1998 for the WB's IDA and 2003 for Chinese Steel), so that the first probability is already based on at least two observations. Table A24 uses a constant probability from the third year of the respective sample onwards, i.e., 1998 for the WB's IDA, and 2003 for Chinese Steel, as in Nunn and Qian (2014). Table A21 drops the 10 highest leverage region-year observations. The IV is robust to all these choices and specifications.

Moreover, Table A18 reports reduced form estimates. Table A19 uses a lead of aid as a placebo treatment in the first stage, which always shows up statistically insignificantly. Table 17

[34] Although we control in later specifications for linear trends on the country and regional level, we would not capture the variation incorporated in the interaction of a linear trend with the time-varying exposure term.

reports the first stage including the coefficient for the probability.

Non-linear estimators: In line with Berman et al. (2017), we also run a Poisson Pseudo Maximum Likelihood estimation in Table 46, which is suitable for binary outcomes with a large fraction of zeros. The results are generally in line with the main findings in terms of coefficient signs. However, note that the models converge only when restricting us to the use of year fixed effects.

Temporal dependence: As conflict might be highly persistent over time, we include a lagged dependent variable in Table 53. The results are very similar, with mostly negative and partly significant coefficients for the WB and China.

Overlapping panels: Our main tables use the years 1995-2012 for the WB, and the years 2000-2012 for China. As there could be coordination or competition between the two donors (e.g., Gehring et al., 2015; Humphrey and Michaelowa, 2018), we also want to estimate both jointly in one regression. Tables A55 and A56 show that the coefficients change slightly, with the WB estimates becoming less negative on average. This change seems to be nearly entirely explained by periodical differences in the effect of WB aid. When re-estimating the WB results for the years 2000-2012 in Tables A54 and A52, the point estimates are nearly the same without conditioning on Chinese Aid. Hence, not controlling directly for the other donor does not seem to create a large bias, it seems rather that the effects differ between different observation periods. As limiting the WB period creates a weak IV problem with country-year FE (see Table A52), we choose our two main specifications with differing sample periods in order to exploit the maximum available information for each donor.

6 Conclusion

Our paper aims to provide a comprehensive analysis of the relationship between development aid and conflict at the subnational level. The contribution of our paper is to bridge the gap between existing studies using various countries at the aggregated country level (Bluhm et al., 2016; Nielsen et al., 2011; Nunn and Qian, 2014), and studies focusing on specific types of aid or individual countries (Berman et al., 2011; Child, 2018; Crost et al., 2014). To achieve that aim, we examine two donors that represent two contrasting approaches to development, the WB and China. One is a multilateral donor that emphasizes human right conditions and expert knowledge, the other an emerging South-South donor that emphasizes "mutual benefits" without many official strings attached (Asmus et al., 2017).

Our results on aid and conflict in the same region show no signs of a conflict-fueling effect on average. Rather, aid seems to be able to somehow reduce the likelihood of conflict in particular for WB projects. When distinguishing between different sectors, we find the strongest and most significant conflict-reducing effects for projects in the transport sector (both donors). Distinguishing different conflict types suggests that the reduction in conflict is driven by less lethal violence by governments against civilians.

We examine claims that in particular Chinese projects lead to civilian unrest in Africa by ignoring local traditions and circumstances, or replacing people. For none of the two donors, we find evidence that demonstrations, strikes, or riots increase significantly. When focusing on non-lethal repression by recipient governments, however, we find consistent evidence that regions in which China is engaged show an increased likelihood of repressive measures. The precise reasons for this should be explored in future research. It seems in line with a rationale where China is eager to avoid violent conflict that endangers its workers and investment, but less opposed to repression than the Western donors.

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Part

Appendix

Table of Contents

A Data Appendix

A.1 Independent Variables (Development Aid)

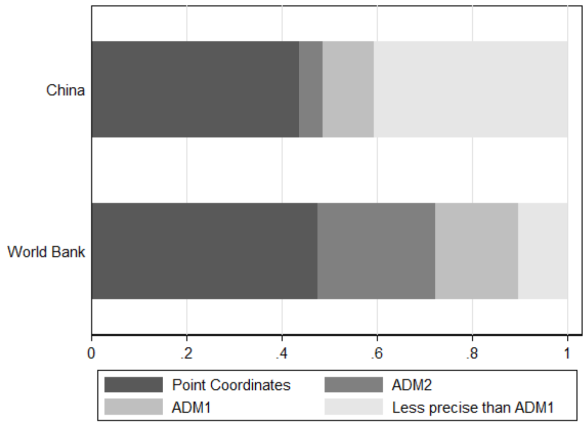
WB's IDA & IBRD disbursements

For our analysis, we draw on the "WB IBRD-IDA, Level 1, Version 1.4.1" provided by the AidData consortium, which covers approved loans under the IBRD-IDA lending line between 1995 and 2014.[35] These data correspond to project aid disbursed from 5684 projects in 61,243 locations. The data build on information provided by the WB, 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. While for some projects exact locations including latitude and longitude were assigned, other projects, which had a more policy or regulation oriented purpose, could only be assigned to an administrative level (e.g., the first

[35] As the number of documented projects declines steeply after 2012, we focus on the 1995-2012 period.

level of subnational regions (provinces) or the second level (districts)). In order to include as many disbursements as possible, but to be also able to grasp the advantages of georeferenced data, we focus our analysis on these administrative levels. 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 more 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.

Figure 6 displays the development finance locations coded by donor, distinguishing all projects (precision 1-8), projects coded at least at the first administrative level (precision 1-4), projects coded at least at the second administrative level (precision 1-3) and projects coded more precise (precision 1-2).



(a)

Figure 6: No. of Project Locations by Precision Codes

One challenge arises in projects with a multitude of locations, where it is not possible to derive a distinct value of disbursements. In this regard, we suggest two 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. 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. 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 p is the project, i is the country, j is the region and t is the period for which we estimate the allocation shares.

Finally, our dataset comprises development finance from IBRD and IDA. However, only IDA disbursements can be classified as Official Development Assistance. For this purpose, disbursements were disentangled into IDA (development aid) and IBRD (development finance) disbursements.

Allocation scheme (more detailed)

Location weighting

The WB geocoded data release comes in the format of projects and several corresponding locations. For instance, a typical project report would mention the transaction amounts, the project purpose as well as different project locations. The latter can be classified in different degrees of precision (e.g., precision codes smaller than 4 correspond to locations that refer to an ADM2 region or even more precise, while precision code 4 corresponds to locations at the ADM1 level). When allocating the development aid across locations on the ADM1 and ADM2 level, we make the following assumptions based on a three-step procedure.[36] First, we subtract the share of development aid, which corresponds to locations, which are coded less precise than ADM1 (e.g., large geographic regions or aid at the country level). For example, if three out of 10 locations in a project are coded less precise than ADM1, the further analysis focuses on the remaining 70% of development aid. Second, we then allocate all aid with precision codes 1-3 to the corresponding ADM2 regions. This is done by taking the location share (either by equal or population weights) of the transaction amount per location. A certain ADM2 regions might have several locations per project or even several projects, we collapse our data by ADM2 region. Third, we then allocate all aid with precision code 4 to the corresponding ADM1 regions. This is done by taking the location share (either by equal or population weights) of the transaction amount per location. A certain ADM1 regions might have several locations per project or even several projects, we collapse our data by ADM1 region. In order to allow for inference on the ADM2 level, we make the assumption that transactions coded with precision 4 are attributable equally to all corresponding ADM2 regions. In practice, this is done by merging the ADM1 regions with all corresponding ADM2 regions and then splitting the aid with location or population weights. Finally, data with precision codes 1-3 and precision code 4 can be simply added upon the ADM2 level yielding our treatment variable of interest. For inference on the ADM1 level, totals of ADM2 level development assistance are created on the geounit-year level.

[36] Throughout the paper we allocate the aid either assuming equal weights per location or weighting each location by population.

Table 11: Aid Allocation Formula Example

Example of Weighted Aid Allocation										
Proj. ID	Year	Aid Val.	Loc. ID	ADM1 ID	ADM2 ID	Prec. Code	ADM1 Weight	Prec. 4 Aid to ADM2	Prec. 1–3	Total Aid
	1995	100	2	1	1	1	1/7		14.29	14.29
1	1995	100	3	1	2	2	1/7		14.29	14.29
1	1995	100	4	2	1	4	1/7	14.29		14.29
1	1995	100	5	3	1	3	1/7		14.29	14.29
1	1995	100	6	3	2	1	1/7		14.29	14.29
1	1995	100	6	3	3	4	(1/7)*(1/3)	4.76		4.76
1	1995	100	6	3	1	4	(1/7)*(1/3)	4.76		4.76
1	1995	100	7	3	2	4	(1/7)*(1/3)	4.76		4.76
1	1995	100	8	4	1	4	1/7	14.29		14.29
Totals:								42.86	57.14	100.00

Population weighting

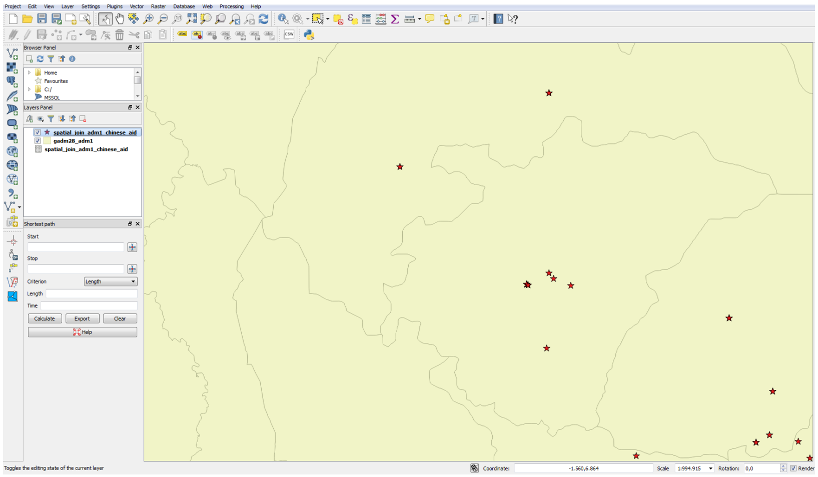
Analogous to the location weighted aid, we also distribute aid with population weights. Our population data are from the Center for International Earth Science Information Network (CIESIN) Columbia University (2016). However, some projects only consist of locations without population estimates (e.g., deserts). In this case, we assume a population of one citizen per location in order to be able to distribute those aid disbursements. We then consequently attribute population of ADM1 regions to project locations, which are coded at the ADM1 level (precision 4), and ADM2 populations to project locations, which are coded at least as precise as the ADM2 level (precision 1-3).

Similar to the location-weighing, we construct the total population of each project-year $pop_{project}$. For the projects coded with precision 4, we then attribute disbursements via the regional share in population pop_{ADM1}. This is then divided by $pop_{project}$ and multiplied with the project disbursements $TransactionValue_{proj}$ in each year: $ADM1Precision_4 = \frac{pop_{ADM1}}{pop_{proj}} * TransactionValue_{proj}$. As there might be several active projects per ADM1 region, we aggregate the disbursements on the ADM1 level. In order to break those numbers down to the ADM2 level, we merge all corresponding ADM2 regions to the ADM1 regions. We then divide the population in each ADM2 region by the population in each ADM1 region and multiply this share with the yearly disbursements per region, $ADM2Precision_4 = \frac{pop_{ADM2}}{pop_{ADM1}} * ADM1Precision_4$. For the precision codes 1-3 (at least coded as precise as the ADM2 level), we then attribute disbursements via the regional share in population divided by $pop_{project}$. This is then multiplied with the project disbursements in each year: $ADM2Precision_{123} = \frac{pop_{ADM2}}{pop_{proj}} * TransactionValue_{proj}$. As there might be several active projects per ADM2 region, we aggregate the disbursements on the ADM2 level. Finally, we merge the precision code 1-3 and 4 data on the ADM2 level to obtain our variables of interest. Those can then be aggregated on the ADM1 level.

Chinese Aid (ODA-like and OOF flows)

In order to create our data on the ADM2 and ADM1 level, we make use of the feature that aid can be defined on the ADM2 level and then aggregated to the ADM1 level. One challenge with the data is, however, that we lack information on the ADM2 regions for some countries (as there are no ADM2 regions in small countries). Therefore, we create two spatial joins of ADM1 and ADM2 regions from the GADM dataset with Chinese aid point features. This yields matches of the specific project locations with the administrative regions as depicted in Figure 7.

In order to create our data, we first load our ADM2 data into Stata and drop the ADM0 and ADM1 identifiers in order to be later able to rely on the identifiers from the ADM1-Aid spatial join.



Notes: Graphical depiction based on Quantum GIS.

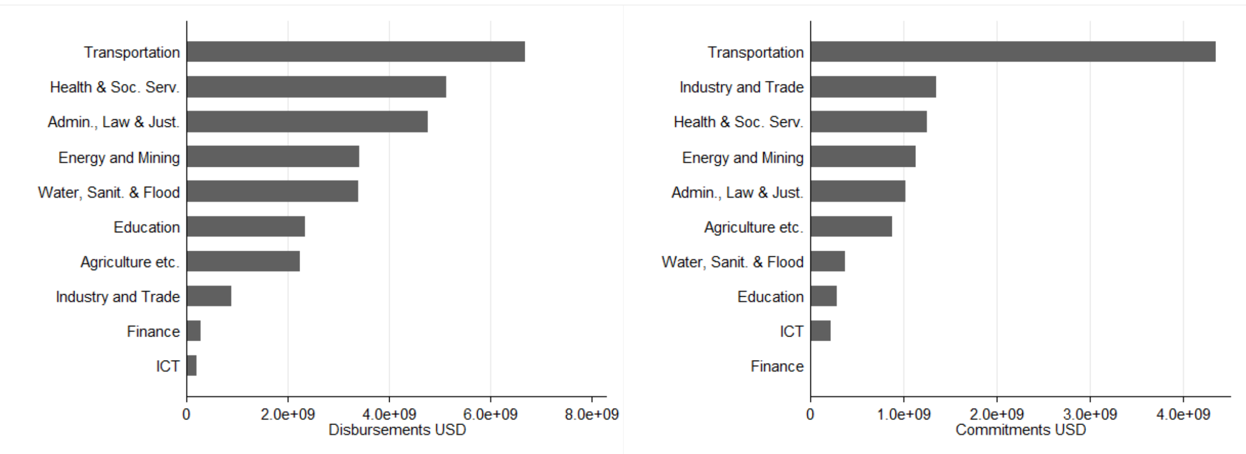
Figure 7: Chinese Aid ADM1 Spatial Join

The next step involves merging the ADM2-Aid spatial join with the ADM1-Aid spatial join by the target-fid, which uniquely identifies the points from the Dataset ”aiddata_china_1_1_1.xlsx” by Dreher et al. (2016) and Strange et al. (2017). Based on this data, we create unique identifiers for all ADM1 and ADM2 regions, whereby we treat ADM1 regions as ADM2 regions in cases that ADM2 regions are missing (e.g., in Cape Verde). This assumption can be made as sizes of administrative regions are rather arbitrary and several ADM2 regions are larger than other countries' ADM1 regions. After getting the regional identifiers right, we can merge (a) the spatial joins of ADM regions & Chinese aid locations with (b) data on flows of Chinese aid. In a first step, we clean these data from entries that only relate to pledges of Chinese aid (information is from the variable status254). Although the data on Chinese finance to Africa also contain information on official investment, the focus of this paper is on development aid. Thus, we focus on flows, which correspond to ”ODA-like” funds as those would correspond closest to development aid (following individual correspondence with the authors of Strange et al. (2017)). The data are then merged with population data from the gridded population of the world data in order to be able to allocate financial flows with population weights in case one project had commitment locations in different administrative regions. Yet, one further challenge has to be resolved before allocating the commitments to regions, as the Chinese aid commitments are coded like WB disbursements with different precision (e.g., some are coded only for geographic features, which involve several administrative regions or are funds which go to central ministries or the government). For our commitment allocation, we only consider those projects, which are at least coded at the ADM1 level. This means that we proportionally exclude commitments, which provide information on the central level and on sub-regional level as indicated before. We furthermore distinguish between projects, which are coded only at the ADM1 level and ones that provide information on the ADM2 level (or more precise). The former are proportionally split over the underlying ADM2 regions. Although the latter can be precisely traced back to the ADM2 region, it might happen that projects have commitments in several ADM2 regions. In this case, we also split the commitments proportionally by locations or population as indicated earlier.

To exploit sectoral variation in development finance both for the WB and China, we make use of the information provided by Strange et al. (2017) on Chinese aid's sectoral allocation using the OECD's Creditor Reporting System (CRS) codes. To achieve comparability with the broad sectors indicated for the WB, we assign sectors as follows: "Agriculture, Fishing and Forestry" (CRS-310:"Agriculture, Forestry and Fishing"), "Public Administration, Law and Justice" (CRS-150), "Information and communication" (CRS-220: "Communications"), "Education" (CRS-110: "Education"), "Finance" (CRS-240: "Banking and Financial Services"), "Health and other social services" (CRS-120: "Health," CRS-160: "Other Social infrastructure and services"), "Energy and mining" (CRS-230: "Energy Generation and Supply"), "Transportation" (CRS-210: "Transport and Storage"), "Water, sanitation and flood protection" (CRS-140: "Water Supply and Sanitation"), "Industry and Trade" (CRS-330: "Trade and Tourism," CRS-320: "Industry, Mining, Construction").

Sectoral distribution of aid disbursements

We use additional information on the financier for each disbursement for each project. Based on this information, we can construct sectoral distributions of aid flows. While both donors are investing heavily in transportation across Africa, further priorities differ. The WB supports Health and Social Services strongly, whereas China commits a large share of its funds to Industry & Trade.



(a) (b)

Figure 8: Sectoral Distribution of Aid: (a) WB's IDA; (b) China

A.2 Dependent Variables (Conflict data)

As AidData 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 ADM1 level (precision codes 1-4).

Again for the more precise data (precision codes 1 and 2), we use a point to polygon analysis on the ADM level. As one conflict event is always coded in one discernible location (UCDP, 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 do not distribute battle-related deaths by population weights across ADM2 regions.

One further useful feature of the UCDP data is that it is possible to discern three different types of violence. Those are namely the government against organized groups (type 1), organized non-governmental groups versus the government (or against another non-governmental group) (type 2), and one-sided violence by the government against civilians (type 3 governmental) and by non-governmental groups against civilians (type 3 non-governmental).[37]

UCDP data can be considered as comprehensive for our 1995 to 2012 sample, despite for Syria for which no battle-related deaths information are provided. Hence, all missing values are treated as zeros except for the Syrian case, which is not part of our analysis.

SCAD data

UCDP data focus on organized violence with lethal outcomes. However, along with the different theories, it could be hypothesized that discontent and aid appropriation do not necessarily need to be linked to full-fledged conflict. What is more, recent empirical work by Bluhm et al. (2016) underscores the role of aid in conflict dynamics. Thus, we also consider social conflict as a further outcome, in terms of demonstrations and repressions, based on the Social Conflict Analysis Database (Hendrix and Salehyan, 2013). SCAD involves demonstrations, riots, strikes, coups, pro-, anti- and extra-government violence, which can, but do not necessarily have to involve casualties. In this way, SCAD complements the UCDP data.[38] SCAD mainly builds on data compiled by the Lexis-Nexis services from searches of Agence France Presse and Associated Press (Lexis Nexis, 2018). Based on the available information, data are georeferenced by web searches of the locations mentioned in the event reports. Analogous to UCDP data, precision codes are provided, which are used to allocate events in a similar manner.

[37] For a more detailed decription of the different types of violence, please consult Croicu and Sundberg (2015).

[38] Prior to 2014 armed conflict was not included in SCAD data and is now also distinguished from ”social disturbances” (Salehyan and Hendrix, 2017).

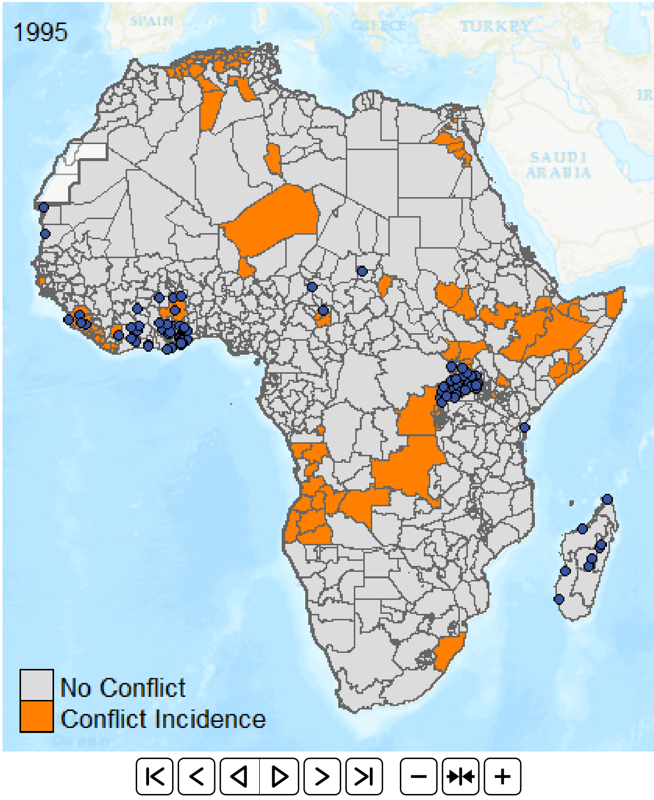


Figure 9: WB Aid and Conflict - By Year

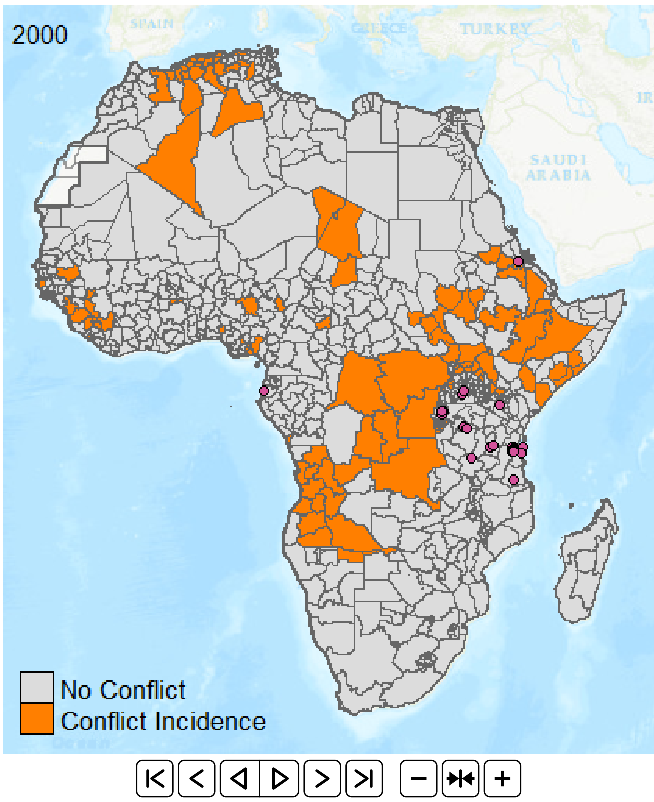


Figure 10: Chinese Aid and Conflict - By Year

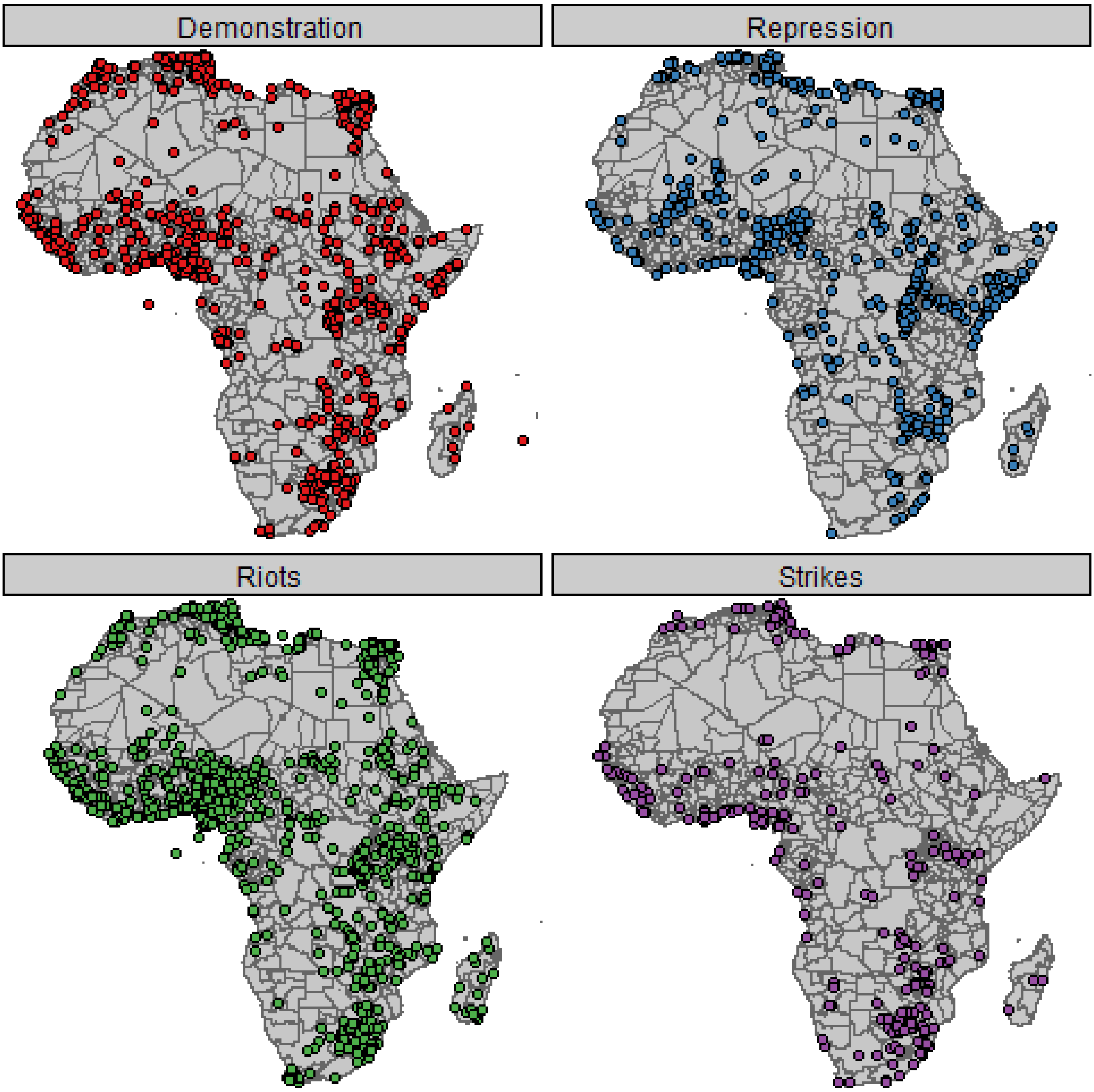


Figure 11: SCAD Data for precision codes 1-4

A.3 Sources

Table 13 lists descriptions and sources of our independent, dependent and control variables.

Matching EPR to GREG

To measure ethnic homelands, we use the GREG dataset (Weidmann et al., 2010), which is a georeferenced version of the initial locations of ethnic homelands based on the Soviet Atlas Narodov Mira. The information about the power status comes from the time-variant Ethnic Power Relations (EPR) dataset (Vogt et al., 2015). Wherever possible, we match the group power status from EPR in a particular year to one of the time-invariant GREG group homelands. The original dataset assigns eight different power statuses to groups. The differences are sometimes marginal and hard to interpret, which is why to minimize measurement error we only use the more precise information on whether a group was part of the governing coalition or not. We then intersect the ethnic group polygons with the administrative regions to classify regions as one of the three categories.

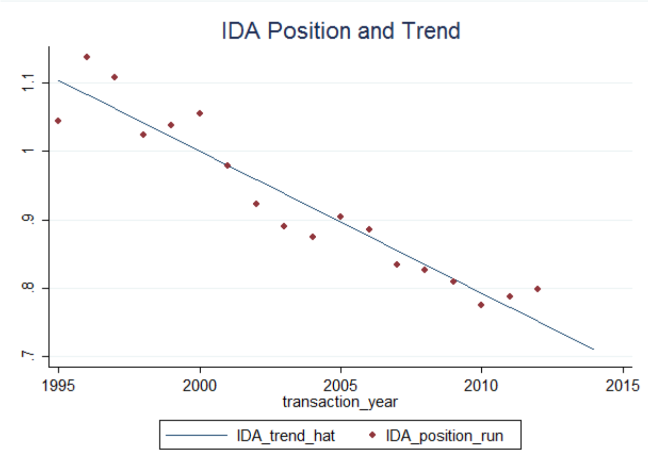
Variable Name	*Variable Description*	Time Period	*Variable Source*
WB Aid	log of WB Aid disbursements in a given region-year	1995-2012	Strandow et al. (2011)
Chinese Aid	log of Chinese Aid commitments in a given region-year	2000-2012	Dreher et al. (2017)
Strikes, Riots, Demonstrations	Binary indicator (100;0) if any violent event of this type in a given region-year took place	1995-2012	Salehyan et al. (2012)
Intensity 1/2	Binary indicator (100;0) if >=5/>=25 persons were killed in a given region-year	1995-2014	Croicu and Sundberg (2016)
Population	Continuous indicator of regional population	1995-2014	(CIESIN 2016)
Drought (end of rainseason)	SPI value of drought severity of the region's entire rainy season	1995-2014	Tollefsen et al. (2012) and Guttman (1999)
Drought (start of rainseason)	SPI value of drought severity during the first month of the region's rainy season	1995-2014	Tollefsen et al. (2012) and Guttman (1999)
Temperature	Mean temperature (in degrees Celsius) per region-year	1995-2014	Tollefsen et al. (2012) and Fan and Van den Dool (2008)
Precipitation	Total amount of precipitation (in millimeter) per region-year	1995-2014	Tollefsen et al. (2012) and Schneider et al. (2015)
Chinese Steel	Production of Chinese Steel in tonnes	1999-2013	World Steel Association (2009, 2014)
IDA Funding Position	"Bank‘s net investment portfolio and its non-negotiable, non-interest-bearing demand obligations (on account of members‘ subscriptions and contributions)" divided "by the sum of the Bank‘s undisbursed commitments of development credits and grants."(Dreher et al., 2017)	1995-2012	Dreher et al. (2017)
Elevation	Standard deviation of regional elevation as an indicator of ruggedness of terrain	Constant	USGS Global 30 Arc-Second Elevation (GTOPO30)
Ocean, Rivers, Lakes	Binary indicator of presence of rivers, lakes or ocean in a given ADM1 region	Constant	Natural Earth, available at Natural Earth.com
Landarea	Area of a given region	Constant	Hijmans et al. (2010)
Travel Time (Mean)	Gives the mean regional estimate of the travel time to the nearest major city	Constant	Tollefsen et al. (2012) and Uchida and Nelson (2009)
Borders	Binary indicator if a given ADM1 region borders another country	Constant	Own estimations based on Hijmans et al. (2010)

Table 13: Data Sources

B Analytical Appendix

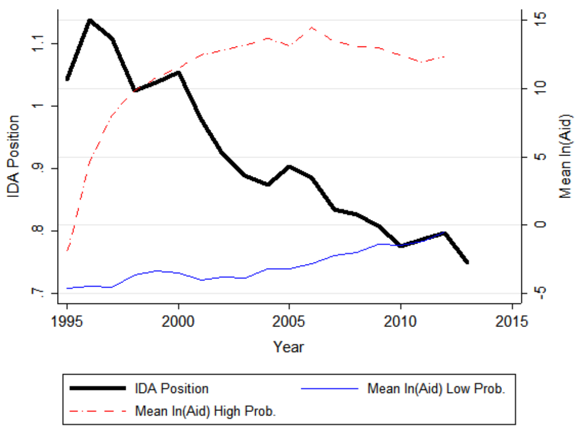
B.1 Instrumental Variable

B.1.1 Motivation of Instrumental Variable

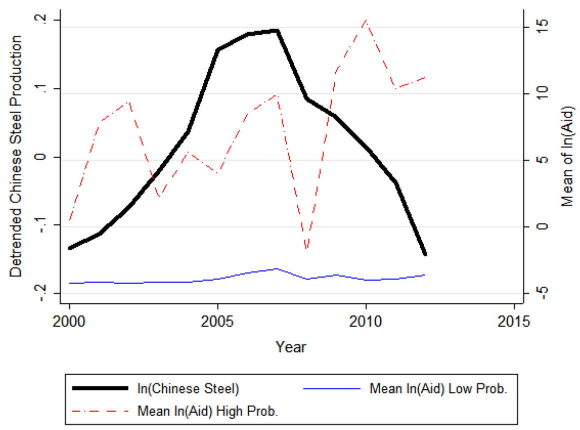


Notes: Yearly values of $IDA - Position_t$ based on Dreher et al. (2017).

Figure 12: IDA Position



(a)



(b)

Figure 13: (a) WB IDA funding position and mean of ln(WB Aid) and (b) Deviations from trend in steel production and mean of ln(Chinese Aid).

Note: Figure 13 a) displays the IDA funding position (thick line), the mean of logged WB aid disbursements per low probability recipient regions (thin line) and the mean of logged WB aid disbursements per high probability recipient regions (dashed line). Figure 13 b) displays the log of the detrended Chinese Steel Production (thick line), the mean of logged Chinese aid per low probability recipient regions (thin line) and the mean of logged Chinese aid per high probability recipient regions (dashed line).

Table 14: ADM1 - Leads and further Lags

	(1)	(2)
Panel A: WB Aid		
Two Leads and Lags: World Bank		
ln(World Bank Aid $_{t+1}$)	-0.0059	0.1559
	(0.1298)	(0.1199)
ln(World Bank Aid $_{t}$)	-0.1089	-0.2128*
	(0.1152)	(0.1157)
ln(World Bank Aid $_{t-1}$)	0.0214	-0.0933
	(0.0973)	(0.0956)
ln(World Bank Aid $_{t-2}$)	0.0516	0.1424
	(0.0939)	(0.1212)
ln(World Bank Aid $_{t-3}$)	-0.0811	-0.0535
	(0.0877)	(0.1076)
N	10150	10150
Panel B: Chinese Aid		
Lead and Lag: China		
ln(Chinese Aid $_{t+1}$)	0.1681	0.2083*
	(0.1244)	(0.1258)
ln(Chinese Aid $_{t}$)	-0.0127	0.0231
	(0.1268)	(0.1358)
ln(Chinese Aid $_{t-1}$)	-0.0086	-0.0481
	(0.1514)	(0.1600)
ln(Chinese Aid $_{t-2}$)	0.0121	-0.0506
	(0.1165)	(0.1313)
ln(Chinese Aid $_{t-3}$)	0.0572	-0.0308
	(0.0986)	(0.1102)
N	6525	6525
Exogeneous Controls	Yes	Yes
Exogeneous Controls $\times$ Year FE	Yes	Yes
Linear Regional Trends	Yes	Yes
Country- $\times$ Year	No	Yes

Notes: Dependent variable: Category 1 binary conflict indicator (100 if BRD$\geq$5, 0 if BRD<5). Standard errors in parentheses, two-way clustered at the country-year and regional level. The sample includes African countries for the sampling period of 1995-2012 for the WB and 2000-2012 for Chinese Aid. Conflicts are considered for the WB from 1996 to 2013 and for Chinese aid from 2002 to 2014 due to the lag structure. Both regressions include year and region fixed effects as well as time trends. Time Trends include linear and squared country-specific time trends. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 15: ADM1 IV (First Stage - Extensive Margin)

	(1)	(2)
Panel A: WB Aid		
IV FS Extensive Margin: IDA Position		
IDA Position $_{t-1}$ × Cum. Prob $_{t-2}$	4.0782***	4.8249***
	(0.4140)	(0.5238)
Cum. Prob $_{t-2}$	-4.3155***	-5.0339***
	(0.4512)	(0.5506)
N	12325	12325
Panel B: Chinese Aid		
IV FS Extensive Margin: Chinese Steel		
Steel Prod detrend $_{t-3}$ × Cum. Prob $_{t-3}$	-3.7025***	-3.1905***
	(0.7694)	(0.7572)
Cum. Prob $_{t-3}$	-1.7443***	-1.5365***
	(0.2117)	(0.1989)
N	7975	7975
Exogeneous Controls	Yes	Yes
Exogeneous Controls × Year FE	Yes	Yes
Linear Regional Trends	Yes	Yes
Country-Year FE	No	Yes

Notes: The table displays regression coefficients the first stage of the IV regression, when instead of the aid amount a binary indicator of aid receipts is used. Standard errors in parentheses, two-way clustered at the country-year and regional level. The sample includes African countries for the sampling period of 1995-2012 for the WB and 2000-2012 for Chinese Aid. Both regressions include year and region fixed effects as well as time trends. Time Trends include linear and squared country-specific time trends. The constituent term of the probability is depicted in the appendix. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 16: ADM1 IV (First Stage - Intensive Margin)

	(1)	(2)
Panel A: WB Aid		
IV FS Intensive Margin: IDA Position		
IDA Position $_{\text{t-1}}$ $\times$ Cum. Prob $_{\text{t-2}}$	4.4155	8.5243**
	(3.3348)	(3.7926)
Cum. Prob $_{\text{t-2}}$	-2.3430	-6.3455
	(3.8685)	(4.3700)
N	7091	7081
Country-Year FE	No	Yes
Regional Time Trend	Yes	Yes
Country Time Trend:	Yes	Yes
$CountryTimeTrend^2$:	Yes	Yes
Panel B: Chinese Aid: IV FS Intensive Margin: Chinese Steel		
Steel Prod detrend $_{\text{t-3}}$ $\times$ Cum. Prob $_{\text{t-3}}$	-4.6878	-3.2045
	(13.5122)	(18.1847)
Cum. Prob $_{\text{t-3}}$	-2.7933	-6.1660*
	(5.5180)	(3.4017)
N	232	232
Country-Time Trends	No	Yes

Notes: The table displays regression coefficients the first stage of the IV regression, when constraining the sample only on recipient regions. Standard errors in parentheses, two-way clustered at the country-year and regional level. The sample includes African countries for the sampling period of 1995-2012 for the WB and 2000-2012 for Chinese Aid. All regressions include exogenous controls, region fixed effects and year fixed effects. Country-Year fixed effects and more rigid time trends are not included for Chinese Aid due to the more limited variation. The constituent term of the probability is depicted in the appendix. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 17: ADM1 IV (First Stage with probability constituent term)

Panel A: WB Aid	(1)	(2)
IV First stage: IDA Position		
IDA Position $_{\text{t-1}}$ × Cum. Prob $_{\text{t-2}}$	70.9363***	80.8832***
	(7.1065)	(8.6854)
Cum. Prob $_{\text{t-2}}$	-72.7723***	-82.0994***
	(7.7291)	(9.2698)
N	12325	12325
Panel B: Chinese Aid		
IV First stage: Chinese Steel		
Steel Prod detrend $_{\text{t-3}}$ × Cum. Prob $_{\text{t-3}}$	-70.8763***	-60.6567***
	(14.9526)	(14.9524)
Cum. Prob $_{\text{t-3}}$	-33.3092***	-29.6850***
	(3.9348)	(3.7560)
N	7975	7975
Exogeneous Controls	Yes	Yes
Exogeneous Controls × Year FE	Yes	Yes
Linear Regional Trends	Yes	Yes
Country-Year FE	No	Yes

Notes: The table displays regression coefficients the first stage of the IV regression, displaying additionally the constituent term of the probability, which was also used in Table 4. Standard errors in parentheses, two-way clustered at the country-year and regional level. The sample includes African countries for the sampling period of 1995-2012 for the WB and 2000-2012 for Chinese Aid. Both regressions include year and region fixed effects as well as time trends. Time Trends include linear and squared country-specific time trends. The constituent term of the probability is depicted in the appendix. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 18: ADM1 Reduced Form

	(1)	(2)
Panel A: WB Aid		
Reduced Form: IDA Position		
Cum. Prob $_{\text{t-2}}$	10.8281	19.2994
	(27.3795)	(33.4583)
IDA Position $_{\text{t-1}}$ $\times$ Cum. Prob $_{\text{t-2}}$	-7.1921	-18.2132
	(26.5498)	(33.5818)
N	12325	12325
Panel B: Chinese Aid		
Reduced Form: Chinese Steel		
Cum. Prob $_{\text{t-3}}$	-12.0548	-17.4914*
	(9.1057)	(9.5552)
Steel Prod detrend $_{\text{t-3}}$ $\times$ Cum. Prob $_{\text{t-3}}$	47.2461	39.7102
	(47.4192)	(51.6767)
N	7250	7250
Exogeneous Controls	Yes	Yes
Exogeneous Controls $\times$ Year FE	Yes	Yes
Linear Regional Trends	Yes	Yes
Country $\times$ Year FE	No	Yes

Notes: Dependent variable: Category 1 binary conflict indicator (100 if BRD$\geq$5, 0 if BRD<5). Standard errors in parentheses, two-way clustered at the country-year and regional level. The sample includes African countries for the sampling period of 1995-2012 for the WB and 2000-2012 for Chinese Aid. Both regressions include year and region fixed effects as well as time trends. Time Trends include linear and squared country-specific time trends. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

B.1.2 Robustness of Instrumental Variable

Table 19: ADM1 - Placebo Instrumented Lead of Aid

	(1)	(2)
Panel A: WB Aid		
Placebo (Lead): World Bank		
ln(World Bank Aid $_{t+1}$)	0.2299	0.2332
	(0.3586)	(0.3704)
N	12325	12325
Kleibergen-Paap underidentification test p-value	0.000	0.000
Kleibergen-Paap weak identification F-statistic	99.481	86.444
Panel B: Chinese Aid		
Placebo (Lead): China		
ln(Chinese Aid $_{t+1}$)	-0.1709	-0.8099
	(0.4393)	(0.5778)
N	8700	8700
Kleibergen-Paap underidentification test p-value	0.000	0.000
Kleibergen-Paap weak identification F-statistic	17.628	12.910
Exogeneous Controls	Yes	Yes
Exogeneous Controls × Year FE	Yes	Yes
Linear Regional Trends	Yes	Yes
Country × Year FE	No	Yes

Notes: Dependent variable: Category 1 binary conflict indicator (100 if BRD≥5, 0 if BRD<5). Standard errors in parentheses, two-way clustered at the country-year and regional level. The sample includes African countries for the sampling period of 1995-2012 for the WB and 2000-2012 for Chinese Aid. Both regressions include year and region fixed effects as well as time trends. Time Trends include linear and squared country-specific time trends. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 20: ADM1 IV (IDA-Position$_{t-1}$)

	(1)	(2)
Panel A: WB Aid		
IV Second Stage: IDA Position (t-1)		
ln(World Bank Aid$_{\text{t-1}}$)	-0.1294	-0.0251
	(0.3976)	(0.3868)
IV FS: IDA Position (t-1)		
IDA Position$_{\text{t-1}}$ $\times$ Cum. Prob$_{\text{t-2}}$	51.3655***	65.1984***
	(5.6627)	(6.9103)
Cum. Prob$_{\text{t-2}}$	-52.8484***	-67.1407***
	(6.2620)	(7.5204)
N	12325	12325
Exogeneous Controls	Yes	Yes
Exogeneous Controls $\times$ Year FE	Yes	Yes
Linear Regional Trends	Yes	Yes
Country-Year FE	No	Yes

Notes: Dependent variable: Category 1 binary conflict indicator (100 if BRD$\geq$5, 0 if BRD<5). Standard errors in parentheses, two-way clustered at the country-year and regional level. The sample includes African countries for the sampling period of 1995-2012 for the WB and 2000-2012 for Chinese Aid. Both regressions include year and region fixed effects as well as time trends. Time Trends include linear and squared country-specific time trends. Instead of a running sum of IDA funding position in "t" and "t-1" only the variation in "t-1" is used. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 21: ADM1 IV (Without high leverage region)

	(1)	(2)
Panel A: WB Aid		
IV Second stage: IDA Position		
ln(World Bank Aid $_{t-1}$)	-0.0990	-0.2268
	(0.3761)	(0.4197)
Kleibergen-Paap underidentification test p-value	0.000	0.000
Kleibergen-Paap weak identification F-statistic	99.363	86.752
IV First stage: IDA Position		
IDA Position $_{t-1}$ $\times$ Cum. Prob $_{t-2}$	70.8414***	80.8936***
	(7.1068)	(8.6851)
N	12317	12291
Panel B: Chinese Aid		
IV Second Stage: Chinese Steel		
ln(Chinese Aid $_{t-2}$)	-0.4529	-0.4367
	(0.6166)	(0.8058)
Kleibergen-Paap underidentification test p-value	0.000	0.000
Kleibergen-Paap weak identification F-statistic	22.462	16.449
IV First stage: Chinese Steel		
Steel Prod detrend $_{t-3}$ $\times$ Cum. Prob $_{t-3}$	-70.8804***	-60.6611***
	(14.9554)	(14.9568)
N	7974	7974
Exogeneous Controls	Yes	Yes
Exogeneous Controls $\times$ Year FE	Yes	Yes
Linear Regional Trends	Yes	Yes
Country-Year FE	No	Yes

Notes: Dependent variable: Category 1 binary conflict indicator (100 if BRD$\geq$5, 0 if BRD<5). Standard errors in parentheses, two-way clustered at the country-year and regional level. The sample includes African countries for the sampling period of 1995-2012 for the WB and 2000-2012 for Chinese Aid. Both regressions include year and region fixed effects as well as time trends. Time Trends include linear and squared country-specific time trends. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 22: ADM1 IV (Without first year)

	(1)	(2)
Panel A: WB Aid		
IV Second stage: IDA Position ln(World Bank Aid $_{t-1}$)	-0.2904	-0.2681
	(0.4172)	(0.3975)
Kleibergen-Paap underidentification test p-value	0.000	0.000
Kleibergen-Paap weak identification F-statistic	80.438	78.004
IV First stage: IDA Position IDA Position $_{t-1}$ $\times$ Cum. Prob $_{t-2}$	68.5810***	88.1297***
	(7.6467)	(9.9784)
N	11600	11600
Panel B: Chinese Aid		
IV Second Stage: Chinese Steel		
ln(Chinese Aid $_{t-2}$)	-0.9072	-0.9387
	(0.9329)	(1.2510)
Kleibergen-Paap underidentification test p-value	0.002	0.012
Kleibergen-Paap weak identification F-statistic	9.548	6.144
IV First stage: Chinese Steel		
Steel Prod detrend $_{t-3}$ $\times$ Cum. Prob $_{t-3}$	-52.0807***	-42.3054**
	(16.8548)	(17.0681)
N	7250	7250
Exogeneous Controls	Yes	Yes
Exogeneous Controls $\times$ Year FE	Yes	Yes
Linear Regional Trends	Yes	Yes
Country-Year FE	No	Yes

Notes: Dependent variable: Category 1 binary conflict indicator (100 if BRD$\geq$5, 0 if BRD<5). Standard errors in parentheses, two-way clustered at the country-year and regional level. The sample includes African countries for the sampling period of 1995-2012 for the WB and 2000-2012 for Chinese Aid. Both regressions include year and region fixed effects as well as time trends. Time Trends include linear and squared country-specific time trends. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. The constituent term of the probability is depicted in the appendix.

Table 23: ADM1 IV (WB detrend & Chinese aid no detrend)

	(1)	(2)
Panel A: WB Aid		
IV Second stage: IDA Position		
ln(World Bank Aid $_{\text{t-1}}$)	0.3239	0.0770
	(0.7185)	(0.7595)
Kleibergen-Paap underidentification test p-value	0.000	0.001
Kleibergen-Paap weak identification F-statistic	30.474	15.646
IV First stage: IDA Position		
IDA Position detrend $_{\text{t-1}}$ $\times$ Cum. Prob $_{\text{t-2}}$	49.1363***	59.7776***
	(8.9010)	(15.1125)
Cum. Prob $_{\text{t-2}}$	1.0001	0.3355
	(1.5130)	(1.8596)
N	12325	12325
Panel B: Chinese Aid		
IV Second Stage: Chinese Steel		
ln(Chinese Aid $_{\text{t-2}}$)	-0.0980	0.0374
	(0.2384)	(0.2766)
Kleibergen-Paap underidentification test p-value	0.000	0.000
Kleibergen-Paap weak identification F-statistic	66.567	58.408
IV First stage: Chinese Steel		
Steel Prod $_{\text{t-3}}$ $\times$ Cum. Prob $_{\text{t-3}}$	-54.7934***	-50.5179***
	(6.7158)	(6.6102)
Cum. Prob $_{\text{t-3}}$	634.3188***	585.1439***
	(80.2897)	(79.2510)
N	7975	7975
Exogeneous Controls	Yes	Yes
Exogeneous Controls $\times$ Year FE	Yes	Yes
Linear Regional Trends	Yes	Yes
Country-Year FE	No	Yes

Notes: Dependent variable: Category 1 binary conflict indicator (100 if BRD$\geq$5, 0 if BRD<5). Standard errors in parentheses, two-way clustered at the country-year and regional level. The sample includes African countries for the sampling period of 1995-2012 for the WB and 2000-2012 for Chinese Aid. Both regressions include year and region fixed effects as well as time trends. Time Trends include linear and squared country-specific time trends. The constituent term of the probability is depicted in the appendix. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 24: ADM1 IV (Initial Probability)

	(1)	(2)
Panel A: WB Aid		
IV Second stage: IDA Position		
ln(World Bank Aid $_{t-1}$)	0.2253	-0.3389
	(0.7469)	(0.6205)
Kleibergen-Paap underidentification test p-value	0.000	0.000
Kleibergen-Paap weak identification F-statistic	27.151	26.086
IV First stage: IDA Position		
IDA Position $_{t-1}$ $\times$ Cum. Prob $_{98}$	43.4309***	61.1537***
	(8.3349)	(11.9734)
N	11600	11600
Panel B: Chinese Aid		
IV Second Stage: Chinese Steel		
ln(Chinese Aid $_{t-2}$)	-1.6319	-1.4597
	(1.3706)	(1.4889)
Kleibergen-Paap underidentification test p-value	0.001	0.004
Kleibergen-Paap weak identification F-statistic	10.461	7.880
IV First stage: Chinese Steel		
Steel Prod detrend $_{t-3}$ $\times$ Cum. Prob $_{03}$	-36.7317***	-35.9689***
	(11.3566)	(12.8131)
N	7250	7250
Exogeneous Controls	Yes	Yes
Exogeneous Controls $\times$ Year FE	Yes	Yes
Linear Regional Trends	Yes	Yes
Country-Year FE	No	Yes

Notes: Dependent variable: Category 1 binary conflict indicator (100 if BRD$\geq$5, 0 if BRD<5). Standard errors in parentheses, two-way clustered at the country-year and regional level. The sample includes African countries for the sampling period of 1995-2012 for the WB and 2000-2012 for Chinese Aid. Both regressions include year and region fixed effects as well as time trends. Time Trends include linear and squared country-specific time trends. The probability is based on the third year in the corresponding sample (1998 for the WB's IDA; 2003 for Chinese Steel) and held thereafter constant. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

B.2 Alternative Outcome Variables

Table 25: ADM1 - Actors (clustering at country-year and regional level)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A: WB Aid - OLS								
OLS: WB - Actors	State vs N-State		N-State vs N-State		State vs Civilans		N-State vs Civilians	
ln(World Bank Aid $_{t-1}$)	-0.1229*	-0.1365*	-0.0348	-0.0784	-0.0596	-0.0372	-0.1040**	-0.0979*
	(0.0650)	(0.0707)	(0.0492)	(0.0679)	(0.0452)	(0.0430)	(0.0521)	(0.0578)
N	13050	13050	13050	13050	13050	13050	13050	13050
Panel B: Chinese Aid - OLS								
OLS: China - Actors	State vs N-State		N-State vs N-State		State vs Civilans		N-State vs Civilians	
ln(Chinese Aid $_{t-2}$)	-0.0009	0.0122	-0.0162	0.0016	-0.0702	-0.0625	-0.0338	-0.0334
	(0.0548)	(0.0663)	(0.0554)	(0.0769)	(0.0483)	(0.0542)	(0.0349)	(0.0439)
N	8700	8700	8700	8700	8700	8700	8700	8700
Country-Year FE	No	Yes	No	Yes	No	Yes	No	Yes

Notes: Dependent variable: Category 1 binary conflict indicator (100 if BRD$\geq$5, 0 if BRD<5). Standard errors in parentheses, two-way clustered at the country-year and regional level. The sample includes African countries for the sampling period of 1995-2012 for the WB and 2000-2012 for Chinese Aid. Conflicts are considered for the WB from 1996 to 2013 and for Chinese aid from 2002 to 2014 due to the lag structure. Exogenous (time-varying) controls are included in all regressions. Time Trends included, consist of linear and squared country-specific time trends as well as linear regional time trends. "State vs N-State" refers to state-based violence against non-government actors, "N-State vs N-State" refers to non-government violence against the other organized non-state groups, and "State vs Civilians" refers to one-sided violence versus civilians by the government and "N-State vs. Civilians" refers to one-sided violence versus civilians by non-government (NG) actors. The categories are mutually exclusive. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 26: ADM1 OLS results (Riots, Demonstrations & Strikes [SCAD])

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Panel A: WB Aid									
ln(World Bank Aid $_{t-1}$)	0.1194	0.1291	0.4360***	0.0106	-0.0140	-0.0035	-0.1421	-0.0092	-0.0447
	(0.0912)	(0.1028)	(0.0885)	(0.0641)	(0.0751)	(0.0848)	(0.1063)	(0.0954)	(0.1133)
N	13104	13104	13104	13104	13050	13050	11017	13050	11017
Panel B: Chinese Aid									
ln(Chinese Aid $_{t-2}$)	0.8761***	1.0301***	1.0445***	-0.1026	-0.0468	-0.0182	-0.0009	0.0141	0.0387
	(0.2247)	(0.1888)	(0.1939)	(0.0880)	(0.1027)	(0.1050)	(0.1013)	(0.1268)	(0.1301)
N	9464	9464	9464	9464	8700	8700	8261	8700	8261
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 Controls $\times$ Year FE	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 $\times$ Year FE	No	No	No	No	No	No	No	Yes	Yes

Notes: The table displays regression coefficients with a binary indicator for any violence of these three types as dependent variable. Standard errors in parentheses, two-way clustered at the country-year and regional level. The sample includes African countries for the sampling period of 1995-2012 for the WB and 2000-2012 for Chinese Aid. Time Trends include linear and squared country-specific time trends. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 27: ADM1 IV (Riots, Demonstrations & Strikes [SCAD])

	(1)	(2)
Panel A: WB Aid		
IV Second stage: IDA Position		
ln(World Bank Aid $_{\text{t-1}}$)	-0.3854	-0.2032
	(0.3092)	(0.3362)
N	12325	12325
Kleibergen-Paap underidentification test p-value	0.000	0.000
Kleibergen-Paap weak identification F-statistic	99.639	86.724
IV First stage: IDA Position		
IDA Position $_{\text{t-1}}$ $\times$ Cum. Prob $_{\text{t-2}}$	70.9363***	80.8832***
	(7.1065)	(8.6854)
N	12325	12325
Panel B: Chinese Aid		
IV Second Stage: Chinese Steel		
ln(Chinese Aid $_{\text{t-1}}$)	0.1578	0.2686
	(0.6087)	(0.7312)
N	7975	7975
Kleibergen-Paap underidentification test p-value	0.000	0.000
Kleibergen-Paap weak identification F-statistic	22.468	16.456
IV First stage: Chinese Steel		
Steel Prod detrend $_{\text{t-3}}$ $\times$ Cum. Prob $_{\text{t-3}}$	-70.8763***	-60.6567***
	(14.9526)	(14.9524)
N	7975	7975
Exogeneous Controls	Yes	Yes
Exogeneous Controls $\times$ Year FE	Yes	Yes
Linear Regional Trends	Yes	Yes
Country-Year FE	No	Yes

Notes: The table displays regression coefficients for any violence of these three types as dependent variable. Standard errors in parentheses, two-way clustered at the country-year and regional level. The sample includes African countries for the sampling period of 1995-2012 for the WB and 2000-2012 for Chinese Aid. Both regressions include year and region fixed effects as well as time trends. Time Trends include linear and squared country-specific time trends. The constituent term of the probability is depicted in the appendix. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 28: ADM1 OLS results (Demonstrations)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Panel A: WB Aid									
ln(World Bank Aid $_{t-1}$)	0.0578	0.1247*	0.3399***	0.0514	0.0414	0.0491	-0.0224	0.0390	0.0364
	(0.0684)	(0.0708)	(0.0705)	(0.0472)	(0.0699)	(0.0763)	(0.0816)	(0.0745)	(0.0824)
N	13104	13104	13104	13104	13050	13050	11017	13050	11017
Panel B: Chinese Aid									
ln(Chinese Aid $_{t-2}$)	0.7830***	0.8995***	0.9203***	-0.1090	-0.0865	-0.0781	-0.0704	-0.1094	-0.0888
	(0.1899)	(0.1649)	(0.1700)	(0.0766)	(0.0919)	(0.0985)	(0.1011)	(0.1233)	(0.1236)
N	9464	9464	9464	9464	8700	8700	8261	8700	8261
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 Controls $\times$ Year FE	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 $\times$ Year FE	No	No	No	No	No	No	No	Yes	Yes

Notes: The table displays regression coefficients with a binary indicator for demonstrations as dependent variable. Standard errors in parentheses, two-way clustered at the country-year and regional level. The sample includes African countries for the sampling period of 1995-2012 for the WB and 2000-2012 for Chinese Aid. Time Trends include linear and squared country-specific time trends. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 29: ADM1 OLS results (Riots)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Panel A: WB Aid									
ln(World Bank Aid $_{t\text{-}1}$)	0.0920	0.0037	0.2350***	0.0129	-0.0060	-0.0060	-0.0831	-0.0853	-0.1080
	(0.0620)	(0.0856)	(0.0617)	(0.0533)	(0.0559)	(0.0617)	(0.0682)	(0.0804)	(0.1049)
N	13104	13104	13104	13104	13050	13050	11017	13050	11017
Panel B: Chinese Aid									
ln(Chinese Aid $_{t\text{-}2}$)	0.4258***	0.5248***	0.5289***	0.0006	0.0399	0.0316	0.0521	0.0424	0.0613
	(0.1482)	(0.1261)	(0.1292)	(0.0814)	(0.0956)	(0.0986)	(0.0991)	(0.1200)	(0.1313)
N	9464	9464	9464	9464	8700	8700	8261	8700	8261
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 Controls $\times$ Year FE	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 $\times$ Year FE	No	No	No	No	No	No	No	Yes	Yes

Notes: The table displays regression coefficients with a binary indicator for riots as dependent variable. Standard errors in parentheses, two-way clustered at the country-year and regional level. The sample includes African countries for the sampling period of 1995-2012 for the WB and 2000-2012 for Chinese Aid. Time Trends include linear and squared country-specific time trends. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 30: ADM1 OLS results (Strikes)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Panel A: WB Aid									
ln(World Bank Aid $_{t-1}$)	0.0020	0.0302	0.1288***	-0.0197	-0.0252	-0.0377	-0.0549	-0.0717	-0.0758
	(0.0310)	(0.0391)	(0.0377)	(0.0309)	(0.0445)	(0.0578)	(0.0656)	(0.0582)	(0.0695)
N	13104	13104	13104	13104	13050	13050	11017	13050	11017
Panel B: Chinese Aid									
ln(Chinese Aid $_{t-2}$)	0.1611*	0.1832**	0.1931**	-0.1785**	-0.2042**	-0.1845*	-0.1800*	-0.1620	-0.1605
	(0.0847)	(0.0810)	(0.0846)	(0.0712)	(0.0887)	(0.1043)	(0.1036)	(0.1073)	(0.1122)
N	9464	9464	9464	9464	8700	8700	8261	8700	8261
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 Controls $\times$ Year FE	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 $\times$ Year FE	No	No	No	No	No	No	No	Yes	Yes

Notes: The table displays regression coefficients with a binary indicator for strikes as dependent variable. Standard errors in parentheses, two-way clustered at the country-year and regional level. The sample includes African countries for the sampling period of 1995-2012 for the WB and 2000-2012 for Chinese Aid. Time Trends include linear and squared country-specific time trends. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 31: ADM1 IV (Repression (non-lethal) - Regions with UCDP Violence Against Civilians coded as zero)

	(1)	(2)
Panel A: WB Aid		
IV: IDA Position - Actors		
ln(World Bank Aid $_{t\text{-}1}$)	0.1543	0.0885
	(0.1042)	(0.1177)
N	12325	12325
Kleibergen-Paap underidentification test p-value	0.000	0.000
Kleibergen-Paap weak identification F-statistic	99.639	86.724
Panel B: Chinese Aid		
IV: Chinese Steel - Actors		
ln(Chinese Aid $_{t\text{-}2}$)	0.9798***	1.3059***
	(0.3663)	(0.5025)
N	7975	7975
Kleibergen-Paap underidentification test p-value	0.000	0.000
Kleibergen-Paap weak identification F-statistic	22.468	16.456
Exogeneous Controls	Yes	Yes
Exogeneous Controls $\times$ Year FE	Yes	Yes
Linear Regional Trends	Yes	Yes
Country-Year FE	No	Yes

Notes: The table displays regression coefficients for a binary pro-governmental violence indicator as dependent variable. Standard errors in parentheses, two-way clustered at the country-year and regional level. The sample includes African countries for the sampling period of 1995-2012 for the WB and 2000-2012 for Chinese Aid. Both regressions include year and region fixed effects as well as time trends. Time Trends include linear and squared country-specific time trends. The constituent term of the probability is depicted in the appendix. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 32: Non-lethal pro-government Violence [SCAD] - Continuous measure

Panel A: WB Aid	(1)	(2)
IV Second stage: IDA Position		
ln(World Bank Aid $_{t-1}$)	0.0011	0.0012
	(0.0014)	(0.0013)
N	12325	12325
Kleibergen-Paap underidentification test p-value	0.000	0.000
Kleibergen-Paap weak identification F-statistic	99.639	86.724
Panel B: Chinese Aid		
IV Second Stage: Chinese Steel		
ln(Chinese Aid $_{t-1}$)	0.0146***	0.0197**
	(0.0056)	(0.0092)
N	7975	7975
Kleibergen-Paap underidentification test p-value	0.000	0.000
Kleibergen-Paap weak identification F-statistic	22.468	16.456
Country-Year FE	No	Yes

Notes: The table displays regression coefficients for a continuous measure of non-lethal pro-government violence as dependent variable. Standard errors in parentheses, two-way clustered at the country-year and regional level. The sample includes African countries for the sampling period of 1995-2012 for the WB and 2000-2012 for Chinese Aid. Both regressions include year and region fixed effects as well as time trends. Time Trends include linear and squared country-specific time trends. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Other versions of UCDP conflict measure

Table 33: ADM1 OLS results (Battle-related Deaths)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Panel A: WB Aid									
ln(World Bank Aid $_{t\text{-}1}$)	-0.0164*	-0.0014	-0.0025	-0.0174***	-0.0165**	-0.0142*	-0.0019	-0.0142*	-0.0100
	(0.0092)	(0.0071)	(0.0065)	(0.0060)	(0.0068)	(0.0074)	(0.0083)	(0.0081)	(0.0093)
N	13104	13104	13104	13104	13050	13050	11017	13050	11017
Panel B: Chinese Aid									
ln(Chinese Aid $_{t\text{-}2}$)	-0.0119	0.0034	0.0068	-0.0055	-0.0008	0.0004	0.0007	0.0034	0.0029
	(0.0087)	(0.0065)	(0.0054)	(0.0048)	(0.0072)	(0.0066)	(0.0068)	(0.0064)	(0.0071)
N	9464	9464	9464	9464	8700	8700	8261	8700	8261
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 Controls $\times$ Year FE	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 $\times$ Year FE	No	No	No	No	No	No	No	Yes	Yes

Notes: The table displays regression coefficients with the log of battle-related deaths + 0.01 as dependent variable (category 3). Standard errors in parentheses, two-way clustered at the country-year and regional level. The sample includes African countries for the sampling period of 1995-2012 for the WB and 2000-2012 for Chinese Aid. Time Trends include linear and squared country-specific time trends. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 34: ADM1 IV (Battle-Related Deaths)

	(1)	(2)
Panel A: WB Aid		
IV Second stage: IDA Position		
ln(World Bank Aid $_{t-1}$)	-0.0179	-0.0340
	(0.0340)	(0.0358)
Kleibergen-Paap underidentification test p-value	0.000	0.000
Kleibergen-Paap weak identification F-statistic	99.639	86.724
IV First stage: IDA Position		
IDA Position $_{t-1}$ $\times$ Cum. Prob $_{t-2}$	70.9363***	80.8832***
	(7.1065)	(8.6854)
N	12325	12325
Panel B: Chinese Aid		
IV Second Stage: Chinese Steel		
ln(Chinese Aid $_{t-1}$)	-0.0413	-0.0270
	(0.0470)	(0.0635)
N	7975	7975
Kleibergen-Paap underidentification test p-value	0.000	0.000
Kleibergen-Paap weak identification F-statistic	22.468	16.456
IV First stage: Chinese Steel		
Steel Prod detrend $_{t-3}$ $\times$ Cum. Prob $_{t-3}$	-70.8763***	-60.6567***
	(14.9526)	(14.9524)
N	7975	7975
Exogeneous Controls	Yes	Yes
Exogeneous Controls $\times$ Year FE	Yes	Yes
Linear Regional Trends	Yes	Yes
Country-Year FE	No	Yes

Notes: The table displays regression coefficients for the log of battle-related deaths +0.01 as dependent variable (category 3). Standard errors in parentheses, two-way clustered at the country-year and regional level. The sample includes African countries for the sampling period of 1995-2012 for the WB and 2000-2012 for Chinese Aid. Both regressions include year and region fixed effects as well as time trends. Time Trends include linear and squared country-specific time trends. The constituent term of the probability is depicted in the appendix. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 35: ADM1 OLS results (Intensity 2)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Panel A: WB Aid									
ln(World Bank Aid $_{t\text{-}1}$)	-0.1061	-0.0440	-0.0703	-0.1810***	-0.1522**	-0.1528**	-0.0544	-0.1386*	-0.1453
	(0.0659)	(0.0551)	(0.0536)	(0.0528)	(0.0669)	(0.0668)	(0.0747)	(0.0764)	(0.0927)
N	13104	13104	13104	13104	13050	13050	11017	13050	11017
Panel B: Chinese Aid									
ln(Chinese Aid $_{t\text{-}2}$)	-0.0917	-0.0209	0.0184	-0.0285	-0.0140	0.0059	-0.0001	-0.0022	-0.0099
	(0.0614)	(0.0504)	(0.0378)	(0.0446)	(0.0530)	(0.0496)	(0.0543)	(0.0568)	(0.0645)
N	9464	9464	9464	9464	8700	8700	8261	8700	8261
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 Controls $\times$ Year FE	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 $\times$ Year FE	No	No	No	No	No	No	No	Yes	Yes

Notes: Dependent variable: Category 2 binary conflict indicator (100 if BRD$\geq$25, 0 if BRD<25). Standard errors in parentheses, two-way clustered at the country-year and regional level. The sample includes African countries for the sampling period of 1995-2012 for the WB and 2000-2012 for Chinese Aid. Time Trends include linear and squared country-specific time trends. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 36: ADM1 IV (Intensity 2)

	(1)	(2)
Panel A: WB Aid		
IV Second Stage: IDA Position		
ln(World Bank Aid $_{t\text{-}1}$)	-0.1437	-0.4581
	(0.3075)	(0.3301)
IV First stage: IDA Position		
IDA Position $_{t\text{-}1}$ × Cum. Prob $_{t\text{-}2}$	70.9363***	80.8832***
	(7.1065)	(8.6854)
N	12325	12325
Panel B: Chinese Aid		
IV Second Stage: Chinese Steel		
ln(Chinese Aid $_{t\text{-}2}$)	0.1980	0.2563
	(0.3729)	(0.4669)
IV First stage: Chinese Steel		
Steel Prod detrend $_{t\text{-}3}$ × Cum. Prob $_{t\text{-}3}$	-70.8763***	-60.6567***
	(14.9526)	(14.9524)
N	7975	7975
Exogeneous Controls	Yes	Yes
Exogeneous Controls × Year FE	Yes	Yes
Linear Regional Trends	Yes	Yes
Country-Year FE	No	Yes

Notes: Dependent variable: Category 2 binary conflict indicator (100 if BRD≥25, 0 if BRD<25). Standard errors in parentheses, two-way clustered at the country-year and regional level. The sample includes African countries for the sampling period of 1995-2012 for the WB and 2000-2012 for Chinese Aid. Both regressions include year and region fixed effects as well as time trends. Time Trends include linear and squared country-specific time trends. The constituent term of the probability is depicted in the appendix. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

B.3 Channels - Ethnic groups and governing coalition

Conflicts are not only driven by economic considerations, but often strongly influenced by existing cleavages between groups. Ethnic identities are the most salient traits and ethnic groups the most important reference group in most African countries. To measure ethnic homelands, we use the GREG dataset (Weidmann et al., 2010), which is a georeferenced version of the initial locations of ethnic homelands based on the Soviet Atlas Narodov Mira. These locations were determined before our sample, and, even though immigration becomes more important over time, prior studies suggest that a large share of Africans still live in their ethnic home region (Nunn and Wantchekon, 2011). This makes those group polygons a noisy, but still informative measure.

A first important question is whether the effect of aid projects differs between more and less ethnically fractionalized regions. Theoretically, one might expect more potential for dissatisfaction about an unequal allocation of projects or the distribution of the associated benefits in ethnically fractionalized regions. We compute standard fractionalization measures in line with the literature (Alesina and Ferrara, 2005; Fearon and Laitin, 2003), and split the sample between countries in regions with fractionalization above or below the mean or median. Appendix Tables 38 and 39 show no large differences. When including country-year FE, the negative relationship between aid and conflict becomes even a bit stronger, but the difference is small. Even in the more fractionalized regions, it does not turn positive. [39]

More important than considering ethnic cleavages in general is to define which ethnic groups are allies and form a joint coalition and which groups are outside that coalition. To classify administrative regions, our unit of analysis, we distinguish whether all groups (Coalition), at least one group (Mixed), or no group (N-Coalition) in a region is part of the governing coalition in a particular year. The information about the power status comes from the time-variant Ethnic Power Relations (EPR) dataset (Vogt et al., 2015). Wherever possible, we match the group power status from EPR in a particular year to one of the time-invarying GREG group homelands. The original dataset assigns 8 different power statuses to groups. The difference are sometimes marginal and hard to interpret, which is why we only use the more precise information on whether a group was part of the governing coalition or not. We then intersect the ethnic group polygons with the administrative regions to classify regions as one of the three categories.

This distinction aims at testing the plausibility of the existing results, and at uncovering heterogeneous effects that might be hidden in the averages. For instance, it might be that there is no conflict-inducing effect on average. However, assuming that aid project benefit governing groups more often, existing tensions and conflict might be fueled especially in mixed districts where other

[39] Note that for individual aid types, the IV does not perform sufficiently well for China when splitting the samples. Therefore, we show the OLS specifications for all the sample splits for China. We intend to conduct a more in-depth analysis of aid inequality and ethnic groups in an accompanying paper.

groups observe these distributional differences. In contrast, rapacity theory would predict that governing coalition regions with large aid inflows become more attractive for rebels to capture.

We find several interesting differences in Table 37. The results for the WB always change signs depending on the inclusion of country-year fixed effects. Nonetheless, there is again never a significant conflict-inducing effect. For China, all coefficients are negative, even though again statistically insignificant. Even when considering governing coalition structures, on average Chinese aid does not increase conflicts with at least 5 BRDs.[40]

[40] This finding is robust to defining the coalition only as the more powerful senior, dominant or monopoly groups and excluding junior partners. Results are available upon request from the authors. Appendix Table 40 presents the coalition sample split without controlling for fractionalization. Appendix Table 41 shows the results in Table 37 for the WB using OLS and for China using IV. There are overall no large differences that substantially alter our conclusions.

Table 37: ADM1 results (Power status - Member of Coalition Group)

Panel A: WB - IV	(1)	(2)	(3)	(4)	(5)	(6)
Conflict in region belonging to ...	N-Coalition	N-Coalition	Coalition	Coalition	Mixed	Mixed
ln(World Bank Aid $_{t-1}$)	-0.7052	0.2016	0.0686	-0.6372	0.1552	-0.3712
	(0.9362)	(1.3680)	(0.4500)	(0.4716)	(0.5181)	(0.5339)
N	2144	2075	3750	3651	4569	4537
Kleibergen-Paap underidentification test p-value	0.000	0.003	0.000	0.000	0.000	0.000
Kleibergen-Paap weak identification F-statistic	35.086	18.726	41.902	26.417	63.396	66.952
Panel B: China- OLS:						
Conflict in region belonging to...	N-Coalition	N-Coalition	Coalition	Coalition	Mixed	Mixed
ln(Chinese Aid $_{t-2}$)	-0.2049	-0.2949	-0.0675	-0.0331	-0.0057	-0.0197
	(0.2185)	(0.3223)	(0.1328)	(0.1455)	(0.2442)	(0.2647)
N	1466	1412	2698	2626	3220	3198
Country $\times$ Year FE	No	Yes	No	Yes	No	Yes
Control for Fractionalization	Yes	Yes	Yes	Yes	Yes	Yes

Notes: Dependent variable: Category 1 binary conflict indicator (100 if BRD$\geq$5, 0 if BRD<5). Standard errors in parentheses, two-way clustered at the country-year and regional level. The sample includes African countries for the sampling period of 1995-2012 for the WB and 2000-2012 for Chinese Aid. Conflicts are considered for the WB from 1996 to 2013 and for Chinese aid from 2002 to 2014 due to the lag structure. Both regressions include (time-varying) exogenous controls, year and region fixed effects as well as time trends. Time Trends include linear and squared country-specific time trends as well as linear regional time trends. Columns (1) & (2) refer to all regions without members of the governing coalition, whereas columns (3) & (4) to mixed regions with some groups in and out of the coalition, and columns (5) & (6) to regions that contain groups exclusively from the coalition. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

B.4 Ethnic Groups

Table 38: ADM1 results (Sample split - Mean of Fractionalization)

Panel A: WB Aid - IV:				
ln(World Bank Aid $_{t-1}$)	0.0492	-0.5546	-0.0498	-0.0256
	(0.4419)	(0.4796)	(0.6270)	(0.8597)
N	6715	6698	3757	3740
Kleibergen-Paap underidentification test p-value	0.000	0.000	0.000	0.000
Kleibergen-Paap weak identification F-statistic	79.593	56.722	63.955	45.934
Panel B: Chinese Aid - OLS:				
ln(Chinese Aid $_{t-2}$)	-0.0069	-0.0044	-0.0990	0.0527
	(0.1222)	(0.1434)	(0.1845)	(0.1641)
N	4740	4728	2652	2640
Country $\times$ Year FE	No	Yes	No	Yes

Notes: Dependent variable: Category 1 binary conflict indicator (100 if BRD≥5, 0 if BRD<5). The sample is split in regions, which are below the country level mean of ethnic fractionalization (0) [columns (1) & (2)] or above the mean (1) [columns (3) & (4)]. Ethnic fractionalization is based on $1 - \sum s^2$, where s is the ethnic groups area share in the administrative region. Standard errors in parentheses, two-way clustered at the country-year and regional level. The sample includes African countries for the sampling period of 1995-2012 for the WB and 2000-2012 for Chinese Aid. Conflicts are considered for the WB from 1996 to 2013 and for Chinese aid from 2002 to 2014 due to the lag structure. Both regressions include (time-varying) exogenous cont+rols, year and region fixed effects as well as time trends. Time Trends include linear and squared country-specific time trends as well as linear regional time trends. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 39: Sample-split: Median Fractionalization

Panel A: WB Aid - IV:				
ln(World Bank Aid $_{t-1}$)	-0.2585	-0.6189	0.1471	-0.0455
	(0.4163)	(0.4904)	(0.5688)	(0.7054)
N	5474	5474	4998	4998
Kleibergen-Paap underidentification test p-value	0.000	0.000	0.000	0.000
Kleibergen-Paap weak identification F-statistic	71.721	49.454	75.067	65.391
Panel B: Chinese Aid - IV:				
ln(Chinese Aid $_{t-2}$)	-0.7075	-0.8209	0.0282	1.3653
	(0.8256)	(1.0744)	(0.8463)	(1.1783)
N	3542	3542	3234	3234
Kleibergen-Paap underidentification test p-value	0.000	0.000	0.001	0.007
Kleibergen-Paap weak identification F-statistic	30.983	21.080	15.370	9.900
Country $\times$ Year FE	No	Yes	No	Yes

Notes: Dependent variable: Category 1 binary conflict indicator (100 if BRD≥5, 0 if BRD<5). The sample is split in regions, which are below the country level median/mean of ethnic fractionalization (0) [columns (1) & (2)] or above the median/mean (1) [columns (3) & (4)]. Ethnic fractionalization is based on $1 - \sum s^2$, where s is the ethnic groups area share in the administrative region. Standard errors in parentheses, two-way clustered at the country-year and regional level. The sample includes African countries for the sampling period of 1995-2012 for the WB and 2000-2012 for Chinese Aid. Conflicts are considered for the WB from 1996 to 2013 and for Chinese aid from 2002 to 2014 due to the lag structure. Both regressions include (time-varying) exogenous cont+rols, year and region fixed effects as well as time trends. Time Trends include linear and squared country-specific time trends as well as linear regional time trends. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 40: ADM1 results (Power status - Coalition - Not Controlling for Fractionalization)

Panel A: Coalition groups						
WB Aid:						
	N-Coalition	N-Coalition	Coalition	Coalition	Mixed	Mixed
ln(World Bank Aid $_{t-1}$)	-0.6275	0.1616	0.0568	-0.6527	0.1139	-0.4289
	(0.9584)	(1.4459)	(0.4507)	(0.4697)	(0.5138)	(0.5259)
N	2144	2075	3750	3651	4569	4537
Kleibergen-Paap underidentification test p-value	0.000	0.003	0.000	0.000	0.000	0.000
Kleibergen-Paap weak identification F-statistic	34.890	18.952	41.411	26.677	63.691	67.559
Chinese Aid:						
	N-Coalition	N-Coalition	Coalition	Coalition	Mixed	Mixed
ln(Chinese Aid $_{t-2}$)	0.7974	-7.7164	-1.1273	-1.6313*	1.0984	2.1281
	(3.3008)	(10.3143)	(0.7450)	(0.9361)	(1.0069)	(1.7389)
N	1335	1285	2487	2420	2944	2924
Kleibergen-Paap underidentification test p-value	0.349	0.318	0.000	0.000	0.001	0.020
Kleibergen-Paap weak identification F-statistic	0.951	0.879	56.524	40.500	12.471	6.859
Country $\times$ Year FE	No	Yes	No	Yes	No	Yes
Control for Fractionalization	No	No	No	No	No	No

Notes: Dependent variable: Category 1 binary conflict indicator (100 if BRD≥5, 0 if BRD<5). Standard errors in parentheses, two-way clustered at the country-year and regional level. The sample includes African countries for the sampling period of 1995-2012 for the WB and 2000-2012 for Chinese Aid. Conflicts are considered for the WB from 1996 to 2013 and for Chinese aid from 2002 to 2014 due to the lag structure. Both regressions include (time-varying) exogenous cont+rols, year and region fixed effects as well as time trends. Time Trends include linear and squared country-specific time trends as well as linear regional time trends. Columns (1) & (2) refer to all regions without members of the coalition, whereas columns (3) & (4) refer to mixed regions with some groups in and out of the coalition/ dominant, monopoly or senior partner power groups. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 41: ADM1 results (Power status - Coalition), corresponds to Table 37

Panel A: Coalition groups						
WB Aid: OLS						
World Bank: Conflict in region belonging to...	N-Coalition	N-Coalition	Coalition	Coalition	Mixed	Mixed
ln(World Bank Aid $_{t-1}$)	-0.1304	-0.1532	-0.0567	-0.2146	-0.1383	-0.1930
	(0.2290)	(0.2961)	(0.1725)	(0.1873)	(0.1494)	(0.2113)
N	2287	2215	3962	3860	4837	4804
Chinese Aid: IV						
Conflict in region belonging to ...	N-Coalition	N-Coalition	Coalition	Coalition	Mixed	Mixed
ln(Chinese Aid $_{t-2}$)	0.4579	-7.2834	-1.1125	-1.6389*	1.0909	2.1283
	(3.4111)	(9.7063)	(0.7415)	(0.9371)	(1.0101)	(1.7629)
N	1335	1285	2487	2420	2944	2924
Kleibergen-Paap underidentification test p-value	0.349	0.307	0.000	0.000	0.001	0.021
Kleibergen-Paap weak identification F-statistic	0.913	0.918	57.165	40.299	12.402	6.735
Country $\times$ Year FE	No	Yes	No	Yes	No	Yes
Control for Fractionalization	Yes	Yes	Yes	Yes	Yes	Yes

Notes: Dependent variable: Category 1 binary conflict indicator (100 if BRD$\geq$5, 0 if BRD<5). Standard errors in parentheses, two-way clustered at the country-year and regional level. The sample includes African countries for the sampling period of 1995-2012 for the WB and 2000-2012 for Chinese Aid. Conflicts are considered for the WB from 1996 to 2013 and for Chinese aid from 2002 to 2014 due to the lag structure. Both regressions include (time-varying) exogenous cont+rols, year and region fixed effects as well as time trends. Time Trends include linear and squared country-specific time trends as well as linear regional time trends. Columns (1) & (2) refer to all regions without members of the coalition, whereas columns (3) & (4) refer to mixed regions with some groups in and out of coalition and columns (5) & (6) include exclusively groups with the coalition power stati. These are the corresponding OLS and IV results to Table 37. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

B.5 Spatial Dimension (Aggregation Levels and Spill Overs)

Table 42: ADM2 IV (Intensity 1)

	(1)	(2)
Panel A: WB Aid		
IV Second stage: IDA Position		
ln(World Bank Aid $_{t-1}$)	0.2599	0.1522
	(0.1644)	(0.1171)
N	99367	99367
Panel B: Chinese Aid		
IV Second Stage: Chinese Steel		
ln(Chinese Aid $_{t-2}$)	-0.0151	-0.0289
	(0.1116)	(0.1459)
N	64285	64285
Exogeneous Controls	Yes	Yes
Exogeneous Controls $\times$ Year FE	Yes	Yes
Linear Regional Trends	Yes	Yes
Country-Year FE	No	Yes

Notes: Dependent variable: Category 1 binary conflict indicator (100 if BRD$\geq$5, 0 if BRD<5). Standard errors in parentheses, two-way clustered at the country-year and regional level. The sample includes African countries for the sampling period of 1995-2012 for the WB and 2000-2012 for Chinese Aid. Both regressions include year and region fixed effects as well as time trends. Time Trends include linear and squared country-specific time trends. The constituent term of the probability is depicted in the appendix. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 43: ADM2 OLS results (Intensity 1)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Panel A: WB Aid									
ln(World Bank Aid $_{\text{t-1}}$)	0.0288	0.0188	0.0068	-0.0740***	-0.0674***	-0.0580**	-0.0354	-0.0627**	-0.0535*
	(0.0209)	(0.0196)	(0.0219)	(0.0245)	(0.0234)	(0.0251)	(0.0294)	(0.0262)	(0.0316)
N	105354	105354	105354	105354	105214	105214	91333	105214	91333
Panel B: Chinese Aid									
ln(Chinese Aid $_{\text{t-2}}$)	0.0105	0.0104	0.0579*	-0.0392	-0.0499	-0.0410	-0.0455	-0.0501	-0.0500
	(0.0407)	(0.0402)	(0.0331)	(0.0318)	(0.0392)	(0.0327)	(0.0347)	(0.0449)	(0.0446)
N	76089	76089	76089	76089	70132	70132	64482	70132	64482
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 Controls $\times$ Year FE	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 $\times$ Year FE	No	No	No	No	No	No	No	Yes	Yes

Notes: Dependent variable: Category 1 binary conflict indicator (100 if BRD$\geq$5, 0 if BRD<5). Standard errors in parentheses, two-way clustered at the country-year and regional level. The sample includes African countries for the sampling period of 1995-2012 for the WB and 2000-2012 for Chinese Aid. Time Trends include linear and squared country-specific time trends. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Analyzing spill-overs between capital and non-capital regions has the advantage of not relying on the EPR data and the ethnic homelands, and the disadvantage that it plots one region against all others. We run two sets of regressions. In some, we use only the aid payments we included so far, in the second set we assign all aid that could not be allocated to an ADM1 region to the capital region. These specifications indicate no significant spill-overs between capital and other regions.

Table 44: Spill-Overs from capital to non-capital- OLS

	(1)	(2)
Panel A:		
Including Non-GeoCoded Aid		
Conflict in other Region - World Bank	Capital	Non-Capital
ln(WB Aid non-cap $_{t-1}$)	-0.2524	-0.6459
	(0.4017)	(0.4376)
ln(WB Aid cap $_{t-1}$)	0.3004	0.3525
	(0.3901)	(0.4779)
N	836	836
Conflict in other Region - China	Capital	Non-Capital
ln(Chinese Aid non-cap $_{t-2}$)	-0.1586	-0.0330
	(0.1545)	(0.1655)
ln(Chinese Aid cap $_{t-2}$)	-0.0368	0.1892
	(0.1330)	(0.2081)
N	792	792
Panel B:		
Excluding Non-GeoCoded Aid		
Conflict in other Region - World Bank	Capital	Non-Capital
ln(WB Aid non-Capital $_{t-1}$)	-0.3725	-0.3694
	(0.2928)	(0.4252)
ln(WB Aid Capital $_{t-1}$)	0.3953	-0.0802
	(0.2417)	(0.4529)
N	836	836
Conflict in other Region - China	Capital	Non-Capital
ln(Chinese Aid non-Capital $_{t-2}$)	-0.1047	0.0585
	(0.1647)	(0.1813)
ln(Chinese Aid Capital $_{t-2}$)	-0.2147*	-0.1836
	(0.1190)	(0.1983)
N	792	792
Country FE	Yes	Yes
Year FE	Yes	Yes

Notes: Dependent variable: Category 1 binary conflict indicator (100 if BRD$\geq$5, 0 if BRD<5). Standard errors in parentheses are clustered at the level of country. The sample includes African countries for the sampling period of 1995-2012 for the WB and 2000-2012 for Chinese Aid. Conflicts are considered for the WB from 1996 to 2013 and for Chinese aid from 2002 to 2014 due to the lag structure. Both regressions include year and country fixed effects as well as time trends. Time Trends include linearcountry-specific time trend. Column (1) refers to aid and its effect in the capital regions, whereas column (2) refers to aid and its effect in non-capital regions. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 45: Aggregate - Cross-country Analysis - OLS

	Geocoded	Non-Geocoded
$ln(WB\ Aid_{\text{t-1}})$	-0.3419	0.2110
	(0.4410)	(0.4843)
$ln(Chinese\ Aid_{\text{t-2}})$	-0.2081*	-0.1678
	(0.1158)	(0.1966)
R^2	0.318	
N	792	
Non-geocoded aid as control:	No	Yes

Notes: Dependent variable: Category 2 binary conflict indicator (100 if BRD≥25, 0 if BRD<25). Estimates refer to the country level, where aid and battle-related deaths were aggregated at the country level. Columns (1) and (2) refer to one regression. Column (1) depicts coefficient for geocoded aid aggregated at the country level. Column (2) depicts coefficients for non-geocoded aid, which is aid coded less precise than the ADM1 level (refer to Figure **??**). The sample includes African countries for the sampling period of 1995-2012 for the WB and 2000-2012 for Chinese Aid. Conflicts are considered for the WB from 1996 to 2013 and for Chinese aid from 2002 to 2014 due to the lag structure. The regression includes country and year fixed effects as well as a linear county-trend. Standard errors in parentheses are clustered at the level of the country. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

B.6 Estimations - Miscellaneous

Table 46: PPML

	(1)	(2)	(3)
Panel A: WB Aid main			
ln(World Bank Aid $_{\text{t-1}}$)	-0.0005	0.0178	-0.0171
	(0.0063)	(0.0149)	(0.0173)
N	6246	1476	7344
Panel B: Chinese Aid main			
ln(Chinese Aid $_{\text{t-2}}$)	-0.0128*	0.0023	-0.0328*
	(0.0076)	(0.0131)	(0.0189)
N	3783	962	4589

Notes: Dependent variables: In column (1) a binary conflict indicator (100 if BRD≥5, 0 if BRD<5), in column (2) a binary indicator if any event of non-lethal pro-government violence took place, in column (3) a continuous measure of logged battle-related deaths. Standard errors in parentheses, clustered at the regional level. The sample includes African countries for the sampling period of 1995-2012 for the WB and 2000-2012 for Chinese Aid. All regressions include year fixed effects. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 47: ADM1 - Aid Subtypes

WB Aid Subtypes - OLS	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Panel A: No Country-Year FE	AX	BX	CX	EX	FX	JX	LX	TX	WX	YX
ln(World Bank Aid $_{t-1}$)	0.0293	-0.1873**	0.1229	0.0215	-0.0958	-0.1575**	0.0236	-0.1479**	-0.0339	-0.1125
	(0.0753)	(0.0918)	(0.1575)	(0.0793)	(0.0919)	(0.0798)	(0.0941)	(0.0729)	(0.0898)	(0.0951)
Panel B: Country-Year FE										
ln(World Bank Aid $_{t-1}$)	-0.0617	-0.2672***	0.0048	-0.0209	-0.0912	-0.1667*	-0.0317	-0.1137	0.0013	-0.2080*
	(0.0950)	(0.1031)	(0.1790)	(0.1062)	(0.1474)	(0.0977)	(0.1043)	(0.1021)	(0.1131)	(0.1139)
N	13050	13050	13050	13050	13050	13050	13050	13050	13050	13050
Chinese Aid Subtypes - IV										
Panel C: No Country-Year FE	AX	BX	CX	EX	FX	JX	LX	TX	WX	YX
ln(Chinese Aid $_{t-2}$)	29.9239	-5.9930	2.4455	9.4914		6.0147	-1.7181	-14.3933	-7.0558	37.6114
	(49.5442)	(5.4875)	(5.5354)	(40.3416)		(15.7536)	(3.0469)	(34.3126)	(24.8028)	(88.4269)
Kleibergen-Paap underid. test p-value	0.609	0.213	0.631	0.733		0.664	0.346	0.661	0.730	0.673
Kleibergen-Paap weak id. F-statistic	0.244	2.105	0.204	0.094		0.157	0.939	0.187	0.104	0.207
Panel D: Country-Year FE										
ln(Chinese Aid $_{t-2}$)	31.3584	-6.4790	0.7303	12.3422	N.A.	2.2117	13.0243	-43.1764	-1.7639	93.8070
	(52.2393)	(7.5040)	(0.8107)	(44.3311)	(N.A.)	(4.4871)	(49.4362)	(412.3877)	(9.2212)	(894.9630)
N	8700	8700	8700	8700	8700	8700	8700	8700	8700	8700
Kleibergen-Paap underidentification test p-value	0.605	0.260	0.191	0.685	–	0.446	0.734	0.912	0.460	0.911
Kleibergen-Paap weak identification F-statistic	0.274	1.472	1.949	0.135	–	0.476	0.107	0.011	0.492	0.012

Notes: Dependent variable: Category 1 binary conflict indicator (100 if BRD$\geq$5, 0 if BRD<5). The sample includes African countries for the sampling period of 1995-2012 for the WB and 2000-2012 for Chinese Aid. Conflicts are considered for the WB from 1996 to 2013 and for Chinese aid from 2002 to 2014 due to the lag structure. Regressions account for (time-varying) exogenous controls and time trends. Time Trends include linear and squared country-specific time trends as well as a linear regional trend. AX - "Agriculture, fishing, and forestry" BX - "Public Administration, Law, and Justice" CX - "Information and communications" EX - "Education" FX - "Finance" JX - "Health and other social services" LX - "Energy and mining" TX - "Transportation" WX - "Water, sanitation and flood protection" YX - "Industry and Trade" Standard errors in parentheses, two-way clustered at the country-year and regional level: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 48: ADM1 IV (Clustering at Regional Level)

	(1)	(2)
Panel A: WB Aid		
IV Second stage: IDA Position		
ln(World Bank Aid $_{t-1}$)	-0.1014	-0.2252
	(0.3276)	(0.3899)
N	12325	12325
Kleibergen-Paap underidentification test p-value	0.000	0.000
Kleibergen-Paap weak identification F-statistic	237.269	132.466
Panel B: Chinese Aid		
IV Second Stage: Chinese Steel		
ln(Chinese Aid $_{t-2}$)	-0.4509	-0.4276
	(0.6147)	(0.8096)
Kleibergen-Paap underidentification test p-value	0.000	0.000
Kleibergen-Paap weak identification F-statistic	28.972	18.960
Exogeneous Controls	Yes	Yes
Exogeneous Controls $\times$ Year FE	Yes	Yes
Linear Regional Trends	Yes	Yes
Country-Year FE	No	Yes

Notes: Dependent variable: Category 1 binary conflict indicator (100 if BRD$\geq$5, 0 if BRD<5). Standard errors in parentheses, clustered at the regional level. The sample includes African countries for the sampling period of 1995-2012 for the WB and 2000-2012 for Chinese Aid. Both regressions include year and region fixed effects as well as time trends. Time Trends include linear and squared country-specific time trends. The constituent term of the probability is depicted in the appendix. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 49: ADM1 OLS results (Clustering at regional level)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Panel A: WB Aid									
ln(World Bank Aid $_{t-1}$)	-0.1918***	0.0010	-0.0496	-0.2129***	-0.2057***	-0.1608**	-0.0419	-0.1772**	-0.1420
	(0.0709)	(0.0643)	(0.0666)	(0.0611)	(0.0624)	(0.0672)	(0.0775)	(0.0799)	(0.0906)
N	13104	13104	13104	13104	13050	13050	11017	13050	11017
Panel B: Chinese Aid									
ln(Chinese Aid $_{t-2}$)	-0.1753**	-0.0233	-0.0026	-0.1090**	-0.0663	-0.0654	-0.0641	-0.0347	-0.0369
	(0.0761)	(0.0664)	(0.0676)	(0.0540)	(0.0605)	(0.0680)	(0.0687)	(0.0743)	(0.0757)
N	9464	9464	9464	9464	8700	8700	8261	8700	8261
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 Controls $\times$ Year FE	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 $\times$ Year FE	No	No	No	No	No	No	No	Yes	Yes

Notes: The table displays regression coefficients with low Intensity Conflict (>5 battle-related deaths) as dependent variable. Standard errors in parentheses, clustered at the regional level. The sample includes African countries for the sampling period of 1995-2012 for the WB and 2000-2012 for Chinese Aid. Time Trends include linear and squared country-specific time trends. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 50: ADM1 IV: Population Weighted Aid Allocation

Panel A: WB Aid	(1)	(2)
IV Second stage: IDA Position		
ln(World Bank Aid $_{t-1}$)	-0.1026	-0.2286
	(0.3798)	(0.4256)
N	12325	12325
Kleibergen-Paap underidentification test p-value	0.000	0.000
Kleibergen-Paap weak identification F-statistic	100.841	88.424
Panel B: Chinese Aid	**(1)**	**(2)**
IV Second Stage: Chinese Steel		
ln(Chinese Aid $_{t-2}$)	-0.4569	-0.4323
	(0.6251)	(0.8160)
N	7975	7975
Kleibergen-Paap underidentification test p-value	0.000	0.000
Kleibergen-Paap weak identification F-statistic	22.601	16.535
Country-Year FE	No	Yes

Notes: Dependent variable: Category 1 binary conflict indicator (100 if BRD$\geq$5, 0 if BRD<5). Standard errors in parentheses, two-way clustered at the country-year and regional level. The sample includes African countries for the sampling period of 1995-2012 for the WB and 2000-2012 for Chinese Aid. Both regressions include exogenous (time-varying) controls. Year and region fixed effects as well as time trends are included in all regressions. Time Trends include linear and squared country-specific time trends and a linear regional trend. The constituent term of the probability is depicted in the appendix. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 51: OLS results: Population Weighted Aid Allocation

Panel A: WB Aid	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
ln(World Bank Aid $_{t-1}$)	-0.1898*	0.0062	-0.0440	-0.2217***	-0.2153***	-0.1664**	-0.0457	-0.1867**	-0.1502
	(0.1005)	(0.0788)	(0.0692)	(0.0667)	(0.0712)	(0.0797)	(0.0856)	(0.0872)	(0.1066)
N	13104	13104	13104	13104	13050	13050	11017	13050	11017
Panel B: Chinese Aid									
ln(Chinese Aid $_{t-2}$)	-0.1776**	-0.0246	-0.0037	-0.1137**	-0.0718	-0.0696	-0.0679	-0.0390	-0.0408
	(0.0865)	(0.0704)	(0.0648)	(0.0576)	(0.0789)	(0.0833)	(0.0881)	(0.1021)	(0.0919)
N	9464	9464	9464	9464	8700	8700	8261	8700	8261
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 Controls $\times$ Year FE	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 $\times$ Year FE	No	No	No	No	No	No	No	Yes	Yes

Notes: Dependent variable: Category 1 binary conflict indicator (100 if BRD$\geq$5, 0 if BRD<5). Standard errors in parentheses, two-way clustered at the country-year and regional level. The sample includes African countries for the sampling period of 1995-2012 for the WB and 2000-2012 for Chinese Aid. Conflicts are considered for the WB from 1996 to 2013 and for Chinese aid from 2002 to 2014 due to the lag structure. Time Trends include linear and squared country-specific time trends. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 52: ADM1 IV (WB Aid - Same Years as Chinese Aid)

	(1)	(2)
Panel A: WB Aid		
IV Second stage: IDA Position		
ln(World Bank Aid $_{t-1}$)	-0.6227	-2.3417
	(1.0568)	(1.6897)
Kleibergen-Paap underidentification test p-value	0.000	0.005
Kleibergen-Paap weak identification F-statistic	22.619	6.960
IV First stage: IDA Position		
IDA Position $_{t-1}$ $\times$ Cum. Prob $_{t-2}$	57.2759***	63.9080***
	(12.0429)	(24.2241)
N	7975	7975
Panel B: Chinese Aid		
IV Second Stage: Chinese Steel		
ln(Chinese Aid $_{t-2}$)	-0.4509	-0.4276
	(0.6168)	(0.8068)
N	7975	7975
Kleibergen-Paap underidentification test p-value	0.000	0.000
Kleibergen-Paap weak identification F-statistic	22.468	16.456
IV First stage: Chinese Steel		
Steel Prod detrend $_{t-3}$ $\times$ Cum. Prob $_{t-3}$	-70.8763***	-60.6567***
	(14.9526)	(14.9524)
N	7975	7975
Exogeneous Controls	Yes	Yes
Exogeneous Controls $\times$ Year FE	Yes	Yes
Linear Regional Trends	Yes	Yes
Country-Year FE	No	Yes

Notes: Dependent variable: Category 1 binary conflict indicator (100 if BRD$\geq$5, 0 if BRD<5). Standard errors in parentheses, two-way clustered at the country-year and regional level. The sample includes African countries for the sampling period of 2001-2012 for the WB and 2000-2012 for Chinese Aid. Both regressions include year and region fixed effects as well as time trends. Time Trends include linear and squared country-specific time trends. The constituent term of the probability is depicted in the appendix. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 53: OLS results: Lagged dependent variable

Panel A: WB Aid	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
ln(World Bank Aid $_{t-1}$)	-0.0844	-0.0069	-0.0173	-0.1659***	-0.1575**	-0.1406**	-0.0350	-0.1647**	-0.1355
	(0.0520)	(0.0551)	(0.0458)	(0.0585)	(0.0618)	(0.0707)	(0.0812)	(0.0808)	(0.1025)
N	13104	13104	13104	13104	13050	13050	11017	13050	11017
Panel B: Chinese Aid									
ln(Chinese Aid $_{t-2}$)	-0.0965*	-0.0300	-0.0082	-0.0983*	-0.0634	-0.0661	-0.0645	-0.0345	-0.0365
	(0.0563)	(0.0589)	(0.0588)	(0.0589)	(0.0771)	(0.0871)	(0.0921)	(0.1029)	(0.0913)
N	9464	9464	9464	9464	8700	8700	8261	8700	8261
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 Controls $\times$ Year FE	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 $\times$ Year FE	No	No	No	No	No	No	No	Yes	Yes

Notes: Dependent variable: Category 1 binary conflict indicator (100 if BRD$\geq$5, 0 if BRD<5). This regression controls for the first lag of the binary indicator. Standard errors in parentheses, two-way clustered at the country-year and regional level. The sample includes African countries for the sampling period of 1995-2012 for the WB and 2000-2012 for Chinese Aid. Applying the lag structure of our regression equation, this means that conflicts are considered for the WB from 1996 to 2013 and for China from 2002 to 2014. Time Trends include linear and squared country-specific time trends. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 54: OLS results: (WB Aid - Same Years as Chinese Aid)

Panel A: WB Aid	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
ln(World Bank Aid $_{t-1}$)	-0.1505	0.0559	0.0811	-0.0606	-0.0976	0.0657	0.0672	-0.0795	-0.0949
	(0.1197)	(0.0949)	(0.0910)	(0.0864)	(0.0922)	(0.0906)	(0.0886)	(0.0981)	(0.0957)
N	8736	8736	8736	8736	8700	8700	8261	8700	8261
Panel B: Chinese Aid									
ln(Chinese Aid $_{t-2}$)	-0.1753**	-0.0233	-0.0026	-0.1090*	-0.0663	-0.0654	-0.0641	-0.0347	-0.0369
	(0.0865)	(0.0705)	(0.0642)	(0.0572)	(0.0783)	(0.0827)	(0.0877)	(0.1015)	(0.0916)
N	9464	9464	9464	9464	8700	8700	8261	8700	8261
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 Controls $\times$ Year FE	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 $\times$ Year FE	No	No	No	No	No	No	No	Yes	Yes

Notes: Dependent variable: Category 1 binary conflict indicator (100 if BRD$\geq$5, 0 if BRD<5). Standard errors in parentheses, two-way clustered at the country-year and regional level. The sample includes African countries for the sampling period of 2001-2012 for the WB. Conflicts are considered for the WB from 2002 to 2013 due to the lag structure. Time Trends include linear and squared country-specific time trends. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 55: OLS results - Both Donors (Intensity 1)

WB & Chinese Aid	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
ln(World Bank Aid $_{t-1}$)	-0.1460	0.0571	0.0808	-0.0603	-0.0973	0.0661	0.0674	-0.0793	-0.0948
	(0.1194)	(0.0951)	(0.0913)	(0.0864)	(0.0926)	(0.0904)	(0.0889)	(0.0979)	(0.0958)
ln(Chinese Aid $_{t-2}$)	-0.1278	-0.0291	0.0070	-0.1060*	-0.0660	-0.0656	-0.0644	-0.0345	-0.0367
	(0.0854)	(0.0700)	(0.0590)	(0.0595)	(0.0787)	(0.0824)	(0.0880)	(0.1018)	(0.0912)
N	8736	8736	8736	8736	8700	8700	8261	8700	8261
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 Controls × Year FE	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

Notes: Dependent variable: Category 1 binary conflict indicator (100 if BRD≥5, 0 if BRD<5). Standard errors in parentheses, two-way clustered at the country-year and regional level. The sample includes African countries for the sampling period of 2000-2012. Time Trends include linear and squared country-specific time trends. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 56: ADM1 IV - Both Donors (Intensity 1)

	(1)	(2)
IV Second stage: IDA Position		
ln(World Bank Aid $_{t-1}$)	-0.7692	-2.4159
	(1.0994)	(1.7067)
ln(Chinese Aid $_{t-2}$)	-0.4485	-0.4033
	(0.6271)	(0.8310)
Kleibergen-Paap underidentification test p-value	0.000	0.004
Kleibergen-Paap weak identification F-statistic	12.042	3.511
IV First stage: IDA Position		
IDA Position $_{t-1}$ $\times$ Cum. Prob $_{t-2}$	57.3141***	63.8098***
	(12.0387)	(24.1928)
Steel Prod detrend $_{t-3}$ $\times$ Cum. Prob $_{t-3}$	-0.5590	-0.5283
	(4.6845)	(4.3082)
N	7975	7975
IV First stage: Chinese Steel		
IDA Position $_{t-1}$ $\times$ Cum. Prob $_{t-2}$	-18.0734*	-9.5155
	(9.3582)	(12.7548)
Steel Prod detrend $_{t-3}$ $\times$ Cum. Prob $_{t-3}$	-70.7017***	-60.7419***
	(14.9511)	(14.9668)
N	7975	7975
Exogeneous Controls	Yes	Yes
Exogeneous Controls $\times$ Year FE	Yes	Yes
Linear Regional Trends	Yes	Yes
Country-Year FE	No	Yes

Notes: Dependent variable: Category 1 binary conflict indicator (100 if BRD$\geq$5, 0 if BRD<5). Standard errors in parentheses, two-way clustered at the country-year and regional level. The sample includes African countries for the sampling period of 2000-2012. Both regressions include year and region fixed effects as well as time trends. Time Trends include linear and squared country-specific time trends. The constituent term of the probability is depicted in the appendix.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$