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Aid and Conflict at the Sub-National Level: Evidence from World Bank and Chinese Development Projects in Africa

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Abstract
Does aid fuel conflict in recipient countries? Existing studies of aggregate country level data or specific aid types in individual countries do not conclusively answer this question. We use georeferenced data on development projects by the World Bank (WB) and China, two donors with strongly contrasting approaches to development, to provide a comprehensive analysis of the effect of aid on conflict at the sub-national level in Africa. The results using fixed effects and instrumental variables strategies indicate that aid from both donors, on average, reduces rather than fuels lethal conflict. Our analysis suggests that this is driven by projects in the transport and financial sector, and relates to less lethal government violence against civilians. There is also no increased likelihood of demonstrations, strikes, or riots, but more government repression in regions with Chinese aid. Analysis of Afrobarometer survey data is consistent with this and highlights differences between the two donors.

Keywords: *Development Aid, Conflict, Repression, World Bank, China, Africa, Geolocation*

JEL Classification: *H77, N9*

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1 Introduction

According to the UNHCR, an unprecedented 65.3 million people were displaced from their homes by war, internal conflicts, natural disasters or poverty in 2018. As developed countries like those in the European Union increasingly feel the impact of this instability and conflict through increased migratory flows, a frequent reaction is a call for larger amounts of development aid, to reduce poverty and other root causes of displacement.[1] Still, while the literature on growth effects of aid converges towards a small, mostly positive, effect on development outcomes (Clemens et al., 2011; Dreher et al., 2018a; Galiani et al., 2017; Kilby, 2015), other studies have raised the question whether aid might fuel conflict, instead of reduce conflict (e.g., Nunn and Qian, 2014; Child, 2018; Crost et al., 2014, 2016).

Our paper provides a comprehensive evaluation of the aid-conflict nexus. We combine the strengths of existing approaches on the country level (e.g., Bluhm et al., 2016; Nunn and Qian, 2014), with the advantages of studies focusing on sub-national aid data in specific sectors in individual countries (e.g., Berman et al., 2011; Child, 2018; Sexton, 2016; Van Weezel, 2015). By considering a large set of all aid-eligible countries in Africa, the continent most consistently plagued by reoccurring conflicts, our results can be meaningfully interpreted beyond the context of an individual country. We use sub-national georeferenced project-level data concerning the World Bank (WB) and China in order to link aid projects, as well as conflict events, more directly than previous country-level studies. Our identification strategies use specifications with comprehensive sets of fixed effects (FE) and time trends, as well as instrumental variable (IV) estimates. The IV strategy adapts those in Nunn and Qian (2014) and Dreher et al. (2017), and interacts the predetermined probability of a region receiving aid with exogenous temporal variation in the WB's IDA liquidity and Chinese steel (over-)production.

Our results provide several important insights. Most importantly, a wide range of fixed effects specifications, as well as IV specifications, provide no indication that on average aid fuels lethal conflict. Using a fixed effects specification, a standard deviation change of one in the WB aid decreases the conflict likelihood by about 1.6 percentage points. The effect remains negative but becomes insignificant when using an IV specification. Nor is there any evidence for a conflict-fueling effect of Chinese aid. The IV estimates are negative, but close to zero and statistically insignificant.

To explore the potential heterogeneity in the results, we then consider aid projects in different sectors individually. We find a significant negative effect on the likelihood of conflict from projects in the finance sector (concerning the WB only), as well as for those in the transportation sector (the

[1] Fragile, conflict-prone states are also described as the "new frontier of development", and many important donors plan to increase their activities in those countries. See The Economist (2017), last accessed 30.01.2019.

WB and China). There is no specific sector in which aid significantly increases conflict. Moreover, when considering the actors involved in, and responsible for, a conflict, both WB and Chinese engagement consistently lead to a *reduction* in lethal violence by governments against civilians. For both donors, we find no positive effect on lower-level, non-lethal types of conflict like demonstrations, riots, and strikes. We do, however, find that increased Chinese engagement leads to an increase in government repression against their citizens. Survey evidence, using georeferenced Afrobarometer data, supports these results on the effects of Chinese aid.

We make four main contributions. First, we provide causal evidence on two important donors: the WB and China. The WB is a multilateral donor that emphasizes scientific expertise, frequently imposes human-right, as well as, sustainability conditions, and specifically engages in "conflict-sensitive programming" (e.g. Bannon, 2010). China, in contrast, has become one of the most important bilateral donors, but is often portrayed as a "rogue" donor (Naím, 2007), with economic targets, such as securing resource supply, as a central part of its aid strategy. Although, in some regards, China does not seem drastically different than other bilateral donors (see Dreher and Fuchs, 2015), but there are some objective differences. China propagates a policy of "non-interference" in the internal affairs of recipient countries, emphasizes "mutual economic benefits" over political freedom as well as democracy, and grants high levels of discretion for the host governments to distribute and use aid resources as they see fit. Analyzing the WB and China, thus, covers donors that represent the two ends within the broad spectrum of potential approaches to development and their impact on conflict.

Our second contribution is that we cover aid projects in a broad set of developing countries, while simultaneously assigning project locations to specific sub-national administrative units (based on Strandow et al., 2016; Strange et al., 2017). Our geographical focus on Africa is determined by a trade-off between external and internal validity. On the one hand, we augment the literature by studying comparable aid projects in more than one country, so as to increase the relevance of our results beyond the narrow single-country context. On the other hand, we want to make sure that the results can be meaningfully interpreted within our sample. We restrict ourselves to Africa because conflicts here differ in important dimensions from Latin America or the Middle East; for instance, with regard to the role of ethnic groups, religious tensions, as well as the production and trafficking of illegal drugs. Moreover, Africa is comprised of major recipient regions of WB as well as Chinese aid during our sample period; and offers the best quality of data regarding aid and violent and non-violent conflict.

Third, the degree of precision in our dataset allows us to link conflict events to aid in the same region. We can thus rule out the possibility that, aid in one region and conflict in another region, are coincidentally correlated with each other. Moreover, the data structure enables us to flexibly control for a wide range of potentially distorting factors through time trends, country-year, and region-specific fixed effects which hence, eliminates bias arising from unobserved conflict trends, region-specific time-invariant factors and country-level time-variant factors. We find that across a wide range of specifications that eliminate more or less potentially biasing variation, the average effect of aid on conflict is either significantly negative or indistinguishable from zero. Our IV strategy essentially emulates a difference-in-difference approach during the first stage, in that we compare the effect of donors' budget expansion on regions with differing pre-determined probabilities. As the assumptions for this type of instrument are comparable to a simple version of a Bartik or shift-share instruments, we carefully examine and rule out potential problems highlighted by Christian and Barrett (2017) and Goldsmith-Pinkham et al. (2018). The average null effect of aid on conflict also holds at both a smaller and a larger administrative level of aggregation, as well as when using different definitions of conflict and aid, or various different variations of the IV strategy.

Fourth, our distinctions between aid sectors, conflict actors, and types of conflict expand upon results from the existing literature. The sectoral distinction augments, for instance, the findings in Child (2018) on intersectoral differences in Afghanistan, as well as previous results on aid projects in specific sectors within specific countries (e.g., Crost et al., 2016; Berman et al., 2011). Our finding of a significant reduction in conflicts enacted by states against civilians, resulting from aid given by both the WB and China, suggests that the fear of losing aid money seems to notably affect recipient governments. This adds to the scarce evidence on differing incentives related to development projects like Crost et al. (2014), who focus on changing incentives for rebel groups.

While we observe no significant increase in citizen protest related to aid projects, the observed increases in government repression associated with Chinese aid supports the hypotheses in Kishi and Raleigh (2016), that China puts less weight on conditions regarding human rights. The results also match both within-China policies, which rank stability over political freedom, as well as previous results that Chinese aid correlates with more corruption (Isaksson and Kotsadam, 2018a) and lower unionization (Isaksson and Kotsadam, 2018b). Our own estimations using geolocalized Afrobarometer responses suggest that WB aid is linked to supporting democratic values, while the result of Chinese aid tends to be less opposition to autocratic regimes within the regions. Survey answers also suggest more political intimidation and the strong belief that one must always abide by the rule of law in those regions. Despite the correlational nature of this final piece of evidence, it matches the previous results suggesting that Chinese aid increases stability, however this stability to some extent comes at the cost of democratic development.

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 Theoretical considerations and existing literature:

The next paragraphs consider the relationship between aid and conflict in different dimensions, mostly distinguishing between opportunity cost and contest effects as the two dominating theories in the literature. While doing that, we outline and explain potential differences between the WB and China with regard to these issues.

2.1 Conflict-reducing: Opportunity costs effects

Aid can affect conflict if it alters income and hence the opportunity costs of fighting. The aid effectiveness literature converges towards either a null effect (Doucouliagos and Paldam, 2009), or small positive effects (Galiani et al., 2017) of aid on growth. This effect, however, depends on whether aid was politically motivated or had a clear development focus (Dreher et al., 2018a). In that regard, the WB approach mostly reflects a model of conditional aid, which integrates expert knowledge with a clear focus on development. Although there is also some political influence on WB decisions (Dreher et al., 2018b), their projects are less politically motivated than other types of aid (e.g., Dreher et al., 2009). Still, traditional donors have also been criticized for a lack of "ownership" and underutilizing local knowledge in recipient countries.[2] Proponents of the Chinese engagement in Africa highlight a less complicated, bureaucratic process, with quicker implementation times (Humphrey and Michaelowa, 2018). China's flexibility and emphasis on economic "mutual benefits" may boost growth more than the WB approach (Dreher et al., 2017).[3]

Aid projects do not solely constitute an income shock. Donors can, and often do, impose conditions and required processes in the aid-receiving country. Minasyan et al. (2017), for instance, demonstrate the importance of donor quality for aid effectiveness; Berman et al. (2013) hypothesize that projects are more successful in reducing violence if they require the integration of development experts. The WB is considered to be a global leader in "conflict-sensitive programming" (Van der Windt and Humphreys, 2016; World Bank, 2011). Conflict-sensitive programming involves the identification of conflict escalators and de-escalators using a detailed Conflict Analysis Framework (CAF) (Wam, 2006).[4] Based on this assessment, the WB's Operational Procedures 2.30 outline specific levels on how the WB should engage within a conflict-affected country (World Bank, 2001; Bannon, 2010). Moreover, the CAF aims to help WB staff to better understand country-specific

[2] See Fuchs and Vadlamannati (2013) for an allocation analysis of India, the second large emergent donor.
[3] Anthony Germain on CBC, "China in Africa: No strings attached," last accessed 31.01.2019.
[4] The WB recently also started to employ new approaches to monitor conflict and assess risks based on remote sensing and machine learning (United Nations and World Bank, 2018).

sources of conflicts, and an independent "Inspection Panel" investigates complaints about human rights abuses or local conflict provoked by the WB (Zvogbo and Graham, 2018). Finally, a development approach to actively build trust and social cohesion is applied for post-conflict and conflict-affected countries (Bannon, 2010). Such an approach may include projects with a focus on community-driven development, integration programs, and capacity building, for example, and could matter especially in countries with strong existing ethnic tensions. The Kecamatan Development program in Indonesia, for instance, attempted to reduce the conflict threat via transparency through a particularly participatory approach (Gibson and Woolcock, 2005; Barron et al., 2011).

To the best of our knowledge, China does not have an analogous set of policies, institutions, or operational tools in place to encourage conflict-sensitive development programming.[5] It specifically highlights non-interference, as well as room to maneuver for the recipient governments.[6] For example, China's president has both personally visited and welcomed Zimbabwe's former dictator, Robert Mugabe. At another instance, Uganda turned to China to increase its engagement after Western donors protested against strict "anti-gay" laws in the country. Isaksson and Kotsadam (2018a) also suggest that Chinese engagement is associated with higher local corruption. Such acts contrasts efforts of Western donors to sanction the country for electoral fraud and human rights abuses.[7]

2.2 Conflict-fueling: Contest Effects

When comparing the impact of aid projects on conflict to the impact of resource-related income shocks (Berman et al., 2017; Gehring et al., 2018), it becomes clear that, in both cases, the distribution of gains is important. Whether potential gains from aid are used for short-term consumption, invested in fostering development, or end up in the foreign bank accounts of government officials, affects the impact on conflict. The WB aims for aid allocation in line with conflict prevention policies within the realms of humanitarian action, development, and security. In contrast, Chinese aid comes with fewer strings attached. Dreher et al. (2016) find that Chinese projects in Africa are more likely to benefit the birth regions of the respective leader. However, Chinese infrastructure projects are found to lead to a more equal distribution of economic activity in the localities where they are implemented (Bluhm et al., 2018), which could lead to a reduction in conflicts.

As Dal Bó and Dal Bó (2011) show, the impact of a wealth-increasing shock on conflict can also depend on the affected industry. Dube and Vargas (2013) demonstrate that, in Colombia, higher resource prices reduce conflict if production in the sector is labor-intensive, and the gains

[5] China only established its first specialized aid Agency CIDCA with a centralized evaluation mandate in 2018. Heiner Janus on DIE, "Next Steps for China's New Development Agency," last accessed 22.02.2019.
[6] David Shinn on Chinausfocus, "Africa Test's China's Non-interference Policy," last accessed 31.01.2019.
[7] Washington Post, "When China gives aid to African governments, they become more violent," last accessed 31.01.2019.

are distributedto a large share of people. Regarding the distribution of profits, some observers highlight the large use of Chinese workers in Africa (officially 227,407 by 2016).[8] Moreover, Chinese engagement seems to decrease trade union membership (Isaksson and Kotsadam, 2018b), which could lower the labor share of profits. As aid is often earmarked for certain projects or sectors, these issues serve as one motivation to investigate its effect by seperate aid sectors for both the WB and China.

The literature also describes "aid as a price" that can be acquired as a result of winning a fight or conflict. This "aid as a price" theory has both a direct goods-related, and a political dimension. Regarding specific goods, Nunn and Qian (2014) show that US food aid leads to more conflict, as it can be looted and sold on black markets. Expensive equipment associated with investments in healthcare and communication infrastructure can also be sold on black markets. To remedy these issues, some traditional donors like the WB seek to "conflict-proof" their aid by avoiding projects that provide lootable/fungible resources over which warring parties might fight, and instead provide aid in a more discrete manner, such as social programmes (Berman et al., 2013; Crost et al., 2014; Lyall et al., 2018).

Political dimensions of the "aid as a price" theory include that, with high aid flows, the rent-seeking possibilities associated with capturing a (regional) government increase. For instance, large-scale infrastructure projects, a specific focus of China, offer many opportunities to reward the leader's patronage networks. The hypothesis rests on the assumption that aid would still flow if the faction in power would change. This might be plausible; it is hard for donors to stop aid payments in the face of suffering civilians, even if they have to expect that a significant share of aid money ends up in the wrong pockets.[9] Still, if governments overstep their boundaries too much, public pressure in donor countries can build up and cause payments to stop (Lebovic and Voeten, 2009). The fear of losing aid thus also sets an incentive for incumbent governments to avoid violating the norms/rules imposed by donors, such as abstaining from excessive violence against citizens. Tir and Karreth (2018) emphasize the important role of international organizations, like the WB, in setting positive incentives through explicit conditions. This underlines the importance of distinguishing between the actors and aggressors in the conflicts we cover.

WB and Chinese aid can also affect sub-national variation in state capacity, and thereby can elevate, or diminish, the risk of local conflict. On the one hand, infrastructure projects can strengthen the capacity of the state by extending the spatial reach of its monopoly. The establishment of infrastructure like highways, bridges, railroads, tunnels, and ports makes it easier for state agents

[8] Others state that Western firms also do not, in generall, have higher localization rates. See http://www.sais-cari.org/data-chinese-workers-in-africa/ and https://www.reporting-focac.com/myth-1-chinese-workers.html, last accessed 31.01.2019

[9] The share of aid not being used for its initial purpose is extremely hard to estimate. Estimates range from less than 1% to about 70%. See Charles Kenny at CGD, last accessed 31.01.2019.

to reach remote areas. This strengthens the state's capacity to broadcast power as well as wrest control away from rebel groups, tribal leaders, gangs, and foreign-backed militias . Agents of the state – e.g. police officers, judges, and tax collectors – can use their increased capacity from aid in significantly different ways. If they wield it to impartially enforce the rule of law, levy taxes, and deliver public services, improvements in capacity and legitimacy may result in a "virtuous circle" of better state capability (Levi et al., 2009) and conflict reduction (Berman et al., 2011).

On the other hand, if state agents exploit their increased capacity to enrich themselves, favor some groups over others, or weaken political opponents (Wig and Tollefsen, 2016), the resulting erosion of state legitimacy can lay the foundation for violent protests or local conflict.[10] The WB has a large range of safeguards to ensure projects comply with democratic standards. China's unconditional,discretionary aid practices, and lax enforcement of anti-bribery rules (see Brazys et al., 2017; Isaksson and Kotsadam, 2018a) might be more detrimental to the perception of the state, and citizens' willingness to both interact with state officials, and participate democratically. To investigate this, we also examine lower-level, non-lethal types of violence like riots, demonstrations and strikes, as well as perceptions of state legitimacy.

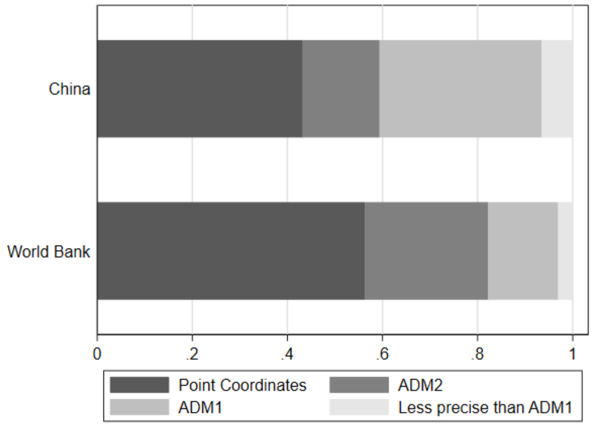
Moreover, the enhancement of state capacity also affects the handling of protests. China is well-known to emphasize maintaining social stability domestically, including the use of force to constrain opposition forces or protesters. Thus, even if China does not actively encourage repression, Chinese domestic behavior may be a signal to recipient governments. Further, Chinese aid might financially support repressive governments (Kishi and Raleigh, 2016); together with enhancing state capacity through infrastructure projects, this could contribute to more repression. Repression can incur anger and unrest, but also leads to a deterrence effect that increases stability. The net effect of more repression on the likelihood of outright conflict, or joining a protest, is then theoretically ambiguous. For that reason, we also investigate the effects on government repression, which we can then compare to the other conflict outcomes.

To sum up, there are distinct reasons for studying aid and conflict sub-nationally by directly linking aid projects to conflict in the same region.[11] Being able to compare two donors with strongly contrasting approaches to development enables us to investigate the effect of those approaches on the risk of fueling conflict. Beyond the average effect, we examine theories in more detail by differentiating between (i.) different aid sectors, (ii.) the actors involved and responsible for a conflict, and (iii.) the types of conflict. To understand the results, and their plausibility better, we

[10] For instance, insurgents might sabotage projects if they would not benefit sufficiently and success weakens their support in the population (Crost et al., 2014).

[11] To mitigate issues about selecting the right spatial unit of analysis, for instance due to spatial spill-overs, we consider results at both more disaggregated and the more aggregated country level as robustness tests. We relegate a more substantive and deep analysis of spatial spill-overs as well as spatial inequalities in the aid distribution to an accompanying follow-up paper. Analyzing these issues in satisfactory detail would exceed the scope of this paper.

Figure 1: Disbursement/Commitment Amounts by Precision Codes



also use survey data to investigate the mechanisms underlying the main results.

3 Data

3.1 Aid Data: World Bank and China

We focus our analysis on Africa, considering all countries with more than one million inhabitants on the OECD's DAC recipient list in 1995, the initial year of our sample period. Our unit of observation is the country-region-year, with region as the unit of analysis referring to the first level of sub-national administrative division (ADM1: "provinces", "states", or "regions") (data from Hijmans et al., 2010). This level is the most suitable choice, as it allows us to distinguish between considerable sub-national variation, while still capturing over 90% of the overall spending by China and the WB (see Figure 1).[12] Moreover, this administrative level is also highly relevant for aid allocation, as many projects are assigned to specific regions, and the regional governments can influence how, or where, to spend the funds.

Our approach to assigning aid projects to regions is the following. Precisely georeferenced projects, as well as projects where we possess information about the ADM2 and ADM1 regions, are assigned to the respective ADM1 region. To cope with the fact that most projects have several project locations, we assume that aid is distributed equally across locations, following Dreher and Lohmann (2015). This means that for a project implemented in 10 locations, with four locations in region A and six in region B, 40% of the project volume would be assigned to A and 60% to B.

[12] Lower level administrative regions (ADM2) would only capture between 60 and 80%. Using smaller grid cells would require only relying on projects with exact data on latitude and longitude, which is only about 50% for the WB and less than 50% for China.

The data appendix provides more details about the procedure.[13]

WB aid disbursements are from AidData (Strandow et al., 2011), covering the 1995 to 2012 period. We focus on disbursements by IDA, the WB's arm for development aid (qualified as financial support with a significant concessionary component). Disbursements that we can assign to the ADM1 level sum up to USD 29.4 billion, distributed over 1,472 projects in 25,041 locations in Africa. For China, we use the media-based data set on Chinese ODA-like commitments from Dreher et al. (2016), which were georeferenced by Strange et al. (2017). Since graduating from IDA eligibility in 1999 (Galiani et al., 2017), China's overseas portfolio of grants, loans, and export credits has rapidly expanded as part of its 'Going Out' strategy. In Africa, the total volume of Chinese official financing was roughly comparable to U.S. official financing between 2000 and 2012 (Strange et al., 2017). In total, Chinese aid amount to USD 13.2 bn, from 333 projects in 1,308 locations.

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.

The remaining sample comprises 728 ADM1 regions in 45 countries. Table 1 shows a comparison of the two donors in some important dimensions. Both the WB and China are active in most African countries, with significant overlap in their presence between countries; the WB is active in 35 countries, and China is active in 41 countries (Humphrey and Michaelowa, 2018). While information for aid disbursements by the WB's IDA is available from 1995 to 2012, information on

[13] Hence, our aid attribution formula is: $Aid_{pijt} = \frac{Aid_{pit}}{\int Locations_{pi}} * \int Locations_{pj}$, 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 53 and 54 display the main results using population weights. For instance, if a project has project locations in two regions of a country, two million inhabitants reside in region A, and three million reside 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 has to be imputed, the data is subject to a certain degree of measurement error . The remaining project locations, with less precise location information, are 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 administrative regions.

Chinese aid commitments in Africa is constrained to the years 2000 to 2012.[14] One interesting difference is that the WB actually finances a larger number of projects than China; these projects are present in more locations across countries. China finances fewer projects, however they are larger in scope. Accordingly, China spends nearly twice as much per project, and nearly ten times as much per project location.[15]

Table 2 provides summary statistics of the most important variables at the country-region-year level. With regard to the main treatment variables, namely WB and Chinese Aid, it becomes visible that WB aid is, on average, higher per region-year: USD 2.2 million versus USD 1.4 million, respectively. However, the standard deviation of Chinese aid indicates the large differences in scale. The maximum Chinese spending per region-year is USD 900 million; nearly twice as large as the highest value for the WB. This corresponds to many Chinese ”mega-projects”, like railroads, dams and power plants. Figure 2a, which depicts the geographical distribution of development aid locations, shows that the engagement of both donors exhibits sufficient variation across, as well as within, countries.

Table 2: Descriptive statistics - ADM1 Region

	Mean	SD	Min	Max
World Bank Aid	2,240,340	8,991,909	0	488,643,178
ln(WB Aid)	6	9	-5	20
Chinese Aid	1,391,272	22,843,120	0	900,000,000
ln(Chinese Aid)	-4	4	-5	21
Battle Related Deaths	21	342	0	33,417
Conflict Incidence in Percent	12	32	0	100

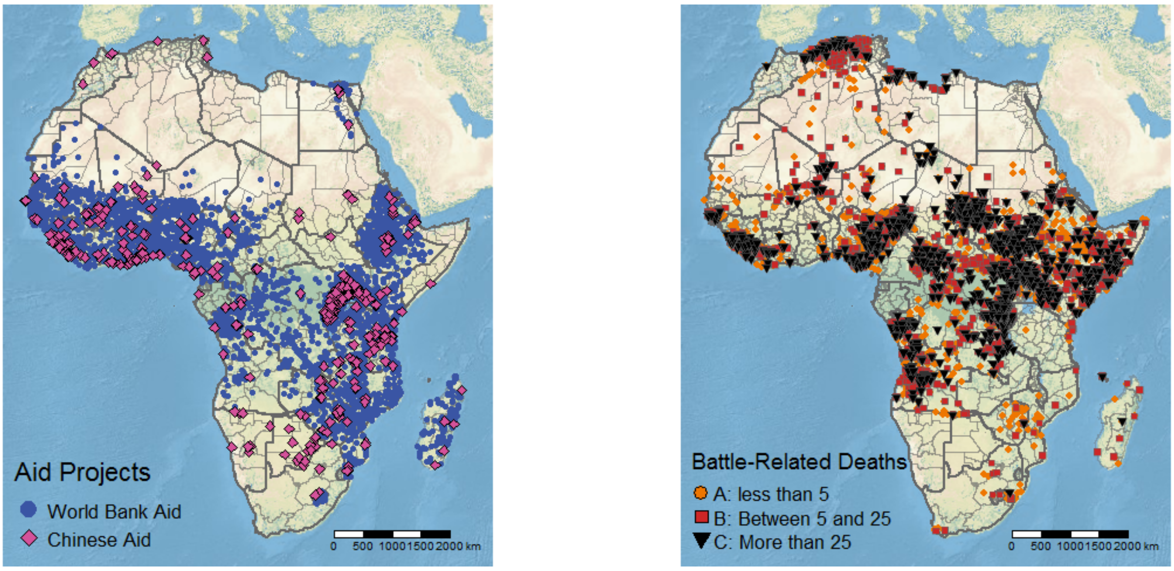
Notes: Descriptive statistics for our main variables. ln(Aid) is based on aid +0.01USD.

3.2 Conflict Data

Our main specification defines conflict based on the number of battle-related deaths (BRD) from 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

[14] This analysis focuses on Official Development Aid (ODA) flows in contrast to other official finance (OOF). OOF 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] AidData cannot distinguish exactly how much money from the Chinese commitments is disbursed in a particular year. If, plausibly, Chinese aid commitments would be disbursed over several tranches, other leads and lags of our measure could also affect the conflict risk one year or two years later. Still, an examination of further lags in Table A14 shows that this timing is not driving the subsequently reported results.



(a) (b)

Figure 2a Chinese (2000-2012) and WB (1995-2012) development aid. Authors' depiction based on AidData (2017) and Dreher et al. (2016).
Figure 2b 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).

well as secondary sources, namely field reports and 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. Figure 2b shows a map with all conflict events in our sample period, distinguishing between conflict with less than 5 BRD, between 5 and 25, and more than 25 BRD. Studies at the country level usually use thresholds of 25 or 100 to define a conflict. As our study is at the smaller regional level, we choose 5 per region-year as the threshold for our binary conflict indicator at the region-year. We will show robustness tests using 25 BRD as the threshold, as well as the log of battle-related deaths as a continuous indicator. To examine non-lethal conflict, we define similar binary variables for smaller scale conflict events like demonstrations, strikes or riots, as well as for non-lethal government repression based on the Social Conflict Analysis Database (SCAD, Salehyan et al., 2012). Table A11 in the data appendix provides a more detailed overview about the different outcome variables.

[16] Alternatives are 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 partly ambiguous inclusion criteria and vague geo-coding (Eck, 2012).

3.3 Control Variables

Even though we will not decisively rely on control variables due to the bad control problem, we provide specifications using the most important aspects highlighted in the previous literature. Initial regional development is proxied using nighttime light (Henderson et al., 2012). Regional population is calculated based on the *Gridded Population of the World* dataset(Center for International Earth Science Information Network (CIESIN) Columbia University, 2016). Regional population changes are integral for aid allocation and to scale the potential for conflict for regions of different size (Hegre and Sambanis, 2006). From the PRIO Gridded data (Tollefsen et al., 2012), we use several natural resource indicators including oil, gold, gemstones, and narcotics, as well as measures on temperature and precipitation, that can be linked to conflict (Miguel et al., 2004). In order to match the gridded data to the respective region-year, we intersect the PRIO-Grid with the AMD1 shapefile and calculate area-weighted averages for each region. Finally, robustness tests use data from Cederman et al. (2014) and Wucherpfennig et al. (2011) to control for the distribution of ethnic groups.

4 Empirical Strategy

It is important to note that aid projects are not randomly allocated. Donors might be more or less likely to select a region based on its conflict potential, which causes concerns about endogenous selection. Over the long term, reverse causality might also cause problems if regions formerly plagued by conflict receive more aid afterward. Considering Figures 2a and 2b again helps to understand our two different approaches to identification. The first approach is to use the possibilities of the sub-national data and conditions step-by-step on more and more observables and unobservables through various fixed effects, time trends, and controls.

First, precise coding helps. Angola, for instance, receives more aid projects in regions that also experience more conflict. In contrast, the regions in Sudan that receive aid often differ from those that experience conflict. Country-level studies, in contrast, would code both countries as cases where a country received aid and also experienced conflict. Second, the correlation between aid and conflict is affected by unobserved region-specific factors that can make both receiving aid projects and conflict more likely. Region-fixed effects can eliminate time-invariant differences that affect this joint likelihood of receiving aid and experiencing conflict.

Third, country times year (from now on country-year) fixed effects go one step further and eliminate the effect of any spurious event at the country-year level that could affect conflict and, by chance, coincides with changes in aid allocation, which could include a change in political regime. It is important to eliminate variation step-by-step in order to avoid overlooking a potentially conflict-enhancing effect by canceling out too much variation. We will show that our dataset exhibits enough variation to allow for the use of very restrictive sets of fixed effects and time trends that rule out many concerns raised in the existing literature. Of course, this does not fully eliminate concerns about endogenous selection. We will, in the following sections, show in which direction this bias seems to tilt and propose an IV strategy for each donor.

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

Our baseline empirical specification is

$$C_{i,c,t} = \beta_1 A_{i,c,t-1/t-2} + \lambda_c + \tau_t + \delta_i + \lambda_c T + \lambda_c T^2 + X^{Ex}_{i,c,t}\beta_2 + \delta_i T + X^{En}_{i,c,t-2}\beta_3 + \kappa_{c,t} + \epsilon_{i,c,t}, \quad (1)$$

where $C_{i,c,t}$ is our conflict indicator of interest in region i, in country c and year t. $A_{i,c,t-1/t-2}$ is log of per capita aid. 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 the available data on Chinese aid commitments.

We 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 – country, time, and region fixed effects, respectively. Furthermore, we add country-specific linear $\lambda_c T$, quadratic time trends $\lambda_c T^2$, and later, regional linear time trends $\delta_i T$ to control for any differing linear conflict trends across regions. Country-year fixed effects $\kappa_{c,t}$ need to be considered carefully, as they eliminate not only many potentially critical omitted variable problems, but also a lot of variation in the data. In essence, including the country-year fixed effects asks a subtly different question: conditional on the whole country being in conflict or not in a particular year, how did previous aid receipts affect the conditional likelihood of a particular region to be in conflict? For that reason, we always consider one specification with and one specification 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 for the effect of time-invariant controls like elevation or ruggedness of terrain 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 twice lag potentially "bad controls" like nighttime light (as a proxy for economic activity), or population, which can be affected directly by aid projects. Using "pre-determined" 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 $\epsilon_{ir,t}$.

Standard errors are two-way clustered at both the country-year and the 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. Tables A50 and A51 show similar results for other options.

4.2 Instrumental Variable approach

4.2.1 General Approach

Our IV strategies exploit the heterogenous impact of a plausibly exogenous time-series interacted with either apre-determined or fixed cross-sectional difference (as in , e.g., Nunn and Qian, 2014).[17] The identifying assumption is that, in absence of a change in the time series, there would be common trends in aid allocation, within low and high aid probability recipient regions. As in any Difference-in-Difference (DiD) setup, both regression stages control for the main constituting terms forming the interaction, and only the interaction term is used as the conditionally exogenous instrument in the first stage. For both the WB and China, we use a cumulative, either initial or pre-determined, probability over the whole sample period as the cross-sectional difference. This is computed by dividing the number of years a region i has received aid in the past, by the number of years passed until year t.[18] The identification strategies for WB aid and Chinese aid, hence, differ in the donor-specific probability, and in the time-varying factor T_t, used to induce variation in project allocations over time.

4.2.2 Application to WB aid

For the World Bank we exploit the heterogeneous effect of yearly variation in the availability of additional IDA resources on regions with an initially lower or higher likelihood of receiving aid.[19]

[17] Nunn and Qian exploit temporal variation in US wheat production, which they 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 $t+1, t+2, ...$. 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. A further alternative would be the use of a rolling time window over which we estimate the probability. The results in Tables A24 and A25 indicate robustness of our main estimates for two to four year windows for the WB. Due to the Chinese strategy to implement larger but fewer projects, the rolling probability varies less over the short time frames and leads, thus, to weak IV problems.

[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.

Details may differ in individual cases, but based on discussions and insights from the WB, as well as recipient country personnel, the mechanism we exploit and document in the data is the following. If there are more funds available, the Bank has an interest to exhaust the funds and allocate them to recipient countries. Countries and regions which were, or currently are, already involved in projects receive a larger share of the additional funds, partly because the costs of information screening and other preparation are lower. Variation in the funding position, 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), can be caused by internal adjustments, the timing of payments by the shareholders, and repayments by large borrowers like India. Conflict in any individual sub-national African region, in particular conditional on country or even country-year fixed effects, cannot plausibly affect the position significantly.

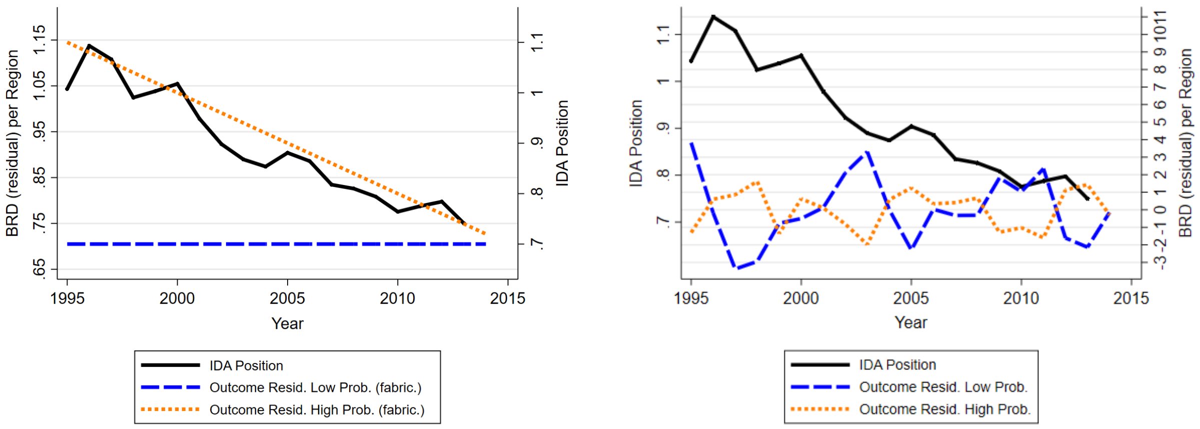
From 1995 to 2007 we rely on the reconstructed time series by Dreher et al. (2017); starting in 2008, we use the measure publicly disclosed in the annual financial reports.[20] This time-varying variable is interacted with the pre-determined probability of a region to receive aid, $p_{i,c,t-2}$, in order to capture that higher probability regions should profit more from higher funding positions. The first stage equation has the following form:

$$Aid_{i,c,t-1} = \alpha_1 p_{i,c,t-2} + \alpha_2 IDA_{t-1} + \alpha_3 p_{i,c,t-2} IDA_{t-1} + X^{Ex}_{i,c,t}\alpha_4 + \epsilon_{i,c,t-1} \tag{2}$$

One potential problem associated with approaches like ours is that, even if the temporal variation is plausibly exogenous, trends in the time series might overlap with differing trends in the outcome variable, leading to a spurious IV effect. This risk is exacerbated if the time series is relatively short and dominated by long-term trends (Christian and Barrett, 2017). The left-hand side of Figure 2 shows how differences in the long term conflict trend, within both low and high probability regions, could lead to such biased estimates. The right-hand side figure then shows that the actual residual variation net of fixed effects and time trends in conflict that we exploit exhibits no such trend. Moreover, despite a general decline in the funding position, there is also sufficient year-on-year variation. For instance, the position initially increases between 1996 and 1997, before falling sharply in the following years. Table A16 and A17 indicate that this works both through the extensive and intensive margin. High probability regions have a higher likelihood to profit by receiving aid in a particular year, and conditional on receiving aid in a given year, the size of the disbursements also becomes larger.[21]

[20] Because the WB's fiscal year ends in June, the reported position in the fiscal years t and t-1 can both affect 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.

[21] To allow the reader to assess the trends in the treatment variables, Figure A11 depicts the time series for the means of logged WB and Chinese aid per high and low exposure regions.



(a) Problematic trends (fabricated) in outcomes

(b) Actual trends in outcomes

Figure 2: WB- IDA funding position and conflict outcomes for low and high probability regions.

Note: Figure (a) displays the temporal variation we use in our interacted instrument, the IDA Funding Position (solid line), along with fabricated trends in the conflict outcomes for low (long-dashed line) and high probability (short-dashed line) recipient regions. The trends are fabricated to illustrate potentially problematic trend differences that could induce a spurious correlation. Figure (b) displays the IDA Funding Position (solid line), along with the actual trends in the conflict outcomes for low (long-dashed line) and high probability (short-dashed line) recipient regions. The displayed outcomes in (b) are the residuals net of the fixed effects and time trends that we use in Table 3, column (4), the remaining unexplained variation in the outcomes used in our preferred specification.

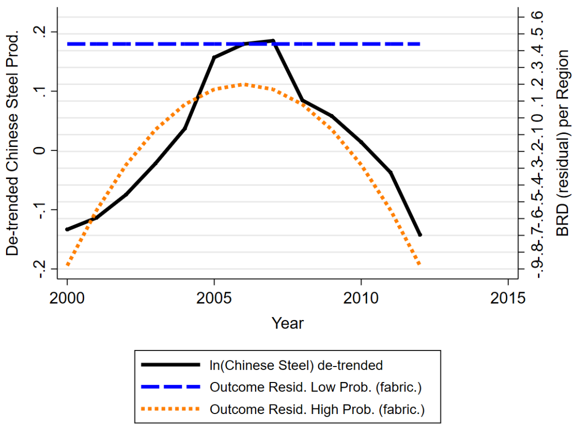
4.2.3 Application to China

Regarding China, we make use of the fact that the economic structure and political incentives frequently lead to excess domestic production in particular years, most prominently in the country's over-sized steel sector. To clear markets and protect domestic companies from potential losses, China commits to more aid projects abroad (Dreher et al., 2016), a pattern not entirely unknown from European agricultural overproduction. These additional projects are often large-scale infrastructure projects that directly use overproduced goods as inputs (Bräutigam, 2011), but Bluhm et al. (2018) show that steel production also induces variation in other sectors like education or health. As the Chinese "mega-deals" (Strange et al., 2017) cannot easily be duplicated or scaled within regions, and the country tries expanding its influence during our sample period, the additional projects are often implemented in low probability regions that had initially no, or very few, projects.

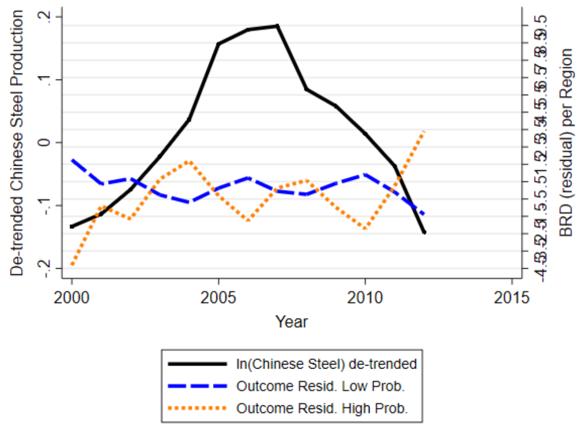
We construct a time series on Chinese steel production, $T_{i,c,t}$, from the statistical yearbooks of the World Steel Association. Due to a clear long-term upward trend in Chinese steel overproduction, and little year-on-year variation, we detrend the time series for our main specification. We show results without detrending in a robustness test; even though theoretically relevant, the transformation makes little difference. Again, the time-varying variable is then interacted with the pre-determined probability of a region to receive aid, $p_{i,c,t-3}$, to capture that lower probability regions should profit more from Chinese steel overproduction. The first stage equation has the following form:

$$Aid_{i,c,t-2} = \alpha_1 p_{i,c,t-3} + \alpha_2 Steel_{t-3} + \alpha_3 p_{i,c,t-3} Steel_{t-3} + X^{Ex}_{i,c,t}\alpha_4 + \epsilon_{i,c,t-2} \tag{3}$$

Again, the left-hand side of Figure 3 illustrates a fabricated, problematic, relationship with differing long-term conflict trends in low and high probability regions. The detrended steel variable is inverse U-shaped; if conflict trends in either low or high probability regions would, for other reason than aid, also follow such a pattern, the IV results would be driven by these spurious trends. To be as cautious as possible, we use the detrended time series, as there is an upward trend in the outcome residual among high probability recipient regions, though it is small (see Figure A13). The right-hand side graph assures us that there is no overlap with such trend in the variation we exploit.[22] Table A16 supports our theoretical prior that the first stage relationship is mainly driven by the extensive margin, e.g., the likelihood of having at least one active project in a specific region-year. Regions without pre-existing projects are more likely to receive a project as the Chinese development budget expands.



(a) Problematic trends (fabricated) in outcomes



(b) Actual trends in outcomes

Figure 3: China: Chinese steel production and conflict outcomes for low and high probability regions.

Notes: Figure (a) displays the temporal variation we use in our interacted instrument, the log of detrended Chinese Steel Production (solid line), along with fabricated trends in the conflict outcomes for low (long-dashed line) and high probability (short-dashed line) recipient regions. The trends are fabricated to illustrate potentially problematic trend differences that could induce a spurious correlation. Figure (b) displays the detrended log of Chinese Steel Production (solid line), along with the actual trends in the conflict outcomes for low (long-dashed line) and high probability (short-dashed line) recipient regions. The displayed outcomes in (b) are the residuals net of the fixed effects and time trends that we use in Table 3, column (4), the remaining unexplained variation in the outcomes used in our preferred specification.

[22] For the WB we do not observe overlapping trends in the non-detrended time series in Figure 2. Thus, there would be limited additional advantage from detrending. Figure A13 depicts the detrended variation in our instrument. Using this variation in our interacted instrument leaves the main result of a non-significant effect of aid on lethal conflict unchanged (see Table A21).

5 Results

5.1 OLS, fixed effects and time trends

To allow readers to evaluate a potential trade-off between eliminating bias and over-controlling, we begin by showing simple correlations, and then add fixed effects, time trends, and different categories of control variables step-by-step.[23] Beginning with WB aid in Table 3, we find that the raw correlation with conflict incidence is negative. Adding country and year fixed effects shifts the coefficient upward (column 2); adding country-specific linear and quadratic trends to capture country-specific conflict dynamics moves the coefficient slightly downward to -0.05 (column 3). When adding region fixed effects, which capture region-specific, time-invariant attributes, that can explain heterogeneity within countries, the point estimate nearly quadruples in size to -0.21 and becomes 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 then is 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. The coefficient of -0.1772 suggests that a one standard deviation change in log WB aid decreases the conflict likelihood by $9 \times 0.1772 \approx 1.59$ percentage points. To put this into perspective, the average of conflict incidence with our threshold of five battle-related deaths (BRD) is 12 percent; accordingly, this is small, however it is a non-trivial change. The coefficient 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 theoretical prior was that certain arguments suggest a positive relationship with conflict to be more likely when involved with Chinese aid. Nonetheless, the raw correla-

[23] A second trade-off is whether to show both donors over the same period and in the same equation. The advantage is increased comparability and accounting for aid from one donor as a potential omitted variable in the other donors equation. Table A55 (Table A56) shows that the OLS (IV) results also suggest no conflict-fueling effects when including both donors jointly. There are two reasons why we chose to estimate the two equations separately. First, it allows us to use five more years of data for the WB (1996-2001). Most importantly, when estimating the IV specifications jointly for both donors and the restricted time period, the K-P F-statistics for the WB are much smaller (Table A56), giving rise to concerns about weak IV problems. Still, this table also shows that the two instruments actually capture distinct variation: the interaction instrument for the WB is still significant in explaining variation in WB aid, and the IV for China still significant in explaining variation in Chinese aid. Even with the weak IV, the table indicates no conflict-fueling effects for both donors. Moreover, Humphrey and Michaelowa (2018) find no systematic relationship between the selection of locations by the two donors, also indicating that this choice does not bias our results.

tion with conflict is also negative. The coefficient drops drastically in size when adding country and time fixed effects, as well as country-specific time trends (columns 2 and 3), but loses significance. Overall, the coefficients are much smaller and closer to zero than those 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 increasing log Chinese aid by one standard deviation decreases the conflict likelihood by $4 \times 0.0654 \approx 0.26$ percentage points.

Table 3 reveals how many degrees of freedom researchers possess in selecting their preferred specification in such a setting. 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 projects. Relating to the ideas about assessing coefficient changes when moving towards more restrictive specifications in Altonji et al. (2005), we also see that the effect of adding additional FE, trends, and covariates neither suggests a strong systematic upward, nor a downward bias. The confidence interval comprises negative, zero, and some positive effects. Still, considering the rich set of specifications we examined, it seems highly unlikely that other unobserved factors would push the average effect towards a statistically, and economically, significant conflict-fueling effect. Even if there would be large changes in Chinese aid, their average effect on conflict would be rather small, when compared to the average likelihood of conflict of 12 percent. For further tests, we continue examining specifications based on the set of control variables in columns 6 and 8, and we address the potentially remaining selection-bias with our IV estimations.

5.2 Instrumental Variables

Table 4 shows the IV results for our preferred specifications. The first stages work well for both donors. The interaction term between the prior probability to receive aid and the IDA position, respectively Chinese steel production, is highly significant 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); all F-statistics, however, are well above the critical value of 10. In addition to being relevant, the signs of the coefficients align with our priors. Regions with a higher pre-determined probability profit more from a higher WB liquidity, and regions with an initially lower probability profit more from an expansion of the Chinese aid budget.

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

Panel A: WB Aid	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
$ln(World\,Bank\,Aid_{\text{t-1}})$	-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									
$ln(Chinese\,Aid_{\text{t-2}})$	-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 × 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$\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. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

The second stage results largely confirm the OLS results. Both specifications yield negative coefficients 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, however they remain insignificant. There is again no evidence for a conflict-fueling effect of aid projects for either of the two donors. Taken at face value, increasing log WB aid by a one standard deviation decreases the conflict likelihood by about $9 \times 0.2252 \approx 2.03$ percentage points. Raising log Chinese aid by one standard deviation would decrease conflict by $4 \times 0.4276 \approx 1.71$ percentage points.

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 that is caused by the excluded instrument, the interaction term. Nonetheless, comparing the IV point estimates with OLS shows only minor differences in size, and 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. More specifically, Table A14 shows three lags, the contemporaneous value, and a lead term of the treatment variable. 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 into regions that are more likely to have experienced a conflict in the past years; this is potentially due to China being less worried about conflict, or because of 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 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 aid sectors, the actors involved in conflict, and different types of conflict.

[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.

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

Panel A: World Bank Aid	(1)	(2)
IV Second stage: World Bank		
$ln(World\,Bank\,Aid_{\text{t-1}})$	-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: World Bank		
$IDA\,Position_{\text{t-1}} \times$ Cum. Prob$_{\text{t-2}}$	70.9363***	80.8832***
	(7.1065)	(8.6854)
N	12325	12325
Panel B: Chinese Aid	**(1)**	**(2)**
IV Second Stage: China		
$ln(Chinese\,Aid_{\text{t-2}})$	-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: China		
$Steel\,Prod\,detrend_{\text{t-3}} \times$ Cum. Prob$_{\text{t-3}}$	-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 A18. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

5.3 Channels - Aid Sectors

As outlined before, aid in different sectors could be more or less likely to fuel or calm down a conflict. We examine aid projects in eight subcategories for our two preferred specifications, with and without country-year FE. Note that, in almost all cases, the country-year FE only affect the coefficients' sizes, not their signs. For the WB, the IV strategy works well using sector-specific probabilities. For China, there are severe weak IV problems due to limited observations in certain sectors. We show results for China using OLS, building on the fact that OLS and IV results turned out to be very similar before.

Interesting differences across sectors emerge, suggesting that aid in different sectors indeed has different effects on subsequent conflict. Table 5 shows that there are positive coefficients of WB (Chinese) aid in a few categories, but it never becomes statistically significant. The insignificant negative average effects in previous tables seem to be driven by significantly negative, conflict-reducing effects for the sectors "finance" (WB only) and "transportation" (WB and China), both in the less and more restrictive specification with country-year FE. In the latter specification, a 100% increase in WB finance aid leads to a 1.59 percentage point reduction in the likelihood of conflict – relative to the baseline likelihood of 12 percent. Our investigation of a sample of the 1,361 projects in this sector shows that finance projects typically support both existing, and new projects to induce structural or sectoral reforms; these projects also provide technical assistance and consulting, concerning topics like regulation and financial or business services.[25] The actual monetary disbursements are rather small; hence, the main impact must stem from the knowledge transfer and technical support to modernize and develop capital markets, banks and insurances. This includes privatization programs, the development and restructuring of banks, as well as technical assistance to enhance transparency and regulation.

Regarding the transportation sector, a 100% increase in WB (Chinese) aid leads to a 6 (1.35) percentage points reduction in the likelihood of conflict . This sector comprises many projects, often large-scale infrastructure projects, as well as large disbursements in dollar terms. The negative effect suggests that existing constraints on movement or high transportation costs were significant obstacles for exchange, consumption, public good provision and eventually economic growth (see also Berman and Couttenier, 2015; Storeygard, 2016). This seems to dominate both potentially negative effects on corruption (Isaksson and Kotsadam, 2018a), and disputes over land usage. It is in line with Bluhm et al. (2018), who show that Chinese infrastructure projects reduce economic inequality and, hence, potential reasons for conflict.

Overall, these heterogeneities across aid categories within the sector-specific results are a first explanation for the relatively broad confidence interval when studying the average effect of WB and Chinese aid. It is reassuring that we find no significant conflict-fueling effect on any aid sector for either one of the two donors. The overall average negative relationship does not seem to mask strong conflict-fueling effects in certain sectors.[26]

[25] Out of 40 projects, 26 were in one of those categories. Appendix section A.5 documents how we retrieve detailed information on World Bank aid in the finance sector.

[26] Table A52 presents the regressions for the WB using OLS and for China using IV. The OLS results differ in some cases with regard to the sign of the effect, but again there is no significant positive effect for any sector. Note that generally, one caveat of these regressions is that due to high collinearity and insufficient power we cannot run the regressions with all individual sectoral aid variables jointly included, in particular with IV estimators.

Table 5: ADM1 - Aid Sectors

World Bank Aid Sectors - 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
$ln(World\, Bank\, Aid_{\text{t-1}})$	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										
$ln(World\, Bank\, Aid_{\text{t-1}})$	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 Sectors - OLS										
Panel C: No Country-Year FE	AX	BX	CX	EX	FX	JX	LX	TX	WX	YX
$ln(Chinese\, Aid_{\text{t-2}})$	-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										
$ln(Chinese\, Aid_{\text{t-2}})$	-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$\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: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

5.4 Channels - Actors

For donors, it can be a crucial difference whether the government is fighting against rebel groups, uninvolved third parties (i.e., civilians) are attacked, or rebel groups are fighting each other. Actions *against* some rebel groups might be accepted or even encouraged by donors. In contrast, attacks on civilians are often condemned by donors, even if they happen during an existing conflict, and might be a reason to withhold aid or reduce future payments (Lebovic and Voeten, 2009; Tir and Karreth, 2018). Even for purely self-interested recipient politicians, the withdrawal of aid can be a viable threat.[27] We can distinguish between state violence, rebel (labeled non-state-) 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 6 shows the results with and without country-year FE. The coefficients for state-based violence against rebels (column 1 and 2), conflict between different rebel groups (column 3 and 4), and rebel violence against civilians (column 7 and 8) are partly of an economically significant size, but even though they vary in the direction of the effect are all far from being statistically significant. When considering state conflict against civilians (column 5 and 6), we find that in a region that receives more WB aid, there is significantly less conflict. A one standard deviation change in log WB aid decreases the likelihood of violence against civilians with at least 5 BRD by $9 \times 0.29 \approx 2.61$ percentage points. This is plausible as the WB is known to punish human right violations by governments. For instance, the WB suspended important aid payments in Indonesia so as to push the government towards finding peaceful bargaining solutions on the island of Timor (Tir and Karreth, 2018).

Although Tir and Karreth (2018) focus their arguments on international organizations like the WB, which impose strong conditionality, we find a conflict-reducing effect for Chinese aid as well. Changing log Chinese aid by one standard deviation decreases the conflict likelihood substantially by $4 \times 0.89 \approx 3.47$ percentage points. 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 convince recipient governments to abstain from engaging in actions that cause civilian casualties and endanger stability.[28]

[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.

[28] While Tir and Karreth (2018) argue that the prospect of gaining access to aid can also constrain rebels, the coefficients for one-sided rebel violence against civilians are negative for both donors, but remain statistically insignificant.

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

Panel A: World Bank Aid - IV	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
IV: World Bank - Actors	State vs. N-State		N-State vs. N-State		State vs. Civilans		N-State vs. Civilians	
$ln(World\,Bank\,Aid_{\text{t-1}})$	-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: China - Actors	State vs. N-State		N-State vs. N-State		State vs. Civilans		N-State vs. Civilians	
$ln(Chinese\,Aid_{\text{t-2}})$	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-state actors. The categories are mutually exclusive. Standard errors in parentheses, two-way clustered at the country-year and regional level: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Table A37 depicts corresponding OLS results.

5.5 Channels - Types of Violence

Raleigh et al. (2010) emphasize "dire consequences" of Chinese aid, and state that "political violence rates involving state forces also increase." Should we then conclude that these fears are unwarranted? Not necessarily. Our analysis has focused on violent conflict that involves battle-related deaths, but Kishi and Raleigh highlight that states "use this aid to finance their hold on power by repressing political competitors." It seems plausible that China is interested in avoiding outright battles; however using government repression to ensure stability is also 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.[29]

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. First, we code binary variables that take on a value of one if there was at least one riot, strike, or demonstration in a district in order 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 previous results.

Panel A of table 7 shows the results for our two main specifications, but now, replacing the outcome variable with an indicator, measuring whether at least one demonstration, riot, or strike took place.[30] For the WB, both specifications yield a negative coefficient but remain statistically insignificant. Regarding China, we observe positive coefficients. Although they are rather large (10% more aid increase the likelihood of riots by 0.026%), they remain statistically insignificant. Accordingly, despite reports indicating increasing protests against the presence of Chinese buisness(Wegenast et al., 2017), we find no clear relationship between Chinese aid and citizen protests over our sample period.[31]

Recipient governments might achieve this absence of protests and outright conflict by intensifying non-lethal repression. Panel B of table 7 tests whether aid is related to more reports of non-lethal government repression.[32] The results indicate neither a positive nor significantly nega-

[29] Washington Post, last accessed 02.02.2019.

[30] Table A38 depicts corresponding OLS results. Tables A31, A32 and A33 show OLS regressions separately for demonstrations, riots and strikes; Table A34 separate IV estimates. None of them turns out significant once region FE are included.

[31] See, for instance, The Telegraph, last accessed 02.02.2019.

[32] Table A36 reports results for a count variable of non-lethal pro-government violence events, which are robust to this change in the outcome variable. Table A35 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.

tive relationship for the WB. The results for China contrast our previous findings and establish that repression intensifies in regions where China is present. A 10% increase in Chinese aid increases the likelihood of experiencing repression by about 0.13%, which is significant considering an average of 2.26%.

Table 7: Non-lethal Government Repression [SCAD]

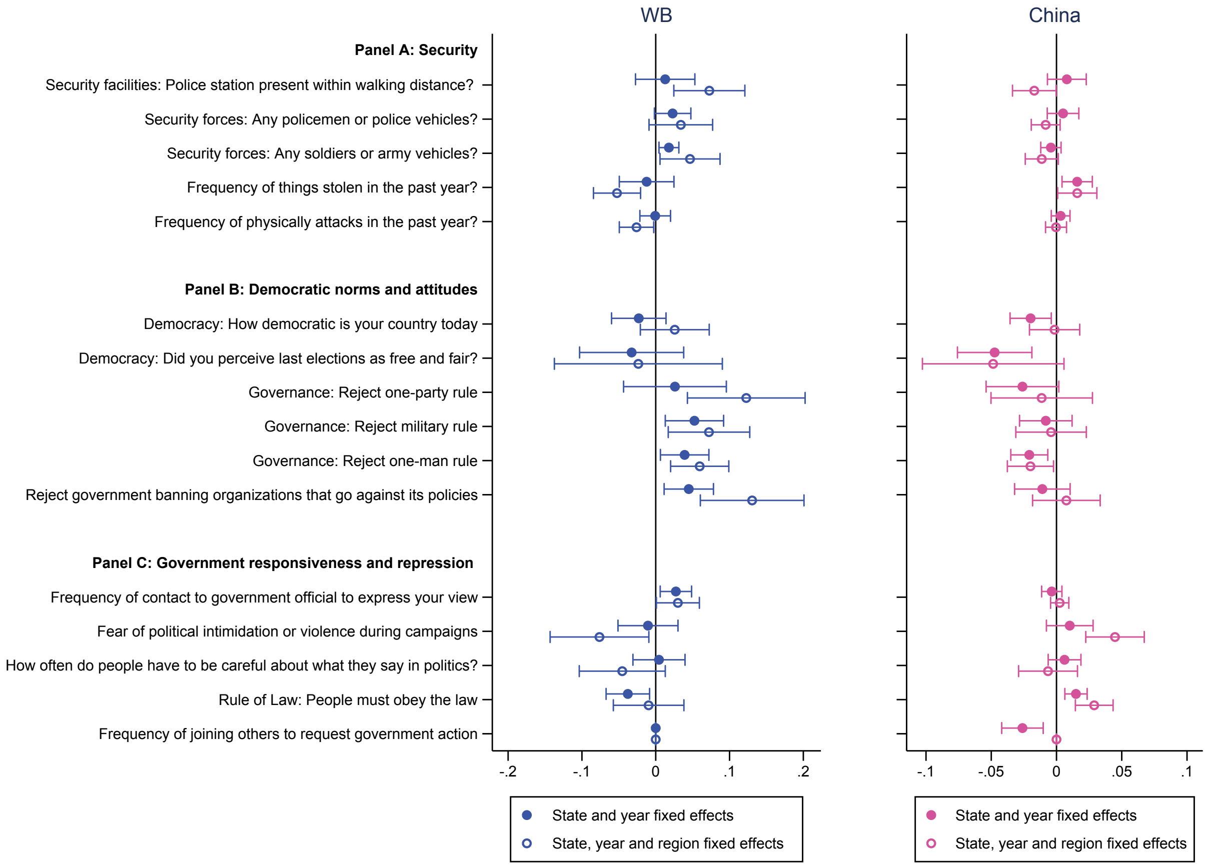
Panel A: Riots, demonstrations and strikes	(1)	(2)
IV Second stage: World Bank		
$ln(World\,Bank\,Aid_{\text{t-1}})$	-0.3854	-0.2032
	(0.3092)	(0.3362)
N	12325	12325
Kleibergen-Paap underidentification test p-value	0.000	0.000
Kleibergen-Paap weak identification F-statistic	99.639	86.724
IV Second Stage: China		
$ln(Chinese\,Aid_{\text{t-2}})$	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
Panel B: Non-lethal Government Repression		
IV Second stage: World Bank		
$ln(World\,Bank\,Aid_{\text{t-1}})$	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
IV Second Stage: China		
$ln(Chinese\,Aid_{\text{t-2}})$	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
Country-Year FE	No	Yes

Notes: The table displays regression coefficients for a binary dependent variable of the occurrence of riots, demonstrations and strikes in Panel A and non-lethal repression (pro-government violence) in Panel B. 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 Channels: Survey Evidence

Examing the associated mechanisms for all effects is beyond the scope of this paper. Still, we can present some correlational evidence using georeferenced Afrobarometer data to investigate the plausibility of some of our results. To do so, we match data, from all Afrobarometer waves, to the regions and years in our sample, and compute the region-year level average of each question we use. Details are provided in Appendix Table A12. Note that the survey covers varying subsets of all African countries in selective years, so that the resulting dataset comprises an unbalanced panel with gaps. The temporal variation is not sufficient for a strong first stage using the IV, and we can only use less restrictive sets of fixed effects than in our main specifications. Figure 4, thus, plots the coefficients from individual OLS regressions of selected relevant questions on WB and Chinese aid: model 1 uses country and time FE, model 2 region and time FE.

Figure 4: OLS regressions on mechanisms using Afrobarometer for WB and China



Notes: The figure shows coefficient plots along with 90% confidence intervals of individual OLS regressions of log WB and log Chinese aid on the respective questions from Afrobarometer. All outcome question responses were standardized with mean zero. Respondents were matched to the ADM1 regions using the provided geocoordinates. Table A47 provides the full regression results. Afrobarometer was conducted in the years 1999-2015 for a varying number of 12 to 36 countries, resulting in an unbalanced panel with uneven gaps between years.

The results are grouped in three categories. Panel A refers to questions signaling the presence of state security forces as a measure for state capacity within the area, and the ability to maintain a monopoly of violence. Moreover, we use two questions asking whether respondents or their families were the victims of robbery or physical attacks in the past year. The results suggest that the WB engagement is associated with an increase in security forces and a reduction in crimes. There is no such increase for China. However, one needs to keep in mind that these are conditional correlations, and China might select into regions more likely to experience conflict and deteriorations in state capacity.

Panel B examines democratic norms and attitudes. Even though the results are not necessarily causal, some differences stand out that reflect the differential approaches the two donors take. There are some indications that the perception of democracy, and the fairness of elections, deteriorate in regions with Chinese aid projects. The WB seems to have a consistent impact on democratic norms. Respondents are more likely to reject one-party rule, military rule, and one-man rule, which is not the case for China. With the coefficients being consistently significant in both models regarding one-man rule, respondents are less likely to reject these authoritarian governance forms . This could indicate that China helps some authoritarian regimes to stay in power. Note that in a more detailed examination Isaksson and Kotsadam (2018a) also find a deterioration in norms, and an increase in local corruption, associated with Chinese projects.

Panel C examines questions indicating the way the government interacts with its citizens and its use of repression. In regions with more WB aid, people report being more apt to frequently contact their government officials and express their views. This, at least, corresponds to the norms and conditions that the WB tries to enforce; there is no such effect for China. In regions with WB aid, the fear of political intimidation or violence is lower, while it is higher in regions with Chinese aid activities. At the same time, there is no clear difference in whether people think they have to be careful what they say privately about politics. Finally, two results stand out. In regions with more Chinese aid, respondents state much more clearly that people must always obey the law. Moreover, there is a negative correlation between Chinese aid and the willingness to join others to request government action.

Importantly, all of these results on mechanisms need to be interpreted cautiously, and do not necessarily signal causality. Still, they underline that the different approaches taken by the two donors matter. Against this background, it is important to reconsider that aid by both donors is, if anything, leading to less conflict. The results on mechanisms suggest that, for the WB, this is going along with an improvement in the democratic norms and security provision by the government. For China, one interpretation is that the country is exporting stability which results in a reduction in the likelihood of certain types of conflict. Still, this increase in stability seems to come at the cost of increased government repression in addition to a weakening of democratic processes.

5.7 Sensitivity

Modifiable area unit problem - different aggregation levels: First, we aggregate at the country level. This allows us to see the aggregate impact of potential spill-overs to other regions, and enables us to compare our main results to studies at the country level. We show results both with and without controlling for the share of aid projects that could not be assigned to a particular

ADM1 region. These are, to a large extent, projects where money flows directly to the central government. The coefficients are also negative for both donors in both specifications. Thus, our results at the local level do not seem to be driven by choosing a particular spatial unit.[33]

In Table A42 (A43), 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, especially, when conditioning on more restrictive fixed effects, and all insignificant. The IV point estimates differ somehow, but never become 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 A27 (A28) presents alternative regression results with a higher conflict threshold of at least 25 BRD per region-year using the OLS (IV) specifications. Table A29 (Table A30) 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 using OLS (IV). We find largely negative OLS coefficients for the WB and slightly positive ones for China. However, with IV, both coefficients turn negative, in line with previous results.

Instrumental variable: We conduct the majority of robustness tests with regard to our IV strategy. As outlined, we detrended the Chinese steel production time series because it is dominated by a long-term trend, but did not do that regarding IDA liquidity, which offers sufficient year-to-year variation.[34] Table A21 shows that our first stages are still valid when using the detrended IDA position or the unadjusted Chinese steel excess production. Our results are*, thus,* not driven by problematic, linear or quadratic trends in conflict that differ between low and high probability regions. The second stage results remain small and insignificant for the average effects.

The second component of the IV, the probability term, may be computed in different ways. We test various plausible options. Using the cumulative probability is advantageous, as it only uses pre-determined values; yet, it could create problems if the probability in the first year(s) is not sufficiently informative. Table A22 drops the first year of the respective panel (starting 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 A23 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 A26 drops the 10 highest leverage region-year observations. Figures A14 and

[33] Point estimates for the less precisely coded aid can be found in Table A45. Although the coefficient for non-geocoded WB aid at the country level turns positive it remains small and insignificant, further supporting that there is also a null effect at the country level. OLS and IV point estimates for geo-coded aid aggregatred at the country level can be found in Table A44. The coefficients remains small and insignificant, as well.

[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.

A15 display the IV estimates dropping country-by-country, so as to avoid the possibility of the relationship being driven by one particular state. Both first and second stage results are robust to all these choices and specifications.

Moreover, Table A19 reports reduced-form estimates. Table A15 uses a lead of aid as a placebo treatment in the first stage, which always shows up as statistically insignificantly. Table A18 reports the first stage, including the coefficient for the probability.

Spatial spillovers Potential spill-overs of aid leading to conflict in other regions are important to consider. While our data allows us to study spill-overs of various forms, we relegate this to another paper that provides enough space to study spill-overs as well as inequalities in the aid distribution more thoroughly. We distinguish between regions that host the capital of a country compared to the remaining regions of the country in Appendix Table A46, as a significant share of aid often flows to capital regions.[35] Kishi and Raleigh (2016) suggest that, since aid is fungible, governments can shift expenditures towards strengthening their military. Improved military forces could then be used to strike down rebel groups and to target other areas of the country. However, governments could also use available funds to appease potential opponents in non-capital regions (Nielsen et al., 2011). Consistent with the main findings, estimates generally indicate insignificant negative correlations of aid with conflict in the own region. Only one specification suggests conflict reducing spill-overs to the capital region if Chinese aid is allocated to non-capital regions.

Non-linear estimators: In line with Berman et al. (2017), we also run a Poisson Pseudo Maximum Likelihood estimation in Table A48, 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 A49. The results are very similar, with mostly negative and partly significant coefficients for the WB and China.

Remaining limitations There are of course remaining limitations of our study, mostly with regard to Chinese aid. It would be advantageous to possess actual Chinese disbursement data instead of event-based data, to possess newer data to analyze the further intensified Chinese engagement in recent years, and to possess an instrument that uses more year-on-year variation. We hope that at least some of those can be improved upon in the future if new data become available. Until this happens, we plan to use the existing data and address the issues of inequality in aid allocation and spatial spill-overs in more detail in a follow-up project.

[35] A more detailed description of how we estimate the underlying IV regressions is given in Appendix B.3.

6 Conclusion

Our paper contributes to the literature on aid and conflict by providing, as we hope, the most comprehensive analysis of the relationship between development aid and conflict at the sub-national level this far. Our paper aims to bridge the gap between existing studies that analyze panels of countries at the aggregated macro level (Bluhm et al., 2016; Nunn and Qian, 2014), and studies that focus on specific types of aid or individual countries at a more micro-level (Berman et al., 2011; Child, 2018; Crost et al., 2014). To achieve that aim, we examine two donors that represent strongly contrasting approaches to development, the World Bank and China. The former is a multilateral donor that emphasizes human right conditions, expert knowledge, and specifically engages in conflict-sensitive programming. The latter is the major emerging donor, emphasizing mutual economic benefits without the weight of numerous explicit conditions for recipient governments and without officially accounting for potential conflict risks (Asmus et al., 2017).

Our results using aid projects and conflict in the same region show no signs of a conflict-fueling effect. Rather, aid seems to be able to reduce the likelihood of conflict, on average; WB aid, in particular, has a significant effect. When distinguishing between different sectors, we find the strongest and most significant conflict-reducing effects for projects in the transport sector (both donors) and in the finance sector (the WB). Distinguishing between different actors in conflicts suggests that the threat of losing out on future aid payments by any of the two donors leads to a reduction in lethal violence by governments against civilians.

In contrast to a substantial amount of anecdotal media reports, we also find no evidence that aid, in particular large Chinese projects, lead to civilian unrest and protests in Africa. At the same time, we do, however, find consistent evidence that regions in which China is engaged experience an increased likelihood of government repression. Complementary evidence from Afrobarometer surveys suggests that WB aid has positive effects on perceived safety, democratic norms, and democratic values. While Chinese aid is associated with more stability through a higher adherence to the rule of law, it is also associated with a deterioration in democratic norms, and a higher fear of holding government accountable. The precise mechanisms behind this final result deserve to be examined with more scrutiny in future research. It suggests a rationale where China is eager to export stability and avoid violent conflict that endangers its workers and investment, while also being less opposed to repression and autocratic rule than Western donors like the WB.

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Appendix

Table of Contents

A Data Appendix

A.1 Sources

Table 8 lists descriptions and sources of our independent, dependent and control variables.

Table 8: Data Sources

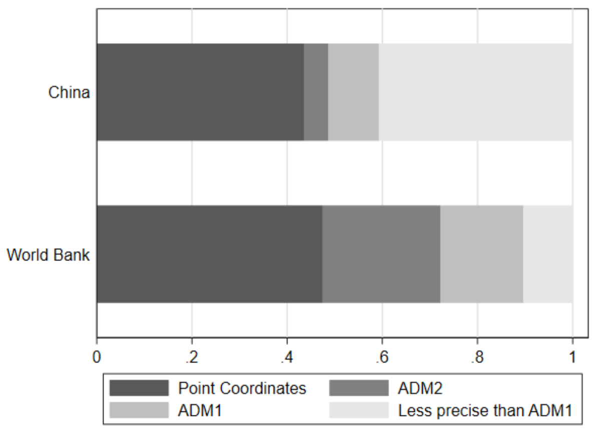
Variable Name	*Variable Description*	Time Period	*Variable Source*
WB Aid	log of WB Aid disbursements in a given region-year	1995-2012	Strandow et al. (2011)
Chinese Aid	log of Chinese Aid commitments in a given region-year	2000-2012	Dreher et al. (2017)
Strikes, Riots, Demonstrations	Binary indicator (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) 1 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	Chinese steel production (tons)	1999-2013	World Steel Association (2009, 2014)
IDA Funding Position	"Bank's net investment portfolio & its non-negotiable, non-interest-bearing demand obligations (on account of members' subscriptions and contributions)" divided by "sum of the Bank's undisbursed commitments of development credits and grants."	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)

A.2 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.[36] These data correspond to project aid disbursed from 5,684 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 level of sub-national 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 5 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 5: No. of Project Locations by Precision Codes

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

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.[37] 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)

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

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.

Table 10: Aid Allocation Formula Example

Example of Weighted Aid Allocation										
ID	Year	Aid Value	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

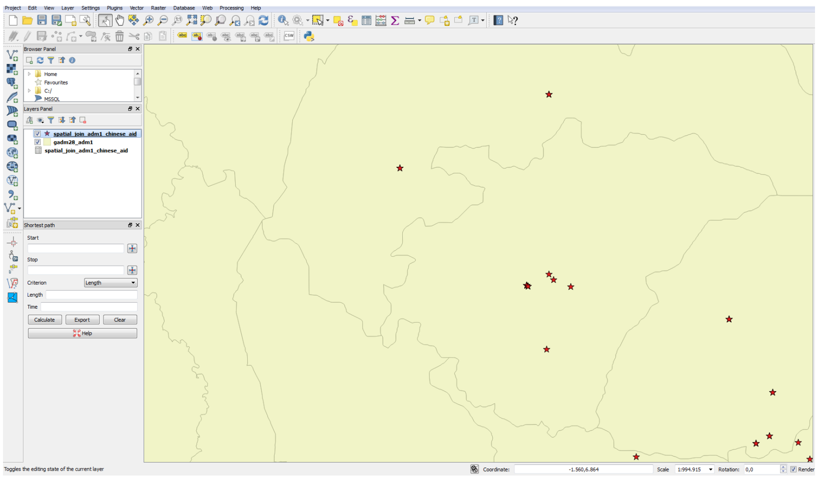
Population weighting

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 6.



Notes: Graphical depiction based on Quantum GIS.

Figure 6: Chinese Aid ADM1 Spatial Join

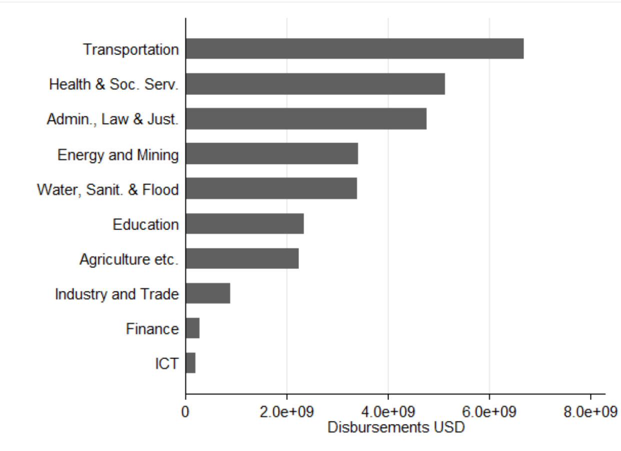
In order to create our data, we first load our ADM2 data into Stata and drop the ADM0 and ADM1 identifiers in order to be later able to rely on the identifiers from the ADM1-Aid spatial join.

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.

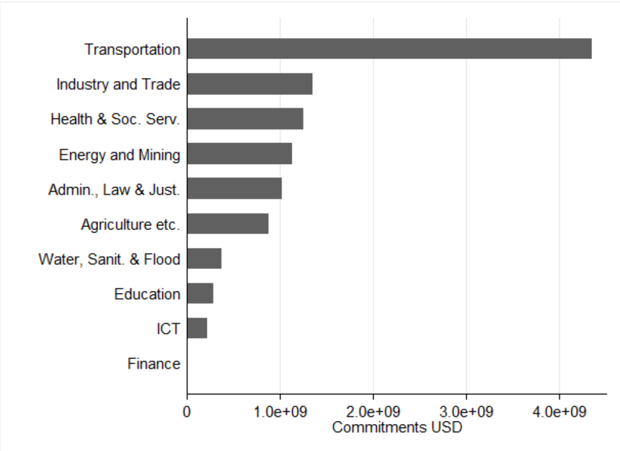
To exploit sectoral variation in development finance both for the WB and China, we make use of the information provided by Strange et al. (2017) on Chinese aid's sectoral allocation using the OECD's Creditor Reporting System (CRS) codes. To achieve comparability with the broad sectors indicated for the 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 7: Sectoral Distribution of Aid: (a) WB's IDA; (b) China

A.3 Dependent Variables (Conflict data)

Table 11 provides an overview about the different conflict outcomes considered in this paper. The construction of the data and sources are described in more detail in the subsequent paragraphs.

Table 11: Descriptive statistics - ADM1 Region

	Mean	SD	Min	Max
Conflict Incidence	11.65	32.08	0	100
State Based Conflict	7.01	25.54	0	100
Non-State Based Conflict	3.74	18.97	0	100
State Violence vs. Civilians	1.83	13.39	0	100
Non-State Violence vs. Civilians	3.41	18.14	0	100
Riots, Strikes, Demonstrations	13.59	34.27	0	100
Riots	8.08	27.26	0	100
Strikes	7.53	26.40	0	100
Demonstrations	2.92	16.83	0	100
Non-lethal Pro-GVMT Violence	1.16	10.71	0	100

Notes: Descriptive statistics for our main outcome variables. The sample period is 1995-2014 in order to account for the different lag structures. Click here to go back to section 3.2.

UCDP Data

AidData and UCDP use the same coding framework, so we can use similar coding rules and restrict us to events coded at least at the ADM1 level (precision codes 1-4). For the more precise data (precision codes 1 and 2), we again 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).[38] 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

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

the Syrian case, which is not part of our analysis.

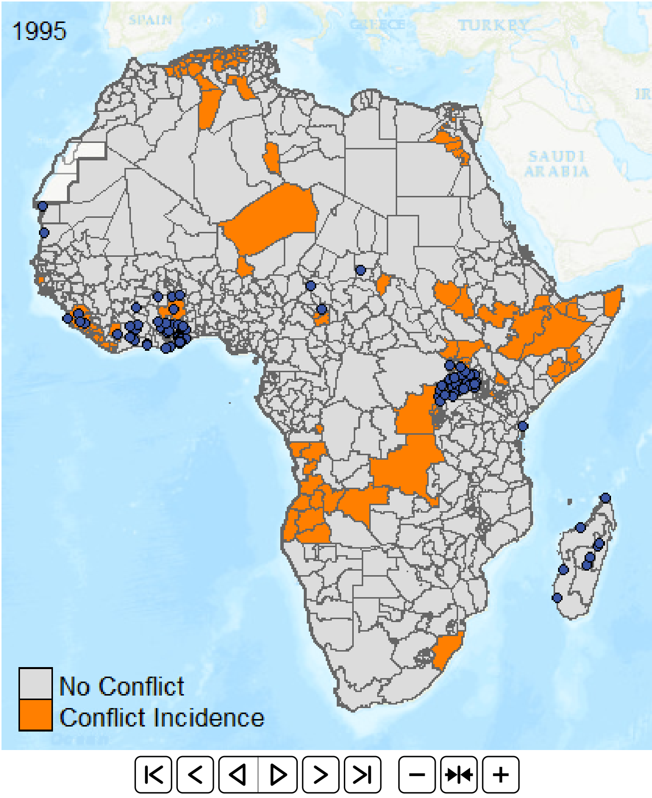


Figure 8: WB Aid and Conflict - By Year

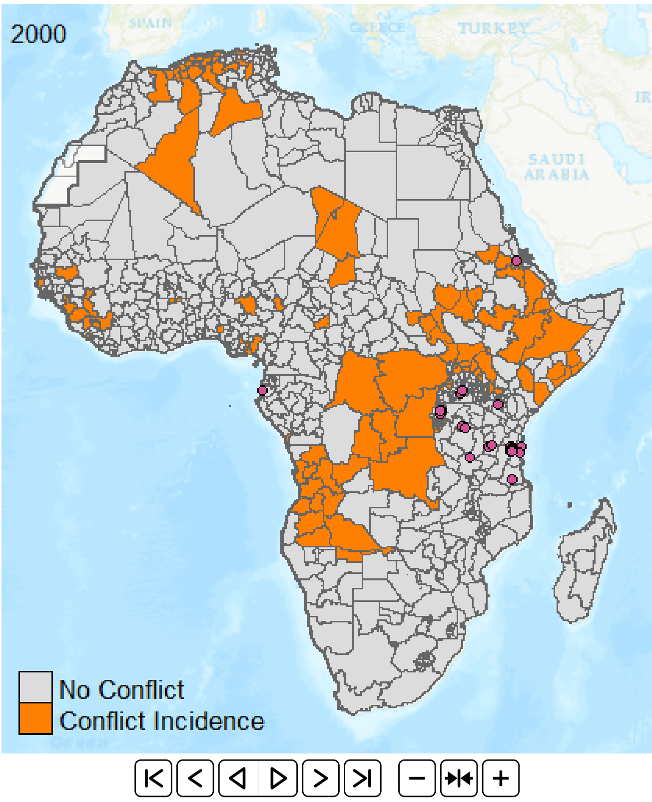


Figure 9: Chinese Aid and Conflict - By Year

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 (Salehyan et al., 2012). 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.[39] SCAD mainly builds on data compiled by the Lexis-Nexis services from searches of Agence France Presse and Associated Press. 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.

[39] Prior to 2014 armed conflict was not included in SCAD data and is now also distinguished from "social disturbances".

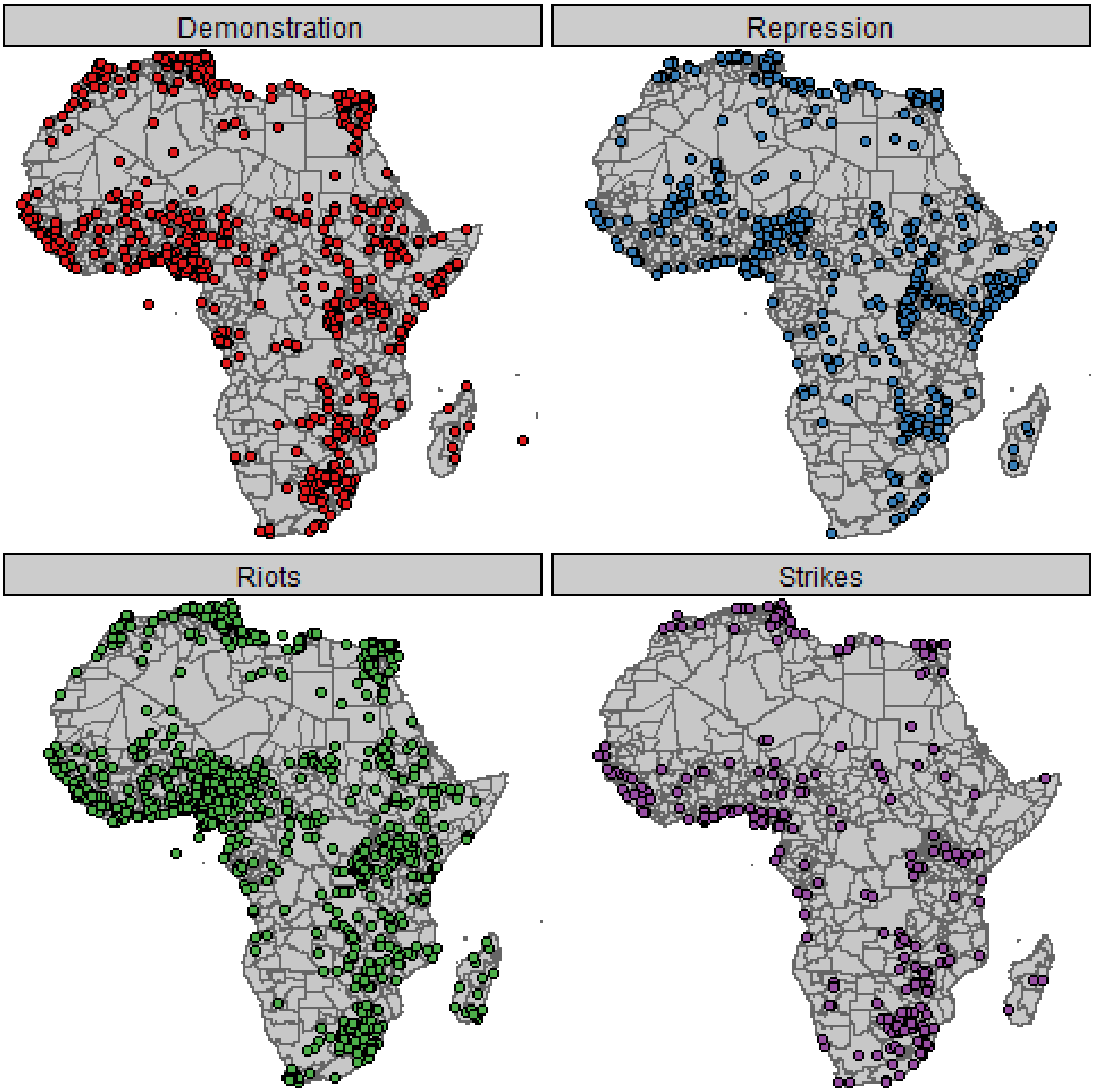


Figure 10: SCAD Data for precision codes 1-4

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.

A.4 Afrobarometer

Table 12: Afrobarometer - Labels, questions and sources

Variable Name	Variable Description	Availability	Code
Panel A: Security			
Security facilities: Police station present within walking distance?	Are the following facilities present in the primary sampling unit/enumeration area, or within easy walking distance: Police station?	2008-2009, 2011-2014	ea-fac-c
Security forces: Any policemen or police vehicles?	Are the following facilities present in the primary sampling unit/enumeration area, or within easywalking distance: Police station?	2008-2009, 2011-2014	ea-sec-a
Security forces: Any soldiers or army vehicles?	In the PSU/EA, did you (or any of your colleagues) see: Any soldiers or army vehicles?	2008-2009, 2011-2014	ea-sec-b
Frequency of things stolen in the past year?	During the past year, have you or anyone in your family: Had something stolen from your house?	2002-2006, 2008-2009, 2011-2014	q11a-x
Frequency of physical attacks in the past year?	During the past year, have you or anyone in your family: Been physically attacked?	2002-2006, 2008-2009, 2011-2014	q11b-x
Panel B: Democratic norms and attitudes			
Democracy: How democratic is your country today?	In your opinion how much of a democracy is your country today?	1999-2006, 2008-2009, 2011-2014	q40
Democracy: Did you perceive last elections as free and fair?	On the whole, how would you rate the freeness and fairness of the last national election, held in your country?	1999-2001, 2005-2006, 2008-2009, 2011-2014	q22-x
Governance: Reject one-party rule	There are many ways to govern a country. Would you disapprove or approve of the following alternatives: Only one political party is allowed to stand for election and hold office?	1999-2006, 2008-2009, 2011-2014	q28a
Governance: Reject military rule	There are many ways to govern a country. Would you disapprove or approve of the following alternatives: The army comes in to govern the country?	1999-2006, 2008-2009, 2011-2014	q28b
Governance: Reject one-man rule	There are many ways to govern a country. Would you disapprove or approve of the following alternatives: Elections and Parliament are abolished so that the president can decide everything?	1999-2006, 2008-2009, 2011-2014	q28c
Reject government banning organizations that go against its policies	Which of the following statements is closest to your view? Choose Statement 1 or Statement 2. Statement 1: Government should be able to ban any organization that goes against its policies. Statement 2: We should be able to join any organization, whether or not the government approves of it.	2005-2006, 2008-2009, 2011-2014	q16-x
Panel C: Government responsiveness and repression			
Frequency of contact to government official to express your view	During the past year, how often have you contacted any of the following persons about some important problem or to give them your views: An official of a government agency?	1999-2006, 2008-2009, 2011-2014	q24c-x
Fear of political intimidation or violence during campaigns	During election campaigns in this country, how much do you personally fear becoming a victim of political intimidation or violence?	2008-2009, 2011-2014	q49-x
How often do people have to be careful about what they say in politics?	In your opinion, how often, in this country: do people have to be careful of what they say about politics?	2002-2006, 2008-2009, 2011-2014	q51a-x
Rule of Law: People must obey the law	For each of the following statements, please tell me whether you disagree or agree: The police always have the right to make people obey the law.	2002-2006, 2008-2009, 2011-2014	q42b
Frequency of joining others to request government action	Here is a list of actions that people sometimes take as citizens when they are dissatisfied with government performance. For each of these, please tell me whether you, personally, have done any of these things during the past year. If not, would you do this if you had the chance: Joined others in your community to request action from government.	2014	q27a

A.5 World Bank Aid in the Financial Sector

A deeper classification exercise on the World Bank's financial sector aid reveals that sectoral reforms may play a crucial part in mitigating conflict. To classify IDA projects that are sufficiently targeted at the financial sector, we select projects where at least 10% of disbursementsare directed at the recipient's financial sector. Moreover, we restrict the classification to projects that are precisely coded, i.e., projects where money flow to ADM1 regions is traceable. Finally, we obtain the reports for each project and develop a classification of IDA aid in the financial sector based on the project goals and descriptions.

Table 13 shows that 50% of all aid projects that are significantly targeted at the financial sector are aimed at sectoral reforms. Projects in this category supports existing government efforts for sectoral reforms and development, but includes mainly new projects that are launched outside the initiative of the recipient government.

Class.	Classification Name	Share of Projects	Description
I.	Support services to enterprises	15%	Financial and non-financial support to (selected) enterprises or enterprise sectors
II.	Support services to NGOs	2.5%	Financial and non-financial support to NGOs or welfare organisations
III.	Support services to individuals or groups	15%	Financial and non-financial support to individuals, socio-economic or geographical groups
IV.	Capacity building	10%	Capacity building in socio-economic or geographical groups or supporting other capacity building projects
V.	Sectoral reforms	50%	New projects or support of existing government efforts that primarily target sectoral adjustment and reforms
VI.	Environmental Protection	2.5%	Projects aimed at protecting or improving the environment or wildlife
VII.	Emergency support	2.5%	Projects providing emergency support
VIII.	Research support	2.5%	Research or evaluation focused projects

Specific project examples		
Class.	Project Number	Project goals
I.	P083082 Micro, Small and Medium Enterprise Project, Nigeria	Increase performance and employment levels of micro, small and medium enterprises in selected non-oil industry sub-sectors + 3 targeted states of the country through i.) Improving access to financial services, ii.) Developing the market for business development services, iii.) Development of business climate etc. **http://documents.worldbank.org/curated/en/333691474574170700/pdf/000020051-20140625225024.pdf**
III.	P052186 Microfinance Project, Madagascar	Improve income and living standards of low-income Malagasy by i.) Establishing appropriate legal, regulatory and supervisory framework for microfinance, ii.) Expanding micro-financial skills and iii.) Developing strong and sustainable local institutions. **http://documents.worldbank.org/curated/en/933341474899762755/pdf/000020051-20140625070634.pdf**
V.	P035620 Financial Institutions Development Project, Tanzania	i.) Restructuring and privatizing the National Bank of Commerce and restructuring the smaller People's Bank of Zanzibar for competition and efficiency in the banking sector, ii.) Continuation of strengthening of Bank Supervision Directorate, iii.) Improving payments system, iv.) Creating a private credit information bureau, v.) Developing the insurance industry and capital markets. **http://documents.worldbank.org/curated/en/899741468311395554/pdf/multi-page.pdf**

Table 13: World Bank Aid in the Financial Sector

B Analytical Appendix

B.1 Instrumental Variable

B.1.1 Motivation of Instrumental Variable

In order to reduce the risk of the instrument being subject to spurious trends and correlations, we need to understand the underlying mechanisms. This section is dedicated to providing a more detailed description. In a first step, Table 14 shows OLS correlations of our conflict measure with two leads and lags of aid. The second lead of Chinese aid is correlated with conflict, suggesting China selects into post-conflict settings. We also test more formally if the instrument is suitable to tackle the selection bias, by regressing conflict on an instrumented lead term and find no significant relationship in Table 15. The instrumental variable approach is, thus, warranted to reduce selection bias.

Figure 11 depicts the funding positions for both donors along with corresponding aid flows for high and low probability regions. Evidently, aid flows in high probability regions respond more strongly to changes in the funding positions. In line with stronger first stage Kleibergen-Paap F-statistics, the relationship is more nuanced for the WB. Table 16 suggest that the instrumental variables for both donors affect the extensive margin (e.g., the probability to have at least one active aid project in a given region-year). Table 17, in turn, indicates that for the WB the intensive margin matters as well (e.g., given at least one active aid project, how much funds does a region receive?).

Table 19 depicts the reduced form estimates. In line with the main results, both interacted instruments are not significantly correlated with lethal conflict outcomes at the regional level.[40] For transparency, Table 18 displays the first stage including the constituent probability term, which, however, is not an instrument itself as we control for it in the second stage (see Section 4).

[40] While the probability constituent term enters significantly, it is not part of the instrument and we control for it in the second stage.

Table 14: ADM1 - Leads and further Lags

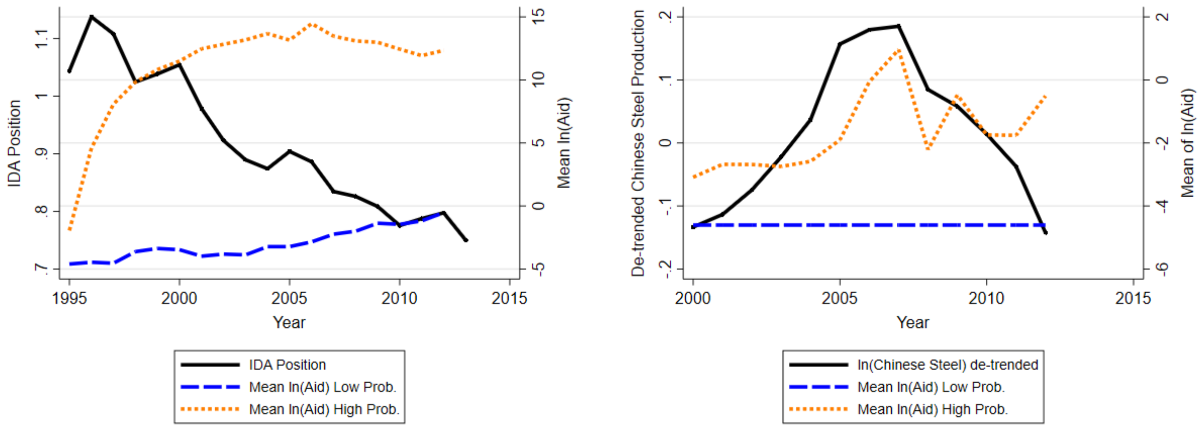
	(1)	(2)
Panel A: WB Aid		
Two Leads and Lags: World Bank		
$ln(World\,Bank\,Aid_{\text{t+1}})$	-0.0059	0.1559
	(0.1298)	(0.1199)
$ln(World\,Bank\,Aid_{\text{t}})$	-0.1089	-0.2128*
	(0.1152)	(0.1157)
$ln(World\,Bank\,Aid_{\text{t-1}})$	0.0214	-0.0933
	(0.0973)	(0.0956)
$ln(World\,Bank\,Aid_{\text{t-2}})$	0.0516	0.1424
	(0.0939)	(0.1212)
$ln(World\,Bank\,Aid_{\text{t-3}})$	-0.0811	-0.0535
	(0.0877)	(0.1076)
N	10150	10150
Panel B: Chinese Aid		
Lead and Lag: China		
$ln(Chinese\,Aid_{\text{t+1}})$	0.1681	0.2083*
	(0.1244)	(0.1258)
$ln(Chinese\,Aid_{\text{t}})$	-0.0127	0.0231
	(0.1268)	(0.1358)
$ln(Chinese\,Aid_{\text{t-1}})$	-0.0086	-0.0481
	(0.1514)	(0.1600)
$ln(Chinese\,Aid_{\text{t-2}})$	0.0121	-0.0506
	(0.1165)	(0.1313)
$ln(Chinese\,Aid_{\text{t-3}})$	0.0572	-0.0308
	(0.0986)	(0.1102)
N	6525	6525
Exogeneous Controls	Yes	Yes
Exogeneous Controls × Year FE	Yes	Yes
Linear Regional Trends	Yes	Yes
Country- × 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. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$ Click here to go back to section 5.2.

Table 15: ADM1 - Placebo Instrumented Lead of Aid

	(1)	(2)
Panel A: WB Aid		
Placebo (Lead): World Bank		
$ln(World\, Bank\, Aid_{\text{t+1}})$	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		
$ln(Chinese\, Aid_{\text{t+1}})$	-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. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$ Click here to go back to section 5.7.



(a) (b)

Figure 11: (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 11 a) displays the IDA funding position (solid line), the mean of logged WB aid disbursements per low probability recipient regions (long-dashed line) and the mean of logged WB aid disbursements per high probability recipient regions (short-dashed line). Figure 11 b) displays the log of the detrended Chinese Steel Production (solid line), the mean of logged Chinese aid per low probability recipient regions (long-dashed line) and the mean of logged Chinese aid per high probability recipient regions (short-dashed line). Click here to go back to section 4.2.2.

Table 16: ADM1 IV (First Stage - Extensive Margin (Likelihood of at least one active project))

	(1)	(2)
Panel A: WB Aid		
IV FS Extensive Margin: World Bank		
$IDA\,Position_{\text{t-1}} \times \text{Cum. Prob}_{\text{t-2}}$	4.0782***	4.8249***
	(0.4140)	(0.5238)
$Cum.\,Prob_{\text{t-2}}$	-4.3155***	-5.0339***
	(0.4512)	(0.5508)
N	12325	12325
Panel B: Chinese Aid		
IV FS Extensive Margin: China		
$\text{Steel Prod detrend}_{\text{t-3}} \times \text{Cum. Prob}_{\text{t-3}}$	-3.7025***	-3.1905***
	(0.7695)	(0.7572)
$\text{Cum. Prob}_{\text{t-3}}$	-1.7443***	-1.5365***
	(0.2117)	(0.1989)
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 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. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$ Click here to go back to section 4.2.2.

Table 17: ADM1 IV (First Stage - Intensive Margin)

	(1)	(2)
Panel A: WB Aid		
IV FS Intensive Margin: World Bank		
$IDA\,Position_{\text{t-1}} \times \text{Cum. Prob}_{\text{t-2}}$	4.4155	8.5243**
	(3.3360)	(3.7977)
$Cum.\,Prob_{\text{t-2}}$	-2.3430	-6.3455
	(3.8699)	(4.3885)
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: China		
$Steel\,Prod\,detrend_{\text{t-3}} \times \text{Cum. Prob}_{\text{t-3}}$	-4.6878	-3.2045
	(13.5836)	(18.0233)
$Cum.\,Prob_{\text{t-3}}$	-2.7933	-6.1660**
	(5.5468)	(3.0931)
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. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$ Click here to go back to section 4.2.2.

Table 18: ADM1 IV (First Stage with probability constituent term)

Panel A: WB Aid	(1)	(2)
IV First stage: World Bank		
$IDA\,Position_{\text{t-1}} \times \text{Cum. Prob}_{\text{t-2}}$	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: China		
$Steel\,Prod\,detrend_{\text{t-3}} \times \text{Cum. Prob}_{\text{t-3}}$	-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. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$ Click here to go back to section 5.7.

Table 19: ADM1 Reduced Form

	(1)	(2)
Panel A: WB Aid		
Reduced Form: World Bank		
$Cum. Prob_{\text{t-2}}$	10.8281	19.2994
	(27.3795)	(33.4583)
$IDA\ Position_{\text{t-1}} \times \text{Cum. Prob}_{\text{t-2}}$	-7.1921	-18.2132
	(26.5498)	(33.5818)
N	12325	12325
Panel B: Chinese Aid		
Reduced Form: China		
$Cum. Prob_{\text{t-3}}$	-12.0548	-17.4914*
	(9.1057)	(9.5552)
$Steel\ Prod\ detrend_{\text{t-3}} \times \text{Cum. Prob}_{\text{t-3}}$	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. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$ Click here to go back to section 5.7.

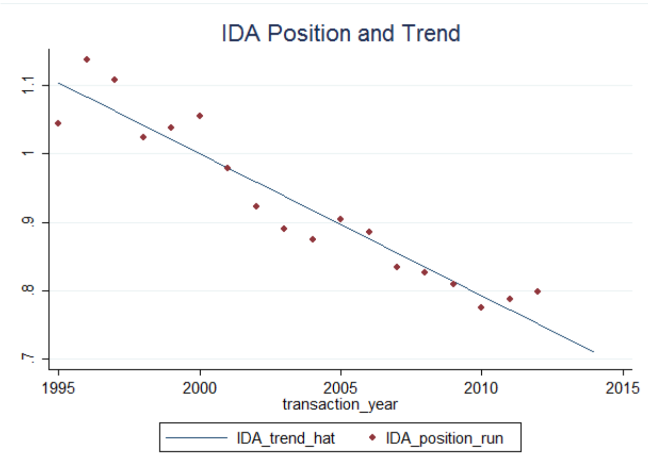
B.1.2 Robustness of Instrumental Variable

As a main specification we use the rolling average of the WB's IDA position (e.g., averaging across t and $t-1$) because the Bank's fiscal year ends already in June. For robustness, Table 20 depicts instrumental variable results using only the variation in $t-1$. Results are largely unchanged.

Another trade-off concerns the decision of using raw or detrended time series of funding positions (e.g., reducing first stage instrumental power versus reducing risks of correlations with spurious trends). For transparency, we also display results presenting a non-detrended steel production time series for China and a detrended IDA position in Table 21 and Figure 13.

Moreover, there are several degrees of freedom regarding the definition of the interacted probability term. We indicate the robustness of an insignificant conflict-aid link when using an interacted instrument based on an initial probability from the first three sampling years in Table 22 or if excluding probability observations based only on the first sampling year in Table 23. Additionally, Tables 24 and 25 demonstrate that effects also do not turn significant, when using a rolling probability based on a time window of two, three or four years.

Finally, first stage results might be susceptible to a small share of very influential observations. Table 26 indicates that results are qualitatively unchanged if we exclude the ten high leverage region-years from the sample. Figures 14 and 15 display the first stage relationship leaving out single countries, suggesting that there are no individual states driving the relationship.



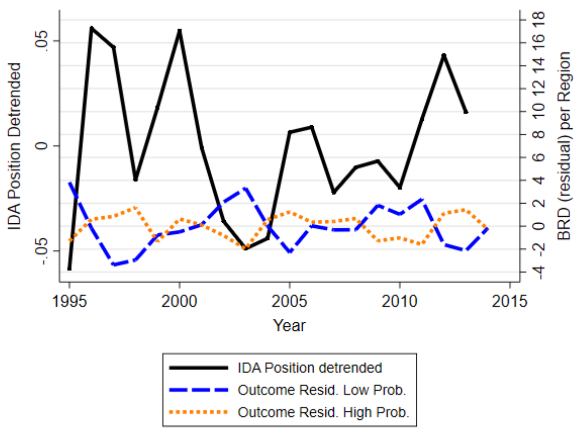
Notes: Yearly values of $IDA-Position_t$ based on Dreher et al. (2017).

Figure 12: IDA Position

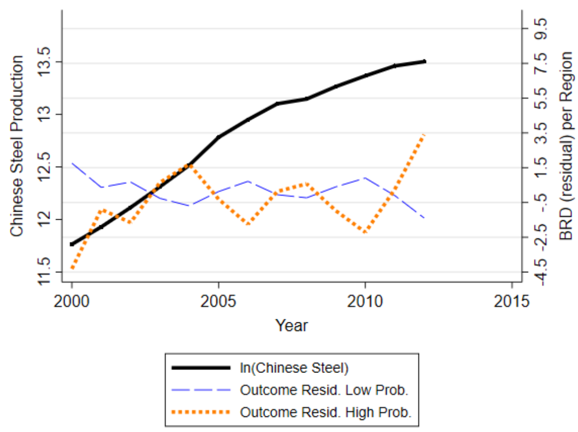
Table 20: ADM1 IV (IDA-Position$_{t-1}$)

	(1)	(2)
Panel A: WB Aid		
IV Second Stage: World Bank (t-1)		
$ln(World\,Bank\,Aid_{\text{t-1}})$	-0.1294	-0.0251
	(0.3976)	(0.3868)
IV FS: World Bank (t-1)		
$IDA\,Position_{\text{t-1}} \times \text{Cum. Prob}_{\text{t-2}}$	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 × 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. Instead of a running sum of IDA funding position in "t" and "t-1" only the variation in "t-1" is used. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$ Click here to go back to section 4.2.2.



(a) Detrended IDA position & actual trends in outcomes



(b) Steel production & actual trends in outcomes

Figure 13: China: Chinese steel production and conflict outcomes for low and high probability regions.

Notes: Figure 13(a) displays an alternative detrended temporal variation of the IDA position we use in our interacted instrument (solid line). Figure 13(b) displays an alternative non-detrended version of the temporal variation we use in our interacted instrument (solid line). The graph presents Chinese Steel Production along with the actual trends in the conflict outcomes for low (long-dashed line) and high probability (short-dashed line) recipient regions. The displayed outcomes are the residuals net of the fixed effects and time trends that we use in Table 3, column (4), the remaining unexplained variation in the outcomes used in our preferred specification. Click here to go back to section 4.2.3.

Table 21: ADM1 IV (WB detrend & Chinese aid no detrend)

	(1)	(2)
Panel A: WB Aid		
IV Second stage: World Bank		
$ln(World\,Bank\,Aid_{\text{t-1}})$	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: World Bank		
$IDA\,Position\,detrend_{\text{t-1}} \times \text{Cum. Prob}_{\text{t-2}}$	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: China		
$ln(Chinese\,Aid_{\text{t-2}})$	-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: China		
$Steel\,Prod_{\text{t-3}} \times \text{Cum. Prob}_{\text{t-3}}$	-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 × 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. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$ Click here to go back to section 4.2.3 or section 5.7.

Table 22: ADM1 IV (Without first year)

	(1)	(2)
Panel A: WB Aid		
IV Second stage:World Bank $ln(World\,Bank\,Aid_{\text{t-1}})$	-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: World Bank $IDA\,Position_{\text{t-1}} \times \text{Cum. Prob}_{\text{t-2}}$	68.5810***	88.1297***
	(7.6467)	(9.9784)
N	11600	11600
Panel B: Chinese Aid		
IV Second Stage: China		
$ln(Chinese\,Aid_{\text{t-2}})$	-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: China		
$Steel\,Prod\,detrend_{\text{t-3}} \times \text{Cum. Prob}_{\text{t-3}}$	-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. Click here to go back to section 5.7.

Table 23: ADM1 IV (Initial Probability)

	(1)	(2)
Panel A: WB Aid		
IV Second Stage: World Bank		
$ln(World\,Bank\,Aid_{\text{t-1}})$	0.2253	-0.3389
	(0.7469)	(0.6206)
Kleibergen-Paap underidentification test p-value	0.000	0.000
Kleibergen-Paap weak identification F-statistic	27.090	26.027
IV First stage: World Bank		
$IDA\,Position_{\text{t-1}} \times \text{Con. Prob}_{98}$	43.4391***	61.1537***
	(8.3414)	(11.9820)
N	11600	11600
Panel B: Chinese Aid		
IV Second Stage: China		
$ln(Chinese\,Aid_{\text{t-2}})$	-1.6319	-1.4597
	(1.3707)	(1.4891)
Kleibergen-Paap underidentification test p-value	0.001	0.004
Kleibergen-Paap weak identification F-statistic	10.421	7.850
IV First stage: China		
$Steel\,Prod\,detrend_{\text{t-3}} \times \text{Con. Prob}_{03}$	-36.7317***	-35.9689***
	(11.3575)	(12.8141)
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. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$ Click here to go back to section 5.7.

Table 24: ADM1 IV World Bank (Rolling Probability)

	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: WB Aid						
IV Second stage: World Bank	2 Years	2 Years	3 Years	3 Years	4 Years	4 Years
$ln(World\,Bank\,Aid_{\text{t-1}})$	-1.0528	0.0685	-0.6788	-0.7613	-0.6563	-0.6860
	(1.0029)	(0.8988)	(0.6880)	(0.8862)	(0.5015)	(0.6273)
Kleibergen-Paap underidentification test p-value	0.001	0.007	0.000	0.000	0.000	0.000
Kleibergen-Paap weak identification F-statistic	12.388	9.482	25.687	13.616	58.967	32.838
IV First stage: World Bank	2 Years	2 Years	3 Years	3 Years	4 Years	4 Years
$Roll.\,Prob_{\text{t-2}}$	-9.0968**	-11.7743**				
	(4.4367)	(5.8552)				
$IDA\,Position_{\text{t-1}} \times$ Roll. Prob $_{\text{t-2}}$	16.4822***	20.0570***				
	(4.6781)	(6.5071)				
$Roll.\,Prob_{\text{t-2}}$			-21.0066***	-18.9022***		
			(5.0242)	(6.5878)		
$IDA\,Position_{\text{t-1}} \times$ Roll. Prob $_{\text{t-2}}$			26.5815***	26.0337***		
			(5.2389)	(7.0504)		
$Roll.\,Prob_{\text{t-2}}$					-41.8977***	-40.3329***
					(5.7021)	(7.6241)
$IDA\,Position_{\text{t-1}} \times$ Roll. Prob $_{\text{t-2}}$					46.7521***	47.5634***
					(6.0810)	(8.2929)
N	11600	11600	10875	10875	10150	10150
Exogeneous Controls	Yes	Yes	Yes	Yes	Yes	Yes
Exogeneous Controls $\times$ Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Linear Regional Trends	Yes	Yes	Yes	Yes	Yes	Yes
Country-Year FE	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. Columns (1) and (2) use a cumulative probability based on two previous years, Columns (3) and (4) based on three previous years and Columns (5) and (6) based on four previous years. All regressions include year and region fixed effects as well as time trends. Time Trends include linear and squared country-specific time trends. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$ Click here to go back to section 4.2.

Table 25: ADM1 IV China (Rolling Probability)

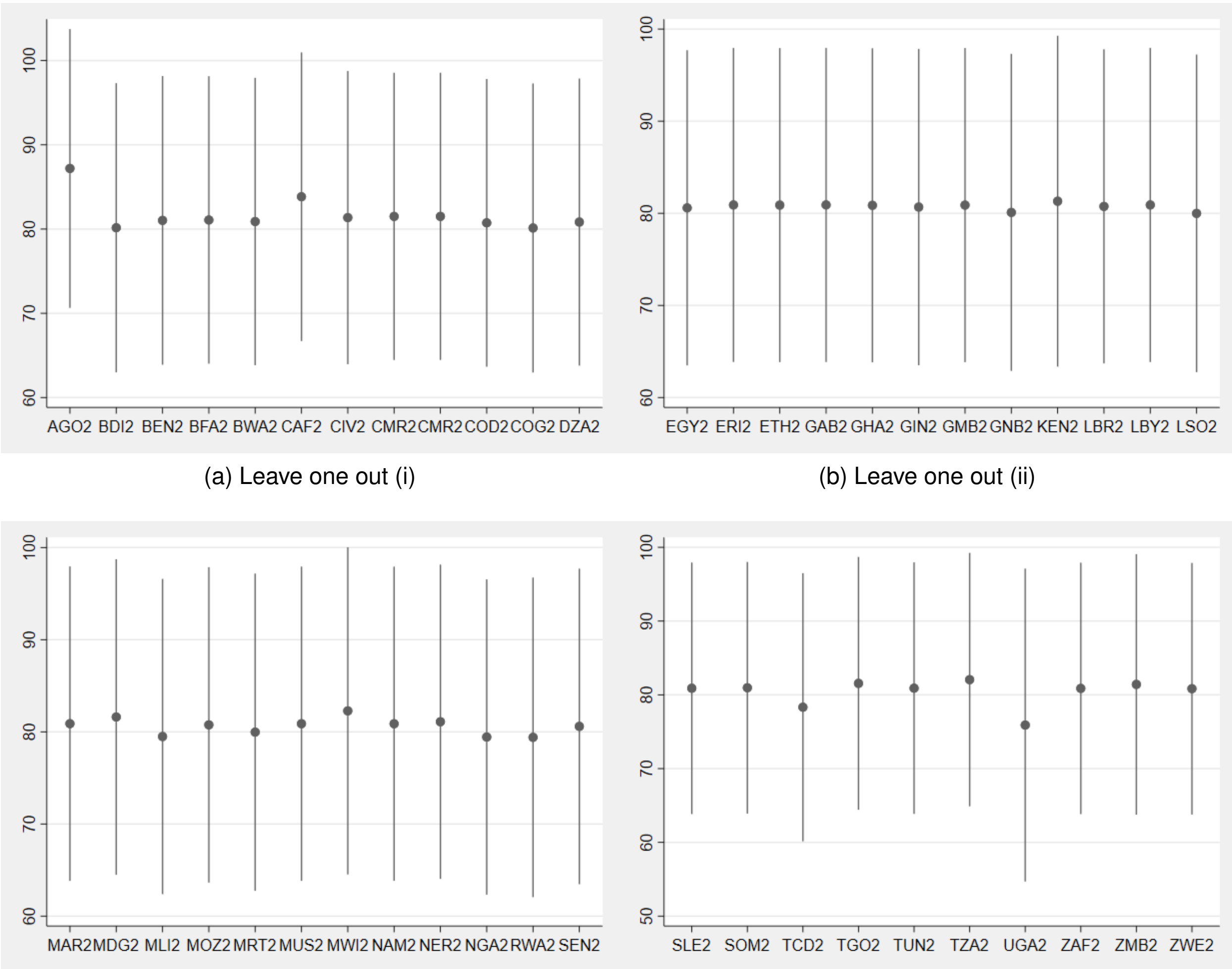
	(1)	(2)	(3)	(4)	(5)	(6)
Chinese Aid						
IV Second stage: China	2 Years	2 Years	3 Years	3 Years	4 Years	4 Years
$ln(Chinese\ Aid_{\text{t-2}})$	-4.0238	-4.0238	0.2311	0.2311	-0.0559	-0.0559
	(12.1740)	(12.1740)	(8.0849)	(8.0849)	(3.7147)	(3.7147)
Kleibergen-Paap underidentification test p-value	0.683	0.683	0.636	0.636	0.374	0.374
Kleibergen-Paap weak identification F-statistic	0.147	0.147	0.185	0.185	0.623	0.623
IV Second stage: China	2 Years	2 Years	3 Years	3 Years	4 Years	4 Years
$Roll.\ Prob_{\text{t-3}}$	-9.3018***	-9.3018***				
	(1.3918)	(1.3918)				
$Steel\ Prod\ detrend_{\text{t-3}} \times \text{Roll. Prob}_{\text{t-3}}$	-4.1494	-4.1494				
	(10.8178)	(10.8178)				
$Roll.\ Prob_{\text{t-3}}$			-19.1660***	-19.1660***		
			(2.5314)	(2.5314)		
$Steel\ Prod\ detrend_{\text{t-3}} \times \text{Roll. Prob}_{\text{t-3}}$			6.0226	6.0226		
			(13.9825)	(13.9825)		
$Roll.\ Prob_{\text{t-3}}$					-34.9571***	-34.9571***
					(4.2960)	(4.2960)
$Steel\ Prod\ detrend_{\text{t-3}} \times \text{Roll. Prob}_{\text{t-3}}$					13.9414	13.9414
					(17.6212)	(17.6212)
Exogeneous Controls	Yes	Yes	Yes	Yes	Yes	Yes
Exogeneous Controls × Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Linear Regional Trends	Yes	Yes	Yes	Yes	Yes	Yes
Country-Year FE	No	Yes	No	Yes	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 2000-2012 for Chinese Aid. Columns (1) and (2) use a cumulative probability based on two previous years, Columns (3) and (4) based on three previous years and Columns (5) and (6) based on four previous years. All regressions include year and region fixed effects as well as time trends. Time Trends include linear and squared country-specific time trends. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$ Click here to go back to section 4.2

Table 26: ADM1 IV (Without high leverage region)

	(1)	(2)
Panel A: WB Aid		
IV Second stage: World Bank		
$ln(World\,Bank\,Aid_{\text{t-1}})$	-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: World Bank		
$IDA\,Position_{\text{t-1}} \times$ Cum. Prob$_{\text{t-2}}$	70.8414***	80.8936***
	(7.1068)	(8.6851)
N	12317	12291
Panel B: Chinese Aid		
IV Second Stage: China		
$ln(Chinese\,Aid_{\text{t-2}})$	-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: China		
$Steel\,Prod\,detrend_{\text{t-3}} \times$ Cum. Prob$_{\text{t-3}}$	-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. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$ Click here to go back to section 5.7.



(a) Leave one out (i)

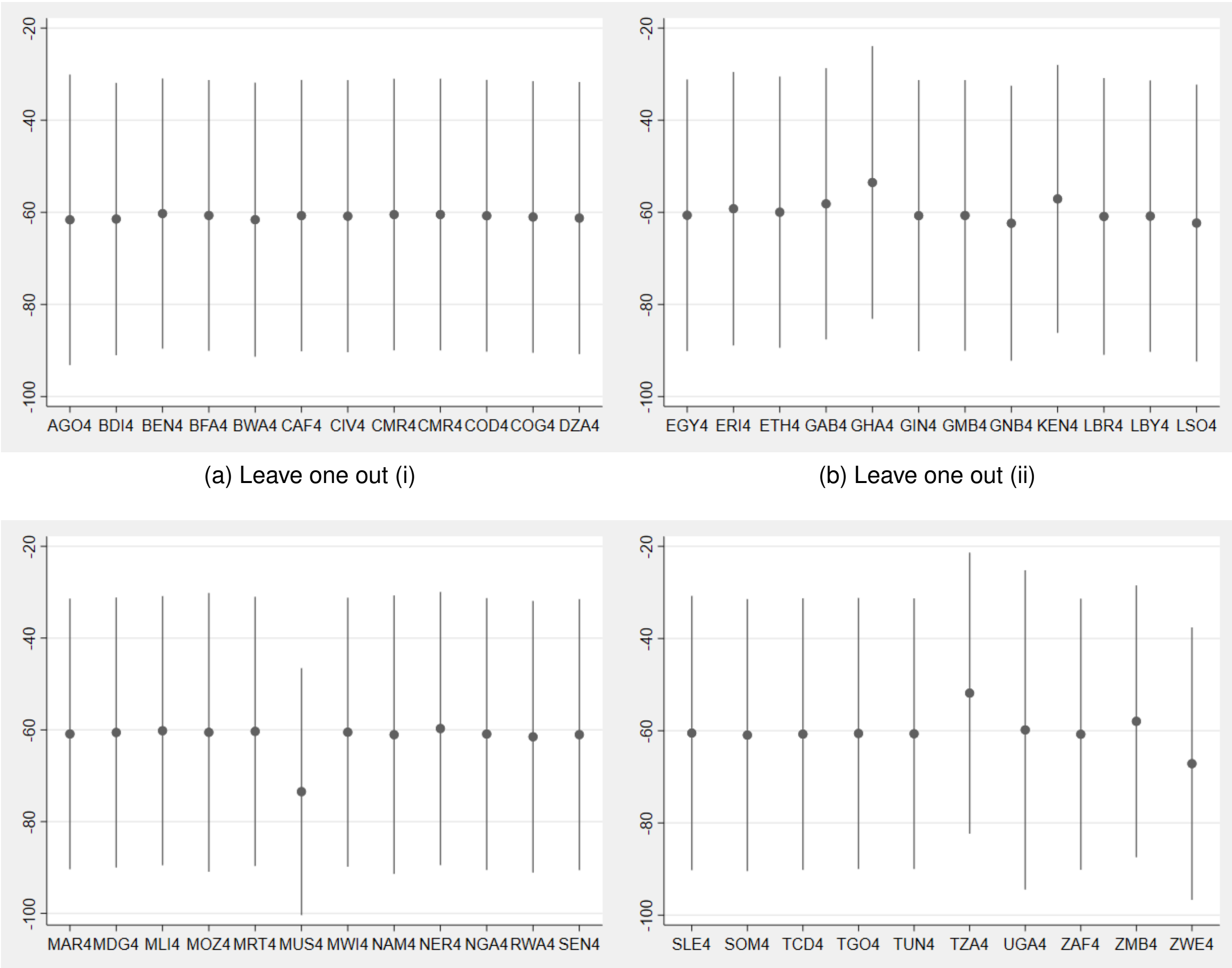
(b) Leave one out (ii)

(c) Leave one out (iii)

(d) Leave one out (iv)

Figure 14: Robustness of first stage for World Bank Aid - Leaving one country out

Note: Results depict coefficients of the instrumental variable $probability_{i,c,t-2} \times IDAPosition_{t-1}$ for different regressions leaving one country out from the estimation. Labels in the graph refer to ISO codes of recipients. Click here to go back to section 5.7.



(a) Leave one out (i)

(b) Leave one out (ii)

(c) Leave one out (iii)

(d) Leave one out (iv)

Figure 15: Robustness of first stage for Chinese Aid - Leaving one country out

Note: Results depict coefficients of the instrumental variable $probability_{i,c,t-3} \times ln(Steel_{t-3})$ for different regressions leaving one country out from the estimation. Labels in the graph refer to ISO codes of recipients. Click here to go back to section 5.7.

B.2 Alternative Outcome Variables

Robustness of results on lethal violence (UCDP measures)

As thresholds of five battle-related deaths or one incidence per region-year are arbitrary, we depict for robustness also other intensity thresholds. First, aid could matter for rather more intense conflicts in line with the evidence on conflict dynamics made by Bluhm et al. (2018). Tables 27 (OLS) and 28 (IV) indicate for a higher threshold of 25 battle-related deaths mainly insignificant coefficients, which also remain negative for the few significant OLS results. Second, this also holds in Tables 29 (OLS) and 30 (IV) when using a continuous measure of logarithmized battle-related deaths.

Robustness of results on non-lethal violence (SCAD)

The measurement of conflict is non-trivial and in this respect we display in the main part beyond lethal violence measures of social conflict based on Salehyan et al. (2012). Both anecdotal evidence and research studies alike suggest increased social conflict linked to Chinese investment activities. We take these concerns serious by disentangling the results from Table 7 from the main part. We consider the effects on demonstrations, riots and strikes separately with OLS in Tables 31 ,32 and 33 as well as using IV in Table 34. Results do not correspond to a statistically significantly positive effect of aid on neither riots, demonstrations and strikes. An explanation could be that these accounts mostly cover commercial investment activities, which are not conflict sensitively programmed (Wegenast et al., 2017; Christensen, 2017).

Additionally, we consider robustness of the main results relating to repression fueling effects of Chinese aid. First, to separate clearly between regions with lethal pro-government and non-lethal pro-government activities, we constrain the sample on regions, which *did not* encounter any one-sided violence by the government registered in the UCDP dataset. Results in Table 35 support a robust link between Chinese aid and repression. Second, when using instead of a dichotomous repression measure from SCAD a continuous indicator, a consistently positive effect of Chinese aid on repression is suggested by the IV estimates of Table 36.

Table 27: ADM1 OLS results (Intensity 2)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Panel A: WB Aid									
$ln(World\,Bank\,Aid_{\text{t-1}})$	-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									
$ln(Chinese\,Aid_{\text{t-2}})$	-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. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$ Click here to go back to section 5.7.

Table 28: ADM1 IV (Intensity 2)

	(1)	(2)
Panel A: WB Aid		
IV Second Stage: World Bank		
$ln(World\,Bank\,Aid_{\text{t-1}})$	-0.1437	-0.4581
	(0.3075)	(0.3301)
IV First stage: World Bank		
$IDA\,Position_{\text{t-1}} \times \text{Cum. Prob}_{\text{t-2}}$	70.9363***	80.8832***
	(7.1065)	(8.6854)
N	12325	12325
Panel B: Chinese Aid		
IV Second Stage: China		
$ln(Chinese\,Aid_{\text{t-2}})$	0.1980	0.2563
	(0.3729)	(0.4669)
IV First stage: China		
$Steel\,Prod\,detrend_{\text{t-3}} \times \text{Cum. Prob}_{\text{t-3}}$	-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: 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. 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. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$ Click here to go back to section 5.7.

Table 29: ADM1 OLS results (Battle-related Deaths)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Panel A: WB Aid									
$ln(World\,Bank\,Aid_{\text{t-1}})$	-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									
$ln(Chinese\,Aid_{\text{t-2}})$	-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. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$ Click here to go back to section 5.7.

Table 30: ADM1 IV (Battle-Related Deaths)

	(1)	(2)
Panel A: WB Aid		
IV Second stage: World Bank		
$ln(World\,Bank\,Aid_{\text{t-1}})$	-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: World Bank		
$IDA\,Position_{\text{t-1}} \times \text{Cum. Prob}_{\text{t-2}}$	70.9363***	80.8832***
	(7.1065)	(8.6854)
N	12325	12325
Panel B: Chinese Aid		
IV Second Stage: China		
$ln(Chinese\,Aid_{\text{t-1}})$	-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: China		
$\text{Steel Prod detrend}_{\text{t-3}} \times \text{Cum. Prob}_{\text{t-3}}$	-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 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. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$ Click here to go back to section 5.7.

Table 31: ADM1 OLS results (Demonstrations)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Panel A: WB Aid									
$ln(World\, Bank\, Aid_{\text{t-1}})$	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									
$ln(Chinese\, Aid_{\text{t-2}})$	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. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$ Click here to go back to section 5.5.

Table 32: ADM1 OLS results (Riots)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Panel A: WB Aid									
$ln(World\,Bank\,Aid_{\text{t-1}})$	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									
$ln(Chinese\,Aid_{\text{t-2}})$	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. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$ Click here to go back to section 5.5.

Table 33: ADM1 OLS results (Strikes)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Panel A: WB Aid									
$ln(World\,Bank\,Aid_{\text{t-1}})$	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									
$ln(Chinese\,Aid_{\text{t-2}})$	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. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$ Click here to go back to section 5.5.

Table 34: ADM1 IV (Riots, Demonstrations & Strikes [SCAD])

Panel A: WB Aid	(1)	(2)	(3)	(4)	(5)	(6)
IV Second stage: World Bank						
	Demonstr.	Demonstr.	Riots	Riots	Strikes	Strikes
$ln(World\,Bank\,Aid_{\text{t-1}})$	-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: China						
	Demonstr.	Demonstr.	Riots	Riots	Strikes	Strikes
$ln(Chinese\,Aid_{\text{t-1}})$	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. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$ 5.5

Table 35: ADM1 IV (Repression (non-lethal) - Regions with UCDP Violence Against Civilians coded as zero)

	(1)	(2)
Panel A: WB Aid		
IV: World Bank - Actors		
$ln(World\, Bank\, Aid_{\text{t-1}})$	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: China - Actors		
$ln(Chinese\, Aid_{\text{t-2}})$	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. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$ Click here to go back to section 5.5.

Table 36: Non-lethal Repression [SCAD] - Continuous measure

Panel A: WB Aid	(1)	(2)
IV Second stage: World Bank		
$ln(World\,Bank\,Aid_{\text{t-1}})$	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: China		
$ln(Chinese\,Aid_{\text{t-1}})$	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. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$
Click here to go back to section 5.5.

Comparison with OLS estimates

Finally, in order to see if results substantially change when using OLS, we consider the results corresponding to the IV estimates on actors (Table 6) and the aggregated outcome for riots, demonstrations and strikes (Table 7). Table 37 suggests mostly neutral effects, while significantly negatively coefficients of WB aid occur for state-based violence. Regarding riots, demonstrations and strikes, Table 38 shows that the different actors' results become insignificant once we condition on regional level fixed effects.

Table 37: 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	
$ln(World\,Bank\,Aid_{\text{t-1}})$	-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	
$ln(Chinese\,Aid_{\text{t-2}})$	-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. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$ Click here to go back to Table 6.

Table 38: ADM1 OLS results (Riots, Demonstrations & Strikes [SCAD])

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Panel A: WB Aid									
$ln(World\,Bank\,Aid_{\text{t-1}})$	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									
$ln(Chinese\,Aid_{\text{t-2}})$	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. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$ Click here to go back to section 5.5.

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 among the most salient traits and ethnicities constitute a very 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 median. Appendix Table 41 shows 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. [41]

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 ot-

[41] Note that for individual aid sectors, 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.

her 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 39. 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.[42] Moreover, we control in all regressions for fractionalization, which we define in this case as $1 - \sum s^2$, where s is the ethnic groups area share in the administrative region. In order to account for the important role that ethnic fractionalization takes in the politico-economic literature (e.g., Alesina et al., 2003), we consider also a sample split at the median of ethnic fractionalization in Table 41. In the subsample the instrumental variable retains strength. Although coefficients change signs, when considering the more fractionalized regions, results support robustness of the neutral effects.

[42] 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 shows the results in Table 39 for the WB using OLS and for China using IV. There are overall no large differences that substantially alter our conclusions.

Table 39: 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
$ln(World\,Bank\,Aid_{\text{t-1}})$	-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
$ln(Chinese\,Aid_{\text{t-2}})$	-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. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 40: ADM1 results (Power status - Coalition), corresponds to Table 39

Panel A: Coalition groups						
WB Aid: OLS						
World Bank: Conflict in region belonging to...	N-Coalition	N-Coalition	Coalition	Coalition	Mixed	Mixed
$ln(World\,Bank\,Aid_{\text{t-1}})$	-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
$ln(Chinese\,Aid_{\text{t-2}})$	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 39. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 41: Sample-split: Median Fractionalization

Panel A: WB Aid - IV:				
$ln(World\,Bank\,Aid_{\text{t-1}})$	-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:				
$ln(Chinese\,Aid_{\text{t-2}})$	-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. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

B.4 Spatial Dimension (Spill Overs and Aggregation Levels)

Aggregation levels

Despite the many advantages of geospatial analysis (e.g., precision, geographical control variables), robustness is subject to the modifiable are unit problem (MAUP). More specifically, other conflict mechanisms can be at play when considering different levels of aggregation. Testing robustness on different spatial levels, hence, reduces the risk of ecological fallacy (Maystadt et al., 2014), which is specifically relevant in the aid-conflict nexus where different political entities might appropriate funds to engage in violent or peace-building activity. For this reason, we consider conflict and aid in the subordinate ADM2 regions both with OLS (IV) in Table 42 (43). Results are generally consistent with the main finding of a neutral effect of aid on conflict. Although the IV estimates for China turn positive, they do not attain statistical significance at any conventional level.

Additionally, we turn to an analysis on the country level as conflict might not manifest on the regional level, but spill over to other localities. Also on the country-level Table 44 does provide neither for the WB nor for China any evidence of a significant link between aid and conflict. While both OLS coefficients are negative, the WB IV coefficient turns positive, though insignificant. In order to address concerns that our analysis misses non-geocoded aid flows of the two donors, we make use of the feature that we can include those flows on a country-level. Consistently, results in Table 45 indicate significantly negative to neutral effects.[43] Only one of the coefficients for non-geocoded WB aid turns positive, though remaining statistically insignificant.[44]

[43] Ideally, we would have liked to consider results in Table 45 also via an instrumental variable approach, which was not possible due to weak IV concerns in the first stage.

[44] As those non-geocoded flows are mostly allocated to line ministries or the central government, we consider this question more specifically in the subsequent paragraph.

Table 42: 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. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$ Click here to go back to section 5.7.

Table 43: ADM2 IV (Intensity 1)

	(1)	(2)
Panel A: WB Aid		
IV Second stage: World Bank		
$ln(World\,Bank\,Aid_{\text{t-1}})$	0.2599	0.1522
	(0.1644)	(0.1171)
N	99367	99367
Panel B: Chinese Aid		
IV Second Stage: China		
$ln(Chinese\,Aid_{\text{t-2}})$	-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. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$ Click here to go back to section 5.7.

Table 44: Aggregate - Cross-country Analysis - OLS/IV

	(1)	(2)	(3)	(4)
Cross-Country Analysis				
$ln(WB\,Aid_{\text{t-1}})$	-0.0003	0.0306		
	(0.0040)	(0.0217)		
$ln(Chinese\,Aid_{\text{t-2}})$			-0.0023	-0.0050
			(0.0017)	(0.0113)
Kleibergen-Paap under-ID p-val		0.000		0.002
Kleibergen-Paap weak ID F-stat		14.374		10.024
OLS:	Yes	No	Yes	No
IV:	No	Yes	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 OLS/IV coefficients for WB geocoded aid aggregated at the country level. Columns (3) and (4) depict OLS/IV coefficients for Chinese geocoded aid aggregated at the country level. This includes aid, which is coded at least at the ADM1 level (refer to Figure 1). 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. Standard errors in parentheses are clustered at the level of the country. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$ Click here to go back to section 5.7.

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$\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) 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 1). 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. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$ Click here to go back to section 5.7.

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 (2016) 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 whether a region is the capital region or not.

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. We predict aid flows on the regional level via the IV strategy used in the main part of the paper (Table 4). The predicted values are then aggregated on the country level. In order to derive interpretable standard errors, we bootstrap standard errors on the country level clustering on the year and country level based on Stata's boottest command (Roodman et al., 2018). These specifications indicate no significant spill-overs between capital and other regions.

B.5 Mechanisms - Afrobarometer

Table 47: Mechanisms - Afrobarometer

	WB	WB	China	China
Panel A: Security				
Security facilities: Police station present within walking distance?	0.001 (0.003)	0.008* (0.003)	0.002 (0.002)	-0.004*** (0.003)
Security forces: Any policemen or police vehicles?	0.002 (0.002)	0.004 (0.003)	0.001 (0.002)	-0.002 (0.002)
Security forces: Any soldiers or army vehicles?	0.002* (0.001)	0.005*** (0.003)	-0.001 (0.001)	-0.003 (0.002)
Frequency of things stolen in past year?	-0.001 (0.002)	-0.006** (0.002)	0.004* (0.002)	0.004*** (0.002)
Frequency of phsysical attacks in the past year?	-0.000 (0.001)	-0.003*** (0.002)	0.001 (0.001)	-0.000 (0.001)
Panel B: Democratic norms and attitudes				
Democracy: How democratic is your country today?	-0.002 (0.002)	0.003 (0.003)	-0.005* (0.002)	-0.000 (0.003)
Democracy: Did you perceive last elections as free and fair?	-0.003 (0.005)	-0.003 (0.007)	-0.012** (0.004)	-0.012 (0.008)
Governance: Reject one-party rule	0.003 (0.005)	0.013* (0.005)	-0.006 (0.004)	-0.003 (0.006)
Governance: Reject military rule	0.006* (0.003)	0.008* (0.004)	-0.002 (0.003)	-0.001 (0.004)
Governance: Reject one-man rule	0.004* (0.002)	0.006* (0.003)	-0.005* (0.002)	-0.005*** (0.003)
Reject government banning organizations that go against its policies	0.005* (0.002)	0.014** (0.005)	-0.003 (0.003)	0.002 (0.004)
Panel C: Government responsiveness and repression				
Frequency of contact to government official to express your view	0.003* (0.001)	0.003*** (0.002)	-0.001 (0.001)	0.001 (0.001)
Fear of political intimidation or violence during campaigns	-0.001 (0.003)	-0.008*** (0.004)	0.003 (0.003)	0.011** (0.003)
How often do people have to be careful about what they say in politics?	0.000 (0.002)	-0.005 (0.004)	0.002 (0.002)	-0.002 (0.003)
Rule of Law: People must obey the law	-0.004* (0.002)	-0.001 (0.003)	0.004** (0.001)	0.007** (0.002)
Frequency of joining others to request government action			-0.006** (0.002)	
Country	Yes	Yes	Yes	Yes
Region	No	Yes	No	Yes
Year	Yes	Yes	Yes	Yes

Notes: Significance levels: * 0.10 ** 0.05 *** 0.01. Click here to go back to section 5.6.

Table 46: Spill-Overs from capital to non-capital- IV (Bootstrapped SE)

	(1)	(2)
Panel A:		
Including Non-GeoCoded Aid		
Conflict in other Region - World Bank	Capital	Non-Capital
$ln(WB\,Aid\,non-Capital_{\text{t-1}})$	0.9583	-0.2338
	(0.7826)	(0.9927)
	[0.4234]	[0.8418]
$ln(WB\,Aid\,Capital_{\text{t-1}})$	-0.4348	-0.3192
	(0.8101)	(1.0030)
	[0.7147]	[0.8124]
N	770	770
Conflict in other Region - China	Capital	Non-Capital
$ln(Chinese\,Aid\,non-Capital_{\text{t-2}})$	-1.8591*	-2.2054
	(1.0580)	(1.5341)
	[0.0881]	[0.2573]
$ln(Chinese\,Aid\,Capital_{\text{t-2}})$	-0.0119	1.0609
	(0.7918)	(1.3948)
	[0.9930]	[0.5195]
N	707	707
Panel B:		
Excluding Non-GeoCoded Aid		
Conflict in other Region - World Bank	Capital	Non-Capital
$ln(WB\,Aid\,non-Capital_{\text{t-1}})$	0.9380	0.5586
	(0.6611)	(0.8175)
	[0.1602]	[0.5265]
$ln(WB\,Aid\,cap_{\text{t-1}})$	-0.3022	-1.1701
	(0.6752)	(0.8172)
	[0.6356]	[0.1361]
N	836	836
Conflict in other Region - China	Capital	Non-Capital
$ln(Chinese\,Aid\,non-Capital_{\text{t-2}})$	0.0579	-0.1535
	(0.4919)	(0.5957)
	[0.9570]	[0.7718]
$ln(Chinese\,Aid\,Capital_{\text{t-2}})$	-0.1861	0.0533
	(0.5168)	(0.4684)
	[0.6757]	[0.9349]
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. 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. Wild-cluster bootstrapped p-values in brackets were obtained via Stata's boottest command (Roodman et al., 2018). * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$ Click here to go back to section 5.7.

B.6 Estimations - Miscellaneous

Estimation approach

Data sets with many zero outcome observations can ask for different estimation approaches (Silva and Tenreyro, 2006). Therefore, we also consider a Poisson Pseudo Maximum Likelihood (PPML) estimator in Table 48. In line with the main findings results are mostly non-significant and have a negative sign if turning statistically significant.[45] Due to the persistent nature of conflicts, the use of lagged dependent variables is a recurring topic in the conflict literature (e.g., Bazzi and Blattman, 2014). Table

$$C_{i,c,t} = \beta_1 A_{i,c,t-1/t-2} + \beta_2 C_{i,c,t-1} + \lambda_c + \tau_t + \delta_i + \lambda_c T + \lambda_c T^2 + X^{Ex}_{i,c,t}\beta_2 + \delta_i T + X^{En}_{i,c,t-2}\beta_3 + \kappa_{c,t} + \epsilon_{i,c,t}, \quad (4)$$

None of the coefficients in Table 49 is positive, stressing the robustness of our main findings.

Although less often considered, the choice of standard error clustering can affect results substantially. Tables 50 and 51, thus, depart from our use of two-way clustering on the country-year and regional level, but only cluster on the region. Despite this adaptation, results ensure us that the insignificant findings are not driven by our choice of standard error clustering.

Table 48: 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. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$ Click here to go back to section 5.7.

[45] A clear caveat is that we can only use year fixed effects with PPML in our setting due to convergence issues. Thus, as results do not differ substantially, we rely in the main part on OLS and instrumental variable estimators.

Table 49: OLS results: Lagged dependent variable

Panel A: WB Aid	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
$ln(World\,Bank\,Aid_{\text{t-1}})$	-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									
$ln(Chinese\,Aid_{\text{t-2}})$	-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. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$ Click here to go back to section 5.7.

Table 50: ADM1 OLS results (Clustering at regional level)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Panel A: WB Aid									
$ln(World\,Bank\,Aid_{\text{t-1}})$	-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									
$ln(Chinese\,Aid_{\text{t-2}})$	-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 × 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: 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. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$ Click here to go back to section 4.1.

Table 51: ADM1 IV (Clustering at Regional Level)

	(1)	(2)
Panel A: WB Aid		
IV Second stage: World Bank		
$ln(World\,Bank\,Aid_{\text{t-1}})$	-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: China		
$ln(Chinese\,Aid_{\text{t-2}})$	-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. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$ Click here to go back to section 4.1.

Definition of aid (Sectors and weighting scheme)

Table 52 reports the OLS/IV estimates corresponding to sectoral aid in Table 5. Although significance is affected the negative signs in the transport and finance sectors are retained.

In order to attribute aid across different localities of a given project, we have to make assumptions. In the main part of this paper we assume an equal distribution across localities. An alternative and plausible assumption would be a weighting scheme according to population size. Tables 53 and 54 implement the alternative measure, indicating that results are not driven by this assumption.

Table 52: 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
$ln(World\,Bank\,Aid_{\text{t-1}})$	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										
$ln(World\,Bank\,Aid_{\text{t-1}})$	-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
$ln(Chinese\,Aid_{\text{t-2}})$	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										
$ln(Chinese\,Aid_{\text{t-2}})$	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: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$ Click here to go back to section 5.3.

Table 53: OLS results: Population Weighted Aid Allocation

Panel A: WB Aid	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
$ln(World\, Bank\, Aid_{\text{t-1}})$	-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									
$ln(Chinese\, Aid_{\text{t-2}})$	-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. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$ Click here to go back to section 3.1.

Table 54: ADM1 IV: Population Weighted Aid Allocation

Panel A: WB Aid	(1)	(2)
IV Second Stage: World Bank		
$ln(World\,Bank\,Aid_{\text{t-1}})$	-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	100.636	88.243
Panel B: Chinese Aid	(1)	(2)
IV Second Stage: China		
$ln(Chinese\,Aid_{\text{t-2}})$	-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	22.527	16.481
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. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$ Click here to go back to section 3.1.

Both donors

Comparing both donors jointly comes at the disadvantage of losing five years of observations for the WB and - linked to this - a reduction of IV strength. Although the coefficients remain largely negative or insignificant in Tables 55 (OLS) and 56 (IV), the effects for the WB becomes less negative. Tables 55 (OLS) and 56 (IV) indicate that this is mostly driven by the different sampling years, rather than attributable to strong interactions between the two donors.It is important to see in Table 56 that the respective first stages for both donors become weaker when trying to estimate them simultaneously, but the exogenous instruments remains significant for the respective donor (column 2). This further supports that the interaction terms capture a specific variation linked to the allocation process of the two donors, instead of general trends or conflict patterns in the receiving regions. Still, the K-P F-statistics of 3.5 in our preferred specification with country-year FE underlines why we chose to estimate both first stages separately.

Table A57 and Table A58 show that the results also hold when restricting the WB results to the same years data for Chinese aid is available, once for OLS and once for IV.

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

WB & Chinese Aid	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
$ln(World\,Bank\,Aid_{\text{t-1}})$	-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)
$ln(Chinese\,Aid_{\text{t-2}})$	-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. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$ Click here to go back to section 5.1.

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

	(1)	(2)
IV Second stage		
$ln(World\,Bank\,Aid_{\text{t-1}})$	-0.7692	-2.4159
	(1.0994)	(1.7067)
$ln(Chinese\,Aid_{\text{t-2}})$	-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: World Bank		
$IDA\,Position_{\text{t-1}} \times \text{Cum. Prob}_{\text{t-2}}$	57.3141***	63.8098***
	(12.0387)	(24.1928)
$Steel\,Prod\,detrend_{\text{t-3}} \times \text{Cum. Prob}_{\text{t-3}}$	-0.5590	-0.5283
	(4.6845)	(4.3082)
N	7975	7975
IV First stage: China		
$IDA\,Position_{\text{t-1}} \times \text{Cum. Prob}_{\text{t-2}}$	-18.0734*	-9.5155
	(9.3582)	(12.7548)
$Steel\,Prod\,detrend_{\text{t-3}} \times \text{Cum. Prob}_{\text{t-3}}$	-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. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$ Click here to go back to section 5.1.

Table 57: OLS results: (WB Aid - Same Years as Chinese Aid)

Panel A: WB Aid	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
$ln(World\,Bank\,Aid_{t\text{-}1})$	-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									
$ln(Chinese\,Aid_{t\text{-}2})$	-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 58: ADM1 IV (WB Aid - Same Years as Chinese Aid)

	(1)	(2)
Panel A: WB Aid		
IV Second stage: IDA Position		
$ln(World\,Bank\,Aid_{\text{t-1}})$	-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: World Bank		
$IDA\,Position_{\text{t-1}} \times \text{Cum. Prob}_{\text{t-2}}$	57.2759***	63.9080***
	(12.0429)	(24.2241)
N	7975	7975
Panel B: Chinese Aid		
IV Second Stage: China		
$ln(Chinese\,Aid_{\text{t-2}})$	-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	22.394	16.402
IV First stage: China		
$\text{Steel Prod detrend}_{\text{t-3}} \times \text{Cum. Prob}_{\text{t-3}}$	-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: 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. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$